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Ana María Paez-Trujillo

AN OPTIMISATION FRAMEWORK FOR PLANNING DROUGHT MANAGEMENT MEASURES

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DISSERTATION

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and
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by

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An expert is a person who has found out by his own painful experience all the mistakes that one can make in a very narrow field.

Niels Bohr

To the memory of Clara, Ana Lucía, Bernardo,

Béatriz and Lilia

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SUMMARY

Droughts trigger various pervasive effects on society, the environment and the economy. Drought-associated societal impacts include food insecurity, malnutrition, chronic respiratory illnesses, and increased social conflict (UNDRR, 2021). Regarding environmental damage, droughts can lead to overexploitation of forests, ponds, riverbanks and groundwater and biodiversity loss (FAO, 2017b; UNDRR, 2021). For the economy, it is estimated that droughts cause 84% of the agriculture sector's total economic damage and losses (FAO, 2015, 2020) and bring critical losses to economic sectors such as power generation, commercial shipping and tourism (UNDRR, 2021; Van Vliet et al., 2016).

Accordingly, there is a pressing need to take actions contributing to the transition towards drought-resilient societies and ecosystems. Implementing Preventive Drought Management Measures (PDMM) arises as a suitable strategy to reduce social and economic vulnerability to droughts (FAO, 2019; Sayers et al., 2017; H. Wang & Asefa, 2019; World Bank, 2019). These measures aim to reduce social, environmental and economic vulnerability to droughts (FAO, 2019; Sayers et al., 2017). PDMM can be classified into two main categories: short-term and long-term actions; within both types, there are technical and regulatory measures (Assimacopoulos et al., 2015; Sayers et al., 2017). They are developed and applied before the drought occurs (Bressers et al., 2013).

The consistent application of PDMMs has the potential to reduce the negative impact of droughts on society, the environment and the economy (Global Water Partnership Central and Eastern Europe, 2015; Wilhite, 2016). However, the actual contribution of PDMMs to drought mitigation or alleviation still needs to be determined. Overall, PDMMs applied to local initiatives are rarely part of a structured drought management plan. Consequently, measures are not appropriately informed by knowledge of the region's drought likelihood and possible impacts on the basin's hydrology. Moreover, selecting and allocating PDMMs poses multiple challenges yet to be addressed. For instance, in a given region, there is a collection of measures, sites, scales and potential configurations suitable for drought management.

In this context, the main objectives of this research are to identify drought-prone areas and the hydroclimatic parameters influencing the severity of agricultural and hydrological droughts, identify long-term structural and non-structural interventions (potential PDMMs) applicable to drought management and develop a multi-objective optimisation engine to determine the near-optimal allocation of PDMMs that reduce the severity of agricultural and hydrological droughts.

To realise these objectives, we first introduce a methodology that assesses the non-linear relationship between climate, basin processes and drought severity to identify the drivers

of droughts at a basin scale. The method combines hydrological modelling and a machine learning tool. It provides relevant information about the interplay between the hydroclimatic factors influencing drought severity and determines the most exposed areas to drought events.

Subsequently, the process of assessing potential interventions suitable for drought management is addressed in two distinct stages. The initial stage involves a qualitative assessment, represented by the literature review on strategic drought management, with a specific emphasis on PDDMs. In this stage, we employ modelling, field studies, and knowledge products to document previous experiences analysing or implementing hydrological-based PDMMs. The review results in an extensive compilation of interventions designed to optimise water use across the land and water phases of the hydrological cycle.

Then, we present a quantitative evaluation of PDDMs' performance in alleviating droughts. First, we examine the efficacy of three specifically chosen PDMMs—rainwater harvesting ponds, forest conservation, and check dams—in mitigating the severity of agricultural and hydrological droughts. Further, we advance this analysis by employing an optimisation engine to automatically formulate numerous management scenarios, encompassing diverse combinations of PDMMs. The most relevant scenarios are selected, and the combined impact of PDMMs on agricultural and hydrological drought severity is evaluated.

This dissertation provides three main scientific contributions. The study contributes to a better understanding of the hydroclimatic parameters influencing the severity of droughts by applying a methodology that allows identifying the multiple drivers of droughts, isolating their influence on the severity of agricultural and hydrological droughts and defining the most exposed areas to these two types of droughts. Moreover, it introduces a systematic approach to strategic drought management that defines plausible management scenarios grounded in a comprehensive understanding of the region's specific drought drivers and characteristics. This approach enables the formulation of long-term management strategies to mitigate the severity of different types of droughts. Lastly, this thesis can be seen as an effort to develop hybrid tools that combine physics, data-based models, and expert knowledge to analyse and reduce the chance of droughts and prevent persistent water shortages resulting from a pronounced imbalance between water supply and demand

SAMENVATTING

Droogte heeft diverse ingrijpende gevolgen voor de samenleving, het milieu en de economie. Maatschappelijke gevolgen van droogte zijn onder meer voedselonzekerheid, ondervoeding, chronische ademhalingsziekten en meer sociale conflicten (UNDRR, 2021). Wat de milieuschade betreft, kan droogte leiden tot overexploitatie van bossen, vijvers, rivieroevers en grondwater en verlies van biodiversiteit (FAO, 2017b; UNDRR, 2021). Voor de economie wordt geschat dat droogte 84% van de totale economische schade en verliezen van de landbouwsector veroorzaakt (FAO, 2015, 2020) en kritieke verliezen met zich meebrengt voor economische sectoren zoals elektriciteitsopwekking, commerciële scheepvaart en toerisme (UNDRR, 2021; Van Vliet et al., 2016).

Bijgevolg is er dringend behoefte aan maatregelen die bijdragen tot de overgang naar droogtebestendige samenlevingen en ecosystemen. Het implementeren van preventieve beheersmaatregelen voor droogte (PDMM) komt naar voren als een geschikte strategie om de sociale en economische kwetsbaarheid voor droogte te verminderen (FAO, 2019; Sayers et al., 2017; H. Wang & Asefa, 2019; World Bank, 2019). Deze maatregelen zijn erop gericht om de sociale, ecologische en economische kwetsbaarheid voor droogte te verminderen (FAO, 2019; Sayers et al., 2017). PDMM kan worden ingedeeld in twee hoofdcategorieën: kortetermijn- en langetermijnmaatregelen; binnen beide typen zijn er technische en regelgevende maatregelen (Assimacopoulos et al., 2015; Sayers et al., 2017). Ze worden ontwikkeld en toegepast voordat de droogte optreedt (Bressers et al., 2013).

De consistente toepassing van PDMMs heeft het potentieel om de negatieve gevolgen van droogte voor de samenleving, het milieu en de economie te verminderen (Global Water Partnership Central and Eastern Europe, 2015; Wilhite, 2016). De werkelijke bijdrage van PDMMs aan de beperking of verlichting van droogte moet echter nog worden vastgesteld. Over het algemeen maken PDMMs die worden toegepast op lokale initiatieven zelden deel uit van een gestructureerd plan voor droogtebeheer. Bijgevolg worden de maatregelen niet goed onderbouwd met kennis over de waarschijnlijkheid van droogte in de regio en mogelijke gevolgen voor de hydrologie van het stroomgebied. Bovendien bevat de selectie en toewijzing van PDMMs meerdere uitdagingen die nog moeten worden aangepakt. Bijvoorbeeld, in een bepaalde regio is er een verzameling maatregelen, locaties, schalen en potentiële configuraties die geschikt zijn voor droogtebeheer.

In deze context zijn de belangrijkste doelstellingen van dit onderzoek het identificeren van droogtegevoelige gebieden en de hydroklimatologische parameters die de ernst van agrarische en hydrologische droogte beïnvloeden, identificeren structurele en niet-structurele langetermijninterventies (potentiële PDMMs) die van toepassing zijn op droogtebeheer en een multi-objectieve optimalisatiemotor ontwikkelen om de bijnaoptimale toewijzing van PDMMs die de ernst van agrarische en hydrologische droogtes verminderen.

Om deze doelstellingen te bereiken, introduceer ik eerst een methode die de niet-lineaire relatie tussen klimaat, stroomgebiedprocessen en de ernst van droogte beoordeelt. De methode combineert hydrologische modellering en een tool voor machinaal leren. Het levert relevante informatie op over de wisselwerking tussen de hydroklimatologische factoren die van invloed zijn op de ernst van droogte en identificeert de gebieden die het meest zijn blootgesteld aan droogtegebeurtenissen.

Vervolgens wordt de beoordeling van potentiële interventies die geschikt zijn voor droogtebeheer in twee verschillende fasen uitgevoerd. De eerste fase omvat een kwalitatieve beoordeling, bestaande uit een literatuuronderzoek naar strategisch droogtebeheer, met de specifieke nadruk op PDDMs. In deze fase gebruik ik modellering, veldstudies en kennisproducten om eerdere ervaringen met het analyseren of implementeren van op hydrologie gebaseerde PDMMs te documenteren. De beoordeling resulteert in een uitgebreide compilatie van interventies ontworpen om watergebruik door het land en water fasen van de hydrologische cyclus te optimaliseren.

Vervolgens presenteer ik een kwantitatieve evaluatie van de prestaties van PDDM's bij het verlichten van droogte. Eerst onderzoek ik de effectiviteit van drie specifiek gekozen PDDMs—regenwatervijvers, bosbehoud en dammen— bij het verminderen van de ernst van agrarische en hydrologische droogte. Daarnaast ga ik verder met deze analyse door gebruik te maken van een optimalisatie engine om automatisch duizenden beheerscenario's te formuleren, die verschillende combinaties van PDMMs omvatten. De meest relevante scenario's worden geselecteerd en het gecombineerde effect van PDMMs op de ernst van droogte in landbouw en hydrologie wordt geëvalueerd.

Dit proefschrift levert drie belangrijke wetenschappelijke bijdragen. Het onderzoek draagt bij aan een beter begrip van de hydroklimatologische parameters die de ernst van agrarische en hydrologische droogtes beïnvloeden door een methodologie toe te passen die het mogelijk maakt om de meerdere oorzaken van droogte te identificeren, hun invloed op de ernst van agrarische en hydrologische droogte te isoleren en om de gebieden die het meest zijn blootgesteld aan deze twee soorten droogte te definiëren. Bovendien wordt een systematische aanpak van strategisch droogtebeheer geïntroduceerd die plausibele beheersscenario's definieert op basis van een alomvattend begrip van de specifieke oorzaken en kenmerken van droogte in de regio. Met deze aanpak kunnen langetermijnbeheerstrategieën worden geformuleerd om de ernst van verschillende typen droogte te verminderen. Tot slot kan dit proefschrift worden gezien als een poging om hybride instrumenten te ontwikkelen die natuurkunde, op gegevens gebaseerde modellen en kennis van experts combineren om de kans op droogte te analyseren en te verkleinen en aanhoudende watertekorten te voorkomen die het gevolg zijn van een uitgesproken onbalans tussen vraag en aanbod van water.

CONTENTS

1 INTRODUCCION

1.1 BACKGROUND

Projections indicate that drought frequency, severity and duration are expected to increase globally in the twenty-first century, affecting almost all societal and environmental dimensions (Madruga De Brito & Pacheco, 2021; UNDRR, 2021). Drought-associated societal impacts include food price volatility, food insecurity, a broad range of public health problems (e.g., malnutrition, waterborne, vector-borne, airborne diseases and mental health issues), limitation of public water supply, and increased social conflict (FAO, 2020; Stahl et al., 2016; Stanke et al., 2013). Further, the intensification of drought characteristics (in combination with other factors) could force the migration of up to 216 million people by 2050 (Clement et al., 2021). In terms of environmental damage, droughts can lead to overexploitation of forests and groundwater, tree mortality, and increased disease in wild animals and endangered species, among other impacts on ecosystems (UNDRR, 2021; Vicente-Serrano et al., 2020). For the economy and industry, it is estimated that moderate to extreme droughts reduce the gross domestic product by between 0.39 and 0.85 percentage points, depending on the country's development stage and baseline climatic conditions (Zaveri et al., 2023). Droughts are estimated to cause 84% of the agriculture sector's total economic damage (FAO, 2020) and bring critical losses to power generation, commercial shipping and tourism (Van Vliet et al., 2016; Vogt et al., 2018).

The traditional approach to drought management has been reactive, primarily focused on mitigating the ongoing adverse effects of droughts (Global Water Partnership Central and Eastern Europe, 2015; Mapedza & McLeman, 2019; Wilhite, 2016). However, climatic projections anticipating more frequent and severe droughts and the associated pervasive effects point to the pressing need for developing drought management plans which respond to a proactive approach; that is to say, drought management that recognises drought planning as a permanent and continuing need (Duel et al., 2022; FAO, 2019; Sayers et al., 2017), not a reactive intervention to minimise the consequences specific drought events.

Proactive drought management aims to create resistance and resilience to droughts, minimising negative impacts in advance (Tsegai et al., 2018). This approach relies on three pillars: 1) drought monitoring and early warning, 2) drought vulnerability and impact assessment, and 3) drought mitigation and preparedness and response (Wilhite, 2019). Advantages of proactive drought management include wise stewardship of natural resources, more efficient investment of financial resources, and reduced conflicts between water users (Tsegai et al., 2018).

Particularly, the third pillar of proactive drought management refers to measures to mitigate the potential negative of droughts and prepare to respond to drought more effectively (Wilhite, 2019). These measures can be grouped into four categories according to their purpose: preventive or strategic, operational, organisational and restoration (Global Water Partnership Central and Eastern Europe, 2015). They vary from interventions at the field level applied before the drought occurs to negotiated global compensation for damage to land due to droughts (Assimacopoulos et al., 2015; King-Okumu, 2021a; World Bank, 2019). This thesis analyses preventive drought management measures (PDMMs) applied at the basin level. PDMMs are developed before the drought occurs and work with natural processes alongside structural and non-structural solutions to minimise short-term and long-term drought consequences (Sayers et al., 2017).

At the basin level, PDMMs encompass a variety of management actions for different land use types (King-Okumu, 2021a; Sanz et al., 2017; UNCCD, 2019). Interventions include: for water bodies floodplains and wetlands restoration, for croplands soil conservation and best management practices (terracing, mulching, cover crops), water harvesting and recharge, for forest and woodlands conservation and reforestation and agroforestry, and agropastoralism for mix land uses.

1.2 MOTIVATION

Preventive Drought Management Measures (PDMMs) application in a consistent way has the potential to limit the negative impact of droughts on society, the environment and the economy (Global Water Partnership Central and Eastern Europe, 2015; Wilhite, 2016). However, the actual contribution of PDMMs to drought mitigation or alleviation still needs to be determined.

Overall, PDMMs applied to local initiatives are rarely part of a structured drought management plan. Consequently, measures are not appropriately informed by knowledge of the region's drought likelihood and possible impacts on the hydrological cycle (Islam et al., 2019; UNDRR, 2021). Additionally, there is very little coordination to guarantee their operation in the long term; in consequence, PDMMs' performance for drought mitigation is hardly ever assessed.

Only a few modelling studies have presented a quantitative assessment of the PDMMs' performance in alleviating droughts. Querner et al. (2001) used the transient model SIMGRO to evaluate the impact of modifying land drainage on hydrological and groundwater drought. The authors found that raising the water levels in the primary watercourses and raising the beds of the small watercourses mitigate groundwater droughts but intensify streamflow droughts in terms of duration and discharge deficits. Assimacopoulos et al. (2015) presented a quantitative assessment of interventions for drought risk mitigation measures such as the construction of cisterns, groundwater recharge with treated wastewater and wetland management.

Assessment of potential PDMMs performance mainly relies on their effectiveness in increasing infiltration and water availability, improving soil water-holding capacity and preventing land degradation or desertification (Basche, 2017; King-Okumu, 2021a; Oweis et al., 2012; Sanz et al., 2017; UNCCD, 2019; Wambura et al., 2018; WWAP, 2018; Yadav et al., 2018). While these criteria provide relevant insights into the measures' applicability for drought management, they do not explicitly appraise their effectiveness in alleviating drought's characteristics (e.g., duration, spatial extent, severity) and the measures' contribution to drought alleviation is not explicitly appraised. As such, the actual contribution of PDMMs to drought mitigation is still to be determined. Additionally, there is a lack of assessments that directly link the implementation of drought adaptation strategies and their effectiveness in creating resistance or resilience to droughts (Hagenlocher et al., 2019).

Moreover, selecting and allocating PDMMs poses multiple challenges that still need to be addressed. In a given region, there is a collection of multiple measures, sites, scales and potential configurations suitable for drought management. Further, measures appropriate for agricultural drought management may exacerbate hydrological drought conditions (and vice versa). Of equal importance, implemented actions may lessen the drought in the targeted area while aggravating it downstream or in adjacent areas.

Equally important, there is a pressing need to develop drought management strategies to alleviate or minimise drought-associated damages. In practice, drought adaptation mainly occurs in two directions: 1) individual actions made by farmers and communities whose day-to-day life is impacted by the adverse effects of droughts, and 2) crisis recovery actions taken by governments focus on ameliorate negative impacts after the drought emergencies occur (Mapedza & McLeman, 2019; UNDRR, 2021). In contrast, drought management that recognises drought planning as a permanent and continuing need, proactive drought management, is rare (Kreibich et al., 2022). Moreover, there is a lack of assessments that directly link the implementation of drought adaptation strategies and their effectiveness in creating resistance or resilience to droughts (Hagenlocher et al., 2019). Thus, the study of adaptation measures aiming to mitigate the potential negative of droughts and prepare to respond to drought more effectively, along with systematic optimisation of such measures, remains to be developed, and this motivativates the main topic of this study.

1.3 RESEARCH OBJECTIVES

The general objective of this dissertation is *to develop an optimisation framework to identify near-optimal allocation of preventive drought management measures informed by a comprehensive understanding of the drought drivers and characteristics in the study areas.*

To realise this aim, we formulate the following specific objectives:

1. Formulate a model-based methodology to identify the hydroclimatic parameters (climate and basin processes) driving the severity of agricultural and hydrological droughts at the basin scale.
2. Identify long-term structural and non-structural interventions (potential PDMMs) applicable to agricultural and hydrological drought management and the parameters to represent the interventions in a hydrological model.
3. Develop a methodology integrating a conceptual hydrological model and multi-objective optimisation to identify near-optimal allocation of PDMMs that contribute to reducing the severity of agricultural and hydrological droughts at the basin level.
4. Utilise the optimisation results (drought management scenarios) to estimate the effect of PDMMs on the severity of agricultural and hydrological droughts.

1.4 RESEARCH QUESTIONS

Considering the research objectives, we formulate the following research questions:

1. How can conceptual and data-driven models be used to assess the interplay between the drivers of droughts and the severity of these events at the basin scale?
2. What are the long-term structural and non-structural PDMMs applicable for agricultural and hydrological drought management?
3. How to represent the PDMMs in a modelling system?
4. How to formulate and solve the problem of selecting and allocating PDMMs as a multi-objective optimisation problem?
5. How can the optimisation results be interpreted and used to estimate the impact of PDMMs on the severity of agricultural and hydrological droughts.

1.5 SCIENTIFIC RELEVANCE

Drought-generating process Effective drought management requires an adequate understating of the drought-generating process and the hydroclimatic parameters influencing the characteristics of droughts (King-Okumu, 2021a). The study contributes to a better understanding of the hydroclimatic parameters influencing the severity of agricultural and hydrological droughts by applying a methodology that allows identifying the multiple drivers of droughts, isolating their influence on the severity of agricultural and hydrological droughts and defining the most exposed areas to these two types of droughts.

Drought management and decision-making This research contributes to drought management planning in multiple ways. Firstly, it introduces a systematic approach to strategic drought management that defines plausible management scenarios grounded in a comprehensive understanding of the region's specific drought drivers and characteristics. Secondly, by framing the selection and allocation of PDMMs as an optimisation problem, the study facilitates the analysis of the trade-offs inherent in managing both agricultural and hydrological droughts. This approach enables the formulation of long-term management strategies to mitigate the severity of both types of droughts. Third, in the context of proactive drought management, the optimisation engine developed in this study serves as a decision support tool. Its application empowers drought managers to make well-informed decisions and minimise the detrimental consequences associated with drought events. Lastly, it is noteworthy that the practical application of the methods proposed in this research is developed in South America, a region considerably underrepresented in the academic literature on drought analysis and mitigation.

Combining process-based and data-driven models in hydrological science Nearing et al.(2021) posed the existential question about hydrological science's role in the machine learning age. In addition, the authors raised their concerns about the hydrological community's resistance towards adopting data-driven approaches in a structured and fundamental way. We believe that in the age of machine learning (and a warmer and more populated world with more climatic extremes), hydrological science must embrace multiple approaches and sources of information. This necessity arises not merely for preserving hydrological science as an independent discipline but, more critically, to actively contribute to solving the challenge of optimising water resource utilisation. This thesis can be seen as an effort to develop hybrid tools that combine physics, data-based models, and expert knowledge to analyse and reduce the chance of droughts and prevent persistent water shortage because of the pronounced imbalance between water supply and demand.

1.6 OUTILINE

Given the research motivation, objectives, research questions, and scientific relevance already presented, this dissertation is structured in seven chapters. After this introductory section, the next six chapters are organised as follows:

Chapter 2 presents the theoretical background of the research. The chapter describes concepts and existing theories to underpin the development of this research. The theoretical background of this study includes 1) a description of the hydrological model used to simulate the basin hydrology, 2) drought basic definitions, main drivers, characterisation and management, 3) a description of the data-driven model employed in this research and 4) description of the optimisation algorithm used in the study. Lastly, a general description of the methodology is introduced to provide the overall picture of the methodological phases applied to achieve the research objectives.

Chapter 3 describes the study areas selected to test the methods developed in this thesis. The Torola River basin is located within the Central America Dry Corridor, and the Cesar River basin is located in Colombia (South America). Chapter 3 describes the basins' geography, climate, land use, soils and drought sensitivity.

Chapter 4 applies hydrological modelling and a machine learning tool to assess the relationship between hydroclimatic characteristics and the severity of agricultural and hydrological droughts. The Soil Water Assessment Tool is used for hydrological modelling. Model outputs, soil moisture and streamflow, are used to calculate two drought indices, namely the Soil Moisture Deficit Index and the Standardized Streamflow Index. Then, drought indices are utilised to identify the agricultural and hydrological drought events during the analysis period, and the index categories are employed to describe their severity. Finally, the multivariate regression tree (machine learning technique) is applied to assess the relationship between hydroclimatic characteristics and the severity of agricultural and hydrological droughts. A concrete application of this methodology is developed in the Cesar River basin (Colombia).

Chapter 5 evaluates the effects of three potential PDMMs on agricultural and hydrological drought severity: rainwater harvesting ponds, forest conservation, and check dams. The Soil Water Assessment Tool is used for hydrological modelling and representing PDMMs. The threshold level method is applied to analyse droughts and evaluate the impact of PDMMs on drought severity. The analysis is developed in the Torola River Basin (El Salvador).

Chapter 6 introduces an optimisation approach to allocate interventions to reduce the severity of agricultural and hydrological droughts. To this aim, an optimisation engine integrating the Soil Water Assessment Tool modelling system and the Unified Evolutionary Algorithm for Single, Multiple, and Many-Objective Optimisation.

Chapter 7 examines the research findings in the light of the research questions. This section details the insights derived from applying the proposed modelling framework and delineates its advantages and constraints. Additionally, the chapter offers a forward-looking perspective, proposing potential opportunities for future research. The chapter concludes with the outlook of the research

2 THEORETICAL BACKGROUND AND GENERAL METHODOLOGY

2.1 INTRODUCTION

This chapter presents the definitions and methods applied in this research. Firstly, Section 2.2 details the hydrological model used in the research. Section 2.3 offers an overview of key drought concepts, including definition, different types of droughts and generating process. Further, the section describes the most common approaches to analysing drought events quantitatively. Section 2.4 provides a description of strategic drought management and preventive drought management measures. Sections 2.5 and 2.6 describe the application of machine learning and metaheuristics optimisation for water management and the use of these techniques within the context of this study. Section 2.7 details the study's methodological phases, describing the methodology's components and how they are related. This section aims to provide clarity on the rationale behind each methodological choice. Finally, the concluding remarks are presented in Section 2.8. When applying the concepts to a specific case, we will give the definitions within the context of the respective chapter.

2.2 HYDROLOGICAL MODELING

A hydrological model is an input-output model that simulates the change of water storage, water fluxes, and potentially associated chemical and physical properties at the land surface and subsurface, applying the water balance equation (Horton et al., 2022). According to the conceptualisation of the basic processes, hydrological models are classified as empirical, conceptual and physically based. Empirical models take only the information from the existing data with little or no attempt to apply the knowledge of the physical processes involved (e.g. unit hydrograph). Conceptual models describe all of the component hydrological processes, but the processes are represented using algebraic equations as opposed to primarily partial differential equations in the physically-based models. The physically based model is the approach that provides the most accurate representation of basin hydrology (Devia et al., 2015; Sahu et al., 2023). These types of models use state variables which are measurable and vary in time and space. Partial differential equations represent the water movement throughout the hydrological cycle, and they are solved by one of the numerical schemes. In this study, we use the conceptual model Soil and Water Assessment Tool (SWAT) model.

2.2.1 SWAT model

SWAT is the acronym for Soil and Water Assessment Tool, a basin model developed by the Agricultural Research Service of the United States Department of Agriculture (ARS-USDA) (Arnold et al., 2012). SWAT is a conceptual model, continuous-time, semi-distributed, river-watershed-scale model designed to simulate the quality and quantity of surface and groundwater and predict the environmental impacts of land use, land management, and climate change (Neitsch et al., 2011). The entire basin area up to the selected outlet point is divided into subbasins. Each subbasin is further divided into a number of hydrological response units (HRUs), which are land areas within the subbasin with common combinations of land cover, soil type, and slope (Arnold et al., 2012).

Using daily rainfall data, maximum and minimum temperature, solar radiation, humidity and wind speed, the model simulates water and sediment circulation, vegetation growth and nutrient circulation (Arnold et al., 2012). The hydrological cycle is simulated using the water balance equation (Equation (2.1)):

$$SW_t = SW_O + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right), \tag{2.1}$$

where, SW_t is the final soil water content (mm); t is the time (days); SW_O is the initial water content (mm); R_{day} is the amount of precipitation on day i (mm); Q_{surf} is the amount of surface runoff on day i (mm); E_a is the amount of evapotranspiration on day i (mm); W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm); Q_{gw}: the amount of return flow on day i (mm). Surface runoff refers to the portion of rainwater that is not lost to interception, infiltration, and evapotranspiration; surface runoff occurs whenever the precipitation rate exceeds the infiltration rate.

The methods used in SWAT to simulate the major processes of water movement in a basin (water balance components) are presented below. Further information on these methods and other simulated processes in SWAT can be found in (Neitsch et al., 2011).

Surface runoff

SWAT provides two methods for simulating surface runoff: the SCS curve number method (Soil Conservation Service, 1972) and the Green & Ampt infiltration method (Heber Green & Ampt, 1911). This study applies the SCS curve number method, Equation (2.2).

$$Q_{surf} = \frac{\left(R_{day} - I_a\right)^2}{\left(R_{day} - I_a + S\right)} \tag{2.2}$$

where, Q_{surf} is the accumulated runoff or rainfall excess (mm H_2O), R_{day} is the rainfall depth for the day (mm H_2O), I_a is the initial abstractions which include surface storage, interception and infiltration prior to runoff (mm H_2O), S and is the retention parameter (mm H_2O).

Potential evapotranspiration

In SWAT, three methods are incorporated to estimate potential evapotranspiration: Penman-Monteith (Monteith, 1965), Priestley-Taylor (Priestley & Taylor, 1972), and Hargreaves (Hargreaves & Samani, 1985). This study applies the Hargreaves method, Equation (2.3).

$$\lambda E_0 = 0.0023 \times H_0 \times (T_{mx} - T_{mn})^{0.5} \times (\bar{T}_{av} + 17.8), \tag{2.3}$$

where, λ is the latent heat of vaporization (MJ kg^{-1}), E_0 is the potential evapotranspiration (mmd^{-1}), H_0 is the extraterrestrial radiation (MJ $m^{-2}d^{-1}$), T_{mx} is the maximum air temperature for a given day (°C), T_{mn} is the minimum air temperature for a given day (°C), and $\bar{T}_{av}$ is the mean air temperature for a given day (°C).

Water routing

In SWAT, water is routed through the channel network using the variable storage routing (Williams, 1969) (used in this study) or the Muskingum river routing (Brakensiek, 1967; Overton, 1966) methods. For a given reach segment, storage routing is based on the Equation (2.4):

$$V_{in} - V_{out} = \Delta V_{stored}, \tag{2.4}$$

where, V_n is the volume of inflow during the time step (mm^3 H_2O), V_{out} is the volume of outflow during the time step (mm^3 H_2O), and ΔV_{stored} is the change in the volume of storage during the time step (mm^3 H_2O).

2.2.2 SWAT model calibration and validation

We use the SWAT-CUP software package with Sequential Uncertainty Fitting version 2 (SUFI-2) for automatic model calibration and validation. SUFI-2 operates by performing several iterations. The calibration parameters are sampled in each iteration using the Latin hypercube technique against the objective function values (Abbaspour et al., 2018). The model's performance for simulating streamflow is evaluated using the Nash-Sutcliffe Efficiency (NSE) and percent bias (PBIAS), represented by (2.5) and (2.6) respectively:

$$NSE = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2}, \tag{2.5}$$

$$PBIAS = \frac{\sum_{i=1}^{N}(O_i - P_i) \times 100}{\sum_{i=1}^{N} O_i}, \tag{2.6}$$

where O_i is the observed data, P_i the predicted data, $\bar{O}$ the mean of the observed data and N the number of observations during the simulation period.

The NSE is a dimensionless indicator ranging from -∞ to 1, with 1 representing a perfect match between the observed and simulated values (Moriasi et al., 2007). The PBIAS measures the average tendency of the simulated values to be larger or smaller than the observed values. The ideal PBIAS is 0, with low-magnitude values indicating accurate model simulation (Moriasi et al., 2007).

2.3 Drought analysis

2.3.1 Definitions and main drivers

This study uses the definition of drought introduced by Wilhite and Glantz (1985): "*drought is defined as a lack of water compared to normal conditions which can occur in different components of the hydrological cycle*".

Traditionally, droughts are grouped into four categories: meteorological, agricultural, hydrologic, and socio-economic droughts. Meteorological drought is defined as a deficit of precipitation over a region for a period. Agricultural drought refers to insufficient soil moisture in the root zone to compensate for evapotranspiration losses. Hydrological drought refers to below-normal surface water levels (e.g., rivers, reservoirs, lakes). Lastly, socio-economic drought is associated with the impacts of the types mentioned above and occurs when the water demand of a sector (e.g., domestic, agriculture, industry) fails to be met (Iglesias, Assimacopoulos, & Van Lanen, 2018; H. Wang & Asefa, 2019). In a more recent classification of droughts, categorisation based on natural processes is integrated with drought classes based on human-related processes. Accordingly, the natural drought types can be clustered as "climate-induced" droughts and the types related to human processes are called "human-induced" (Van Loon et al., 2016). The term "anthropogenic drought" is posed for a drought strengthened due to human-related processes (AghaKouchak et al., 2021).

Drought occurs due to climatic extremes, which may be enhanced or alleviated by region characteristics (Hao et al., 2022; Seneviratne et al., 2012; Tijdeman et al., 2018). Usually, droughts are caused by weather systems and atmospheric circulation working together to produce either lower-than-normal precipitation or higher-than-normal evaporation in a particular area (Destouni & Verrot, 2014; Sheffield & Wood, 2011a). Insufficient precipitation or high evapotranspiration results in diminished soil moisture, leading to agricultural drought. When there is a notable depletion of soil moisture, replenishment occurs during the wet season. However, this process contributes to reduced subsurface flow and groundwater recharge, giving rise to hydrological drought (Iglesias, Assimacopoulos, & Van Lanen, 2018). Regional characteristics such as soil type, elevation, slope, vegetation cover, drainage networks, water bodies and groundwater systems play a relevant role in response to the climate anomalies that affect drought propagation and contribute to different levels of agricultural and hydrological drought (Sheffield & Wood, 2011a; X. Zhang et al., 2022). In addition, anthropogenic influence in the hydrological cycle can potentially exacerbate drought conditions. Interventions such as reservoir construction, water diversion, deforestation, excessive groundwater extraction, overgrazing, and urbanisation can diminish water supplies, potentially triggering or intensifying drought events (Rangecroft et al., 2019; M. Wang et al., 2021).

2.3.2 Drought characterisation

Developing drought management requires an adequate characterisation of the drought events. Accordingly, two different approaches are utilised to analyse drought events quantitatively. The first is the threshold level method (TLM), which characterises droughts throughout the time series of a variable of interest (e.g., precipitation, soil moisture streamflow) and the definition of a truncation level (Van Huijgevoort et al., 2012). The second one comprises the drought indices, numerical representations of drought severity resulting from aggregating one or more hydrological variables (Hao & Singh, 2015; Keyantash & Dracup, 2002).

The main difference between the two methods is that the TLM relies on the original time series and the indices in the normalised variates. This allows the TLM to quantify the actual water deficit; therefore, the method is a practical approach to managing water resources locally (de Matos Brandão Raposo et al., 2023). On the other hand, using standardised indices allows the assessment of drought dynamics in distinct catchments and climates (Rivera et al., 2018; Teutschbein et al., 2022). In the following, we describe these two approaches.

Treshold level method

The TLM is a method to analyse droughts in terms of their characteristics (e.g., duration, intensity, volume deficit, and affected area) (Yevjevich, 1967). Per this methodology, a drought is a sequence of intervals (days, weeks, months) in which a variable of interest (e.g., precipitation, soil moisture, or streamflow) remains below a set threshold (τ) (Van

Huijgevoort et al., 2012). Generally, the threshold lies between the variable distribution's fifth and thirtieth percentiles (Herrera-Estrada et al., 2017; Heudorfer & Stahl, 2017; Van Lanen et al., 2013).

Chapters 5 and 6 apply the TLM to analyse agricultural and hydrological droughts. The simulated soil moisture and streamflow at each subbasin (obtained from the hydrological models of the areas of study) are used to represent agricultural and hydrological droughts and compute the drought thresholds. The hydrological models of the study areas do not include the parametrisation of any PDMM, and their results are considered the study's baseline scenario.

Setting the threshold to identify droughts

This study uses the SWAT model outputs, namely, soil moisture and streamflow, to calculate agricultural and hydrological drought thresholds, respectively. SWAT results obtained at the subbasin level allow us to estimate the drought severity at each subbasin and assess the differential effect of the mitigation measures in upstream and downstream subbasins.

The simulated soil moisture $A_i(t)$ at the subbasin i $(1,2,\ldots,N)$ in the baseline scenario is used to set the monthly agricultural threshold τ_{ij}^{A}, where j $(1,2,\ldots,12)$. The monthly threshold at each subbbasin corresponds to the twentieth percentile of the empirical distribution function of the series $\left(A_{ij1}, A_{ij2}, \ldots A_{ijn}\right)$, where n is the simulation year. Similarly, the simulated streamflow $H_i(t)$ at the subbasin i $(1,2,\ldots,N)$ in the baseline scenario is used to set the monthly hydrological threshold τ_{ij}^{H}, where j $(1,2,\ldots,12)$. The monthly threshold at each subbbasin corresponds to the twentieth percentile of the empirical distribution function of the series $\left(H_{ij1}, H_{ij2}, \ldots H_{ijn}\right)$, where n is the simulation year.

Identifying drought events and calculating the severity

A soil moisture deficit is assumed to occur in a subbasin when the monthly simulated soil moisture $A_i(t)$ remains below the set threshold $\left(A_i(t) < \tau_{ij}^{A}\right)$. Similarly, a streamflow deficit is assumed to happen in a subbasin when the monthly simulated streamflow $H_i(t)$ falls below the set threshold $\left(H_i(t) < \tau_{ij}^{H}\right)$. In both cases, the deficit condition begins when the variable of interest falls below the threshold and continues until it exceeds the threshold again. To prevent considering short periods of soil moisture or streamflow below normal conditions as deficits associated with droughts, the 'below normal' situation in a subbasin (i) must persist for at least two consecutive time steps to be labelled as a deficit. Equations (2.7) and (2.8) indicate the procedure applied to identify agricultural and hydrological deficits at the subbasins during the simulation period:

$$\delta_i^A(t) = \begin{cases} 1 \text{ if } A_i(t) < \tau_{ij}^A \ \textit{and} \ \left(A_i(t-1) < \tau_{ij}^A \ \textit{or} \ A_i(t+1) < \tau_{ij}^A \right) \\ 0 \text{ if } \qquad\qquad\qquad\qquad\qquad\qquad A_i(t) \geq \tau_{ij}^A \end{cases}, \tag{2.7}$$

$$\delta_i^H(t) = \begin{cases} 1 \text{ if } H_i(t) < \tau_{ij}^H \ \textit{and} \ \left(H_i(t-1) < \tau_{ij}^H \ \textit{or} \ H_i(t+1) < \tau_{ij}^H \right) \\ 0 \text{ if } \qquad\qquad\qquad\qquad\qquad\qquad H_i(t) \geq \tau_{ij}^H \end{cases}, \tag{2.8}$$

where $\delta_i^A(t)$ and $\delta_i^H(t)$ are binary variables indicating a deficit state per subbasin at time (t); $A_i(t)$ and $H_i(t)$ represent the soil moisture and the streamflow in the subbasin (i) at time step (t); and τ_{ij}^A and τ_{ij}^H are the set thresholds.

After identifying the subbasins in agricultural and hydrological deficits, the drought events can be determined. A drought (agricultural or hydrological) event is assumed to occur in the basin when a number of subbasins (covering at least 30 % of the basin's total area) is in a soil moisture or streamflow deficit for at least two consecutive time steps (in this study we adopt a monthly time step). According to the spatial and temporal conditions applied, a drought event begins when both conditions are met ($t = 1$) and continues until one fails to be met ($t = T$). It is worth highlighting that the minimal extension of a drought is not defined, but it is accepted that droughts typically occur on a large scale (Sheffield & Wood, 2011b). Setting a spatial constraint is a common practice to maintain a minimum drought-affected and prevent identifying isolated areas experiencing dry spells as drought events (Brunner et al., 2021).

The equations (2.9) and (2.10) are applied to calculate the duration of the events identified:

$$A\Delta_k = \sum_{t=1}^{T} \delta_i^A(t) \cdot \Delta t, \tag{2.9}$$

$$H\Delta_k = \sum_{t=1}^{T} \delta_i^H(t) \cdot \Delta t, \tag{2.10}$$

where $A\Delta_k$ is the duration of the agricultural event drought k; $H\Delta_k$ is the duration of the hydrological drought event k; T is the end of the drought event; and Δt is the time step (t) (in this study: 1 month).

Lastly, the agricultural and hydrological drought severity in each subbasin is estimated using Equations (2.11) and (2.12):

$$S_i^A(t) = \begin{cases} \tau_{ij}^A - A_i(t) & \text{if } A_i(t) < \tau_{ij}^A \\ 0 & \text{if } A_i(t) \geq \tau_{ij}^A \end{cases}, \tag{2.11}$$

$$S_i^H(t) = \begin{cases} \tau_{ij}^H - H_i(t) & \text{if } H_i(t) < \tau_{ij}^H \\ 0 & \text{if } H_i(t) \geq \tau_{ij}^H \end{cases}, \tag{2.12}$$

where $S_i^A(t)$ represents the deviation from the threshold τ_{ij}^A (agricultural drought severity) at the subbasin (i) at time step (t) (in mm), and $S_i^H(t)$ represents the deviation from the threshold τ_{ij}^H (hydrological drought severity) at the subbasin (i) at time step (t) (in mm d^{-1}).

Comparison of drought severity between the baseline scenario and the PDMMs scenarios

The drought severity change is evaluated by comparing the severity in the baseline scenario to the severity in the PDMMs scenarios. In Chapter 5, PDMMs scenarios are the three modelling scenarios simulating the selected PDMMs (rainwater harvesting ponds, forest conservation, and check dams). In Chapter 6 the PDMMs scenarios are obtained from the optimisation. Equations (2.13) and (2.14) were employed for this purpose.

$$\Delta S_i^A(t) = \frac{S_i^A(t)_{BL} - S_i^A(t)_{PDMM}}{S_i^A(t)_{BL}} \times 100, \tag{2.13}$$

$$\Delta S_i^H(t) = \frac{S_i^H(t)_{BL} - S_i^H(t)_{PDMM}}{S_i^H(t)_{BL}} \times 100, \tag{2.14}$$

where $\Delta S_i^A(t)$ is the change in agricultural drought severity (%) at the subbasin i at time step t; $\Delta S_i^H(t)$ is the change in hydrological drought severity (%) at the subbasin i at time step t; BL is the baseline scenario; and $PDMM$ are the management scenarios. A positive change reflects a reduction in the severity of the drought relative to the baseline scenario, and a negative value shows an increase in the severity of the drought.

Drought indices

Drought indices are computed numerical representations of drought severity (Hao & Singh, 2015; Keyantash & Dracup, 2002). Per this method, severity refers to the degree of deficit of a hydroclimatic variable (e.g., precipitation, soil moisture, or streamflow) (Cavus & Aksoy, 2020). Generally, severity is divided into different categories (e.g. moderate, severe, extreme), providing a qualitative assessment of the drought state in a region during a given period.

Drought indices (and their categories) are crucial for computing statistics of a particular drought event, the rates of development and recovery and tracking or anticipating drought-related damage and impacts (WMO & GWP, 2016). In the last decades, multiple indices have been proposed; the Handbook of Drought Indicators and Indices contains an exhaustive list of the most commonly used (WMO & GWP, 2016). In Chapter 5, we apply the Soil Moisture Deficit Index to represent agricultural droughts and the Standardised Streamflow Index to represent hydrological droughts.

Soil Moisture Deficit Index

The present study uses the Soil Moisture Deficit Index (SMDI) to analyse agricultural droughts. The SMDI is specifically designed to use simulated soil moisture as the input parameter for its computation (Narasimhan & Srinivasan, 2005).

The computation procedure to determine the soil moisture deficit utilises the long-term soil moisture characteristics and the soil moisture conditions during the drought period. The indicator is scaled between -4 and 4 to allow the comparison with the commonly used Palmer Drought Severity Index (Narasimhan & Srinivasan, 2005). Negative values of SMDI indicate dry periods, while positive values indicate wet periods (compared to the region’s normal conditions). Per the SMDI, agricultural drought severity is divided into three categories: moderate drought (SMDI -2.0 to -2.99), severe drought (SMDI -3.0 to -3.99) and extreme drought (SMDI -4). The following procedure is applied to compute the SMDI at each subbasin:

$$SD_{ij} = \frac{SW_{ij} - MSW_j}{MSW_j - minSW_j} \times 100, \qquad if\ SW_{ij} \leq MSW_j \tag{2.15}$$

$$SD_{ij} = \frac{SW_{ij} - MSW_j}{maxSW_j - MSW_j} \times 100, \qquad if\ SW_{ij} > MSW_j \tag{2.16}$$

where SD_{ij} is the soil moisture deficit (%), SW_{ij} is the monthly soil water available in the soil profile (mm) and MSW_j is the long-term median available soil water in the soil profile (mm), $maxSW_j$ and $minSW_j$ are the maximum and minimum soil water available in the soil profile (mm), ($i = 1987 - 2018\ and\ j = 1 - 12$).

The $SMDI_j$ of any given month is calculated using Equation (2.17):

$$SMDI_j = 0.5 \times SMDI_{j-1} + \frac{SD_j}{50}, \tag{2.17}$$

where $SMDI_{j-1}$ is the SMDI from the previous month.

Standarized Streamflow Index

We use the Standardised Streamflow Index (SSI) to represent hydrological droughts. The indicator was introduced by Modarres (2007) and further investigated by Vicente-Serrano et al. (2011). The index is statically analogous to the commonly used Standardised Precipitation Index (SPI) introduced by Mckee et al. (1993). SSI values mainly range from -2.0 (extremely dry) to 2.0 (extremely wet), and hydrological drought severity is divided into three categories: moderate drought (SSI -1.0 to -1.49), severe drought (SSI -1.5 to -1.99) and extreme drought (SSI -2.0 or less). The procedure to calculate SSI consists of converting streamflow values to standardised anomalies (i.e. z-scores). To this aim, in this study, the monthly simulated streamflow at each subbasin in the analysis period (1987 to 2018) was fitted to the gamma probability distribution function.

2.4 DROUGHT MANAGEMENT: PREVENTIVE DROUGHT MANAGMENT MEASURES

Extensive drought impacts and climate change projections anticipating more frequent and severe droughts worldwide show the pressing need to develop drought management plans (Carrão et al., 2018; Cottrell et al., 2019; Haile et al., 2020; UNCCD, 2022; Vicente-Serrano et al., 2020). Scholarly discourse accentuates the pivotal role of proactive drought management strategies (FAO, 2019; Gerber & Mirzabaev, 2017; Wilhite, 2016). This approach recognises drought planning as a permanent and continuing need, not a reactive intervention, to minimise the consequences of specific drought events. Proactive drought management aims to create resistance and resilience to droughts, minimising negative impacts in advance and relies on three pillars: first, drought monitoring and early warning systems; second, drought risk and vulnerability assessment; and third, drought preparedness and mitigation (Pischke & Stefanski, 2017; Tsegai et al., 2018; Wilhite, 2019).

Particularly, the third pillar of proactive drought management refers to measures to mitigate the potential negative of droughts and enhance the capacity of ecosystems and communities to withstand the impacts of drought more effectively. This comprehensive approach involves a structured program tailored for each drought stage (i.e., normal, pre-alert, alert, and emergency), categorising interventions according to their purpose: preventive or strategic, operational, organisational and restoration (Global Water Partnership Central and Eastern Europe, 2015). These interventions span a spectrum from field-level measures applied before the drought occurs to negotiated global compensation for damage to land due to droughts (Assimacopoulos et al., 2015; King-Okumu, 2021a; World Bank, 2019). They can also be classified into two main categories: short-term actions and long-term actions. Both types consist of technical and regulatory measures (Assimacopoulos et al., 2015; Sayers et al., 2017). This study focuses on long-term PDMMs applied at the basin level.

Table 2.1 presents a list of measures applicable to drought management for different land use types; interventions cover the land and water phases of the hydrological cycle.

Table 2.1. PDMMs applicable for drought management.

Land use	Measure	Main selecetion criteria	Advantages	Limitations	References
Croplands	Rain water harvesting, soil conservati on practices	Rainfall intensity, slope, soil properties, crop characteristi cs	Improves infiltration and soil water holding capacity. Reduces runoff and soil erosion. Minimises direct impact of raindrops on the soil surface. Slows down surface runoff. Minimises degradation of soil structure	High dependency on rainfall. Exposition of the storage systems to evaporation and infiltration	(Alataway & El Alfy, 2019; Filho & de Trincheria Gomez, 2017; Nyagumbo et al., 2019; Wambura et al., 2018; Welderufael et al., 2013)
Water bodies	Water retention measures and floodplains and wetlands restoration	Stream network and flow system, recharge and discharge zones, floodplain land use	Stores and slows runoff and river water. Increases infiltration and\or groundwater recharge	Requires high technical design skills and high costs of implementation and maintenance. Requires land availability and landowners' consent	(Dessie et al., 2014; Fossey and Rousseau, 2016; Martinez-Martinez et al., 2013; Wang et al., 2018.)
Forest	Conservati on, reforestatio n and agroforestr y	Forest conditions, soil degradation stage, plant species, climatic region	Improves infiltration, saturated hydraulic conductivity, and groundwater recharge. Provides a slight buffer in the soil water storage, maintaining the soil moisture during the last days of the dry seasons	Long-term horizon for perceiving results. Applying commercial and exotic tree plantations is suitable only in degraded lands. Water consumption varies according to afforestation age	(Bonnesoeur et al., 2019; Buendia et al., 2016; Krishnaswamy et al., 2018; Nan et al., 2019; Roa-García et al., 2011)

At the basin level, PDMMs encompass multiple management actions for different land use types (C King-Okumu, 2021; Sanz et al., 2017; Sayers et al., 2017; UNCCD, 2019). Interventions include: for croplands, water harvesting and soil conservation practices to capture and concentrate rainfall-runoff and improve soil structure and water holding capacity; for water bodies, natural water retention measures and floodplains and wetlands restoration; for forest and woodlands, conservation, reforestation and agroforestry, and agropastoralism for mix land uses. The measures apply different mechanisms to increase infiltration, groundwater recharge, and soil water holding capacity. We targeted these water stores and fluxes, considering these are the main land surface processes and water stores linked to droughts (Iglesias et al., 2018b).

2.5 MACHINE LEARNING FOR WATER MANAGEMENT

Machine learning (ML) is an advanced analytics method. It is data-driven and requires extensive computing resources. ML is a subset of artificial intelligence that develops algorithms trained on data to create self-learning models capable of making predictions and classifying information (Dhall et al., 2020; Zhou, 2021). The learning algorithms inherent to ML can be categorised into three primary types (Dhall et al., 2020; Sarker, 2021): 1) supervised learning, where there are input and output variables; 2) unsupervised learning using only the input data; and 3) reinforcement learning algorithms that use trial and error to train algorithms and create models. These algorithms are used to perform different types of analysis, such as classification, regression, clustering, and dimensionality reduction, among other tasks (Sarker, 2021).

ML algorithms are currently used in water-related research and have proven to be highly effective in various subfields of hydrology. A prevalent application of data-driven methods has been the development of predictive, empirically-based models of the hydrologic system operating within a catchment (Mount et al., 2016). This application extends to numerous instances, including using ML algorithms to predict flood and streamflow magnitudes at different temporal scales, precipitation, evapotranspiration at different spatiotemporal resolutions, estimating sediment load concentration, and anticipating groundwater levels and quality. A detailed literature review on the application of ML in hydrology was developed by Danish (2022), Mosaffa et al. (2022), and Mount et al. (2016).

Chapter 4 employs a machine learning tool, namely a Multivariate regression tree (MVRT), to assess the non-linear relationship between climate, basin processes and drought severity and identify the drivers of droughts at a basin scale. The characteristics of the algorithm are presented below.

2.5.1 Multivariate regression tree

MVRT is a regression method introduced by De'ath (2002). MVRT is an extension of the popular regression tree (Breiman, 2001), but it differs in that it allows for multiple outputs. It recursively splits a quantitative response variable (predictand, output) controlled by a set of numerical or categorical explanatory variables (predictors, input). The approach yields a non-linear numerical prediction model, being a combination of piece-wise linear regression models (of zero order).

An MVRT result is a tree whose terminal groups (leaves) of instances (input-output vectors) comprise subsets of samples selected to minimise the within-group sums of squares. Each successive split is given by a threshold value of the explanatory variables (Borcard et al., 2018). MVRT is applied to dataset exploration, description and prediction (De'ath, 2002). In this study, the explanatory variables are the hydroclimatic parameters at each subbasin, represented by the average value of each parameter during the analysis period (1987 to 2018). The multivariate response is the number of months observed in the three drought severity categories (moderate, severe and extreme) at each subbasin. The analyses for agricultural and hydrological droughts are conducted separately; thus, two MVRTs are obtained.

The following MVRT attributes are relevant for the analysis presented in Chapter 4. First, MVRT can capture the non-linear interactions between the parameters influencing droughts and their severity. Second, the technique can handle numerical and categorical hydroclimatic parameters influencing drought severity (explanatory variables). Third, MVRT's capability to handle multiple outputs allowed us to evaluate the influence of the hydroclimatic parameters on moderate, severe and extreme drought conditions simultaneously (response variables). Simultaneous analysis of different drought categories provides a comprehensive understanding of the drought-generating process and the factors influencing severe (or mild) drought conditions. Fourth, MVRT results can be easily visualised and interpreted. The resulting tree structure provides a clear representation of the relationship between the drivers of droughts and the severity of agricultural and hydrological droughts.

2.5.2 Building the MVRT: Constrained partitioning of the data and cross-validation

Building the MVRT consists of two processes: (1) the constrained partitioning of the data and (2) the cross-validation of the results. The two procedures are briefly explained below; a more detailed description can be found in Borcard et al. (2018). In this study, we use R software, namely, package *mvpart* (De'ath, 2002) for building the MVRT.

The data partitioning consists of three steps. First, for each explanatory variable are generated all possible partitions of the sites (subbasins) into two groups. Second, for each partition, it is calculated the resulting sum of within-group sums of squared distances to the group means for the response data (within-group SS). Within-group SS is equivalent to standard deviation. Lastly, the partition into two groups to minimise the within-group SS and the threshold value/level of the explanatory variable is retained. These steps are repeated within the two previously established subgroups until all the objects form their groups. For each tree that is computed, the relative error is calculated as the sum of the within-group SS of all leaves divided by the overall SS of the data. This procedure for MVRT is equivalent to the one initially proposed by Breiman (2001) for his regression tree technique.

A cross-validation procedure is used to prune the tree and identify the optimal tree size (Kuhn and Johnson, 2013; Legendre and Legendre, 2012). Per this procedure, the data is randomly divided into roughly equal-sized test groups. Each test group is held out in turn while the tree is fitted using the remaining groups. The distances between the centroids of the objects at tree leaves and each object of the test group are then calculated. Finally, the objects of the test group are allocated to the closest leaf of the constructed tree. An overall relative error statistic (relative cross-validation error, CVRE) is calculated for each group using all *n* objects, per Equation (2.18):

$$CVRE_{(k)} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{p}\left(y_{ij(k)} - \hat{y}_{j(k)}\right)^2}{\sum_{i=1}^{n}\sum_{j=1}^{p}\left(y_{ij} - \bar{y}_j\right)^2}, \tag{2.18}$$

where $y_{ij(k)}$ is the value of variable (drought severity categories, in this case) j for object i belonging to test group k, $\hat{y}_{j(k)}$ is the value of that same variable at the centroid of the leaf closest to object i, and the denominator is the overall sum of squares of the response data.

This cross-validation process is repeated several times for consecutive and independent divisions of the data into test groups. For each group, the mean and standard deviation of all CVRE is computed. The CVRE varied from 0 for perfect predictors to close to 1 for poor predictors (as error increases, CVRE increases indefinitely).

To choose the size of the tree that retained the most descriptive partition, we apply the approach suggested by De'ath (2002). According to the author, the tree with the smallest CVRE offers the best combination of explanatory power and interpretability. Once the tree is built, the proportion of explained variance (EV) is calculated as $1 - RE_{tree}$ (tree relative error) (Cannon, 2012).

2.6 METAHEURISTIC OPTIMISATION FOR WATER MANAGMENT

Due to the fact that objective functions in water-related problems are rarely expressed analytically (since, for their computation, there is a need to run a computer model), classical non-linear optimisation methods can hardly be used. That is why such problems are typically solved by using randomised search techniques, also called "metaheuristic optimisation". Metaheuristics refers to an algorithm structure designed to solve approximately a wide range of complex optimisation problems without deeply adapting to each problem (Abdel-Basset et al., 2018). A metaheuristic contains two stages: exploration (diversification) and exploitation (intensification). During the exploration are recognised sectors in the search space with high-quality solutions. Exploitation focuses on the search for a solution in those identified regions. Metaheuristics success in solving an optimisation problem depends on the balance between exploration and exploitation (Morales-Castañeda et al., 2020).

Metaheuristic are grouped into two categories: trajectory-based and population-based metaheuristics. In broad terms, trajectory-based metaheuristics are exploitation-oriented, whereas basic population-based metaheuristics are exploration-oriented (Boussaïd et al., 2013). Further information on metaheuristics algorithms can be found in the works Boussaïd et al. (2013), Abdel-Basset et al. (2018) and Rajwar et al. (2023).

Several multi-objective optimisation models have been applied to optimise types and allocation of management strategies to improve water quality and stream health (Geng et al., 2019; Liu et al., 2019; Raschke et al., 2021; Uribe, 2023; Zhang et al., 2023). Additionally, these models have been applied to address challenges related to flood management and water availability (Lewis and Randall, 2017; Liu et al., 2023; Woodward et al., 2014), as well as to mitigate soil degradation (Hildemann et al., 2023; Naseri et al., 2021; Wu et al., 2018). In the field of drought preparedness, Cai et al. (2015) developed a multi-objective stochastic optimisation model to identify the optimal combination of preventive and tactical measures under different future climate scenarios.

This study uses population-based metaheuristics, particularly the Unified Evolutionary Algorithm (U-NSGA-III) for Single, Multiple, and Many-Objective Optimisation. In the following, we describe the characteristics of this algorithm.

2.6.1 Unified Evolutionary Algorithm for Single, Multiple, and Many-Objective Optimisation

We use the U-NSGA-III to identify strategic portfolios of PDMMs that minimise the severity of hydrological and agricultural droughts in the study area. U-NSGA-III is an algorithm developed to solve constrained and unconstrained optimisation problems with one to more than three objective functions (Seada and Deb, 2016). As part of the NSGA-III family of algorithms, U-NSGA-III is an elitist population-based method that uses non-domination sorting, evolutionary operators such as crossover and mutation, and reference directions to find near-optimal Pareto solutions. Compared to the original NSGA-III version, U-NSGA-III introduces a niching-based selection procedure with no extra parameters to allow a seamless degeneration to mono- and bi-objective problems (Seada and Deb, 2016). Using the unified version of NSGA-III is intended to maintain consistency among solutions when increasing or reducing the number of objective functions and working with the same decision variables.

In Chapter 6, we implement U-NSGA-III using the *pymoo* library in Python 3.7 (Blank et al., 2021). Algorithm parameters include the number of reference directions (which equals the population size), the maximum number of generations (which operates as the stopping criterion), crossover and mutation probabilities, the distribution indices for simulated binary crossover (SBX) and polynomial mutation. We generate well-spaced reference directions using the Riesz s-Energy method (Blank et al., 2021). Table 2.2 presents the parameter values used in Chapter 6, which are standard and recommended.

Table 2.2. U-NSGA-III parameters and their values for this study

Parameter	Value
Number of reference directions (population size)	350
Max. number of generations	350
Crossover probability	0.9
Mutation probability	1/3650
Distribution index – SBX (Crossover)	10
Distribution index – Polynomial mutation	20

On the other hand, we compute the Hypervolume Indicator at the end of each generation to evaluate convergence to a near-optimal Pareto solution. The hypervolume represents the region collectively dominated by a set of Pareto solutions in the objective space (Auger et al., 2012). Therefore, the Hypervolume Indicator is usually employed for convergence assessment since it simultaneously accounts for the proximity of the points to the actual Pareto front, diversity, and spread. Since a larger hypervolume occurs when the Pareto solutions are closer to the origin of the objective space, a higher Hypervolume Indicator is considered better in minimisation problems. Moreover, if the Hypervolume Indicator shows a near-steady behaviour with increasing generations, it indicates that the Pareto front has stabilised and that convergence has eventually occurred (Raschke et al., 2021).

2.6.2 Preferred trade-off solutions

Once we obtain the near-optimal Pareto set, we select a few preferred solutions balancing the objective functions using two different multi-criterion decision-making (MCDM) approaches. In the first approach, we compute a pseudo-weight vector for each solution in the Pareto set (Deb, 2001). In this vector, the i-th element represents the relative importance of the i-th objective function for a particular solution and is computed using Equation (2.19)

$$w_i = \frac{(f_i^{max} - f_i)/(f_i^{max} - f_i^{min})}{\sum_{m=1}^{M}(f_m^{max} - f_m)/(f_m^{max} - f_m^{min})}, \tag{2.19}$$

It is worth noting that when computing the pseudo-weight vector, the sum of all elements is forced to one. This study identifies the most balanced solution with a pseudo-weight close to (0.5, 0.5). Two additional preferred solutions are obtained using additional target vectors, (0.25, 0.75) and (0.75, 0.25), to indicate a preference for one of the objective functions. In the second approach, we identify knee points in the Pareto set, which are solutions showing high trade-offs. These points result in a slight gain in one objective while having a high loss in the other when moving along neighbouring solutions. Defining whether a trade-off is high or low requires the definition of a threshold, which in this study is taken as the average trade-off plus twice the standard deviation using the entire Pareto set. We implement the high trade-off procedure proposed by Rachmawati and Srinivasan (2009), included in *pymoo*, to identify any knee points. Then, we select the knee point with the most balanced pseudo-weight vector as a preferred solution.

2.7 GENERAL METHODOLOGY

Figure 2.1 illustrates three distinct methodological phases applied in this study.

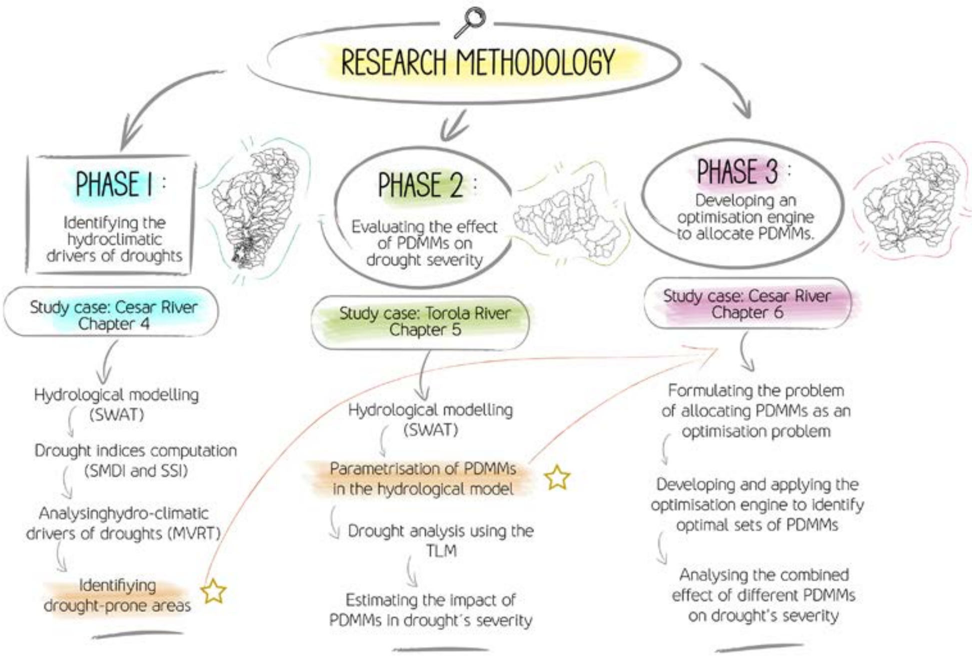

Figure 2.1. Flowchart of the general methodology.

In the first phase, we built an 'explanatory AI' model to identify hydroclimatic parameters influencing the severity of agricultural and hydrological droughts. For this purpose, the SWAT model is used to represent the basin hydrology. (Section 2.2.1). Model outputs, soil moisture and streamflow, are used to calculate two drought indices introduced in 2.3.2; drought indices categories are employed to describe drought severity. Finally, the MVRT (Section 2.5) is applied to assess the relationship between hydroclimatic characteristics and the severity of agricultural and hydrological droughts. A concrete application of this approach is developed in the Cesar River (Colombia).

In the second phase, we evaluate the impact of three distinct PDMMs on the severity of agricultural and hydrological droughts. This phase is based on the literature review on PDMMs presented in Section 2.4. In addition, the SWAT model is used to represent the basin hydrology and the PDMMs. A concrete application of this approach is developed in the Torola River (El Salvador). Lastly, in the third phase, we develop and apply an optimisation tool which integrates the SWAT modelling system and the U-NSGA-III (Section 2.6) to identify the optimal allocation of PDMMs that minimises the severity of agricultural and hydrological droughts. A concrete application of this approach is developed in the Cesar River (Colombia). At the beginning of Chapters 4, 5 and 6, Figures 4.1, 5.1 and 6.1 present more details of various phases components of the presented methodology.

2.8 CONCLUSION

This chapter presents the definitions, methods and modelling approaches applied in the following chapters. This theoretical background focuses on the main concepts to contextualise the research in the field and does not intend to present a critical review.

This research applies a methodology structured into three sequential phases *to develop an optimisation frameworkto identify near-optimal allocation of preventive drought management measures informed by a comprehensive understanding of the drought drivers and characteristics in the study areas*. The three methodological phases are intricately interlinked. The characterisation of agricultural and hydrological droughts in the first phase facilitates the identification of areas most susceptible to droughts for the subsequent analysis of drought management scenarios in the third phase. In the second phase, the literature review on drought management and PDMMs enables us to identify measures applicable to drought management and define their representation within the hydrological model. Additionally, the PDMMs examined in the second phase serve as decision variables in the optimisation problem formulated in the third phase.

Through the structured methodology presented in Section 2.7, the research navigates from understanding the hydroclimatic drivers of droughts to assessing specific PDMMs and ultimately proposing comprehensive drought management scenarios.

3 Description of the Study Areas

3.1 Introduction

A practical application of the techniques covered in Chapters 4 through 6 is developed in two selected cases of study, namely the Torola River basin (El Salvador, Central America) and the Cesar River basin (Colombia, South America). As a result of climate anomalies and social and economic growth in both study areas, the water demand is rising continuously, resulting in significant pressure on the water resources.

In the Torola River basin, the anomalous distribution of precipitation within the rainy period, increasing temperature and human interventions such as deforestation, soil degradation, and inadequate basin management have increased the frequency and severity of drought events (World Bank et al., 2015). In the last decade, subsistence crops have declined, and communities living in the region are suffering from food insecurity (Läderach et al., 2021).

In turn, the Cesar River basin faces high water demand from mono-crops and the overexploitation of forest resources. In addition, at a national level, the basin ranks first as the most threatened area by climate change. Climate change projections indicate that by 2070, the basin's temperature may increase by 2.7°C, and precipitation may reduce by 10 % compared to the reference period 1971-2000 (Universidad del Magdalena et al., 2017). Accordingly, multiple initiatives are oriented to improve water management and create resilience to hydroclimatic extremes (Ministerio de Ambiente y Desarrollo Sostenible (Colombia), 2015).

3.2 Study area 1 — Torola River basin

The Torola River Basin is a transboundary basin between 88°22′ W 88°16′ W and 13°50′ N 13°53′ N latitude (Central America). It has an area of 1575 km^2, distributed between Honduras (557 km^2) and El Salvador (1018 km^2). This study is conducted in the area corresponding to El Salvador, located in the northern part of the country. Figure 3.1 presents the basin topography and land use.

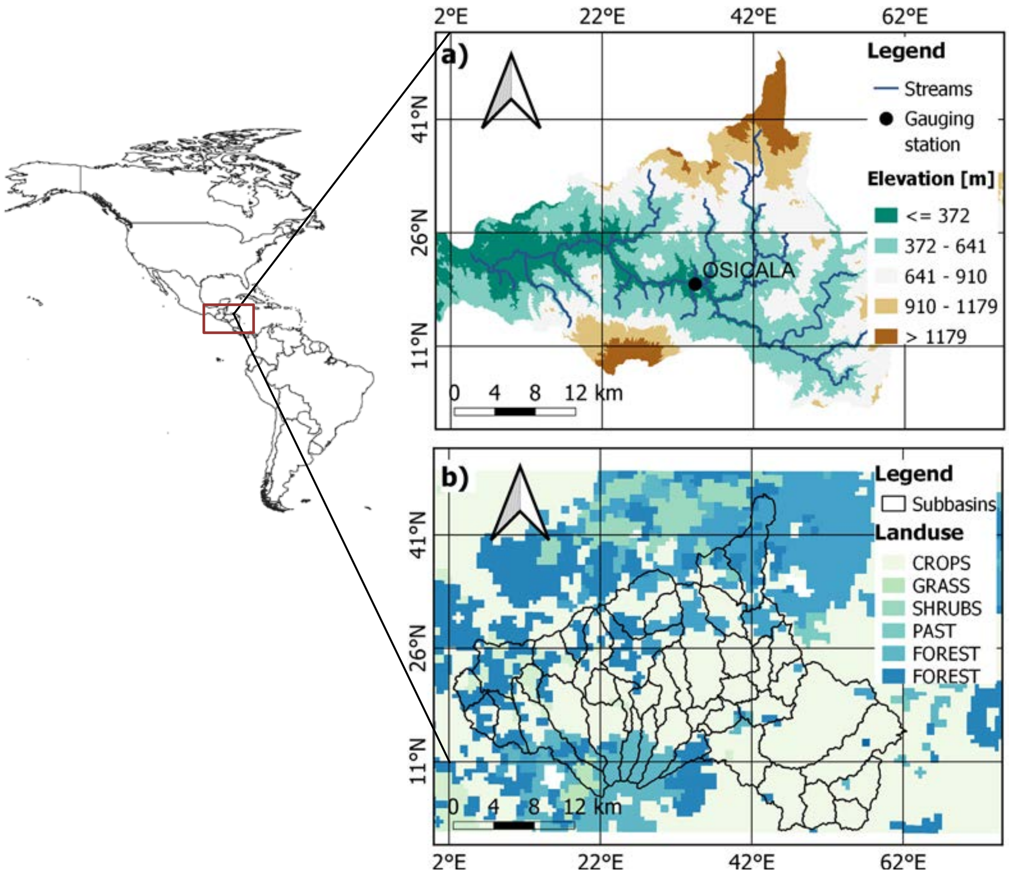

Figure 3.1. Torola River a) Basin topography, b) basin land use.

3.2.1 Geography and climate

The basin's topography is characterised by steeply sloped mountains, with elevations ranging from 100 m above sea level (masl) to 1450 masl. Some flat land areas can be found adjacent to the main river course. The river slope varies from flat to gentle (0 to 5%) (Agencia de Coperacion Internacional del Japón (JICA) and Comision Ejecutiva Hidroelectrica del Río Lempa (CEL), 2004). The areas at lower altitudes exhibit a tropical savanna climate; the climate in the mountainous areas is highland temperate.

Mean annual rainfall varies from 1900 to 2700 mm; the mean annual evapotranspiration is 1000–1100 mm (Brutsaert et al., 2020; UNESCO, 2006). The annual rainfall pattern is defined by a dry season from November to April, followed by a rainy season from May to October. The intermediate period of decreased precipitation from July to August is known as the "mid-summer drought" (Depsky and Pons, 2020). The main rainfall events occur in September and October, with up to 500 mm monthly average. Figure 3.2 shows the monthly mean precipitation at the Oscicala gauging station. Temperatures range from

19 °C to 23 °C in the mountainous areas and from 25 °C to 30 °C in lower-altitude regions. The highest temperature in the basin is observed in May, with an average value of 30 °C, and the lowest is in December, with an average value of 25.5 °C.

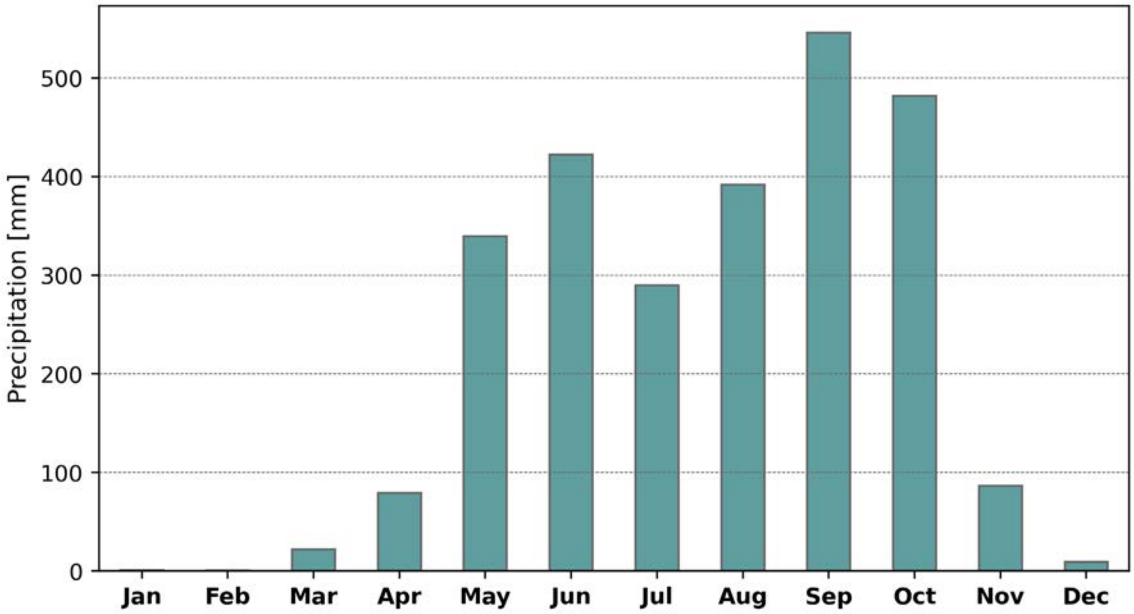

Figure 3.2 Monthly mean precipitation at the Oscicala gauging station (see Figure 3.1)

3.2.2 Land use and soils

The dominant land use is agriculture, mainly pastures and crops such as corn, beans, and sorghum, although the soil is unsuitable for agriculture. Most farms are less than 2 ha in size and are utilised to produce basic grains (Bouroncle et al., 2014). Family farms are essential to ensuring food security, but they can only operate profitably with the help of fertiliser and seed donations (World Bank et al., 2015). Forest covers around 30% of the basin and is located in mountainous areas above 1100 masl and along the river sides (riparian buffer). In the basin area, intense deforestation is causing erosion, which is aggravated during the rainy season when stormwater hits the bare soil. Predominant soils in the basin are classified as shallow sandy loam with abundant rocky outcrops, typical soils of regions with steep topography. These soils exhibit low water-holding capacity and low agricultural potential. The soil's recommended use is cattle raising, timber exploitation or forest conservation.

3.2.3 Drought situation in the basin

The Torola River basin is located within the Central America Dry Corridor (CADC), a drought-prone area threatened by erratic and unpredictable seasonal rainfall patterns and increasing temperature (World Bank et al., 2015). The CADC is a tropical dry forest region on Central America's Pacific side stretching from the Pacific Coast of Chiapas, Mexico, to the western part of Costa Rica and the western provinces of Panama (Depsky and Pons, 2020). Recurrent droughts, excessive rains and severe flooding mainly represent climate risks in the CADC. Additionally, human interventions such as deforestation and unsustainable farming practices have caused soil erosion and degradation, sedimentation of rivers and drying of rivers during part of the year (Burgeon et al., 2018).

According to the drought intensity map of the CADC developed by van der Zee Arias et al. (2012), the Torola basin is in the category of "severe drought potential impacts". Drought sensitivity assessment considers hydroclimatic characteristics such as precipitation, evapotranspiration, soil type and the adaptation capacity to changes in agriculture and the potential loss of suitable areas for subsistence crops. Multiple El Niño events have affected the Torola basin in the past decade, causing crop losses, food insecurity and rural migration. Along with international partners, the local authorities are implementing projects to increase the resilience of agricultural production and restore degraded ecosystems.

3.3 Study area 2– Cesar River basin

The basin is located between 72º53'W 74º04'W longitude and 10º52'00'N 7º41'00''N latitude (Colombia's northeast), and it extends for an area of 22,312 km^2. Figure 3.3 presents the basin topography and land use. Within the basin area is allocated the Zapatosa marsh, one of the most important wetlands in the country. This ecosystem was declared a Ramsar site in 2018 (Ramsar sites are wetlands of international importance for containing rare or unique wetland types or for their relevance in conserving biological diversity). The Cesar River is the principal tributary of the Zapatosa marsh.

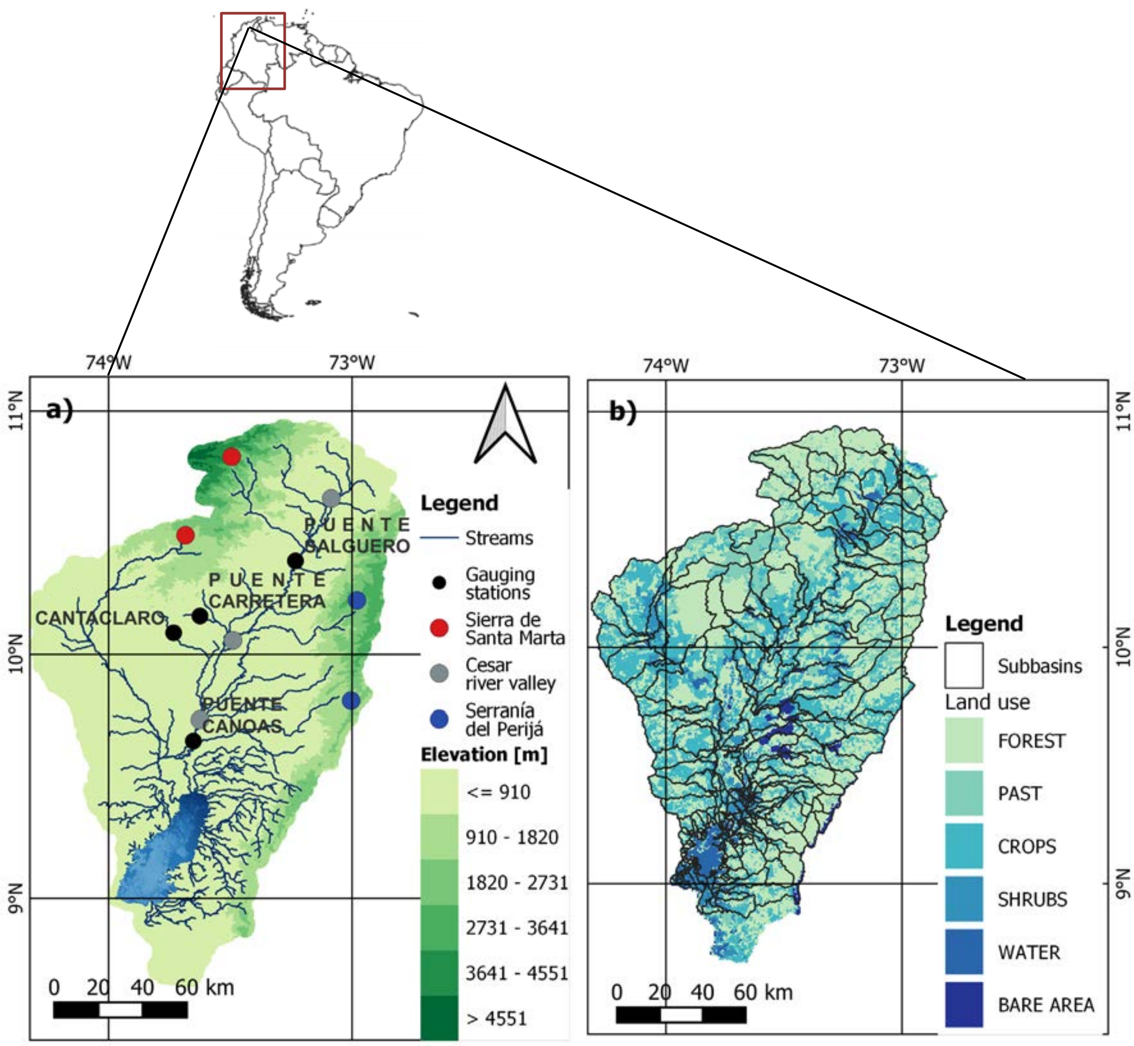

Figure 3.3 Cesar River a) Basin topography, b) basin land use.

3.3.1 Geography and climate

The basin's topography defines three distinct climatic regions (Universidad del Atlantico, 2014). In the north is La Sierra Nevada de Santa Marta. This sector is characterised by steeply sloped mountains reaching up to 5,700 meters above sea level (masl). The temperature ranges from 3°C to 6°C, and the mean annual precipitation is 1,000 mm. In the east is La Serranía del Perijá. This mountainous area is an extension of the eastern branch of the Andes range. In this sector, the altitude ranges from 1,000 to 2,000 masl. The average temperature is 24°C, and annual precipitation varies from 1,000 mm to 2,000 mm. Lastly, the valley of the Cesar River and the Zapatosa marsh are in the west and south of the basin, respectively. Flat topography is dominant in the river valley, and the system of marshes formed by the Cesar River floodplains and its confluence with the Magdalena River. The average temperature is 28°C, and the mean annual precipitation is 1,500 mm.

The basin's annual rainfall pattern is bimodal. The dry season occurs from December to March, followed by a rainy season from April to May. Precipitation decreases from June to July, and the main rainfall events occur between August and November.

Figure 3.4 shows the monthly mean precipitation at the Puente Canoas gauging station.

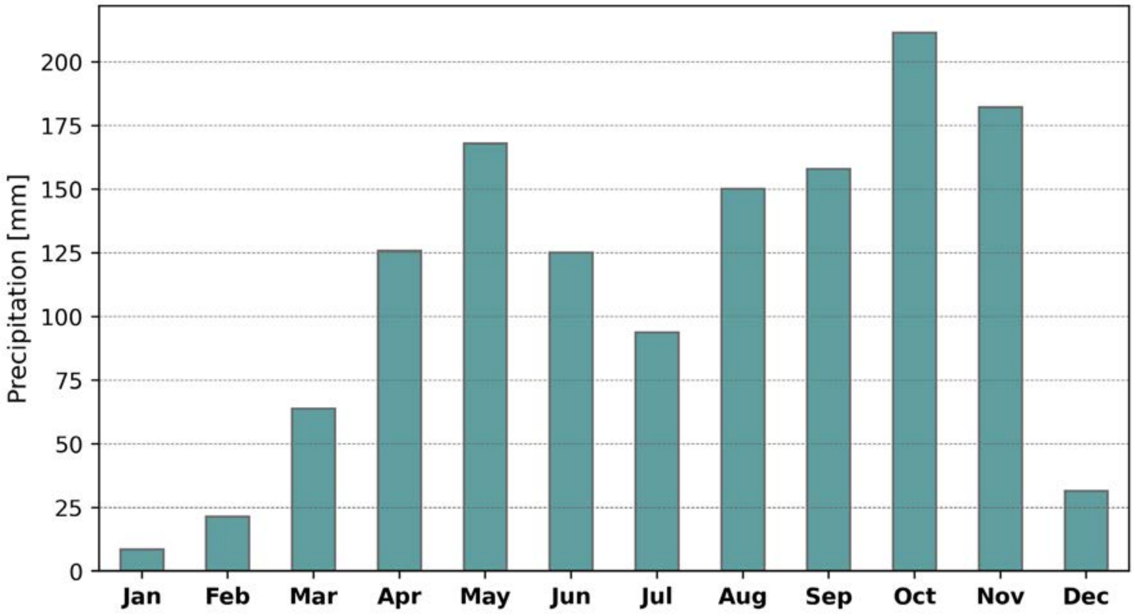

Figure 3.4 Monthly mean precipitation at the Puente Canoas gauging station (see Figure 3.3)

3.3.2 Land use and soils

The predominant land use is pasture, followed by agriculture (Universidad del Atlantico, 2014). The primary land use in La Sierra Nevada foothills is pastures for cattle farming. In La Serranía del Perijá, the high-altitude areas are covered by forests in very good condition; at the lower altitudes, the principal land use is agriculture, particularly subsistence crops. The Cesar River valley's soils are rich in nutrients, providing favourable conditions for agriculture. The riverbanks are covered by forests with low tree density.

The three landforms in the basin define the soil's characteristics (Agencia de Desarrollo Rural et al., 2019; Instituto Geografico Agustin Codazzi and Corporacion Autonoma Regional del Cesar, 2018). In mountainous areas, soils vary from shallow to moderately deep; the dominant texture is medium and presents a low natural fertility. In La Sierra Nevada and Serranía del Perijá foothills, the soil is deep and exhibits a coarse texture, the natural fertility varies from moderate to low, and some sectors present rocky outcrops. In the river valley, the streams influence soils during the wet months, limiting soil-forming processes. In this area, soils vary from shallow to deep, have a medium texture to moderately fine, and have moderate to high natural fertility.

According to the Regional study of soil suitability for agriculture (2016), suitable agricultural land is found in the middle part of the valley and the river floodplains and in la Serranía del Perijá and Sierra foothills. In practice, agricultural land allocation considerably differs from the soil's suitability. Particularly, the river valley is underused, and the soils in the basin's northwest and the Serranía del Perijá foothills are overexploited.

3.3.3 Drought situation in the basin

The expansion of water-intensive crops, inappropriate cropping patterns, and lack of land suitability analysis for agriculture severely impact the basin's water availability (Universidad del Atlantico, 2014). In La Sierra Nevada de Santa Marta and La Serranía del Perijá, land use conversion of forest to areas used for agriculture has impacted the discharge of Cesar river tributaries. Less than 30% of the primary forest remains in these areas (Agencia de Desarrollo Rural et al., 2019). In La Sierra and Serranía foothills, cattle raising and intensive agriculture have compromised soil structure, reducing infiltration rates (generally associated with high soil compaction).

Paez-Trujillo et al. (2023) evaluated the drought severity in the basin and identified the most sensitive areas to agricultural and hydrological droughts. The authors showed that the upper part of the river valley is very susceptible to agricultural and hydrological drought. Precipitation shortfalls and high potential evapotranspiration drive severe agricultural drought, whereas limited precipitation influences severe hydrological drought. In the middle part of the river, inadequate rainfall partitioning and an unbalanced water cycle that favours water loss through evapotranspiration and limits percolation cause severe agricultural and hydrological drought conditions. Finally, droughts are moderate in the basin's southern part (Zapatosa marsh and the Serrania del Perijá foothills). Moderate sensitivity to agricultural and hydrological droughts is related to the capacity of the subbasins to retain water, which lowers evapotranspiration losses and promotes percolation.

4 MACHINE LEARNING APPROACH TO EVALUATE THE RELATIONSHIP BETWEEN CLIMATE, BASIN PROCESSES AND DROUGHT SEVERITY

ABSTRACT

This chapter[1] applies hydrological modelling and a ML tool to assess the relationship between hydroclimatic characteristics and the severity of agricultural and hydrological droughts.

The results presented in this chapter indicate that multiple parameters influence the severity of agricultural and hydrological droughts in the Cesar River Basin. The upper part of the river valley is very susceptible to agricultural and hydrological drought. Precipitation shortfalls and high potential evapotranspiration drive severe agricultural drought, whereas limited precipitation influences severe hydrological drought. In the middle part of the river, inadequate rainfall partitioning and an unbalanced water cycle that favours water loss through evapotranspiration and limits percolation cause severe agricultural and hydrological drought conditions. Finally, droughts are moderate in the basin's southern part. Moderate sensitivity to agricultural and hydrological droughts is related to the capacity of the subbasins to retain water, which lowers evapotranspiration losses and promotes percolation.

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[1] This chapter is based on the publication: Paez-Trujilo, A., Cañon, J., Hernandez, B., Corzo, G., Solomatine, D., 2023. Multivariate regression trees as an "explainable machine learning" approach to explore relationships between hydroclimatic characteristics and agricultural and hydrological drought severity: case of study Cesar River basin. *Natural Hazards and Earth System Sciences* 23, 3863–3883. https://doi.org/10.5194/NHESS-23-3863-2023

4.1 INTRODUCTION

Projections indicate that drought frequency, severity and duration are expected to increase globally in the twenty-first century (UNDRR, 2021). Upcoming soil moisture drought scenarios predict statically significant large-scale drying, especially in scenarios with strong radiative forcing in Central America and tropical South America (Lu et al., 2019). A similar trend is predicted for hydrological drought severity, which is expected to increase by the end of the twenty-first century, with regional hotspots in central and western Europe and South America, where the frequency of hydrological drought may increase by more than 20 % (Prudhomme et al., 2014).

It is essential that we better understand drought drivers if we are to foster preparedness and resilience to projected drought events. Remarkable progress has been achieved in understanding drought propagation through the hydrological cycle (Van Loon et al., 2012). Drought occurs due to climatic extremes, which may be enhanced or alleviated by region characteristics and anthropogenic influence (Hao et al., 2022; Seneviratne et al., 2012; Tijdeman et al., 2018). Typically, droughts are triggered by atmospheric circulation and weather systems that combine to cause lower-than-normal precipitation and/or higher-than-normal evaporation in a region (Destouni and Verrot, 2014; Sheffield and Wood, 2011a). Reduced precipitation leads to a decrease in soil moisture, causing agricultural drought. When soil moisture depletion is high, it is restored in the wet season, thus reducing subsurface flow and groundwater recharge and giving rise to hydrological drought (Iglesias et al., 2018a). Regional characteristics such as soil type, elevation, slope, vegetation cover, drainage networks, water bodies and groundwater systems play a relevant role in response to the climate anomalies that affect drought propagation and contribute to different levels of agricultural and hydrological drought (Sheffield and Wood, 2011a; Zhang et al., 2022). Equally important, human interventions in the hydrological cycle (e.g. reservoirs, water diversion, deforestation, over-pumping groundwater, overgrazing, urbanisation) can reduce water supplies, triggering a drought situation or exacerbating a climate-driven drought (Rangecroft et al., 2019; M. Wang et al., 2021).

Drought planning also uses research progress on drought characterisation. Using drought indices is a widespread methodology for drought characterisation. (Zargar et al., 2011). Drought indices are computed numerical representations of drought severity (Hao and Singh, 2015; Keyantash and Dracup, 2002). Severity refers to drought strength, also described as the degree of deficit (Cavus and Aksoy, 2020), soil moisture deficit in the case of agricultural droughts and streamflow deficit in the case of hydrological droughts. Generally, severity is divided into different categories (e.g. moderate, severe, extreme), providing a qualitative assessment of the drought state in a region during a given period.

Drought indices (and their categories) are crucial for tracking or anticipating drought-related damage and impacts (WMO and GWP, 2016).

Despite remarkable progress achieved in understanding the drought-generating process and drought characterisation, there is still a need for studies that assess the complex interplay between the different drivers of droughts and how their combined effect influences drought characteristics (e.g. duration, severity, intensity) (Valiya Veettil and Mishra, 2020). Previous studies focus on the influence of one driver (Margariti et al., 2019; Mastrotheodoros et al., 2020; Shah et al., 2021; Xu et al., 2019), and some of the methodologies applied cannot adequately address the non-linear relationship between climate, basin processes and droughts characteristics (Peña-Gallardo et al., 2019; Saft et al., 2016; Van Loon, 2015).

We have found two studies employing ML to assess the non-linear relationship between climate and basin processes and droughts (Konapala and Mishra, 2020; Valiya Veettil and Mishra, 2020). The studies reported relevant findings on the parameters driving droughts; however, the selected techniques showed a limitation for the drought analysis since they allow only one output variable. In both cases, it was necessary to apply the chosen technique multiple times to find the relationships between hydroclimatic parameters and the different categories of the evaluated drought characteristics. For example, Valiya Veettil et al. (2020) used a classification and regression tree (CART) to identify the variables influencing drought duration. CART allows one output variable; then, the authors applied the approach three times to evaluate the variables influencing short-term, medium-term and long-term drought events. Meanwhile, Konapala et al. (2020) used a random forest (RF) algorithm to identify the climate and basin parameters influencing the characteristics (duration, frequency and intensity) of three different drought regimes (long duration and mild intensity, moderate duration and intensity, short duration and high intensity). As the core of RF is a decision tree that allows one output variable (in this case, each characteristic of each drought regime), the authors repeated the procedure nine times, one for each drought regime and characteristic.

The aforementioned research shows the potential of ML techniques for drought-related analysis; nevertheless, it also suggests that assessing the parameters driving drought characteristics requires techniques capable of simultaneously handling the different categories of drought characteristics. Commonly used in ecology to relate independent environmental conditions to populations of multiple species, the multivariate regression tree (MVRT) (De’ath, 2002) arises as a suitable technique for this purpose. MVRT is a numerical prediction (regression) technique employing progressively constrained clustering of data that links explanatory variables to multiple response variables while maintaining the individual characteristics of the responses (De’ath, 2002). This technique results in a non-linear model and allows for building the so-called “interpretable ML” models that can be understood by humans (as opposed, e.g. to artificial neural networks) (Molnar, 2022). MVRT interpretably is a relevant attribute for drought researchers and planners since it allows them to identify the parameters influencing severe (or mild) drought conditions.

In this chapter, we employ a three-step methodology to understand the relationship between the drivers of droughts and the individual categories of agricultural and hydrological droughts severity. First, we use SWAT to simulate the hydroclimatic parameters required to analyse droughts and apply the MVRT approach. Second, SWAT outputs, soil moisture and streamflow are used to calculate the drought indices (SMDI and SSI). Drought indices are utilised to identify the agricultural and hydrological drought events in the analysis period. Then, we calculate the months for each drought severity category during the observed droughts. Finally, the MVRT approach is applied to assess the relationship between hydroclimatic characteristics (represented by the simulated parameters in each subbasin) and drought severity categories (represented by the total number of months for each drought severity category in each subbasin). The agricultural and hydrological droughts analyses are conducted separately; thus, two MVRTs are obtained.

4.2 METHODOLOGY

Figure 4.1 illustrates the three-step methodology applied in this chapter. Section 4.2.1 describes the hydrological model set-up calibration and validation, Section 4.2.2 the drought analysis, and Section 4.2.3 presents the application of the MVRT technique.

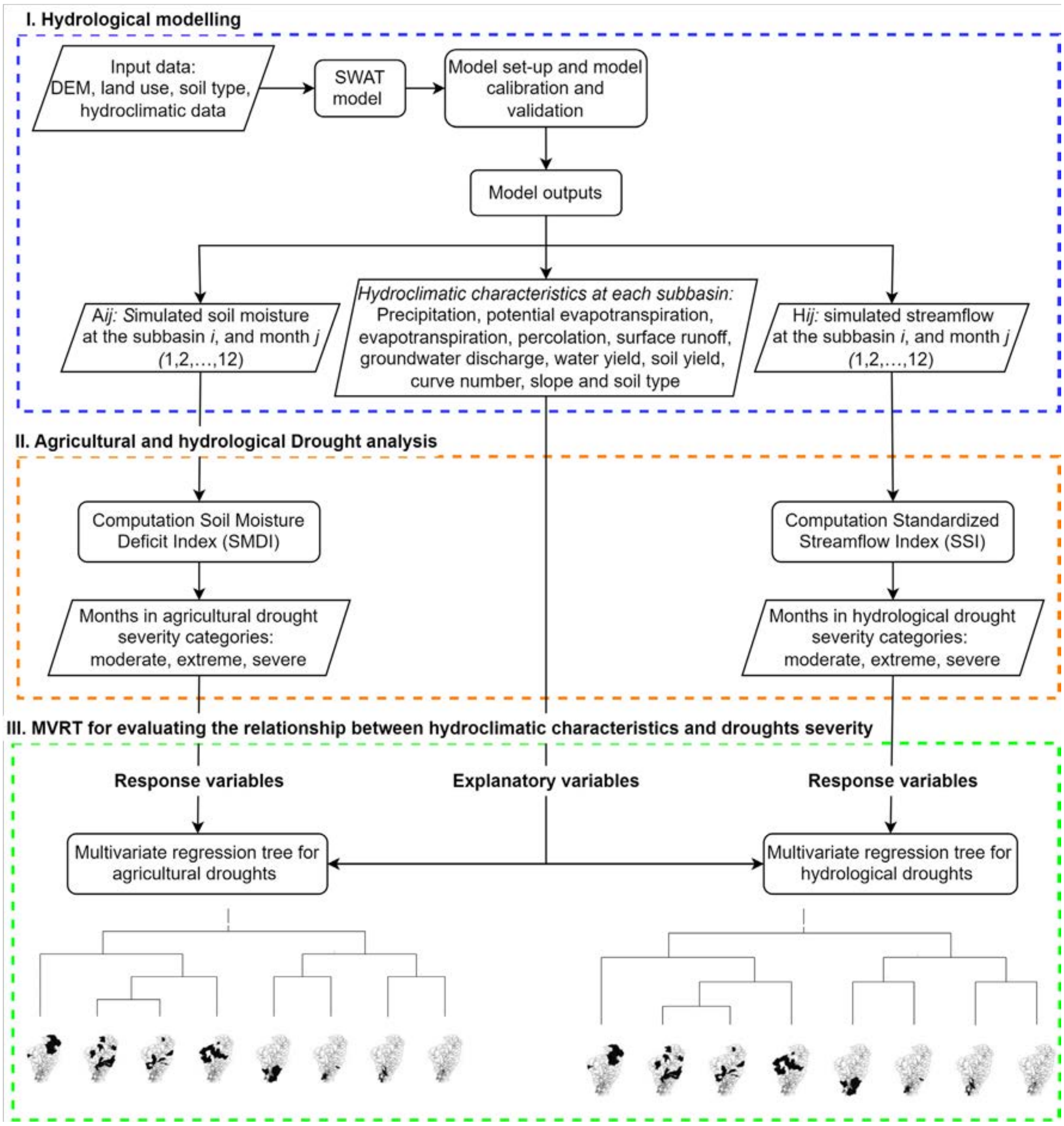

Figure 4.1. Flowchart of the methodology applied in Chapter 4 (research phase 1).

4.2.1 Hydrological model set-up, calibration and validation for the Cesar River Basin

The hydrological model of the Cesar River Basin (SWAT, Section 2.2.1) was built for the period from 1987 to 2018. The Cesar River basin was divided into 313 subbasins with a median area of 70 km^2. Four slope classes were set for the HRUs generation: flat (0 %–2 %), gentle (2 %–10 %), steep (10 %–35 %), and considerably steep (> 36 %) (GEF et al., 2021, 2020). The following methods were used to model the principal hydrological processes: the soil conservation service curve number (SCS-CN) was used to simulate surface runoff, potential evapotranspiration was estimated using the Hargreaves method, and water was routed through the channel network using the variable storage routing method. The details and sources of the SWAT model input data are presented in Table 4.1.

Table 4.1. SWAT model input data Cesar River Basin.

Data type	Details	Source
Digital elevation model	25 × 25 m	Dataset ALOS PALSAR L1.0, Cartography 1:25000 Geographic Institute Agustín Codazzi (IGAC), Colombia
Soil map	300 × 300 m	Soil profiles Project GEF Magdalena–Cauca VIVE, GEF, BID, Fundación Natura, Colombia
Land use map	25 × 25 m	Land use map Geographic Institute Agustin Codazzi (IGAC), Colombia
Daily precipitation and daily minimum and maximum temperature	Period 1985–2018 (34 years)	Institute of Hydrology, Meteorology and Environmental Studies (IDEAM), Colombia

Based on expert judgement and the available literature (ASABE, 2017; Arnold et al., 2012), the following SWAT parameters were used in the calibration and validation process: baseflow alpha factor (ALPHA_BF), effective hydraulic conductivity in main channel alluvium (CH_K), Manning's value for the main channel (CH_N2), SCS runoff curve number for moisture condition II (CN2), soil evaporation compensation factor (ESCO), groundwater delay (GW_DELAY), threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN), deep aquifer percolation fraction (RCHRG_DP), threshold depth of water in the shallow aquifer for percolation to the deep aquifer to occur (REVAPMN), and available water capacity of the soil layer (SOL_AWC). In the calibration process, a physically meaningful range is set for each parameter in each iteration. Then, a new parameter value (within the range) is selected and applied at each HRU or subbasin.

The model was calibrated from 1985 to 2002 and validated from 2003 to 2018 using the streamflow series from four stream gauges (Figure 3.3) and the methodology presented in Section 2.2.2. The source of the discharge data is the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM), Colombia. The first two years were used as a warming-up period in both cases. Thus, performance indicators were calculated for 1987 to 2002 (calibration) and 2005 to 2018 (validation).

4.2.2 Agricultural and hydrological drought analysis

SMDI and SSI were calculated monthly using the simulated soil water and streamflow values at each subbasin (Section 2.3.2). SMDI was not calculated for the subbasins that correspond to the Zapatosa marsh. In these subbasins, the predominant land cover is water, see Figure 4.4. The drought events during the period of analysis were then identified. A drought (agricultural or hydrological) event was assumed to occur in the basin when a number of subbasins (covering at least 30 % of the basin's total area) were in a drought state (moderate, severe or extreme) for at least two consecutive time steps (i.e. in this chapter month). According to the spatial and temporal thresholds, a drought event began when both conditions were met and continued until one of them failed to be met.

4.2.3 Multivariate regression tree approach for evaluating the hydroclimatic drivers of droughts

R software was used to build the MVRT (Section 2.5), namely package *mvpart* (De'ath, 2002). Before the analysis, the sets of explanatory and response variables were transformed to compare the descriptors measured in different units and to modify the variables' weights. The matrix of explanatory variables was standardised to a mean of 0 and a standard deviation of 1. The matrix of response variables was standardised by the column maximum, then again by the row total (Wisconsin double standardisation).

Set of explanatory variables

To select the set of explanatory variables, we used the outcomes of previous studies on governing drivers of droughts (Sheffield and Wood, 2011a; Zhang et al., 2022). Table 4.2 describes the 11 parameters selected as the potential drivers of droughts. The used values correspond to the parameters' average in the analysis period (1987 to 2018). The averages were computed using the SWAT model results at each subbasin. We used the dominant category at each subbasin for the curve number, the slope, and the soil type (categorical variables).

Set of response variables

We used the drought analysis outcomes to define the response variables (Table 4.3). Following the methodology presented in Sections 2.3.2 and 4.2.2, we identified the agricultural and hydrological drought events during the analysed period. After identifying the drought events, we counted the months for each drought severity category at each subbasin. The observed months for each one of the three drought categories were used as response variables. The analyses for agricultural and hydrological droughts were conducted separately; thus, two sets of response variables were obtained.

Table 4.2. Explanatory variables used in MVRT.

Hydroclimatic parameter	Abbreviation	Unit	Definition
Precipitation	PRECP	mm	Average precipitation at each subbasin
Potential evapotranspiration	PET	mm	Average potential evapotranspiration at each subbasin
Evapotranspiration	ET	mm	Average actual evapotranspiration at each subbasin
Percolation	PERC	mm	Average percolation past the root zone
Surface runoff	SURFQ	mm	Average surface contribution to the streamflow at each subbasin
Groundwater	GRWQ	mm	Average groundwater contribution to the streamflow at each subbasin
Water yield	WYLD	mm	Average amount of water that leaves the subbasin and contributes to the streamflow at each subbasin
Sediment yield	SYLD	metric tons/ha	Average sediment from the subbasin transported into the reach
Curve number	CN	–	Dominant curve number at each subbasin
Slope	SLP	–	Dominant slope at each subbasin
Hydrologic soil group	STY	–	Dominant hydrologic soil group (A, B, C, and D) at each subbasin. The soil hydrologic groups refer to the soil's infiltration characteristics. Properties of each soil type can be found in USDA (2007)

Table 4.3. Response variables used in MVRT.

Drought category	Abbreviation	Unit	Definition
Moderate agricultural/hydrological drought	MOD	month	Number of months in the moderate agricultural drought category during the drought events identified in the simulation period at each subbasin
Severe agricultural/hydrological drought	SEV	month	Number of months in the severe agricultural drought category during the drought events identified in the simulation period at each subbasin
Extreme agricultural/hydrological drought	EXT	month	Number of months in the extreme agricultural drought category during the drought events identified in the simulation period at each subbasin

4.3 RESULTS

4.3.1 Model calibration and validation

Table 4.4 summarises the calibration and validation performance indicators for the SWAT model at each gauging station. The calibration and validation models simulated monthly stream flows with NSE values equal to or greater than 0.50 and relatively low PBIAS values (GEF et al., 2021, 2020). According to the performance indicators for calibrating and validating hydrological models, NSE and PBIAS values indicated that the model was appropriate for simulating streamflow (Moriasi et al., 2007). Figure 4.2 presents the model hydrographs at each gauging station for the calibration and validation periods. The locations of the stations can be found in Figure 3.3.

Table 4.4. SWAT model performance simulating streamflow.

Gauging station	Calibration		Validation	
	NSE	**PBIAS [%]**	**NSE**	**PBIAS [%]**
Puente Salguero	0.61	4.28	0.52	-8.3
Puente Carretera	0.50	-5.34	0.52	7.6
Cantaclaro	0.58	-11.30	0.50	-11.7
Puente Canoas	0.70	-1.34	0.57	10.64

Since the analysis focuses on droughts, the model performance simulating streamflow in the dry season was analysed separately. Performance indicators were calculated for the period corresponding to the basin's dry season (December to March). The intermediate period of precipitation decrease from June to July was also included in this analysis. Table 4.5 summarises the calibration and validation performance indicators in the dry season. According to the rating guidelines, the model performance simulating streamflow in the dry season is satisfactory (ASABE, 2017).

Table 4.5. SWAT model performance simulating flows in the dry season.

Gauging station	Calibration		Validation	
	NSE	**PBIAS [%]**	**NSE**	**PBIAS [%]**
Puente Salguero	0.65	-19.4	0.53	-21.3
Puente Carretera	0.67	-15.3	0.53	17.2
Cantaclaro	0.67	-3.6	0.58	16.3
Puente Canoas	0.55	-15.7	0.60	-13.5

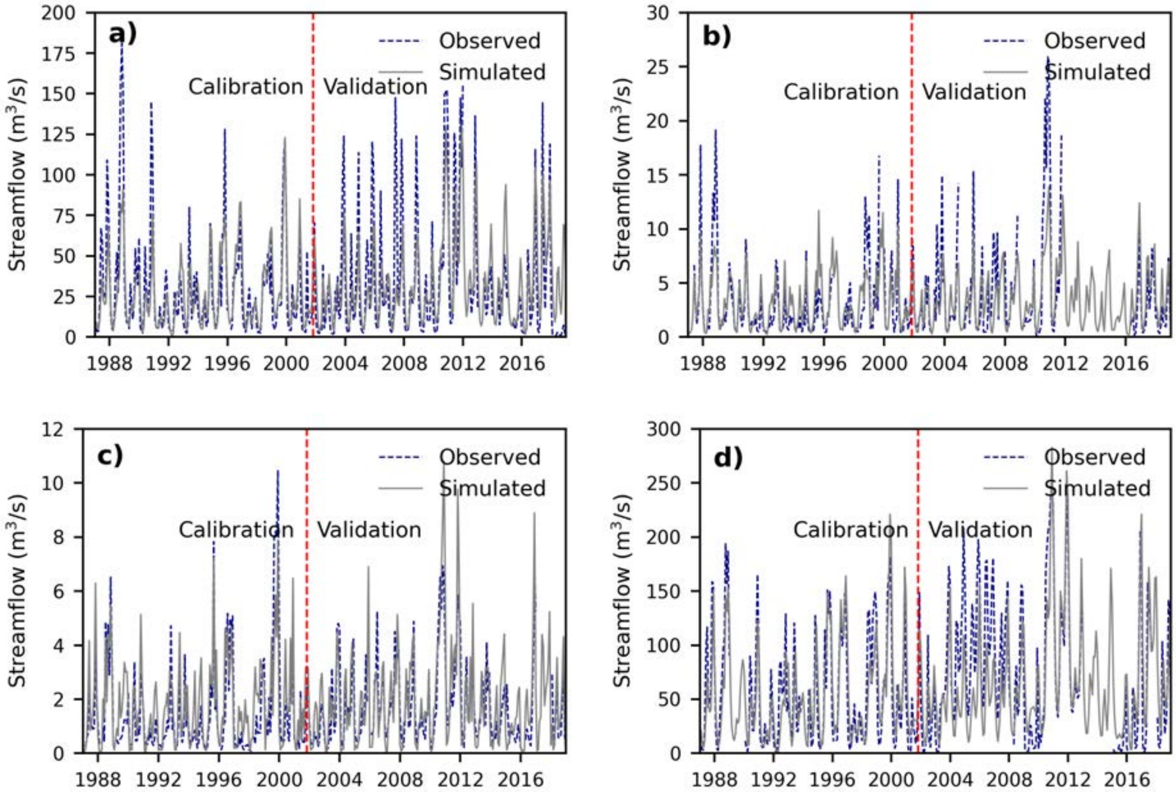

Figure 4.2. Monthly calibration and validation for streamflow at: a) Puente Salguero, b) Puente Carretera, c) Puente Canoas and d) Cantaclaro.

4.3.2 Hydroclimatic drivers of droughts

Figure 4.3 presents the numerical and categorical hydroclimatic parameters used as potential drivers of droughts. Figure 4.3a to h presents the multi-annual average of the numerical hydroclimatic drivers of droughts at each subbasin. The average was calculated using the hydrological model's results during the simulation period (1987 to 2018). Figure 4.3i to k presents the categorical drivers: the curve number, slope and soil type. The dominant category at each subbasin is shown in Figure 4.3i to k. The dataset of explanatory variables was created from the values presented in Figure 4.3.

4.3.3 Severity and duration of agricultural and hydrological droughts in the period of analysis

We identified the drought events and estimated their duration following the definition of droughts presented in Sections 2.3.2 and 4.2.2. The identified droughts in the simulation period were in good agreement with the chronology of drought events in Colombia described at the National Study of Water (Instituto de hidrología meteorología y estudios ambientales (IDEAM), 2019). Table 4.6 shows the dates and durations of the drought events.

Table 4.6. Agricultural and hydrological droughts during the period of analysis.

Event	Agricultural droughts		Hydrological droughts	
	Date	**Duration [months]**	**Date**	**Duration [months]**
I	May 1991 – Jun 1992	13	Apr 1991 – May 1992	14
II	Jun 1997 – April 1998	11	Apr 1997 – Feb 1998	11
III	Jun 2001 – Aug 2001	3	May 2001 – Jun 2001	2
IV	Oct 2009 – Jan 2010	4	Sep 2009 – Nov 2009	3
V	Jun 2014 – Aug 2014	3	Jun 2014 – Jul 2014	2
VI	May 2015 – Jul 2016	15	Apr 2015 – Apr 2016	13

After identifying the agricultural and hydrological drought events, it was possible to determine the number of months for each drought category in each subbasin, as represented in Figure 4.4 and Figure 4.5. The results presented in these figures are the response variables for the MVRT technique.

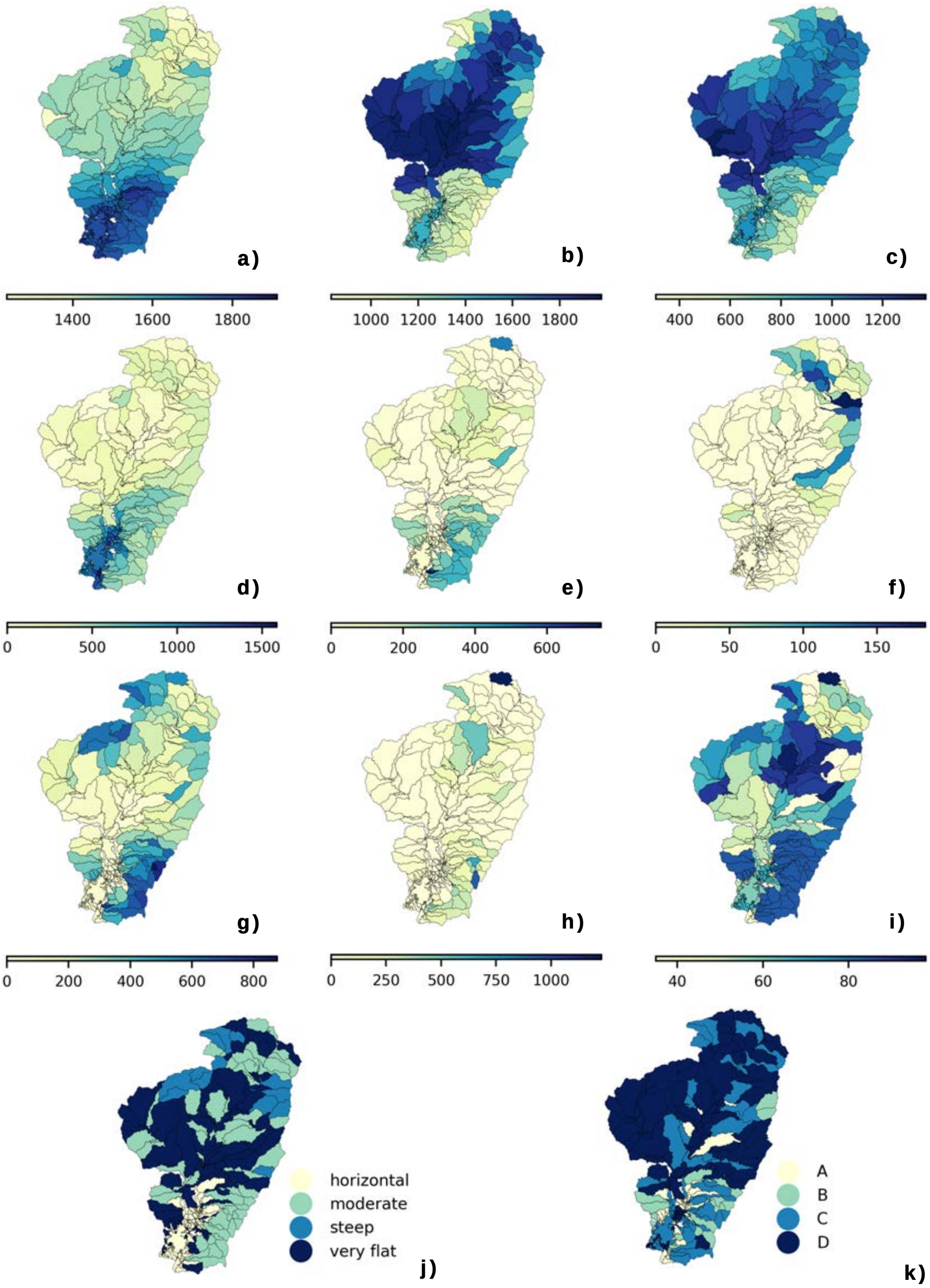

Figure 4.3. Average value of hydroclimatic parameters during the simulation period at each subbasin: a) precipitation in mm, b) potential evapotranspiration in mm, c) actual evapotranspiration in mm, d) percolation in mm, e) surface runoff in mm, f) groundwater contribution to streamflow in mm, g) water yield in mm, h) sediment yield in metric tons/ha, i)

curve number, j) slope and k) soil type, the soil hydrologic groups A, B, C and D refer to the soil's infiltration characteristics.

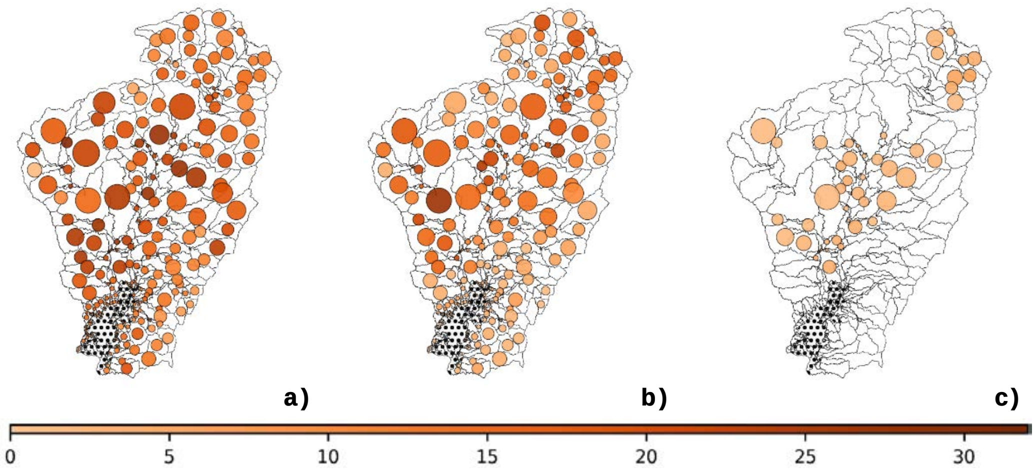

Figure 4.4. Months in each agricultural drought category: a) moderate, b) severe and c) extreme. SMDI was not calculated in the wetland subbasins (i.e. hatched area).

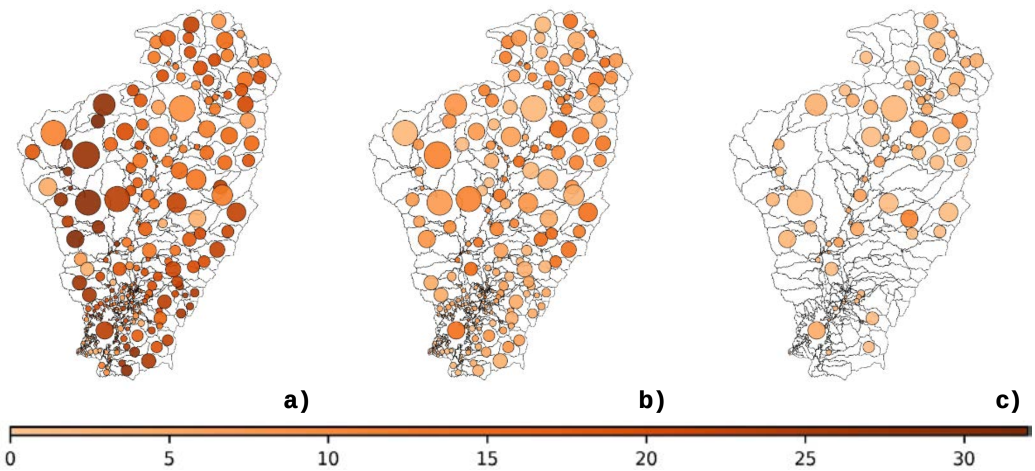

Figure 4.5. Months in each hydrological drought category: a) moderate, b) severe and c) extreme.

4.3.4 Machine learning model for identifiying hydroclimatic drivers of agricultural droughts

Figure 4.6 presents the tree generated by R software, the number of subbasins clustered at each terminal group (variable "*n*"), and the spatial distribution of these subbasins. The tree consists of 5 levels of split and 12 leaves. The minimum value of the cross-validation error (CVRE=0.46) was used to select the tree size. The relative error of the MVRT was 0.19, and the EV was 0.81; Figure 4.7 presentes the tree's numerical output, namely, the number of months for each drought category. The scattering of the outputs in each leaf allows us to identify the most susceptible subbasins to agricultural droughts.

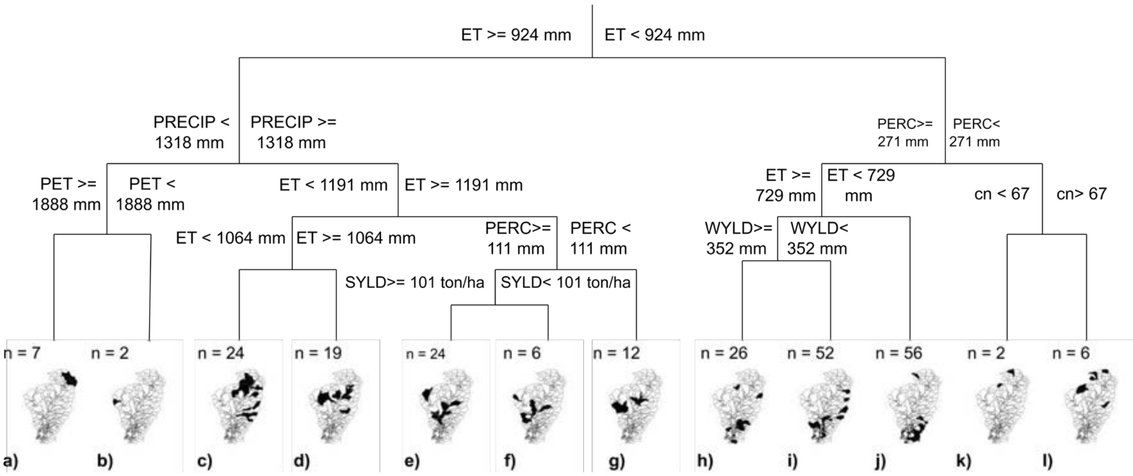

Figure 4.6 MVRT of hydroclimatic drivers of agricultural droughts at the Cesar River basin and spatial distribution of the subbasins clustered at each leaf. Tree leaves are named from *a* to *l*, and *n* indicates the number of subbasins clustered at each leaf. The wetland subbasins are not included in the analysis for agricultural drought.

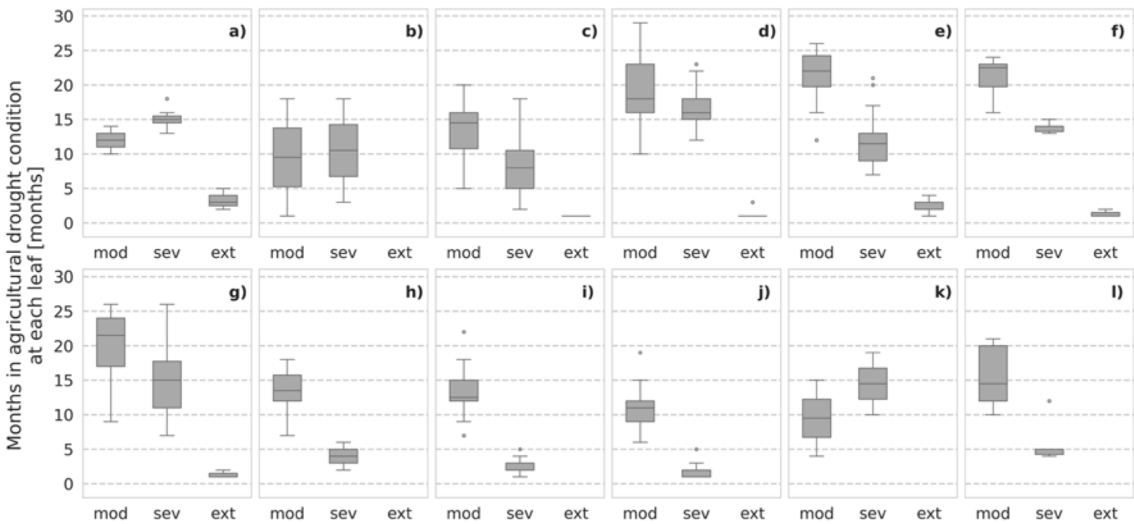

Figure 4.7 Months in agricultural drought categories (moderate, severe, extreme) at each leaf. Tree leaves are named from *a* to *l*.

The MVRT indicated that actual evapotranspiration was a strong driver of agricultural droughts; it appeared three times at different tree levels of split (Figure 4.6). The subbasins were split at the first level according to ET (924 mm). At the second level of split, precipitation (1318 mm) was used for the left branch of the tree and percolation (271 mm) for the right branch. Then, the left branch was recursively split as follows: at the third level, according to potential evapotranspiration (1888 mm) and evapotranspiration (1191 mm); at the fourth level, according to evapotranspiration (1064 mm) and percolation (111 mm); and at the fifth level, according to sediment yield (101 t ha^{-1}). The left branch accounts for 7 out of the tree's 12 leaves. Regarding the right branch, splitting was done according to evapotranspiration (729 mm) and the curve number (67) at the third level and according to the water yield (352 mm) at the last level. In the following, we describe agricultural drought MVRT terminal groups.

Leaf *a* clusters seven subbasins in the north part of the basin. In this area, actual evapotranspiration and potential evapotranspiration were above the basin average, while precipitation was below average (Figure 4.3c, b, and a, respectively). Figure 4.7a shows that these subbasins experienced the highest number of months in extreme agricultural drought and a median of 15 months in severe agricultural drought. Leaf *b* clusters two subbasins in the western part of the basin. In this leaf, there are no months in the extreme drought category. The median of months in the moderate and severe agricultural drought categories is 10 months, one of the lowest among the terminal groups (Figure 4.7b).

Leaves *c* and *d* cluster 24 and 19 subbasins, respectively. Leaf *c* groups subbasins located in the upper part of the river course and the basin east. Precipitation was slightly below the basin average in the subbasins located in the north and close to the average in subbasins in the east (Figure 4.3a). Leaf *d* groups subbasins located in the upper course of the river and in the basin's western part. The actual evapotranspiration threshold to split leaves *c* and *d* is 1064 mm, a value above the basin average (Figure 4.3c). For subbasins with actual evapotranspiration below the threshold, leaf *c*, the median of months in the severe drought category is below 10 (Figure 4.7c). For subbasins with actual evapotranspiration above the threshold, leaf *d*, the median of months in the severe drought category is 16, one of the highest among the terminal groups (Figure 4.7d).

Leaves *e*, *f*, and *g* cluster 24, 6, and 12 subbasins, respectively. Subbasins are located in the river valley and the basin's western part. In these subbasins, precipitation was below the basin average (Figure 4.3a), and actual evapotranspiration was above the average (Figure 4.3c). The percolation threshold to split leaves *e* and *f* from leaf *g* is 111 mm, a value considerably below the basin average (Figure 4.3d). At the fifth level of split, the sediment yield threshold to split leaves *e* and *f* is 101 t ha^{-1}, a value close to the average in the basin (Figure 4.3h). Figure 4.7e, f, and *g* show that subbasins clustered in these leaves are prone to agricultural droughts. The median of months in the moderate drought category was above 20 months, the severe category was above 10 months, and the three leaves exhibited months in the extreme drought category.

Leaves *h*, *i*, and *j* cluster 26, 52, and 56 subbasins, respectively. Subbasins are mainly located in the wetland surroundings, La Serranía (leaf *i*), and some outliers are located in the basin's north (leaves *h* and *j*). Percolation in leaves *h*, *i*, and *j* was close to the basin average (Figure 4.3d). Actual evapotranspiration in terminal groups *h* and *i* was relatively close to the basin average (Figure 4.3c). The water yield threshold to split clusters *h* and *i* is 352 mm. Overall, subbasins clustered at leaves *h*, *i*, and *j* presented low susceptibility to severe and extreme agricultural drought conditions. The median of months in the moderate drought category was slightly higher than 10; the median for months in the severe category was the lowest for the study area and showed no months in the extreme drought category (Figure 4.7h, i, and j).

Leaves *k* and *l* cluster two and six subbasins, respectively. Subbasins are located towards the basin's north, and one outlier is observed in the subbasin east (leaf *l*). In these subbasins, percolation was lower than 271 mm, a value relatively low compared to other basin areas (Figure 4.3d). In leaf *k*, the curve number was lower than 67, while in leaf *l*, it was higher. In leaf *k*, the median of months for the moderate category is 10, and for the severe category, it is 14. In leaf *l*, the median of months in the moderate category is above 10, and the subbasins experienced some months in severe drought. Leaves *k* and *l* show no months in the extreme drought category (Figure 4.7k and l).

4.3.5 MVRT for identifiying hydroclimatic drivers of hydrological droughts

Figure 4.8 presents the hydrological drought MVRT, the number of subbasins clustered at each terminal group (variable "*n*"), and the spatial distribution of these subbasins. The tree consists of four levels of split and eight leaves. The minimum value of the cross-validation error (CVRE=0.67) was used to select the tree size. The relative error of the MVRT was 0.52, and the EV was 0.48. Figure 4.9 presents the tree's numerical output, namely, the number of months for each drought category. This information allowed us to identify the clusters of subbasins prone to hydrological droughts.

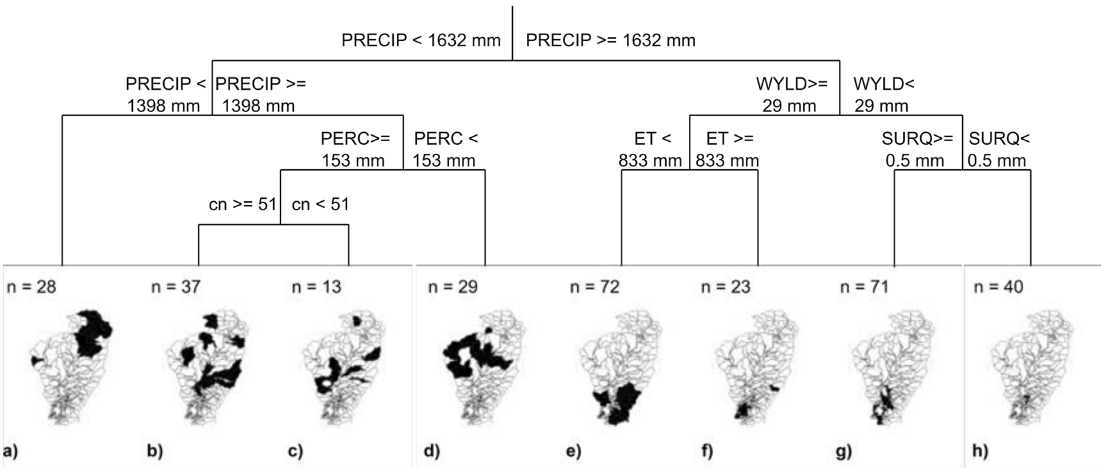

Figure 4.8 MVRT of hydroclimatic drivers of hydrological drought at the Cesar River basin and spatial distribution of the subbasins clustered at each leaf. Tree leaves are named from *a* to *h*, and *n* indicates the number of subbasins clustered at each leaf.

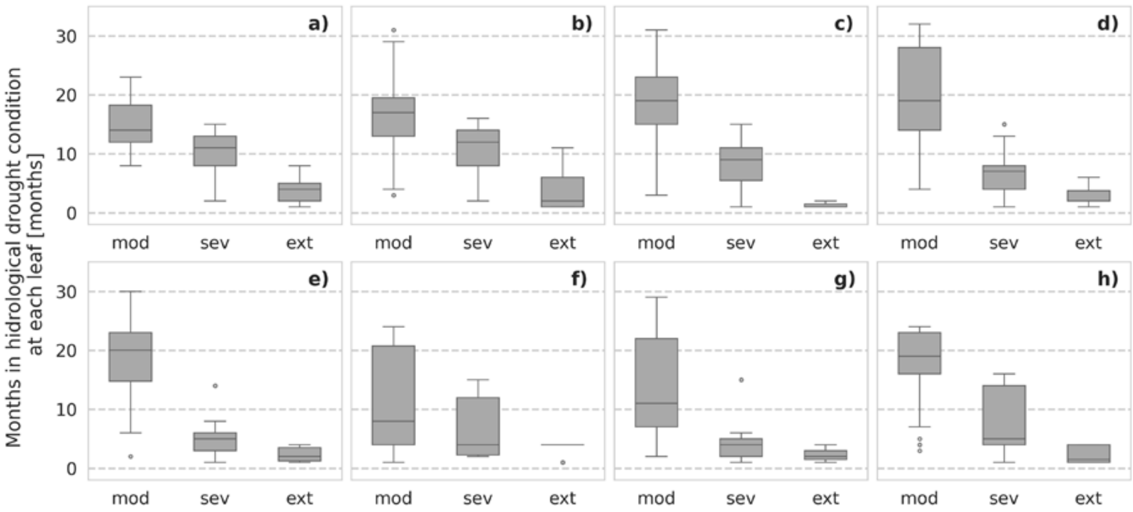

Figure 4.9 Months in hydrological drought categories (moderate, severe, extreme) at each leaf. Tree leaves are named from *a* to *h*.

The MVRT demonstrated that precipitation was a primary driver of hydrological drought; it appeared two times at different levels of split. The subbasins were separated at the first split level according to precipitation (1632 mm). At the second split level, precipitation (1398 mm) was used as the left branch of the tree, and water yield was used as the right branch (29 mm). The left branch was then further divided according to percolation (153 mm) at the third level and according to curve number (51) at the fourth level. At the third level, the right branch was split according to evapotranspiration (833 mm) and surface runoff (0.5 mm). The MVRT terminal groups were then examined in detail.

Leaf *a* clusters 28 subbasins in the upper basin and one outlier located in the western part of the subbasin (Figure 4.8a). In these subbasins, precipitation was considerably below the basin average (Figure 4.3a). Figure 4.9a shows that the subbasins in this terminal group repeatedly experienced moderate, severe, and extreme hydrological drought.

Leaves *b* and *c* cluster 37 and 13 subbasins, respectively. Subbasins clustered at leaf *b* are relatively distant; most are towards the eastern part of the basin, and the rest are in the north and west of the basin. Subbasins in leaf *c* are located in the river's middle course towards the western part of the basin and some outliers in the north. Precipitation and percolation were slightly above the basin average in subbasins clustered at leaves *b* and *c* (Figure 4.3a and d). The curve number threshold to split leaves *c* and *d* is 51. Subbasins with a curve number above the threshold, leaf *b*, experience months in extreme drought and present one of the highest median of months for severe drought (Figure 4.9b). For subbasins with curve number below the threshold, leaf *c*, the median of months at moderate drought is almost 20 and experienced months at severe and extreme category (Figure 4.9c).

Leaf *d* clusters 29 subbasins in the river's middle course and the basin's eastern part. Figure 4.9d indicates that in this terminal group, the subbasins experienced fewer months in the severe and extreme drought categories than the other clusters in the tree's left branch; however, subbasins experienced one of the highest medians of months at moderate drought.

In leaves, *e* (n = 72) and *f* (n = 23), precipitation exceeded the basin average and water yield was considerably high in the subbasins in La Serranía del Perijá (Figure 4.3a and g). The actual evapotranspiration threshold to split leaves *e* and *f* is 833 mm, a value below the basin average (Figure 4.3c). Both terminal groups describe moderate exposure to hydrological drought. At leaf *e*, the median of months in the severe and extreme drought categories is below 10, while the median of months in the moderate drought category is 20 (Figure 4.9e). The hydrological drought exposure of the subbasins clustered at leaf *f* is also mild. In these subbasins, actual evapotranspiration is above the threshold and close to the basin average. These subbasins present the lowest median of months for all drought categories (Figure 4.9f). Notably, the Zapatosa marsh and upstream subbasins are clustered in this terminal group (Figure 4.8f).

Leaves *g* and *h* cluster 71 and 40 subbasins, respectively. Subbasins clustered at these leaves are located upstream of the Zapatosa marsh. The surface runoff threshold to split the leaves *g* and *h* is 0.5 mm. Figure 4.9g shows that the subbasins grouped at leaf *g* present the low susceptibility to hydrological drought. The median of months for all categories is the lowest in the basin. In leaf *h*, the surface runoff was lower than 0.5 mm. In these subbasins, the medians of months in the severe and extreme categories are relatively low, while the median of months in the moderate category is 18 (Figure 4.9h).

4.4 DISCUSSION

4.4.1 Hydroclimatic drivers of agricultural droughts

The left branch of the MVRT clustered the subbasins susceptible to severe agricultural drought (Figure 4.7 a, d, e, f, and g). Conversely, the right branch of the MVRT clustered the subbasins experiencing moderate agricultural drought severity. The subbasins in leaves *h*, *i*, and *j* predominately experienced months in the moderate drought category (Figure 4.7 h, i, and j).

Interestingly, agricultural drought severity in leaves *a*, *e*, *f*, and *g* is comparable but governed by different parameters. For instance, leaf a presents the highest median of months for severe and extreme agricultural drought (Figure 4.7 a). The drought drivers in this terminal group, namely precipitation and potential evapotranspiration, indicate that agricultural drought results from an imbalance between the soil moisture supply (i.e.

precipitation relatively close to the minimum value at the basin) and soil moisture demand (i.e. moderately high potential evapotranspiration). Leaves *b*, *c*, and *d* corroborate the significant influence of evapotranspiration on agricultural drought severity. A comparison of clusters *a* and *b* and *c* and *d* indicates that the leaves with higher evapotranspiration are more prone to experiencing severe drought. It is interesting to notice that in clusters *c* and *d*, the actual evapotranspiration threshold causes a notable difference in drought severity. While leaf *c* clustering subbasins with actual evapotranspiration below 1064mm presents the lowest median of months at severe category at the left branch of the tree, leaf *d* shows the highest median of months at the same category in the tree.

This finding aligns well with studies demonstrating that potential evapotranspiration considerably enhances the severity of agricultural droughts in water-limited areas (Ding et al., 2021; Manning et al., 2018; Teuling et al., 2013). According to such studies, potential evapotranspiration influence on agricultural drought severity may be explained by the significant increase in net radiation during droughts, as the lack of rainfall usually concurs with decreased cloud cover.

In contrast, the MVRT outcomes suggest that a lack of precipitation was not a primary driver of agricultural drought in the subbasins clustered at leaves *e*, *f*, and *g*. Particularly, leaf *e* groups the subbasins that experienced the most severe agricultural drought in the analysis period. The median of months in the moderate drought category was above 20; the severe category was above 10, and subbasins experienced months in extreme category (Figure 4.7e). The observed evapotranspiration and percolation thresholds might indicate poor precipitation partitioning and a disturbed water regime that favours water lost by runoff and evapotranspiration. Furthermore, the sediment yield threshold (notably above the median) may be linked to poor soil structure, thus compromising soil water retention capacity and enhancing drought severity.

The results from leaf *e* showed that a higher sediment yield slightly increases the occurrence of extreme droughts (Figure 4.7e), as compared to the results from leaf *f*. This agrees with earlier findings concluding that soil degradation enhances agricultural drought characteristics (Masroor et al., 2022; Santra and Santra Mitra, 2020; Trnka et al., 2016). Further, our results were consistent with previous studies that indicate the incidence of droughts is caused not only by extreme weather events but also by the inefficient soil–water management associated with land and soil degradation (Cornelis et al., 2019; Wildemeersch et al., 2015).

The right branch of the tree provided valuable information on the hydroclimatic parameters that reduce the severity of agricultural droughts. Moderate drought susceptibility in leaves *h*, *i*, and *j* was linked to relatively low evapotranspiration thresholds; accordingly, it may be asserted that evapotranspiration-controlling measures (e.g. surface cover, crop rotation, agroforestry, intercropping) are relevant interventions for building resistance to agricultural drought. At terminal groups *h* and *i*, water yield was found to influence the severity of agricultural drought. Notably, the subbasins at leaf i were slightly more resistant to drought (Figure 4.7i); this indicates that measures aimed at increasing the subbasins' water storage capacity (e.g. rainwater and floodwater harvesting techniques) are suitable interventions to reduce the severity of agricultural drought.

Some of the subbasins grouped at leaf *i* showed high exposure to hydrological drought (Figure 4.8b and c). Contrasting exposure to agricultural and hydrological droughts suggests that the water retention capacity in these subbasins reduces the severity of agricultural drought events but limits the contribution of surface runoff, lateral flow, and groundwater to the streamflow, thus exacerbating the water deficit and hydrological drought severity. Therefore, drought management interventions require the prior assessment of the potential effects on both types of droughts.

4.4.2 Hydroclimatic drivers of hydrological droughts

The subbasins clustered on the left branch of the tree were prone to hydrological drought (Figure 4.9a, b, c, d). Leaf *a* presented the highest median for months in the severe and extreme hydrological categories. The analysis results confirmed that precipitation deficits caused the severe hydrological drought conditions in the upper part of the basin.

Conversely, the MVRT also showed that in terminal groups *b*, *c*, and *d*, hydrological drought severity was linked to the inefficient partition of precipitation. Selected drivers (precipitation, percolation and curve number representing land use) are widely recognised as predominant drivers of hydrological droughts (Iglesias et al., 2018a; Stoelzle et al., 2014; Van Lanen et al., 2013; Van Loon, 2015). The difference observed between the precipitation and percolation thresholds suggests that a large part of rainwater was lost either by evapotranspiration or surface runoff (or other water abstractions; e.g. human consumption, agriculture). Low percolation values limited the groundwater contribution to the streamflow, enhancing the streamflow deficit during drought periods.

Interestingly, the curve number was selected as a driver of hydrological drought for leaves *b* and *c* (Figure 4.8b and c). The subbasins in leaf *b* presented higher curve numbers than those in leaf *c* and higher exposure to hydrological drought. High curve number values are commonly the result of anthropogenic changes in land cover, which modifies evapotranspiration and the division of precipitation into evapotranspiration and streamflow. The present selection of the curve number at the third level of split is consistent with previous studies, which established that hydroclimatic parameters and human activities influence hydrological droughts; however, the influence of both drivers is uneven. Results indicate that hydroclimatic parameters are more influential (Jehanzaib et al., 2020; Saidi et al., 2018).

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The right branch of the MVRT grouped subbasins with moderate and intermediate exposure to hydrological drought. The hydroclimatic parameters and the thresholds used to define leaves *e* and *f* (precipitation, water yield, and evapotranspiration) demonstrate that in these subbasins, precipitation values compensated for the water abstraction by evapotranspiration. When we compare the severity of the hydrological droughts observed in leaves *e* and *f*, we find that lower evapotranspiration values reduce exposure to severe and extreme hydrological drought but increase the incidence of moderate hydrological drought.

The subbasins in terminal group *g* experienced the lowest median number of months for all hydrological drought categories (Figure 4.9g). The water yield threshold indicates good water retention capacity in these subbasins. It can be explained by the proximity of the subbasins to the marsh (which acted as a natural control), the low slope in the area (which reduced streamflow velocity), and the presence of water bodies (which collected and stored runoff during the rainy season). The runoff threshold indicates that part of rainwater reaches the streamflow; nevertheless, the subbasins in cluster *g* have one of the lowest runoff potentials in the basin (Figure 4.3e). On the contrary, in these subbasins, percolation is considerably high (Figure 4.3d). This seems to confirm that low susceptibility to hydrological droughts is linked to subbasin water retention capacity. The present findings suggest that the water storage capacity of the Zapatosa marsh can compensate for the increased evaporation that occurs during drought events, thereby alleviating hydrological drought severity upstream. Our results concur with previous analyses concluding that wetlands (located in different climatic regions) significantly alleviate hydrological drought severity when direct evaporation from the water body does not significantly reduce water storage (Wu et al., 2023).

The hydrological drought conditions in the subbasins clustered at leaf h were mild despite water yield values below 29mm (Figure 4.8h). Negligible surface runoff values indicated that in leaf *h*, rainfall is stored in the soil profile, is lost by evapotranspiration, or percolates in an area of minimal baseflow contribution to streamflow. This limits the amount of water reaching the streamflow and enhances the severity of hydrological droughts, compared to leaf *g*.

4.4.3 Comparison of the hydroclimatic parameters influencing the severity of agricultural and hydrological droughts

Crucial similarities and differences emerge from contrasting the parameters influencing the severity of droughts and the spatial distribution of the subbasins experiencing severe and mild drought conditions. MVRTs indicate that severe agricultural and hydrological drought conditions occurred in the upper and middle course of the river. Nevertheless, the severe droughts were influenced by different hydroclimatic factors. Severe agricultural drought in the headwater was driven by the interaction between precipitation shortfalls and high potential evapotranspiration (Figure 4.6). Conversely, severe hydrological drought conditions were solely driven by limited precipitation. It is worth highlighting that the severe hydrological situation extends from the headwater to the subbasins in the middle course (Figure 4.8). Downstream, in subbasins located in the middle course, the agricultural and hydrological drought situation was also severe. In this area, drought severity was linked to inadequate rainfall partitioning and an unbalanced water cycle that favours water loss through evapotranspiration and low percolation values (Figure 4.6d, e, f, and g and Figure 4.8b, c, and d). Significantly, agricultural and hydrological droughts in these leaves were more severe than in leaves experiencing precipitation deficits (Figure 4.6a and Figure 4.8a). Results also suggest that poor soil structure enhanced severe agricultural drought conditions (Figure 4.6e), and high curve numbers seem to increase hydrological drought severity (Figure 4.8b).

MVRTs also showed subbasins experiencing mild agricultural and hydrological drought severity. Overall, these subbasins were located in the southern part of the basin. However, for agricultural drought, a few cases were observed in the north of the basin (Figure 4.6h, i, and j). Subbasins presenting mild hydrological drought severity are allocated upstream of the Zapatosa marsh (Figure 4.8g). Moderate agricultural drought severity was linked to low evapotranspiration losses and the subbasins' capacity to retain water in the soil profile, improving percolation (Figure 4.6). In turn, moderate hydrological drought severity is related to the subbasins' proximity to the marsh (which acted as a natural control reducing the water yield) and surface runoff contributions to the streamflow (Figure 4.8g). Remarkably, some of these subbasins also showed mild agricultural drought conditions (Figure 4.6i).

4.4.4 Accuracy of the MVRTs

The high EV (0.81) value indicates the good explanatory power of the tree built for agricultural drought. This confirms that the selected explanatory variables significantly influence the severity of agricultural drought. Nevertheless, two potential disadvantages of the tree are identified. First, clusters *h* and *i* are very similar. Drought severity is alike in these leaves, and the parameters influencing droughts are the same. This suggests that the two clusters can be merged into one. Second, leaves *b* and *k* cluster only two subbasins. Accordingly, the distribution presented in the boxplots must be interpreted cautiously. Neither of these disadvantages compromises the analysis' main findings; however, further work is recommended to determine the size of the tree (number of clusters) that better fits the assessment of the hydroclimatic drivers of droughts.

Conversely, the explanatory power of the tree built for hydrological drought is not very high (EV=0.48). This may be related to the inaccurate representation of groundwater contribution to the streamflow. Streams depend significantly on groundwater during droughts to maintain flow; nevertheless, groundwater contribution to the streamflow was not included as a key drought driver in the MVRT, although it was in the list of explanatory variables. It is possible that the model's simplifications for the simulation of groundwater flow and storage did not adequately represent the groundwater contribution to the streamflow (Molina-Navarro et al., 2019). The lack of adequate information about this relevant factor hydrological drought may have compromised the MVRT's accuracy. Unexplained variability may also link to factors that influence hydrological drought but were not considered in the dataset of explanatory variables (e.g. abstractions such as water for irrigation, industry, or human consumption).

4.5 CONCLUSION

In this chapter, a ML technique, MVRT, was applied. The main aim was to build an "explanatory AI" model to explicitly identify relationships between a subbasin's hydroclimatic characteristics (i.e. explanatory variables) and the severity categories of agricultural and hydrological drought (i.e. response variables). The results show that the ML technique identifies drought severity's primary drivers and critical thresholds reasonably well. The MVRT also identifies parameters which can contribute to reducing agricultural and hydrological drought severity.

The outcomes of the MVRT provide valuable information on the hydroclimatic parameters influencing the drought-generating process in the Cesar River basin. MVRTs indicate that severe agricultural and hydrological drought conditions observed in the upper and middle course of the river are influenced by different hydroclimatic factors. The interaction between precipitation shortfalls and high potential evapotranspiration drives severe agricultural drought in the headwater. Conversely, severe hydrological drought conditions are mostly caused by limited precipitation. In subbasins in the middle course, drought severity is linked to inadequate rainfall partitioning and an unbalanced water cycle, favouring water loss through evapotranspiration and low percolation values. Notably, results suggest that poor soil structure enhances severe agricultural drought conditions, and high curve numbers seem to increase hydrological drought severity. In the southern region, subbasins experience moderate agricultural and hydrological drought severity. Mild agricultural drought is linked to low evapotranspiration losses and subbasins' capacity to retain water in the soil profile, improving percolation. In turn, moderate hydrological drought severity relates to the subbasins' proximity to the marsh (which acted as a natural control reducing the water yield) and surface runoff contributions to the streamflow.

The outcomes presented in this chapter also demonstrate that the combined effect of parameters with low impact can trigger a drought situation as severe as the one produced by one or two of the most influential parameters. It is worth mentioning that the outcomes of the analysis indicate that slope and soil type do not influence the severity of agricultural and hydrological droughts in the Cesar River basin.

The issue of combining human and artificial intelligence and knowledge of physics with ML is currently a point of great interest (see Jiang et al. (2020) on 'physics-aware deep learning models' and Moreido et al. (2021) and Bertels et al. (2023), on the role of experts in constraining machine-learning and hydrological models). However, the mentioned approaches directly incorporate physical knowledge into ML models, and domain experts still see the resulting models as "black boxes". This work contributes to developing and testing tools to better incorporate 'explanatory' ML, leading to models that can be overviewed and analysed by experts and, hence, have a better potential for inclusion into existing modelling and management practices.

The identified areas exhibiting the highest susceptibility to agricultural and hydrological droughts are prioritised in formulating the optimisation problem presented in Chapter 6.

In addition, the findings on the hydroclimating parameters driving drought severity are used in Chapters 5 and 6 to select PDMMs that may contribute to restoring disturbed components of the water cycle.

5 ANALYSIS OF THE PDMMS EFFECTS ON AGRICULTURAL AND HYDROLOGICAL DROUGHT SEVERITY

ABSTRACT

PDMMs aim to reduce the chance of droughts and minimize drought-associated damages. This chapter [1] *evaluates the effects of three potential PDMMs on agricultural and hydrological drought severity, rainwater harvesting ponds, forest conservation, and check dams. The SWAT model is used for hydrological modelling and representing PDMMs. The threshold level method is applied to analyze droughts and evaluate the impact of PDMMs on drought severity.*

Findings show that rainwater harvesting ponds applied on agricultural land reduce the severity of agricultural droughts and hydrological droughts, particularly during the first months of the drought events observed in the rainy season. Results also reveal that forest conservation contributes to reducing the severity of hydrological droughts by up to 90%. Finally, check dams and ponds in upstream subbasins considerably reduce agricultural and hydrological drought severity in the areas where the structures are applied; however, they exacerbate drought severity downstream. The analysis is carried out for the Torola River Basin (El Salvador).

[1] This chapter is based on the publication: Paez-Trujillo, A.; Corzo, G.A.; Maskey, S.; Solomatine, D. Model-Based Assessment of Preventive Drought Management Measures' Effect on Droughts Severity. *Water* 2023, 15, 1442. https://doi.org/10.3390/w15081442.

5.1 INTRODUCTION

Droughts trigger a range of pervasive effects on society, the environment, and the economy. Drought-associated societal impacts include food insecurity and increased social conflict (UNDRR, 2021). In terms of environmental damage, droughts can lead to the overexploitation of forests, riverbanks, and groundwater, as well as biodiversity loss (FAO, 2017a; UNDRR, 2021). For the economy, it is estimated that droughts cause 84% of the agriculture sector's total economic damage and losses (FAO, 2020) and bring critical losses to multiple economic sectors (Van Vliet et al., 2016).

Therefore, there is an urgent need to develop drought policies and management plans to alleviate or minimize drought-associated damages. A key element of these policies and plans is the Preventive Drought Management Measures (PDMMs), also known as the Strategic Drought Management Measures or Drought Risk Reduction Measures (FAO, 2019; World Bank, 2019). A wide range of measures can be considered PDMMs. For instance, the United Nations World Water Assessment Program includes rainwater harvesting (RWH), gully control structures and terraces, and nonstructural interventions such as soil conservation practices and forest conservation (WWAP, 2018). The GlobalWater Partnership Central and Eastern Europe (2015) encourages the use of natural water retention measures (NWRM), such as floodplains and wetlands restoration, to limit the adverse effects of droughts. Together with the previous measures, the United Nations Convention to Combat Desertification (UNCCD, 2019) presented and assessed 14 categories of drought-smart land management practices in four land-use types (agriculture, grazing, forests and woodlands, mixed land use).

Despite the broad list of interventions applicable to drought management, the actual contribution of PDMMs to drought mitigation or alleviation remains to be determined. While some interventions have been widely applied to local initiatives, they are rarely part of a structured drought management plan. As such, there is very little coordination to guarantee their operation in the long term, and PDMM performance for drought mitigation is hardly ever assessed. Consequently, local measures are not appropriately informed by knowledge of a region's drought likelihood and potential impacts on the hydrological cycle (Islam et al., 2019; UNDRR, 2021).

Of equal importance is the lack of studies that examine the applicability and effectiveness of PDMMs in alleviating drought. Assessment of these measures relies on their applicability to increase infiltration and water availability, improving soil water-holding capacity and preventing land degradation or desertification (UNCCD, 2019; WWAP, 2018). While these criteria provide valuable insights into the applicability of these measures, they do not explicitly appraise their effectiveness in alleviating drought's characteristics (e.g., duration, spatial extent, severity).

Therefore, the key question is: How should the contribution of PDMMs to drought alleviation be assessed? To address this, a modelling-based approach is applied to assess changes in agricultural and hydrological drought severity after applying three potential PDMMs: RWH ponds on agricultural lands, forest conservation in forested areas, and ponds and check dams in upstream subbasins. A concrete application of this methodology is carried out for the Torola River basin (El Salvador, Central America).

5.2 METHODOLOGY

This phase of the study used the soil and water assessment tool (SWAT) for hydrological modelling and to represent the PDMMs (Section 2.2.1). The threshold level method (Section 2.3.2) is applied to assess the effects of PDMMs on drought's severity. Figure 5.1 presents the flowchart of the methodology applied.

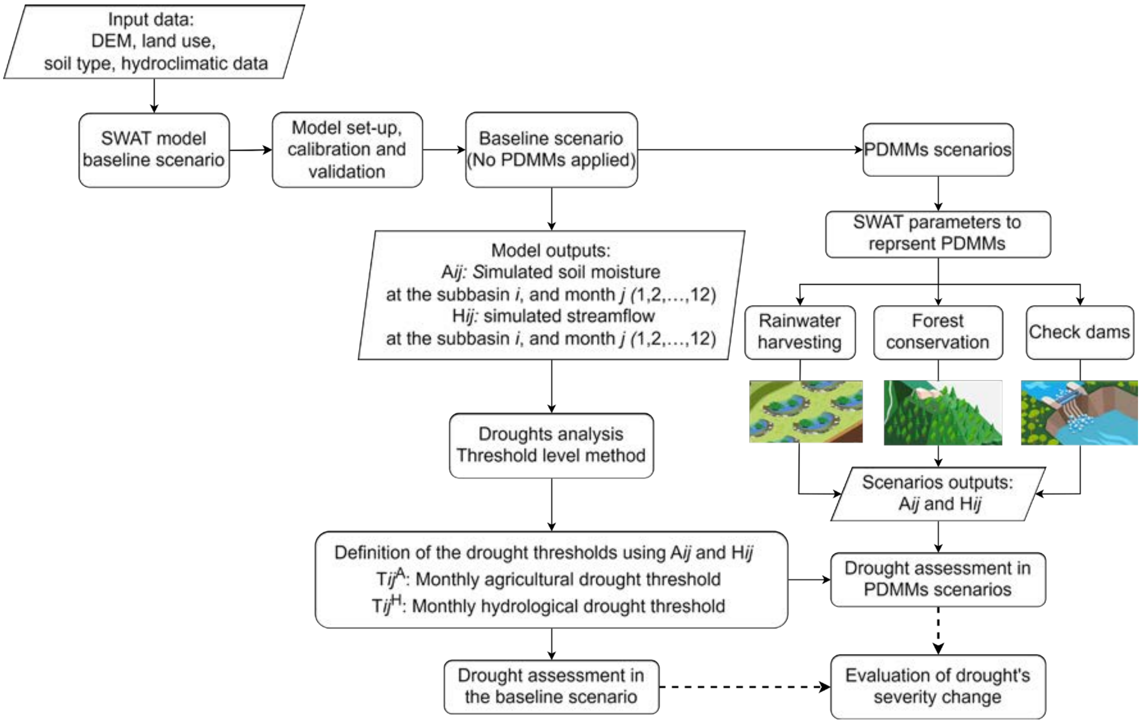

Figure 5.1 Flowchart of the methodology applied in Chapter 5 (research phase 2).

5.2.1 Hydrological model set-up, calibration and validation

The hydrological model of the Torola River Basin (SWAT, Section 2.2.1) was built for the period spanning 2004 to 2018. The Torola basin was divided into 44 subbasins with a median area of 15 km^2. Four slope classes were set for the HRUs generation: gentle (0–10%), moderate (11–20%), steep (21–30%), and considerably steep (>31). The following methods were used to model the major hydrological processes: the soil conservation services-curve number (SCS-CN) was used to simulate surface runoff; potential evapotranspiration was calculated using the Hargreaves method; and water was routed through the channel network using the variable storage routing method. The details and sources of the SWAT model input data are presented in Table 5.1.

Table 5.1 SWAT model input data Torola River Basin

Data type	Details	Source
Digital elevation model	5 × 5 m	Ministry of Environment and Natural Resources, El Salvador.
Soil map	300 × 300 m	Digital Soil Map of the World (FAO and UNESCO, 2007).
Land use map	300 × 300 m	Global land cover distribution, by dominant land cover type (FGGD) (FAO, 2007).
Rainfall and temperature, daily data (2 stations)	Period 2004–2018 (15 years)	Ministry of Environment and Natural Resources, El Salvador.

Monthly automatic calibration and validation were conducted to evaluate the model's performance in simulating streamflow (Section 2.2.2). The model was calibrated from 2004 to 2010 and validated from 2010 to 2018. In both cases, the first year was used as a warming-up period. Thus, performance indicators were calculated for 2005 to 2010 (calibration) and 2011 to 2018 (validation).

5.2.2 Describing and modeling PDMMs

Table 5.2 presents the evaluation criteria for identifying suitable interventions for drought management in the study area. The criteria included intervention requirements for an adequate operation, compatibility with the basin's land use, and availability of parameters to model the intervention. Applying the criteria and comparing these requirements with the basin characteristics, RWH ponds in agricultural land, forest conservation in forested areas, and check dams in upstream subbasins were selected to assess their effectiveness for drought management.

The first measure of RWH ponds traps and collects runoff from a relatively small catchment area (10–500m^2) (Berhane, 2017). The RWH ponds were modeled using SWAT's pothole routine. Potholes are water bodies located off the main channel, and water flows to them from the subbasin (Neitsch et al., 2011). The potholes were applied at the HRU level, wherein the user indicated the flow fraction from the upland HRUs that contributed to the pothole HRU and the maximum water depth over the entire HRU (Du et al., 2005). The storage capacity of that pothole was determined by the area of each HRU multiplied by the maximum water depth. As there could be only one pothole in each HRU, for this analysis, the sequence of the RWH ponds' storage capacity was aggregated into one pothole (Wambura et al., 2018).

The second measure was the conservation of forested areas, which aims to maintain forest cover and limit soil degradation to slow runoff and increase infiltration and groundwater recharge. Such actions include forest regeneration, species diversity, and unevenly aged stands (Brancalion and Chazdon, 2017). In the SWAT model, the CN2 value of forested HRUs could be reduced from the calibrated value to the recommended value for forested areas in good hydrological conditions. In the present study, the CN2 value was modified according to the HRU’s hydrologic soil group (Mishra and Singh, 2003).

The last measure, check dams, are small barriers constructed across channels or gullies to obstruct flow. These structures store floodwater and allow more time for water percolation to recharge aquifers, among other purposes (Abbasi et al., 2019; Lucas-Borja et al., 2021). Check dams were simulated in the SWAT model as ponds (Waidler et al., 2009). The SWAT model defined ponds as water bodies located off the stream network that only receive loadings from the subbasin’s HRUs. Predicted runoff from the HRUs was aggregated and routed into ponds, regardless of the pond’s location in the subbasin (Jalowska and Yuan, 2019). The required inputs were the pond’s storage capacity and surface area.

5.2.3 Applying the Threshold Level Method to Analyze the Effect of PDMMs on Drought Severity

The TLM application described in 2.3.2 was used to identify the drought events during the analysis period and estimate the effect of PDMMs on droughts’ severity. Notably, the monthly threshold calculated in the baseline scenario was utilised to identify droughts and calculate severity in the baseline and PDMM scenarios. SWAT results obtained on the subbasin level were suitable for evaluating the drought severity at each subbasin and assessing the differential effect of mitigation measures in upstream and downstream subbasins. Drought severity was calculated separately for the baseline and management scenarios to assess the PDMMs’ effectiveness in alleviating drought. The severity change was estimated by comparing the severity in the baseline scenario (no PDMMs applied) to the severity in the PDMMs scenarios.

Table 5.2 Evaluation criteria to identify interventions for drought management in study area.

Criteria	**RWH Ponds**	**Forest Conservation**	**Check Dams**
Description	Designed to trap and collect runoff from a relatively small catchment area (10–500 m2) (Berhane, 2017).	Forest conservation aims to maintain forest cover and limit soil degradation (Brancalion and Chazdon, 2017).	Small barriers constructed across channels to obstruct flow (Lucas-Borja et al., 2021).
Annual rainfall	200–1000 mm (Woldegiorgis, 2017).	NA.	Used frequently in arid or mountainous environments with ephemeral hydrology (Polyakov et al., 2014).
Topography	Steeply and mild slopes (Kahinda et al., 2008).	NA.	Steep and mild slopes (Piton et al., 2016).
Soil type	Sandy loam, sandy clay loam, and sandy clays (Kahinda et al., 2008).	NA.	On areas with coarse soil texture (Polyakov et al., 2014).
Land use compatibility	Applied in agricultural land (Oweis et al., 2012).	Land where forest is, or is planned to become, the dominant land use (Brancalion and Chazdon, 2017).	Where the slope is mild and the area is sufficient to store discharge and sediment (Piton et al., 2016).
Parameter(s) to model the measure in SWAT	Pothole routine: POT_FR [a] (0.3), POT_VOLX [b] (20 cm), (Wambura et al., 2018).	CN2 [c] value of forested HRUs was reduced from the calibrated value to the recommended value for forest in good hydrological conditions (Mishra and Singh, 2003).	Ponds: PND_FR [d] (0.3), PND_PVOL [e] (5×10^4 m^3), PND_PSA [f] (1 ha) (Du et al., 2005).
No. of PDMM applied	140 potholes were applied at HRU level (140 HRUs met the allocation criteria).	–	17 ponds were applied at the subbasin level (17 subbasins met the allocation criteria).
Measures allocation			

Notes: [a] Fraction of the HRU area that drains into a pothole; [b] maximum volume of water stored in the pothole (mm) over the entire HRU; [c] initial SCS runoff curve number for moisture condition II; [d] fraction of subbasin area that drains into ponds; [e] volume of water stored in ponds when filled to the principal spillway (10^4 m^3. H_2O); [f] surface area of ponds when filled to principal spillway (ha).

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5.3 RESULTS AND DISCUSSION

5.3.1 Model sensitivity analysis and calibration

Table 5.3 presents the top 10 most sensitive parameters from the model setup. These parameters are used for model calibration and validation. The NSE is 0.73 for calibration and 0.62 for validation, and the PBIAS is 6.7% for calibration and −7.6% for validation. According to Moriasi et al. (2007), the model performance is considered appropriate for simulating streamflow.

Table 5.3 Sensitivity analysis rankings for streamflow model output.

Parameter [a]	Description in SWAT	Range	Default Value	Calibrated Value
r__SOL_Z().sol	Depth from soil surface to bottom of layer (mm).	0–3500	Soil and layer specific	300–1000 [b]
r__SOL_BD().sol	Moist bulk density (g/cm^3).	0.9–2.5	Soil and layer specific	1.0–1.3 [b]
r__SOL_AWC().sol	Available water capacity of the soil layer (mm H20/mm soil).	0–1	Soil and layer specific	0.1–0.2 [b]
r__SOL_K().sol	Saturated hydraulic conductivity (mm/h).	0–2000	Soil and layer specific	8.0–45.0 [b]
r__CN2.mgt	SCS runoff curve number.	35–98	Specific HRU	70–85 [b]
v__RCHRG_DP.gw	Deep aquifer percolation fraction.	0–1	0.05	0.02
v__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur.	0–5000	1000	4642
v__GW_DELAY.gw	Groundwater delay (days).	0–500	31	4.0
r__ESCO.hru	Soil evaporation compensation factor.	0–1	0.95	0.51
v__CH_N2.rte	Manning's for the main channel.	−0.01–0.3	0.014	0.10

Notes: [a] v: parameter value is replaced by a value from the given range; r: parameter value is multiplied by (1 + a given value), [b] range of calibrated values.

Figure 5.2 shows the model's performance at Osicala station (See Figure 3.1a). Although peak discharges are underestimated in specific years of the calibration and validation periods, the overall performance of the SWAT model is acceptable for simulating streamflow.

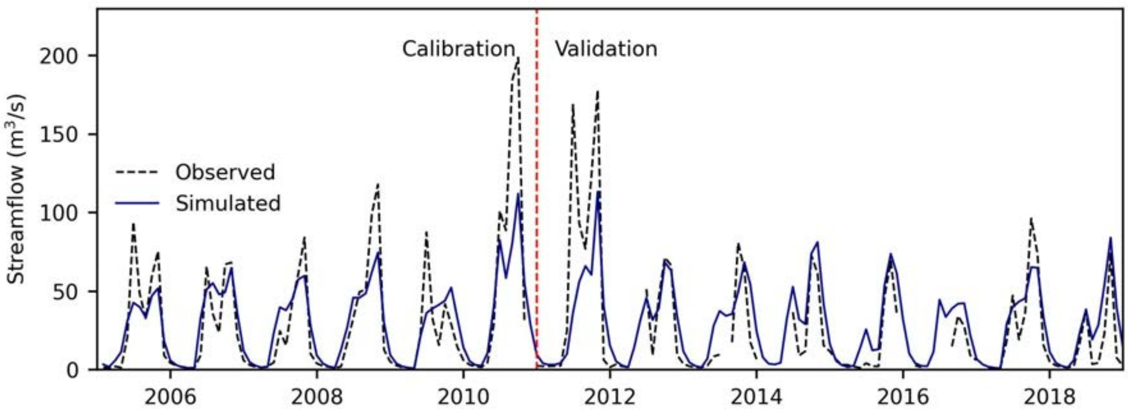

Figure 5.2 Monthly calibration and validation for streamflow at Osicala station.

5.3.2 Agricultural and hydrological droughts in the baseline scenario

Applying TLM described in 2.3.2, seven agricultural droughts and five hydrological droughts were identified during the simulation period. Figure 5.3 shows the timeline of the drought periods. Agricultural drought events are named from I to VII, and hydrological drought events are named from I to V. The events are consistent with the drought chronology in the region (FAO, 2017b). Even more, the results are in line with previous studies indicating that between 2015 and 2019, the region experienced a multiyear meteorological drought, one of the main drivers of agricultural and hydrological droughts (Depsky and Pons, 2020; Pascale et al., 2021). According to the results, in the simulation period (15 years), there were 26 months of agricultural drought and 14 months of hydrological drought. Figure 5.4 and Figure 5.5 present the monthly severity of the agricultural and hydrological droughts at each subbasin. Results reveal that agricultural drought event II is the most prolonged and severe episode in the period of analysis (Figure 5.4b). Regarding hydrological droughts, event I is the most extended episode (Figure 5.5a).

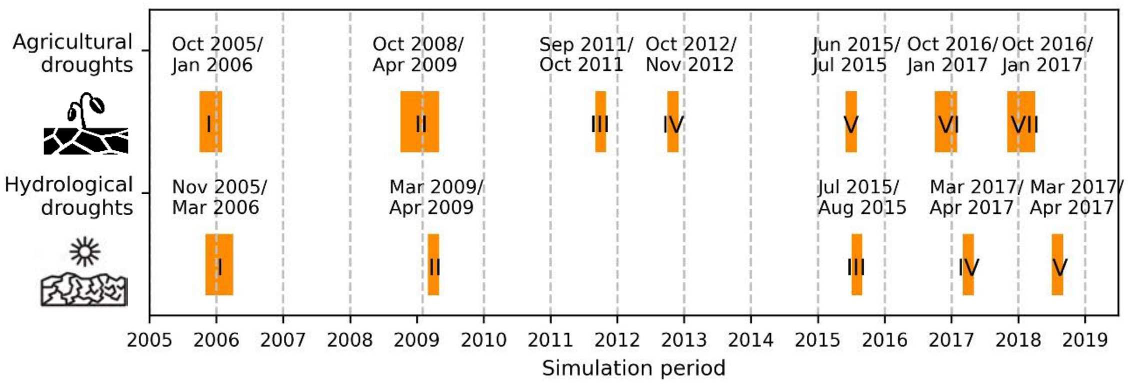

Figure 5.3 Agricultural and hydrological drought events identified. Roman numerals indicate the name of the drought event. Agricultural drought events are named from I to VII, and hydrological drought events are named from I to V.

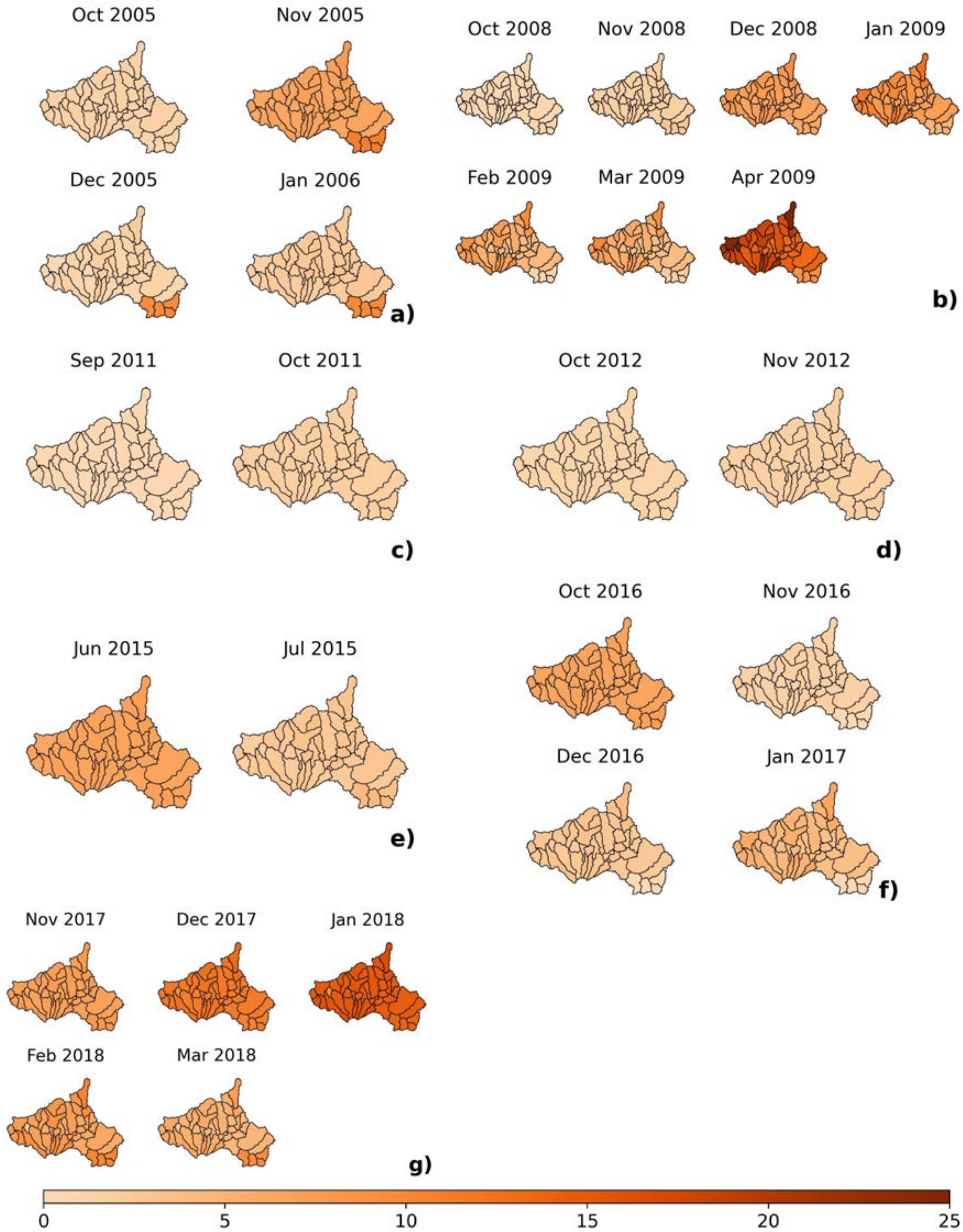

Figure 5.4 Monthly agricultural drought severity in mm expressed as a deviation from the threshold (baseline scenario): event I (a), event II (b), event III (c), event IV (d), event V (e), event VI (f), and event VII (g). Higher values represent larger deviation (or moisture deficit) and more severe drought.

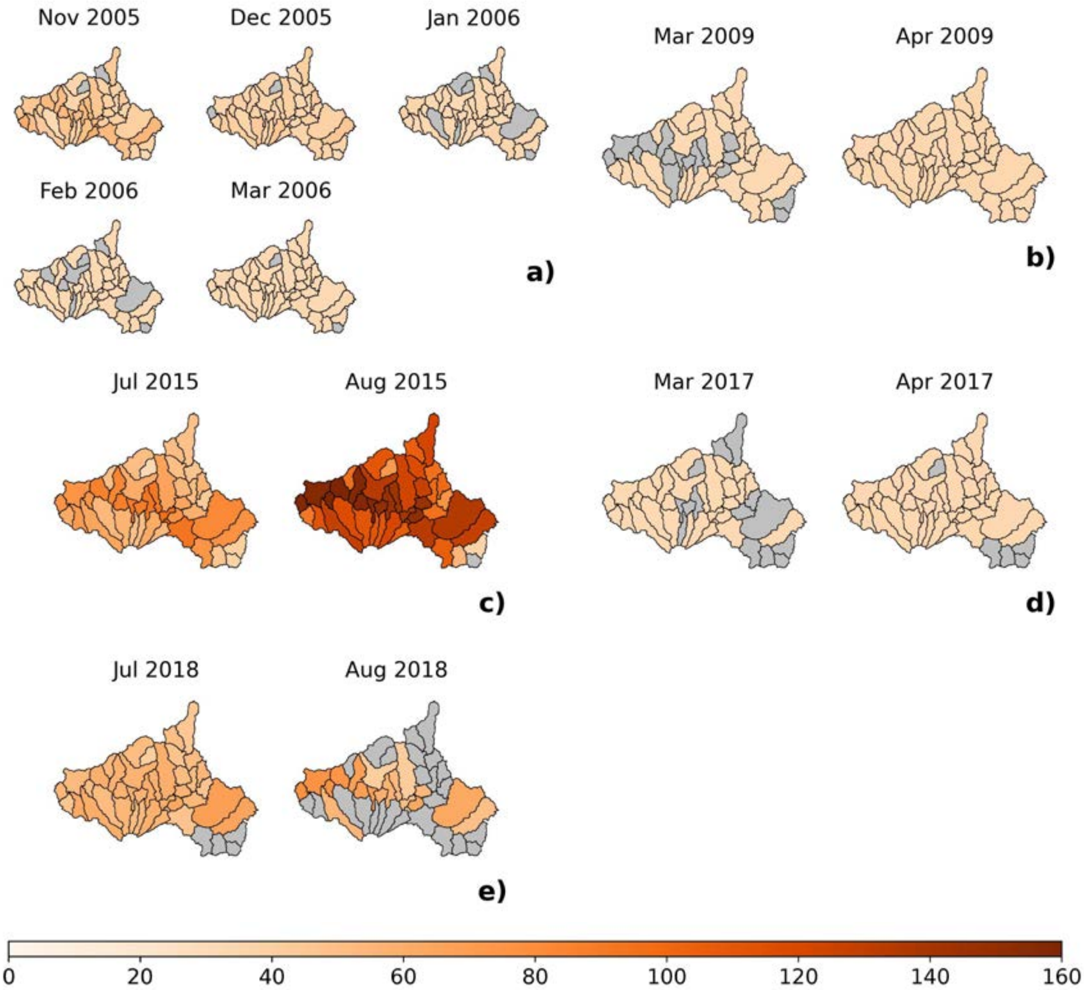

Figure 5.5 Monthly hydrological drought severity in mm expressed as a deviation from the threshold (baseline scenario): event I (a), event II (b), event III (c), event IV (d), event V (e). Higher values represent larger deviation (or moisture deficit) and more severe drought.

5.3.3 Effect of PDMMs on drought severity

This section presents the drought severity change after applying PDMMs. According to the methodology presented in Section 2.3.2 and Equations (2.13) and (2.14), a positive change indicates a decrease in drought severity compared to the baseline scenario, and a negative value represents the worsening of drought severity.

Effect of RWH Ponds on drought severity

Figure 5.6 presents changes in the agricultural drought severity in subbasins where RWH ponds are applied. Results indicate that the severity of agricultural droughts reduces during the first months of events I, II, and IV (Figure 5.6a, b, d). Severity alleviation continues until the end of the events, declining gradually. This suggests that the surface runoff collected and sorted during the rainy season continues to be available for infiltration at the beginning of the dry season when the droughts are more likely to start.

These findings are consistent with previous studies, which found that RWH ponds improve water availability during drought events (Dile et al., 2013; Woldegiorgis, 2017). The reduced severity of agricultural drought may also be linked to improved soil structure. Model outputs indicate that soil erosion decreases by up to 30% in the subbasins where RWH ponds are applied. Previous studies have found that RWH techniques reduce soil erosion, improve soil structure, and enhance soil water retention capacity (Oweis et al., 2012).

Figure 5.7 presents the changes in hydrological drought severity in the subbasins where the measure is applied and in subbasins downstream of where it is applied. Findings reveal that RWH ponds help alleviate the severity of the events observed in the dry season. In event I (Figure 5.8a), drought severity reduces by up to 90%. This severity alleviation continues until the end of the event. Similarly, severity reduces by up to 50% and 80% during event II and the first month of event IV (Figure 5.8b, d). According to the modelling outputs, RWH ponds improve percolation and groundwater recharge during the rainy season. Consequently, more groundwater is stored, and baseflow contribution to the river flow increases, particularly during the dry season, alleviating the severity of the hydrological droughts observed in that period.

After applying the RWH ponds, hydrological drought severity worsens slightly during events that occur in the rainy season (events III and V). One reason for this could be that surface runoff remains stored in the RWH ponds, reducing the surface runoff contribution to the streamflow during the rainy season. Consequently, the streamflow deficit increases and the severity of the hydrological droughts rises in most subbasins where the ponds are applied (Figure 5.7c, e and Figure 5.8b). Interestingly, most of these subbasins correspond to those showing a reduced agricultural drought severity.

It is important to note that, overall, the severity change of the agricultural droughts V, VI, and VII (Figure 5.6e–g) and hydrological droughts III, IV, and V (Figure 5.7c–e) remain below 20%. The limited impacts on these events may be linked to the precipitation anomalies observed between 2015 and 2019. In that period, the region experienced the lowest five-year mean May to September precipitation over the last century. The lack of precipitation markedly reduces the surface runoff available to collect and store in the RWH ponds. Compared to 2005 and 2008, in 2015, 2016, and 2017, the volume of water collected in the ponds declined by 45% on average. Our findings align with previous studies that concluded that the performance of RWH ponds highly depends on rainfall availability (Woldegiorgis, 2017; Zelelew et al., 2018).

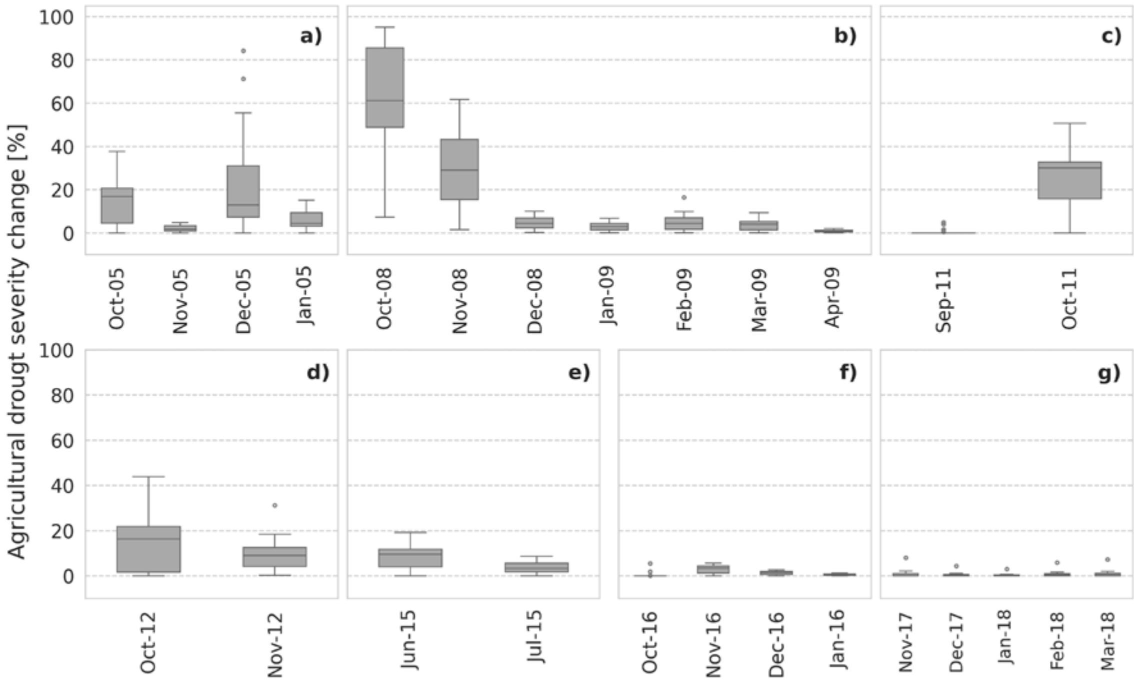

Figure 5.6 Agricultural drought severity changes in subbasins where RWH ponds are applied: event I (a), event II (b), event III (c), event IV (d), event V (e), event VI (f), and event VII (g).

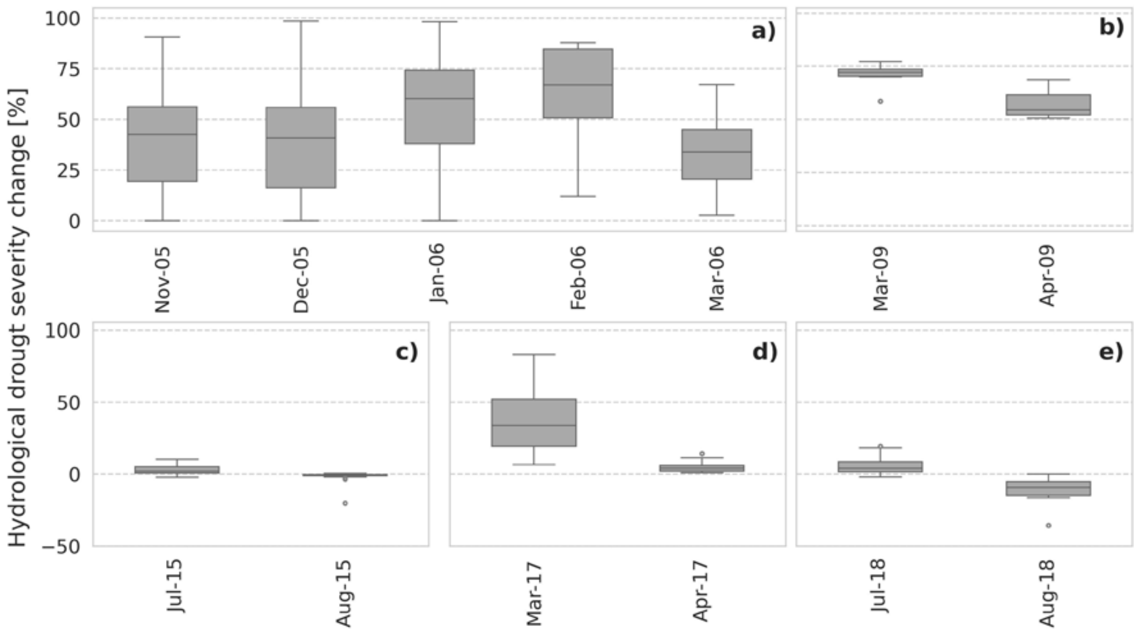

Figure 5.7 Hydrological drought severity changes in the subbasin where RWH ponds are applied and in subbasins downstream of where they are applied: event I (a), event II (b), event III (c), event IV (d), event V (e).

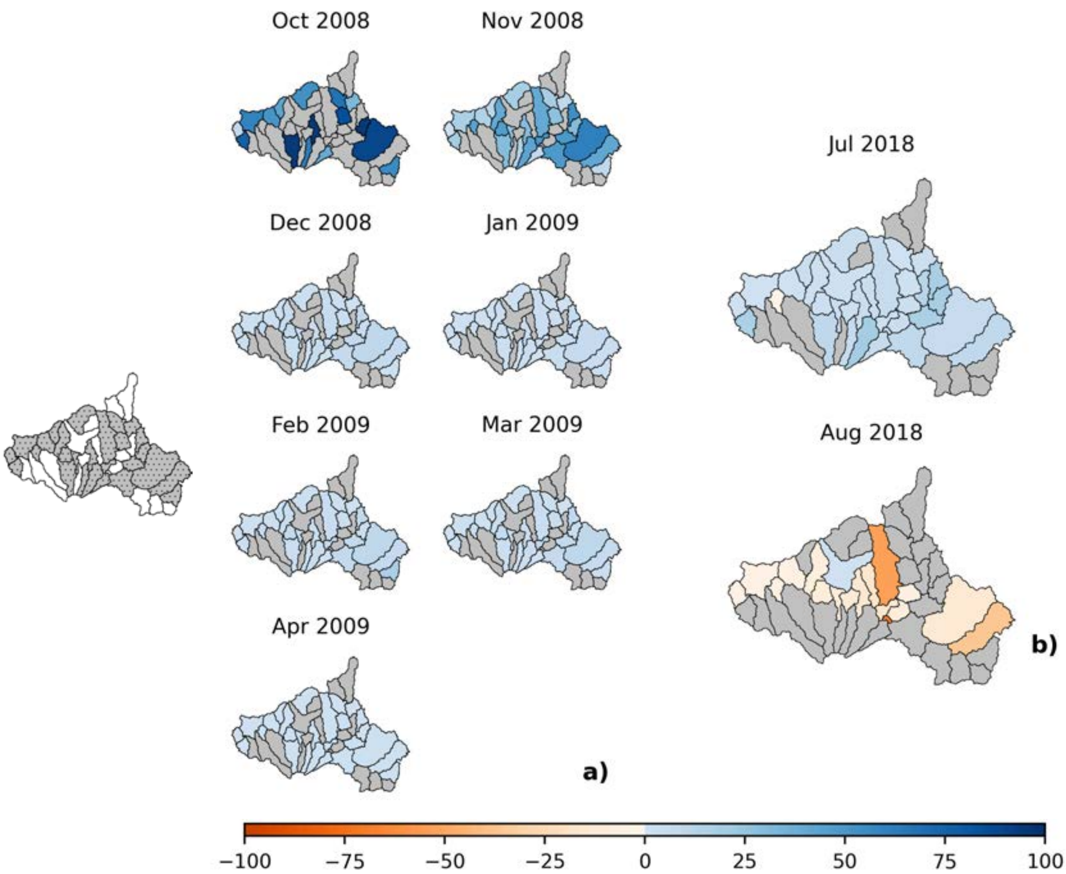

Figure 5.8 Drought severity change in percentage in the subbasins where the RWH ponds are applied, agricultural drought event II (a). Drought severity change in percentage in the subbasins where the measure is applied and in downstream subbasins, hydrological drought event V (b). The location of the measure is presented on the left side of the figure.

Effect of Forest Conservation on Droughts Severity

The outcomes of the drought analysis indicate that forest conservation has a minimal effect on agricultural drought severity. Although minor changes are observed at the beginning of events II and IV, these changes remain below 3% compared to the baseline scenario. The limited impact of the intervention on agricultural drought severity may be linked to rainfall distribution over the year and soil storage capacity. Modelling outputs indicate that surface runoff decreases in the subbasins when the measure is applied during the rainy season. Nevertheless, the intercepted surface runoff evaporates or percolates before the dry season starts; consequently, the water is not stored in the soil column or kept available to infiltrate when agricultural droughts are more likely to occur.

Concerning hydrological droughts, the findings indicate that forest conservation helps reduce the severity of the events observed during the dry season. Figure 5.9 presents the changes in hydrological drought severity in the subbasins where the measure is applied and downstream subbasins. Figure 5.9a, b, and d demonstrate that the severity of events I, II, and IV decreased. For example, the positive effect lasts until the end of event I

(Figure 5.9a and Figure 5.10a). The analysis reveals that while surface runoff reduction caused by forest conservation has little impact on agricultural droughts, it may contribute to alleviating the severity of hydrological droughts. Results also suggest that surface runoff reduction leads to increased percolation, favouring groundwater contribution to the streamflow and alleviating the water deficit. Groundwater contribution to the streamflow improves primarily during the dry season, when droughts are more likely to occur.

The results highlight the relevance of maintaining forest cover in headwater areas for hydrological drought alleviation. These findings are consistent with previous analyses showing that basins with forest cover present more stable seasonal flows, better soil structure and infiltration capacity, and less streamflow reduction during the dry season than those with less forest cover (Krishnaswamy et al., 2018; Mohammad and Adam, 2010).

Conversely, the results indicate that forest conservation has minimal impact on droughts that occur in the rainy season and even slightly worsens drought severity in some subbasins (Figure 5.9c, e and Figure 5.10b). This may be linked to surface runoff contribution to the streamflow during the wet season. After applying forest conservation, surface runoff declines, thus exacerbating the streamflow deficit.

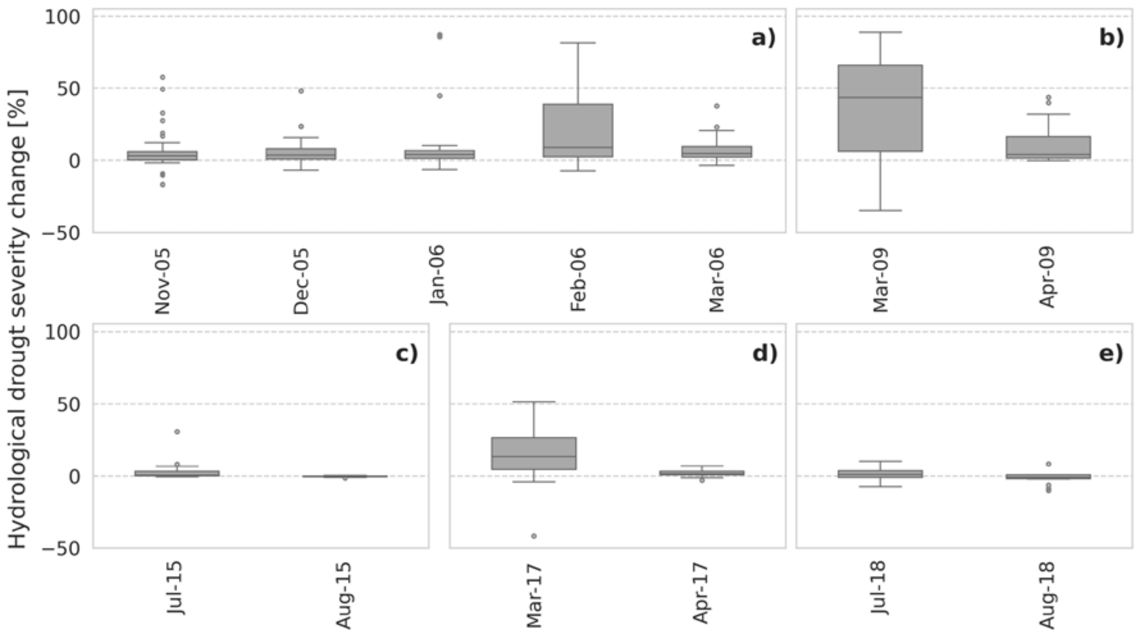

Figure 5.9 Hydrological drought severity changes in subbasins where forest conservation is applied and in subbasins downstream of where it is applied: event I (a), event II (b), event III (c), event IV (d), event V (e).

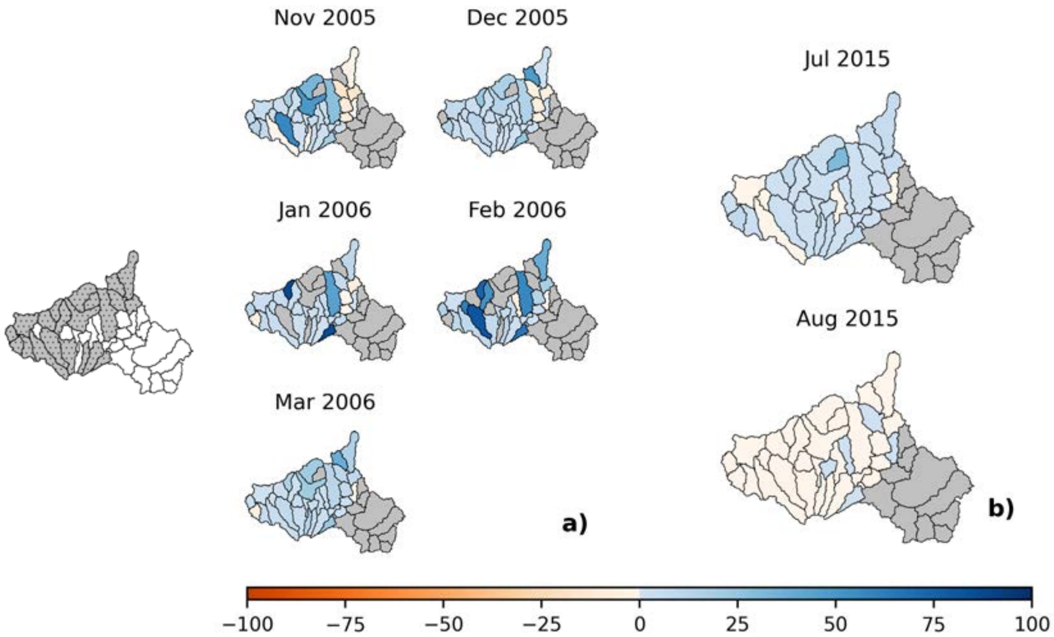

Figure 5.10 Drought severity change in percentage in the subbasins where forest conservation is applied and in downstream subbasins: hydrological drought event I (a) and hydrological drought event III (b). The location of the measure is presented on the left side of the figure.

Effect of Check Dams and Ponds on Droughts Severity

Figure 5.11 presents the changes in agricultural drought severity in the subbasins where check dams and ponds are applied. Notably, the duration of event II reduces by two months, and the severity decreases by more than 40% on average Figure 5.11b). The severity of event V, the most severe event during the simulation period, declines by up to 80% Figure 5.11g). Similarly to the effects of RWH ponds on agricultural land, the check dams and ponds store surface runoff, making the water available for infiltration. This compensates for soil moisture deficits during drought events, thus alleviating the severity of agricultural droughts. Additionally, modelling results show that soil erosion is reduced by up to 40% in the subbasins where the measure is applied; this contributes to maintaining the soil structure and enhances soil water-holding capacity. However, it is important to note that impoundments applied in forested areas (mainly upstream subbasins) perform better at alleviating agricultural drought severity despite the reduced available surface runoff in forested areas compared to agricultural areas. This may be because impoundments can be applied at a larger scale in forested areas.

Figure 5.12 presents the changes in hydrological drought severity in the subbasins where the measures are applied and in the downstream subbasins. The impacts of check dams and ponds on hydrological drought severity vary. The measures reduce severity in the subbasins where applied, but an equivalent drought worsening is observed downstream (Figure 5.13b).

Applying check dams and ponds increases percolation and groundwater recharge during the rainy season, which contributes to alleviating drought severity in the dry season. These results are observed only in the upstream subbasins. Modelling outputs indicate that in these subbasins, the surface runoff contribution to streamflow reduces by up to 70% during the rainy season, while groundwater contribution to the streamflow increases by up to 40% during the dry season. Conversely, the change in the groundwater contribution to the streamflow is minimal in the downstream subbasins. Additionally, the streamflow into these subbasins is reduced by up to 55% during the dry season. This suggests that although impoundments that store surface runoff allow more time for infiltration, the soil's infiltration capacity is low, constraining groundwater recharge. Accordingly, a significant volume of water evaporates or remains stored in the upstream subbasins (in the impoundments and the soil profile), exacerbating the streamflow water deficit downstream.

These results support previous studies, which report that check dams in the upper reaches can disrupt the downstream transfer of water (Polyakov et al., 2014). Studies also indicate that for check dams to increase groundwater availability, high local infiltration and specific aquifer characteristics, such as smaller lateral than vertical transmission and a low-permeability bottom layer, are required (Glendenning et al., 2012).

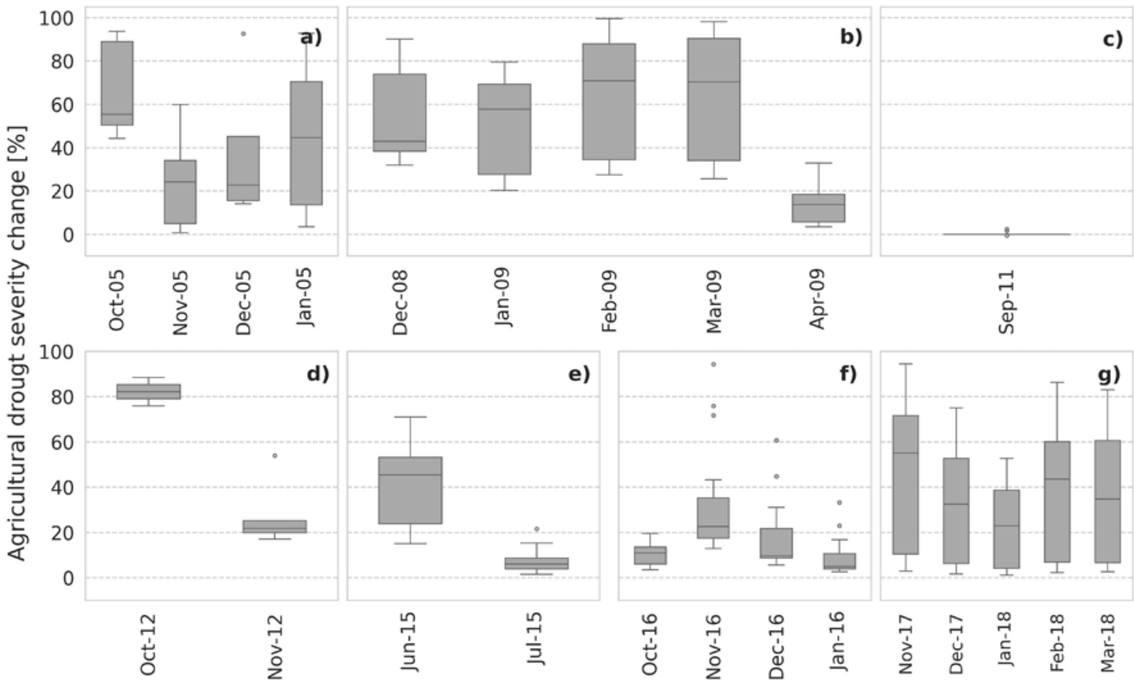

Figure 5.11 Agricultural drought severity changes in subbasins where check dams and ponds are applied: event I (a), event II (b), event III (c), event IV (d), event V (e), event VI (f), and event VII (g).

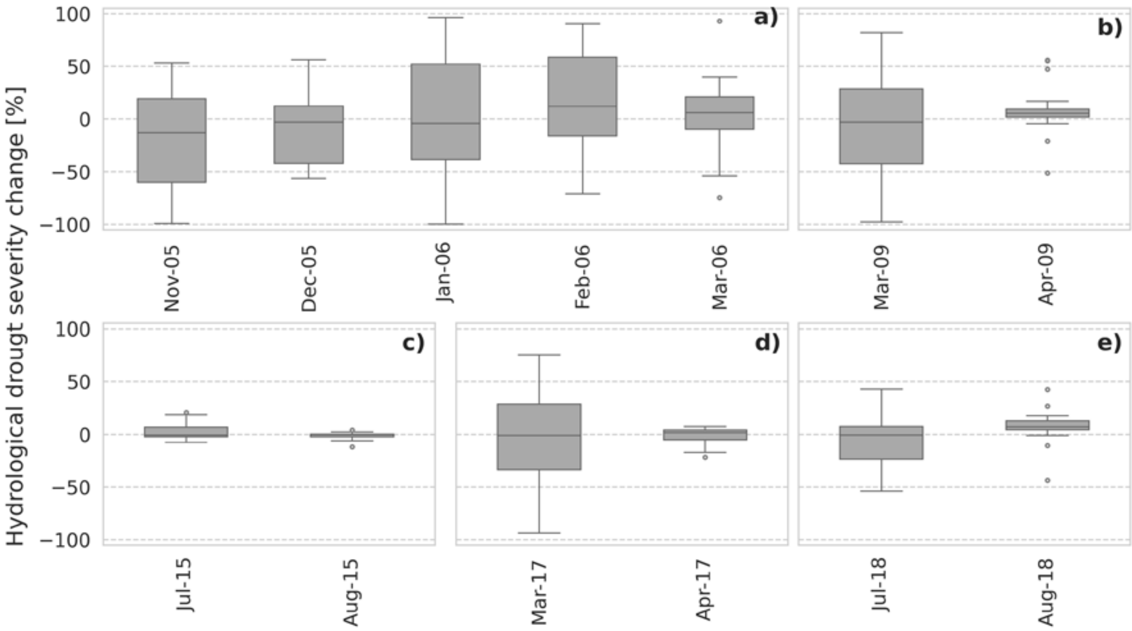

Figure 5.12 Hydrological drought severity changes in subbasins check dams and ponds are applied and in subbasins downstream of where they are applied: event I (a), event II (b), event III (c), event IV (d), event V (e).

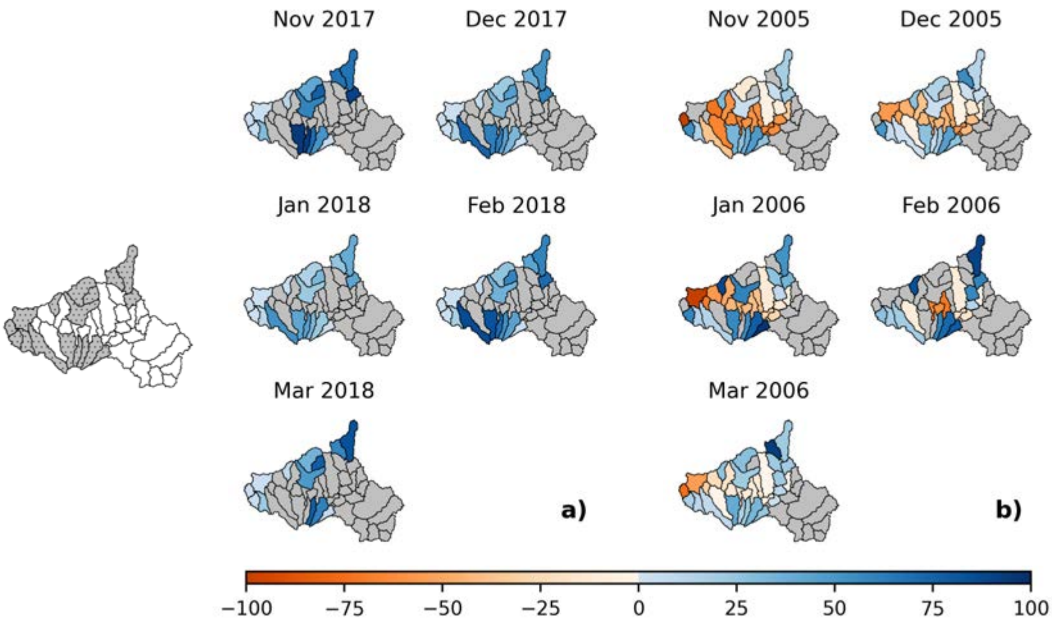

Figure 5.13 Drought severity change in percentage in the subbasins where check dams and ponds area pplied, agricultural drought event VII (a). Drought severity change in percentage in the subbasins where the measure is applied and in downstream subbasins, hydrological drought event I (b). The location of the measure is presented on the left side of the figure.

5.4 Conclusion

The modelling-based approach applied in this analysis allowed for assessing the impacts of three potential PDMMs (RWH ponds, forest conservation, and check dams) on the severity of agricultural and hydrological droughts in the Torola Basin. The RWH ponds alleviated the severity of agricultural and hydrological droughts in the dry season but slightly worsened the severity of hydrological droughts in the rainy season. Forest conservation did not affect the severity of agricultural droughts and had minimal impact on the severity of hydrological droughts observed in the rainy season. In contrast, it considerably reduced the severity of hydrological droughts in the dry season. Finally, check dams and ponds significantly alleviated the severity of agricultural and hydrological droughts in upstream subbasins but enhanced hydrological droughts downstream.

The findings suggest that basin characteristics (e.g., rainfall distribution over the year, soil infiltration capacity, and topography) and the season (rainy or dry) in which the drought event occurs influence the effectiveness of PDMMs in alleviating drought severity. In addition, the results reveal that PDMMs can reduce the severity of agricultural droughts but produce the opposite effect on the severity of hydrological droughts. Therefore, the selection and allocation of PDMMs must be tailored to each region and require prior assessment of the basin and drought characteristics and the evaluation of the measures' potential effects on each type of drought. The outcomes of this work are relevant for planning authorities and the agriculture sector in developing or improving proactive drought management plans.

The qualitative and quantitative assessment of potential PDMMs outlined in this chapter serves as a starting point for Chapter 6, informing the selection of interventions included in the optimization problem formulation. Furthermore, the parametrization of PDMMs defined in this chapter is applied in Chapter 6.

6 OPTIMISATION APPROACH FOR PLANNING PREVENTIVE DROUGHT MANAGEMENT MEASURES

ABSTRACT

Application of Preventive Drought Management Measures (PDMMs) in a structured and strategic way is a suitable avenue to reduce the likelihood of drought and ameliorate associated damages. However, selecting and allocating PDMMs is challenging due to the high number of decision variables involved in the process and possible trade-offs between objectives representing impacts on soil moisture and streamflow. In this chapter[1], we use an optimisation approach followed by a multicriteria decision-making method to allocate interventions that reduce the severity of agricultural and hydrological droughts. To this aim, we developed an optimization framework that integrates the Soil Water Assessment Tool (SWAT) modelling system with the Unified Non-dominated Sorting Genetic Algorithm III (U-NSGA-III) as an optimisation algorithm.

The analysis' outcomes indicate that implementing PDMMs contributes to reducing the severity of both agricultural and hydrological droughts, and the obtained management scenarios (near-optimal solutions) highlight the suitability and efficacy of employing multi-objective optimisation for PDMM planning. However, the effect of PDMMs on drought severity exhibits temporal and spatial variations, which prompts a careful analysis of the results obtained through model-based optimisation. Additionally, analysed scenarios show that PDMMs can reduce the severity of agricultural droughts while producing the opposite effect for hydrological droughts (and vice versa).

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[1] This chapter is based on: Paez-Trujilo, A, Hernandez-Suarez, J., Alfonso, L., Hernandez, B., Maskey, S., Solomatine, D. (2024). An optimisation approach for planning preventive drought management measures. *Science of The Total Environment* 174842. https://doi.org/10.1016/j.scitotenv.2024.174842.

6.1 INTRODUCTION

Drought, directly and indirectly, impacts society, the environment and the economy (Duel et al., 2022; UNDRR, 2021; Vogt et al., 2018). Direct impacts result from the interaction between water deficit and social, economic or environmental components and are observed in drought-affected areas (UNDRR, 2021; Vogt et al., 2018). These impacts include limited water supplies, crop loss, wetland drying, and reduced energy production. Indirect consequences relate to secondary effects on natural or economic resources and can be observed in areas far away from where the drought originated and continue long after the drought has ended (UNDRR, 2021; Vogt et al., 2018). Indirect consequences can impact biodiversity and food prices and, in extreme cases, may affect human health and result in loss of income and food insecurity (UNDRR, 2021).

Extensive drought impacts and climate change projections showing more frequent and severe droughts worldwide highlight the pressing need to develop drought management plans (Carrão et al., 2018; Cottrell et al., 2019; Haile et al., 2020; UNCCD, 2022; Vicente-Serrano et al., 2020). Literature on drought management stresses the importance of proactive drought management (FAO, 2019; Gerber and Mirzabaev, 2017; Wilhite, 2016). This approach does not respond to specific events but recognises drought planning as a permanent and continuing need. Proactive drought management aims to create resistance and resilience to droughts, minimising negative impacts in advance and relies on three pillars: 1) drought monitoring and early warning systems, 2) drought risk and vulnerability assessment, 3) drought preparedness and mitigation (Pischke and Stefanski, 2017; Tsegai et al., 2018; Wilhite, 2019). Particularly, the third pillar of proactive drought management refers to measures to mitigate the potential negative of droughts and to enable ecosystems and communities to withstand the effects of droughts more effectively (Wilhite, 2019). These measures can be grouped into four categories according to their purpose: preventive or strategic, operational, organisational and restoration (Global Water Partnership Central and Eastern Europe, 2015). They vary broadly, e.g. from interventions at the field level applied before the drought occurs to negotiated global compensation for damage to land due to droughts (Assimacopoulos et al., 2015; King-Okumu, 2021; World Bank, 2019). This study analyses preventive drought management measures (PDMMs) applied at the basin level.

Overall, modelling and field studies on PDMM focus on one specific measure. Assessment of measures' performance mainly relies on interventions' effectiveness in increasing infiltration and water availability, improving soil water-holding capacity and preventing land degradation or desertification (Basche, 2017; Beets and Beets, 2020; Oweis et al., 2012; Sanz et al., 2017; Wambura et al., 2018; Yadav et al., 2018). While these criteria provide relevant insights into the measures' applicability for drought management, there is a lack of information on the water deficit reduction during drought periods and measures' contribution to drought alleviation is not explicitly appraised.

Application of drought mitigation measures in a consistent and structured way has the potential to limit the negative impact of droughts on society, the environment and the economy (Global Water Partnership Central and Eastern Europe, 2015). Nevertheless, planning mitigation measures at the basin scale is not a trivial task. In a given region, a collection of measures, sites, scales, and possible configurations suitable for drought management exists. In addition, measures appropriate for reducing one type of drought may adversely impact another type of drought, e.g. agricultural drought management measures may exacerbate hydrological drought conditions. This conflict can be explained by the fact that alleviating agricultural droughts requires storing water in the soil profile, implying a reduction in rivers' discharge, increasing, in turn, hydrological droughts (Cai et al., 2015). Accordingly, selecting the right set of drought management measures is effectively a multi-objective problem.

Several multi-objective optimisation frameworks have been applied to optimise types and allocation of management strategies to improve water quality and stream health (Deb et al., 2023; Geng et al., 2019; Liu et al., 2019; Raschke et al., 2021; Zhang et al., 2023), flood management and water availability (Lewis and Randall, 2017; Liu et al., 2023; Woodward et al., 2014), or prevent soil degradation (Hildemann et al., 2023; Naseri et al., 2021; Wu et al., 2018). Regarding drought preparedness and PDMMs planning, Cai et al. (2015) developed a multi-objective stochastic optimisation model to identify the optimal combination of preventive and tactical measures under different future climate scenarios. Particularly, they provided relevant information on the required investments to mitigate drought damage and identified the trade-off between managing agricultural and hydrological droughts. In their study, the effects of the preventive measures on drought characteristics (intensity, duration, frequency) were not evaluated.

This study uses an optimisation approach to define near-optimal drought management scenarios (sets of different PDMMs combinations and allocations), estimate their impact on the severity of agricultural and hydrological droughts and analyse the trade-off between managing both types of droughts. Accordingly, we develop an optimisation engine integrating a semi-distributed hydrological model – the Soil Water Assessment Tool (SWAT) (Neitsch et al., 2011) – with an evolutionary optimisation algorithm – the Unified Non-dominated Sorting Genetic Algorithm III (U-NSGA-III) (Seada and Deb, 2016). The SWAT model simulates the PDMMs and their impacts on the basin hydrology. The U-NSGA-III identifies near-optimal allocations of PDMMs that minimise the severity of both agricultural and hydrological droughts. The methodology is tested in the upper part part of the Cesar River Basin (Colombia).

6.2 METHODOLOGY

The proposed workflow consists of hydrological modelling, drought analysis and optimisation steps (see Figure 6.1). Firstly, hydrological modelling was used to represent the basin hydrology, simulate the variables required to analyse droughts in the baseline scenario, i.e., soil moisture and streamflow, and parametrise the PDMMs. The baseline scenario represents the current drought situation and is the basis for comparing the effect of implementing PDMMs on droughts. Secondly, we applied the TLM (Section 2.3.2) to identify the drought events during the analysis period and estimate their severity levels. Thirdly, we developed and applied an optimisation engine to identify the optimal sets of PDMMs that contribute to reducing the severity of droughts. To solve the optimisation problem in Python, we used the optimisation framework *pymoo* (Blank and Deb, 2020) coupled with a Python wrapper for executing SWAT (i.e., *SWAT-pytools*; (Hernandez-Suarez and Nejadhashemi, 2022)). Once the optimisation was completed and the Pareto-optimal solution set was obtained, two MCDM methods were applied to select a few preferred solutions that balance the objective functions. Lastly, we compared the drought severity in the baseline scenario with the severity in the optimal solution for each objective function and the preferred solutions. A detailed description of the methodology is presented below.

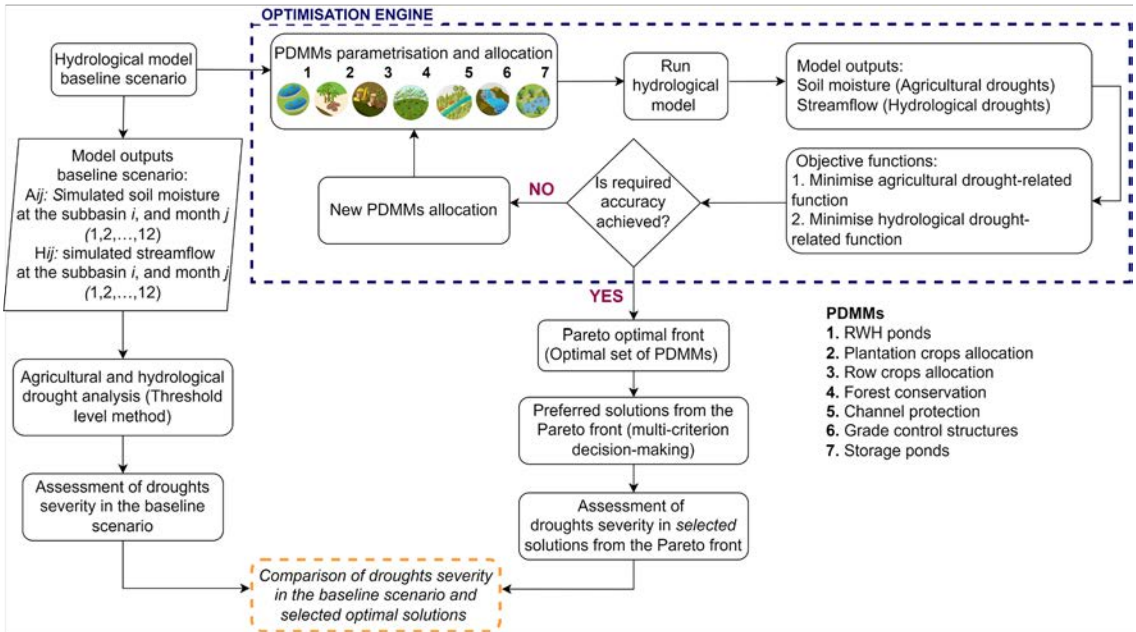


Figure 6.1. Flowchart of the methodology applied in Chapter 6 (research phase 3).

6.2.1 Hydrological modelling

The hydrological model of the upper part of the Cesar River basin (SWAT, Section 2.2.1) was built for the period from 1987 to 2018. Four slope classes were set for the HRUs generation: flat (0–2%), gentle (2–10%), steep (10–35%) and considerably steep (>36%). The model was calibrated from 1985 to 2002 and validated from 2003 to 2018. Table 4.1 presents the details and sources of the input data utilised for the model setup. A detailed description of the input data, the model setup, calibration, and validation can be found in GEF et al. (2021, 2020).

6.2.2 PDMMs selection and parametrization in SWAT

In this phase of the study, we selected seven interventions and practices to evaluate their effectiveness as PDMMs. Interventions were selected to cover the land and water phases of the hydrological cycle. Additional selection criteria included compatibility with the basin's land use and availability of parameters to represent the intervention in the SWAT model. The selected PDMMs, the parameters used to represent them in SWAT, and their values are summarized in Table 6.1. A detailed description of each PDMM is provided below.

PDMM-1: ***Infiltration ponds***

Infiltration ponds are a Rainwater Harvesting technique (RWH) aiming to increase the soil water content in the soil profile by storing rain when it falls (Huang et al., 2021). This intervention contributes to increasing infiltration and groundwater recharge and decreases soil erosion by reducing surface runoff velocity (Nyagumbo et al., 2019; Piemontese et al., 2020). The Infiltration ponds were modelled in SWAT using the pothole routine (Wambura et al., 2018). Potholes are water bodies located off the main channel, and water flows to them from the subbasin (Du et al., 2005). The potholes were applied at the HRU level and represented by two parameters: the fraction of flow from the upland HRUs that contributed to the pothole HRU (POT_FR) and the maximum water depth inside the pothole (POT_VOLX). The storage capacity of that pothole was given by the area of each HRU multiplied by the maximum water depth. For the present study, the RWH pond's storage capacity was aggregated into one pothole, as there could be only one in each HRU.

*PDMM-2 and PDMM-3****: Crops allocation***

Allocating crops regarding climate, hydrology, terrain, and soil qualities maximises land production, prevents water scarcity, and reduces topsoil and groundwater depletion (Akpoti et al., 2019; Mosleh et al., 2017). Adequate crop allocation is crucial for maintaining sustainable production and reducing environmental impact (Bhat et al., 2023). In SWAT, the allocation of the main crops in the basin (oil palm coffee, corn and cassava) was simulated using the SCS runoff curve number for moisture condition II (CN2), the plant identification (PLANT_ID), the management operation number (MGT_OP) 1 for planting and 5 for harvest and kill, and the month and day in which the operation takes place (MONTH/DAY). The CN2 value was assigned for each hydrologic soil-cover complex (combination of hydrological soil group and land use) according to SWAT's crop database. The MONTH/DAY of planting, harvest and kill operations of each crop were set conforming to the National Agricultural Survey (2019).

PDMM-4: ***Woodlands allocation***

Forest conservation/restoration includes forest regeneration, species diversity, and unevenly aged stands. This intervention contributes to limiting soil degradation to slow runoff and increase infiltration and groundwater recharge. In this work, the CN2 value for forested areas in good hydrological conditions represented the intervention. The CN2 value was assigned for each hydrologic soil-cover complex according to SWAT's crop database.

PDMM-5 and PDMM-6: ***Channel restoration and grade control***

Channels restoration refers to changes in the physical structure of a river channel, its riparian zone or the floodplain through reshaping, reconstruction, or replanting (Muhar et al., 2018; Wohl et al., 2015). These modifications aim to amend hydrologic, geomorphic, and/or ecological processes within degraded or altered water bodies. Over the last few years, river restoration has shifted to a process-based restoration approach considering rivers' geomorphology and function (Greene et al., 2023; Wohl et al., 2015). There is a comprehensive list of interventions used for channel restoration, e.g., reconfiguration of stream channels, floodplain reconnection, and riparian revegetation (Ciotti et al., 2021; Inamdar et al., 2023). In this analysis, we focus on the bank and bed channel protection and grade control.

Channel protection controls the river's bank degradation, balances the sediment load, and reduces water velocity adjacent to the streambank (Li and Eddleman, 2002; Pinto et al., 2016; Rosgen, 2001). In this study, channel protection was modelled using SWAT model parameters such as the Manning's "n" value for the main channel (CH_N(2)) and the channel cover factor (CH_COV2). Grade stabilization refers to any intervention that provides stability to the streambed. These interventions range from loose rock structures (e.g., steep-pool sequence) to reinforced concrete weirs, and they vary in scale from small to large rivers (Wang et al., 2017). Controlling channel degradation prevents failures of the channel banks by over-heightening and preventing potential groundwater table lowering caused by channel widening and bank erosion (Natural Resources Conservation Service, 2007). Here, channel protection was modelled using SWAT parameters such as the average slope of the main channel along the channel length (CH_S(2)) and the channel cover factor (CH_COV2).

PDMM-7: ***Storage ponds***

Check dams, small barriers constructed across channels or gullies, serve the purpose of impeding the flow. These structures store floodwater, increase the basin's retention capacity and allow more time for water percolation to recharge aquifers, among other functions (Abbasi et al., 2019; Lucas-Borja et al., 2021; T. Wang et al., 2021). In the SWAT model, we simulated check dams as ponds (Waidler et al., 2009). SWAT defines ponds as water bodies within the subbasin area, exclusively receiving loadings from the subbasin's HRUs. The model allows the allocation of only one pond at each subbasin; then, the predicted runoff from the HRUs is aggregated and routed into the pond situated at each subbasin (Jalowska and Yuan, 2019; Rabelo et al., 2021). SWAT model parameters employed to represent the intervention are the fraction of the subbasin that drains into ponds (POND_FR), the surface area of ponds when filled to the principal spillway (POND_PSA), and the volume of water stored in ponds when filled to the principal spillway (POND_PVOL).

6.2.3 Agricultural and hydrological droughts analysis

Drought analysis was conducted using the TLM (Section 2.3.2). In this chapter, simulated soil moisture and streamflow using the SWAT model (Section 2.2.1) are the variables used to represent agricultural and hydrological droughts, whereas severity is the characteristic of interest. Drought severity was estimated separately for the baseline or current scenario (represented by the calibrated models of the Cesar River basin) and the management scenarios (selected most-preferred trade-off solutions from the Pareto front) obtained from the optimisation.

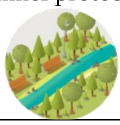
The change in drought severity was evaluated by comparing the severity in the baseline scenario to the severity in the near to optimal drought management scenarios obtained from the optimisation. Equations (2.13) and (2.14) and were employed for this purpose.

6.2.4 Formulation of the optimization framework for PDMM planning

The optimisation process starts by initialising a population of drought management scenarios (diverse allocations of the PDMMs evaluated). For each drought management scenario, the measures and their potential allocations are put into SWAT to simulate the PDMMs' impact on the basin hydrology, particularly on soil moisture and streamflow. Then, agricultural and hydrological drought objectives are computed using the hydrological modelling outcomes. U-NSGA-III is applied to obtain near-optimal solutions, minimising both agricultural and hydrological drought objectives. Thus, the outcome of the optimisation process is a Pareto front containing a set of solutions (management scenarios with different PDMMs combinations and allocations) that contribute to reducing the severity of agricultural and hydrological droughts. To solve the optimisation problem in Python, we used the optimisation framework *pymoo* (Blank and Deb, 2020) coupled with *SWAT-pytools* (Hernandez-Suarez and Nejadhashemi, 2022), which includes a wrapper for modifying SWAT input files. The optimisation runs were executed in the Snellius supercomputer (Dutch National Supercomputer Snellius, 2023). In Snellius, the compute nodes are grouped into partitions; we ran the optimisation in the

Genoa partition, which includes 128 cores per node and the memory per node is 336 GiB. To run the simulation, the number of CPUs per task was one and the requested memory per CPU was 3GB. Below, we describe the formulation of the problem of allocating PDMMs as an optimisation problem.

Table 6.1 PDMM applied to reduce the severity of agricultural and hydrological droughts.

ID	Preventive drought management measures (PDMM)	Parameter(s) used in SWAT	Value when PDMM is applied in a HRU or subbasin
PDMM-1	RWH ponds 	POT_FR [a] (.hru), POT_VOLX [b] (.hru)	0,3, 20 [cm]
PDMM-2	Plantation crops allocation (e.g., oil palm or coffee) 	CN2 [c] (.mgt) MGT_OP MONTH/DAY	45, 66, 77 or 80 1 1/1
PDMM-3	Row crops allocation (e.g., corn or cassava) 	CN2 [c] (.mgt) PLANT_ID MGT_OP MONTH/DAY MGT_OP MONTH/DAY	67, 77, 83 or 87 CORN 1 3/1 (main harvest) 7/1 (second harvest) 5 8/1 (main harvest) 11/1 (second harvest)
PDMM-4	Woodlands allocation 	CN2 [c] (.mgt)	25, 55, 70 or 77
PDMM-5	Channel protection 	CH_N(2) [d] (.rch), CH_COV2 [e] (.rch)	CH_N2 reduced 0,15 from the default value 0,0 (fully protected river channel)
PDMM-6	Grade control 	CH_S(2) [f] (.rch), CH_COV2 [e] (.rch)	Reduced by 10% from the default value 0,0 (fully protected river channel)
PDMM-7	Storage ponds 	POND_FR [g] (.pnd), POND_PSA [h] (.pnd), POND_PVOL [i] (pnd)	0,3, 20 [Ha] 1,5 [104 m3]

Notes: [a] Fraction of the HRU area that drains into a pothole; [b] maximum volume of water stored in the pothole over the entire HRU (mm); [c] initial SCS runoff curve number for moisture condition II; [d] Manning's "n" value for the main channel, [e] channel cover factor, [f] average slope of main channel along the channel length (m/m), [g] fraction of subbasin area that drains into ponds; [h] surface area of ponds when filled to principal spillway (ha), [i] volume of water stored in ponds when filled to the principal spillway (10^4 m^3 H_2O).

6.2.5 Formulation of the optimization framework for PDMM planning

The optimisation process starts by initialising a population of drought management scenarios (diverse allocations of the PDMMs evaluated). For each drought management scenario, the measures and their potential allocations are put into SWAT to simulate the PDMMs' impact on the basin hydrology, particularly on soil moisture and streamflow. Then, agricultural and hydrological drought objectives are computed using the hydrological modelling outcomes. U-NSGA-III is applied to obtain near-optimal solutions, minimising both agricultural and hydrological drought objectives. Thus, the outcome of the optimisation process is a Pareto front containing a set of solutions (management scenarios with different PDMMs combinations and allocations) that contribute to reducing the severity of agricultural and hydrological droughts. To solve the optimisation problem in Python, we used the optimisation framework *pymoo* (Blank and Deb, 2020) coupled with *SWAT-pytools* (Hernandez-Suarez and Nejadhashemi, 2022), which includes a wrapper for modifying SWAT input files. The optimisation runs were executed in the Snellius supercomputer (Dutch National Supercomputer Snellius, 2023). In Snellius, the compute nodes are grouped into partitions; we ran the optimisation in the Genoa partition, which includes 128 cores per node and the memory per node is 336 GiB. To run the simulation, the number of CPUs per task was one and the requested memory per CPU was 3GB. Below, we describe the formulation of the problem of allocating PDMMs as an optimisation problem.

Objective functions

Formulation of objective functions is never an easy task since it has to take into account a large number of factors and preferences. In this phase of the study, we have taken an exploratory approach, where only the two most important factors are considered, leaving finetuning to subsequent research. These two competing objective functions were formulated to be aiming at reduction of of agricultural and hydrological droughts severity.

The first objective is based on minimisation of the agricultural drought severity (Eq. (6.1)). The Objective Function 1 (OF1) was formulated as the aggregation of the difference between the average available water capacity (AWC) and the simulated soil moisture at each subbasin in the dry season months (Dec, Jan, Feb, Mar, Apr, May, Jun, Jul). AWC refers to the soil's ability to store and provide water to plant roots and depends on the soil properties, particularly soil texture (Rabot et al., 2017). Further information on typical AWC values for different soil textures can be found at de Jong van Lier et al. (2023). Minimising the difference between the AWC and the simulated soil moisture aimed to maintain an adequate content of water in the soil profile (informed by the dominant soil texture at each subbasin) and prevent this value from falling below the agricultural drought threshold. We focused on the dry months to force the optimisation tool to select drought management scenarios that contribute to reducing the soil water deficit during the dry season when droughts are more likely to occur, and their severity tends to increase.

$$Min \sum_{i=1}^{m}\sum_{j=1}^{n}\left|AWC_{ST} - SW_{ij}\right| \tag{6.1}$$

where, $i = 1, 2, 3 \dots n$ are the subbasins, $j = 1,2,3 \dots m$ are the dry months over the years of the simulation period, AWC_{ST} is the average available water capacity of the dominant soil texture at the i^{th} subbasin (in mm) and SW_{ij} is the soil moisture during the j^{th} dry month at the i^{th} subbasin (in mm).

The Objective Function 2 (OF2) (Eq. (6.2)) deals with hydrological drought and was formulated as the aggregation of the simulated streamflow at the outlet of each subbasin. Maximising the discharge aimed to increase the streamflow and prevent this value from falling below the hydrological drought threshold. The optimisation framework *pymoo* minimises all the objective functions. If an objective function is maximised ($\max f_i$), the objective function can be formulated to minimise its negative value ($\min - f_i$) (Blank and Deb, 2020).

$$Min \; -\sum_{i=1}^{m}\sum_{j=1}^{n} q_{ij} \tag{6.2}$$

where, $i = 1, 2, 3 \dots n$ are the subbasins, $j = 1,2,3 \dots m$ are the months over the years of the simulation period, and q_{ij} is the discharge during the j^{th} month at the outlet of the i^{th} subbasin (in mm d^{-1}).

Decision variables

Decision variables are the drought management scenarios, i.e. diverse allocations of the PDMMs. Figure 6.2 shows a schematic of the decision variable matrix for planning drought mitigation measures. In this study, each matrix row (decision variable vector) represented a member of the population that consisted of genes defining a specific combination of PDMMs, or what is referred to as an allele. Each gene can have either a one or zero state, one indicating the measure is applied in a specific spatial unit (HRU or subbasin) and zero indicating the measure is not applied in that spatial unit. When the state is “one” in a spatial unit, all the parameters representing the measure are modified according to the values presented in Table 6.1. The number of alleles in a gene was given by the number of PDMMs applicable at each spatial unit. Four out of the seven evaluated PDMMs were applied at the HRU level (infiltration ponds, plantation and row crops allocation and forest restoration), and the other three PDMMs were applied at the subbasin level (channel protection, grade stabilization and storage ponds). Accordingly, the number of alleles in an HRU gene was four and three in a subbasin gene.

Considering the significant number of spatial units in the basin model, the most susceptible spatial units to agricultural and hydrological droughts were selected for the optimisation process, that is to say, 855 out of 2699 HRUs and 78 out of 108 subbasins. Then, the number of decision variables (length of the decision variables vector) was given by the equation $N = (No_{HRU} \times 4) + (No_{sub} \times 3)$, where No_{HRU} is the number of HRUs selected to apply the PDMMs and No_{sub} is the number of subbasins selected to apply the PDMMs. The number of decision variables for the optimisation of PDMM in the Cesar River model was 3654, and the size of the matrix X was 3654 multiplied by the population size; in this work, 350 individuals.

To narrow down the decision variable space, the most susceptible subbasins to agricultural and hydrological droughts were selected using the study outcomes by Paez-Trujillo et al. (2023). In this paper it was found that subbasins located in the upper and middle part of the river valley are drought-prone areas, and multiple hydroclimatic factors influence their susceptibility to agricultural and hydrological droughts.

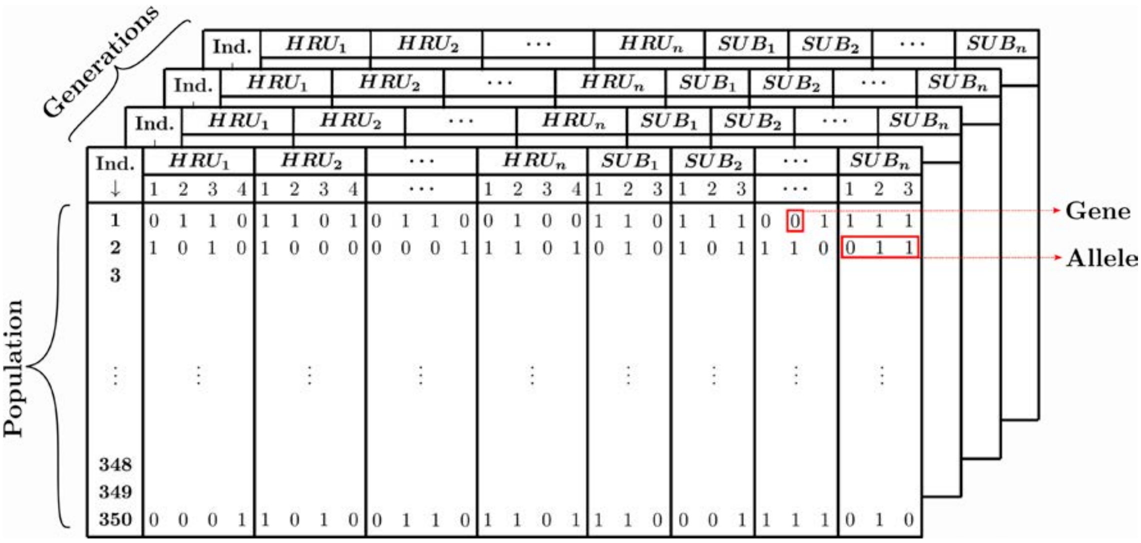


Figure 6.2. Schematic of a decision variable matrix for planning drought mitigation measures.

6.3 RESULTS

6.3.1 Drought events in the baseline scenario

We identified the drought events in the analysis period by applying the TLM described in Section 2.3.20. The date and duration of the identified droughts were consistent with the agricultural and hydrological drought events found by Paez-Trujillo et al. (2023) using the Soil moisture deficit index (SMDI) and the Standardized Streamflow Index (SSI). Furthermore, drought events agreed with the chronology of drought events in Colombia described at the National Study of Water (Instituto de hidrología meteorología y estudios ambientales (IDEAM), 2019). Table 6.2 shows the dates and duration of the drought events. Figure 6.3a and b show the monthly drought severity of the agricultural drought events V and VI, and Figure 6.4a and b show the monthly drought severity of the hydrological drought events V and VI. These two events were the most severe droughts observed in the analysis period and were selected to assess the effect of PDMM on the severity of short-term and long-term droughts.

Overall, the drought severity of the drought events evaluated varied in time and space. For agriculture droughts, the highest deficit was observed in the basin west, in the river valley, and upstream of the basin outlet (Figure 6.3a and b). During the short-term event, agricultural severity was alike in the first two months and in the last month, the area in drought condition and the severity reduced (Figure 6.3a). In the long-term event, severity slightly increased for the first five months. In October and November, there was a recovery period. Then, in December, the severity increased until March (Figure 6.3b). Regarding hydrological droughts, the highest deficit occurred in the mountainous areas in La Sierra and La Serranía. During the short-term event, the drought severity did not vary markedly (Figure 6.4a). In the long-term event, the highest deficits were observed in May, June, September and October (Figure 6.4b).

Table 6.2 Agricultural and hydrological droughts during the period of analysis.

Event	Agricultural droughts		Hydrological droughts	
	Date	**Duration [months]**	**Date**	**Duration [months]**
I	May 1991 – Jun 1992	13	Apr 1991 – May 1992	14
II	Jun 1997 – April 1998	11	Apr 1997 – Feb 1998	11
III	Jun 2001 – Aug 2001	3	May 2001 – Jun 2001	2
IV	Oct 2009 – Jan 2010	4	Sep 2009 – Nov 2009	3
V	Jun 2014 – Aug 2014	3	Jun 2014 – Jul 2014	2
VI	May 2015 – Jul 2016	14	Apr 2015 – Apr 2016	13

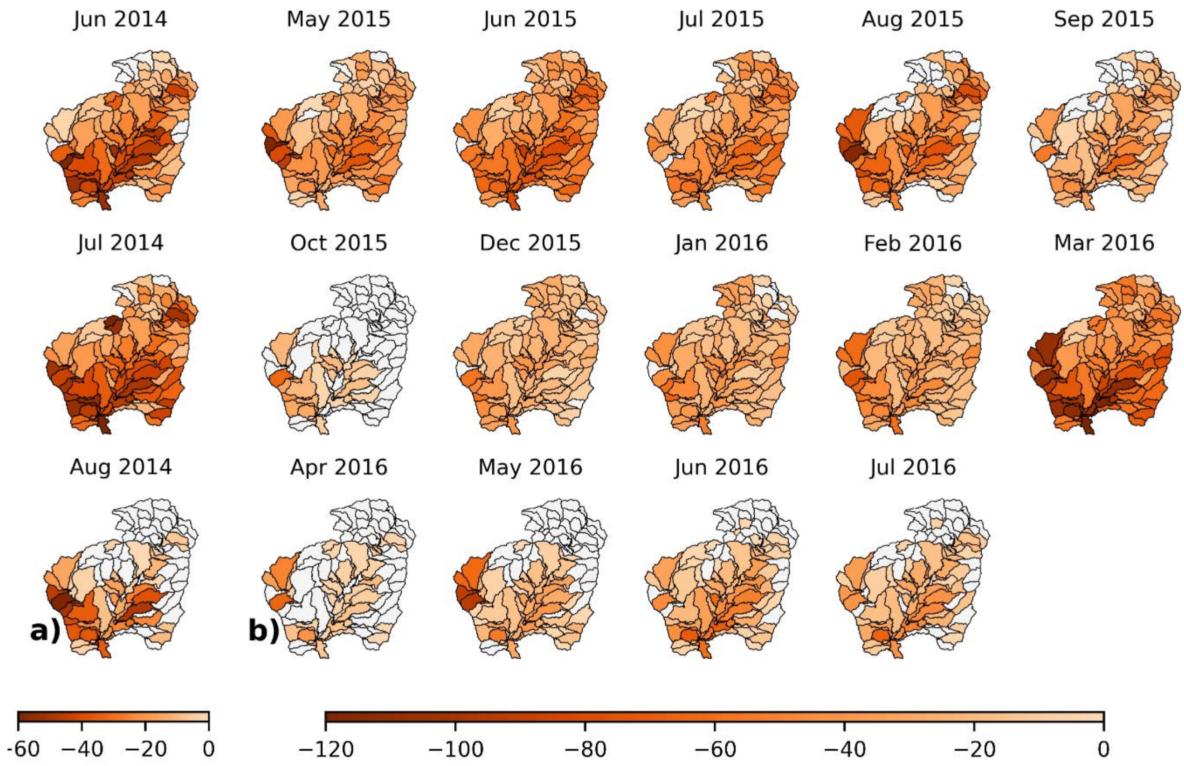


Figure 6.3. Agricultural drought severity events a) V and b) VI in mm.

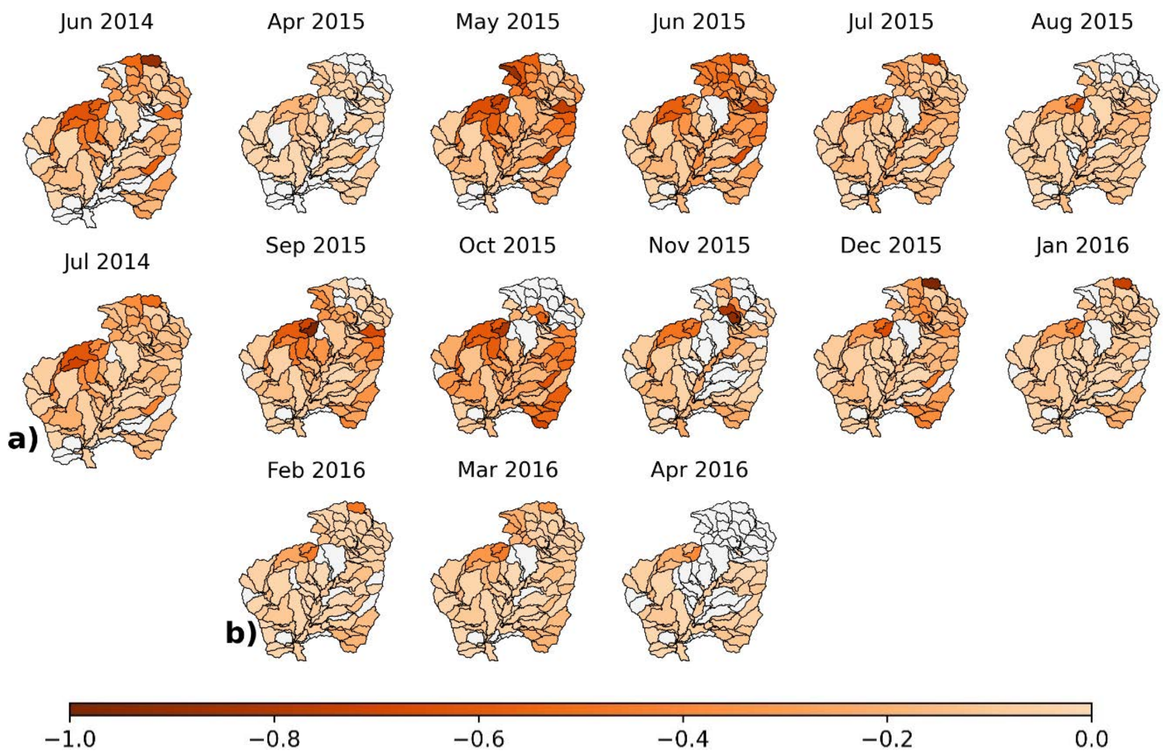


Figure 6.4 Hydrological drought severity events a) V and b) VI in mmd^{-1}.

6.3.2 Pareto optimal front and allocation of the PDMMs for the Most-Preferred Trade-Off Solutions

Figure 6.5 shows that U-NSGA-III progressed (towards a near-optimal Pareto front which is not known) and stabilised, considering the stable behaviour of the Hypervolume indicator at the end of the optimisation run. A relatively uniform distribution of the objective vectors in the front is presented in Figure 6.6.

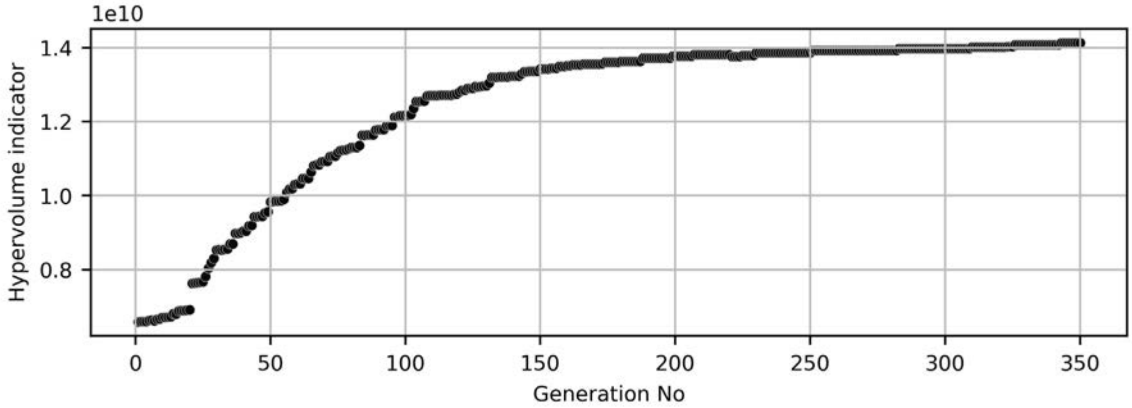


Figure 6.5 Hypervolume indicator at the end of each U-NSGA-III generation.

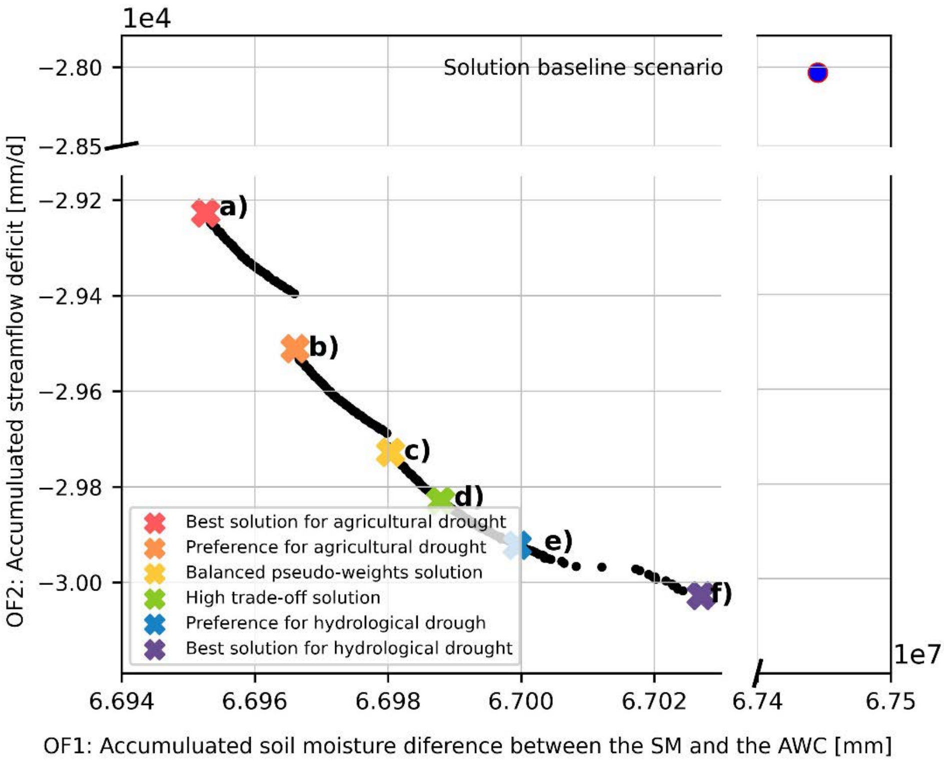


Figure 6.6 Optimal Pareto front obtained from the 350th generation and most-preferred trade-off solutions for the PDMM allocation problem. Each point represents a set of PDMMs to be

allocated (points *a* to *f*). The solution of the baseline scenario (blue dot, right upper corner) is also shown for reference.

The initial population consisting of 350 randomly generated individuals evolved into a well-spread and evenly distributed convex Pareto front. The final Pareto front consisted of 258 optimal solutions and was obtained after 350 generations (i.e., 122500 function evaluations, and for each a SWAT model run was needed). Once the optimisation was completed, we selected six solutions from the Pareto-optimal front (Figure 6.6 points *a* to *f*) to analyse the spatial distribution of the seven PDMMs evaluated (see Table 6.1) and compare the droughts' severity in the baseline scenario with the severity in the selected solutions. The MCDM approaches utilised to select the solutions *b*, *c*, *d* and *e* are described in Section 2.6.

6.3.3 Optimal allocation of the PDMMs for the Most-Preferred Trade-Off Solutions

Once the optimisation was completed, we selected six solutions from the Pareto-optimal front (Figure 6.6 points *a* to *f*) to analyse the spatial distribution of the seven PDMMs evaluated (see Table 6.1) and compare the droughts' severity in the baseline scenario with the severity in the selected solutions. Figure 6.7 presents the PDMMs allocation in the optimal solutions for agricultural (Figure 6.7a) and hydrological (Figure 6.7f) drought management, the selected most-preferred trade-off solutions, obtained through pseudo-weight and high trade-off methods (Figure 6.7c and d) and the preferred trade-off solutions with preference for agricultural and hydrological droughts, selected through the pseudo-weight method (Figure 6.7b and e). The MCDM approaches utilised to choose the solutions *b*, *c*, *d* and *e* are described in 2.6.

Figure 6.7a and b (PDMM-1) show that in scenarios with preference for agricultural drought management, RWH ponds were allocated in the river valley and in a strip that extends from the basin's north-east towards the west and in some subbasins at the basin's west and south. In the scenarios with preference for hydrological drought management, RWH ponds were applied to a lesser extent (Figure 6.7e and f, PDMM-1). RWH ponds were allocated in the northeast strip, especially at elevations >1000 m and in the mountainous areas in the basin's west. RWH ponds allocated at the river valley considerably decreased compared with scenarios with a preference for agricultural droughts.

RWH ponds allocation in the different solutions concurs well with previous studies concluding that suitable sites for RWH ponds depend on the intended application. For increasing soil moisture areas with low runoff potential given by precipitation ranging between 100 mm/year and less than 1000 mm/year, sandy soils and moderate slopes are recommended (Kahinda et al., 2008; Terêncio et al., 2017). Factors such as altitude, topography, and lithology are also evaluated to allocate RWH for groundwater recharge (Pacheco and Van Der Weijden, 2014).

In the solutions with preference for agricultural drought management, plantation crops (e.g., oil palm, coffee) were concentrated in the middle course of the river valley, and crop patches were observed in the headwater and the basin's south (Figure 6.7a and b PDMM-2). Overall, crop allocation obtained from the optimisation process in solutions *a* and *b* agrees with the Regional study of soil suitability for agriculture (2018). In the best-trade-off solutions and solutions with preference for hydrological droughts, plantation crops were allocated in mountainous areas at relatively high altitudes (replacing woodlands), the basin's west and southeast (Figure 6.7e and f PDMM-2). Earlier studies demonstrate that runoff, baseflow, and streamflow generation in oil palm plantations vary due to previous land cover, soil, and topographic conditions, showing a general increase compared to forest cover (Gómez et al., 2023). Nevertheless, other studies conclude that streamflow tends to decrease during low-flow months in land areas converted to oil palm (Heidari et al., 2020). In light of contrasting evidence, careful attention should be paid to crop allocation.

In the solutions with preference for agricultural drought management, the allocation of row crops was limited (Figure 6.7a and b PDMM-3). These crops were allocated in scattered strips in the river valley and towards the basin's south. On the contrary, in solutions *e* and *f*, the allocation of row crops notably increased throughout the basin (Figure 6.7e and f PDMM-3), including areas at relatively high altitudes. The allocation of corn in solutions *e* and *f* seems connected to the runoff potential of the curve number representing these crops. Curve number values to represent these crops are significantly high; then, it is expected that runoff contribution to the streamflow increases in the wet season, favouring the maximisation of the streamflow (second objective function).

For solutions with preference for agricultural drought, forests in good hydrological condition spread over the basin area (Figure 6.7a and b PDMM-4). Woodlands were allocated in the downhills of la Sierra Nevada, La Serranía del Perijá, the middle part of the river valley and in the basin's west. For solutions with preference for hydrological drought management, woodlands were allocated in the la Sierra and the Serranía del Perijá at relatively high altitudes. Overall, woodland allocation is consistent with the regional study of soil suitability for agriculture (2018). The study indicates that a thin topsoil and drainage density limits soil fertility in mountainous areas at elevations >2000 m. Hence, the land is suitable for forest conservation or restoration. Additionally, the allocation of woodlands in management scenarios aligns with findings in the literature indicating that planting native trees and fostering natural regeneration have regulated the annual streamflow and base flow since the first phases of restoration (Jones et al., 2022).

Channel protection structures are allocated towards the basin's west and in the middle part of the river valley in solutions giving more weight to agricultural droughts (Figure

6.7a and b PDMM-5). It should be pointed out that the SWAT model parameters used to represent this intervention does not influence the soil water content simulation; in consequence it has no impact on the severity of agricultural droughts. Considering this, in the solutions *a* and *b* the number of channel protection structures is low, mainly at the basin's west. In solutions giving more weight to hydrological droughts, channel protection allocates in the basin's west and in the river valley from the headwater to the basin outlet.

Similarly, to channel protection structures, SWAT model parameters used to represent grade stabilization structures do not influence soil water content simulation. In solutions a and b, stabilization structures are observed towards the basin's west and the river valley (Figure 6.7a and b PDMM-6). Most of these subbasins experienced the highest streamflow deficit during the drought events evaluated (Figure 6.4a and b). The number of grade stabilization structures increases in solutions with preference for hydrological drought management. The more weight is given to hydrological droughts the more protection structures are applied in the main course of the Cesar River (Figure 6.7e and f PDMM-6).

In solutions *a* and *b,* storage ponds allocate in the subbasins showing high runoff potential (Figure 6.7a and b PDMM-7). According to the analysis of the hydroclimatic parameters influencing droughts in the Cesar River basin by Paez-Trujillo et al. (2023), low infiltration capacity in these subbasins is associated with the soil hydrological group and land use that limits the infiltration. In solutions with preference for hydrological drought management, the storage ponds are allocated in the main channel from the headwater to the basin outlet. A few numbers of ponds are observed in basin east and in the Serranía del Perijá foothills.

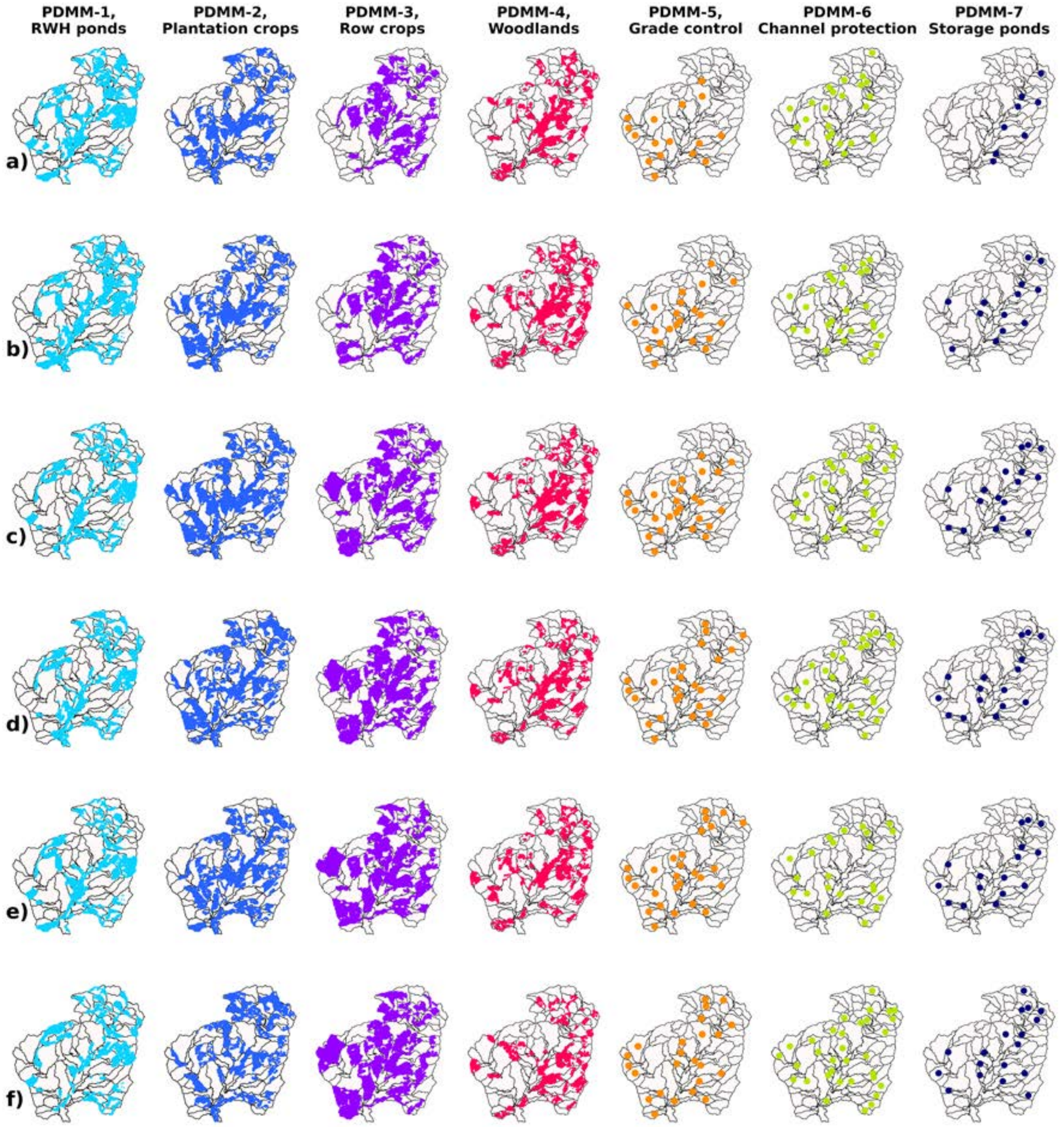


Figure 6.7 Relevant Pareto-optimal solutions: (a) best solution for agricultural drought management, (b) trade-off solution with preference for agricultural droughts, (c) most-preferred trade-off solution selecting the most balanced pseudo-weight, (d) most balanced high trade-off solution, (e) trade-off solution with preference for hydrological droughts, and (f) best solution for hydrological drought management.

6.3.4 Assessment of drought severity change by comparing drought severity in the baseline and the Most-Preferred Trade-off Solutions

The effect of PDMMs on the severity of agricultural and hydrological droughts was evaluated by comparing the drought severity in the baseline scenario to the drought severity in the selected solutions from the Pareto front (see Equations (2.13) and (2.14)).

In the following, we describe the changes observed in the Pareto front solutions *a*, *c* and *f*.

Agricultural drought severity changes in solutions a, c and f

In solution *a*, the severity of agricultural droughts was reduced compared to the baseline scenario. This improvement was well-marked in the northwest of the basin and the middle part of the river valley. In these areas were allocated RHW ponds, plantation and row crops and woodlands (Figure 6.7a). The alleviation of agricultural drought manifested consistently across the wet and dry months, and the short and long-term events analysed, as depicted in Figure 6.8a and b. The examination of the model outputs revealed that the agricultural drought severity drop (soil moisture enhancement) was connected to a reduction of the surface runoff volume in the subbasins where the PDMMs were applied and reduced sediment yield values, commonly associated with adequate soil structure, which improves the soils water retention capacity.

Similar results were obtained in solution *c*. The severity of agricultural droughts decreased in the basin's northwest and the middle part of the river valley, as in solution *a*; however, the deficit reduction was lower in solution *c*. While solution *a* exhibited a substantial decline of up to 100% in drought severity (Figure 6.8b Dec 2015, Jan 2016 and Apr 2016), in solution *c*, it remained below 20%, with the majority of values not exceeding 10%, as seen in Figure 6.8d.

Conversely, in solutions *a* and *c*, agricultural drought severity intensified *c* in the basin's west and La Serranía del Perijá. Figure 6.8a shows that in solution *a*, agricultural drought increased up to 60% in the basin's west and up to 20% in La Serranía del Perijá during event V. A comparable trend was observed during event VI (Figure 6.8b). Although agricultural drought severity rose in both solutions, in solution *a*, worsen of the drought situation was higher than in solution *c*, as evident in Figure 6.8a, b, c, and d. Model results suggest that converting pastures (current land use) to row crops increased the surface runoff, and replacing pastures for plantation crops increased evapotranspiration in the subbasins where crops were allocated, leading to water loss through surface runoff and evapotranspiration and subsequently enhancing the soil moisture deficit.

In contrast to solutions *a* and *c*, agricultural drought severity mainly increased in solution ***f*,** with rare exceptions. In event V, very little alleviation was observed, as shown in Figure 6.8e. During event VI, agricultural drought severity reduction seems more connected to the rainy period in March and April than the drought mitigating effect produced by the PDMMs. In 2015, drought severity decreased in May, Jun and Jul immediately after the precipitation events, and in 2016, drought severity decreased only in March and April (Figure 6.8f). Despite these slight variations, the results indicate that PDMMs in scenario *f* leads to a considerable increase in the soil moisture deficit in most of the subbasins. Figure 6.7a, c and f illustrate that PDMMs plots in solutions *a* and *c* are alike in the areas where the PDMMs allocate. Nevertheless, the application scale of plantation and row crops and woodland increases gradually from solution *a* to *f*, while the application of RWH ponds reduces. Accordingly, results indicate that the same PDMMs can mitigate or enhance one type of drought depending on the application scale of the intervention.

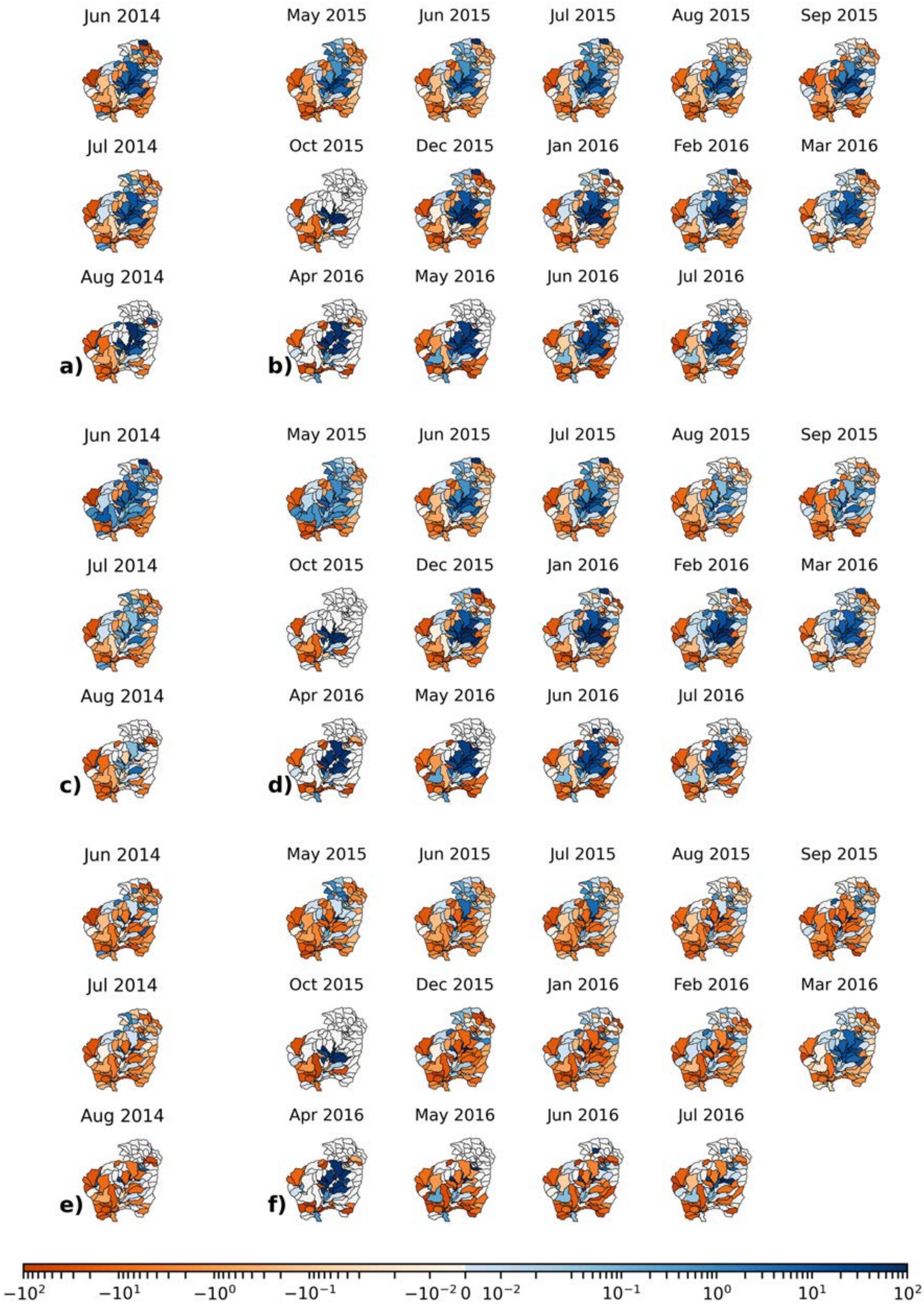


Figure 6.8 Agricultural drought severity change in events V and VI for solutions *a*, *c*, and *f*. Solution *a* a) event V, b) event VI, solution *c* c) event V d) event VI, and solution *f* e) event V f) event VI.

Hydrological drought severity changes in solutions a, c and f

Hydrological drought severity mainly increased in solution *a* (Figure 6.9a and b). Considering that the main rainfall events in the basin occur between August and November, hydrological drought alleviation in October and November (Figure 6.9b) may be linked to the increased precipitation in these months rather than the implementation of PDMMs. Model outputs revealed that surface runoff was reduced during both events analysed. It suggests that PDMMs increased soil water-holding capacity in solution *a*. However, a consequential outcome was a diminished contribution of surface runoff to streamflow during wet periods. Further, model results also showed that no significant change in the groundwater contribution to the streamflow was observed in the subbasins where the interventions were applied. Interestingly, although several interventions were applied in the channels, they did not significantly alleviate drought severity, confirming that the efficiency of these interventions depends on the volume of water reaching the streamflow.

In solution *c,* a positive change in the severity of hydrological droughts was observed in the basins’s west and in La Serranía del Perijá, while hydrological drought tends to increase in the headwater and in the river valley (Figure 6.9c and d). Figure 6.9c and d show that the areas where agricultural drought severity decreased, hydrological drought severity worsened and vice-versa. It is relevant to mention that solution *c* exhibited one of the highest densities of PDMMs allocated, but the alleviation of the two types of droughts is lower compared to the drought alleviation in the best solution for each type. It implies that a considerable number of PDMMs is required to satisfy both management objectives; however, the water input (mainly represented by precipitation), that seems insufficient to satisfy both objectives constraining the interventions performance.

In solution *f*, hydrological drought severity consistently decreased in the river valley; alleviation extended from the headwater to the basin outlet during event VI. Figure 6.9f illustrates that positive hydrological drought response is the result of PDMMs plot consisting of RWH ponds allocated in the strip (also observed in solutions *a* and *c*), plantation crops in the basin’s north, row crops distributed all over the basin, and woodlands allocation in the upper part of La Serranía del Perijá, and channel protection and storage ponds in the river’s main course from the headwater up to the basin outlet. This reveals that alleviating the hydrological drought severity in the middle course of the river results from the combined effect of different PDMMs allocated over the entire basin. Locally PDMMs’ allocation seems problematic. For example, the allocation of row crops aggravated the hydrological drought in the basin’s north and west. Similarly, woodlands allocation in the upper part of La Serranía del Perijá enhanced the drought deficit in some of the subbasins where the intervention was allocated.

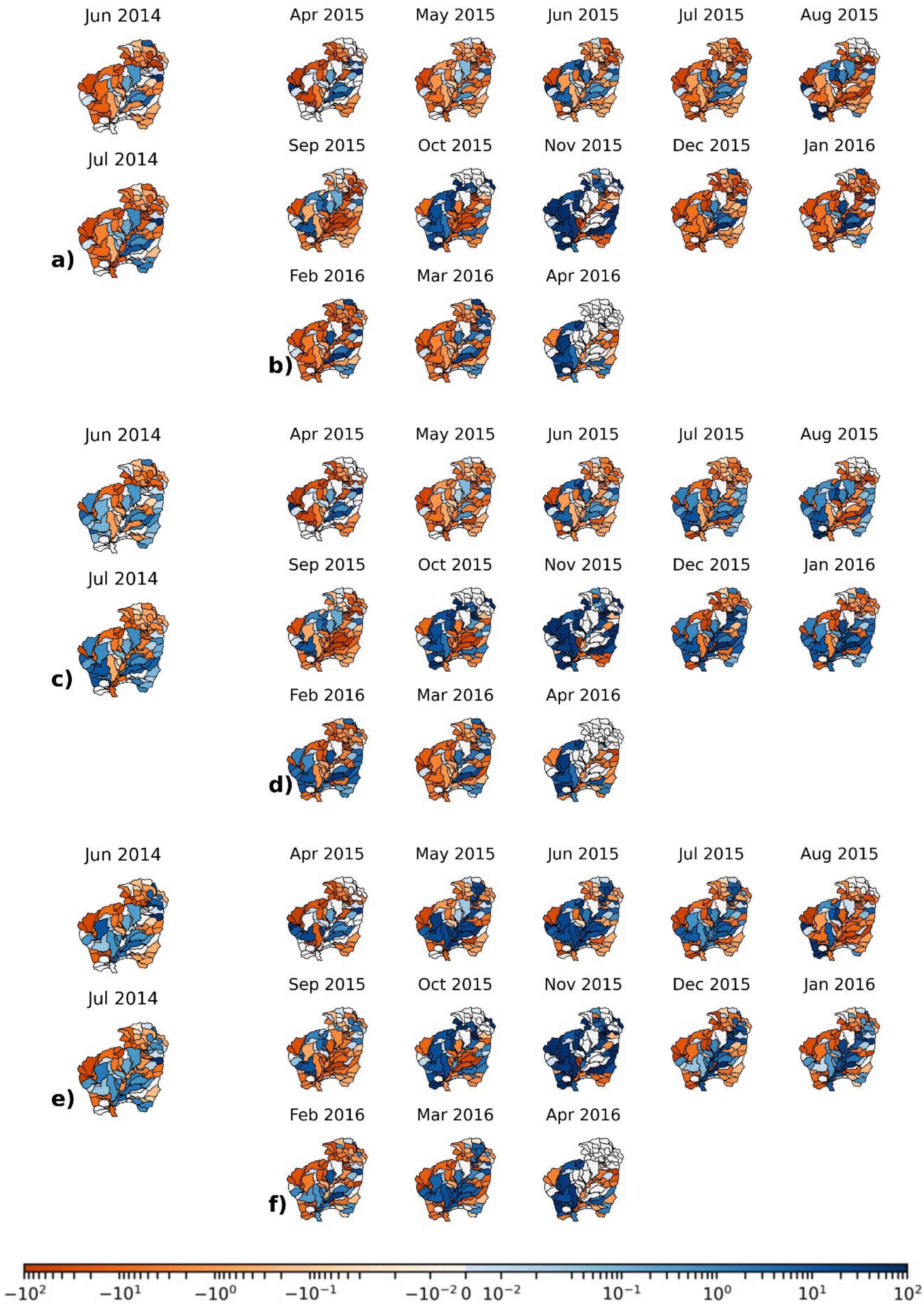


Figure 6.9 Hydrological drought severity change in events V and VI for solutions *a*, *c*, and *f*. Solution *a* a) event V, b) event VI, solution *c* c) event V d) event VI, and solution *f* e) event V f) event VI.

6.4 DISCUSSION

6.4.1 Insights on the PDMMs performance reducing severity of droughts

The outcomes of our study confirm that applying PDMMs has the potential to reduce the severity of agricultural and hydrological droughts. Nevertheless, it demonstrates that selecting and allocating the PMDDs is a complex task since results indicate that managing agricultural and hydrological droughts are conflicting objectives. For instance, in solution *a*, applying RWH ponds and land use change to plantation crops and woodlands alleviated the severity of agricultural droughts in the basin's northwest and the middle part of the river valley. These results are consistent with previous studies asserting that combined interventions (e.g., adequate crops allocation, conservation agriculture, storage ponds, bench terracing) have a significant effect on water balance components such as infiltration and soil water holding capacity (Palumbo Silva et al., 2023; Uniyal et al., 2020).

Agricultural drought alleviation contrasts with the increased hydrological drought severity in areas where agricultural drought severity is reduced. According to previous findings reported in the literature, surface runoff, soil water flow, and groundwater recharge tend to decrease after the conversion of grasslands to croplands or forests. The groundwater recharge decline occurs from factors such as lower and shallow pore connectivity, higher evapotranspiration rates, and the top soil texture; for example, clayey soils exhibit lower infiltration rates, limiting the groundwater recharge (Owuor et al., 2016). Hydrological drought reduced from the headwater to the basin outlet in the river valley, while agricultural drought increased in the same area. Then, the solutions analysed demonstrate that PDMMs application reduces the severity of agricultural droughts but may produce the opposite effect on the severity of hydrological droughts (or vice versa).

The above fits well with the results obtained by Cai et al. (2015). The authors presented an optimisation framework to select preventive and tactical measures for drought management under different climate scenarios. Although the authors did not assess the measures' effect on the drought severity (or another drought characteristic), they identified the trade-off relationship between maximising the crop yield (variable representing the agricultural drought) and maximising the low flows (variable representing the hydrological drought). They also concluded that the climate-change scenarios would aggravate the trade-offs due to more limited water resources availability.

Moreover, the PDMMs' effect may vary in time and space. In this study, variation in time may be linked to the rainy season. In the three solutions analysed, the most considerable drought severity change is observed during the rainy season. Drought alleviation lasts until the dry season and declines gradually until the wet season starts again. Our findings indicate that the performance of PDMMs balancing the water cycle relies on rainfall availability.

Regarding variation in space, PDMMs can be beneficial for one type of drought in a specific area but produce the opposite effect in another sector. In solution a, converting pastures (current land use) to plantation crops alleviated the severity of agricultural droughts in the basin’s northwest and the middle part of the river valley. However, the same interventions exacerbated the agricultural drought severity in the basin’s west. This concurs well with earlier studies showing that well-maintained grasslands can exhibit higher infiltration values compared to the same soil under cultivation due to shallow-rooted systems and lower evapotranspiration rates (Basche and Delonge, 2019; Krishnaswamy et al., 2018; Robinson et al., 2022).

For hydrological droughts, locally applied interventions can maximise the drought situation in the area where the measure is applied but alleviate the drought condition in the surrounding or downstream areas, as observed in solution f with the allocation of row crops in the basin’s west and woodlands application in the basin’s southeast. In both cases, hydrological drought worsens in the subbasins where the interventions are applied and reduced downstream. It poses an additional challenge to the implementation of PDMMs, considering the positive impact of the interventions may not be reflected in the areas where the intervention is applied.

Our findings indicate that PDMMs must be tailored to each region, and planning requires careful assessment of basin characteristics (e.g., rainfall distribution over the year, soil properties, current land use, and topography), drought characteristics, and likelihood. Equally important, PDMMs’ performance in reducing the severity of each type of drought should be quantified and monitored. This requires introducing appropriate indicators or criteria to measure PDMMs’ effectiveness in alleviating droughts. All the above confirms that incremental, autonomous adjustments made by farmers and reactive measures taken by governments and institutions after drought emergencies are not the best and most effective strategies for long-term drought management (Mapedza and McLeman, 2019).

6.4.2 Insights on using optimisation for PDMMs planning

The obtained solutions corroborate the benefit of using multi-objective optimisation for PDMMs planning. Despite the significant number of decision variables, the algorithm progressed towards a near-to-optimal set of solutions, namely multiple drought management scenarios, including different PDMMs aiming to balance land and water phases of the hydrological cycle and reduce the severity of agricultural and hydrological droughts. In the context of drought management, the optimisation engine can be seen as a decision support tool applicable to identifying the most appropriate areas to implement PDMMs and estimate their impacts on the basin’s hydrology. Even more, the solutions in the Pareto front allow decision-makers to assess the trade-off between managing agricultural and hydrological droughts.

In this study, the most significant alleviation for both types of droughts is observed in the river's middle course. This is consistent with the formulation of the objective functions, which aggregate the values of the variables representing each type of drought at each HRU or subbasin. The river middle course presents the highest values of soil moisture and streamflow; thus, variable changes in that area tend to impact the objective functions more. In the areas where the variables representing agricultural and hydrological droughts are relatively lower or the aridity index decreases (ratio between the precipitation and the evapotranspiration), drought severity alleviation is mainly observed in the best solutions for each type of drought. Weights can be assigned to underrepresented areas, preventing uneven contribution to the computation objective functions.

6.5 CONCLUSION

In this phase of the study, we framed the task of selecting and allocating preventive drought management measures (PDMMs) as an optimisation problem. Accordingly, we integrated the Soil Water Assessment Tool (SWAT) modelling system and the Unified Evolutionary Algorithm for Single, Multiple, and Many-Objective Optimization (U-NSGA-III) to develop an optimisation framework for identifying a set of PDMMs to be considered for implementation. The optimisation approach allows the representation of seven PDDMs, namely RWH ponds, plantation and row crops allocation, woodlands allocation, channel protection, grade control and storage ponds within various management scenarios (solutions) and simulation of their impact on the soil moisture and the streamflow, variables used to represent agricultural and hydrological droughts. Then, we assessed the PMDMs' performance in mitigating droughts, comparing the agricultural and hydrological drought severity in the baseline scenario to the severity in selected drought management scenarios.

The findings from our study confirm that implementing PDMMs has the potential to reduce the severity of agricultural and hydrological droughts, and the obtained management scenarios (solutions) underscore the utility of multi-objective optimisation for PDMMs planning. Analysed scenarios reveal that PDMMs can reduce the severity of agricultural droughts while producing the opposite effect for hydrological droughts (or vice versa). Moreover, the impact of PDMMs exhibits temporal and spatial variations. PDMMs implemented in a particular subbasin may ameliorate the severity of one type of drought in a particular month but worsen the drought situation in the preceding or coming months. In the case of hydrological droughts, the measures can intensify the streamflow deficit in the subbasins where the interventions are allocated while reducing the hydrological downstream (or vice versa).

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 INTRODUCTION

This dissertation comprehensively analysed hydro-climatic parameters influencing drought severity, planning drought mitigation interventions, and their effectiveness in reducing drought severity. This concluding chapter discusses the manner in which the outcomes of this study have contributed to addressing the research questions and objectives outlined in Chapter 1.

Following the summary of the research outcomes, this chapter reflects on challenges encountered throughout the research process and research-associated topics, such as the challenges to putting into practice strategic drought management, the application of data-driven models within hydrological sciences and data availability for hydrological studies. This chapter concludes by providing recommendations for subsequent research grounded in the limitations and the appearance of novel inquiries encountered during the course of this study.

7.2 RESEARCH OUTCOMES

This study started by posing four research questions. Below, we discuss how the research outcomes addressed these questions.

The first question was: *How can conceptual and data-driven models be used to assess the interplay between the drivers of droughts and the severity of these events at the basin scale?* This question was addressed in Chapter 4 by proposing and applying a methodology that assesses the relationship between climate, basin processes and drought severity. The method combined hydrological modelling and a machine learning tool and provided relevant information about the interplay between the hydroclimatic factors influencing drought severity.

The outcomes of a concrete application of the method in the Cesar River Basin reveal that hydroclimatic parameters such as evapotranspiration, potential evapotranspiration, and precipitation significantly influence agricultural droughts. Additionally, parameters like sediment yield, percolation, and the curve number are found to influence droughts to a lesser extent. In turn, precipitation and water yield are the main drivers of hydrological droughts, while percolation, surface runoff and the curve number exhibit a lower influence. Interestingly, the results indicate that the combined effect of parameters with low impact can trigger a drought situation as severe as the one produced by one or two of the most influential parameters. This points out the complexity of the drought-generating process.

The results also demonstrate that the MVRT (and supposedly other machine learning techniques that generate 'explainable AI' models) is a relevant tool for identifying the hydroclimatic parameters governing drought exposure and drought-prone areas.

The second and third questions were: *What are the long-term structural and non-structural PDMMs measures applicable for agricultural and hydrological drought management? And how to represent the PDMMs in a modelling system?* The assessment of interventions suitable for drought management was addressed in two distinct stages through Chapters 2, 5 and 6.

The initial stage involved a qualitative assessment, represented by the literature review on strategic drought management, with a specific emphasis on PDDMs. In this stage, I used modelling, field studies, and knowledge products to document previous experiences analysing or implementing hydrological-based PDMMs. The review resulted in a compilation of interventions designed to optimise water use across the land and water phases of the hydrological cycle.

Then, in Chapters 5 and 6, we presented a quantitative evaluation of PDDMs' effectiveness in alleviating. Chapter 5 examined the efficacy of three specifically chosen PDMMs—rainwater harvesting ponds, forest conservation, and check dams—in mitigating the severity of agricultural and hydrological droughts. Chapter 6 advanced this analysis by employing an optimisation framework that allowed for the automatic generation and assessment of hundreds of thousands of management scenarios, encompassing diverse combinations of PDMMs. The most relevant scenarios were selected, and the combined impact of PDMMs on agricultural and hydrological drought severity was evaluated.

The fourth question was: *How to formulate and solve the problem of selecting and allocating PDMMs as an multi-objective optimisation problem?* This question was answered in Chapter 6. An optimisation problem consists of three main elements: objective functions (conflicting objectives), decision variables and constraints. The conflicting management objective under consideration involves mitigating agricultural and hydrological droughts simultaneously. This presents a conundrum, as alleviating agricultural droughts requires storing water in the soil profile, implying a reduction in the rivers' discharge, increasing, in turn, hydrological droughts.

Accordingly, we framed the problem of selecting and allocating PDMMs for agricultural and hydrological management as a multi-objective optimisation with binary variables. Two objective functions were formulated, one representing the management of agricultural droughts and the other the management of hydrological droughts. The decision variables were represented by the spatial units (HRUs and subbasins) where the PDMMs were allocated, 3650 in total. The optimisation problem is initially formulated without the inclusion of constraints; nevertheless, in section 7.4, I elaborate on the potential enhancement in planning PDMMs by including constraints in the optimisation process.

To solve the optimisation problem, we used Python as the programming language and the library of optimisation algorithms *pymoo* (Blank and Deb, 2020) coupled with the *SWAT-pytools* wrapper for executing SWAT (Hernandez-Suarez and Nejadhashemi, 2022). Considering the complexity of the optimisation problem, given the significant number of decision variables, the population size and the number of generations required to find a near-optimal Pareto front, the problem was solved in parallel utilising the computational capabilities of the Snellius supercomputer (Dutch National Supercomputer Snellius, 2023).

Lastly, the fifth question was: *How can the optimisation results be interpreted and used to estimate the impact of PDMMs on the severity of agricultural and hydrological droughts?* This question was answered in Chapters 6. Through a modelling approach, we conducted simulations of diverse drought management scenarios, employing hydrological-based PDMMs and estimated their impact on drought severity.

The study's results suggest that PDMMs have the potential to reduce the severity of agricultural and hydrological droughts; nevertheless, their performance must be carefully assessed. The findings corroborated that the trade-off between managing agricultural and hydrological droughts means that measures and plots appropriate for agricultural drought management may exacerbate hydrological drought conditions and vice versa. It was also observed that depending on the measure, the reduction of drought severity in the intervention area may trigger the enhancement of the drought condition downstream. This highlights the complexity of managing drought conditions and the need to understand the spatial dynamics involved comprehensively. Equally important is the influence of hydroclimatic parameters, such as annual precipitation, soil type, and topography, along with the initial conditions of the area under intervention, encompassing land use and crop type. These factors (among others) shape the applicability and effectiveness of drought management interventions.

According to the outcomes of the analysis, there is no unique answer to the question of the PDMMs' performance in alleviating droughts. Instead, diverse factors emerge as influential in either enhancing or limiting the PDMMs' effects and performance. The developed model-based optimisation framework is seen as a pertinent tool to support the decision-making process of planning drought management scenarios and evaluate the PDMMs' applicability in alleviating droughts' severity.

7.3 Reflections

On drought management Shift from a reactive approach for drought management to a proactive one opens the possibility of defining structured and long-term interventions that create resistance and resilience to drought events. Nevertheless, hydrological science (and other disciplines) must continue progressing on different topics to take the approach from definitions to practice.

It is of particular relevance linking basin characteristics and drought characterisation to planning mitigation strategies. Generally, studies focus either on the description of the drought situation or the definition of management strategies, and it is rare to find a comprehensive analysis that integrates the drought diagnosis and a prescriptive analysis recommending a course of action to alleviate the drought situation. Drought management studies that propose mitigation strategies adequately informed by the region's drought likelihood and characteristics are equally scarce. I found examples of this disconnection in the literature and knowledge products consulted for this study. For instance, check dams and retention ponds implementation without information on the region's hydrology and data on the non-drought conditions, implementing soil conservation practices without quantitative evidence of their suitability for drought mitigation, or conservation programs of mountainous ecosystems without monitoring programs to assess the performance buffering drought conditions quantitatively. As a result, evaluating which interventions effectively mitigate droughts (or not) is challenging, invested resources in drought mitigation measures are lost, and credibility within affected communities is undermined. The disconnection between drought characterisation and management, together with droughts of unprecedented magnitude, may explain why, despite the attempts to implement PDMMs, the impacts of droughts are still increasing (Kreibich et al., 2022).

Considering different types of droughts for planning and implementing drought management strategies is paramount. As explained throughout this study, managing different types of droughts are conflicting objectives, and usually, mitigating one category of drought enhances the other types. Accordingly, equal attention should be paid to managing agricultural and hydrological droughts, as well as environmental, groundwater drought and socio-economic droughts. This prevents management bias and efforts to avoid one type of drought, precipitating imbalances in the water cycle and ultimately leading to a persistent water deficit state.

Beyond the questions that hydrological science still needs to address, it is also necessary to refer to the socio-economic barriers that the practical implementation of drought management strategies has to overcome. Documented cases of managing droughts suggest that the most successful strategies result from measures with considerable installation and maintenance costs or major changes in land use, agricultural practices and governance (Kreibich et al., 2022). A recent example of these strategies is the Dutch policy “Water and soil leading in land use planning”, announced by the government after the severe drought that affected Europe in 2022. The policy refers to the idea that instead of adapting the land and water management to preferred uses, the use should be adapted to the (semi-) natural condition. This means, for example, no water-intensive farming in regions with limited water supply (Bartholomeus et al., 2023). Initiatives like this corroborate that creating resistant and resilient communities and ecosystems to drought events requires a fundamental change in water and land management; however, the practical implementation of such strategies represents a significant challenge for most countries.

The cases of study used in this study are good examples of this situation. In the Torola basin, the predominant land use is subsistence agriculture. However, the region’s characteristics, namely, topography, soil type, and the unpredictable seasonal rainfall observed in the last decades, indicate that suitable land use is forest conservation. Then, what is the feasibility of adapting the land use towards (semi-) natural condition basin when communities depend on agriculture to meet their basic needs? Moreover, adapting to (semi-) natural conditions in the Cesar basin requires solving land use conflicts and re-locating profitable agro-businesses that benefit private companies and represent a source of income for the local communities, thus, how to interfere with and potentially limit agricultural activities when recognized as crucial drivers of the region’s economic growth.

In light of this, planning drought mitigation measures becomes a transdisciplinary task that transcends the domain of hydrological science and reaches social and economic studies (Hagenlocher et al., 2023). Social studies are paramount to facilitating (creating) the dialogue between the hydrological science community, decision-makers, and the general public. Particularly, it is necessary to enhance our understanding of the personal and cultural factors influencing the community’s perception of drought risk, defining more effective strategies to communicate drought conditions, the factors that contribute to drought status and the potential consequences for the different societal and environmental dimensions (Ward et al., 2022; Weitkamp et al., 2020). In addition, social scientists argue that, it is required to evaluate the uneven distribution of drought impacts associated to the communities’ and ecosystems’ levels of exposure and explicitly engage politics and social power that drive human activities and their interactions with hydrometeorological processes in analysing drought crisis, resilience and adaptation.

In turn, economic sciences are advocated to comprehensively explore the impacts and economic costs generated by drought across multiple dimensions (e.g., human health and well-being, productive sectors, ecosystems, macroeconomy) (Fleming-Muñoz et al., 2023) and compare the costs of inaction — pricing damages that will result from allowing droughts to continue unabated — to the costs of implementing mitigation plans. Finally, transversal to all disciplines is the discussion of debt-for-nature/climate swap as a tool to address liquidity problems and foster investments in effective drought mitigation actions.

On the role of machine learning for hydrological studies In the late 19th century, the rational method was used to design sewers; later, in the 1940s, the task of constructing small dams to help retain soils and reduce runoff from agricultural watersheds resulted in the development of the Curve Number Method by the US Department of Agriculture. It can be said that employing conceptual models and machine learning techniques in a hybrid setting (as presented in this work) is a suitable strategy for addressing the challenge of optimising water resource utilisation in the climate change and increasing human water demand times.

However, merging two different modelling strategies would not only bring the benefits of each one but also its unsolved matters. For instance, despite hydrologic modelling being a mature field, the uncertainty and estimation of the parameters, sensitivity to initial conditions, and representation of human interventions in the hydrological cycle are still topics of discussion (Ogden, 2021). Conversely, the difficulty of reproducing the spatial and temporal variation of hydrological processes, the lack of high-quality and sufficient data to train the models and the associated risk of overfitting and underfitting, and the lack of physical interpretability are good examples of the challenges to address when applying machine learning in hydrology (and other disciplines) (Mosaffa et al., 2022; Shen et al., 2021; Solomatine and Ostfeld, 2008; Xu and Liang, 2021). Amidst this array of potential sources of error, expert knowledge is even more crucial than ever. Only trained experts can critically assess the model's results, validate the outcomes, and detect potential errors. This underscores the importance of educating hydrologists equipped with a solid theoretical background and proficiency in the application of both conceptual and data-driven models.

On the data availability for hydrological studies Hydrologic data are at the core of our understanding of hydrologic processes and the foundation of effective water management. Nevertheless, in some regions, obtaining accurate and consistent data at an adequate spatial resolution and period of interest poses a significant challenge for the hydrologist. In this study, acquiring the data for building up and calibrating the hydrological models and developing the drought analysis was not straightforward. Particularly, in the Torola Basin, spatial information on land use and soil type was unavailable, and the available time series of the hydroclimatic data, namely, precipitation and temperature and discharge data for the model set-up, calibration and validation, were relatively short (fifteen years). To address the lack of spatial data, the land use raster was obtained from the USGS Global Land Cover Characterization (GLCC) database, and the soil type raster was obtained from the FAO-UNESCO Soil Map of the World for soil type. In the Cesar River Basin, the lack of information about human activities (irrigation systems, groundwater abstraction, water diversion for human consumption or industrial purposes) in the basin limited the analysis of the degree of influence of anthropogenic activities on drought characteristics.

Despite the wealth of hydroclimatic information available, the ground truth is that the information is mainly focused on the macro-or large-scale catchments and using the data for analysis at the catchment scale requires pre-processing the information using adequate methods for downscaling the measured variable and quantifying the uncertainty associated to this process; both tasks are time-consuming and computationally costly. Accordingly, researchers conducting studies in data-limited regions must consider the time and resources required for hydrological data acquisition and pre-processing from the planning stage of the study. Equally important during the studies review process, researchers must be prepared to address inquiries on the hydrological model uncertainly associated with the datasets downscaling, representing the basing hydrology using time series shorter than 30 years or the absence of the model calibration on a variable of particular interest for the study. For instance, in reviewing the studies developed in the Torola and Cesar basins, the reviewers inquired about the importance of calibrating the models for soil moisture since the variable was used to represent agricultural droughts. Although the observation was appropriate, and calibration and validation of the model using soil moisture may contribute to reducing the uncertainty for the drought analysis, monthly soil moisture data is needed for calibrating and validating the model, either in-situ measurements, satellite-derived soil moisture or reanalysis soil moisture, at subbasin level. However, in the study areas, there are no in-situ soil moisture measurements in the study area, and the spatial resolution of the available datasets of satellite-derived soil moisture or reanalysis soil moisture is coarse (0.25°×0.25°). Accordingly, data availability constrained that validation.

7.4 LIMITATIONS AND FUTURE RESEARCH

This thesis covered various topics related to analysing and managing agricultural and hydrological droughts. The following research directions are suggested to continue advancing our understanding of the interplay between the hydroclimatic parameters influencing drought severity and the most suitable measures for drought management:

Human activities increasingly influence the hydrological cycle. Thereby, the occurrence of droughts can no longer be attributed solely to natural climate variability but rather to the combination of natural-anthropogenic drivers. Numerous studies have investigated the impact of human activities on droughts, consistently revealing an exacerbating effect (AghaKouchak et al., 2021; de Matos Brandão Raposo et al., 2023; Van Loon et al., 2022). In this study, anthropic activity was represented in the hydrological model by the land cover, the crop type, and the management operations that control the crop's growth cycle, including planting, irrigation (only from the streams) and harvest. Nevertheless, *more research is needed to extend the representation of human activities in a modelling system used to represent the basin hydrology*. Specifically, it is necessary to simulate water abstraction for households, industries, and livestock. This is particularly relevant in the Cesar River Basin, where substantial pasture areas are dedicated to cattle raising, alongside a coal mining activity in the southeastern basin. Equally important is the inclusion of existing irrigation systems, particularly those supporting the industrial cultivation of oil palm and exploring the utilisation of additional modelling tools to simulate groundwater abstraction for agricultural and industrial use.

The central focus of this dissertation was the analysis of management scenarios applicable to reducing the severity of agricultural and hydrological droughts. The hydrological model used to represent basin hydrology and simulate the variables representing droughts (soil moisture and streamflow) was built up using climatic data spanning from 1987 to 2019. Nevertheless, projections indicate that climatic extremes (of unprecedented magnitude) are expected to increase globally in the twenty-first century (UNDRR, 2021). This trend, coupled with escalating human water demands, is expected to intensify pressure on water resources, leading to the occurrence of ecological droughts (Crausbay et al., 2017), groundwater droughts (Peters et al., 2005) and more severe socio-economic droughts (Mehran et al., 2015). *Future research can explore the use of projected climatic variables (e.g. precipitation, temperature) to build up a hydrological model representing future hydrology*. This model can be integrated into the optimisation tool to generate drought management scenarios that account for future hydrological dynamics in the region of interest. Moreover, *future work should improve drought management planning by including ecological, groundwater and socio-economic droughts in formulating the optimisation problem of selecting and allocating PDMMs.*

This dissertation presents a modelling framework for drought analysis and management. *The use of additional modelling tools can contribute to refining the obtained results*. Basin hydrology was simulated using SWAT model. Considering the model emphasises the representation of surface water processes, *forthcoming work may use available modelling tools to improve the representation of groundwater hydrology*. This contributes to a better representation of hydrological droughts since streams depend significantly on groundwater to maintain flow, particularly during droughts, and would allow the analysis of groundwater droughts.

Regarding data-driven models, only one ML technique (MVRT) was employed to analyse the non-linear relationship between climate, basin processes, and drought severity. *Further extensions of this work should explore the use of other ML techniques*. For instance, M5 model trees (rather than regression trees) have shown their effectiveness in solving water-related problems. These result in linear models in tree leaves rather than constants like regression trees (see Solomatine and Xue (2004) and Solomatine and Dulal (2003)).

Lastly, the dissertation relied exclusively on a single optimization algorithm, NSGE-III, for defining and testing the optimisation engine. *Subsequent research should explore the use of other optimization algorithms.* This is a recommended practice to assess algorithms' effectiveness (how close the algorithm gets to the global minimum), efficiency (running time, measured by the number of function evaluations needed) and reliability (robustness, measured by the number of successes in finding the global minimum (Maskey et al., 2002; Solomatine, 1998).

APPENDIX A
Optimisation tool and other knowlegde products

The optimisation tool code (developed and tested in Chapter 6) is available on the **GitHub repository**, QR below.

Swat-Pytools-Optimisation

The input data and the calibrated and validated models of the areas of study, Torola (case of study Chaper 5) and Cesar River Basin (case of study Chaper 4 and 6), can be found on the **HydroShare** platform, QRs below.

Hydrological model Torola River Basin

Hydrological model Cesar River Basin

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LIST OF ACRONYMS

PDMMs	Preventive Drought Management Measures
SWAT	Soil Water Assessment Tool
ARS-USDA	Agricultural Research Service of the United States Department of Agriculture
HRU	Hydrological response unit
SUFI-2	Sequential Uncertainty Fitting version 2
NSE	Nash-Sutcliffe Efficiency
PBIAS	Percent bias
TLM	Threshold level method
SMDI	Soil Moisture Deficit Index
SSI	Standardised Streamflow Index
SPI	Standardised Precipitation Index
ML	Machine learning
AI	Artificial Intelligence
MVRT	Multivariate Regresion Tree
SS	Sum of squared distances
CVRE	Relative cross-validation error
EV	Explained variance
U-NSGA-III	Unified Evolutionary Algorithm for Single, Multiple, and Many-Objective Optimization
SBX	Simulated binary crossover
MCDM	Multi-criterion decision-making
CADC	Central America Dry Corridor
RWH	Rainwater Harvesting
AWC	Available water capacity

LIST OF TABLES

LIST OF FIGURES

About the author

Ana María Páez Trujillo graduated with a Bachelor's degree in Civil Engineering from Universidad Nacional de Colombia in 2011, followed by a Masters in Water Resources Management from Escuela Colombiana de Ingeniería Julio Garavito in 2015.

Ana María's professional experience encompasses different roles in the private and public sectors. In the private sector, she participated as a hydraulic specialist in the engineering design of hydroelectric projects, irrigation systems, and the expansion of regional highways. She also has experience modelling river hydraulics to design scour protection. Moving into the public sector, Ana María contributed to governmental initiatives in Colombia, focusing on reducing the vulnerability of rural aqueducts to droughts and formulating methodologies for urban flood risk assessment.

Ana María started her PhD research at the Hydroinformatics and socio-technical innovation department at IHE Delft Institute for Water Education, and Delft University of Technology in 2018. The Ministry of Education Colombia, Programa Colombia Cientifica financially supported the research project (Grant No. 3597287).

In 2024, Ana María transitioned to a new role as a Post-Doctoral researcher in the Department of Physical Geography at Utrecht University, where she became part of the World Water Map project. This initiative aims to analyse in detail the causes of freshwater shortages worldwide and explore strategies to reduce the water deficit.

Journals publications

Paez-Trujilo, A, Hernandez-Suarez, J., Alfonso, L., Hernandez, B., Maskey, S., Solomatine, D. (2024). An optimisation approach for planning preventive drought management measures. *Science of The Total Environment* 174842. https://doi.org/10.1016/j.scitotenv.2024.174842.

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born on 20 July 1987 in Bogota, Colombia

has successfully fulfilled all requirements of the
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Delft, 30 September 2024

SENSE coordinator PhD education

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The SENSE Research School declares that **Ana Maria Paez Trujillo** as successfully fulfilled all requirements of the educational PhD programme of SENSE with a work load of 38.4 EC, including the following activities:

SENSE PhD Courses

- Environmental research in context (2019)
- Research in context activity: 'Organising the IHE PhD Symposium 2021 "Collaborative Water Resources Management for a water-secure world"'

Other PhD and Advanced MSc Courses

- Python for Engineers, TU Berlin Summer University (2021)
- Nature Based Solutions for Water and Land Management, Cranfield University (2021)
- Computational Intelligence and Operational Water Management, IHE Delft (2022)
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- Self-awareness and autonomy in the research process, TU Delft (2018)
- Conversation skills, TU Delft (2018)
- English for academic purposes, TU Delft (2019-2020)
- Self-presentation: focus, structure, TU Delft (2019)
- Brain Management, TU Delft (2019)
- Popular scientific writing, TU Delft (2019)
- Analytic Storytelling, TU Delft (2019)
- Writing a dissertation PROM-3, TU Delft (2020-2021)
- Designing Scientific Posters and Covers, TU Delft (2022)

Oral Presentations

- *Framework for spatio- temporal multi-objective optimization of preventive drought management measures (Phd Proposal)*. IHE PhD Symposium 2019: Innovations for Sustainability, 10-11 October 2019, Delft, The Netherlands
- *Evaluation of hydrological response to drought alleviation measures through mathematical and conceptual models; Case of study: Torola basin*. IHE PhD Symposium 2020: Collaboration for sustainability, 7-8 October 2020, Delft, The Netherlands
- *Optimization of preventive drought management measures to alleviate the severity of agricultural and hydrological droughts*. EGU General Assembly, 23-27 May 2022 Vienna, Austria
- *Multivariate regression trees as an 'explainable machine learning' approach to exploring relationships between hydroclimatic characteristics and agricultural and hydrological drought severity*. EGU General Assembly, 23-28 April 2023, Vienna, Austria

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Projections indicate that drought frequency, severity, and duration will increase globally in the twenty-first century, impacting nearly all societal and environmental dimensions. Therefore, transitioning to drought-resilient societies and ecosystems is urgent. Implementing Preventive Drought Management Measures (PDMMs) is a suitable strategy to mitigate the potential negative impacts of droughts and to respond to droughts more effectively.
This dissertation aimed at developing an optimisation framework to identify near-optimal allocation of PDMMs based on a comprehensive understanding of the drivers and characteristics of droughts. The study first assesses the non-linear relationship between climate, basin hydrological processes, and drought severity to determine what causes droughts and identify drought-prone areas at a basin scale. Subsequently, potential interventions suitable for drought management are identified through a review of existing research on strategic drought management, with a specific emphasis on PDMMs.
The PDMMs analysis is further advanced using an optimisation approach to create numerous drought management scenarios with multiple PDMMs combinations. The most relevant scenarios are selected, and their impacts on the severity of agricultural and hydrological droughts are evaluated.

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