Technical University of Crete
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Multi-origin water resource optimisation framework for industrial purposes

Graduate Thesis

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“(…) und wieviel verdankt die Physik dem Schrei nach besseren Webstühlen!”

“And how much Physics owes to the [merchants’] cries for better looms!”
Leben des Galilei, B. Brecht

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Περίληψη

Η παγκόσμια κλιματική κρίση έχει αναδείξει την ευπάθεια των υδάτινων πόρων, οδηγώντας σε αυξημένη ξηρασία, εξάντληση των αποθεμάτων νερού και αυξημένη ζήτηση, ιδίως στην περιοχή της Μεσογείου. Βιομηχανίες, όπως οι ζυθοποιίες, που είναι υδροβόρες, αντιμετωπίζουν σημαντικές απειλές. Η παρούσα μελέτη αποσκοπεί στη βελτιστοποίηση της πρόσληψης από εναλλακτικές πηγές νερού για την ελαχιστοποίηση της εξάρτησης από το δημόσιο δίκτυο. Η έρευνα διεξήχθη σε μια μονάδα ζυθοποιίας στην Κρήτη, και διερευνά τη χρήση τεσσάρων εναλλακτικών πηγών νερού.

Αναπτύσσεται ένα μοντέλο Γραμμικού Προγραμματισμού (LP) για την αποτελεσματική κατανομή των υδάτινων πόρων, ελαχιστοποιώντας το κόστος και τις περιβαλλοντικές συνέπειες, με σεβασμό στους περιορισμούς δυναμικότητας κάθε εναλλακτικής πηγής νερού. Ένας πρωτότυπος αλγόριθμος χρησιμοποιείται για την αντιμετώπιση του ζητήματος αυτού, με ημερήσια δεδομένα που καλύπτουν 365 ημέρες, με αποτέλεσμα ημερήσιες και ετήσιες λύσεις.

Ο αλγόριθμος αποδείχθηκε πολύ αξιόπιστος στον εντοπισμό του ολικού βέλτιστου. Τα αποτελέσματα της μελέτης απέδειξαν ότι το ισοσταθμισμένο κόστος του νερού μπορεί να μειωθεί κατά περισσότερο από 10%, μειώνοντας ταυτόχρονα τον περιβαλλοντικό αντίκτυπο (GHG) κατά περισσότερο από 25%. Το βέλτιστο σύστημα περιορίζει την πρόσληψη νερού από το δημόσιο δίκτυο μεγιστοποιώντας τη συμβολή των υπόγειων υδάτινων πόρων και ενός παρακείμενου ποταμιού.

Η έρευνα αυτή οδηγεί σε ελπιδοφόρα αποτελέσματα και πρακτικές λύσεις για τις βιομηχανίες που έχουν υψηλές απαιτήσεις νερού, υπογραμμίζοντας την επείγουσα ανάγκη για προσαρμοστικές στρατηγικές ενόψει της κλιματικής αλλαγής. Η παρούσα μελέτη αποτελεί κρίσιμο σημείο αναφοράς για τις βιομηχανίες που στοχεύουν στην επίτευξη βιώσιμης και οικονομικά αποδοτικής διαχείρισης των υδάτινων πόρων εν μέσω της διογκούμενης κλιματικής κρίσης.

Abstract

The global climate crisis has highlighted the vulnerability of water resources, leading to increased droughts, depletion of water reserves, and increased demand for water, especially in the Mediterranean region. Industries heavily reliant on water, such as breweries, face significant threats from droughts and potential water scarcity. This study aims to optimise the intake from alternative water sources to minimise reliance on municipal water. Conducted in Crete, Greece, the research explores the utilisation of four alternate water sources.

A Linear Programming (LP) model is developed to distribute water resources effectively, minimising costs and environmental consequences while respecting the capacity limitations of each water source. A newly created algorithm is used to address this issue, with datasets covering 365 days, resulting in daily and yearly solutions.

The algorithm has been proved very reliable in locating the global optimum, requiring reasonable computational effort. The outcomes of the study proved that the levelised cost of water can be reduced by more than 10%, by also concurrently diminishing the greenhouse gas emissions (GHGs) by more than 25%. The optimal solution suggests a system that restricts municipal water intake by maximising the contribution of the ground water resources and the river ones, as well.

This research leads to promising results and practical solutions to water-intensive industries, emphasising the urgent need for adaptive strategies in the face of a changing climate. This study stands as a critical reference point for industries aiming to achieve sustainable and cost-effective water resource management amidst the burgeoning climate crisis.

List of Abbreviations

IPCC	Intergovernmental Panel on Climate Change
MedECC	Mediterranean Experts on Climate and Environmental Change
MAR1	Mediterranean Assessment Report on Climate and Environmental Changes
IWRM	Integrated Water Resource Management
RWHS	Rainwater Harvesting System
RO	Reverse Osmosis
UF	Ultrafiltration
NF	Nanofiltration
MF	Microfiltration
MBR	Membrane Bioreactor
UV	Ultraviolet
RFB	River Bank Filtration
AFB	Artificial Bank Filtration
LCA	Life-Cycle Analysis
BWRO	Brackish Water Reverse Osmosis
CapEx	Capital Expenditure
OpEx	Operational Expenditure
TDS	Total Dissolved Solids
EDS	Electrodialysis Reversal
LpH	Litres per Hour
WDP	Water Deprivation Potential
PPCPs	Pharmaceuticals and Personal Care Products

OSRO	One-Step Reverse Osmosis
OMPs	Organic Micro-pollutants
FAT	Full-advanced Treatment
FO	Forward Osmosis
UFO-MBR	Ultrafiltration Osmotic Membrane Bioreactor
CIP	Clean-in-Place
DEIAVA	Municipal Enterprise for Water Supply and Sewerage of Northern Axis of Platanias Municipality
O&M	Operational and Maintenance
VND	Vietnamese Dong
EUR	Euro
USD	United Stated Dollar
AUD	Australian Dollar
GBP	Great Britain Pound
EAC	Equivalent Annual Cost
kWh	kilowatt-hour
LCOW	Levelised Cost of Water
LCOE	Levelised Cost of Energy
DEIACH	Municipal Enterprise for Water Supply and Sewerage of Chania
SWAT	Soil and Water Assessment Tool
KSWAT	Karst-Soil and Water Assessment Tool
MWh	megawatt-hour
LP	Linear Programming

1. Introduction

1.1 The global environmental crisis through the IPCC AR6 Synthesis Report

In the last few years, the discussion concerning climate change has become more widespread and, in some cases, even more heated. This can obviously be attributed to the fact that, year after year, the consequences of the climate catastrophe that our global ecosystem suffers from prove to be severe as well as unpredictable. Indeed, it has now been proven that the acceleration by which environmental change impacts our ecosystems was underestimated by the last few decades' research. Thus, it has now become clearer to many that humanity is in front of the biggest, perhaps, challenge it has ever been compelled to face.

The 2023 AR6 Synthesis Report (H. Lee and J. Romero (eds.), 2023) headline statements by the Intergovernmental Panel on Climate Change (IPCC) seem disturbingly revealing. After attributing the increase of global greenhouse gas emissions to the unsustainability of past and current way of living followed by portions of the global population (A.1 statement), the report goes on by consolidating the fact that it is vulnerable communities, otherwise less responsible for the current situation, that get affected the worse (A.2 statement). Later, and after assessing the adaptations made by policy makers as insufficient (A.3 statement), it predicts that warming will probably exceed 1.5°C in the current century (A.4 statement). Statements B.1 to B.7 are concerned with the deepening of the crisis that will occur by maintaining the current situation (B.1 and B.2), the irreversibility of some already predicted future changes in the global ecosystem (B.3), the decreased effectiveness of present adaptation options in the future (B.4), the urgency of achieving net zero CO_2 (Carbon Dioxide) emissions (B.5 and B.6) and, finally, the ways of reducing the global temperature after the possible exceedance of the 1.5°C limit – and the great threats this scenario will pose to both the planet and humanity. Statements C.1 to C.7 are concerned with necessary responses to the crisis in the near term, with statement C.3 explicitly concluding that all sectors and systems are required to implement all available mitigation and adaptation options in order to secure a sustainable future.

1.2 Assessing the climate change in the Mediterranean Basin through the First Mediterranean Assessment Report (MAR1)

The Mediterranean Basin is widely considered to be one of the main climate change hotspots on Earth (Cos et al., 2022; Tuel & Eltahir, 2020). The network of Mediterranean Experts on Climate and Environmental Change (MedECC) published the complete Mediterranean Assessment Report on Climate and Environmental Changes (MAR1) in November 2020 (Cramer et al., 2020), reaching specific conclusions. Some of the key findings of the research were that the region has warmed at a 20% faster pace than the global average so far and, without further measures, the temperature will keep increasing –reaching a 2.2°C by 2040 or even surpassing 3.8°C in places. This will result in longer and more acute heat waves, with extreme droughts becoming a common phenomenon. Sea-level rise, sea water acidification, invasion of foreign species in the local ecosystems and loss of habitat for native ones, increased food demand and decreased quality and quantity of agricultural products, acute health problems especially for the more vulnerable, lower classes of society and conflicts related to the limited resources resulting in human suffering and migration waves; all the above findings of the report are painting a dark picture of the future in the region (Fig.1). Main contributors to the fastpaced degradation of the Mediterranean ecosystem are the sectors of transportation, shipping, the unsustainable practices in agriculture and the industry.

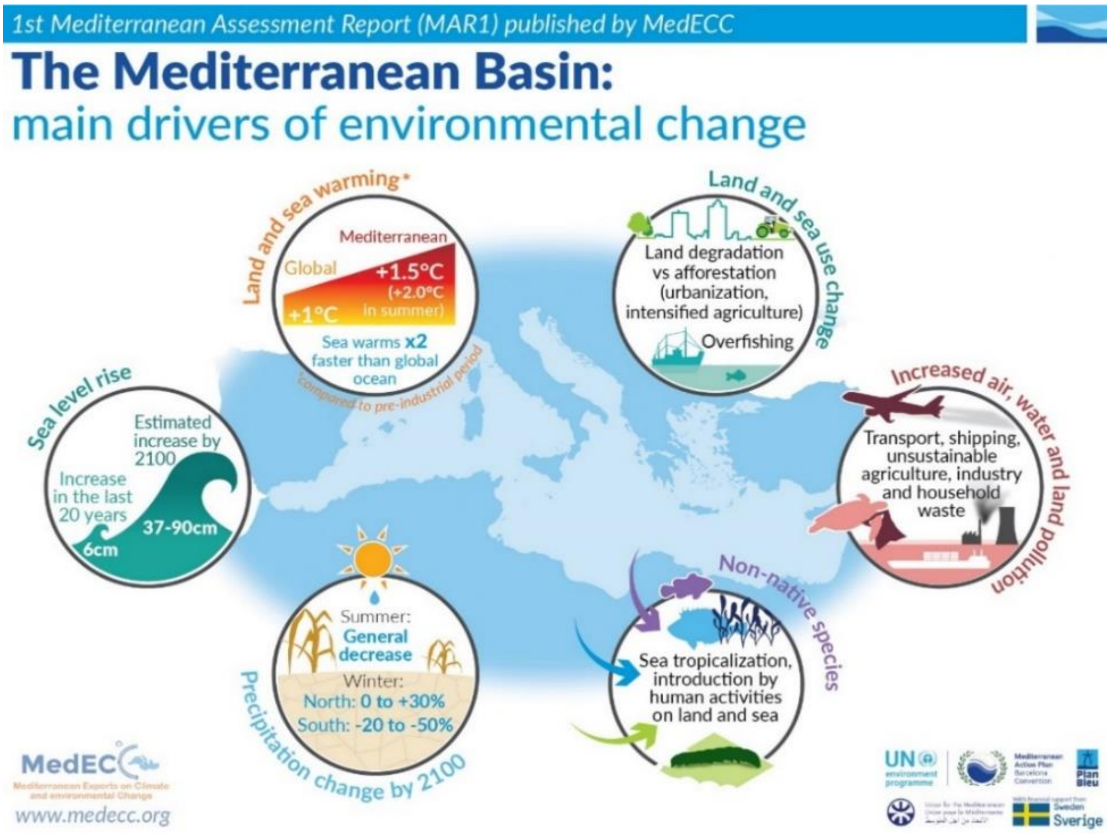

Fig.1. The Mediterranean Basin: main drivers of environmental changes.
From: (*MedECC (2022). The Mediterranean Basin: Main Drivers of Environmental Changes*, 2022)
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1.2.1 Focusing on water scarcity in the region and evaluating ways to address the problem

Water sources in the Mediterranean region have already been put under great stress and the future scenario of the environmental crisis deepening would only prove to deteriorate the current situation. The MAR1 specifically indicates that freshwater resources are not only deficient, but also unevenly distributed within the countries of the region; with Southeastern countries sharing a 26-28% of the total freshwater in the Basin. In the, currently considered optimistic, scenario of a 1.5-2°C global warming, the Mediterranean region will see a severe decline in soil moisture, a drop in runoff due to a combination of reduced precipitation and snowfall and increased evaporation, an increased floods risk, an increase in both the duration and the intensity of droughts, a reduction in aquifer recharge leading to groundwater depletion and a drop in its quality due to salt-water intrusion and other issues (Fig. 2).

When examining the impact of higher levels of global warming (emission scenario RCP8.5), which would lead to the crossing of 4°C above the pre-industrial period before the end of the century, the situation regarding water availability seems to become extremely adverse. An ostensive figure of this future scenario would be the predicted relative change in annual runoff, which at some areas in the Mediterranean could reach up to 50% (Fig. 3).

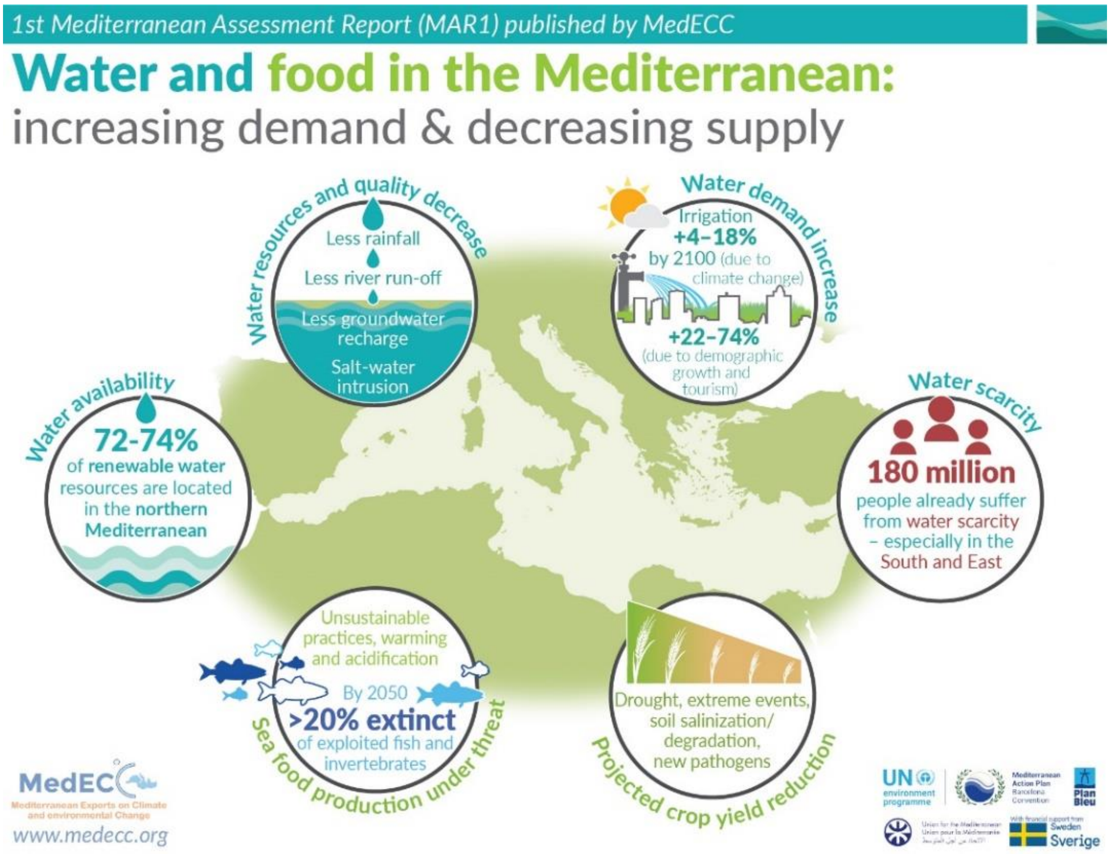

Fig. 2. Water and food in the Mediterranean: increasing demand and decreasing supply. From: (*MedECC (2022). The Mediterranean Basin: Main Drivers of Environmental Changes*, 2022). Licensed under a Creative Commons Attribution-Noncommercial-ShareAlike 4.0 International License

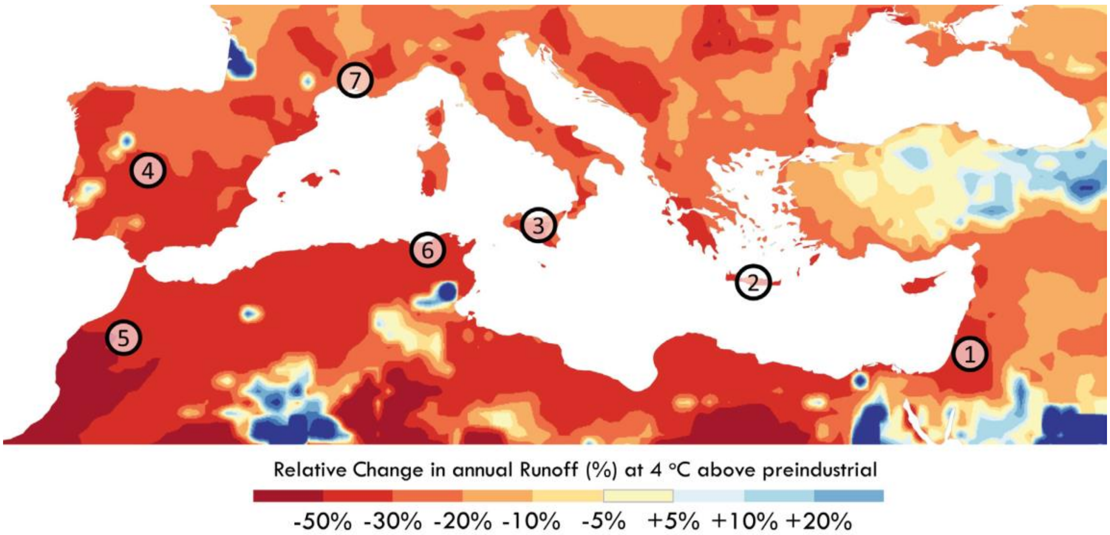

Fig. 3. Relative Change in annual Runoff at 4 °C above pre-industrial. From: (Cramer et al., 2020)

These circumstances underline the urgent need to confront the consequences of the environmental crisis on the Mediterranean region's water resources. Thus, the MAR1 report suggests and analyses strategies for the mitigation of the problem; namely, Integrated Water Resource Management (IWRM) and adaptation measures. IWRM is a process aimed at fostering coordinated development and administration of water, land, and associated resources to maximise societal and economic well-being in an equitable manner while safeguarding the sustainability of crucial ecosystems and the environment. Economic efficiency, equity, and environmental sustainability form the fundamental principles of IWRM. To implement IWRM effectively, three pillars must be established: the development of management tools for institutions and stakeholders, the creation of a supportive environment conducive to IWRM implementation, and the establishment of an institutional framework to enact policies, strategies, and legislation. By employing suitable approaches at the appropriate levels, encouraging participation in management practices and policy formulation, and ensuring consideration of vulnerable groups, IWRM instruments directly assist communities in dealing with climate variability. Although there are similarities between IWRM and climate change adaptation, the key distinction lies in their temporal focus: IWRM addresses present and historical concerns, whereas adaptation primarily considers long-term future implications. Traditional water management systems have relied on historical climate and hydrological data, assuming stable system behavior. However, the recognition of non-stationarity and the inadequacy of relying solely on historical data necessitate new approaches to plan for variability and extremes brought about by climate change. Particularly in regions such as the Mediterranean Basin, characterised by uneven water distribution, spatial disparities, and recurring droughts, effective planning and management, accounting for climate change impacts, are of paramount importance.

The presence of uncertainties in evaluating future climate change impacts should not hinder the analysis and implementation of adaptation measures though, especially in the vulnerable Mediterranean region. Adaptation must adopt a flexible and comprehensive approach, considering climate change as well as socioeconomic and environmental changes. The impacts of climate change will affect both private (e.g., irrigation communities) and public (e.g., environmental impact, quality, and supply reliability) contexts. The market for adaptation technologies is rapidly growing due to the high cost of repairing damages compared to adaptation costs. According to the report, adaptation measures can be categorised into demand-side measures (e.g., water demand control, efficiency management, economic instruments) and supply-side measures (e.g., complementary resources, improved allocation and availability of water, aquifer recharge techniques), with both types of measures playing crucial roles in adapting to climate change impacts on water resources.

The report also suggests and analyses supply-side adaptation measures, such as wastewater treatment and reuse, recharge of groundwater, the construction of dams, inter-basin transfer and desalination. While most of these measures clearly involve the undertaking of large-scale projects, there are some, as in the case of water reuse, that could be implemented in the scale of a private business. Regarding the demand-side adaptation measures, which are considered the ones that contribute to water saving, the report focuses on efficient water use in households and economic sectors, including the potential of Rainwater Harvesting Systems (RWHS), proper agricultural management for water conservation and reduction of water losses.

1.3 Alternative Water Sources in businesses and industries

In the face of such challenges and threats, it is only natural that states, organisations and businesses must act to diversify their water sources in order to ensure long-term viability, environmental sustainability, and operational continuity. The necessity of such action becomes even clearer in regions such as the Mediterranean Basin, where, as seen in the above section, water resources will be under great stress in the years to come.

By proactively diversifying water sources, organizations can mitigate the risks associated with climate change and water scarcity. Alternative sources such as rainwater harvesting, water reuse, groundwater extraction and river water use can provide a buffer against water shortages, allowing organisations to continue their operations even in harsher situations. Implementing such measures ensures a secure water supply for critical operations, reduces vulnerability to disruptions, and safeguards against potential conflicts arising from water scarcity. Moreover, diversifying water sources aligns with sustainable business practices and can be deemed as promoting corporate social responsibility. By reducing reliance on limited freshwater resources, organizations demonstrate to the public, and their consumers, their commitment to environmental protection, resource conservation, and climate crisis mitigation. Taking action now allows businesses to stay ahead of regulatory changes, enhance their reputation, and foster stronger relationships with stakeholders and local communities.

1.3.1 Groundwater use

Groundwater, a valuable resource stored beneath the Earth's surface, has played a crucial role in human development throughout history. Used for drinking, irrigation, and industry, it remains an essential water source today. Groundwater is accessed through wells, tapping into underground aquifers. The process typically begins with the drilling of a well, which serves as a conduit to access the groundwater. The location of the well is carefully determined based on geological surveys and hydrological assessments to identify areas where the aquifer is sufficiently saturated and capable of supplying water. Once the well is drilled, a pump is installed to draw the groundwater to the surface.

Groundwater is utilised by various industries for a wide range of purposes. While agriculture heavily relies on groundwater for irrigation, providing vital water supplies for crop cultivation, there are also manufacturing industries which use groundwater for processes such as cooling, cleaning, and product formulation. It is also a crucial resource for mining and mineral extraction operations and supports the needs of energy production, including power generation and oil and gas extraction. Moreover, groundwater plays a role in the construction industry for activities like concrete mixing. Lastly, Brewers of Europe, an organization representing the national brewers' associations from 29 European countries, mention groundwater as one of the three main water sources using in brewing.

Even though groundwater is considered a major water resource of paramount importance in many areas of the world, it faces great challenges, such as pollution of aquifers from the use of agricultural chemicals, industrial waste, and landfills among others (Fig. 4). Uncontrolled abstraction rates can also lead to aquifer depletion and seawater intrusion (European Academies Science Advisory Council., 2010), something which seems to be the case in many sites around the Mediterranean coast (European Academies Science Advisory Council, 2010; Mas-Pla et al., 2014). Overreliance on groundwater can impact natural ecosystems that depend on groundwater for their survival. Reduced groundwater levels can also disrupt stream flows, wetlands, and habitats that rely on groundwater inputs, leading to ecosystem degradation and loss of biodiversity. Unsustainable groundwater use practices can undermine long-term water security for both industrial and domestic water users. Continued reliance on groundwater without considering its recharge rates and sustainable extraction limits can lead to water shortages, affecting various sectors of the economy and compromising the overall resilience of the water supply system. Lastly, new research (Seo et al., 2023) suggests that groundwater extraction rates during the last decades have been so vast that they have resulted in the rise of sea levels by 6.24 mm in the years 1993-2010 -with the unnatural movement of such mass being the second most important contributor to the drift of Earth's rotation axis. In the face of such threats, direct actions need to be taken in order to preserve this valuable water source and the balance of the global ecosystem.

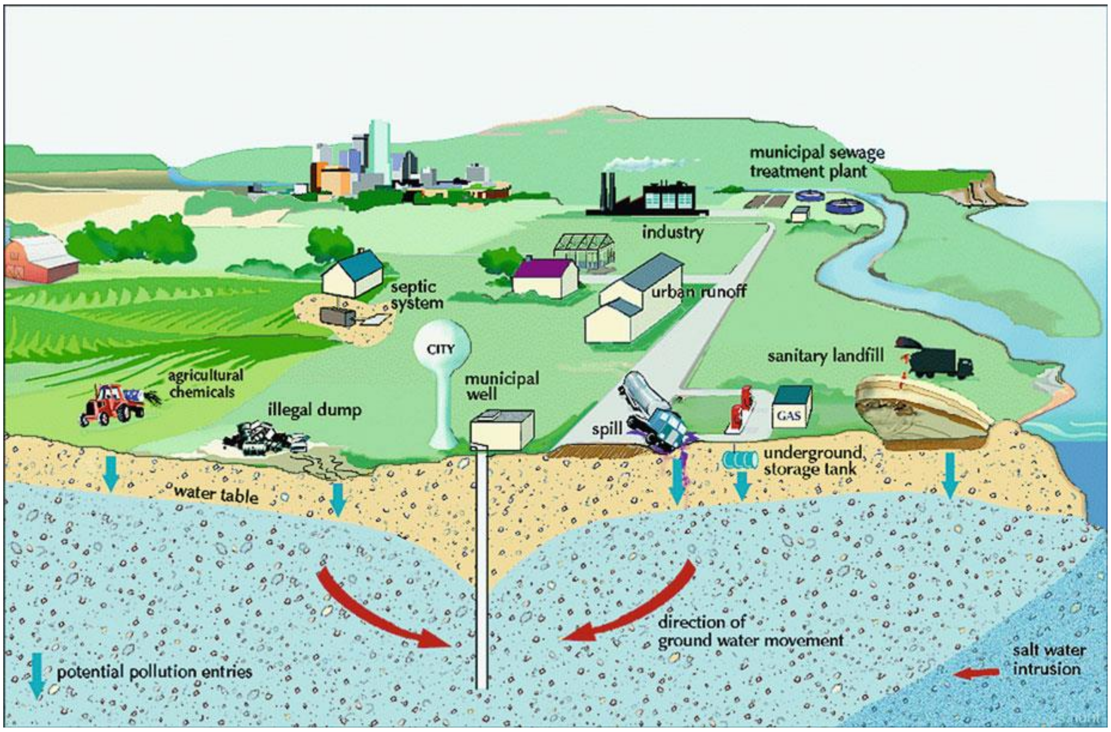

Fig. 4. Main groundwater pollution factors. From: (Hiscock, 2011).

1.3.2 Rainwater Harvesting Systems (RWHS)

Rainwater Harvesting Systems (RWHSs) have served as an effective means of collecting and utilising rainwater throughout history. Dating back thousands of years, ancient civilizations, such as the Ancient Greeks, Romans and the Mayans, employed various techniques to harness rainwater for domestic and agricultural purposes. Today, RWHSs continue to be employed in diverse geographical locations and industries, showcasing their versatility and efficacy.

RWHSs are utilised in both rural and urban areas, addressing water scarcity challenges and enhancing water sustainability.They have gained prominence in agriculture as a sustainable method to supplement irrigation needs. By capturing and storing rainwater from rooftops, paved areas, and fields, farmers can mitigate the impacts of irregular rainfall and water scarcity. This stored water can be used during dry spells, reducing the dependency on conventional water sources and ensuring consistent water supply for crops. Often, a simple water collection system consisting of a small tank and a watering hose, as in Fig. 5, can be a critical element for a small crop in times when water can be scarce. Implementing RWHS in agriculture not only promotes efficient water use but also reduces the strain on overburdened groundwater reserves and local water bodies. In urban settings, where paved surfaces limit natural infiltration, rainwater harvesting offers a solution to reduce stormwater runoff and supplement municipal water supplies. Commercial buildings, residential complexes, schools, and hospitals are increasingly integrating RWHSs to meet non-potable water needs such as landscaping, toilet flushing, and cooling tower operations.

Fig. 5. Shot of a big green water tank in the countryside used for supply water to the crops. From: (Pablo Rasero, n.d.) Credit: iStock.com/Pablo Rasero

Furthermore, rainwater harvesting finds applications in industrial processes. Manufacturing facilities, industrial estates, and mining operations utilise RWHSs for non-potable water requirements, such as equipment cooling, dust suppression, and industrial cleaning. Implementing rainwater harvesting in these industries reduces strain on municipal water supplies and promotes responsible water management practices.

Concerning the Mediterranean region in particular, it has been established through research that RWHSs cannot only be financially viable if they are used at the appropriate scale (Farreny et al., 2011), but also contribute to the alleviation of future water crises as well, by providing a “green” solution to the problem (Kakoulas et al., 2022).

1.3.3 River water use

Historically, rivers have served as the birthplace of great civilizations. The Nile in Egypt, Tigris and Euphrates in Mesopotamia, the Yellow River in China; they all account as the starting point of great steps in the history of humanity. Major urban centres are still present along the banks of many rivers, with Danube and Rhine in Europe being two of the most distinctive examples of the importance rivers did and do have. River water continues to be extensively utilised nowadays in various sectors, including agriculture, industry, and public water supply.

In the agricultural sector, river water plays a fundamental role in irrigation, supporting crop cultivation and food production. Through irrigation systems and water diversion structures, river water is distributed to agricultural fields, ensuring proper plant growth. This sector relies heavily on the consistent availability and quality of river water for sustainable agriculture.

In the industrial sector, river water is utilised for a wide range of purposes. It serves as a cooling agent in thermal power plants, enabling efficient heat exchange processes. Industries also rely on river water for manufacturing processes, such as cleaning, dilution, and transportation of goods. Hydroelectric power is also a big part in many countries' energy mix, with some large urban centres relying today mainly on it in order to provide electricity to their residents.

The key components of utilising river water for potable means involve water intake structures, pumping stations, treatment facilities, and distribution networks. Structures such as weirs or dams divert the required water from the river. Pumping stations ensure water delivery to the desired location, while treatment facilities address water quality concerns, removing contaminants and ensuring its suitability for specific applications. Distribution networks transport the treated river water to end-users, ensuring a consistent and reliable supply. Fig. 6 depicts a specific treatment scheme of river water that was implemented by researchers in the facilities of Oasen Drinkwater near the river Lek, Netherlands.

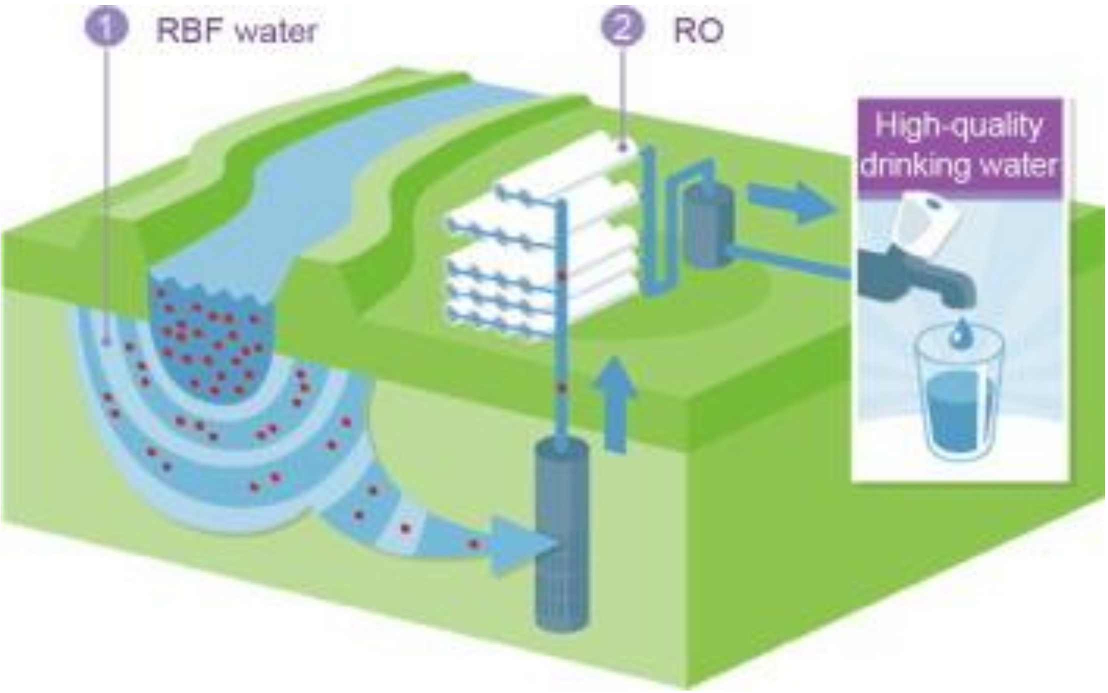

Fig. 6. River water treatment for potable use. From: (Zhai et al., 2022)

The utilisation of river water, however, also poses certain dangers and challenges. Pollution from industrial discharges, agricultural runoff, and urban development can degrade the quality of river water, requiring extensive treatment to reach certain standards. Additionally, the overextraction of river water can lead to ecological imbalances, impacting aquatic ecosystems and endangering biodiversity. The prolonged and severe droughts many places in the planet have faced recently, have also had an impact on rivers throughout the world. Some representative examples include the Colorado River water shortage crisis in Southwest USA, during which the Colorado river has experienced a major drop in its water levels due to a longer than 20 years drought in the region –a megadrought, as they are have been called since 1998– and the Yangtze River shrinkage in China during the summer 2022 drought that caused parts of the river to dry up. Rivers in the Mediterranean Basin have also come under great stress, with Po in Northern Italy, the once called "king of rivers" by Virgil, experiencing a similar shrinkage during the same period; with the extremely mild winter of 2022-23 only contributing to its flow rates being at a low of one third compared to seasonal average in the spring of 2023 (Santalucia, 2023).

1.3.4 Water reuse

Water reuse historically has played a crucial role in addressing water scarcity and promoting sustainable water management practices. Throughout history, civilizations developed innovative methods to reuse water, recognizing its value and scarcity. Ancient societies employed techniques such as wastewater irrigation –with the earliest perhaps known example of such practices in the Mediterranean region being found as far back as the 4th millennium BC in Minoan Crete (Tzanakakis et al., 2007). Today, water reuse has gained prominence in various sectors, including agriculture and industry.

In agriculture, treated wastewater or reclaimed water is utilised for irrigation, supplementing traditional water sources. This practice conserves freshwater resources, reduces the demand for potable water, and supports sustainable agricultural practices. Industries also benefit from water reuse, utilising treated wastewater for cooling, cleaning, dying in the textile sector and other non-potable processes. This not only reduces freshwater intake but also minimises wastewater discharge, mitigating the environmental impact.

Domestic water reuse, or greywater reuse, is another sector that has gained some prominence in the past years. The term greywater includes water originated from domestic activities, such as bathing or laundry, excluding water from kitchen sinks or toilets. The process involves capturing, treating, and utilising greywater on-site. Greywater reuse systems typically involve the collection of greywater from sources within a building, followed by treatment to remove impurities and contaminants. Treatment methods may include physical filtration, biological processes, and disinfection techniques. Once treated, the reclaimed greywater can be used for purposes such as landscape irrigation, toilet flushing, and non-potable household needs.

Water reuse has multiple benefits. It conserves freshwater resources, reduces the dependency on traditional sources, and minimises environmental impacts associated with water extraction and wastewater discharge. It also presents economic advantages by reducing costs associated with water treatment and supply.

However, water reuse also faces challenges. The treatment of wastewater to meet appropriate quality standards is essential to ensure the safety and acceptability of reused water. Developing robust treatment processes and implementing effective monitoring and quality control measures are crucial. Concerning industries whose effluent is such that is in need of capital and energy-intensive treatment, stakeholders may be disheartened from applying the method, despite its obvious and extensive benefits.

1.4 Water Treatment techniques

Below, we outline several techniques employed in the treatment systems of alternative water sources discussed in this thesis. This section provides a succinct overview of each method, highlighting its purpose and functionality, rather than an exhaustive analysis.

1.4.1 Overview of techniques

Reverse osmosis (RO) is a pressure-driven membrane separation process that removes dissolved solutes from water. A semi-permeable membrane allows water molecules to pass through while rejecting most contaminants, including salts, bacteria, and organic compounds. RO is widely used for desalination, producing potable water from seawater, and for purifying freshwater sources. The efficiency and effectiveness of RO depend on factors like membrane type, feed water quality, and operating conditions.

Filtration methods include Ultrafiltration (UF), Nanofiltration (NF) and Microfiltration (MF). UF uses a semi-permeable membrane to separate particles and macromolecules from water. It effectively removes bacteria, viruses, and colloids, to produce high-quality water. Positioned between UF and RO in terms of pore size, NF removes divalent ions, organic substances, and certain monovalent ions, making it suitable for water softening and organic matter removal. MF targets larger particles, and various adsorptive filtration techniques using activated carbon or other materials to remove specific contaminants.

Membrane Bioreactor (MBR) combines conventional activated sludge treatment with membrane filtration. The process integrates biological degradation of waste using bacteria and microorganisms with a membrane separation process, typically ultrafiltration. MBRs produce high-quality effluent suitable for reuse and have a smaller footprint compared to traditional wastewater treatment systems.

Ultraviolet (UV) sterilisation exposes water to UV light, which inactivates harmful microorganisms by damaging their DNA. This method is effective against bacteria, viruses, and some protozoa. UV sterilisation doesn't introduce chemicals or alter the taste and odor of water, making it a preferred choice for disinfection in many applications.

River bank filtration (RBF) involves drawing water from wells located near riverbanks. As river water naturally infiltrates the ground and moves towards the well, it undergoes filtration and natural purification. Contaminants, pathogens, and particulates are largely removed by the soil and subsoil layers. The resulting water is of high quality and often requires minimal post-treatment.

Other techniques include coagulation, which involves adding chemicals to water to form 'flocs' that trap suspended particles. These flocs then settle during sedimentation, producing clearer water. Sand filtration uses a bed of sand to physically remove suspended particles. Ion exchange treats water by exchanging undesirable ions with more desirable ones. Ozonation introduces ozone into water to break down contaminants. Water softening addresses water hardness caused by calcium and magnesium ions. Lastly, chlorination, one of the most common disinfection methods, involves adding chlorine or chlorine compounds to water to kill or inactivate pathogens.

1.4.2 Application on alternative water sources

Each of the sources presented in this thesis present unique challenges and opportunities, necessitating the application of specific water treatment techniques to ensure their safety and suitability for intended uses.

With river water being mainly used for irrigation and industrial purposes, a physical filtration removing debris or other possible objects lying in the body of water would be sufficient most of the times. In case its use requires disinfection, then various techniques can be applied, such as coagulation and flocculation, usually followed by sedimentation and rapid sand filtration. Disinfection methods such as UV, chlorination or ozone treatment can also be used, with membrane filtration, through NF, UF and RO being also popular treatment methods. Pre-treatment methods, such as RFB, are considered to increase the water quality as well as reduce the energy and cost intensity of the whole process by using physical techniques in order to treat the river water.

Depending on the level of groundwater contamination and its uses, it can receive various treatments, such as RO, ion exchange, adsorption, UV disinfection, electrochemical treatment and ozonation. Use of groundwater must be careful in applying to the regulation-based water standards, with regular testing on contaminants, pesticides, heavy metals and other contaminants, as well as on water pH, total dissolved solids and other characteristics being necessary in order to ensure the safety of consumers.

Regarding the treatment of harvested rainwater, various methods have been applied depending on its use. With rainwater widely considered to be cleaner than surface water (Khayan et al., 2019) it may only receive mild treatment, such as chlorination or even boiling. Nevertheless, research has now proven that rainwater does actually get contaminated either with various microbes in the storage tank, or through the catchment area with dust, leaves and faeces among other contaminants (Gwenzi et al., 2015; Lee et al., 2017a). There are also findings of a recent research conducted in Greek cities, where the presence of ions and metals was detected at low, but still noticeable, levels. Significant cytotoxic activity was also observed in rainwater samples, with results being consistent across three cities and over the period of months (Vlastos et al., 2019). Therefore, in order for rainwater to reach potable standards, it should be treated using a variety of techniques or a combination of them, such as rapid sand filtration, carbon filtration and UV disinfection (Latif et al., 2022a).

Water reuse, in its very nature, cannot be easily categorised when discussing its treatment methods. The reason is obvious -and it is of course relevant to the fact that treatment needs are mainly dependent on the water that is planned to be treated and reused. That means that domestic greywater reuse does not have to, and should not have to, be that intensive as when, for instance, a textile industry effluent needs to be treated and reused. Equally important to the decision of the treatment intensity is the intended use of the treated water. If it is to be used for irrigation purposes or if it is to reach potable standards; that is a difference equaling to vastly different methods. According to this, wastewater treatment for reuse purposes can be separated (Abou-Shady & El-Araby, 2023) in three parts; primary treatment, secondary treatment and tertiary treatment (TT) -the last being the one needed for removing the totality of pathogens and organic in the reused water. TT methods include coagulation, flocculation, sedimentation, filtration, UV disinfection, chlorination and the membrane filtration methods (NF, UF, RO).

1.5 The Brewing Industry –history, statistics and trends

The first beer recipe we know of is written in cuneiform –the oldest writing system in the history of human kind. That is perhaps the most characteristic indicator about how this beverage has been our companion since the times we learnt how to reap the benefits of technological progress and advanced civilization –besides burdening ourselves, as Freud famously suggested, with the discontent *[Unbehagen]* derived from it. Today, beer is considered to be one of the most popular beverages in the world and the brewing industry worldwide has been producing it in great volumes. Since 1999, the worldwide production has been steadily over 1.3 billion hectoliters, reaching a climax of 1.97 billion hectoliters in 2013 and a production of 1.86 billion in 2021 (Fig. 7).

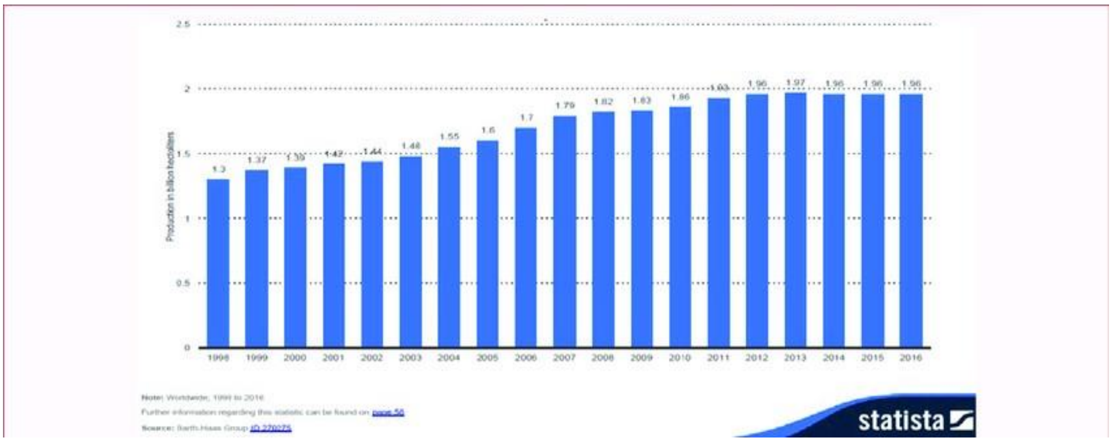

Fig. 7. Global beer production, 1998-2016. From: (Gomaa, 2018)

Concerning European beer industry, the Brewers of Europe, an organisation consisted of national brewers' associations from 29 European countries, calculates that it is generating over 2 million jobs in the continent and nearly 40 billion euros in government tax revenues. The brewing industry, both in terms of large companies and microbreweries, has shown definite signs of expansion in the recent years –especially in the case of the latter. The emergence of microbreweries (or craft breweries as they are sometimes called since the various terms are somewhat vague to the non-expert) in great numbers both in Europe and the rest of the world has certain socio-economic reasons, which are otherwise irrelevant to this thesis' aim. It is worth nothing though that the presence of microbreweries in many distant regions of European countries has been established by now as a way of diversifying the industry in terms of beer variety or specialization and to act as an example of the benefit in the decentralisation of the economy. The sharp increase of microbreweries can be vividly depicted by the statistics of the sector in Greece; with only 6 microbreweries being active in 2009, there were 45 functioning in 2018 and, according to reports by the press, have reached an all-time high of 72 in 2023. Despite this boom in numbers, the maximum total share in domestic sales the sector seems to be able to claim does not exceed a 3%.

1.5.1 Water intensity of the industry, hazards and necessity of action to be taken towards sustainability

Water intensity is a major issue within the brewing industry. It takes a substantial amount of water to grow the crops used in brewing, such as barley and hops, as well as to facilitate the brewing process itself. Additionally, water is required for cleaning and sanitation purposes throughout the production cycle. There have been several studies assessing the environmental footprint of beer production by using Life Cycle Assessment (LCA) –from the growth of the barley, up until the finished product (Amienyo & Azapagic, 2016; Koroneos et al., 2005; Yu et al., 2015). The water-to-product ratio though is an easier to calculate index and quite distinctive by itself when it comes to evaluation of the water intensity of the industry. Thus, an approximate 5 litres of water per 1 litre of produced beer (Fig. 8) is the ideal indicator towards the understanding of how an even small-size brewery can put a considerable stress on local water sources, especially when they have already experienced acute pressure due to climate change and rising demands.

Water consumption rates in beer production (normalized to hL water / hL beer, so as to be comparable)

Water Consumption Rates (hL water / hL beer)	Literature Source
4−10	Fillaudeau, Blanpain-Avet and Daufin 2005
4−10	Hannover 2002
4−11	Perry and De Villiers 2003
4.90−12.64	Kunze 2004
6	Taylor 2018
4.73	van der Merwe and Friend 2002
5−6	Perry and De Villiers 2003
5.5−8.8	Ramukhwatho et al. 2016

Fig. 8. Water consumption rates in beer production. From: (Ioanna Nydrioti et al., 2023)

Water management is, thus, a critical aspect of sustainability within the beer industry. As concerns about water scarcity and environmental impact have increased, breweries must prioritise water-saving initiatives and explore alternative sources to reduce their water footprint. By implementing effective water management strategies, the industry can contribute to the conservation of this vital resource and create a more sustainable future.

One of the primary objectives in water management is to save water throughout the brewing process. Breweries can adopt various measures to minimise water consumption without compromising the quality of the beer. For instance, optimising equipment and processes can help reduce water losses during brewing, cooling, and cleaning operations. Installing water-efficient technologies, such as low-flow nozzles, automatic shut-off valves, and sensor-based controls, can further enhance water conservation efforts.

In addition to saving water, diversifying water sources is another essential aspect of water management in the beer industry. Relying solely on freshwater from local supplies puts immense pressure on these sources. To address this issue, breweries can explore alternative sources such as the ones mentioned in the paragraphs above. The water reuse techniques in particular, being implemented by closed-loop water systems, can not only reduce the industries' reliance on freshwater source, which become more and more scarce and unpredictable in their consistency, but also reduce the cost and environmental burden of wastewater discharge into the environment.

1.6 Objective

Based on the aforementioned data it is obvious that any water-intensive industry retains its former, or hitherto, modus operandi, without taking into consideration the radical environmental changes taking place, is with great certainty going to face challenges in the following years that could soon turn into existential dangers for it. It is therefore imperative to adapt themselves to the new climate balance that is being formed, even by keeping ahead of current legislation which due to various reasons often proves to be insufficient and comes belated.

Especially in the region of the Mediterranean, and even more in a great number of the Mediterranean islands, the economic growth in recent decades driven mainly by the sharp rise of mass tourism has applied great pressure on local ecosystems in general –and water resources in particular. The monoculture of tourism, as profitable as it may have proven to be for sections of the society, creates an underlay for an extensive overexploitation of natural resources in support of a rampant growth –with little or no consideration for the future of the local ecosystem and, therefore, the local population. And yet, as the English proverb says, moths are always drawn to a flame; a truth that other sectors of the economy in such places can definitely confirm. Therefore, while becoming marginalised, they try to attach themselves to tourism as a means of growth, or even survival. Thus, it is not only the tourist sector that directly applies pressure on water resources; but also, a growing agriculture sector (more often than not on the expense of traditional, non-intensified, highly sustainable cultivation of native crops) or even a small or medium-sized industry, both of which struggle to meet the seemingly endless needs of the former. This creates a vicious circle, where the ultimate burden always falls on the shoulders of the local ecosystem and its inhabitants. However, a finite source cannot support infinite growth –and the growth observed for each of these sectors cannot be but short-term if current trends in water consumption do not get upended.

Taking into consideration the above, phenomena such as the presence or even the accelerating emergence of golf courses in semi-arid areas have a great impact on the ecosystems and, exactly due to this, create intractable tensions among stakeholders (Utrero-Gonzalez & Callado-Muñoz, 2014; Wurl, 2019). Such examples are also true for the, located in the Eastern Mediterranean, isle of Crete –the local economy of which is mainly driven by tourism. On an island categorically located in the maelstrom of environmental crisis, with a 37% of its area characterised as critically sensitive to desertification (Morianou et al., 2018), it indeed seems that the unchecked realisation of grand touristic investments only serves as an accelerator towards a desertified future, while also putting other businesses and the local communities in a position where the inevitable water shortages experienced will be severely impactful for the economy and the island's society as a whole.

Taking into account all the above, the aim of this thesis is to set the framework for a small industry, and specifically a brewery, to diversify its water sources without compromising the quality of the end-product. By these means, and after having ensured that safety and quality standards have been met, the industry will be better prepared for future water shortages, strengthening its position in local, national or even wider markets. Lastly, but equally important, a combination of water sources diversification, water use minimisation and renewable energy sources usage is the path any water-intensive industry has to take in order to limit its ecological footprint and become a green industry.

Therefore, the model which will be created will receive inputs associated with specific water source alternatives –either acquired from literature or calculated for the needs of the thesis– and will determine the most efficient balance of water intake among the alternative sources for each day of a year. The output of the algorithm will suggest the most efficient water blend, as well as calculate its cost and environmental impact.

1.7 Structure of the thesis

Chapter 2 delves into a thorough examination of literature related to the various alternative water sources discussed above. Each section provides an in-depth analysis of groundwater, rainwater harvesting systems, river water use, and water reuse. The synthesis and review section amalgamates the insights from various literature sources. The chapter ends with an assessment of the research gap and this thesis' contribution to further advances in the field. Chapter 3 contains a brief account of the case study under consideration for this thesis. Chapter 4, the methodology chapter, constitutes the crux of this thesis. It begins with a discussion on methodological assumptions, covering aspects like capital expenditures and RO recovery rate. This is followed by a detailed exploration of the treatment needs for each water source. Here, extensive calculations concerning cost, environmental impact, and capacity formulation for each source are undertaken. The chapter further delves into the Linear Programming (LP) formulation and its application in the Python environment. Multiple scenarios are formulated and analysed, followed by a comparative review of their results. The chapter concludes with a sensitivity analysis, ensuring robustness in the results and findings. Chapter 5 addresses the research findings and outlines the prospects for potential future research in the field. Chapter 6 contains a list of all the sources cited throughout the thesis. Lastly, Chapter 7 contains the Appendix, providing the reader with the algorithms developed and utilised for this thesis.

2. Literature Review

Research on alternative water sources has seen considerable progress in the recent years. Academic papers examined mainly focused on one of the four main alternative water sources (namely groundwater, RWHSs, river water, water reuse) and most of them examined aspects of the treatment methods, the treatment costs and the feasibility of each method regarding the standards set on water quality.

2.1 Groundwater

(Pearson et al., 2021) investigates the economics and energy consumption of brackish groundwater reverse osmosis (BWRO) desalination processes, focusing particularly on the impact of feedwater quality and innovative approaches. The paper emphasises on the importance brackish groundwater has, due to global water demands increasing. The study examines the economic feasibility of BWRO systems, analyzing factors such as feedwater salinity, pressure, temperature, and recovery ratio. It also evaluates the cost implications of integrating innovative technologies, including energy recovery devices and membrane modifications in order to reduce energy consumption. Focusing on BWRO plants throughout the state of Florida USA, the study ascertains the capital (CAPEX) and operational (COPEX) costs of groundwater extraction and treatment to potable standards. Through a thorough techno-economic analysis, the research highlights the importance of considering feedwater quality and implementing novel solutions in the design and operation of BWRO desalination plants.

(Da'ana et al., 2021) investigates the feasibility of employing cost-effective treatment methods for the removal of toxic elements and microbial contaminants from groundwater sources. The study emphasises the significance of addressing the widespread issue of contaminated groundwater, which poses substantial risks to public health. Through an extensive review and analysis of existing literature, the authors assess various low-cost treatment options, including electrocoagulation, adsorption, filtration, and disinfection techniques. The paper highlights the effectiveness of these methods in reducing the concentrations of toxic elements and eliminating microbial contaminants from groundwater supplies, making it suitable for consumption and safe for human use. Additionally, the researchers discuss the advantages and limitations of these low-cost treatment options, considering factors such as affordability and scalability. Researchers highlight the fact that each groundwater source requires its own treatment needs, with tailored solutions proving to be cost-effective and, therefore, especially beneficial to communities which would otherwise suffer from water shortages. The findings contribute to the development of practical and affordable solutions for the purification of groundwater, enabling communities to mitigate the health hazards associated with toxic elements and microbial pollutants effectively.

(He, 2015) discusses the assessment of groundwater treatment technologies for addressing various inorganic contaminants, such as nitrate, arsenic and selenium. The research emphasises that reverse osmosis (RO) is considered a best available technology for many inorganic contaminants but may not always be the preferred option due to its high energy consumption and brine disposal requirements. The text suggests several alternative technologies that can replace or supplement RO, including ion exchange, adsorption, electrodialysis reversal (EDR), nanofiltration (NF), softening, coagulation and biological filtration. To determine economical and effective groundwater treatment options, the author suggests strategies, such as evaluating treatment requirements and water quality implications, selecting the optimal treatment technology from the available options and maximising treatment efficiency through pretreatment. The paper provides information on typical water quality goals for various inorganic contaminants and suggests comparing raw water quality and treatment goals to determine appropriate treatment requirements and processes. It also discusses different treatment technologies and their applicability for removing specific contaminants. In a list of 10 contaminants, a combination of NF and RO is the only one among 8 alternative technologies that has the ability of removing all of them. In the case of brackish groundwater treatment (total dissolved solids (TDS) above 1,000 mg/L) NF/RO or EDR are recommended as appropriate treatment methods. Overall, the paper emphasises the need to develop customised solutions for groundwater treatment by leveraging one or more treatment technologies based on specific requirements and considering factors such as water quality implications, treatment efficiency, residuals handling, and the potential use of alternative technologies like biological filtration.

(Gracia-de-Rentería et al., 2020) investigates the groundwater demand for industrial purposes in areas where public water supplies are available for drinking purposes. The study aims to understand the factors influencing the choice of using groundwater over publicly supplied water for industrial needs and the potential implications of this choice, focusing mainly on aquifer overexploitation and the threats this poses on stakeholders and natural environment. After assessing the policies for groundwater sustainability as insufficient, the researchers comment on the lack of broader literature and data regarding the groundwater industrial use due to absence of monitoring actions on its extraction and the lack of statistics on its unitary cost. The research utilises microdata analysis techniques, combining data from the Industrial Water Survey conducted in Spain with other relevant datasets. The analysis focuses on industrial sectors that have access to both groundwater and publicly supplied water sources. The authors examine the relationship between various factors, such as water price, water quality, firm characteristics, and the decision to use groundwater for industrial purposes. The findings of the study reveal that the price of water and its quality significantly affect the decision to use groundwater for industrial needs. Higher network water prices and poorer water quality increase the likelihood of industrial firms opting for groundwater. The authors also find that larger firms and those with higher water consumption tend to rely more on groundwater sources. Finally, the researchers discuss the substitutability between publicly supplied water and self-supplied groundwater for industrial use. While this substitutability offers benefits in terms of productive efficiency and cost savings, it raises concerns regarding global efficiency and environmental sustainability. They claim that if companies do not bear the social costs associated with groundwater extraction, such as overexploitation and contamination, the substitution can lead to inefficiencies and environmental unsustainability. As a solution, they propose the imposition of a volumetric fee to tax groundwater abstraction, aligning with the cost recovery principle, as it has been established in the European Water Framework Directive. The study highlights the importance of considering the possibility of water substitution when evaluating the effectiveness of publicly supplied water pricing and emphasises the need for integrated water management and coordination among government agencies.

(Singh Dhillon et al., 2018) focuses on estimating carbon emissions resulting from groundwater pumping in central Punjab. The study highlights the importance of understanding and quantifying the carbon footprint associated with groundwater extraction, as it contributes to climate change and has environmental implications. The research utilises a comprehensive methodology that combines groundwater pumping data, energy consumption, and emission factors to estimate carbon emissions. The findings of the study reveal significant carbon emissions associated with groundwater pumping in central Punjab, indicating the environmental impact of excessive groundwater use. The authors analyze various factors that influence the carbon emissions, shedding light on the key drivers of environmental impact in groundwater use. One of the main factors identified in the study is the depth of the extraction. The authors find that deeper groundwater extraction requires more energy-intensive pumping, leading to higher carbon emissions, thus exacerbating the environmental impact of pumping activities. Additionally, the paper highlights the role of energy consumption in carbon emissions, with inefficient pumping technologies or outdated infrastructure contributing significantly to the environmental burden associated with groundwater extraction. The study also examines the influence of agricultural practices in the region. Given that groundwater pumping in central Punjab is predominantly for agricultural purposes, the authors emphasise that unsustainable agricultural practices, such as excessive irrigation or inefficient water management, can further intensify water extraction needs and, therefore, carbon emissions from groundwater pumping. The authors emphasise the need for sustainable groundwater management practices to reduce carbon emissions and mitigate climate change effects. Additionally, the research suggests potential measures to minimise carbon emissions from groundwater pumping, such as promoting energy-efficient pumping technologies and implementing policies that encourage sustainable water use. By dividing the region of interest (Punjab) into zones characterised by specific traits (examining affiliations of each critical factor with the rest, such as tube-well spatial distribution, groundwater extraction volume, depth and CO_2 emissions) the authors have strived to create an illustrative "map" for policy makers, in order for them to act efficiently towards addressing the problem.

(Bhakar et al., 2016) investigates the environmental impact of groundwater treatment using RO systems in a university campus in India. With RO plants usually measured on the basis of permeate flow rate (meaning the amount of treated water produced by the RO system per unit of time -typically expressed in liters per hour (LPH)), the authors analyse the four more common RO systems in the market; 25 LPH, 50 LPH, 250 LPH and 500 LPH, conducting a Life Cycle Assessment (LCA) on all four of them. Following a cradle-to-grave approach, the researchers assess the various units on many categories common to the LCA method, such as climate change (CO_2-equivalent), fossil depletion (oil-equivalent) and water depletion (Water deprivation potential (WDP)). Through the classic analysis following, the paper highlights the need to a holistic approach on groundwater extraction and treatment, by taking measures in order to mitigate its environmental impact.

2.2 Rainwater Harvesting Systems (RWHSs)

(Lee et al., 2017b) presents a case study conducted in rural Vietnam to analyze the quality of rainwater for drinking purposes based on 1.5 years of monitoring data. The study collected 23 samples from different points within two RWHSs and analyzed them for water quality parameters. Worth noting is the fact that the systems came as an answer to lack of safe drinking water -at least in one of the two sites- due to groundwater and river water having been heavily polluted with sewer discharge and industrial effluent. The study included analysis of 22 parametres referring to water safety standards, excluding those considered to be irrelevant to harvested rainwater (such as presence of pesticides or heavy metals). Results of the research showed that, while most standards were met even prior to treatment, the presence of coliform and E. coli was detected in most untreated samples. After UV sterilisation, water showed no trace of such micro-organisms. The paper compares piped water (surface and groundwater) to harvested rainwater, concluding that, through its lower exposure in contaminants polluting the former, such as pesticides, gasoline leaks, pharmaceutical and personal care products (PPCPs) and industrial wastewater, the harvested rainwater proves to be of significantly good quality.

Nevertheless, the paper highlights the importance of treating rainwater with UV light to remove micro-organisms before using it for drinking purposes. The researchers also point out the need to properly set new guidelines regarding the rainwater quality standards by considering its specific characteristics. This is believed to help further spread the use of RWHSs and mitigate water scarcity in remote areas around the globe.

(Musayev et al., 2018) tries to assess the RWHSs' effectiveness in improving domestic water security in different climate zones under different climate change scenarios. The method used by this paper is the coupled modelling approach; a stochastic weather generator in incorporated in order to simulate daily rainfall using historic weather data from 94 sites around the world where climate stations are located. The locations of the weather stations are in all possible Koppen-Griegel climate classification zones, thus leading to the reliability of the study. The simulations are run up to the year 2099 for three different climate change scenarios. The results of the study indicate that RWHSs can reduce domestic water insecurity even in arid regions, and climate change will have little impact on the ability of RWHSs systems at the household level. A large enough water storage tank and catchment area could lead up to more reliability of the systems even in arid areas. Seasonal rainfall variations, however, can limit the amount of water available during dry periods. The paper also provides design recommendations to achieve levels of reliability for each climatological region. The authors suggest that the implementation of RWHSs should be prioritised in regions where they can be effective and help communities design systems to meet given levels of reliability. Referring to past research, the study suggests that economic viability and high capital costs can be a problem for the implementation of RWHSs and, thus, more consideration is needed towards overcoming these obstacles. It is concluded that RWHSs provide a great benefit, specifically on lowering energy consumption and greenhouse emissions, and on the decentralisation of water supply.

(Senevirathna et al., 2019) discusses the RWHS installed in the Charles Sturt University Engineering building, in Australia. The building has its water produced within its own premises, by utilising a RWHS. The treatment process consists of four consecutive treatment processes; aeration (contributing to the improvement of parameters such as odor and taste), filtration and adsorption (aiming to the elimination of heavy metals and organics), sediment and carbon filtration (handling shock loads of pollutants or even intrusion of insects in the tank) and finally a UV disinfection system (aimed to meeting the potable water standards set by Australian authorities). The research briefly discusses the quantity of water collected and the needs of water consumption the system has to reach up to -with a 5 m^3 storage tank and a 360m2 roof catchment area leading to a capacity of 500 litres per day. The RWHS uses a 35kW solar system to work -with excess power directed to the campus grid. The aeration unit is calculated to consume half of the required energy, while the UV system does not operate until users request water. The paper discusses of two sets of parametres in water quality; primary and secondary. The former refers to values such as metal concentration and suspended solids, while the latter refers to parametres such as taste, colour and odour. The research shows that, in a period of 30 months before its conduct, both the primary and secondary water quality parameters of treated water were well within Australian drinking water quality standards and showed better results than municipal water available in the host town. This research, too, highlights the questionable nature of RWHs' financial viability. Nevertheless, it is clearly stated that use of such systems in water-stressed areas should be assessed without the strict financial standards applied by high threshold values in other, more benefited water-wise, areas. The total treatment cost of water in the facility is calculated as in 4.59 AUD per m^3, which, according to exchange value at the time of this text being written, is 2.80 EUR.

(Tran et al., 2021) focuses on RWHSs in Vietnam, analysing the operation of three systems in the northern provinces of Vietnam throughout a 5-year span. Harvested rainwater was found to contain heavy metals below standard limits. The presence of bacteria however highlighted the need of proper water treatment to reach potable standards. The water also had high turbidity levels and phenol was occasionally detected in higher values. The system consisted of stainless-steel water storage tanks (more than one in two cases), pumps, a complex filtration unit (consisted of a coarse filter, a carbon cartridge, an ultrafiltration membrane and a mineral-adding cartridge) and a UV steriliser. Analysis concluded that after the complex filtration and UV sterilisation water met potable standards. Regarding the cost of the process, researchers conducted a comparison analysis of a full system (sedimentation, filtration and disinfection) and of a simplified one (excluding filtration) -based on the fact that rainwater contamination of metals and organic matter was, in cases, of little concern. Both the capital and the operation and maintenance costs of the systems are calculated, with a full system treatment applied to a 16m^3 water storage tank covering the drinking needs of 300 users calculated in 177 USD per m^3 (capital costs) and 22 USD per m^3 (O&M costs).

(Latif et al., 2022b) discusses the need for treatment and disinfection of harvested rainwater to meet drinking water guidelines and protect public health. The authors adopt a scoping review method to systematically analyze the current literature on harvested rainwater treatment and disinfection methods, assessing their effectiveness. The paper highlights that rainwater is not necessarily pure, clean, and safe to drink -even though it is considered as such- as it can easily get polluted from catchment surfaces such as roofs and gutters. Thus, drinking untreated harvested rainwater is likely to impact human health. The authors emphasise that there has been limited research on small scale disinfection systems, which are especially suitable and sustainable for rainwater harvesting systems in rural areas. The paper suggests that pre-treatment of harvested rainwater is necessary before formal disinfection. Furthermore, treated rainwater needs protection from recontamination similar to network supply water if the water is to be stored over a longer period for subsequent use. The paper suggests that hypochlorite could be an effective disinfectant as it can offer residual effects and is readily available and cost-effective. A sustainable disinfection method, which is easy to operate and cost-effective in rural settings, is needed to achieve maximum advantage of disinfection by hypochlorite. The authors discuss the measurement of chlorine demand and optimum chlorine dose rate required to design such an efficient chlorination system. The paper concludes pretreatment of harvested rainwater before human consumption is of great importance. An adequate chlorination method can easily be adapted to make the harvested rainwater drinkable at the household level, with the proposed technology significantly improving the rural water supply in both developed and developing countries. Finally, the researchers underline the need of designing an automatic chlorination system in order to promote RWHSs' use in domestic environments.

2.3 River water use

(Ahmed & Marhaba, 2017) discusses the use of riverbank filtration (RBF) as a cost-effective in situ water treatment process to remove suspended solids and organic and inorganic pollutants from surface water. The paper presents the effectiveness of RBF in improving the river water quality and discusses its use as a treatment or pretreatment process to remove or decrease pollutants in surface water. RBF is defined as a natural filter of soils and aquifer sediments at the river site, where river water moves through the pores of the natural soils of the riverbed and riverbank. The method is found to improve several physical, chemical, and biological properties of the river water, including filtration, sorption, and biological degradation. The paper presents a review of the literature on RBF as a water treatment process, with the authors conducting a thorough search of relevant databases and selected studies. Those studies were analyzed to provide an overview of the effectiveness of RBF in improving the river water quality. RFB is assessed as highly effective as a pretreatment method since it reduces turbidity, increases dissolved oxygen levels, decreases the levels of, or even removes, several chemical pollutants and removes microorganisms such as bacteria and viruses. Regarding the cost of the method, RFB is considered as cost-effective because it utilises natural filtration processes and requires minimal infrastructure. Existing infrastructure, such as wells and pumps, along the riverbanks can also be used, which in turn reduces the cost of the method even more. Minimal energy and chemical inputs used also add up to the sustainability of the method -making it a river water treatment solution for both the developed as well as the developing world.

(Suprihatin et al., 2017) focuses on biofiltration as a cost-effective method for eliminating both organic and inorganic pollutants from river water. The process consists of a biofilter, which can be of various materials, such as plastic, sand, gravel or carbon particles. The biofilter media is proposed to be quartz sand because of its vast availability, its small size and, lastly, its properties. This paper aims to assess quartz sand biofiltration when it comes to removing turbidity, colour, organic matter, and total suspended solids from polluted river water. The researchers conducted experiments using two biofilter units with quartz sand as philtre media. The results show that the method can be significantly efficient in removing river water pollutants, with removal efficiency depending on the hydraulic retention time. When this is 2 hours, the efficiency of total organics removal was 78% while that of total suspended solids was 91%. The research also proposes a model for designing quartz sand biofiltration using the experimental data.

(Zhai et al., 2022) discusses the challenges faced by water treatment plants due to the presence of newly emerging pollutants in the aquatic environment. These pollutants cannot be efficiently removed by conventional water treatment processes, making technically, economically, and environmentally friendly water purification technologies increasingly important. The paper, thus, introduces a one-step reverse osmosis (OSRO) concept consisting of riverbank filtration (RBF) and reverse osmosis (RO) for drinking water treatment. The OSRO concept combines the relatively low-cost natural pretreatment of river water with an advanced engineered purification system. RBF provides a continuous natural source of water with stable water quality and a robust barrier for contaminants. With the pre-removal of particles, organic matter, organic micro-pollutants (OMPs), and microbes, RBF becomes an ideal source for a purification system based on RO membranes, in comparison with the direct intake of surface water. The OSRO treatment removes almost 99.9% of the particles, pathogens, viruses, and OMPs, as well as the vast majority of nutrients, and thus meets the requirements for the chlorine-free delivery of drinking water with high biostability. The OSRO treatment is cost-effective compared with the standard conventional series of purification steps involving sprinkling filters, softening, and activated carbon. The paper also proposes artificial bank filtration (ABF), which functions as an artificial recharge in combination with a sand filtration system, as an alternative for RBF -where the latter is not applicable due to its requirement of continuous flow of the river water. It is also suggested that the OSRO concept be implemented with wind power as an alternative energy source in order to be more sustainable and renewable. An OSRO-based decentralised water system is proposed for water reclaiming and reuse. Regarding its cost, OSRO is assessed as a cost-effective technique, with energy consumption and O&M costs being comparable to those of traditional methods, while the capital investment it requires is significantly lower.

2.4 Water Reuse

(Holloway et al., 2016) presents an LCA by comparing the environmental impact of two distinct potable water reuse schemes; a full-advanced treatment (FAT) approach and a hybrid ultrafiltration osmotic membrane bioreactor (UFO-MBR). The former treats wastewater using a combination of low-pressure membrane filtration (microfiltration -MF- or ultrafiltration -UF), RO, and UV advanced oxidation processes (UV-AOP). The latter integrates biological treatment processes with forward osmosis (FO) and UF membranes, combined with RO treatment in order to extra pure water. The LCA results indicate that the UFO-MBR technique has a slightly higher energy demand compared to the FAT approach. MBR and RO has the greatest impact on the analysis for that scheme. The research focuses on the importance of considering the life cycle impacts of water reuse underlines the potential of potable reuse of water as a sustainable supply option.

(Tay et al., 2018) examines the feasibility of a novel nanofiltration membrane bioreactor (NF-MBR) followed by RO process for water reclamation at 90% recovery and compares it with a UF-MBR followed by RO process. The process of water reclamation consisted of both MBRs adopting the same external hollow fiber membrane configurations and operating conditions. The collected permeates of the MBRs were subsequently fed to the respective RO systems. The results showed that the NF-MBR achieved superior MBR permeate quality due to enhanced biodegradation and high rejection capacity of the NF membrane, leading to lower RO fouling rates as compared to the UF-MBR. The analysis indicated that the NF-MBR+RO system at recovery of 90% has comparable energy consumption as the UF-MBR+RO system at recovery of 75%, thus proving the feasibility of the NF-MBR+RO for water reclamation at a high recovery rate.

(Werkneh et al., 2019) provides a review of methods for treating brewery wastewater and the implications of using state-of-the-art biological treatment technologies leading to water reuse and/or energy production. With brewing industry being of the largest users of water and characterised by high levels of organic pollutants, it is established that effluent requires higher attention for remediation before discharge to the environment. The paper highlights the components of various bioreactors, such as membranes bioreactors, fluidised bed bioreactor, and anaerobic bioreactors, and how efficiently these reactors can be utilised for treating and reusing brewery wastewater. The paper also discusses resource recovery as a sound and economic approach to alleviate fresh water scarcity and shortage of energy supply. The authors suggest that resource recovery can be achieved by using brewery wastewater as a source of nutrients and energy for other processes. This approach can help to reduce the environmental impact of the brewery industry and provide economic benefits by reducing the need for fresh water and energy.

(Toran et al., 2021) focuses on brewery water reuse, evaluating a combination of various treatment methods, while also conducting a long-term assessment of membrane performance. The study’s experimental work consists of different sets of brewery wastewater treatment methods; set A, combining UF and RO, and set B, combining ozonation, coagulation, microfiltration with ceramic membranes (MF) and RO. Apart from the obvious comparison of those two sets of methods regarding the quality of treated wastewater, the research also adds another two criteria as means of comparison; namely, plant optimisation in order to determine optimal operating conditions and Clean-In-Place (CIP) procedures to restore permeability. Results showed that polymeric UF and ceramic MF membranes produced effluents that fulfill the limits of the national (Spanish) regulatory framework for reuse in industrial services, while

UF membrane filtration was found susceptible to membrane fouling -with decreasing its rate of function, or applying more CIPs, being some of the solutions to the problem. Coupling a RO system to the various physical separation techniques leads to further water polishing and the improvement of water quality.

(Verhuelsdonk et al., 2021) discusses the reuse of brewery wastewater as a solution to freshwater scarcity. After establishing the fact of breweries being major industrial water consumers, and therefore prioritizing the reuse of their wastewater should be an essential necessity, the study proceeds to the investigation of the long-term performance of a modular pilot scale plant that reuses brewery wastewater. The system consists of a flotation device, an MBR, a UF, and a RO system. The system is fed with wastewater from the effluent of a full-scale anaerobic reactor and treats it to reach potable standards. After the treatment, all the major parameters manage to reach German drinking regulation standards, with the exception of water pH being 5.5, compared to the lower limit of 6.5 set. Sodium hydroxide is suggested to improve this. Regarding the yield of the wastewater reuse, the paper suggests that the treatment process achieved a 63.3%, with RO being the main responsible for the loss of wastewater. The paper also discusses the economic viability of reusing brewery wastewater, with a cost estimate, which was carried out for a full-scale application, taking into account the actual hydraulic load of the brewery. In order to predict the uncertainties of cost-sensitive factors, the specific costs for sludge disposal, electrical energy, freshwater supply and wastewater disposal as well as membrane lifespan and yield of the RO unit were expressed by probability distributions. Using the Monte Carlo method, the probability distributions for the costs and economic viability of reusing brewery wastewater were calculated. The estimate found that reusing brewery wastewater can be economically viable in 77.2% of simulated cases showing the strongest dependency on costs for wastewater disposal. The OPEX and CAPEX costs of the treatment method were calculated for each process unit and then compared to extensive data, when available, in literature. The total cost of the treatment was estimated at 1.80 EUR/m^3.

2.5 Synthesis and Review of Literature

2.5.1 Synthesis

With regard to groundwater use, (Pearson et al., 2021) focuses on brackish groundwater treatment through the, very popular in these applications, RO method. After establishing the fact of brackish groundwater importance worldwide, as a source of water becoming increasingly used in order to cover the continuously increasing water demands, the research performs a techno-economic analysis of the method, with figures concerning the CAPEX and OPEX of the method evaluated through case studies in the state of California, USA. Both (He, 2015) and (Da'ana et al., 2021) evaluate the implementation of low-cost treatment techniques and assess them on the basis of water quality -after having identified treatments like RO indeed effective in contaminants removal, but still too costly to be implemented widely. (Gracia-de-Rentería et al., 2020) investigates the use of groundwater for industrial purposes and highlights the absence of extensive literature on the matter. The study focuses on the uncontrolled groundwater extraction by industries and proposes a state-regulated groundwater use environment in order to mitigate the effects of overextraction. (Singh Dhillon et al., 2018) focuses too on the environmental effects of groundwater extraction, by evaluating the environmental implications. The study outlines the drawbacks of current groundwater extraction methods and proposes that great extraction depth, obsolete infrastructure and inefficient pumping technologies exacerbate the environmental impact of groundwater use. (Bhakar et al., 2016) also investigates the environmental impact of the water source, coupled with its treatment through RO plants. Following a cradle-to-grave LCA approach, the study evaluates the impact of groundwater use for potable purposes by analysing it in various categories, such as CO_2-equivalent and water depletion.

RWHSs-related literature focuses heavily on the appropriate treatment techniques and their feasibility, with (Lee et al., 2017b) presenting a case study in Vietnam, where rainwater proved to be a valuable alternative to polluted surface water. It is established that UV sterilisation is an effective method for using treated rainwater as a potable source. (Musayev et al., 2018) focuses on the effectiveness of RWHSs in an ever-changing and unpredictable climate -with the study proving that even in arid areas rainwater harvesting can be used to effectively mitigate water scarcity. (Senevirathna et al., 2019) discusses the implementation of a RWHS in a university campus in Australia, with its treatment utility based on a combination of aeration, filtration and adsorption, carbon filtration and UV disinfection; the harvested water proving to perform better than the municipal water on quality evaluation. (Tran et al., 2021) also studies the use of a complex filtration along with UV sterilisation as a means of treating harvested rainwater to reach potable standards, while also performing a meticulous economic analysis of the both the operational and the capital costs of the system. (Latif et al., 2022b) suggests that the notion of harvested rainwater being generally clean and safe to use as mistaken, with untreated rainwater used posing a threat to public health. The study analyses the contaminants found in rainwater as well as where they can be found (e.g., on the catchment area) -with chlorination being suggested as the most cost-effective and sustainable method of treating harvested rainwater.

Regarding river water use, (Ahmed & Marhaba, 2017) focus on RBF as a pre-treatment method which effectively increases the river water quality, while also being a most sustainable and ecofriendly method because of the absence of chemical inputs and the minimal energy required. (Suprihatin et al., 2017) investigates the use of biofiltration as a method of eliminating contaminant in a body of river water -with the method proving to be extremely efficient, with a total suspended solids removal efficiency at 91%. (Zhai et al., 2022) proposes a novel method of river water treatment (OSRO), which consists of a combination of RBF and RO. The method manages to remove pollutants by leveraging the ecofriendly and cost-effective RBF as a pre-treatment method, while the main treatment is conducted in a RO plant. Because of the requirement of RBF for a continuous flow, ABF is proposed, using an artificial recharge of water to deal with the absence of river water during the dry periods of the year. Analysis shows a high pollutants removal rate -reaching a 99.9%- while its CAPEX remains lower than conventional methods. The study also suggests combining the OSRO method with renewable sources of energy as in to mitigate its environmental impact.

Regarding water reuse, (Tay et al., 2018) proposes a combination of either an NF-MBR followed by a RO process, or a ultrafiltration MBR (UF-MBR) followed by RO, with both options proving to have a high effectiveness in water treatment. NF-MBR + RO showed to have a water recovery rate of 90%, making it the most effective process of the two. (Werkneh et al., 2019), (Toran et al., 2021) and (Verhuelsdonk et al., 2021) all focus on brewery wastewater treatment and reuse, with the first study evaluating the use of bioreactors on brewery effluent treatment and the potential of treated water as a source of nutrients and energy for other purposes. The second study evaluates the combination of various treatment methods, while also conducting a long-term assessment of membrane performance; the two different treatment techniques being an UF-RO system and an ozonation-coagulation-microfiltration-RO system. Finally, the third study proceeds to the investigation of the long-term performance of a modular pilot scale plant that reuses brewery wastewater, with the system mainly consisting of an MBR, UF and a RO system. The treatment achieves a 63% water recovery rate and treats wastewater to potable standards, with the study concluding by calculating the total cost of the process.

2.5.2 Review

When evaluating the latest literature on alternative water sources, one can observe that research focuses on three main aspects; the treatment needs, the capital, operational and maintenance costs of the processes, and the efficiency of the treatment methods on behalf of the water purification. Lastly, some papers, especially those that refer to groundwater extraction- consider the environmental impact of the process. Most of the papers focus on treatment of water so that it reaches potable standards, something that is expected due to the water scarcity problem observed around the globe. The groundwater-related literature sees RO as the main treatment method used, with its high cost, however, being a deterrent for its wide use, especially when the levels of groundwater contamination seem to be low enough that it may be treated using milder, low-intensity methods. The literature is also extensively concerned with the environmental implications of groundwater use; with two main concerns being the uncontrolled overextraction, mainly used for commercial purposes, and the environmental impact of treatment -with RO and other methods of treatment being measured on the basis of their energy consumption and, thus, their implication in the greenhouse effect. RWHSs-related literature seems to be split over the ambiguity regarding the general condition of harvested rainwater: the papers considering the harvested water to some degree clean of dangerous contaminants and heavy metals -or, at least, cleaner than surface water- propose a combination of low-intensity and low-cost techniques to purify it and, therefore, propose its use in unprivileged communities that are in dire need of freshwater sources. The research regarding the notion of “rainwater being relatively pure” as a mistake, or even a myth that has now been proven wrong, proposes the use of high-intensity methods, such as UV sterilisation, along with pre-treatment in order to treat harvested water up to potable standards and, thus, ensure public health risks are minimal. In any case, RWHSs are regarded by all as an efficient way to alleviate water scarcity problems around the globe, having been proven as climate crisis-resistant sources of water even in arid regions. Literature concerning river water is limited, due to the obvious fact that river water is used mainly for irrigation purposes or industrial ones such as cooling, and therefore does not require extensive treatment, if at all. Another two reasons serve as deterrents for extensive river water use: First, the fact of many rivers’ seasonality flows, especially in semi-arid or arid regions, that limits their extensive use throughout the year. Second, the fact that rivers are the habitat of thousands of flora and fauna species and hotspots of biodiversity; with an overextraction of water having visible and direct consequences on that matter. Nevertheless, research concludes that RBF is the ideal pre-treatment method as it combines absence of chemicals with a low operational cost, with RO and biofiltration being methods which manage to have river water reach potable standards. One paper, (Zhai et al., 2022), deals with the problem of flow seasonality, claiming that if RBF as a pre-treatment method is not feasible -since it requires steady flow throughout the year- an alternative, ABF, can be used to artificially outplace the regular flow of river water. Lastly, literature on water reuse seems to be both extensive and aimed at industrial effluent treatment and reuse -with brewery effluent having been intently analysed for its reuse prospects. Research indicates that industrial effluent is in need of extensive treatment in order for it to reach potable, or even lower reusable standards, such as irrigation purposes; with a combination of treatment methods being necessary to achieve that. The most common solutions proposed are the combination of an MBR, a filtration (UF or NF) unit and an RO system. This sort of treatment proves highly effective in achieving water purification at a relatively low cost and medium energy intensity.

2.6 Research gap and innovation

Previous studies have extensively examined each and every alternative water supply system from the perspectives of economic feasibility, water supply efficiency, environmental impact and technical expertise in the water treatment aspect. There is, however, a noticeable research gap regarding a holistic approach to the use of water for commercial and/or industrial purposes. While research has focused on extending knowledge on specific case studies and in situ processes, when it comes to a combining use of current technological progress it lacks depth. With water scarcity becoming a number one problem for vast areas of the world and for large parts of the global population, it is only natural that water supply needs to be diversified, thus ensuring its security and stability over time. And while finance and investment diversification, or even energy diversification are widely considered as obviously reasonable practices, only recently has water supply diversification started to gain prominence as a matter of priority (Ribeiro et al., 2022). So, with previous research primarily focused on the analysis of one water source, either by calculating its implementation cost and environmental impact or by assessing its feasibility, this research gap presents an opportunity for innovation. A study concerned with a holistic approach to water supply is a step forward towards total water supply independence for any organisation or business.

This study aspires to fill the aforementioned research gap by focusing on a rounded approach to alternative water source use; with the multiplicity of alternative water sources examined being not only a step towards water supply security but also towards water sources conservation —two concepts which are actually interdependent. Maximum diversification of water sources combined with good consumption practices leads to less risk of source depletion in cases where it can be depleted -as is the case with all surface water sources as well as aquifers. Therefore, this thesis intends to create a framework where, depending on factors such as cost, environmental impact and natural constraints of water availability (precipitation volume, river flow, etc.) the best compound among the different water sources will be chosen for the supply of the industry. The linear programming optimisation algorithm developed will be set as a point of reference, with a differentiation of specific inputs (different precipitation volumes or harvested water, different groundwater extraction rates, etc.) leading to a different optimal water supply sources compound.

2.7 Past research works

An examination of past research provides valuable insights into the methodologies, challenges, and solutions that have shaped the discourse thus far. The following table encapsulates a curated selection of seminal works in the domain of water resource optimisation. Each study, while distinct in its approach and regional focus, converges on the overarching theme of sustainable and efficient water management. By juxtaposing these researches, we aim to glean a comprehensive understanding of the existing knowledge base, setting the stage for the innovations presented in this thesis.

Table 1. Past research: Date and brief synopsis

Paper	Synopsis
(Asadieh & Afshar, 2019)	Exploring the "Dez" reservoir in Iran, this study introduces the Charged System Search (CSS) algorithm for optimizing reservoir operations. Emphasising its enhanced version (ECSS), the research showcases the algorithm's superiority over other optimisation methods. Through tests across varying periods, the CSS algorithm demonstrates its robustness and speed, effectively addressing the complexities of reservoir operations. The findings underline the potential of CSS for broader water management issues.

(S. Zhang et al., 2023)	Centered on Handan, China, this research delves into water allocation using an enhanced Whale Optimisation Algorithm (HSWOA) combined with a non-cooperative game approach. Balancing ecological, economic, and social needs, the study harmonises the objectives of various administrative levels. Demonstrating its efficacy against benchmarks, the HSWOA emerges as a promising tool for reconciling stakeholder interests, offering solutions that prioritise varying benefits depending on flow conditions.
(Tang et al., 2021)	Set in Wusu City, China, this research aims to balance fairness in water distribution, water shortage risks, and economic gains. The study employs the multi-objective ARNSGA-III algorithm, highlighting its efficiency in managing water resource allocation challenges. Emphasising the competitive nature of the objectives, the findings propose that the new optimisation model can effectively address water distribution fairness and shortage risks.
(J. Zhang et al., 2020)	Focusing on the Huaihe River Basin in China, this paper presents an innovative water resource allocation model championing intergenerational equity. The study employs the NSGA-2 algorithm, aiming to balance current and future generations' water needs. Highlighting social, economic, and environmental benefits, the research offers insights into sustainable water management that respects intergenerational justice, emphasising the need for future-focused resource allocation.
(Li et al., 2022)	Addressing Beijing's water challenges, this study evaluates water quality and optimisation schemes in the Daxing District. Emphasising the potential of entropy theory, especially connection entropy, the research offers solutions to mitigate groundwater overexploitation and pollution. By evaluating different groundwater exploitation modes, the study underscores the importance of harnessing unconventional water sources, advocating for sustainable water management practices to address hydrological complexities.

All the research studies, along with this thesis, converge on the overarching theme of optimising water resources, underscoring the paramount importance of sustainable water management in diverse regions. Both the papers and this thesis employ algorithmic approaches to address water challenges, with several studies, ((Asadieh & Afshar, 2019),(S. Zhang et al., 2023), (Tang et al., 2021)) introducing or leveraging specific algorithms tailored to their unique challenges, while (J. Zhang et al., 2020) employs the widely-utilised genetic algorithm NSGA-II. A shared emphasis across the research is the regional application, with each work, from Iran and Handan to Wusu City, Beijing, and -in our case- Crete, tailoring solutions to specific regional challenges and conditions. Economic considerations are another common thread, with both (Tang et al., 2021) and the thesis delving into the financial implications of water resource management, emphasising the delicate balance between cost, fairness, and environmental considerations. Moreover, the exploration of alternative water sources, as showcased both in the research by (Li et al., 2022) and the thesis, highlights the collective push towards diversifying water sources to ensure resilience and sustainability in the face of ever-evolving environmental challenges.

2.7.1 Innovation

This research pioneers an industry-specific approach to water resource optimisation, focusing explicitly on sectors heavily reliant on water, such as breweries. While previous studies have extensively explored various algorithms and region-specific solutions, this study distinguishes itself by offering a comprehensive framework ideal for industries operating in areas susceptible to droughts, such as Crete. The robustness of the Linear Programming model, combined with the developed algorithm, sets a benchmark in water resource management, particularly in its ability to provide daily and yearly solutions over an extensive dataset of 365 days.

Furthermore, the research delves deep into the intertwined relationship between environmental and economic considerations. A meticulous economic analysis that splits costs into Capital and Operational Expenditures is a testament to the study's aim to a nuanced and holistic perspective. The outcomes, particularly the similarities between the balanced and eco-friendly scenarios, underscore the innovative assertion that environmental conservation and economic feasibility can coexist harmoniously.

Lastly, the sensitivity analysis imbues the proposed solutions with a layer of resilience and adaptability, characteristics often overlooked in traditional water resource management research. By rigorously testing the algorithm's robustness against real-life alterations in bounds, groundwater capacities, and river water capacities, this study ensures that the derived strategies are not just theoretically sound but also practically actionable.

3. Case study description

Cretan brewery S.A "Charma" is a microbrewery established in 2007 and located in Chania prefecture, in the western part of the island of Crete. The brewery produces a variety of fresh, unfiltered and unpasteurised draught beers. Their products are considered high quality craft beers which cover a wide range of flavours and trends. According to the company's figures, the water consumption for 2022 was 5,250 m^3, with the ratio of product to water use being approximately 5:1. Presently, the plant's sole water intake source is the municipal water provided by DEIAVA *(*Municipal Enterprise for Water Supply and Sewerage of Northern Axis of Platanias Municipality*)*. The company has applied a RO system in order to filter the supply water and ensure its quality. An already existing well lying withing the grounds of the company estate has also been proposed as a supplemental groundwater source with a proposed supply capacity of 2.25 m^3 per hour. A concise description of the above can be seen in Fig. 10.

In order to define the water profile of the industry, it would be essential to acquire the day-to-day water intake or volume production data. However, this thesis being a framework study, such data were not leveraged. Instead, we approached the matter ignoring these as well as seasonality patterns. For simplicity reasons, we evenly distributed this volume of water throughout the year, included the non-operational status of the industry during public holidays, and formed the water profile. Fig. 9 illustrates the daily water profile throughout a year.

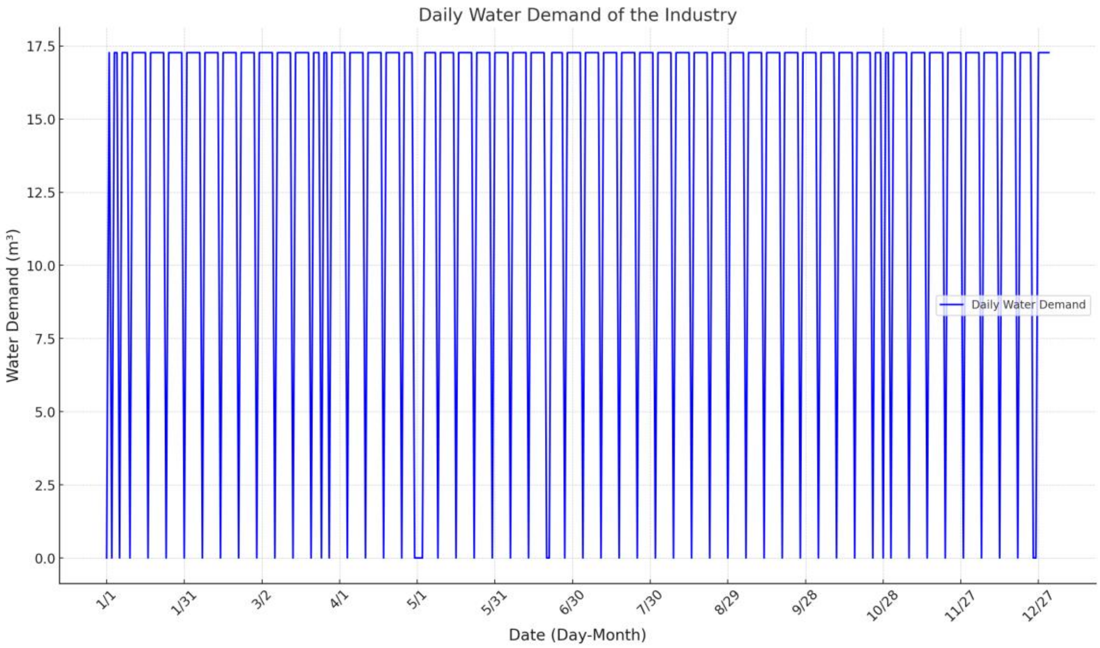

Fig. 9 Water profile of the industry throughout a year

The area of Platanias, where the Cretan Brewery S.A facilities lie, can be considered hydrologically affluent. It is characterised by the Tavronitis river basin, which consists of Tavronitis river itself and its three tributaries, Sebreniotis, Roumatianos and Derianos. The area hosts 55 water occurrence points: 16 boreholes, 38 wells, and 1 spring (Nikolaidis N. & Karatzas G., 2012). DEIAVA itself relies heavily on bore holes and wells for their network supply, while for years now there have been plans for the creation of a complex of dams that would cover the water consumption needs in the wider area both for consumption and for irrigation purposes.

However, the region is also characterised by overextraction of groundwater resources (Charchousi et al., 2017), necessitating stringent water conservation measures.

It must be underlined, however, that the “Charma” brewery serves as a case study solely in an abstract way. That means that this thesis uses it as a model case upon which it will conduct its research while often employing approximate figures to acquire all necessary results instead of focusing on the intricate technicalities and specificities of the “Charma” brewery production. The particularisation of the totality of the factors and the other nuanced aspects of either the Cretan brewery S.A or any other future stakeholder will have to be conducted, if it is indeed needed, in the future.

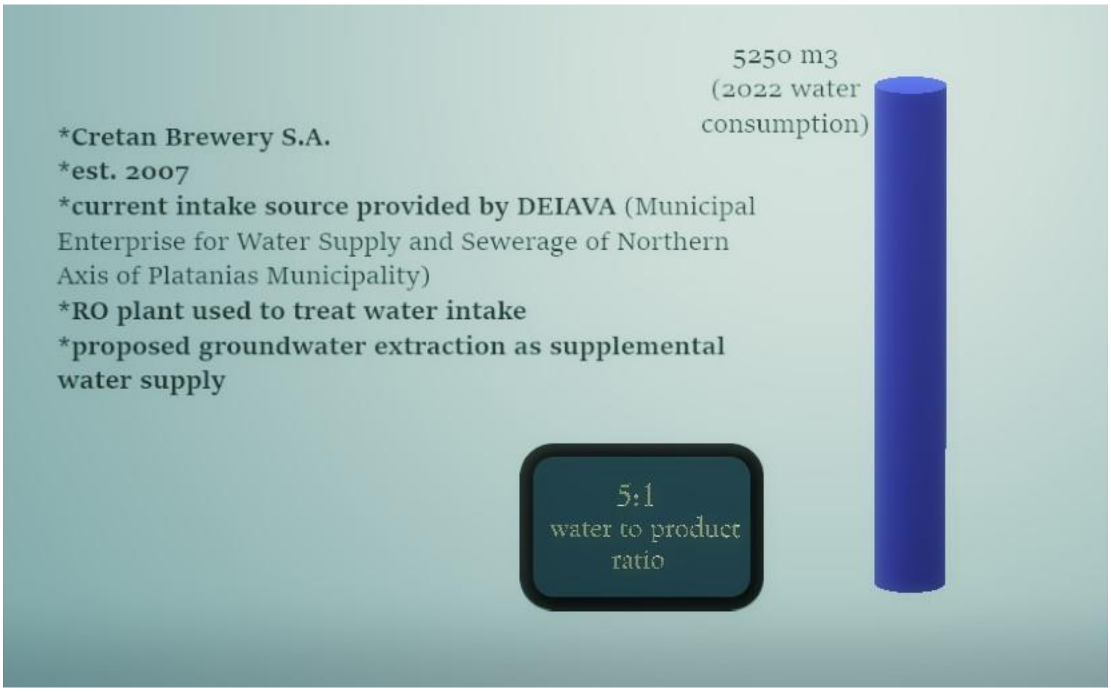

Fig. 10. Cretan Brewery S.A. (“Charma”) profile.

4. Methodology

One of the key objectives of this thesis is to reach a solution by leveraging data that are accurate and precise, i.e., focused as much as possible on the specific technicalities of water use and water treatment in a brewing industry. The main two sets of data required to proceed with the solution are the treatment costs and the environmental impact of each water source. However, a necessary preliminary work is to first define the required treatment method. This is based on two factors: the status of the water as it is derived from the source (pre-treatment status), and the required status of it after its treatment -as it is mandated by its use and the safety standards set by legislation and common practice (post-treatment status). Regarding the latter, the post-treatment status of water in our case is, at a minimum, a potable standards status -with extra treatment which ensures its good quality and ideal physical characteristics (e.g., taste, odour, etc.) also being desirable. Regarding the former, each water source provides a body of water which has its own unique characteristics and, thus, is defined by its distinct qualities. Therefore, the vast research of related literature on each and every water source is necessary to ascertain that the optimal treatment practices are implemented. Furthermore, in those instances where our case study presents its own specific features and, thus, does not appertain to any existing or found research, we conducted calculations to define all necessary values.

Treatment Costs are mainly separated into two distinct sets of costs: Capital costs and Operation and Maintenance (O&M) costs. The capital cost, also known as capital expenditure (CapEx), refers to the one-time costs incurred to design and construct a facility or system. In our case, these costs principally include the design and engineering of the respective facility, costs related to construction of the facility and the costs of purchasing and installing equipment necessary for the operation of the facility. Operational cost, also known as (OpEx), includes the costs necessary to efficiently operate and maintain a facility. These costs recure throughout the life of the facility. In our case, these costs principally include the costs of electricity needed for the operation, the costs of material replacement and those of maintenance. Costs will be measured in Euros. Assumptions on the parity between the Euro and the USD will have to be made. Other currencies met in the research examined will be converted based on accurate exchange rates.

The environmental impact of the various treatments is measured here in kilograms of Carbon Dioxide equivalent. Other metrics can also be used, such as Sulfur Dioxide (SO_2), Nitrogen Oxides (NO_x) and Eutrophication Potential. The CO_2eq. metric is used as an assessment of a treatment's contribution to climate change. Specifically, it demonstrates the treatment's use comparability to the release of a number of kilograms of CO_2 into the atmosphere over the course of 100 years. Here, all treatments are assessed regarding their electricity consumption from the grid. Thus, the CO_2eq. metric was deemed as the most appropriate for the needs of this thesis; with energy consumption being directly related to CO_2 emissions, given the fact that electricity in Greece is mainly generated from fossil fuels, there is a direct link between energy intensity and carbon footprint. The calculations are made using the energy sources mixture used for the production of electricity on the island of Crete.

Regarding the water sources' volume potential capacities, we have calculated the maximum volume of water which can potentially be exploited out of every source on a daily basis over the course of a year (365 days). The needs, data or goals of the industry itself have been taken into account whenever possible. Data on some sources have been acquired through research and other means, and calculations have been conducted when necessary.

4.1 Methodological Assumptions

4.1.1 Capital Expenditures' non-dynamic nature

Research dedicated to establishing the CapEx for appropriate techniques across five distinct water sources encountered a significant challenge: estimating these costs required projections of water intake volumes, which served as the foundational basis for the economic evaluation of each source and its associated treatment technique. However, our research soon grappled with the realization that the static nature of fixed costs, especially CapEx, could introduce inconsistencies in the optimisation process. A foundational aspect of the study became the intricate relationship between these fixed costs and the actual water intake volumes: Any significant deviation in the actual intake from the projected values could substantially alter the per cubic meter cost calculations, leading to potential disparities in the financial feasibility assessment of each water source and its treatment.

The intricacy of this situation lies in the relationship between fixed costs and water intake volumes. Fixed costs remain static, irrespective of how much water is actually treated. Therefore, if actual water intake post-optimisation deviates significantly from initial projections, the cost implications can be profound. A reduced water intake can lead to a surge in the CapEx per cubic meter, challenging the financial rationale behind adopting alternative water sources in the first place.

From an engineering perspective, however, modeling and optimisation are iterative processes that often begin with certain assumptions to establish a foundational framework. The use of an initial CapEx value based on current water intake volumes to model and optimise a system is a logical starting point. This is because CapEx provides an essential financial metric by which various water treatment options can be compared and evaluated. It allows for the establishment of a baseline against which improvements or changes can be assessed. The core objective in such optimisation exercises is not just to minimise costs but also to ensure system efficiency, reliability, and sustainability. Therefore, while the financial metrics like CapEx are crucial, they are part of a broader set of considerations. The process of optimisation, even with initial assumptions, provided valuable insights and laid the groundwork for further refinement and improvement. Thus, considering the CapEx calculated for each source as a static value and independent from the post-optimisation water treatment volume became an integral assumption of this thesis.

4.1.2 RO recovery rate

In the course of this research, a simplifying assumption was made concerning the RO treatment method. Specifically, the study assumes that the RO process exhibits a 100% recovery rate, effectively treating RO as a method without any permeate water losses. This assumption was deemed necessary to manage the complexity of the research. Given the already multifaceted nature of the thesis, introducing variable recovery rates for the RO process would have added another layer of intricacy, potentially diverting focus from the primary objectives of the study.

It's crucial for future stakeholders and researchers to recognise this assumption when interpreting the findings or applying the research in practical scenarios. Should there be a need to align the research with real-world RO plant operations, adjustments will be required to the water intake values to account for actual recovery rates, ensuring that the data accurately reflects on-ground realities.

4.1.3 Euro-USD parity

Throughout the research process, various sources provided pricing information for techniques, materials, equipment, and other essentials in different currencies. While most of these currencies, such as GBP and VND, were converted to Euros based on either the current exchange rate or the rate relevant to the time of the source's publication, a distinct approach was taken for the USD. For the purposes of this study, a parity between the USD and Euro was assumed. This decision was made to streamline calculations and maintain a consistent financial framework throughout the research.

It's also essential to note that the research did not factor in elements like inflation or any other financial variables that might impact the real value of currencies over time. The study aimed to maintain simplicity in its financial assessments, focusing on primary cost variables without the added complexity of fluctuating financial metrics. Future stakeholders should be aware of this assumption when interpreting the findings and consider potential adjustments if aiming for a more nuanced financial analysis.

4.2 Treatment Needs

4.2.1 Municipal Network water

Charma brewery is currently using the Municipal Network water of the area as its sole water source. According to it, the conductivity of the water intake from the local network varies between 500 and 700 μS/cm. Water conductivity -its unit being microsiemens per centimeter- is a measure of the water's ability to conduct an electrical current. This is related to the concentration of ions in the water and serves as a rough indicator of water purity. Such levels of the measured conductivity can be deemed as moderate when applied to brewing purposes, where water quality is indeed a crucial factor. Given the fact that Charma produces high quality unfiltered beers, and with water bring the main ingredient of the beverage, the company has installed a RO system to filter supply water and assure beer quality. A RO system does indeed reduce the conductivity of the water by removing a large proportion of the dissolved salts and minerals and, therefore, lowering the ion concentration. Apart from reducing conductivity, the RO system also removes other contaminants like bacteria, viruses, and particulates, which might be present in the water, thus enhancing the overall water quality.

4.2.1.1 Volume capacity

Currently, the region of Crete and the municipal enterprises for water supply do not apply any limit on water consumption on specific users. Taking into account the industry's needs, we have set a very large number (100 m^3) as the potential municipal water exploitation per day. This will serve as an equivalent to the "infinite" value later on in our algorithm solver. In Fig. 11 the time series of the Municipal water is depicted for a year.

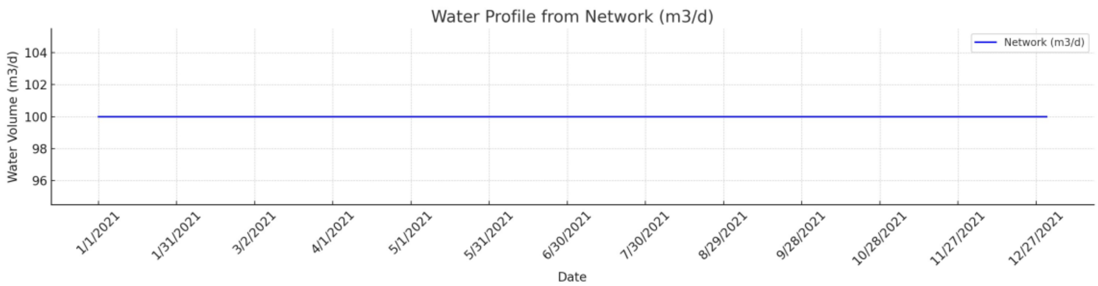

Fig. 11. Time series for the Municipal Network water source

4.2.1.2 Cost

The most prominent concept used in the calculations of the costs for all sources is the one of Equivalent Annual Cost (EAC). The EAC represents the annual cost of owning, operating, and maintaining an investment over its entire lifespan, when the present value of these costs is spread out uniformly over each year of the investment's life. The EAC is calculated using the following formula:

$$EAC = [\frac{P \cdot R}{1 - (1 + R)^{-T}}] \text{ (1)}$$

where *P* represents the initial cost, *R* stands for the discount rate and *T* is the life time period of the asset. Using the EAC in the calculation of both the Capex and the Opex means that comparison between assets with different lifespans is made possible; something of extreme importance in the case of the various components that will be examined in the pages to follow.

The Capex of the Municipal Water intake essentially means calculating the Capex of the RO system installed. Wishing to set the framework of the research instead of strictly following the case study's technicalities -as it has been described previously- we performed our own calculations for an appropriate RO system. First, the industry's annual needs of water are taken into account: Data provided by Charma show a 5,250m^3 of water consumption in 2022. That means that the whole volume of water was treated using the installed RO plant. While Charma itself reports a seasonality in production, and therefore water intake, for simplicity reasons we have evenly distributed this volume of water throughout the year. Having calculated 62 public holidays and Sundays in 2022 -and assuming a similar number in each year- only 304 working days have been taken into account. We have also assumed an 18-hour long workday for the industry. These account for a total of 5,472 working hours per year. Thus, the RO system's capacity was calculated as the quotient of the annual water consumption (volume) divided by the annual working hours. The volume was used in litres, since the RO systems' capacity is measured in Litres per Hour (LpH), indicating the potential of water able to be treated efficiently within an hour of operation. Thus, the proposed RO system's capacity is $LpH = \frac{5250000}{5472} = 959$

This led to the market research of a RO plant with a capacity no less than 1000 LpH. Market research provided a variety of RO plants from several manufacturers. Taking into account the growing expertise of Asian manufacturers towards reverse osmosis technologies and their competitive prices, a KYRO-1000 model was chosen, manufactured by Guangzhou Kaiyuan water treatment equipment co. Ltd. Its cost at the time of the research reached 2,500 USD, with a given Power of 2.25 kW. The expected *T* of the plant is 10 years, while the *R* is safely assumed to be 10%. Thus, the EAC of the plant is,

$$EAC_{\text{mun}} = \frac{(2500 \cdot 0.1)}{1 - (1 + 0.1)^{-10}}] = 406.864 \text{ EUR}$$

The Capex of the RO plant will be calculated as the quotient of the EAC divided by the total volume of water treated throughout the year. Thus, the Capex per m^3 of water treated through the plant is,

$$Capex_{\text{mun}} = \frac{EAC}{volume\ per\ year} = 0.778 \frac{EUR}{m3} \text{ (2)}$$

Regarding the Opex of the RO plant, it is divided into two distinct parts: Operation and Maintenance cost. In our case, Operation costs coincide with electricity consumption costs. Maintenance cost in a RO plant can consist of various components that need replacement over time. However**,** membranes are assumed here to be both the most expensive and the most valuable component, since, if in a good condition, they ensure the unhindered operation of a RO plant and the good quality of the end product**.** Therefore, we assumed that membrane replacement was the major maintenance cost of the process, with the rest being, comparatively, negligible. Labour costs, while normally incorporated in the total cost, were hard to calculate, if not impossible due to the absence of a generalised labour cost for such operations.

The electricity cost is calculated through the nominal power of the plant given by its manufacturer. By multiplying the operational hours per year with it, we obtain the total power consumed per year of operation. Then, we divide this value with the volume of water to be treated in a year and we, thus, obtain the electricity required m^3 of water treated. We assume the price of kWh in Greece to be 0.22 EUR. Thus,

$$Annual\ energy\ demand = 2.25 * 5472 = 12{,}312\frac{kWh}{year}$$

$$Energy\ demand\ per\ m3 = \frac{12{,}312}{5250} = 2.345\frac{kWh}{m3}\ (3)$$

$$Operational\ Electr.Cost = 2.345 * 0.22 = 0.516\frac{EUR}{m3}(4)$$

Maintenance cost, as described above, calculates the EAC of the membranes of the RO treatment plant. The main thing to consider here is the membranes' life expectancy and their price. Membranes' life is dependent on many factors and varies between 3 and 7 years. There have been reports on membranes that have lasted up to 10 years. This information largely comes from experts and manufacturers such as Watts and Dupont. Dupont specifically has produced an informational leaflet in which they describe the main factors that affect the membranes' life expectancy. Among them, there is water temperature, salt concentration, water pH and others. Considering the fact that municipal water in the region of Chania is of relatively high quality, with no salinity or hard minerals, we may safely assume a 5-year life expectancy for the membranes used to treat Municipal water. This is considered a conservative choice and indicated that we have not underestimated the membranes' replacement frequency, since (Jamil et al., 2017) has used a 5-year lifetime for a desalination RO plant. Regarding the initial cost, the market research proved to be hard due to purchase choice being extremely focused on different parameters and nuances focused on the intricate technicalities of each RO system. Prices are subject to various factors, such as salt rejection capacity, operating pressure etc. Thus, with prices of a high-quality set of membranes (Filmtec, Dupont) being 400 EUR, and taking into account that RO plants of this capacity require more than one set to operate, we assumed a 1000 EUR price since we have considered the focus the company places on its end-product quality and the safety of its main raw material; that is, water. In any case, the prices and the market research need to be further examined in the future by stakeholders. Using formula (1), and assuming a steady discount rate at 10%, the EAC of the membranes' replacement is,

$$EAC = \frac{1000 * 0.1}{1-(1+0.1)^{-5}} = 263.797\ EUR$$

$$Replacement\ Cost\ per\ m3 = \frac{EAC}{5250} = 0.05\ \frac{EUR}{m3}\ (5)$$

Lastly, the purchase cost of the Municipal water by DEIAVA was needed to be calculated. Since the municipal enterprise does not publish its pricing on its site, we have only used the volume scale sizing it uses, which is given, and filled in the prices per part of the scale using the pricing given by DEIACH (Municipal Enterprise for Water Supply and Sewerage of

Chania) -Chania being the largest urban centre in the prefecture and the closest one to the site Charma Brewery lies. The possible difference in pricing, therefore, may be considered negligible. Assuming, for simplicity reasons, that the brewery has a uniformly distributed water consumption throughout the year, we have calculated the quarter year water consumption, since that is the period used by municipal enterprises of water in order to conduct their pricing. With a 5,250 m^3 annual consumption, the quarter year was calculated at 1312.5 m^3.

Table 2. Municipal water purchase calculation

Range	Price	Consumption	Difference	Purchase Price
0-30	0.35	30	1282.5	10.5
31-60	0.54	30	1252.5	16.2
61-120	0.79	60	1192.5	47.4
121-240	1.03	120	1072.5	123.6
241-99999	1.16	1072.5	0	1244.1
			SUM	1441.8
			EUR/m^3	1.09

While supplied water in its total worth (here, 1441.8 EUR) is normally subject to 13% VAT, DEIAVA is also known for providing a 10% discount to its clients who are punctual in their payments. Thus, due to uncertainty over the subject and lack of consistency, no tax was calculated here. In any case, the price of water purchase per m^3 was calculated at 1.09 EUR/m^3 (Table 2)

With all distinct costs having been calculated, the Levelised Cost of Water (LCOW) of the Municipal water source was defined. The LCOW is a concept similar to the Levelised Cost of Energy (LCOE) and is used to estimate the cost of producing clean and potable water from various sources or technologies over the lifetime of a water treatment. Here, the LCOW equals the purchase of water as it was calculated previously, along with the values calculated in equations (2), (3), (4). All in all,

$$LCOWmun. = (2) + (4) + (5) + Purchase\ Cost = 1.742\frac{EUR}{m3}\,(6)$$

4.2.1.3 Environmental Impact

The environmental impact analysis of the Municipal water use focused on the energy demand of the processes. The main demand for electricity comes from the operation of the RO plant, something that has already been calculated in equation (3). However, in this case, the environmental impact of the whole water harvesting, saving, and distribution from the source to the end-user has to be taken into account. To this end, extensive literature research was conducted. (Amores et al., 2013) has calculated the energy intensity of each of the municipal network's processes in kWh per m^3 of water for the case of Tarragona, a city in the Mediterranean coast of Spain. The stages of municipal water ad their respective energy demands are the following: Water Abstraction, 0.294; Potable Water Treatment Plant, 0.071; Intermediate Pumping, 0.154; Distribution Network, 0.304; Wastewater treatment plant, 1.09.

Therefore, according to the research, the total energy consumption of a municipal network would be:

$$Tot.en.dem.of\ Mun.netw. = 0.294 + 0.071 + 0.187 + 0.294 + 1.09 = 1.936\frac{kWh}{m3} \quad (6)$$

Thus, the final energy consumption of our Municipal water use would be:

$$Total\ En.Consumption \text{ municipal} = (3) + (6) = 4.281\frac{kWh}{m3}$$

Crete's electricity grid equals to one kg CO_2eq. per kWh value of 0.989 (Sifakis et al., 2021). In addition, (Sifakis, 2021) has used a primary energy factor equal to 2.9 -a value that represents the ratio of the energy primarily produced and the energy used by the end-user, mainly due to losses during the transmission of electricity. Thus, the kg CO_2eq. for the use and treatment of Municipal water is,

$$Environmental\ Impact \text{ mun.} = 4.281 * 2.9 * 0.989 = 12.279\frac{kg\ CO2eq}{m3} \quad (7)$$

4.2.2 River water

Cretan Brewery S.A. facilities are adjacent to Derianos river, a subsidiary of Tavronitis river, and therefore river water has been considered as a possible alternative water source for the industry. Regarding the quality of river water, anthropogenic activities in the river basin area create industrial pollution or agricultural runoff, factors that are responsible for the pollution of the soil, the aquifer and, ultimately, the river itself. Excessive sedimentation, also often caused by human activities such as deforestation, urban development and removal -legal or not- of the sand belonging to the banks of the river, affects the water's quality and suitability for drinking purposes. Focusing on the rivers of Crete, research on Almiros River in Heraklion, eastern Crete, has traced in it Polycyclic aromantic hydrocarbons (PAHs), which are organic compounds created by the incomplete burning of organic substances, such as wood, coal, etc. (Kotti et al., 2018). (Zhai et al., 2022) proposes a new technique, OSRO, which is thoroughly described in a previous chapter of this thesis. The OSRO technique, a combination of RBF -or ABF in this case as Derianos does not present a steady flow throughout the year- with RO filtration is found to be able to purify the river water so that it reaches potable standards. Thus, it can be safely assumed that its implementation in this problem will adequately meet the demands of the brewery of its water source. The hands-on experience of the staff of Charma brewery itself or third-party cooperating technicians with the RO technology has also mattered greatly to the selection of this treatment technique.

4.2.2.1 Capacity

As with many rivers in Crete, Derianos, too, presents a seasonal flow, becoming almost or totally dry during the summer and early autumn months. For Derianos there is no data published regarding its flow in the last years. (Malagò et al., 2016; Nerantzaki et al., 2019) both use a combination of the SWAT (Soil and Water Assessment Tool) model -which is a river basin model- and a karst-flow model (KSWAT) -focused on karst-dominated regions- to assess the water balance, and the climate change impact on it, in the island of Crete. Part of this research was the simulation of the Derianos river and the then-prediction of its flow in m^3/second for many years, including year 2020. For simplicity reasons, we would use the same data for our 2022-based research. The data for the river's flow were kindly provided by the authors. The per second flow was converted to a per day flow and, out of the total daily flow, the 10^{-4} was deemed as exploitable. Considering that overexploitation remains a problem for river basins in Greece (Skoulikidis, 2018), that decision was taken so that the same problem is avoided. Thus, it is ensured that, on the part of the industry, the hydrological regime in the area remains as far as possible unchanged. Fig. 12 illustrates the time series of the river water capacity throughout a year.

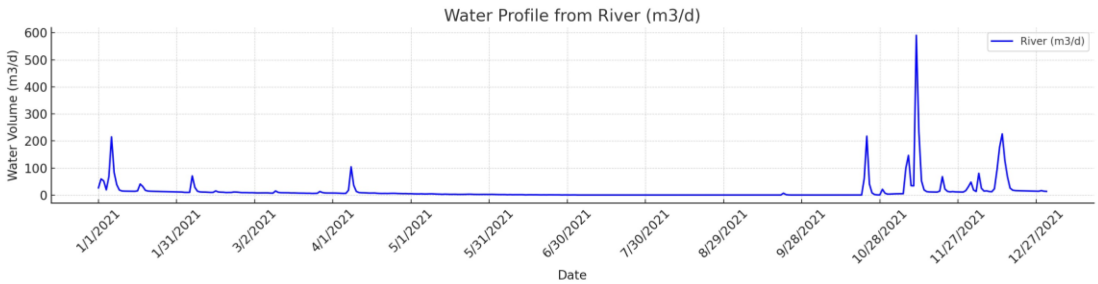

Fig. 12. Time series of Derianos river for a year

4.2.2.2 Cost

Following here, as described previously, the OSRO concept, we need to calculate the Capex and Opex of river water treatment and use. Regarding the former, (Zhai et al., 2022) reports an investment cost of 12-14 million EUR, with traditional treatment processes of river water treatment reported at being at the scale of 18-20 million. This is further validated by (Sarai Atab et al., 2016) who reports a moderate-salinity brackish river water treatment plant using RO, as having a capital cost of 16 million GBP; an amount that, given the then exchange rate, equals to around 22 million EUR. However, both cases of the OSRO plant and the brackish river water treatment plant provided in the previous papers, cannot, in their objective technicalities, allow us to use their calculations uncritically in order to trace the Capex in EUR/m^3 in our case. The reason for this is the capacity of the plants examined: For the former, the paper examined does not provide any data on the volume of water extracted from the river and treated in the plant. For the latter, the paper reports a daily capacity of 28,400 m^3 and calculates a per m^3 cost of 0.2GBP, which equals to 0.274 EUR. Given, however, the vast difference in the volume of water potentially treated between that case and that of Derianos river in Crete, as well as the brewery's demands in water which, annually, are only a fraction of that plant's daily capacity, that is not a value that we can safely adopt. Similarly, in the OSRO plant case, while the volume of treated water is indeed not provided, it is safe to assume it would prove to be on a much larger scale than ours, since Lek river is navigable in contrast to Derianos, which is only a subsidiary of another river and runs dry during the summer months. Thus, to extrapolate this knowledge to another plant of a different scale, we leveraged the power-law relationship often observed in cost scaling across industries. This relationship is given by:

$$C_2 = C_1 \left(\frac{Q_2}{Q_1}\right)^n \quad (8)$$

where, C_1 and C_2 represent the costs of the two plants, Q_1 and Q_2 the capacities of the plants, and n is the scaling exponent, which, if less than 1, accounts for economies of scale, and if more than 1 accounts for diseconomies of scale. Its value and is pivotal for the calculation of the cost of our treatment plant. Considering that a sharp decrease in the capacity of a plant will definitely lead to an analogous, yet non-linear, decrease in its initial capital investment regarding the individual units of equipment, various construction processes etc., a value of n=0.75 was chosen. This is a value that lies very close to the “0.6 rule” (Tribe & Alpine, 1986) and that has actually been observed to lie within the range of actual empirically-calculated scaling exponents for factory equipment, as illustrated in the same research. The annual capacity of the proposed plant for the Charma brewery was chosen at 5096 m^3, following the annual sum of the daily river potential of Derianos, as it was calculated by the river flow data provided. In order for the two capacity values to align, an approximate daily capacity of 14 m^3 was considered. Regarding the cost of the reference treatment plant, we chose 14 million EUR, the maximum value given by (Zhai et al., 2022) for its OSRO concept. For the capacity of the reference plant, we used the capacity reported by (Sarai Atab et al., 2016) in the factory that had an analogous cost to the OSRO concept. Therefore, our calculations for the capital cost of the proposed OSRO plant were these:

$$C2 = 14 * 10^6 * \left(\frac{14}{28400}\right)^{0.75} = 46{,}316\ EUR$$

Then, the EAC had to be calculated, with an R=0.1 and an assumption of life-time period T=25 years (expecting that the facility will definitely prove to vastly outlive a RO plant, whose life-time was calculated at 10 years). Thus, according to formula (1):

$$EAC\text{river} = \frac{46{,}316 * 0.1}{[1 - (1 + 0.1)^{-25}]} = 5{,}103\ EUR$$

and

$$Capex\text{river} = \frac{5{,}103}{5{,}096} = 1.001 \frac{EUR}{m3} \quad (9)$$

Regarding the Opex or O&M cost of the river water treatment, extensive calculations were performed as well. The Opex is not, by its nature, so heavily influenced by the difference in scale, since it does not refer to capital expenditures which can have such vast differences. In the paper examining the OSRO concept, both the energy consumption (0.57-0.66 kWh/m^3) and the O&M costs (0.42-0.43 EUR/m^3) are given. However, it would not be appropriate to light-heartedly use the given Opex, since it is essential to take into account the disparity in electricity costs. Thus, it was deemed necessary to make a distinction between the Operational and the Maintenance costs; the former requiring reassessment and recalculation, while the latter would be safely assumed to remain the same in our case. First, the median of the energy consumption range was calculated at 0.615 kWh/m^3. Then, to trace the electricity price the industry in the case study was charged with, we evaluated the time and place the research took place. We had to assume that since the paper was received at the end of 2020, the research had been conducted a few months before and, approximately, during the summer of 2020. Using data provided by UK.gov, we managed to trace the prices of prices of electricity in European countries and, specifically, the Netherlands, which was the site of the case study. Energy consumers in the Netherlands were charged distinct prices according to their annual consumption. After examining the profile of Oasen Drinkwater company, we observed the following: It supplies water to 750,000 people and 7,500 companies. It treats groundwater, seeped into the ground through riverbanks. It applies a combination of treatment techniques, such as aeration, sand filtration, UV disinfection and active carbon, while also ensuring that the water is softened before it reaches the consumer. These findings lead us to safely assume that a water supply company with such a great customer base size, which additionally treats groundwater -meaning it implements extensive pumping- to potable standards, is located in the scale of "Very large consumers" of electricity (70,000-150,000 MWh/annum). That means that according to the data found, the price for these consumers in June '20 in the Netherlands was 5.66 pence/kWh = 0.0566 GBP/kWh. The exchange rate between the EUR and the GBP in July '20 was found to be 0.89. Therefore, the study was conducted under the price of 0.0635 EUR/kWh. Thus, the median electricity (operation) cost of the treatment was:

$$Operation\ cost = 0.064 \frac{EUR}{kWh} * 0.615 \frac{kWh}{m3} = 0.039\ EUR \frac{EUR}{m3}$$

$$Maintenance\ Cost = O\&M - Operation\ cost = 0.425 - 0.039 = 0.386 \frac{EUR}{m3}$$

Finally, the Opex in our case was calculated to be:

Opexriver =[(median electricity demand of the treatment)*(kWh price in Greece)]+ [(fixed) Maintenance costs]

As previously, we assumed a 0.22 EUR/kWh price in Greece:

$$Opex\text{river} = (0.22 * 0.615) + 0.386 = 0.521 \frac{EUR}{m3}\ (10)$$

Lastly, we calculated the LCOW of the river water treatment and use:

$$LCOW\text{river} = (9) + (10) = 1.522 \frac{EUR}{m3}\ (11)$$

4.2.2.3 Environmental Impact

As previously in the case of Municipal water, the environmental impact analysis of the river water use focused on the energy intensity of the processes. Here, there were no other external factors needed to be included in the calculations. Therefore,

$$Envionmental\ Impact\text{river} = 0.989 * 2.9 * 0.615 = 1.764\ \frac{kg\ CO2eq}{m3}\ (12)$$

4.2.3 Groundwater

Charma brewery has already considered utilising a well near the production facility to collect 2.25 m^3 of underground water per hour as a supplementary water supply. The aquifers in the wider area, as mentioned previously, are extensively exploited with a great number of boreholes being active. (He, 2015) has proposed a plethora of groundwater purification techniques. Despite other techniques' lower costs and other advantages, RO is selected here as the optimal choice for a variety of reasons; namely, the high probability of the presence of salinity in the extracted groundwater, the staff's existing experience with this technology and, most importantly, the contaminant removal capacity of RO in comparison with every other technique. Given the importance the brewery places in the quality of its raw materials, and mainly in used water, RO does indeed seem the ideal choice for ensuring the quality of the extracted groundwater.

4.2.3.1 Capacity

Considering the brewery's proposal of using 2.25m^3/hour as supplementary water supply, we have assumed no more than a 5-hour long groundwater abstraction process per day. This was done both in order not to overestimate the potential of the aquifer in our calculations, and in view of the fact that the area is already, as mentioned previously, characterised by overextraction of groundwater resources. Thus, that leads to a daily capacity of 11.25 m^3 of groundwater. The annual capacity for an operation of 304 days is measured at 3,420 m^3. Fig. 13 shows the groundwater profile time series throughout a year.

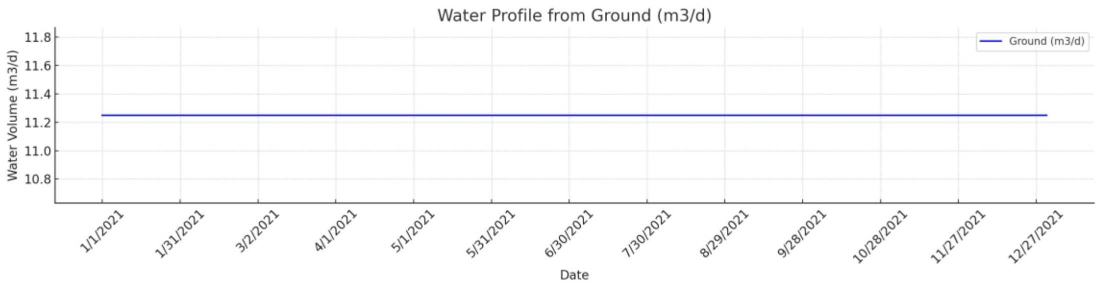

Fig. 13. Time series of Groundwater profile -as it was defined for the purposes of this research

4.2.3.2 Cost

The first equipment to consider in this case was the selection of the submersible pump that would be used for the abstraction of the groundwater from the well. Submersible pumps, as their name implies, are designed to be submerged in liquid, most commonly water. These pumps are commonly used for various applications, including water supply, drainage, and sewage treatment. In the process of selecting an appropriate pump for our research, specific parameters were pivotal in guiding our decision. Regarding the depth of the well, a range of 60-70 meters was assumed (with a median depth of 65 meters). Based on the requirements of the extraction rate, the flow rate (Q) was also determined to be 2.25 m^3/h.

It's imperative to understand the direct relationship between the static head (which is the height a pump can raise water above the source level) and flow rate capacity. Generally, as the head increases, the flow rate tends to decrease due to the greater resistance and work needed to push the water. For the calculation of the appropriate pump the total head needs to be taken into account, whose two main components are static and friction head. Friction head refers to the loss of pressure or head in a system due to the resistance encountered by a fluid as it flows through pipes, fittings, and equipment. This resistance, or friction, results from the interaction between the fluid and the walls of the conduit through which it flows. In essence, friction head accounts for the energy losses within the system that arise from the fluid's movement against surfaces. In our case, assuming a linear pipe from the bottom of the well to the surface, the friction losses on that part were considered to be at minimum. Nevertheless, the length of the pipe would result in some moderate overall friction losses.

For the choice of the appropriate pump for our needs, market research had to be done. However, using the typical formula for an hp-related choice based on required flow and total head, proved to be fruitless. The reason for that is that selecting a pump solely based on its horsepower can be misleading, as the efficiency and performance of a pump are not determined by hp alone. For instance, two pumps with the same horsepower might offer vastly different flow rates due to variations in their impeller designs. Moreover, a pump with higher efficiency, though possibly priced higher initially, can lead to significant energy savings in the long run, making it a more cost-effective choice over its lifespan. Therefore, it's crucial to consider factors like flow rate, pressure requirements, and overall energy efficiency, rather than relying merely on horsepower as the determinant for pump selection.

Focusing our search on pumps with the desired Q and a desired Total Head of $65 + 0.3 * 65 = 84.5m$ (extra 30% added conservatively in order to overcome friction and other losses), and using the pump selection tools available in many manufacturers' websites (Ebara, Grundfos, Franklin) we managed to limit our choices to 4 pumps. Out of the 4, the most economical both on cost and on electricity demands, as well as reliable, was the Ebara OYM 4N2-20/1.1, which according to a manufacturer's detailed leaflet, has the following characteristics:

Model: 4N2-20

Power (kW): 1.1

Power (HP): 1.5

Table 3. H (Total Head) – Q (capacity in m^3/h) relation for the Ebara pump, 4N2-20

H	Q
139	0
131	0.9
127	1.2
121	1.5
113	1.8
103	2.1
75	2.7

In Table 3 We observe that for a desired Q=2.25, the total height will be between 75 and 103. By linear interpolation, the total head results in H=96 m, a value higher than the desired H=84.5m. For confirmation of our choice, we expanded our research on manufacturers and providers of pump services. A detailed graph by Oakville Pump Service, Inc, based in USA, provided another helpful insight in the problem (Fig. 14). The Y-axis refers to the total vertical height, while the X-axis refers to Q (m^3 per hour). The graph makes it evident that, for the pump chosen, on the one hand our calculations above get confirmed, while, on the other hand, it will function within the best efficiency range, thus minimising its energy demand and ensuring good operating practices, which, normally, maximise an equipment's lifespan. Regarding the purchase cost of the EBARA 4N2-20 model, the company does not provide a standardised, or fixed, price. The pump, however, was found available on a British site at the time of the research, at the price of 902.40 GBP. According to the exchange rate at that time, this resulted in a price of 1,038 EUR. Next step was to calculate the pump's EAC. According to (Mogaka, 2006) the average life span period of a pump is T=10 years. We also used, as previously, an R=0.1. Thus, using formula (1):

$$EAC\text{pump} = \frac{1038 * 0.1}{1 - (1 + 0.1)^{-10}} = 168.93\ EUR\ (13)$$

and

$$Capex\text{pump\_ground} = \frac{EACpump}{3420 \frac{m3}{year}} = 0.049 \frac{EUR}{m3}\ (14)$$

Regarding the operational cost of the pump, which is predominantly the electricity cost, the nominal power of the equipment is 1.1 kW, while the operating hours were defined as 5 operation hours per day for 304 days per year. Thus, the pump would operate for 1,520 hours/annum. The total power consumed per year was calculated at $1.1\ kW * 1520\frac{hours}{year} = 1672\frac{kWh}{year}$. With a total capacity per year of 3420 m^3 as defined previously, the energy consumption per m^3 is $\frac{1672\frac{kWh}{year}}{3420\frac{m3}{year}} = 0.489\frac{kWh}{m3}$. Finally, the Operational Cost of Electricity was calculated at:

$$Operational\ Cost\ of\ Elect.\text{pump} = 0.489\ \frac{kWh}{m3} * 0.22\frac{EUR}{kWh} = 0.108\frac{EUR}{m3}\ (15)$$

No pump maintenance costs were able to be calculated here, nor were they spotted in relevant literature.

The post-extraction process of groundwater will require treatment in a RO plant. With a desired input of 2.25m^3/hour, market research was conducted on RO plants of an equivalent capacity. However, RO plant of a 2250 LpH capacity do not get manufactured, while no 2500 LpH plant was found. Thus, we concluded on a scheme with two RO plants working in tandem; one of 2000 LpH and one of 500 LpH capacity. For similar reasons with the Municipal water treatment scheme, we concluded on a KYRO-2000 and a KYRO-500. The plants' specifications follow, along with the total power and prices of the pairing of the two are included in Table 4

Therefore, considering the pairing of the two RO plants as one 5kW RO plant with an initial purchase price of 6950 EUR, we calculated its EAC:

$$EAC\text{ground} = \frac{6950 * 0.1}{1 - (1 + 0.1)^{-10}} = 1131\ EUR\ (16)$$

$$Capex\text{RO\_ground} = \frac{(16)}{3420\frac{m3}{year}} = 0.33\frac{EUR}{m3}\ (17)$$

Regarding the Operational electricity cost of the RO plant, the total power consumed per year was calculated at $5kW * 1520\frac{hours}{year} = 7600\frac{kWh}{year}$. The power consumed per m^3 treated is $\frac{7600}{3420} = 2.222\frac{kWh}{m3}$. Finally,

$$Operational\ Cost\ of\ Electricity\text{RO\_ground} = 2.222 * 0.22 = 0.489\ \frac{EUR}{m3}\ (18)$$

The final Capex for all the whole process of groundwater extraction and treatment:

$$Capex\text{ground} = (14) + (17) = 0.38\ \frac{EUR}{m3}\ (19)$$

The final Operational electricity Cost of the whole process:

$$Operational\ Cost\ of\ Electr.ground = (15) + (18) = 0.596\frac{EUR}{m3}\ (20)$$

Lastly, to conclude with the Opex of the groundwater extraction and treatment, we needed to calculate the Maintenance part of the cost, which we assumed consisted mainly of the membranes' replacement cost. Having assumed a 1000 EUR purchase cost for the Municipal water treatment plant, we now assumed a double price due to the presence of two plants. Thus, with all the remaining variables set on fixed values:

$$EACmembranes_{ground} = \frac{2000 * 0.1}{1-(1+0.1)^{-5}} = 527.595\ EUR\ (21)$$

and

$$Replacement\ Cost\ per\ m3 = \frac{(21)}{3420} = 0.154\frac{EUR}{m3}\ (22)$$

All in all, the LCOW of groundwater extraction and treatment:

$$LCOWground = (19) + (20) + (22) = 1.131\frac{EUR}{m3}\ (23)$$

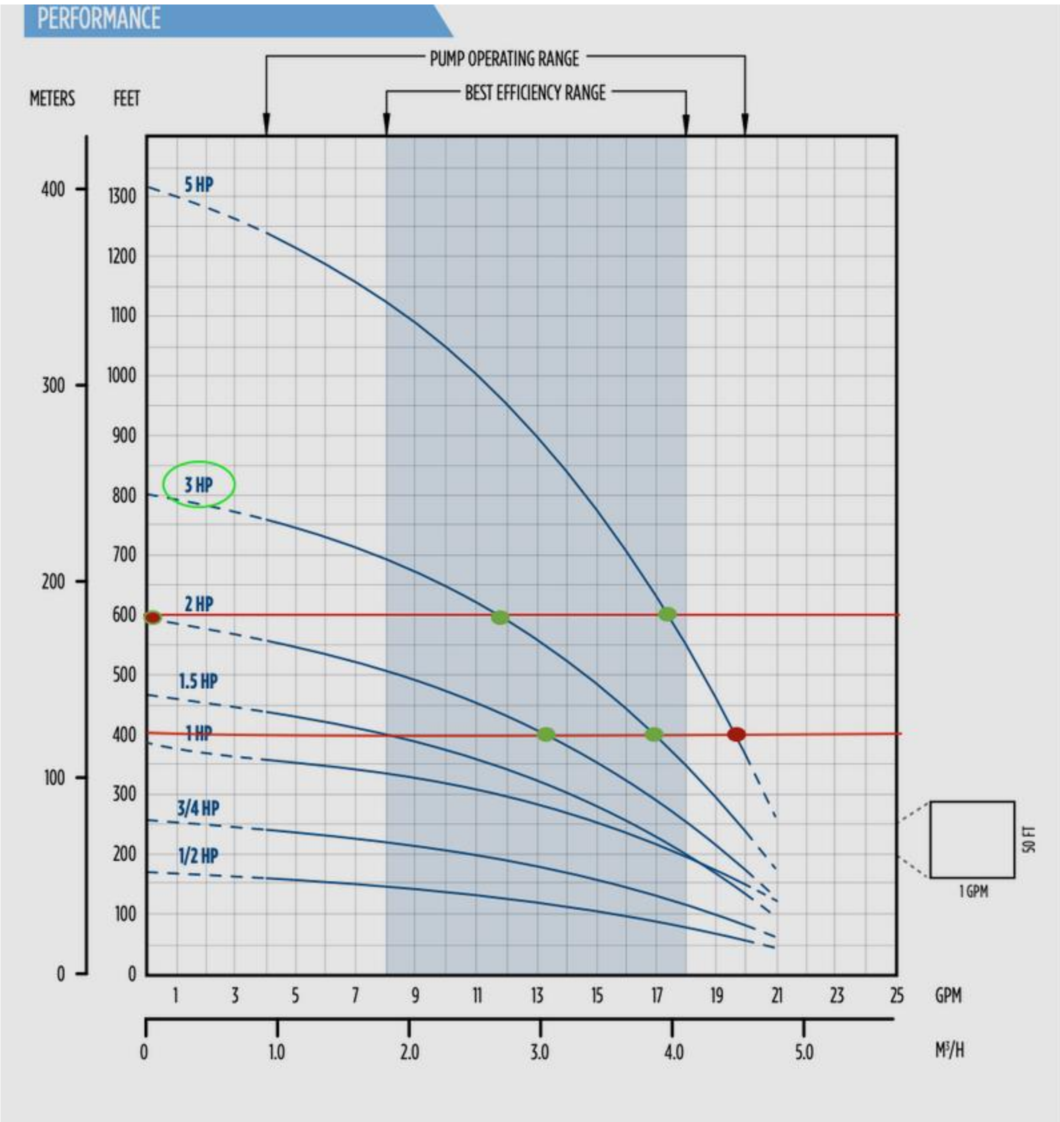

Fig. 14. Pumps operational range curves. From: Oakville Pump Service Inc. blog, 2019. https://oakvillepump.com/blog/2019/6/17/can-i-just-put-any-submersible-pump-in-my-well

Table 4. KYRO models 500 and 2000 RO plants and their specifications

Model	Flow rate (m^3/h)	Power(kW)	Price range (EUR)	(Median) Price EUR
KYRO -500	500	1.5	1950	-
KYRO-2000	2000	3.5	1950-7999	5000
Compound	2500	5	-	6950

4.2.3.3 Environmental Impact

Having calculated the energy consumption of groundwater extraction and the one of groundwater treatment, we only had to use the CO_2eq. factor related to the island of Crete and the 2.9 factor as in (7):

$$Envriron.Impact_{\text{ground}} = 2.9 * 0.989 * (0.489 + 2.222) = 7.775\ \frac{kgCO2eq.}{m3}\ (24)$$

4.2.4 Rainwater

Adhering to the need to ensure that the harvested rainwater reaches potable standards, we have here followed the pattern of two distinct research papers which, nevertheless, face the problem similarly. (Tran et al., 2021) proposes a complex filtration unit, consisted of fiber and ultrafiltration, along with UV light sterilisation. The system proposed includes some components that will be considered superfluous for the needs of this thesis, such as two extra tanks (sedimentation and a second, post-storage one), two pumps and two UV light bulbs. The thesis will follow the treatment pattern, but will discard any excesses that probably apply to the specific needs of that case study. (Yan et al., 2018) proposes a similar treatment method, applying to the process a three-tiered filtration system along with UV light for attenuating contaminants. Both papers report an elevation of the harvested rainwater to potable standards status.

4.2.4.1 Capacity

Before diving into the calculations for a rainwater harvesting system, it's essential to understand key components and factors, including catchment area and runoff coefficient. These elements are foundational for designing an effective system. The catchment area refers to the surface upon which rainwater falls and is collected for harvesting. Typically, this is the roof of a building. The size and type of catchment area significantly affect the volume of rainwater that can be collected. To determine the catchment area, one must measure the horizontal dimensions (length and width) accurately. The runoff coefficient (C) is a dimensionless factor that represents the portion of rainfall that actually becomes runoff and can be collected. It accounts for various factors such as surface type, slope, and land use. The coefficient varies between 0 and 1, with 0 indicating no runoff (100% infiltration) and 1 indicating all rainfall becomes runoff (no infiltration). Different surfaces have different runoff coefficients.

The equation used to calculate the rainwater harvesting potential is:

$$Harv.Pot. = Daily\ Precipitation\ (m) * Runoff\ Coefficient \\ * Catchment\ Area\ (m2)\ (25)$$

Regarding the Daily Precipitation, we acquired data from the Power Data Access Viewer tool provided online by NASA (*POWER | Data Access Viewer, Prediction of Worldwide Energy Resource*, n.d.). We acquired the daily precipitation data for the area the brewery lies from

December ’21 to December ’22. The data were acquired in mm/day and turned into m/day to acquire the result in m^3.

Watching the Charma brewery facilities in Google maps (Fig. 15), it is obvious that it is the main building in the middle that would serve as the potential catchment area. Using the app’s measuring tools, we managed to calculate its surface area as: $28 * 21 = 588m2$. Runoff coefficients for various rooftop materials are depicted in Fig. 16. For our case, without knowledge on the exact material of the Charma brewery’s chosen catchment area, we set the coefficient value at 0.9, which is a usual, and even conservative, value for industrial facilities’ rooftops. Thus, we calculated the daily harvest potential:

$$Daily\ harvest\ pot.(m3) = Daily\ precip.(m) * 588 * 0.9 = Daily\ prec(m) * 529.2 \quad (26)$$

Using eq. (26) we were able to create a dataset with the daily harvest potential of the proposed RWHS for a whole year.

The annual precipitation measured through the NASA tool was of around 452mm in a year. Trying to validate the accuracy of the data acquired, we directed our research at data provided by EMY (Hellenic National Meteorological Service). The only available precipitation data in the area were that of average monthly precipitation rates in the port of Souda -located 20km east of the Charma brewery site. The data consisted of the average precipitation for the years 1958-2010 and they were aggregated at around 615mm/year. There seemed to be a moderate disparity between the two values. Given, however, the hydrologically poor years of lately and the large temporal gap between the two, it was thought safe to assume that the 452mm per year was a value we could implement in our calculations. The rainwater time series for a year is depicted in Fig. 17.

Fig. 15. The Cretan Brewery facilities in Chania prefecture. Retreived from: Google maps

Description of Surface	Rational Runoff Coefficient, C
Unimproved Areas	0.35
Asphalt	0.95
Concrete	0.95
Brick	0.85
Roofs, inclined	1.00
Roofs, flat	0.90
Lawns, sandy soil, flat (<2%)	0.10
Lawns, sandy soil, average (2-7%)	0.15
Lawns, sandy soil, steep (>7%)	0.20
Lawns, heavy soil, flat (<2%)	0.15
Lawns, heavy soil, average (2-5%)	0.20
Lawns, heavy soil, steep (>7%)	0.30
Wooded areas	0.15

Fig. 16. Runoff Coefficient, C, depicting the proportion of the rainfall that will become runoff. From: (North Carolina Department of Environmental Quality, 2017)

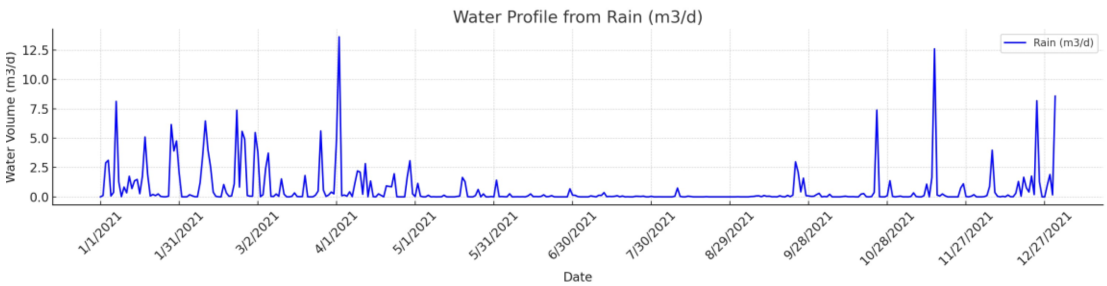

Fig. 17. Harvested rainwater time series

4.2.4.2 Cost

Taking into account the daily water needs of the industry, as they were assumed previously, the rainfall data, the possible rainfall capture, and the investment costs, a tank size of 16m^3 was deemed as appropriate -a full tank of such size being able to almost meet the water needs of one whole day. (Kakoulas et al., 2022) examines the implementation of a RWHS in the island of Chios, Greece and has performed thorough research on the pricing of each RWHS component. Considering that the prices for a 15m^3 non-domestic use tank, as examined in the paper, are very close to the ones for a 16m^3 tank, we used data provided for our own pricing. Table 5 shows the prices for major components of a RWHS with a tank capacity of 15-16 m^3. The adoption of that particular pricing on our part was based on the time proximity between that and this research and the fact that Greek market data were leveraged.

Table 5. Investment costs of a non-potable use RWHS. Adapted from: (Kakoulas et al., 2022)

	Cost (EUR)
Purchase and installation of the tank	2100
Purchase and installation of pump and electric equipment	400
Purchase and installation of drainage pipes in and out of tank	1600
Purchase and installation of rainwater filter	400

These costs account for the installation of a RWHS for non-potable uses. To reach potable standards, extra treatment is required. In our case the rainwater filter prices will serve as a necessary pre-filtration step. (Tran et al., 2021) proposes a rainwater treatment scheme to reach potable standards. The treatment system proposed is a complex filtration system (fiber filtration, coarse filtration, carbon cartridge, and UF) followed by UV sterilisation (2 consecutive bulbs to ensure optimum quality of the treated water). The paper provides detailed capital costs for all components proposed. However, the prices mentioned were not deemed safe to adopt uncritically: The paper was received in Oct. 2019 (meaning research had to be conducted no later than summer 2019) and research was conducted on three different sites in Vietnam. Thus, we performed a market search, only to verify the disparity in pricing: Given the exchange rate of Vietnamese Dong (VND) to USD/EUR, a UV bulb 12W in Vietnam at the time of that research was priced at 86 EUR, while our search provided with a moderately-priced 12W bulb of 128 EUR. The filtration system proposed cost 431 EUR. To avoid underestimation of costs, it was chosen to assume a pricing of 1.5 times more that the mentioned. Thus, our filtration system was priced at 647 EUR. Regarding the O&M costs, and similarly to aforementioned water treatment schemes, we needed to calculated the Electricity operational cost separately from the Maintenance (replacement) cost. Concerning the latter, the researchers' evaluation of the membranes' replacement cost is at a quarter of the complex filtration system's initial capital cost. We had to assume the same ratio, since calculating the exact cost and lifespan of each component in the complex filtration unit when used for rainwater treatment, would require practical experience. Furthermore, such values are hard to trace in literature since rainwater is rarely examined for potable use. For the 12W UV lamp replacement cost, the market search conducted showed a wide range of prices between 26 and 80 EUROS. Choosing conservatively, the cost was set at 60 EUR.

The Electricity (operational) cost was harder to measure and entailed extensive calculations and assumptions in order to be defined since no explicit data on capacity and energy consumption are provided. The researchers report 10,000 litres drinking water per month in the system analysed. Thus, we calculate the volume of treated water in a year to be 120m^3. The power cost was 1,200,000 VND. Our search on the electricity prices in Vietnam in 2019 concluded on an approximate 1864 VND/kWh. Thus, $\frac{1200000}{1864} = 643.78\frac{kWh}{year}$. To conclude on the energy demand per m^3 of treated rainwater: $\frac{643.78}{120} = 5.365\frac{kWh}{m3}$ (27). The proposed system, however, contains two 12W UV bulbs, adding up to the energy consumption. Moreover, two pumps (main pump and pressure pump) are used. In our proposed system, there is one pump and one UV bulb. That would mean we could safely assume an approximate 50% drop in energy consumption. Nevertheless, we assumed a 35% drop, not to underestimate other potential energy-intensive components in the final unit. Therefore, the final energy demand per m^3:

$$\frac{Energy\ demand}{m3} = 0.65 * (26) = 3.487 \frac{kWh}{m3} \quad (28)$$

Compared to other water treatment techniques examined previously, such energy consumption does indeed seem to be high. Nevertheless, it is validated by (Yan et al., 2018), who measures a decentralised rainwater treatment system (using similar treatment techniques) having an energy-intensity of 5.5 kWh/m^3.

Table 6 depicts all the costs related to the RWHS proposed -one that treats extensively the harvested rainwater to elevate its status to potable use.

Table 6. Total Investment Costs relating to Rainwater harvesting and treatment to potable standards

Component:	Tank	Pump	Drain. Pipes	Rainwater Filter (pre-filtration)	Complex filtration unit	UV bulb 12W
Initial Capital Cost:	2100	400	1600	400	647	128
Discount Rate (R)	0.1	0.1	0.1	0.1	0.1	0.1
Life time period (T)	10*	10	10	15	5	5**
EAC (EUR)	341.765	65.098	260.393	52.586	170.677	33.766

***** The tank priced in the study of (Kakoulas et al., 2022) was made of polyethylene. Were it metal or of higher-quality material, a higher life expectancy would have been chosen.

**Given life expectancy in the study (Tran et al., 2021)

Table 7 depicts all the Maintenance (Replacement)-related costs of the RWHS proposed.

Table 7. EAC calculation of the Maintenance-related costs of the RWHS

Component:	Membranes	12W UV bulb
Initial Capital Cost:	162	60
Discount Rate (R)	0.1	0.1
Life time period (T)	1*	5
EAC (EUR)	178.2	15.828

*****Calculated by (Tran et al., 2021) for their specific system and treatment needs

The annual rainwater harvest potential (with 2022 rainfall data) using formula (25):

$$\frac{Supply\ of\ rainw.}{year} = 588 * 0.9 * 452.5 = 239.5 \frac{m3}{year}$$

Table 8 shows the aggregated costs and the annual harvest of the RWHS proposed:

Table 8. Aggregated costs per category (Capital, Operational, Maintenance) for the RWHS

EA Capital Cost (EUR)	924.289
EA Maintenance Cost (EUR)	194.028
Operational (Electr.) Cost (kWh/m^3)	3.487
Harvested rainwater (m^3)	239.5

Thus:

$$Capex\text{RWHS} = \frac{924.289}{239.5} = 3.859\frac{EUR}{m3}\ (26)$$

$$Opex\text{RWHS} = \frac{194.028}{239.5} + 3.487 * 0.22 = 1.577\frac{EUR}{m3}\ (27)$$

$$Levelised\ Cost\ of\ Operation\text{RWHS} = (26) + (27) = 5.437\ (28)$$

4.2.4.3 Environmental Impact

Having calculated the energy consumption per m^3 of the RWHS treatment system, we needed yet to take into account the primary electricity factor and the CO_2eq. factor relating to Crete's grid mix. Thus,

$$Env.Impact\text{RWHS} = 0.989 * 2.9 * 3.487 = 10.001\frac{kg\ CO2eq.}{m3}\ (29)$$

4.2.5 Water Reuse

Brewery effluent is characterised by high organic load (Chen et al., 2021); its uncontrolled discharge can prove lethal for the local fauna (Ariyomo et al., 2021) and may be the cause of significant environmental pollution (Enitan et al., 2015). It is therefore obvious that intensive treatment processes are required for it to be reused safely. (Verhuelsdonk et al., 2021) considers a beer effluent reuse scheme, consisted of a flotation device, an MBR, a UF, and a RO system. It is important to notice that the system is fed by the effluent of a full-scale anaerobic reactor. That means that brewery effluent is pre-treated in the anaerobic reactor before it reaches the analysed system. That may have considerable effects on the overall sustainability of the process or even its ability to treat brewery effluent safely; it is open for examination whether the MBR-UF-RO system may be able to treat brewery wastewater to potable standards without the pre-treatment process. Here, lacking the resources of verifying this, and since the research examined does not provide any insights for the anaerobic reactor's costs and energy demands, we will assume that the aforementioned scheme is enough for the adequate treatment of brewery effluent.

4.2.5.1 Volume Capacity

Data acquired from Charma brewery showed a 5,250 m^3 water consumption for 2022. Out of this volume, the total beer production equaled to 889.820 m^3. The residual volume was assumed to be the potential capacity of the Reuse source. It should be noted, however, that this assumption can vary from industry to industry depending on the specific case's intricacies. Here, the volume of $5250 - 889.820 = 4360.18\ m3$ serves more as an indicator (to illustrate the vast potential of the water reuse scheme) rather than a based to real data value. Assuming a uniformly distributed Reuse capacity, we considered a 0 capacity during Sundays of 2022 and a constant capacity of 13.93 m^3 on the rest of the days. Fig. 18 depicts the time series of water Reuse capacity within a year.

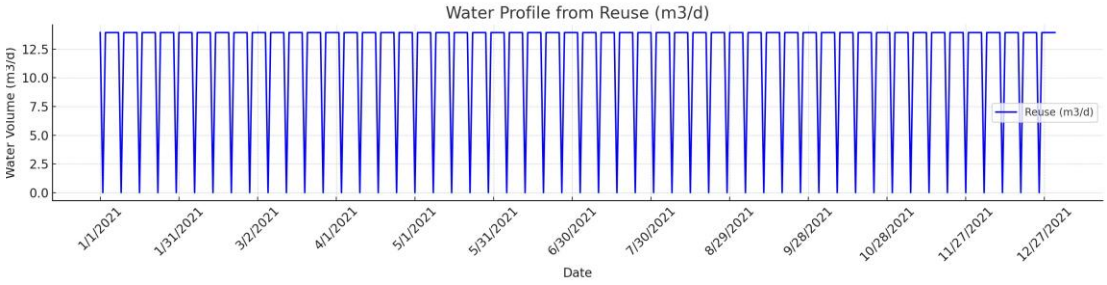

Fig. 18. Time series of the Reuse source profile regarding its 2022-related function

4.2.5.2 Cost

(Verhuelsdonk et al., 2021) provides both the Capex and the Opex for each one of the treatment methods consisting the treatment scheme. However, the assumed price of electricity in the paper was 0.15 EUR/kWh, a price at significant disparity to our assumption of 0.22 EUR/kWh. Had the paper included the electricity consumption (kWh/m^3) for all three treatment methods, we would be able to distinguish between the Operational (Energy) and the Maintenance Cost. Thus, we would be able to apply to the Operation Cost the value of our current kWh price. However, only the electricity consumption of the MBR is explicitly mentioned. Thus, regarding the MBR we were able to calculate the Maintenance cost and, distinctively, the Operational using the price of 0.15 EUR/kWh:

$$Given\ O\&M\text{MBR} = 0.25\frac{EUR}{m3}\ (30)$$

$$Energy\ Cost\text{MBR} = 0.15\frac{EUR}{kWh} * 0.92\frac{kWh}{m3} = 0.138\ \frac{EUR}{m3}\ (31)$$

$$Maintenance\ Cost\text{MBR} = (31) - (30) = 0.112\frac{EUR}{m3}\ (32)$$

$$Energy\ CostMBR_{0.22} = 0.92\frac{kWh}{m3} * 0.22 = 0.202\frac{EUR}{m3} (33)$$

Then, we calculated every part of the O&M cost (Operational-electricity and Maintenance) as to their percentage contribution to the overall O&M cost. These percentages would serve as an assumption base for two remaining treatment techniques (UF and RO). Following the percentage ratio, we calculated the two distinct costs. Lastly, we managed to derive the electricity consumption, which, in turn, was multiplied with the kWh price chosen in this thesis (0.22 kWh) to acquire the Operational Cost values:

$$\frac{Operational\ (Electr.)Cost}{O\&M\ cost} = 0.552 = 55.2\%$$

$$\frac{Maintenance\ Cost}{O\&M\ cost} = 0.448 = 44.8\%$$

Thus,

$$Maintenance\ Cost\text{UF} = 0.448 * GivenO\&M\text{UF} = 0.0672\frac{EUR}{m3}\ (34)$$

$$Operational\ (Electr.)Cost\_0.15\mathrm{UF} = GivenO\&M\mathrm{UF} - (33) = 0.0828\frac{EUR}{m3}\ (35)$$

$$Energy\ Cons.\mathrm{UF} = \frac{(35)}{0.15} = 0.552\frac{kWh}{m3}\ (36)$$

$$Energy\ CostUF_{0.22} = (36) * 0.22 = 0.121\frac{EUR}{m3}\ (37)$$

And considering the RO system:

$$Maintenance\ Cost\mathrm{RO} = 0.448 * GivenO\&M\mathrm{RO} = 0.273\frac{EUR}{m3}\ (38)$$

$$Operational\ (Electr.)Cost\_0.15\mathrm{RO} = GivenO\&M\mathrm{RO} - (38) = 0.337\frac{EUR}{m3}\ (39)$$

$$Energy\ Cons.\mathrm{RO} = \frac{(39)}{0.15} = 2.245\frac{kWh}{m3}\ (40)$$

$$Energy\ CostRO_{0.22} = (40) * 0.22 = 0.494\frac{EUR}{m3}\ (41)$$

The total O&M cost of the reuse treatment scheme was calculated at:

$$Opex\mathrm{Reuse} = (33) + (32) + (37) + (34) + (41) + (38) = 1.27\frac{EUR}{m3}(42)$$

Regarding the Capex, research values were taken unchanged, considering the relative proximity both in time (paper received in 2020) and place (case study taken place in Germany). Apart from the capital costs referring to the three techniques, it also included the cost of a buffer tank and a flotation unit:

$$Capex\mathrm{Reuse} = 0.78\frac{EUR}{m3}(43)$$

$$Levelised\ Cost\ of\ Operation\mathrm{Reuse} = (42) + (43) = 2.05\frac{EUR}{m3}(44)$$

4.2.5.3 Environmental Impact

The total electricity demand of the operation is given by the aggregated:

$$Total\ Electr.Consumption\mathrm{Reuse} = 0.92 + (36) + (40) = 3.717\frac{kWh}{m3}(45)$$

$$Environmental\ Impact\mathrm{Reuse} = (45) * 2.9 * 0.989 = 10.66\ \frac{kg\ CO2eq}{m3}$$

However, the fact of the treatment and reuse of brewery wastewater leads to a drop to the volume of wastewater discharged to the municipal sewer system. From the calculations regarding the Municipal water, it became obvious that a significant part of the consumed energy comes from the operation of the sewerage network and the biological treatment of waste water. Thus, with a great amount of the brewery's effluent not discharged, the environmental impact of the Reuse source should be reduced. Conservatively, a 10% reduction is chosen, ensuring that the overall impact of the process is not underestimated. Therefore, we calculate the final impact of the treatment method as:

$$Environmental\ Impact\mathrm{Reusefinal}\ = 10.66 * 0.9 = 9.594\ \frac{kg\ CO2eq.}{m3}\ (46)$$

4.3 Linear Programming (LP) formulation

Linear Programming (LP) is a mathematical method used to find the best possible outcome or solution from a given set of requirements or constraints. It is particularly useful for making decisions in situations where resources are limited. LP is employed in various fields, from manufacturing to transportation, to optimise processes by minimising costs or maximising profits. In the context of this research, LP aids in identifying the optimal mix of alternative water sources to satisfy the daily water demand of an industry, ensuring minimised costs and environmental impacts.

Our study focused on exploring alternative water sources for an industrial setup. The sources, thoroughly described in the previous chapters, under consideration were:

- Municipal network water
- Groundwater
- River water
- Rainwater
- Water Reuse,

with each of these sources coming with its own set of characteristics in terms of availability (capacity), cost, and environmental impact, as they were defined in the previous chapter.

The decision variables are the daily volumes used by each source: Q1 for Municipal water, Q2 for River water, Q3 for Groundwater, Q4 for Rainwater, and Q5 for Water reuse. Regarding the parameters and constants, we have:

- The upper limit or capacity of each source is represented by U1, U2, U3, U4, and U5 respectively.
- The cost of using each source, in EUR/cubic metre, is given by C1, C2, C3, C4, and C5 respectively.
- The environmental impact of using each source, in kg CO_2eq/cubic metre, is represented by E1, E2, E3, E4, and E5 respectively.
- The daily demand for water in the industry is symbolised as Qd.

The goal is to minimise the combined daily cost and environmental impact of using the water sources. The objective function can be represented as:

$$\min Z = \sum_{i=1}^{5} Qi * (Ci + Ei) \ (47)$$

Regarding the constraints, they ensure that the chosen water sources meet the daily demand without exceeding their respective capacities and are economically viable for the industry. These are:

1. The sum of the water from all sources should meet the daily demand:

$$\sum_{i=1}^{5} Qi = Qd \ \ (48)$$

2. No source should exceed its capacity:

$$Qi \leq Ui \ for \ i = 1, 2, \ldots, 5 \ (49)$$

3. Each source should have the potential to cover at least 10% of the industry’s annual needs to justify its investment cost:

$$Ui \geq 0.1 * 365 * Qd, for \ i = 1, 2, \ldots, 5 \ (50)$$

Overall, and provided succinctly, our LP problem is as such:

Obj. Function: $\min Z = \sum_{i=1}^{5} Qi * (Ci + Ei)$

Subject to: $\sum_{i=1}^{5} Qi = Qd$

$Qi \leq Ui \, for \, i = 1, 2, \ldots, 5$

$Ui \geq 0.1 * 365 * Qd, for \, i = 1, 2, \ldots, 5$

4.4 Formulating the LP in the Python Environment: Scenario-driven analyses and addressing the dynamic Water Profiles complexity

Following the formulation of the LP problem, it was transformed into an algorithm within the Python environment. Python was considered as the ideal choice for this optimisation task, given its strengths in math and data processing. This algorithm aimed to find the best blend of water sources for each day over a year, with a focus on cost and environmental concerns. To do this, the algorithm used data like the cost and environmental impact of each water source, the daily water needs of the industry, and the maximum amount of water available from each source. We also adjusted the weights of cost and environmental impact based on the specific needs and goals of different scenarios. After running the algorithm, we got various results. These results, in numbers and visuals, help clearly understand the best strategy for sourcing water, aiding informed decision-making. In Fig. 19 a flow chart of the main algorithm processes is illustrated. This will help in visually understanding the primary flow of the algorithm.

In the algorithm developed, data related to the daily water capacities of five different sources and the daily water demands are initially loaded. Essential constants such as cost, environmental impact, and their respective weights for the objective function are defined. The data undergoes a normalization process for both cost and environmental impact metrics to ensure a comparable scale. An essential step in the optimisation process involves determining the sources for inclusion in the final calculation based on their annual capacity, ensuring it's at least 10% of the yearly total demand. With the determined sources, a linear programming problem is solved daily, aiming to minimise a weighted sum of cost and environmental impact while adhering to various constraints, such as daily capacities and demand requirements. Post optimisation, the results are stored, visualised, and analysed in various forms including day-to-day water usage per source, total yearly usage, daily costs, and environmental impacts, and the percentage of each water source's capacity that was utilised. The algorithm was formulated in three distinct forms: The first one could be considered a “balanced form”, where the weights assigned to costs and environmental impact values are 65 and 35 respectively. This suggests that the company seeks to perform its water diversification plan having a balanced approach towards the CO_2 emissions of the treatment techniques applied and the cost benefit expected. The other two scenarios could be labeled as the “cost-focused” and the “eco-friendly” scenarios respectively. In the former, the optimisation was mainly focused on the cost benefit of the potential new blend of water coming from various sources, while in the latter the algorithm was tweaked in order to put significant emphasis on achieving the least possible impact on the environment by minimising the treatment processes that, according to our analysis, require much energy and, thus, contribute the most to greenhouse gases emissions.

Investigating various conditions in optimisation offers valuable insight. By adjusting the relative importance of cost-effectiveness and environmental impact, one may model the results under different strategic constraints. Similar methods are helpful for decision-makers who may have to deal with a variety of issues. For example, cost-effectiveness may be crucial during recessions or budgetary restrictions, while an eco-friendly approach might be essential given the growing emphasis on sustainability, environmental laws, and the growing worldwide, and particularly in the West, emphasis on corporate social responsibility.

Regarding the Water profiles' (capacities) modelling in the algorithms, a general outline has to be sketched. The sources may be split into two categories: the first one is consisted of the ones that have a tap-like function in the optimisation algorithm. Municipal, Groundwater and River water provide a relatively consistent amount of water each day: Municipal is set to very large potential, representing the unlimited amount of tap water the industry can currently utilise; Groundwater is set to a steady 11.25 m^3/day, representing the lack of excessive aquifer exploitation, and River water, while highly fluctuating, still exhibits a tap-like contribution to the system -the presence of adequate river flow makes it available, while the months it is inaccessible the system will have to turn to other source in order to replenish the gap. In essence, all the three sources mentioned here remain indifferent towards the internal processes taking place in optimisation.

On the other hand, Rainwater harvest and Reuse exhibit dynamic variations. Water reuse has its availability tied to the daily consumption patterns of the industry, making its profile dynamic in nature. Reuse constitutes a fraction of the previous day's water usage, meaning that its profile has to be updated daily. For simplicity reasons here, we chose a static profile based on the last year's uniformly distributed water residue. However, in future research, the daily reuse potential must account for the 60% of the previous day's water consumption (taking a conservative stance towards effluent availability) and has to be defined in a dynamic way on a daily basis.

Regarding rainwater, the dynamic nature of its profile is incorporated in the algorithm. Rainwater, on its part, is also directly linked to the daily optimisation results regarding its capacity: On days when rainwater isn't tapped for use, the harvested amount is accumulated with previous volumes. This aggregation continues until it reaches a predefined limit, in our case, 16 cubic meters, which is the size of the harvest tank chosen in our analysis in the previous chapters. Once this threshold is reached, further accumulation is halted. On the flip side, when rainwater is utilised on any given day, the volume of its contribution is deducted from the previously aggregated total. This approach, applied throughout the year, consists of the dynamic nature of the Harvested rainwater's profile.

The careful planning of all the problem's intricacies and their proper modelling in the algorithm is crucial for the proper functioning of the proposed systems. Regarding the Cost and Environmental Impact of each source, they were introduced as constants in the algorithm, according to previously-described calculations. Table 9 depicts all these values for the totality of the sources examined. Each one of the two lines would be stored as a list in the Python environment and would serve as a constant which, among others, was to be the basis of the optimisation process.

Table 9. Cost and Environmental Impact values for all 5 sources examined

	Municipal	River water	Groundwater	Rainwater	Reuse
Cost (EUR/m^3)	1.742	1.522	1.131	5.382	2.05
Env. Impact (kg. CO_2eq./m^3)	12.279	1.764	7.775	10.001	9.594

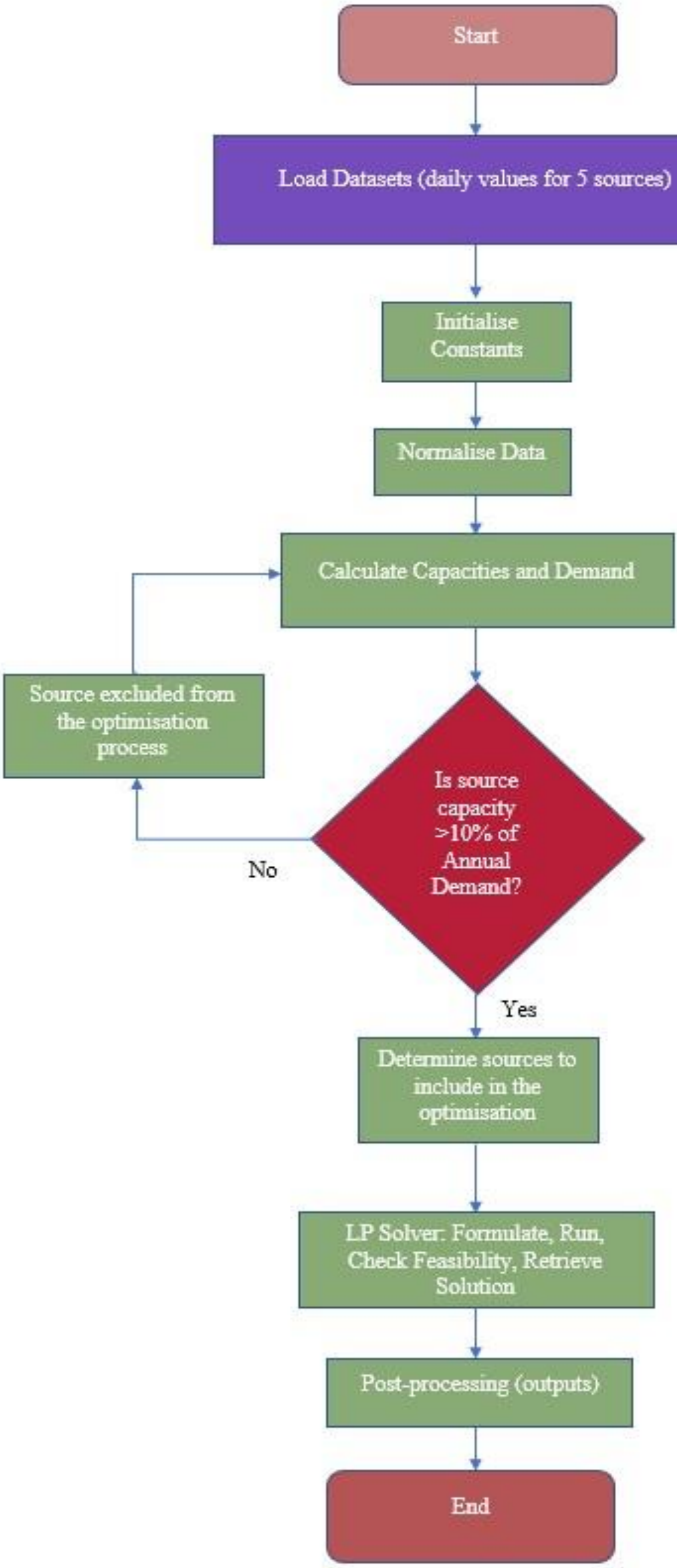

Fig. 19. Flow chart depicting the main processes taking place in the algorithm

4.4.1 Scenario no.1 – “Balanced approach”

4.4.1.1 Structure -Scenario no.1

In our water optimisation model, the initial step is data preparation. To this end, we import the necessary Python libraries and modules essential for our analysis. Two primary datasets are loaded for evaluation: WaterProfiles_Modified.csv, which houses the water profiles delineating the availability from each source for every day, and daily_water_demand_2021.csv that presents the daily water demand values.

The foundation of our analysis hinges on the constants we initialised. These constants represent the cost (denoted by C) and the environmental impact (represented by E) associated with each water source. To provide a balanced perspective in our model, weights are attributed to both the cost and the environmental impact. Specifically, weights w_c and w_e are set at 65 and 35, respectively. Prior to diving into the algorithm's logic, it's imperative to normalise the data. This ensures that the range of cost and environmental impact values are suitably adjusted for subsequent optimisation.

The core logic of the algorithm initiates by identifying eligible water sources. For a source to be deemed eligible, it should be capable of catering to a minimum of 10% of the total annual demand. With the eligible sources pinpointed, the algorithm proceeds with a daily optimisation loop. Throughout the 365 days of the year, the algorithm formulates a linear programming problem for each day. The objective is to strike an equilibrium between the cost and the environmental impact. By solving this problem, we can deduce the optimal daily water intake from the eligible sources, with the caveat that each source's contribution lies between 0 and that day's water requirements. As this loop progresses, the algorithm meticulously logs the daily solutions and the success rate of the optimisation.

Post optimisation, data manipulation is undertaken to render the results more comprehensible. The daily solutions are transformed into a reader-friendly format. From this manipulated data, we can ascertain the annual usage for each water source. In addition, the algorithm computes the daily total costs and environmental impacts. This paves the way for the calculation of two pivotal metrics: the LCOW and the environmental impact per cubic meter.

To encapsulate our findings, a series of visualisations are generated. A composite plot showcases the annual water usage juxtaposed with the capacity utilisation of each source. On a day-to-day basis, the total cost and environmental impact are delineated through graphical plots. For a more segmented view, pie charts illuminate the relative contributions of each water source to the overall cost and environmental footprint. Lastly, an area chart vividly illustrates the distribution of daily water usage. Table 10 depicts the aforementioned structure of the algorithm in a concise way.

Table 10. A concise view of the algorithmic structure designed

Data Preparation	**Imports**	Necessary Python libraries and modules
	Loading Datasets	WaterProfiles_Modified.csv: Contains water profiles (availability for each source on each day).
		daily_water_demand_2021.csv: Represents daily water demand values.
	Constants Initialisation	Cost (C) and environmental impact (E) for each water source
		Weights (w_c and w_e) for cost and environmental impact, respectively are defined in 65 and 35 to illustrate the balanced approach.
	Data Normalization	Adjusts the range of cost and environmental impact values for optimisation.
Algorithm Logic	**Determining Eligible Sources**	Only includes sources capable of meeting at least 10% of the yearly total demand.
	Daily Optimisation Loop	Constructs a linear programming problem to balance cost and environmental impact
		Solves the problem to determine optimal water intake from eligible sources
		Each source must contribute no less than 0 and no more than the daily water demand.
		Records the daily solution and the optimisation's success status
	Data Manipulation	Converts daily solutions into a readable format
		Computes yearly usage per source.
		Calculates daily total costs and environmental impacts
		Computes key metrics: LCOW and environmental impact per m^3
Visualisation and Reporting	**Generates a series of plots to visualise results**	Yearly water usage combined with capacity utilisation of each source
		Daily total cost and environmental impact.
		Pie charts of the relative contributions of each source to total cost and env. impact
		Area chart displays daily water usage distribution
		Heatmaps of sources’ contribution throughout the year

4.4.1.2 Results -Scenario no.1

The algorithm's results towards the sources' overall contribution are depicted in Table 11 below.

Table 11.Contribution results per source for the "Balanced" scenario

	Municipal	River water	Groundwater	River water	Reuse
Total Annual Usage (m^3)	129.13	1910.05	2542.57	0	668.254

Economic and Environmental Metrics:

- Total Annual Cost: €7,377.6
- Total Environmental Impact: 31,134.62 kg CO_2eq
- LCOW (€/m³): 1.405
- Environmental Impact (kg CO_2eq/m³): 5.93

The implemented algorithm reveals insights into the optimised water source utilisation for industrial consumption. Groundwater emerges as the most heavily relied-upon source, accounting for approximately 61.92% of its total annual capacity. This is followed by the river at 37.48% and reuse water at 15.33%. The municipal source witnessed a quite low-volume utilisation and rainwater was not utilised at all since its capacity did not exceed the 10% threshold set in order to be inserted into the optimisation process.

The crucial factor here is the comparison between the newly emerged LCOW and Environmental Impact factors and their pre-optimisation values. Pre-optimisation in our context is considered the exclusive municipal network water usage by the industry, along with its LCOW and Environmental Impact. Thus, the comparison is visualised in Table 12.

Table 12. Pre- and post-optimisation comparison of the major metrics: LCOW and Environmental impact -"Balanced" Scenario algorithm

Metric	**Pre-Optimisation**	**Post-Optimisation**	**Percentile Difference (%)**
LCOW (€/m³)	1.742	1.405	-19.331
Environmental Impact (kg CO_2eq/m³)	12.279	5.93	-51.701

A considerable drop is observed, both in Cost and Environmental Impact of the optimised blend of water. Thus, it is concluded that the diversification of water sources can be beneficial and sustainable, both environmentally and economically.

Next, the plots and charts are depicted for a visual representation of the results and an overview of the balance between the alternative water sources' contribution. The bar chart (Fig. 20) delineates the total yearly water consumption segregated by source. Groundwater distinctly stands out as the most utilised source, followed by the river and reuse sources. In contrast, municipal and rainwater sources have a minimal or no contribution to the annual water intake. The dominance of groundwater signifies its strategic importance in the industry's water supply, along with river water intake. Water reuse has also a considerable contribution the annual blend, thus further enhancing the industry’s sustainability efforts. From the percentage of capacity utilised bars, it becomes evident that all sources have the possibility to considerably increase their contribution.

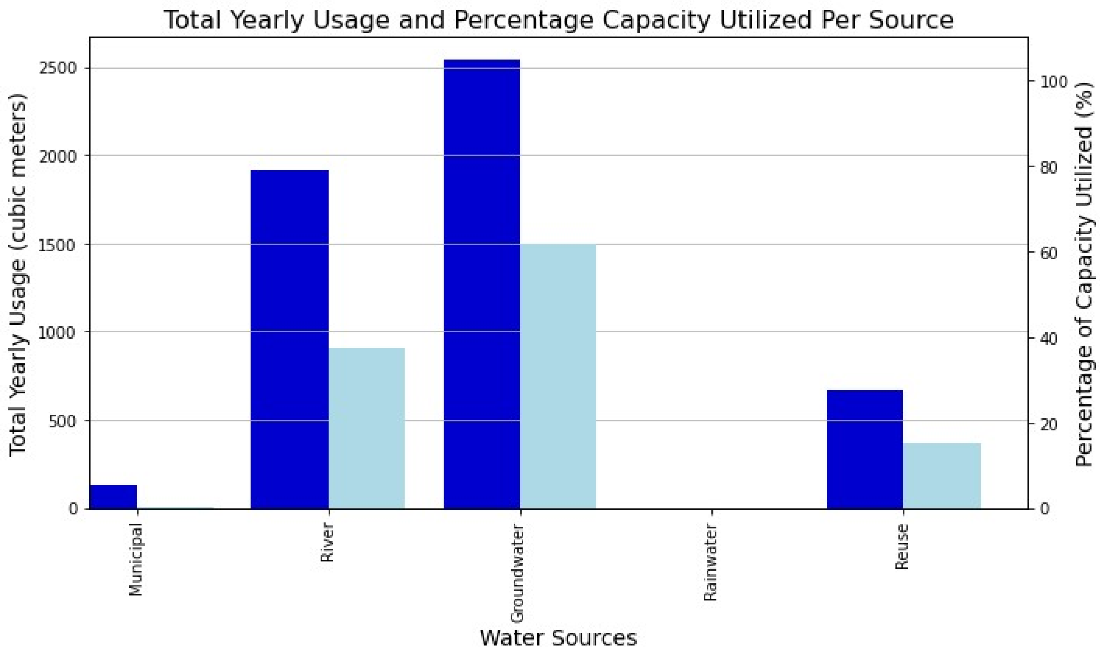

Fig. 20. Total yearly usage per source in volume and as a percentage to the annual capacity (“Balanced scenario” no.1)

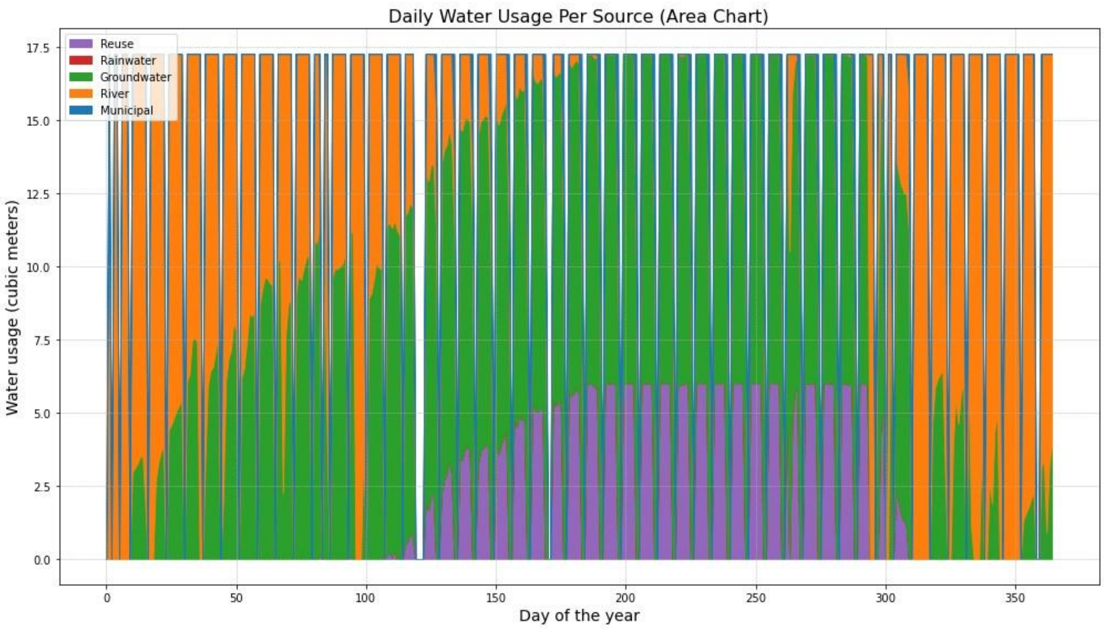

Fig. 21. Area chart depicting the daily usage for each source (“Balanced scenario” no.1)

Fig. 21 is an area chart that showcases the day-to-day water usage for different sources throughout the year. Each source is represented by a distinct line, elucidating its daily contribution to the industry's water supply. Groundwater emerges as the dominant source, with its usage notably consistent across the year, while the river and reuse sources display more variability. The municipal source demonstrates minimal utilisation, and the rainwater source remains, as mentioned, untapped due its exclusion from the optimisation loop.

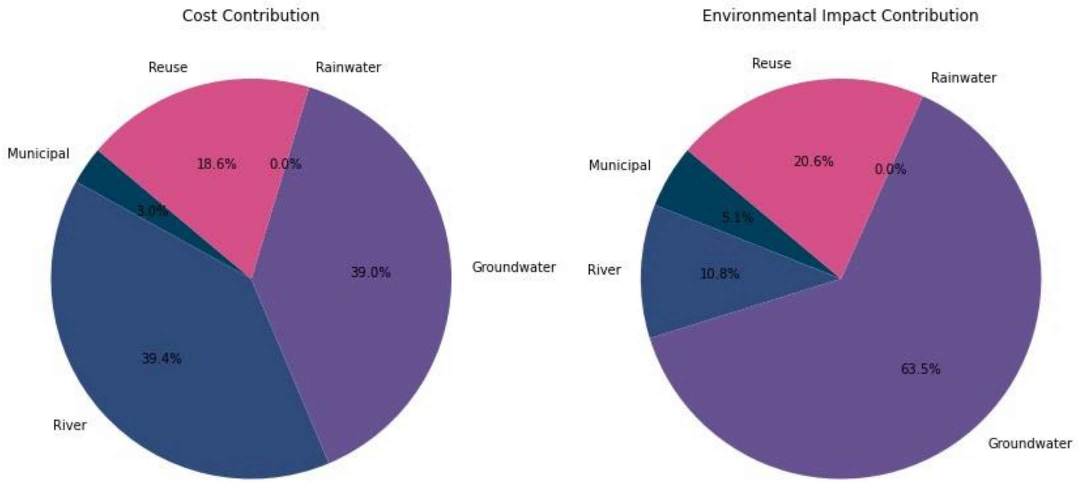

Fig. 22. Contribution of each source to the total cost and environmental impact of the proposed system (“Balanced scenario” no.1)

The pie chart (Fig. 22) is segmented into two pie charts and elucidates the distribution of both economic and environmental contributions of each water source. On the left, the "Cost Contribution" pie chart offers a glimpse into the financial implications of each source. Groundwater, despite being a major contributor in terms of volume, doesn't dominate the cost as might be expected, suggesting its cost-effectiveness. The river and reuse sources also have significant slices, indicating considerable expenses associated with these sources. On the right, the "Environmental Impact Contribution" chart reflects the ecological footprint, measured in kg CO_2 equivalent, of each source. Groundwater, mirroring its heavy usage, has the most pronounced environmental impact. This underscores the need to evaluate the sustainability of relying heavily on this source. The river water source, on the other hand, despite being moderately utilised does not contribute as much to the total impact, suggesting its comparatively small contribution to energy consumption and CO_2 emissions. Reuse emerges as having the second largest impact despite being only the third most utilised source, due to the high energy consumption needed for reusing brewery effluent. In essence, while certain sources may be economically favourable, their environmental repercussions might demand attention, suggesting a complex interplay between cost and sustainability in the water sourcing strategy.

Next, a heatmap is produced: Fig. 23 illustrates the water contribution per source over the course of the year. It is obvious that Groundwater, with its consistent supply, forms the backbone of the industry's water needs. However, the dynamic interplay between River, Municipal, and Reuse sources underscores a strategic approach in water resource management: The industry appears to leverage Reuse water primarily as backup or supplementary sources, stepping in during periods when the River source is insufficient or unavailable (mainly summer and early autumn months). Furthermore, Municipal water is itself utilised as a supplementary source to Reuse; when the latter does not have the capacity to meet the needs of the industry, the former is turned into the main backup source. This adaptive strategy ensures that the industry's water demands are met throughout the year, regardless of external challenges or constraints. Lastly, one may notice that there is a distinct non-contribution day within each week; this reflects one non-operation day in every week (Sunday).

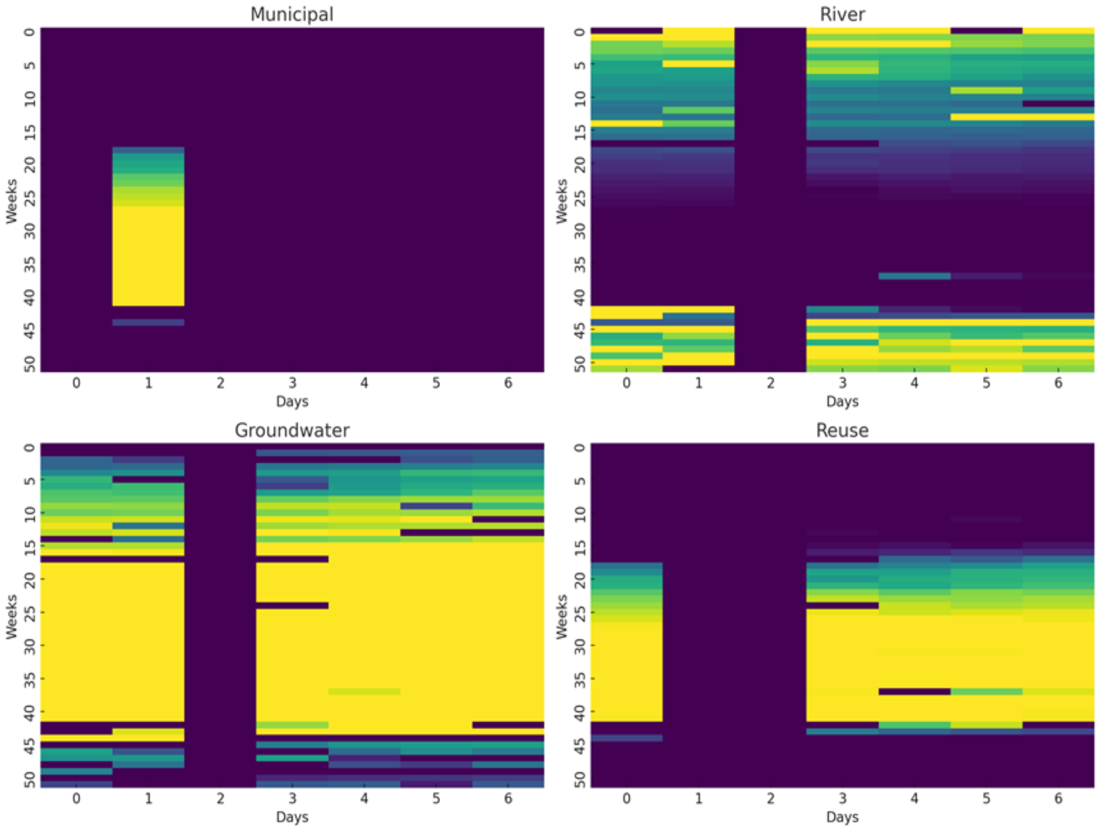

Fig. 23. Heatmap of each (active) source's contribution within the year ("balanced" scenario)

For the last section of the graphs' presentation, we focused on the two months of the year that River water, being the source that -with its fluctuations in availability- plays the most crucial role in the balance of the overall water intake, presents its lowest and highest availabilities. These were found to be August (with multiple days presenting complete cessations of river flow) and November, when a peak of an approximate $600m^3$ flow was observed in one particular day. Fig. 24 illustrates the daily contributions of each water source for August.

It becomes evident that our understanding of the system's internal logic and processes, as explained previously, is here fully demonstrated. With River water having no flow over the course of the month, Reuse fills in the gap. Municipal water serves as a backup to the latter. With River water's absence, a source which is characterised by highly fluctuating capacities and, thus, contributions, the monthly operation of the water intake system seems surprisingly evenly structured.

The water intake system in Fig. 25 presents high variation, precisely because it is now the River water source that mainly feeds it. It is notable how Groundwater is marginalised in its used during that month, with River dominating the blend. Furthermore, the supplementary role of the Reuse and Municipal sources is vividly illustrated by the fact that they contribute to the water intake blend only in the one day that the combined supply by River and Groundwater was not enough to meet the needs if the industry, due to low river flow. Overall, it is explicitly depicted that River water is the most favourable source, when it is available, due to it being characterised by low cost and environmental impact alike.

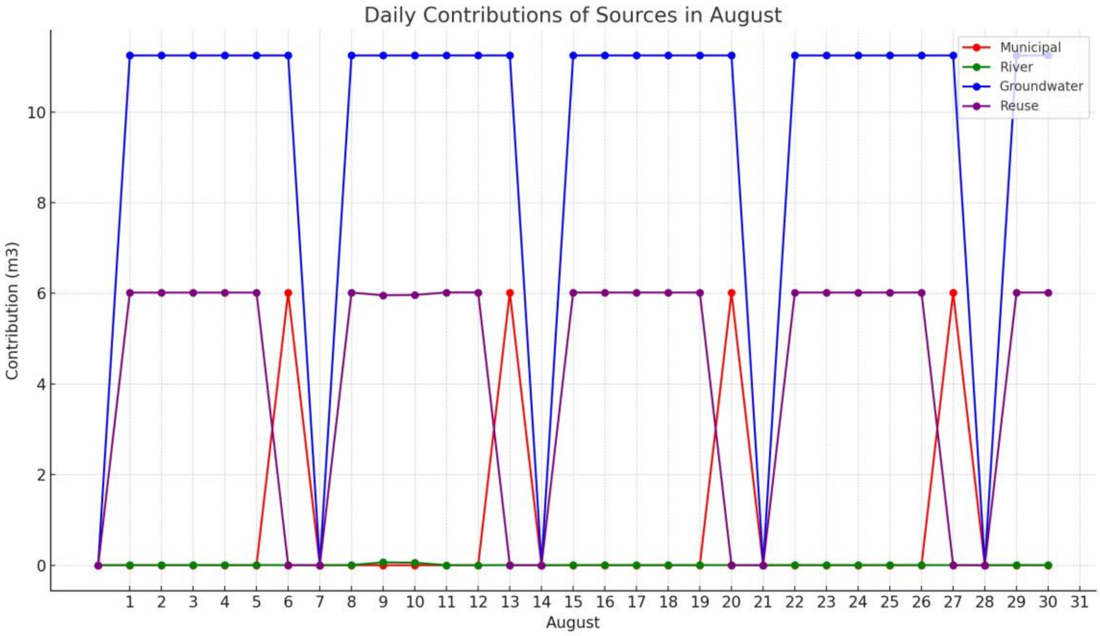

Fig. 24. Daily contributions of all four (active) sources during August ("balanced" scenario)

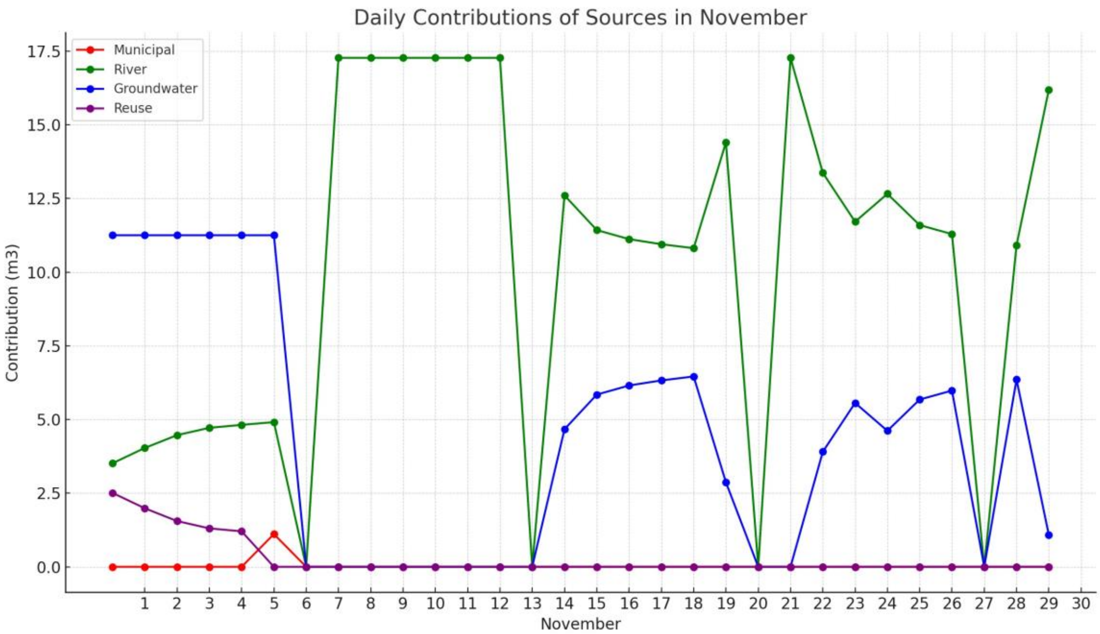

Fig. 25 Daily contributions of all four (active) sources during November ("balanced" scenario)

4.4.2 Scenario no.2 – "Cost-focused"

4.4.2.1 Structure -Scenario no.2

The structure of this algorithm remains practically unchanged in comparison to the previous one. However, in transitioning from a balanced optimisation scenario to a cost-focused one, a significant alteration was made. The weights assigned to the cost and environmental impact were adjusted. While the balanced scenario sought a more even-handed approach with weights of 65% for cost and 35% for environmental impact, the cost-focused scenario heavily prioritised cost with a stark 90-10 split. This shift means that the algorithm will predominantly focus on minimising expenses, even if it results in a higher environmental toll. Practically, the algorithm was made to be more aggressive in prioritizing cost, potentially at the expense of a higher environmental impact or over-reliance on specific water sources.

4.4.2.2 Results -Scenario no.2

The algorithm's results towards source overall contribution for the cost-focused scenario are depicted in Table 13 below.

Table 13. Contribution results per source for the "Cost-focused" scenario

	Municipal	River water	Groundwater	River water	Reuse
Total Annual Usage (m^3)	797.386	1032.614	3420	0	0

Economic and Environmental Metrics:

- Total Annual Cost: €6828.70
- Total Environmental Impact: 38,203.14 kg CO_2eq
- LCOW (€/m^3): 1.301
- Environmental Impact (kg CO_2eq/m^3): 7.2768

In this scenario, groundwater notably emerges as the paramount water source, accounting for a significant 83.29% of its total annual capacity, emphasising its crucial role in fulfilling water demands when driven by cost considerations. Following groundwater, the river source also plays a substantial role, utilising roughly 20.26% of its yearly capacity. In contrast, reuse source is not utilised at all, with the municipal source representing a small but significant contributor the annual blend. This non-reliance on reuse must be attributed to the overarching aim of cost-effectiveness, which sidelines this source due to its non-competitive nature in terms of cost, despite its more favourable positioning than that of municipal water in terms of their environmental impact.

The crucial factor here, again, is the comparison between the newly emerged LCOW and Environmental Impact factors and their pre-optimisation values. The comparison is visualised in Table 14.

Table 14. Pre- and post-optimisation comparison for the "Cost-focused" scenario no.2

Metric	**Pre-Optimisation**	**Post-Optimisation**	**Percentile Difference (%)**
LCOW (€/m^3)	1.742	1.301	-25.333
Environmental Impact (kg CO_2eq/m^3)	12.279	7.277	-40.738

The table illustrates how the cost-focused scenario, even with its great focus on the financial aspect of the problem, still manages to propose a blend of which leads to a 40% smaller CO_2-related impact. Furthermore, the 25% drop in the LCOW is substantial, leading to considerable benefits for the company.

Next, the plots and charts are depicted for a visual representation of the results and an overview of the balance between the alternative water sources' contribution:

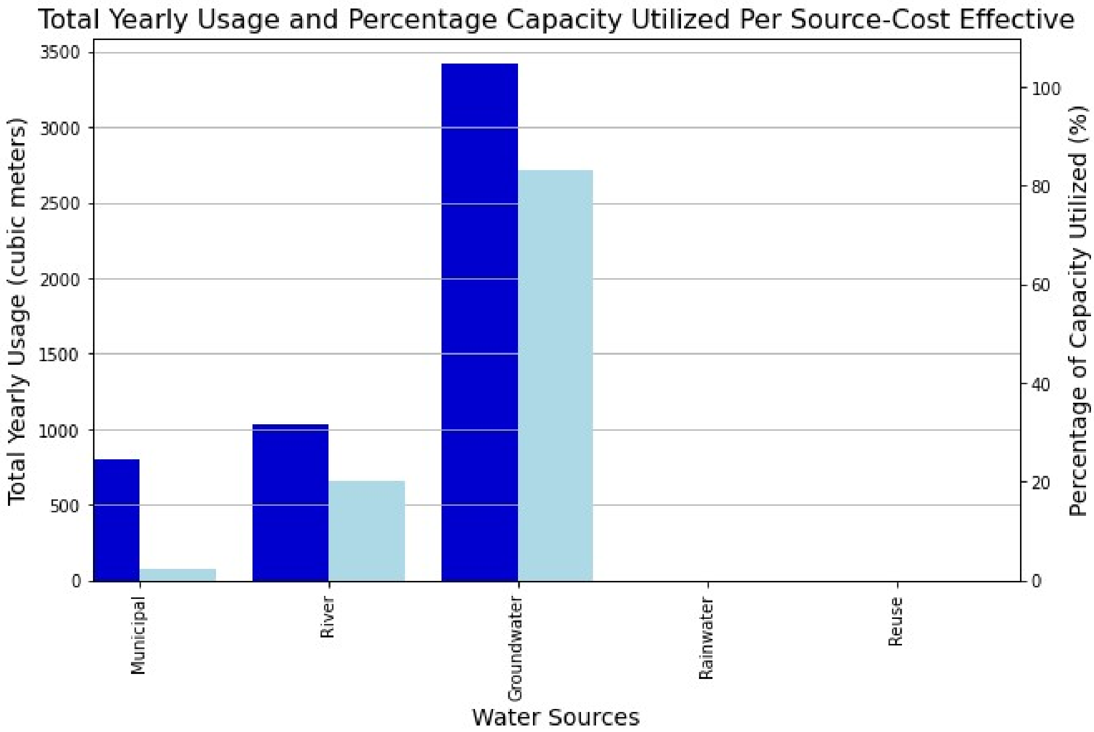

Fig. 26 Total yearly usage per source in volume and as a percentage to the annual capacity ("Cost-focused scenario" no.2)

The bar chart (Fig. 26) confirms that Groundwater and River sources are the primary contributors, with Groundwater being utilised close to its maximum capacity, with River water following. The Municipal water source also has some contribution, with Reuse being totally excluded from the optimised blend.

The area chart (Fig. 27) vividly demonstrates the daily water usage from each source throughout the year. Notably, the Groundwater and River sources are predominant contributors, ensuring a steady supply to meet the daily demand. Groundwater seems to be extracted in a high, steady volume, thus exploiting its cost-effectiveness, while the River water covers the demand gap when there is sufficient flow. We observe a large contribution of Municipal water during the summer and early autumn months, when the River water flow drops to minimal levels.

The pie charts (Fig. 28) elucidate the distribution of cost and environmental impact across the sources. It's evident that the Groundwater not only caters to the majority of the water demand but also accounts for most of the associated cost and environmental impact. However, a noticeable aspect of the pie charts is the position of the River water towards that of the Municipal. Even though its volume contribution is much larger (1032 compared to 797m^3, accounting for a 4.48% difference as to the total annual needs of the industry) its cost contribution difference is only 2.7% higher, with its environmental impact reaching an impressive 20.8% drop out of that of the Municipal water intake. This vividly illustrates the river water source's dominance on both evaluation aspects of this research.

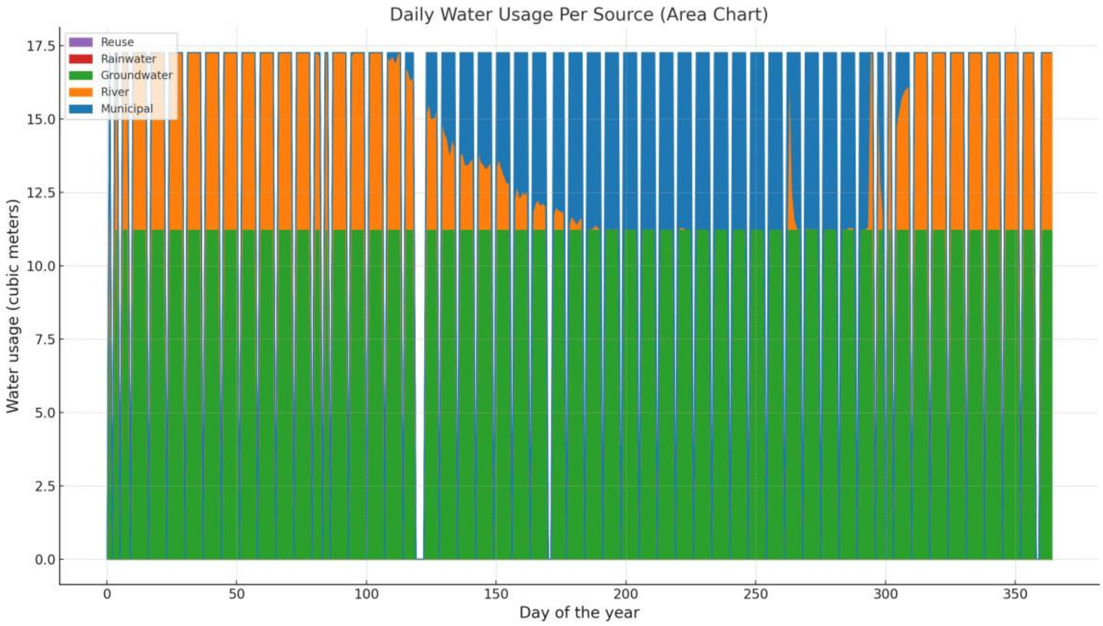

Fig. 27 Area chart depicting the daily usage for each source ("Cost-focused scenario" no.2)

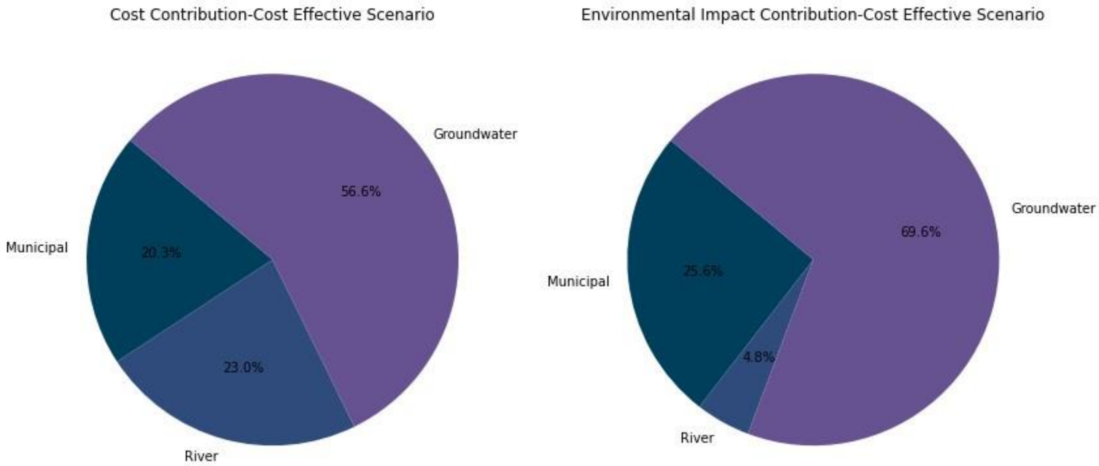

Fig. 28 Contribution of each source to the total cost and environmental impact of the proposed system ("Cost-focused scenario" no.2)

Fig. 29 (heatmap) illustrates the water contribution per source over the course of the year. The industry in this cost-focused scenario primarily operates, as already mentioned, on a dual-source system of Groundwater and River Water, leveraging their substantial contributions. While Groundwater exhibits a steady contribution throughout the year and is heavily utilised, River water has strong periodic contributions with distinct gaps in the summer months when Derianos river becomes dry. Municipal source is, thus, leveraged primarily as a backup or supplementary source. When River Water is insufficient, the industry pivots to Municipal water to ensure continuous operations. This strategic utilisation underscores an adaptive water resource management approach, wherein Municipal water acts as a safety net during periods of reduced river flows. Here too, as mentioned previously, there is a distinct non-contribution day within each week, reflecting a non-operation day for the industry (Sunday).

As in the previous scenario analysis, we also focused on the two months of the year; August and November, when River water presents its lowest and highest availability respectively. Fig. 30 illustrates the daily contributions of each water source for August. With water intake system now utilising only three of the sources, it is obvious that the lack of river water flow and, therefore, contribution, leads to a major contribution of the Municipal water source in order for the daily needs to be met. Both sources utilised, have a steady usage throughout the month.

Fig. 31 presents the daily contributions of each water source in November. The water intake system now does not present such a high variation as it did in the balanced scenario. While in that scenario Groundwater was marignalised, it is now presented as the dominant contributor of the overall water supply. The reason for this is that the optimisation focuses heavily on the Groundwater source due to it having the lowest cost; River water is never utilised as the dominant source in the blend despite its high availability at times. The minimal weight of the environmental impact factor is evidently affecting the optimised solution towards the principal use of Groundwater, leaving the River water as the second most preferred option. The Municipal is, again, supplementary to the River source, with it being utilised only in the days when the former is insufficient to meet the remaining volume of water the industry still needs.

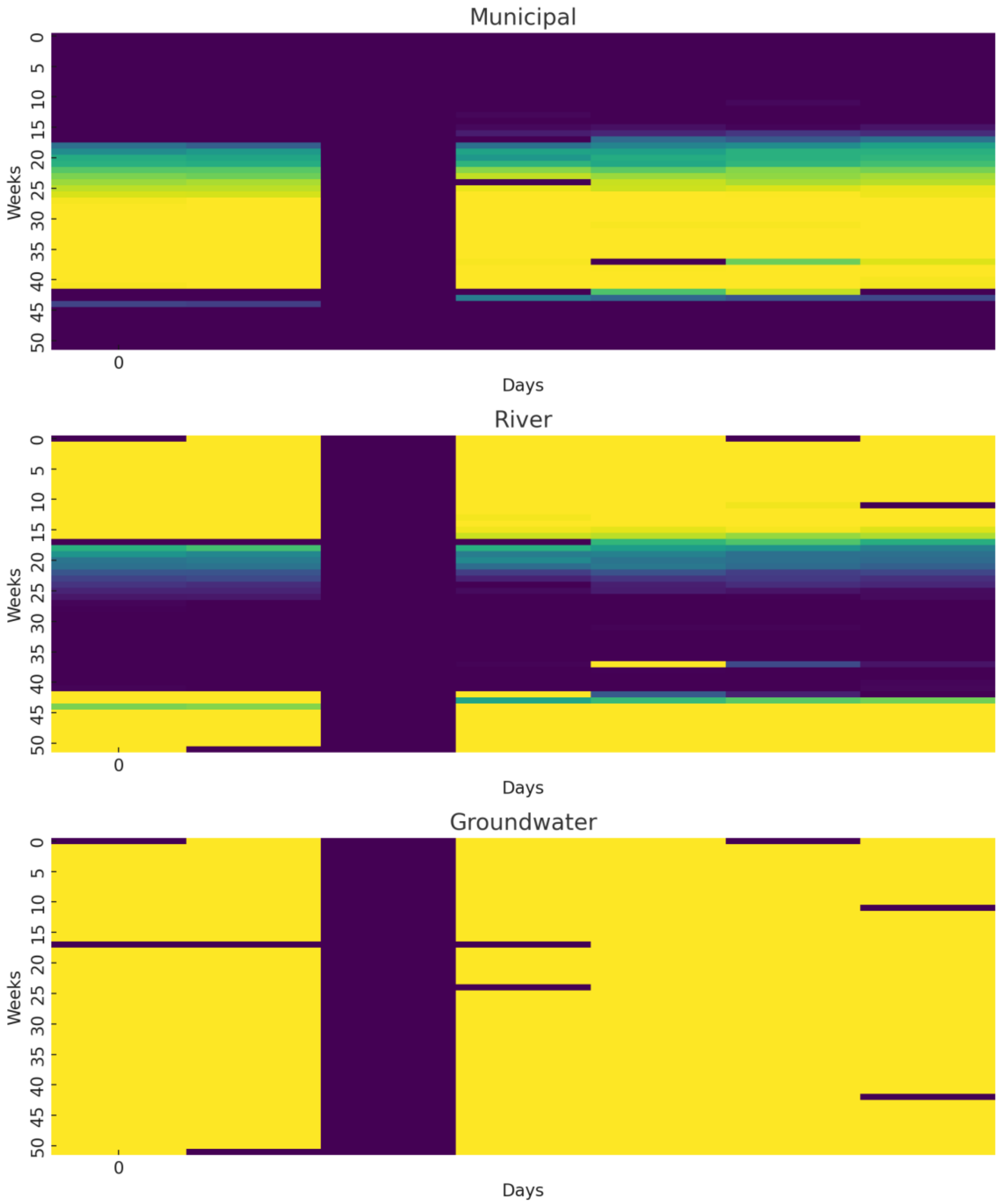

Fig. 29. Heatmap of the (active) sources' contribution within the year ("cost-focused" scenario)

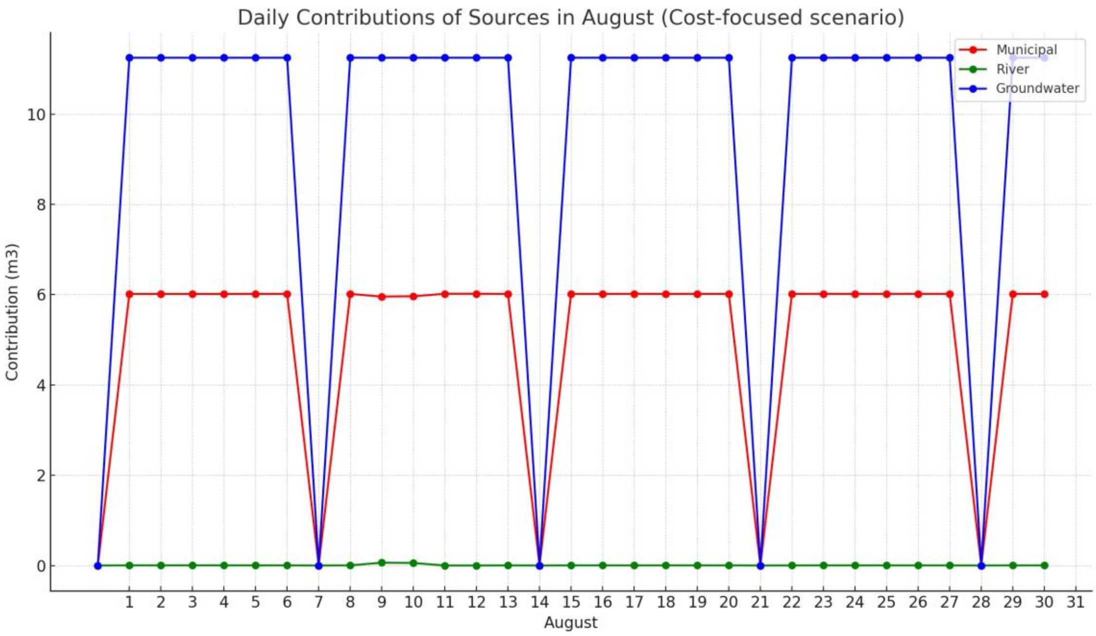

Fig. 30 Daily contributions of all four (active) sources during August (“cost-focused” scenario

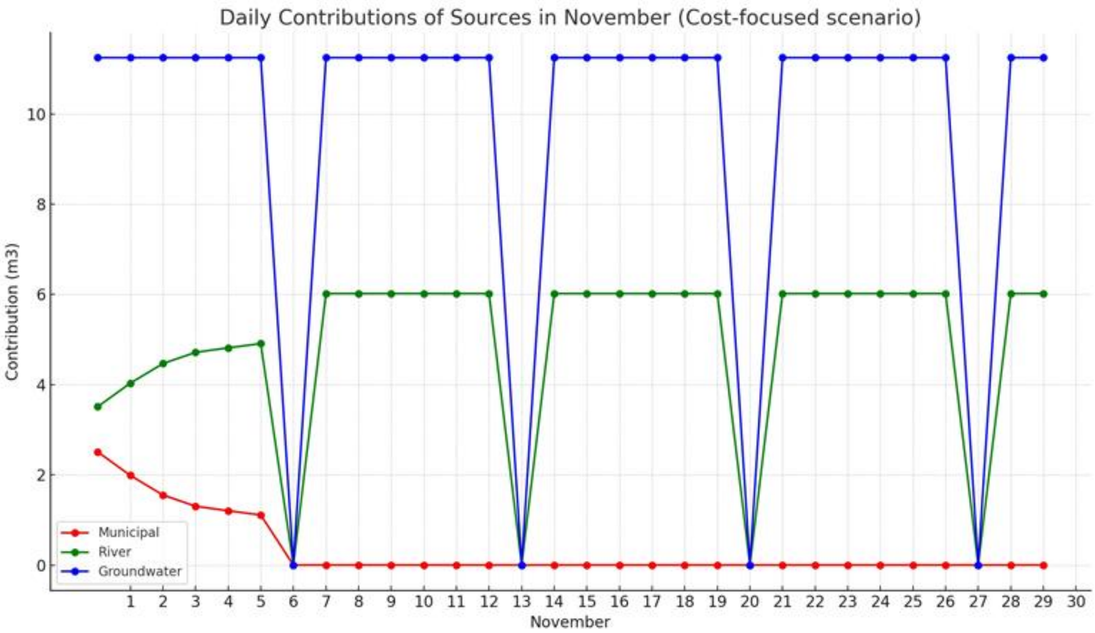

Fig. 31 Daily contributions of all four (active) sources during November (“cost-focused” scenario

4.4.3 Scenario no.3 – "Eco-friendly"

4.4.3.1 Structure -Scenario no.3

The optimisation philosophy of this variation remains the same as before, with similar modifications having been implemented to support the aims of the "eco-friendly" scenario: Weights for cost (w_c) and environmental impact (w_e) were set to 10 and 90 respectively, indicating a strong emphasis on minimising the environmental impact. This shift meant that the algorithm would predominantly focus on minimising the environmental toll, even if it resulted in a higher financial cost.

4.4.3.2 Results -Scenario no.3

The algorithm's results towards source overall contribution for the cost-focused scenario are depicted in Table 15 below.

Table 15. Contribution results per source for the "eco-friendly" scenario

	Municipal	River water	Groundwater	River water	Reuse
Total Annual Usage (m^3)	129.13	1910.05	2542.57	0	668.254

Economic and Environmental Metrics:

- Total Annual Cost: €7377.6
- Total Environmental Impact: 31,134.62 kg CO_2eq
- LCOW (€/m^3): 1.405
- Environmental Impact (kg CO_2eq/m^3): 5.93

Table 16. Pre and post optimisation comparison for the "eco-friendly" scenario no.3

Metric	**Pre-Optimisation**	**Post-Optimisation**	Percentile difference (%)
LCOW (€/m^3)	1.742	1.405	-19.331
Environmental Impact (kg CO_2eq/m^3)	12.279	5.93	-51.701

Table 16 illustrates how the eco-friendly scenario, even with its great focus on the environmental aspect of the problem, still managed to propose a blend which leads to a 19.3% lower cost, while it also created a robust 51.7% drop in the CO_2eq. mass created by the treatment techniques.

The eco-friendly scenario provides insights into water source utilisation with an emphasis on minimising environmental impact. In this scenario, Groundwater remains the primary source, contributing to approximately 60% of its total annual capacity. The river follows closely, using about 38% of its capacity. Reuse water is leveraged to a considerable extent, accounting for an approximate 17% of its yearly potential. The municipal source contributes on a small scale - obviously when other sources prove insufficient to contribute adequately to the daily blend.

This minimum use of the energy-intensive Municipal water source reflects the algorithm's priority on ecological factors.

All aforementioned results of the “eco-friendly” scenario are identical to the ones presented in the “balanced” scenario. It seemed that despite the considerable alteration of weights, the two algorithms resulted in the exact same proposed daily, and annual, blend. Thus, it became obvious that a notable insensitivity to variations in the weighting parameters assigned to cost and environmental impact was the cause of this. This behavior can be attributed to several intertwined factors:

First, one has to focus on the alignment of Cost and Environmental Impact factors: The most cost-efficient water sources also exhibit the least environmental impact (River water and Groundwater). In optimisation terms, this means that the direction of cost minimisation and environmental impact minimisation are largely aligned. As a result, both objectives steer the solution towards a similar optimal blend of water sources. Thus, moderate variations in the weights do not substantially alter the solution, unless pushed to extreme values where one objective overwhelmingly dominates the other.

Second, it has to do with the inherent structure of the optimisation problem: The linear programming structure, coupled with constraints such as daily capacities and availability of sources (large, constant availability of Groundwater, with River water having very high availabilities in the first and last months of the year that sometimes overcome the daily needs) inherently favors certain water sources. These structural biases overshadow the subtler effects of weighting variations, rendering the outcomes less sensitive to weight changes.

Lastly, one has to delve into the intrinsic characteristics of the datasets: The datasets (U and Qd) themselves influence the outcomes. Consistent demand patterns or consistent availability of the most optimal sources (as it is with Groundwater source) naturally push the optimisation results towards certain solutions. Such dataset characteristics reinforce the solution's insensitivity to weight changes, making the outcomes more stable and less variable.

These findings underscore the importance of understanding not just the mathematical structure of optimisation problems, but also the real-world dynamics and intrinsic characteristics of the datasets being used.

Obviously, the visualisations of the “eco-friendly” scenario will be identical to the ones presented in the “balanced” one. Nevertheless, they will be commented upon when deemed necessary, providing additional insight to the results of both scenarios.

The bar chart (Fig. 32) confirms that Groundwater and River sources are the primary contributors, with Groundwater being utilised close to 60% capacity, and with River water following. The Reuse source also has some contribution, with Municipal being dwarfed by the rest of the contributors to the optimised blend due to its high environmental impact.

The area chart (Fig. 33) confirms that the daily water usage from each source throughout the year is. Notably, the Groundwater and River sources are predominant contributors, ensuring a steady supply to meet the daily demand. The contribution per source pattern here resembles that of the “balanced” scenario, with the exception that the reliance on river water is heavier during the winter months, when it provides a large, steady flow. There are days where a total reliance on river water use is observed. Reuse contributes to the daily demand mainly in the summer and early autumn months, when the River water lacks the capacity to contribute enough and, thus, more energy-intensive treatment methods have to be applied.

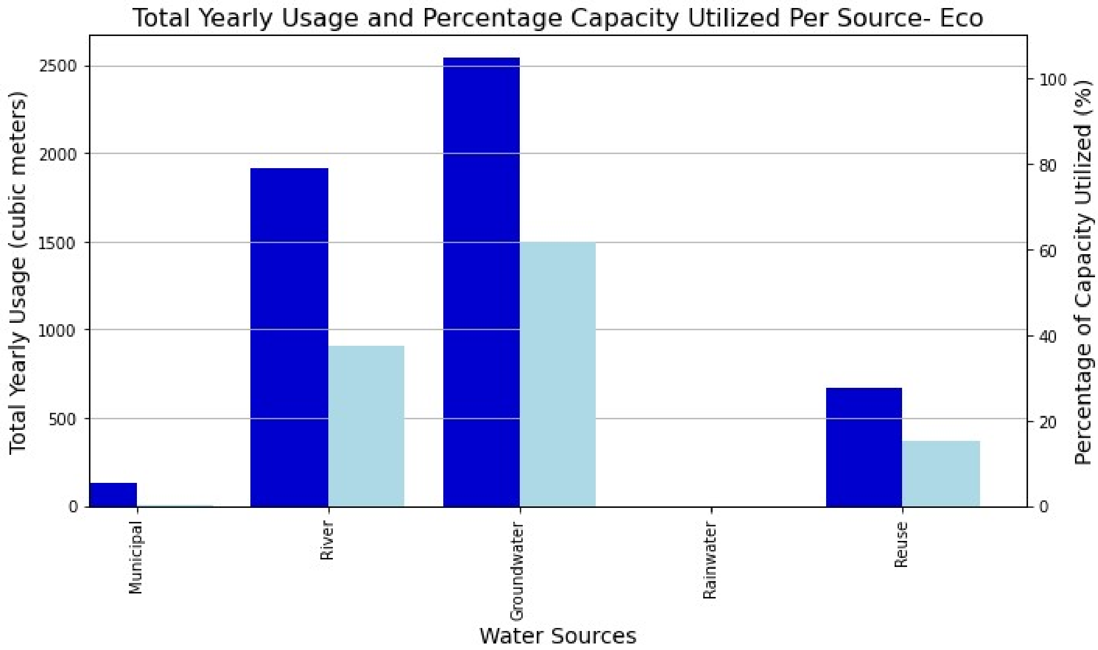

Fig. 32 Total yearly usage per source in volume and as a percentage to the annual capacity ("Eco-friendly scenario" no.3)

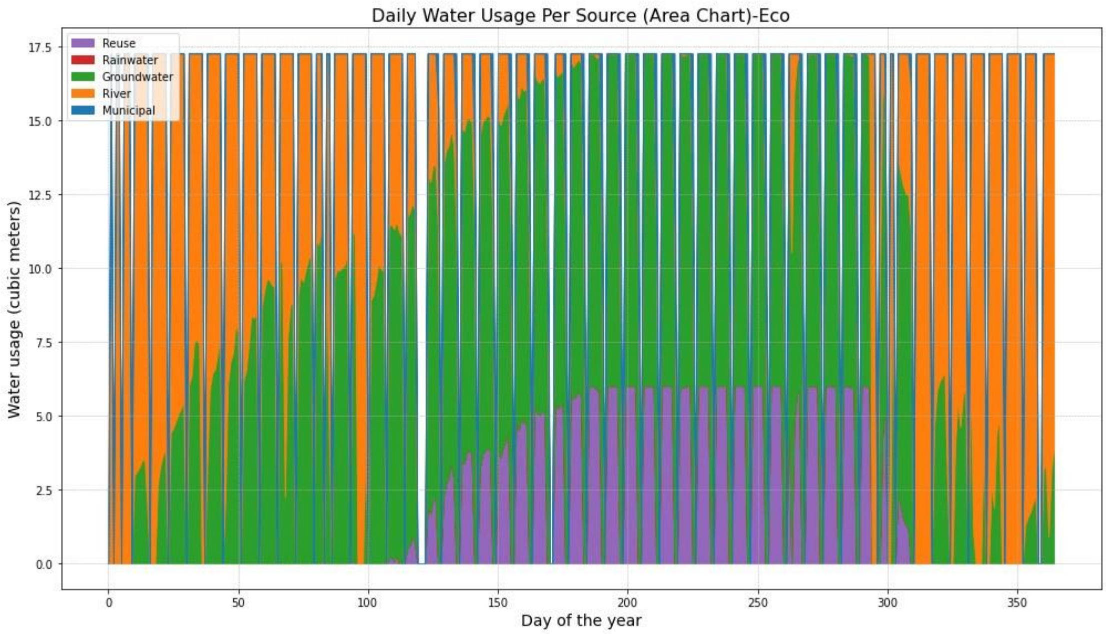

Fig. 33 Area chart depicting the daily usage for each source ("Eco-friendly scenario" no.3)

Observing the pie charts in Fig. 34, we can safely conclude that river water use remains a great asset, especially in the environmental aspect of this optimisation. Despite the great reliance of the system on its use, it only accounts for a 10.8% of the total kg CO_2eq. produced., with Municipal, with its 129m^3-low contribution, makes up for a 5.1% of the environmental impact. The Reuse source, too, has a great impact despite its moderate use, reflecting the delicate balance an industry has to achieve between conformity and a proactive stance towards sustainability.

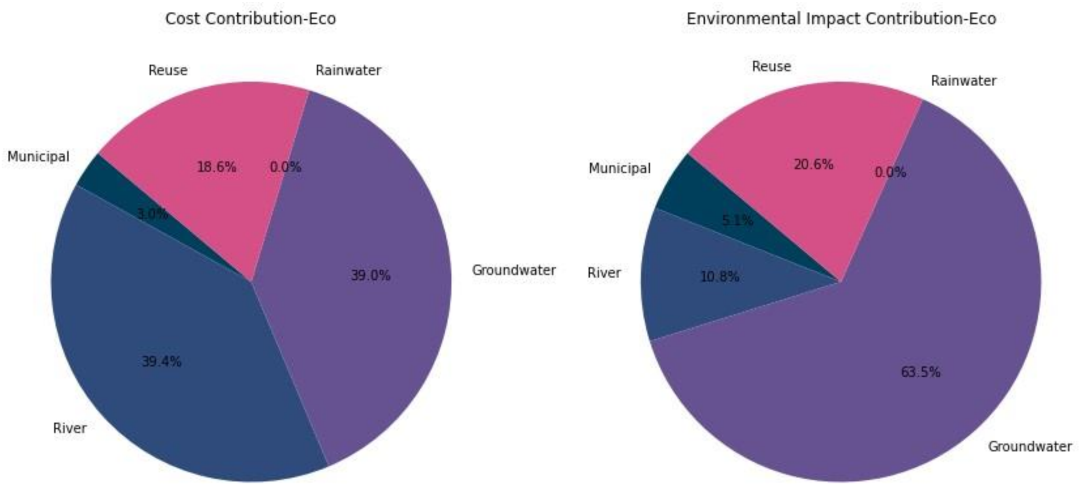

Fig. 34 Contribution of each source to the total cost and environmental impact of the proposed system ("Eco-friendly scenario" no3)

Following, the line charts of the months August and November are presented (Fig. 35 and Fig. 36) as well as the heatmap of all sources' contribution throughout the year (Fig. 37). Since they have been adequately commented upon in the "balanced" scenario chapter, no further commentation was deemed necessary.

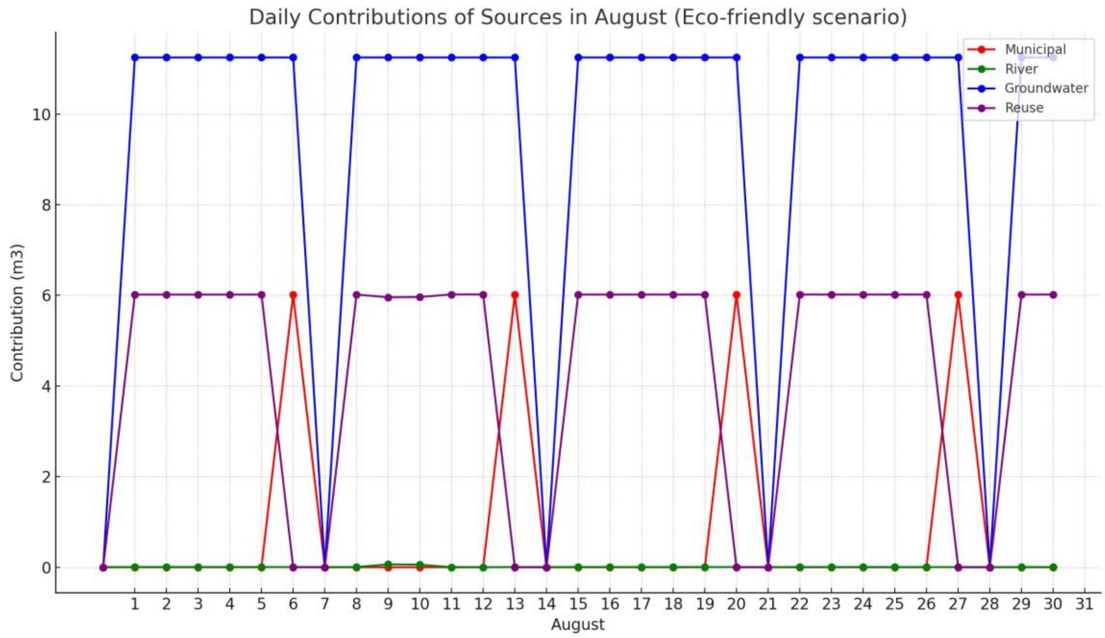

Fig. 35 Daily contributions of all four (active) sources during August ("eco-friendly" scenario)

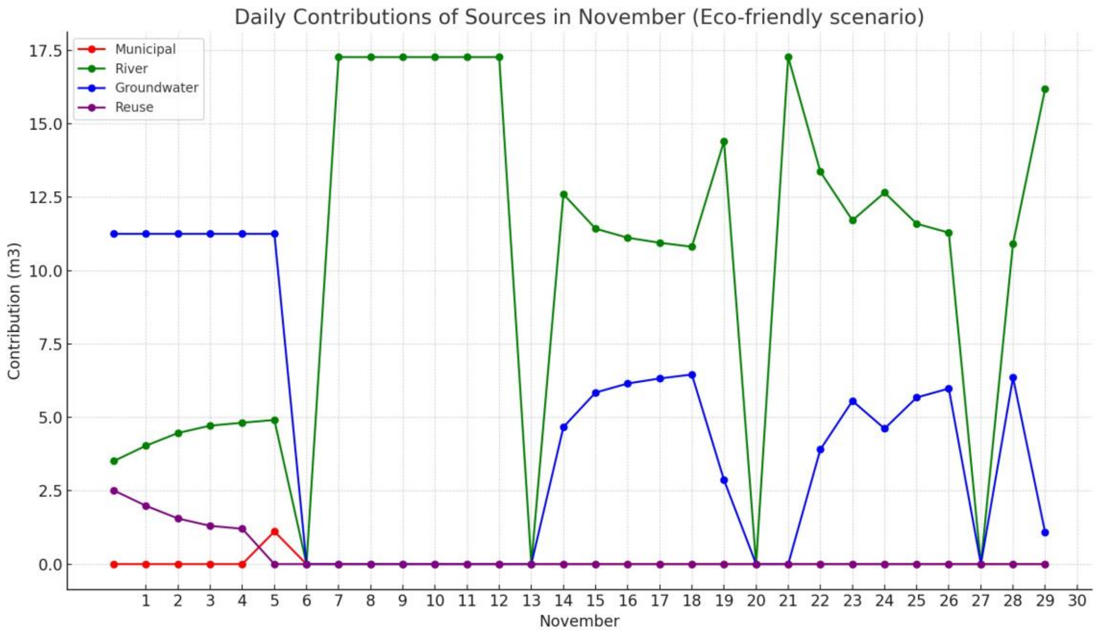

Fig. 36. Daily contributions of all four (active) sources during November ("eco-friendly" scenario)

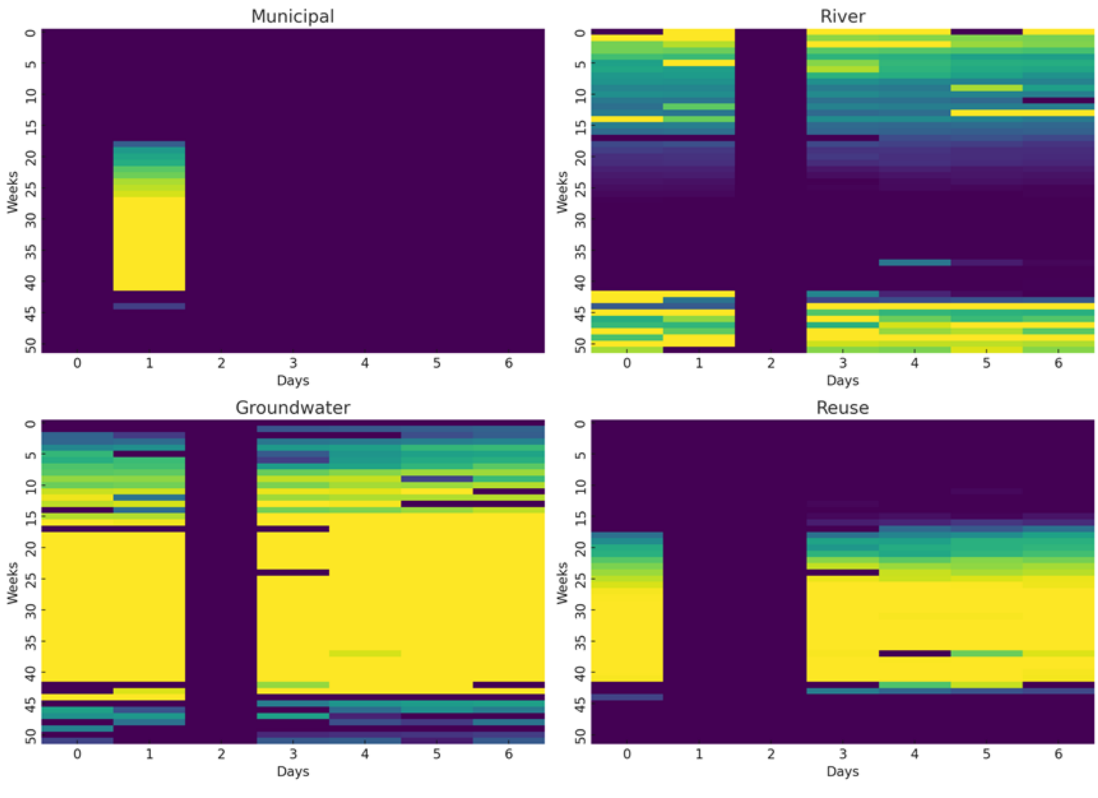

Fig. 37 Heatmap of each (active) source's contribution within the year ("eco-friendly" scenario)

4.4.4 Comparison and Review

Table 17 illustrates the differences in both cost and enviromental impact of the scenarios proposed in reference to the pre-optimisation (exclusive municipal water use) values:

Table 17. LCOW and Environmental Impact values for all three scenarios along with Pre-optimisation

Metric	Pre-Optimisation	Balanced Scenario	Cost-effective Scenario	Eco-friendly Scenario
LCOW (€/m³)	1.742	1.405	1.301	1.405
Environmental Impact (kg CO_2eq/m³)	12.279	5.93	7.277	5.93

We indeed observe the lowest LCOW in the Cost-focused scenario, while the lowest enviornmental impact is presented in the "Balanced" and "Eco-friendly" ones. To more vividly illustrate the efficiencies of all three systems, we used Table 18, which depicts the percentile differences of each one of the scenarios compared to the pre-optimisation status.

Table 18. Percentlile differences of the values exhibited by the three scenarios with respect to the ones exhibited in the pre-optimisation system

Metric	Pre-Optimisation	Balanced Scenario	Cost-effective Scenario	Eco-friendly Scenario
LCOW (€/m³)	1.742	-19.3%	-25.3%	-19.3%
Environmental Impact (kg CO_2eq/m³)	12.279	-51.7%	-40.7%	-51.7%

Percentile differences make it clear that the algorithm variations proved to be efficient in their goals. All of them managed to moderately reduce the cost, while also creating a great drop to the CO_2eq. produced by the treament processes. On the whole, it becomes obvious that the introduction of a multi-origin water source system presents multi-dimensional benefits.

The cost-effective scenario seems ideal for a possibly dominant financially-driven policy in the company. However, it comes at the cost of heavy reliance on groundwater source. Even though the groundwater's profile in our case was designed carefully at a low extraction level, the overreliance on one source -and one that has been particularly popular in the last decades worldwide- underlines the dangers of over extraction and aquifer depletion. Such a strategy, therefore, might be appealing for industries primarily concerned with operational costs, but it could also face public scrutiny or future regulatory challenges due to its potential environmental implications. In addition, concerns could be raised towards reduced resilience against source-specific disruptions. Overall, while the cost-effective scenario might offer immediate financial savings, it also introduces potential environmental and long-term sustainability risks.

The "balanced" and the "eco-friendly" scenarios exhibit strong focus on diversification: While River and Ground are the predominant sources due to their favourable characteristics, reuse and municipal water also provide a moderate, or at least measurable, contribution to the final blend -with the system achieving considerable reductions on both aspects of the optimisation. Such systems can prove invaluable in times of water shortages, or in the case of specific sources' depletion. exhibits a significant reduction on cost and an impressive drop on its environmental impact. All in all, for a company that aims to become "green", this might prove to be an ideal system, with significant and multidimensional benefits.

4.5 Sensitivity Analysis

4.5.1 Introduction

Sensitivity analysis is a powerful and widely employed technique used to understand how the variability in the output of a model or system can be attributed to different sources of uncertainty in its inputs. In essence, it provides insights into the robustness and reliability of the results obtained from the model. By altering the input parameters within certain ranges, one can observe the corresponding changes in the outputs, thereby estimating which parameters have the most significant impact on the results. This kind of analysis is vital, especially when decision-making is based on the model's outputs, as it helps in identifying crucial factors that can significantly influence the outcome.

In the context of algorithms, sensitivity analysis plays a pivotal role in assessing the algorithm's performance across a range of input conditions. For instance, an algorithm may perform exceptionally well under specific conditions but may falter when subjected to slight variations in input parameters. By performing a sensitivity analysis, one can identify potential vulnerabilities or strengths in the algorithm, enabling its refinement and valid optimisation. This chapter delves into the sensitivity analysis of our “balanced” scenario algorithm, shedding light on its robustness and areas of potential improvement.

4.5.2 Alterations for Sensitivity Analysis

In order to gain a comprehensive understanding of the algorithm's performance and robustness, three primary alterations will be explored in this sensitivity analysis. These alterations have been chosen based on their potential impact on the system and their relevance to real-world scenarios and parameters already discussed previously in the thesis. By varying the parameters within these alterations, we aim to grasp the extent to which they influence the algorithm's output. Thus, we may offer insights into its behavior under different conditions.

To gain deeper insights into the behavior and adaptability of our algorithm, we introduced constraints based on the maximum contribution of each water source from the original optimisation results. By setting these upper limits, we ensured that no source in our sensitivity scenarios would be utilised beyond its historical peak. Only exception to this was the Municipal water source, which was set to an infinite constraint reflecting its consistent availability and foundational role in the water supply system. This approach provided a consistent benchmark, allowing for a direct comparison between the original results and the outcomes of each sensitivity test. Through this comparative analysis, we could identify the scale and direction of shifts in source utilisation, highlighting the algorithm's responsiveness to altered conditions. Such a method emphasises not just the absolute performance of the system under various scenarios, but also its relative behavior compared to a known baseline, and offers a clearer understanding of the implications and nuances introduced by the constraints.

4.5.2.1 Altering the Bounds of the sources’ contribution in the optimisation process

4.5.2.1.1 Original Bounds

In the initial configuration of the algorithm, the bounds for each water source's contribution were straightforward: a source could contribute a minimum of zero and a maximum up to the minimum between its capacity and the daily demand. This setup is represented in the algorithm by the line:

```
bounds_revised = [(0, min(U[day, i], Qd[day])) for i in range(5) if sources_to_include[i]]
```

This design choice was grounded in the intent to provide flexibility to the optimisation process. By allowing a water source to potentially meet the entire daily demand, the algorithm had the freedom to favour a specific source if:

1. The source had adequate capacity to meet the demand on that day.
2. The source was the most optimal choice based on the combined metrics of cost and environmental impact.

This flexibility led to scenarios where the system exhibited an overreliance on a singular water source, especially on days when the river source had sufficient flow to cover the entire demand. Such patterns of overreliance were vividly observed and documented in previous chapters, highlighting days where, specifically, the river dwarfed contributions from all other sources due to its favourable conditions.

4.5.2.1.2 Rationale for alteration

The essence of a robust water management system lies not only in its efficiency but also in its resilience. Overreliance on a singular water source, despite the meticulous design of its profile, can harbor potential risks to the continuity and safety of operations. Such a scenario can also inadvertently contribute to the rapid depletion or strain on the primary source, even if, to counteract this, strong precautions have been incorporated in the very design of the water profiles, as it has been mentioned in the previous chapters.

By setting an upper bound on the contribution from each water source, we are essentially forcing the algorithm to diversify its water intake. This act of enforced diversification seeks to test the algorithm's adaptability and its capacity to function optimally without leaning heavily on any single source.

The principle behind this alteration resonates with the broader concept of risk management across various domains – be it financial portfolios or supply chain systems. Diversifying assets or sources reduces the systemic risk and ensures smoother functioning even if one component faces disruptions. In the context of our water management system, such diversification wished to ensure operational resilience, and safeguarding against unforeseen challenges related to a specific source, while also promoting sustainable utilisation of all available resources.

4.5.2.1.3 Specific Alterations

To assess the algorithm's adaptability in diversified environments, a systematic approach to altering the source contribution bounds was implemented. This involved progressively reducing the maximum contribution limits, compelling the algorithm to distribute water sourcing more evenly across available sources rather than leaning heavily on any single one.

The specific alterations to the bounds were as follows:

1. Allowing each source to potentially meet the entire daily demand as it happened in the original configuration (reference scenario).
2. Capping the contribution of any source to 80% of the daily demand.
3. Further reducing the cap to 50% of the daily demand.
4. Setting an even stricter cap at 40% of the daily demand.
5. Lastly, the most stringent constraint allows each source to provide only up to 25% of the daily demand.

By enforcing these bounds, the algorithm is tested under varying degrees of source diversification, illuminating its resilience and optimisation capabilities in different scenarios.

4.5.2.1.4 Results and Analysis

For a clear presentation of the results, we utilised a graphical representation for the direct comparison of the main two factors of the optimisation, namely LCOW and Environmental Impact. Following the graphs, we provide commenting on the results and their implications.

The Y-axis measures either the respective LCOW in EUR/m^3 or the Environmental Impact measured in kgCO$_2$eq/m^3, while the X-axis refers to the factor being analysed on its sensitivity -here being the optimisation bounds regarding the contribution of each source.

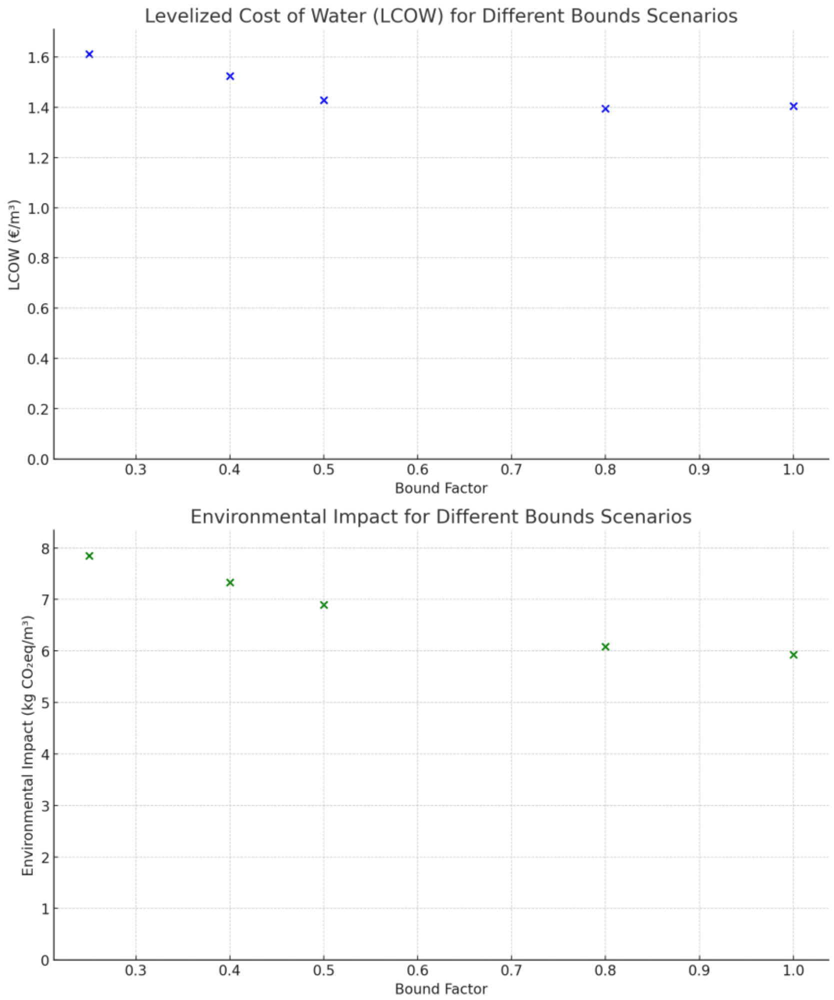

Fig. 38. LCOW and Environmental Impact for different Bounds Scenarios

With unaltered-bounds case serving as reference point, the 0.8-bound case seemed to exhibit the lowest cost and a sufficiently low environmental impact. Fig. 38 illustrates that as the bounds are progressively becoming stricter, the system seems to become less and less efficient, with the final 0.25-bound case exhibiting a utilisation of water at an extra cost of approximately 0.20 EUR per cubic metre (than that of the reference point) and with an extra 1.9 kg CO$_2$eq./m^3. It became obvious that the imposed bounds steered the algorithm away from the reliance on Groundwater and River water use, promoting the use of other, more expensive and more energy intensive, water sources.

Another aspect of paramount importance was the inability of the system to meet the daily demands of the industry in many days as the bounds were becoming stricter. Specifically, the

0.4-bound case saw an annual utilisation 4,852.79 m^3, out of the 5,250 m^3 demand, and the 0.25-bound case utilised a low 2,245.06 $m^{3.}$ In order to explain this, one has to delve into the internal processes of the algorithm. For instance, if one analysed the 0.25-bound case, one would observe that with a double set of constraints being implemented regarding the utilisation of each source (maximum contributions based on the original algorithm as mentioned in chapter 4.5.2, and the 0.25 bound to the maximum contributions) no variation of source contributions is able to be utilised in a volume enough to meet the demands on every single day. The 0.25-bound restriction means that each source must always have a capacity that equals approximately the quaretr of the daily demand, i.e., 4.25 m^3. However, the River water source during the summer and early autumn months exhibits a capacity much lower than that. Thus, the algorithm fails to find a feasible solution on those days.

This sensitivity analysis underscores the value of diversification in water source utilisation. Diversifying across multiple sources can act as a buffer against unforeseen shortages in any single source, ensuring more consistent and reliable water supply. Moreover, diversification can sometimes lead to cost reductions, as it enables the system to tap into the most cost-effective sources available at any given time. However, as the analysis has demonstrated, there is a turning point beyond which diversification can backfire. Over-diversification, or an overemphasis on equally spreading out water source utilisation as in the case of the 0.25-bound, can bind the system's hands, preventing it from leveraging the most efficient sources when they are abundantly available. This can not only inflate costs but also strain sources that are not naturally suited to meet high demands. In essence, while diversification is a prudent strategy, it must be pursued with caution. The right balance between leveraging the strengths of individual sources and ensuring overall system resilience is the key to optimal water source management.

4.5.2.2 Altering Groundwater Capacities

4.5.2.2.1 Original Capacity and Rationale for alteration

In the original model, groundwater capacities were based on the groundwater profile presented in previous chapters. Groundwater has been identified as a significant contributor to the system, underscored by its central role in the optimisation results. Therefore, changes to its available capacities can have profound effects on the overall system's performance and reliability.

Altering groundwater capacities upwards, with factors larger than 1, will test how the system responds to an increased availability of groundwater. This could simulate conditions where technological advancements or policy changes enable enhanced extraction. However, the scenarios with factors less than 1 are of particular interest. By reducing the daily groundwater capacities, we aim to simulate potential depletion scenarios in the aquifer. Given the highlighted risks of over-extraction of groundwater, as previously discussed, such a scenario isn't far-fetched. The system's resilience and adaptability in the face of reduced groundwater availability will be a critical measure of its robustness.

4.5.2.2.2 Specific Alterations

The groundwater capacities will be modified daily using the following factors:

1. A reduction to 40% of the original capacity.
2. A reduction to 80%of the original capacity.
3. The original capacity, represented by a factor of 1 (reference scenario).
4. An increase to 150% of the original capacity, using a factor of 1.5.
5. Doubling the original capacity, using a factor of 2.

Subsequent sections will delve into the results and implications of these alterations, offering insights into the system's flexibility and vulnerabilities.

4.5.2.2.3 Results and Analysis

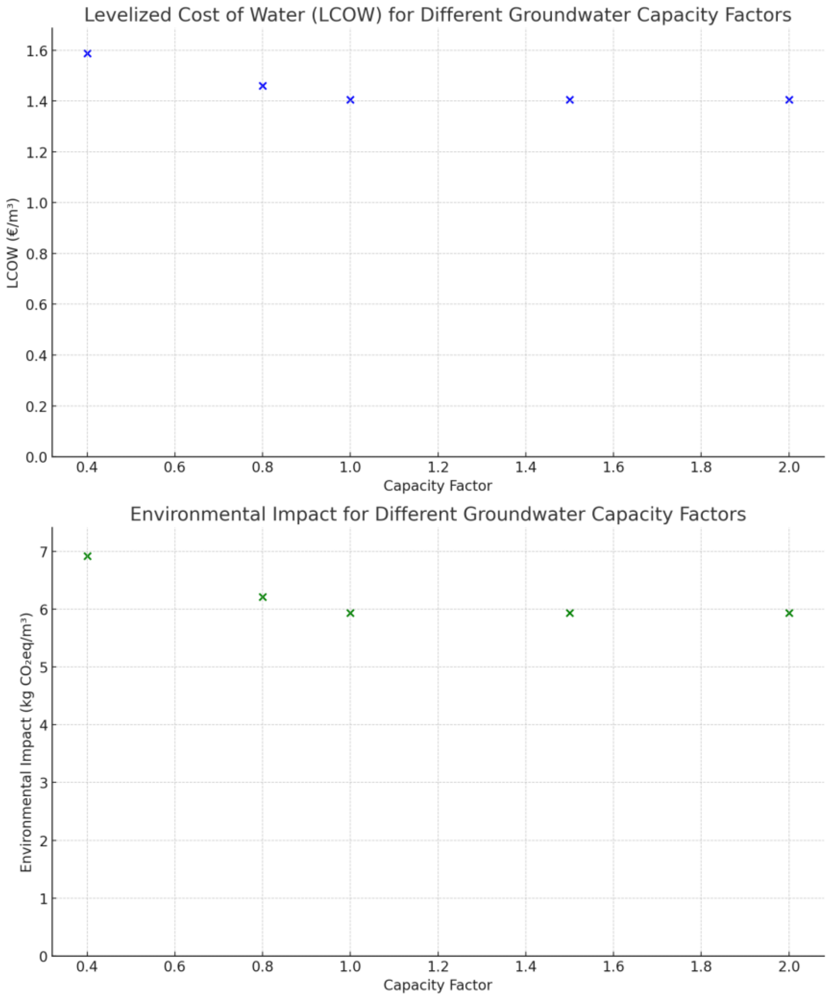

Fig. 39 LCOW and Environmental Impact for different Groundwater capacities Scenarios

With unaltered-capacities case serving as a reference point, the 0.8-capacitiy case exhibited an increase both in cost and in environmental impact. Further down the lowering of groundwater capacities, the 0.4-capacity case saw its costs and impact amounting to a 1.587 EUR and 6.914 $kgCO_2eq$. high. On the other side of the spectrum, an increase in capacities did not exhibit any alteration either on cost or on the environmental impact. Fig. 39 illustrates the values of the two factors for the various scenarios.

Assessing the results brings to light a crucial dependency of the proposed system on this source. The noticeable surge in costs and environmental impact when groundwater availability is reduced underlines its dual significance – it is simultaneously the most cost-effective and the second least energy-intensive source at our disposal. As its availability diminishes, the system naturally gravitates towards alternative sources that are not as cost-efficient and have a more substantial environmental footprint. The lack of significant impact when capacities are increased can be attributed to the very nature of our optimisation algorithm, coupled with the constraints we've imposed. The ceiling set on maximum contributions from each source, based on the original algorithm's maximum utilisations, ensures that even with increased groundwater availability, the system can't exploit it beyond a predefined limit. This constraint illustrates the implications of having a conservative groundwater extraction policy in place: an increased aquifer volume does not directly translate to increased utility for the industry. On the contrary, a decline in groundwater capacities, potentially being a result of aquifer depletion, can have severe repercussions. Such a scenario paints a vivid picture of the results of the ongoing climate crisis and unchecked extraction practices and serves as a stark reminder that the sustainable management of natural resources transcends environmental and moral considerations; it's also an economic imperative.

4.5.2.3 Altering River water Capacities

4.5.2.3.1 Original Capacity and Rationale for alteration

The original capacity for river water was derived from models based on natural flow profiles, providing a realistic representation of its availability throughout the year. Upon analysis of the optimisation outcomes, it became evident that river water was a predominant component of the blend whenever its capacity allowed. This heavy reliance was attributed to its favourable cost attributes and, more crucially, its minimal environmental impact compared to other sources. Such observations were vividly illustrated in the previous chapters.

Given the algorithm's inclination towards river water, it's essential to scrutinise the system's behavior under varying river capacities. Climate change, with its strong effects on hydrological patterns, has the potential to alter river flows significantly. An increase in river flow might not pose a challenge; the real test for the system, however, lies in scenarios of decreased river capacities, essentially simulating conditions like prolonged droughts or near-drought situations. Investigating such scenarios becomes paramount, as it tests the system's resilience and adaptability to potential future challenges.

4.5.2.3.2 Specific Alterations

To explore the system's behavior under varying river capacities, we subjected the river's daily profiles to multiplicative factors, similar to the approach used for groundwater. The chosen factors are 0.4, 0.8, 1 (original capacity), 1.5, and 2. These factors essentially modify the river's daily availability. For instance, a factor of 0.4 indicates a 60% reduction in river capacity, simulating a severe reduction in flow, while a factor of 2 represents a hypothetical doubling of the river's flow.

4.5.2.3.3 Results and Analysis

With unaltered-capacities case serving as a reference point, Fig. 40 illustrates a distinct variation between the cost and the environmental impact patterns: As the river capacity increases, the LCOW of the final blend sees a mild growth, while the environmental impact decreases sufficiently. Thus, the 2.0-capacitiy case serves both as the least cost-effective case and as the most environmentally friendly one. The reason is the inherent characteristics of river water treatment and utilisation: The high initial capital costs make it less cost-effective than the groundwater, while its low energy intensity places it in the first place among all sources when it comes to the least environmental impact. Therefore, as its capacity increases, the algorithm is steered towards utilising its excessive volume at the expense of heavy reliance on groundwater (reference scenario). Thus, the kgCO_2eq. of the blend decreases. The cost, however, of river water utilisation is higher than that of groundwater. Hence, we observe this seemingly paradoxical result of the 2.0-capacity case being at the top of the LCOW graph and the bottom of the Environmental Impact one.

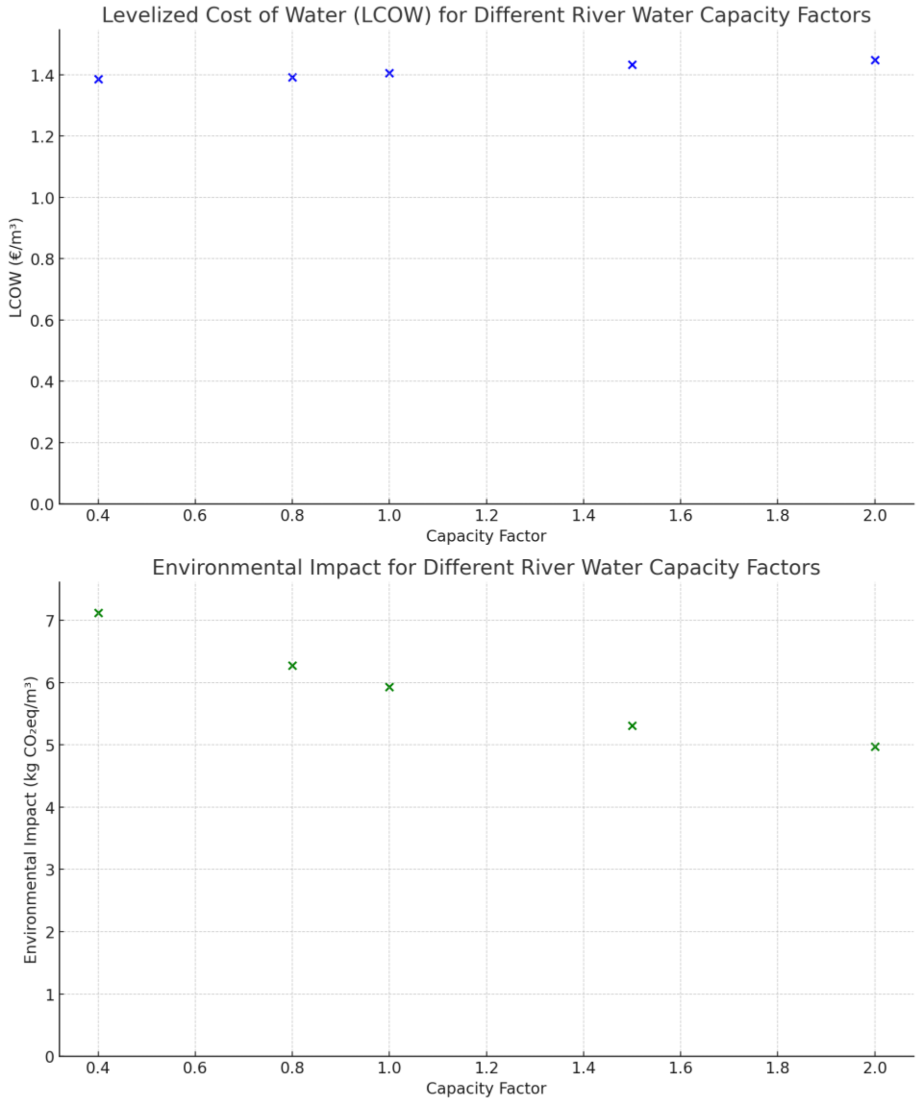

Fig. 40 LCOW and Environmental Impact for different River water capacities Scenarios

This duality in outcomes underscores the importance of holistic decision-making in water resource management. While cost remains a pivotal consideration, the environmental consequences of sourcing decisions cannot be sidelined. The analysis serves as a testament to the age-old proverb: there's no such thing as a free lunch. In the quest for sustainability, there might be costs to bear. They are investments, however, in a more ecologically balanced future.

4.6 Discussion

The methodology employed in this study aims to address the looming water scarcity challenges faced by water-intensive industries, particularly in drought-prone areas such as Crete. By optimising water intake from alternative sources and minimising reliance on municipal water, this research not only contributes to the field of sustainable industrial water management but also aligns with global efforts to mitigate the effects of the climate crisis.

One of the foundational strengths of this research is the emphasis on accurate and precise data. By focusing on the specific technicalities of water use and treatment in the brewing industry, the study ensures that the derived results are both applicable and effective. A detailed examination of the pre-treatment and post-treatment statuses of water from different sources provided a comprehensive understanding of the treatment needs. This methodology ensures that the proposed solutions are grounded in real-world requirements and can be integrated into industrial operations.

The detailed bifurcation of costs into Capital Expenditure (Capex) and Operational Expenditure (Opex) provided a granular insight into the financial implications of sourcing and treating water from different sources. While Capex offers an understanding of the initial investment required for infrastructure and equipment, Opex delves into the recurring costs associated with the day-to-day operations of the water treatment processes.

Incorporating both these cost elements into the Equivalent Annual Cost (EAC) framework allowed for a comprehensive view of the long-term economic viability of each water source. This nuanced approach ensures that the proposed solutions consider both upfront investments and ongoing operational expenses, providing a realistic perspective on the financial feasibility of the water optimisation strategies.

Furthermore, the environmental impact, derived from the energy intensity of each source, seamlessly integrates the ecological perspective into the cost analysis. By quantifying the environmental consequences in terms of kgCO2eq./m^3, the study juxtaposes the economic and ecological implications of each water source. This holistic approach not only reinforces the importance of sustainable water management but also emphasises the interconnectedness of financial and environmental considerations.

The translation of the water optimisation problem into a Linear Programming (LP) model stands as a testament to the rigorous methodological approach adopted in this research. The developed algorithm, tailored to address the complexities of dynamic water profiles, is both innovative and effective. By formulating the algorithm in three distinct scenarios – balanced, cost-focused, and eco-friendly – the study encapsulates various industrial priorities and showcases the versatility of the proposed solutions.

The sensitivity analysis conducted in this research underscores the resilience and adaptability of the proposed solutions. By analyzing the effects of alterations in bounds, groundwater capacities, and river water capacities, the study delves into the robustness of the derived water optimisation strategies. The proposed alterations in bounds, variability in Groundwater capacities, and fluctuations in River water capacities ensured that real-life circumstances were used to test the algorithm's robustness. The comparison between the LCOW and the Environmental Impact of the various cases, provides a visual summary of the trade-offs and synergies between economic and ecological considerations. This not only enhances the comprehensibility of the findings but also facilitates informed decision-making for industries aiming to strike a balance between cost-efficiency and sustainability.

5. Conclusions and Implications

5.1 Assessment of Key Findings

The pressing challenges posed by the global climate crisis, particularly in the Mediterranean region, have necessitated a reevaluation of water resource management strategies. In the face of rising droughts, depleting reserves, and an ever-increasing demand for water, industries heavily reliant on this vital resource are compelled to innovate. This research was anchored in this very premise, aiming to optimise water intake from alternative sources, thereby reducing the dependency on municipal water.

The outcomes of the developed LP model provide a tangible roadmap for industries to navigate the challenges posed by water scarcities. Key metrics, notably the LCOW (measured in EUR/m^3) and the Environmental Impact (measured in kg CO_2eq/m^3), are pivotal in estimating the efficacy and sustainability of the proposed solutions.

The pre-optimisation cost stood at 1.742 €/m^3. The balanced scenario, which aims for a mix of cost-efficiency and environmental conservation, achieved a significant reduction, bringing the cost down to 1.405 €/m^3. The cost-effective scenario further optimised the LCOW to 1.301 €/m^3. The eco-friendly scenario mirrored the balanced scenario, indicating that environmentally conscious solutions can be equally cost-effective.

Before optimisation, the environmental impact was measured at 12.279 kg CO_2eq/m^3. Both the balanced and eco-friendly scenarios slashed this figure by more than half, settling at 5.93 kg CO_2eq/m^3. The cost-effective scenario, while primarily aiming to reduce costs, still managed to achieve a commendable 40.7% reduction in environmental impact.

The similarities between the balanced and eco-friendly scenarios' outcomes are particularly noteworthy. It underscores the point that striking a balance between economic feasibility and environmental conservation doesn't necessarily mean compromising on either. In essence, a solution that's friendly to the environment can also be friendly to the pocket.

Moreover, the evident reduction in both cost and environmental impact in the proposed scenarios, when juxtaposed with the pre-optimisation figures, emphasises the effectiveness of the developed algorithm. The model not only proved its reliability in finding optimal solutions, but also showcased its potential in addressing real-world challenges in a concrete, impactful manner.

In light of these findings, the research underscores the multifaceted benefits of diversifying water sources and intelligently managing their intake. Not only can industries achieve financial savings, but they can also significantly reduce their environmental footprint, making strides towards a more sustainable future in an era defined by climate uncertainties. With many companies' expressed interest to turn "green" due to regulatory pressures and societal expectations, the framework proposed in this study stands as a testament to the feasibility of such ambitions and may prove a valuable tool regarding the necessary pivot towards sustainability.

5.2 Prospects for Further Study

5.2.1 RWHS input

One aspect of possible future considerations is the participation of the RWHS in the optimisation system. To achieve that, the calculated annual harvested rainwater should be increased by considering a large catchment area. The harvest could also be calculated using different -perhaps more accurate- data acquired from local meteorological stations. Another solution would be to run the algorithm by lifting the 10% threshold which prevents the source from entering the optimisation loop. This stance would mean that research focused on maximum diversification of water sources, thus ensuring water security for the industry and, most importantly, minimising the hazard of source depletion.

5.2.2 Nested Optimisation for Water Input System

A promising avenue for further research in the optimisation of water input systems is the nested optimisation approach. This methodology involves embedding one optimisation problem within another, allowing for a more granular exploration of different cost structures. In the context of our water input system, the outer optimisation would address ongoing operational costs (Opex), while the inner optimisation would delve into initial capital expenditures (Capex).

The primary incentive for advancing towards a nested optimisation approach is rooted in the inherent challenges posed by the financial intricacies of Capex. One concern is the potential for overestimation or underestimation of costs when amortising Capex over the expected water output. Given the fixed nature of capital expenditures, they remain constant irrespective of the volume of water sourced or treated. When these fixed costs are distributed over fluctuating outputs, the resultant per unit costs can deviate from actual values, either inflating or diminishing the true economic footprint. Furthermore, the financial landscape is dynamic. External factors like interest rates, inflation, and other macroeconomic variables can alter the real-world implications of capital investments over their lifespan. This ever-evolving financial environment, combined with the static nature of Capex and the potential for misrepresentation of costs, underscores the need for a more nuanced, nested optimisation approach.

One of the primary benefits is the prevention of overestimation or underestimation of costs. By treating Capex and Opex separately, the nested approach avoids the pitfalls of distributing fixed capital costs over fluctuating outputs, thereby ensuring that the per unit costs are a more accurate reflection of reality. Moreover, the nested structure is adept at navigating the dynamic financial environment. It can accommodate shifts in external factors like interest rates and inflation, ensuring that the long-term implications of capital investments are continually aligned with the prevailing economic conditions. Finally, the nested approach facilitates more detailed sensitivity analyses. Future research can examine how variations in either Opex or Capex influence the overall solution, offering invaluable insights for risk management and long-term planning.

6. Literature

Abou-Shady, A., & El-Araby, H. (2023). Treatment Technologies and Guidelines Set for Water Reuse. In B. K. Taşeli (Ed.), *Sewage Management* (p. Ch. 1). IntechOpen. https://doi.org/10.5772/intechopen.109928

Ahmed, A. K. A., & Marhaba, T. F. (2017). Review on river bank filtration as an in situ water treatment process. *Clean Technologies and Environmental Policy*, *19*(2), 349–359. https://doi.org/10.1007/s10098-016-1266-0

Amienyo, D., & Azapagic, A. (2016). Life cycle environmental impacts and costs of beer production and consumption in the UK. *International Journal of Life Cycle Assessment*, *21*(4), 492–509. https://doi.org/10.1007/s11367-016-1028-6

Amores, M. J., Meneses, M., Pasqualino, J., Antón, A., & Castells, F. (2013). Environmental assessment of urban water cycle on Mediterranean conditions by LCA approach. *Journal of Cleaner Production*, *43*, 84–92. https://doi.org/https://doi.org/10.1016/j.jclepro.2012.12.033

Ariyomo, T., Akinsorotan, A. ;, & Nwachukwu, E. (2021). Toxicity of Brewery Effluents (Burukutu Effluent) to Clarias gariepinus and its Effect on some Target Organs. *J. Appl. Sci. Environ. Manage*, *25*(6), 1081–1085. https://doi.org/10.4314/jasem.v25i6.29

Asadieh, B., & Afshar, A. (2019). Optimization of Water-Supply and Hydropower Reservoir Operation Using the Charged System Search Algorithm. *Hydrology*, *6*(1). https://doi.org/10.3390/hydrology6010005

Bhakar, V., Kumar, D. N. S. H., Sai, N. K., Sangwan, K. S., & Raghuvanshi, S. (2016). Life Cycle Assessment of Filtration Systems of Reverse Osmosis Units: A Case Study of a University Campus. *Procedia CIRP*, *40*, 268–273. https://doi.org/10.1016/j.procir.2016.01.119

Charchousi, D., Spanoudaki, K., & Papadopoulou, M. P. (2017). Assessing Groundwater Resources Sustainability Using Groundwater Footprint Concept. *EGU General Assembly Conference Abstracts*, 598.

Chen, J., Liu, Y., Liu, K., Hu, L., Yang, J., Wang, X., Song, Z., Yang, Y., Tang, M., & Wang, R. (2021). Bacterial community composition of internal circulation reactor at different heights for large-scale brewery wastewater treatment. *Bioresource Technology*, *331*, 125027. https://doi.org/https://doi.org/10.1016/j.biortech.2021.125027

Cos, J., Doblas-Reyes, F., Jury, M., Marcos, R., Bretonnière, P.-A., & Samsó, M. (2022). The Mediterranean climate change hotspot in the CMIP5 and CMIP6 projections. *Earth System Dynamics*, *13*(1), 321–340. https://doi.org/10.5194/esd-13-321-2022

Cramer, W., Guiot, J., Marini, K., & (eds.). (2020). *MedECC (2020) Climate and Environmental Change in the Mediterranean Basin – Current Situation and Risks for the Future. First Mediterranean Assessment Report*.

Da'ana, D. A., Zouari, N., Ashfaq, M. Y., Abu-Dieyeh, M., Khraisheh, M., Hijji, Y. M., & Al-Ghouti, M. A. (2021). Removal of Toxic Elements and Microbial Contaminants from

Groundwater Using Low-Cost Treatment Options. *Current Pollution Reports*, *7*(3), 300–324. https://doi.org/10.1007/s40726-021-00187-3

Enitan, A., Adeyemo, J., Kumari, S., Swalaha, F., & Bux, F. (2015). Characterization of Brewery Wastewater Composition. *Engineering and Technology International Journal of Environmental and Ecological Engineering*, *9*. https://hdl.handle.net/10321/2992

European Academies Science Advisory Council. (2010). *Groundwater in the southern member states of the European Union : an assessment of current knowledge and future prospects.* EASAC Secretariat.

European Academies Science Advisory Council. (2010). *Groundwater in the Southern Member States of the European Union: an assessment of current knowledge and future prospects Country report for Greece*.

Farreny, R., Gabarrell, X., & Rieradevall, J. (2011). Cost-efficiency of rainwater harvesting strategies in dense Mediterranean neighbourhoods. *Resources, Conservation and Recycling*, *55*(7), 686–694. https://doi.org/https://doi.org/10.1016/j.resconrec.2011.01.008

Gomaa, A. (2018). Edition 1 | Article 1002 ScienceForecast Publications LLC., | Citation: Gomaa AM. Application of Enzymes in Brewing. *Journal of Nutrition and Food Science Forecast*, *1*(1), 1002. https://doi.org/10.5281/zenodo.3336203

Gracia-de-Rentería, P., Barberán, R., & Mur, J. (2020). The groundwater demand for industrial uses in areas with access to drinking publicly-supplied water: A microdata analysis. *Water (Switzerland)*, *12*(1). https://doi.org/10.3390/w12010198

Gwenzi, W., Dunjana, N., Pisa, C., Tauro, T., & Nyamadzawo, G. (2015). Water quality and public health risks associated with roof rainwater harvesting systems for potable supply: Review and perspectives. In *Sustainability of Water Quality and Ecology* (Vol. 6, pp. 107–118). Elsevier B.V. https://doi.org/10.1016/j.swaqe.2015.01.006

H. Lee and J. Romero (eds.). (2023). *IPCC, 2023: Climate Change 2023: Synthesis Report. A Report of the Intergovernmental Panel on Climate Change. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*.

He, C. (2015). Take a Holistic Approach to Groundwater Treatment. *Opflow*, *41*(11), 22–25. https://doi.org/https://doi.org/10.5991/OPF.2015.41.0069

Hiscock, K. M. (2011). Groundwater in the 21st Century – Meeting the Challenges. In *Sustaining Groundwater Resources* (pp. 207–225). Springer Netherlands. https://doi.org/10.1007/978-90-481-3426-7_13

Holloway, R. W., Miller-Robbie, L., Patel, M., Stokes, J. R., Munakata-Marr, J., Dadakis, J., & Cath, T. Y. (2016). Life-cycle assessment of two potable water reuse technologies: MF/RO/UV–AOP treatment and hybrid osmotic membrane bioreactors. *Journal of Membrane Science*, *507*, 165–178. https://doi.org/https://doi.org/10.1016/j.memsci.2016.01.045

Ioanna Nydrioti, Melina-Margarita Moutsaki, & Nikolaos Leounakis et al. (2023). *Implementation of the Water Footprint as a water performance indicator in industrial manufacturing units located in Greece: Challenges & Prospects*.

Jamil, M. A., Qureshi, B. A., & Zubair, S. M. (2017). Exergo-economic analysis of a seawater reverse osmosis desalination plant with various retrofit options. *Desalination*, *401*, 88–98. https://doi.org/https://doi.org/10.1016/j.desal.2016.09.032

Kakoulas, D., Golfinopoulos, S., Koumparou, D., & Alexakis, D. (2022). The Effectiveness of Rainwater Harvesting Infrastructure in a Mediterranean Island. *Water*, *14*, 716. https://doi.org/10.3390/w14050716

Khayan, K., Heru Husodo, A., Astuti, I., Sudarmadji, S., & Sugandawaty Djohan, T. (2019). Rainwater as a Source of Drinking Water: Health Impacts and Rainwater Treatment. *Journal of Environmental and Public Health*, *2019*, 1760950. https://doi.org/10.1155/2019/1760950

Koroneos, C., Roumbas, G., Gabari, Z., Papagiannidou, E., & Moussiopoulos, N. (2005). Life cycle assessment of beer production in Greece. *Journal of Cleaner Production*, *13*(4), 433–439. https://doi.org/https://doi.org/10.1016/j.jclepro.2003.09.010

Kotti, M., Zacharioudaki, D.-E., Kokinou, E., & Stavroulakis, G. (2018). Characterization of water quality of Almiros river (Northeastern Crete, Greece): physicochemical parameters, polycyclic aromatic hydrocarbons and anionic detergents. *Modeling Earth Systems and Environment*, *4*(4), 1285–1296. https://doi.org/10.1007/s40808-018-0504-3

Latif, S., Alim, M. A., & Rahman, A. (2022a). Disinfection methods for domestic rainwater harvesting systems: A scoping review. In *Journal of Water Process Engineering* (Vol. 46). Elsevier Ltd. https://doi.org/10.1016/j.jwpe.2021.102542

Latif, S., Alim, M. A., & Rahman, A. (2022b). Disinfection methods for domestic rainwater harvesting systems: A scoping review. *Journal of Water Process Engineering*, *46*, 102542. https://doi.org/https://doi.org/10.1016/j.jwpe.2021.102542

Lee, M., Kim, M., Kim, Y., & Han, M. (2017a). Consideration of rainwater quality parameters for drinking purposes: A case study in rural Vietnam. *Journal of Environmental Management*, *200*, 400–406. https://doi.org/10.1016/j.jenvman.2017.05.072

Lee, M., Kim, M., Kim, Y., & Han, M. (2017b). Consideration of rainwater quality parameters for drinking purposes: A case study in rural Vietnam. *Journal of Environmental Management*, *200*, 400–406. https://doi.org/https://doi.org/10.1016/j.jenvman.2017.05.072

Li, C., Men, B., & Yin, S. (2022). Optimized Selection of Water Resource Allocation Schemes Based on Improved Connection Entropy in Beijing’s Southern Plain. *Entropy*, *24*(7). https://doi.org/10.3390/e24070920

Malagò, A., Efstathiou, D., Bouraoui, F., Nikolaidis, N. P., Franchini, M., Bidoglio, G., & Kritsotakis, M. (2016). Regional scale hydrologic modeling of a karst-dominant geomorphology: The case study of the Island of Crete. *Journal of Hydrology*, *540*, 64–81. https://doi.org/https://doi.org/10.1016/j.jhydrol.2016.05.061

Mas-Pla, J., Ghiglieri, G., & Uras, G. (2014). Seawater intrusion and coastal groundwater resources management. Examples from two Mediterranean regions: Catalonia and Sardinia. *Contrib Sci*, *10*, 171–184. https://doi.org/10.2436/20.7010.01.201

MedECC (2022). The Mediterranean Basin: main drivers of environmental changes. (2022). https://www.medecc.org/outputs/infographic-mar1-drivers-2022/

Mogaka, H. (Hezron). (2006). *Climate variability and water resources degradation in Kenya :improving water resources development and management /*. The World Bank,.

Morianou, G. G., Kourgialas, N. N., Psarras, G., & Koubouris, G. C. (2018). Mapping sensitivity to desertification in Crete (Greece), the risk for agricultural areas. *Journal of Water and Climate Change*, *9*(4), 691–702. https://doi.org/10.2166/wcc.2018.148

Musayev, S., Burgess, E., & Mellor, J. (2018). A global performance assessment of rainwater harvesting under climate change. *Resources, Conservation and Recycling*, *132*, 62–70. https://doi.org/https://doi.org/10.1016/j.resconrec.2018.01.023

Nerantzaki, S., Efstathiou, D., Giannakis, G., Kritsotakis, M., Grillakis, M., Koutroulis, A., Tsanis, I., & Nikolaidis, N. (2019). Climate change impact on the hydrological budget of a large Mediterranean island. *Hydrological Sciences Journal*, *64*. https://doi.org/10.1080/02626667.2019.1630741

Nikolaidis N., & Karatzas G. (2012). Specific Water Resources Management Plan for Tavronitis River Basin. In *Technical University of Crete*.

North Carolina Department of Environmental Quality. (2017). *Rational Runoff Coefficient*. https://files.nc.gov/ncdeq/Energy%20Mineral%20and%20Land%20Resources/Stormwater/BMP%20Manual/B%20%20Stormwater%20Calculations.pdf

Pablo Rasero. (n.d.). *iStock*. Retrieved October 13, 2023, from https://www.istockphoto.com/photo/green-water-tank-in-the-countryside-gm1462623235-495968429

Pearson, J. L., Michael, P. R., Ghaffour, N., & Missimer, T. M. (2021). *membranes Economics and Energy Consumption of Brackish Water Reverse Osmosis Desalination: Innovations and Impacts of Feedwater Quality*. https://doi.org/10.3390/membranes

POWER | Data Access Viewer, Prediction of Worldwide Energy Resource. (n.d.). Retrieved October 13, 2023, from https://power.larc.nasa.gov/data-access-viewer/

Ribeiro, F. W., da Silva, S. M. O., de Souza Filho, F. de A., Carvalho, T. M. N., & de M. Lopes, T. M. X. (2022). Diversification of urban water supply: An assessment of social costs and water production costs. *Water Policy*, *24*(6), 980–997. https://doi.org/10.2166/wp.2022.012

Santalucia, P. (2023, April 24). Lack of snow condemns Italy's Po to a desperately dry summer. *The Associated Press*.

Sarai Atab, M., Smallbone, A. J., & Roskilly, A. P. (2016). An operational and economic study of a reverse osmosis desalination system for potable water and land irrigation. *Desalination*, *397*, 174–184. https://doi.org/https://doi.org/10.1016/j.desal.2016.06.020

Senevirathna, S., Ramzan, S., & Morgan, J. (2019). A sustainable and fully automated process to treat stored rainwater to meet drinking water quality guidelines. *Process Safety and Environmental Protection*, *130*, 190–196. https://doi.org/https://doi.org/10.1016/j.psep.2019.08.005

Seo, K.-W., Ryu, D., Eom, J., Jeon, T., Kim, J.-S., Youm, K., Chen, J., & Wilson, C. R. (2023). Drift of Earth's Pole Confirms Groundwater Depletion as a Significant Contributor to Global Sea Level Rise 1993–2010. *Geophysical Research Letters*, *50*(12), e2023GL103509. https://doi.org/https://doi.org/10.1029/2023GL103509

Sifakis, N. (2021). *Formation of the typology for the evaluation of the sustainability of nearly zero energy ports*. Technical University of Crete.

Sifakis, N., Kalaitzakis, K., & Tsoutsos, T. (2021). Integrating a novel smart control system for outdoor lighting infrastructures in ports. *Energy Conversion and Management*, *246*, 114684. https://doi.org/https://doi.org/10.1016/j.enconman.2021.114684

Singh Dhillon, M., Kaur, S., Sood, A., & Aggarwal, R. (2018). Estimation of carbon emissions from groundwater pumping in central Punjab. *Carbon Management*, *9*(4), 425–435. https://doi.org/10.1080/17583004.2018.1518107

Skoulikidis, N. (2018). The State and Origin of River Water Composition in Greece. In N. Skoulikidis, E. Dimitriou, & I. Karaouzas (Eds.), *The Rivers of Greece: Evolution, Current Status and Perspectives* (pp. 97–127). Springer Berlin Heidelberg. https://doi.org/10.1007/698_2016_468

Suprihatin, S., Cahyaputri, B., Romli, M., & Yani, M. (2017). Use of biofilter as pre-treatment of polluted river water for drinking water supply. *Environmental Engineering Research*, *22*(2), 203–209. https://doi.org/10.4491/eer.2016.110

Tang, X., He, Y., Qi, P., Chang, Z., Jiang, M., & Dai, Z. (2021). A New Multi-Objective Optimization Model of Water Resources Considering Fairness and Water Shortage Risk. *Water*, *13*(19). https://doi.org/10.3390/w13192648

Tay, M. F., Liu, C., Cornelissen, E. R., Wu, B., & Chong, T. H. (2018). The feasibility of nanofiltration membrane bioreactor (NF-MBR)+reverse osmosis (RO) process for water reclamation: Comparison with ultrafiltration membrane bioreactor (UF-MBR)+RO process. *Water Research*, *129*, 180–189. https://doi.org/https://doi.org/10.1016/j.watres.2017.11.013

Toran, M. S., Labrador, P. F., Ciriza, J. F., Asensio, Y., Reigersman, A., Arevalo, J., Rogalla, F., & Monsalvo, V. M. (2021). Membrane-Based Processes to Obtain High-Quality Water From Brewery Wastewater. *Frontiers in Chemical Engineering*, *3*. https://doi.org/10.3389/fceng.2021.734233

Tran, S. H., Dang, H. T. T., Dao, D. A., Nguyen, V.-A., Nguyen, L. T., Nguyen, V.-A., & Han, M. (2021). On-site rainwater harvesting and treatment for drinking water supply: assessment of cost and technical issues. *Environmental Science and Pollution Research*, *28*(10), 11928–11941. https://doi.org/10.1007/s11356-020-07977-0

Tribe, M., & Alpine, R. L. W. (1986). Scale economies and the “0.6 rule.” *Engineering Costs and Production Economics*, *10*, 271–278. https://doi.org/10.1016/S0167-188X(86)80025-8

Tuel, A., & Eltahir, E. A. B. (2020). Why Is the Mediterranean a Climate Change Hot Spot? *Journal of Climate*, *33*(14), 5829–5843. https://doi.org/https://doi.org/10.1175/JCLI-D-19-0910.1

Tzanakakis, V. E., Paranychianaki, N. V., & Angelakis, A. N. (2007). Soil as a wastewater treatment system: Historical development. In *Water Science and Technology: Water Supply* (Vol. 7, Issue 1, pp. 67–75). https://doi.org/10.2166/ws.2007.008

Utrero-Gonzalez, N., & Callado-Muñoz, F. (2014). Competing for water: Golf courses in semi-arid regions. The case in Spain. *Water Science and Technology: Water Supply*, *14*, 886–897. https://doi.org/10.2166/ws.2014.047

Verhuelsdonk, M., Glas, K., & Parlar, H. (2021). Economic evaluation of the reuse of brewery wastewater. *Journal of Environmental Management*, *281*, 111804. https://doi.org/https://doi.org/10.1016/j.jenvman.2020.111804

Vlastos, D., Antonopoulou, M., Lavranou, A., Efthimiou, I., Dailianis, S., Hela, D., Lambropoulou, D., Paschalidou, A. K., & Kassomenos, P. (2019). Assessment of the toxic potential of rainwater precipitation: First evidence from a case study in three Greek cities. *Science of the Total Environment*, *648*, 1323–1332. https://doi.org/10.1016/j.scitotenv.2018.08.166

Werkneh, A. A., Beyene, H. D., & Osunkunle, A. A. (2019). Recent advances in brewery wastewater treatment; approaches for water reuse and energy recovery: a review. *Environmental Sustainability*, *2*(2), 199–209. https://doi.org/10.1007/s42398-019-00056-2

Wurl, J. (2019). Competition for water: consumption of golf courses in the tourist corridor of Los Cabos, BCS, Mexico. *Environmental Earth Sciences*, *78*(24), 674. https://doi.org/10.1007/s12665-019-8689-y

Yan, X., Ward, S., Butler, D., & Daly, B. (2018). Performance assessment and life cycle analysis of potable water production from harvested rainwater by a decentralized system. *Journal of Cleaner Production*, *172*, 2167–2173. https://doi.org/https://doi.org/10.1016/j.jclepro.2017.11.198

Yu, J., Zhang, Y., Zhang, S., & Li, J. (2015). Life cycle assessment of beer production. *Huanjing Kexue Xuebao/Acta Scientiae Circumstantiae*, *35*, 1217–1223. https://doi.org/10.13671/j.hjkxxb.2014.0793

Zhai, Y., Liu, G., & van der Meer, W. G. J. (2022). One-Step Reverse Osmosis Based on Riverbank Filtration for Future Drinking Water Purification. *Engineering*, *9*, 27–34. https://doi.org/10.1016/j.eng.2021.02.015

Zhang, J., Dong, Z., & Chen, T. (2020). Multi-Objective Optimal Allocation of Water Resources Based on the NSGA-2 Algorithm While Considering Intergenerational Equity: A Case Study of the Middle and Upper Reaches of Huaihe River Basin, China. *International*

Journal of Environmental Research and Public Health, *17*, 9289. https://doi.org/10.3390/ijerph17249289

Zhang, S., Fang, G., Zhang, D., Ju, M., & Zhong, H. (2023). Water resources optimal allocation model for coordinating regional multi-level water resources managers' interests. *Frontiers in Environmental Science*, *11*. https://doi.org/10.3389/fenvs.2023.1152296

7. Appendix

- **Algorithm no.1 ("balanced" scenario case)**

```python
from scipy.optimize import linprog
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Load the datasets
# U: A 2D numpy array holding the daily capacity values for each of the 5 sources
# Qd: A numpy array holding the daily water demand values
U = pd.read_csv('./WaterProfiles_Modified.csv').iloc[:, 1:].values
Qd = pd.read_csv('./daily_water_demand_2021.csv')['Demand (m3)'].values

# Define the constants
# C: A list holding the cost constants for each source (in €/m³)
# E: A list holding the environmental impact constants for each source (in kg CO₂eq/m³)
# w_c: The weight assigned to the cost in the objective function
# w_e: The weight assigned to the environmental impact in the objective function
C = [1.742, 1.522, 1.131, 5.382, 2.05]
E = [12.279, 1.764, 7.775, 10.001, 9.594]
w_c = 65
w_e = 35

# Min-Max normalization for cost (C) and environmental impact (E) constants
min_cost = np.min(C)
max_cost = np.max(C)
C_normalized = (C - min_cost) / (max_cost - min_cost)

min_impact = np.min(E)
max_impact = np.max(E)
E_normalized = (E - min_impact) / (max_impact - min_impact)


# Calculate the total annual capacity for each source
# This will be used to determine which sources should be included in the optimization
total_annual_capacity_per_source = U.sum(axis=0)
yearly_total_demand = Qd.sum()
sources_to_include = total_annual_capacity_per_source >= 0.1 * yearly_total_demand


#Initialize lists to store the daily solutions and the status of each optimization
daily_solutions = []
daily_status = []

# Initialization of rainwater accumulative profile function
rainwater_storage = 0


# Loop through each day and solve the linear programming problem
# The loop index (day) ranges from 0 to 364, representing each day of the year
for day in range(365):
    # Define the coefficients of the objective function based on the weighted sum of the cost and environmental impact constants for the included sources
    c_revised = [(w_c * C_normalized[i] + w_e * E_normalized[i]) for i in range(5) if sources_to_include[i]]
    # Define the inequality constraints matrix to ensure daily usage from each source does not exceed its daily capacity
    A_ub_revised = [[1 if i == j else 0 for i in range(5) if sources_to_include[i]] for j in range(sum(sources_to_include))]
    # Define the inequality constraints vector based on the daily capacities for the included sources
    b_ub_revised = [U[day, i] for i in range(5) if sources_to_include[i]]
    # Define the equality constraints to ensure the total daily usage meets the daily demand
    A_eq_revised = [[1 for i in range(5) if sources_to_include[i]]]
    b_eq_revised = [Qd[day]]
    # Define the bounds for each source to ensure the usage is between 0 and the daily capacity and does not exceed the daily demand
    bounds_revised = [(0, min(U[day, i], Qd[day])) for i in range(5) if sources_to_include[i]]


# If the daily demand is zero, directly assign a usage of 0 units from all sources
    if Qd[day] == 0:
        solution = [0 if sources_to_include[i] else None for i in range(5)]
        status = True
    else:
        # Solve the linear programming problem using the 'highs' method in the linprog function
        # The objective is to minimize the weighted sum of the cost and environmental impact
        res = linprog(c_revised, A_ub=A_ub_revised, bounds=bounds_revised, b_ub=b_ub_revised, A_eq=A_eq_revised, b_eq=b_eq_revised, method='highs')
        solution_revised = res.x if res.success else [None]*sum(sources_to_include)
        solution = []
        k = 0
        for i in range(5):
            if sources_to_include[i]:
                solution.append(solution_revised[k])
                k += 1
            else:
                solution.append(None)
        status = res.success
    # Store the solution and status for the current day in the respective lists
    daily_solutions.append(solution)
    daily_status.append(status)

    # Update the rainwater storage after optimization
    if solution[3] is not None and solution[3] > 0:  # If rainwater is used on this day
        rainwater_storage -= solution[3]
    else:
        rainwater_storage += U[day, 3]  # Add the harvested amount
        rainwater_storage = min(16, rainwater_storage)  # Limit to max capacity


# Convert the daily solutions list to a dataframe for easier manipulation in the post-processing step
daily_solutions_df = pd.DataFrame(daily_solutions, columns=[f"Source_{i+1}" for i in range(5)])
daily_solutions_df.fillna(0.0, inplace=True)

# Define the source name mapping
source_name_mapping = {
    "Source_1": "Municipal",
    "Source_2": "River",
    "Source_3": "Groundwater",
```

```python
    "Source_4": "Rainwater",
    "Source_5": "Reuse"
}

# Rename the sources in the dataframe for visualization and saving
daily_solutions_df.rename(columns=source_name_mapping, inplace=True)
# Save the daily solutions to an Excel file
# This file will hold the optimized daily usage values for each source
daily_solutions_filepath = './daily_water_solutions_2023_v2.xlsx'
daily_solutions_df.to_excel(daily_solutions_filepath, index=True, index_label='Day')

# Save the yearly usage per source to an Excel file
# This file will hold the total annual usage values for each source
yearly_usage_per_source = daily_solutions_df.sum()
yearly_usage_filepath = './yearly_water_usage_per_source_2023_v2.xlsx'
yearly_usage_per_source.to_excel(yearly_usage_filepath, index=True, index_label='Source')

# Calculate the daily total cost and environmental impact
# We sum the daily usage from each source multiplied by its respective cost and environmental impact constant
daily_total_cost = daily_solutions_df.apply(lambda row: sum(row[source_name] * C[i] for i, source_name in enumerate(source_name_mapping.values())), axis=1)
daily_total_env_impact = daily_solutions_df.apply(lambda row: sum(row[source_name] * E[i] for i, source_name in enumerate(source_name_mapping.values())), axis=1)


#Section where we're comparing between the pre- and post-optimization Costs&Env. Impact
# Calculate the total annual water usage from all sources
total_annual_usage = yearly_usage_per_source.sum()

# Calculate the total annual cost and environmental impact
# We sum the daily usage from each source multiplied by its respective cost and environmental impact constant
total_annual_cost = sum(daily_total_cost)
total_annual_env_impact = sum(daily_total_env_impact)

# Calculate the new LCOW and CO₂ equivalent per cubic meter
# LCOW (€/m³) is calculated as the total annual cost divided by the total annual usage
# CO₂ equivalent (kg CO₂eq/m³) is calculated as the total annual environmental impact divided by the total annual usage
new_LCOW = total_annual_cost / total_annual_usage
new_CO2_eq_per_m3 = total_annual_env_impact / total_annual_usage

# Create a dataframe to store the pre and post optimization values for easy comparison
comparison_df = pd.DataFrame({
    'Metric': ['LCOW (€/m³)', 'Environmental Impact (kg CO₂eq/m³)'],
    'Pre-Optimization': [C[0], E[0]],
    'Post-Optimization': [new_LCOW, new_CO2_eq_per_m3]
})
comparison_df['Percentile Difference (%)'] = ((comparison_df['Post-Optimization'] - comparison_df['Pre-Optimization']) / comparison_df['Pre-Optimization']) * 100

comparison_filepath = './pre_post_optimization_comparison.xlsx'
comparison_df.to_excel(comparison_filepath, index=False)


# Calculate each source's contribution to the total cost and environmental impact
source_contributions = pd.DataFrame({
    'Source': list(source_name_mapping.values()),
    'Cost Contribution (€)': [sum(daily_solutions_df[source_name] * C[i]) for i, source_name in enumerate(source_name_mapping.values())],
    'Environmental Impact Contribution (kg CO₂eq)': [sum(daily_solutions_df[source_name] * E[i]) for i, source_name in enumerate(source_name_mapping.values())]
})

source_contributions_filepath = './source_contributions.xlsx'
source_contributions.to_excel(source_contributions_filepath, index=False)

# Plotting section to visualize the results

plt.figure(figsize=(12, 8))
for source_name in source_name_mapping.values():
    plt.plot(daily_solutions_df.index, daily_solutions_df[source_name], label=source_name)
plt.xlabel('Day of the year')
plt.ylabel('Water usage (cubic meters)')
plt.title('Day-to-Day Water Usage Per Source')
plt.legend()
plt.grid(True)
plt.show()

plt.figure(figsize=(8, 6))
yearly_usage_per_source.plot(kind='bar')
plt.xlabel('Water Sources')
plt.ylabel('Total Yearly Usage (cubic meters)')
plt.title('Total Yearly Usage Per Source')
plt.grid(axis='y')
plt.show()

plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
plt.plot(daily_total_cost, label='Daily Total Cost (EUROS)')
plt.xlabel('Day of the year')
plt.ylabel('Total Cost (EUROS)')
plt.title('Daily Total Cost')
plt.grid(True)
plt.subplot(2, 1, 2)
plt.plot(daily_total_env_impact, label='Daily Total Environmental Impact (kg CO2eq)', color='green')
plt.xlabel('Day of the year')
plt.ylabel('Total Environmental Impact (kg CO2eq)')
plt.title('Daily Total Environmental Impact')
plt.grid(True)
plt.tight_layout()
plt.show()

percentage_capacity_utilized = (yearly_usage_per_source / total_annual_capacity_per_source) * 100
plt.figure(figsize=(10, 6))
percentage_capacity_utilized.plot(kind='bar', color='mediumseagreen', edgecolor='black')
plt.xlabel('Water Sources', fontsize=14)
plt.ylabel('Percentage of Capacity Utilized (%)', fontsize=14)
plt.title('Percentage of Each Water Source\'s Capacity Utilized', fontsize=16)
plt.grid(axis='y')
plt.xticks(rotation=0)
plt.tight_layout()
plt.ylim(0, 110)
plt.show()

percentage_capacity_utilized_df = percentage_capacity_utilized.reset_index()
percentage_capacity_utilized_df.columns = ['Water Source', 'Percentage of Capacity Utilized (%)']
percentage_filepath = './percentage_capacity_utilized.xlsx'
percentage_capacity_utilized_df.to_excel(percentage_filepath, index=False)

# Combining "Total Yearly Usage Per Source" and "Percentage of Capacity Utilized" into a single chart
```

```python
plt.figure(figsize=(10, 6))

# Primary Y-axis: Total Yearly Usage Per Source
ax1 = plt.gca()
yearly_usage_per_source.plot(kind='bar', ax=ax1, position=1, color='mediumblue', width=0.4)
ax1.set_xlabel('Water Sources', fontsize=14)
ax1.set_ylabel('Total Yearly Usage (cubic meters)', fontsize=14)
ax1.set_title('Total Yearly Usage and Percentage Capacity Utilized Per Source', fontsize=16)
ax1.grid(axis='y')

# Secondary Y-axis: Percentage of Capacity Utilized
ax2 = ax1.twinx()
percentage_capacity_utilized.plot(kind='bar', ax=ax2, position=0, color='lightblue', width=0.4)
ax2.set_ylabel('Percentage of Capacity Utilized (%)', fontsize=14)
ax2.set_ylim(0, 110)

plt.xticks(rotation=0)
plt.tight_layout()
plt.show()

# Pie charts with different shades of blue
blue_shades = ['#003f5c', '#2f4b7c', '#665191', '#a05195', '#d45087']

plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.pie(source_contributions['Cost Contribution (€)'], labels=source_contributions['Source'], autopct='%1.1f%%', startangle=140, colors=blue_shades)
plt.title('Cost Contribution')

plt.subplot(1, 2, 2)
plt.pie(source_contributions['Environmental Impact Contribution (kg CO₂eq)'], labels=source_contributions['Source'], autopct='%1.1f%%', startangle=140, colors=blue_shades)
plt.title('Environmental Impact Contribution')
plt.tight_layout()
plt.show()


# Resetting the starting point for the fill
starting_point = np.zeros(365)

# Plotting the corrected area chart
plt.figure(figsize=(14, 8))

colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd']

# Iterating through each source in reverse order to properly stack them
for i, source_name in reversed(list(enumerate(daily_solutions_df.columns))):
    plt.fill_between(daily_solutions_df.index,
                     starting_point,
                     starting_point + daily_solutions_df[source_name],
                     color=colors[i],
                     label=source_name)
    starting_point += daily_solutions_df[source_name]

plt.xlabel('Day of the year', fontsize=14)
plt.ylabel('Water usage (cubic meters)', fontsize=14)
plt.title('Daily Water Usage Per Source (Area Chart)', fontsize=16)
plt.legend(loc='upper left')
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()
```

- **Algorithm no.2 (“cost-focused” scenario case)**

```python
from scipy.optimize import linprog
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Load the datasets
# U: A 2D numpy array holding the daily capacity values for each of the 5 sources
# Qd: A numpy array holding the daily water demand values
U = pd.read_csv('./WaterProfiles_Modified.csv').iloc[:, 1:].values
Qd = pd.read_csv('./daily_water_demand_2021.csv')['Demand (m3)'].values

# Define the constants
# C: A list holding the cost constants for each source (in €/m³)
# E: A list holding the environmental impact constants for each source (in kg CO₂eq/m³)
# w_c: The weight assigned to the cost in the objective function
# w_e: The weight assigned to the environmental impact in the objective function
C = [1.742, 1.522, 1.131, 5.382, 2.05]
E = [12.279, 1.764, 7.775, 10.001, 9.594]
w_c = 90
w_e = 10


# Min-Max normalization for cost (C) and environmental impact (E) constants
min_cost = np.min(C)
max_cost = np.max(C)
C_normalized = (C - min_cost) / (max_cost - min_cost)

min_impact = np.min(E)
max_impact = np.max(E)
E_normalized = (E - min_impact) / (max_impact - min_impact)


# Calculate the total annual capacity for each source
# This will be used to determine which sources should be included in the optimization
total_annual_capacity_per_source = U.sum(axis=0)

# Calculate the yearly total demand
# This will be used to ensure the 4% annual usage constraint is met
yearly_total_demand = Qd.sum()

# Determine which sources to include in the optimization
# A source is included if its total annual capacity is at least 10% of the yearly total demand
sources_to_include = total_annual_capacity_per_source >= 0.1 * yearly_total_demand

# Initialize lists to store the daily solutions and the status of each optimization
daily_solutions = []
daily_status = []

# Initialization of rainwater accumulative profile function
rainwater_storage = 0

# Loop through each day and solve the linear programming problem
# The loop index (day) ranges from 0 to 364, representing each day of the year
for day in range(365):

    # Define the coefficients of the objective function based on the weighted sum of the cost and environmental impact constants for the included sources
    c_revised = [(w_c * C_normalized[i] + w_e * E_normalized[i]) for i in range(5) if sources_to_include[i]]
```

```python
    #c_revised = [(w_c * C[i] + w_e * E[i]) for i in range(5) if sources_to_include[i]]

    # Define the inequality constraints matrix to ensure daily usage from each source does not exceed its daily capacity
    A_ub_revised = [[1 if i == j else 0 for i in range(5) if sources_to_include[i]] for j in range(sum(sources_to_include))]

    # Define the inequality constraints vector based on the daily capacities for the included sources
    b_ub_revised = [U[day, i] for i in range(5) if sources_to_include[i]]

    # Define the equality constraints to ensure the total daily usage meets the daily demand
    A_eq_revised = [[1 for i in range(5) if sources_to_include[i]]]
    b_eq_revised = [Qd[day]]

    # Define the bounds for each source to ensure the usage is between 0 and the daily capacity and does not exceed 50% of the daily demand
    #bounds_revised = [(0, U[day, i]) for i in range(5) if sources_to_include[i]]
    #bounds_revised = [(0, min(U[day, i], 0.5 * Qd[day])) for i in range(5) if sources_to_include[i]]
    #Define the bounds for each source to ensure the usage is between 0 and the daily capacity -- ! having removed the 50% contribution limit to conclude on the cost-effective scenario
    bounds_revised = [(0, min(U[day, i], Qd[day])) for i in range(5) if sources_to_include[i]]

    # If the daily demand is zero, directly assign a usage of 0 units from all sources
    if Qd[day] == 0:
        solution = [0 if sources_to_include[i] else None for i in range(5)]
        status = True
    else:
        # Solve the linear programming problem using the 'highs' method in the linprog function
        # The objective is to minimize the weighted sum of the cost and environmental impact
        res = linprog(c_revised, A_ub=A_ub_revised, bounds=bounds_revised, b_ub=b_ub_revised, A_eq=A_eq_revised, b_eq=b_eq_revised, method='highs')

        # Get the solution and status of the optimization
        # If the optimization was not successful, all values in the solution are set to None
        solution_revised = res.x if res.success else [None]*sum(sources_to_include)
        solution = []
        k = 0
        for i in range(5):
            if sources_to_include[i]:
                solution.append(solution_revised[k])
                k += 1
            else:
                solution.append(None)
        status = res.success

    # Store the solution and status for the current day in the respective lists
    daily_solutions.append(solution)
    daily_status.append(status)

    # Update the rainwater storage after optimization
    if solution[3] is not None and solution[3] > 0:  # If rainwater is used on this day
        rainwater_storage -= solution[3]
    else:
        rainwater_storage += U[day, 3]  # Add the harvested amount
        rainwater_storage = min(16, rainwater_storage)  # Limit to max capacity


# Define the source name mapping
source_name_mapping = {
    "Source_1": "Municipal",
    "Source_2": "River",
    "Source_3": "Groundwater",
```

```python
    "Source_4": "Rainwater",
    "Source_5": "Reuse"
}


# Convert the daily solutions list to a dataframe for easier manipulation in the post-processing step
daily_solutions_df = pd.DataFrame(daily_solutions, columns=[f"Source_{i+1}" for i in range(5)])
daily_solutions_df.fillna(0.0, inplace=True)


# Save the daily solutions to an Excel file
# This file will hold the optimized daily usage values for each source
daily_solutions_filepath = './daily_water_solutions_2023_v2.xlsx'
daily_solutions_df.to_excel(daily_solutions_filepath, index=True, index_label='Day')

# Save the yearly usage per source to an Excel file
# This file will hold the total annual usage values for each source
yearly_usage_per_source = daily_solutions_df.sum()
yearly_usage_filepath = './yearly_water_usage_per_source_2023_v2.xlsx'
yearly_usage_per_source.to_excel(yearly_usage_filepath, index=True, index_label='Source')

# Calculate the daily total cost and environmental impact
# We sum the daily usage from each source multiplied by its respective cost and environmental impact constant
daily_total_cost = daily_solutions_df.apply(lambda row: sum(row[i] * C[i] if row[i] is not None else 0 for i in range(5)), axis=1)
daily_total_env_impact = daily_solutions_df.apply(lambda row: sum(row[i] * E[i] if row[i] is not None else 0 for i in range(5)), axis=1)


#Section where we're comparing between the pre- and post-optimization Costs&Env. Impact
# Calculate the total annual water usage from all sources
total_annual_usage = yearly_usage_per_source.sum()

# Calculate the total annual cost and environmental impact
# We sum the daily usage from each source multiplied by its respective cost and environmental impact constant
total_annual_cost = sum(daily_solutions_df.apply(lambda row: sum(row[i] * C[i] if row[i] is not None else 0 for i in range(5)), axis=1))
total_annual_env_impact = sum(daily_solutions_df.apply(lambda row: sum(row[i] * E[i] if row[i] is not None else 0 for i in range(5)), axis=1))

# Calculate the new LCOW and CO₂ equivalent per cubic meter
# LCOW (€/m³) is calculated as the total annual cost divided by the total annual usage
# CO₂ equivalent (kg CO₂eq/m³) is calculated as the total annual environmental impact divided by the total annual usage
new_LCOW = total_annual_cost / total_annual_usage
new_CO2_eq_per_m3 = total_annual_env_impact / total_annual_usage

# Create a dataframe to store the pre and post optimization values for easy comparison
comparison_df = pd.DataFrame({
    'Metric': ['LCOW (€/m³)', 'Environmental Impact (kg CO₂eq/m³)'],
    'Pre-Optimization': [C[0], E[0]],  # Using the values for the municipal water source
    'Post-Optimization': [new_LCOW, new_CO2_eq_per_m3]
})

# Now, adding the percentile difference
comparison_df['Percentile Difference (%)'] = ((comparison_df['Post-Optimization'] - comparison_df['Pre-Optimization']) / comparison_df['Pre-Optimization']) * 100

comparison_df
# Save the comparison data to an Excel file
comparison_filepath = './pre_post_optimization_comparison.xlsx'
comparison_df.to_excel(comparison_filepath, index=False)
```

```python


# Calculate each source's contribution to the total cost and environmental impact
source_contributions = pd.DataFrame({
    'Source': [f'Source_{i+1}' for i in range(5)],
    'Cost Contribution (€)': [sum(daily_solutions_df[f'Source_{i+1}'] * C[i]) for i in range(5)],
    'Environmental Impact Contribution (kg CO₂eq)': [sum(daily_solutions_df[f'Source_{i+1}'] * E[i]) for i in range(5)]
})

# Save the source contributions to an Excel file
source_contributions_filepath = './source_contributions.xlsx'
source_contributions.to_excel(source_contributions_filepath, index=False)



# Calculate total yearly usage per source
yearly_usage_per_source_cost = daily_solutions_df.sum()

# Plotting section to visualize the results

# Plot the day-to-day usage per source for the year
# This plot shows how the daily usage of each source varies over the year
plt.figure(figsize=(12, 8))
for i in range(5):
    plt.plot(daily_solutions_df.index, daily_solutions_df[f'Source_{i+1}'], label=f'Source {i+1}')
plt.xlabel('Day of the year')
plt.ylabel('Water usage (cubic meters)')
plt.title('Day-to-Day Water Usage Per Source, Cost-effective scenario')
plt.legend()
plt.grid(True)
plt.show()

# Calculate the total yearly usage per source
# This is used in the next plot to show the total usage from each source over the year
yearly_usage_per_source = daily_solutions_df.sum()

# Plot a bar chart for the total yearly usage per source
# This plot gives a visual representation of the total amount of water used from each source over the year
plt.figure(figsize=(8, 6))
yearly_usage_per_source.plot(kind='bar')
plt.xlabel('Water Sources')
plt.ylabel('Total Yearly Usage (cubic meters)')
plt.title('Total Yearly Usage Per Source,Cost-effective scenario')
plt.grid(axis='y')
plt.show()


colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd']
# Resetting the starting point for the fill
starting_point = np.zeros(365)
# Iterating through each source in reverse order to properly stack them
for i, column in reversed(list(enumerate(daily_solutions_df.columns))):
    plt.fill_between(daily_solutions_df.index,
                     starting_point,
                     starting_point + daily_solutions_df[column],
                     color=colors[i],
                     label=source_name_mapping[column])
    starting_point += daily_solutions_df[column]

plt.xlabel('Day of the year', fontsize=14)
plt.ylabel('Water usage (cubic meters)', fontsize=14)
plt.title('Daily Water Usage Per Source (Area Chart)', fontsize=16)
plt.legend(loc='upper left')
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()



# Plot the daily total cost and environmental impact
# These plots show how the total cost and environmental impact vary on a daily basis over the year
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
plt.plot(daily_total_cost, label='Daily Total Cost (EUROS)')
plt.xlabel('Day of the year')
plt.ylabel('Total Cost (EUROS)')
plt.title('Daily Total Cost')
plt.grid(True)
plt.subplot(2, 1, 2)
plt.plot(daily_total_env_impact, label='Daily Total Environmental Impact (kg CO2eq)', color='green')
plt.xlabel('Day of the year')
plt.ylabel('Total Environmental Impact (kg CO2eq)')
plt.title('Daily Total Environmental Impact')
plt.grid(True)
plt.tight_layout()
plt.show()

# Calculate the percentage of each water source's capacity that was used
percentage_capacity_utilized = (yearly_usage_per_source_cost / total_annual_capacity_per_source) * 100

# Bar chart illustrating the percentage of each water source's capacity utilized
plt.figure(figsize=(10, 6))
percentage_capacity_utilized.plot(kind='bar', color='mediumseagreen', edgecolor='black')
plt.xlabel('Water Sources', fontsize=14)
plt.ylabel('Percentage of Capacity Utilized (%)', fontsize=14)
plt.title('Percentage of Each Water Source\'s Capacity Utilized,Cost-effective scenario', fontsize=16)
plt.grid(axis='y')
plt.xticks(rotation=0)
plt.tight_layout()
plt.ylim(0, 110)  # Setting the y-axis limit to 110% to give some headroom
plt.show()


# Create a dataframe for the percentage capacity utilized for each source
percentage_capacity_utilized_df = percentage_capacity_utilized.reset_index()
percentage_capacity_utilized_df.columns = ['Water Source', 'Percentage of Capacity Utilized (%)']

# Save to Excel file
percentage_filepath = './percentage_capacity_utilized.xlsx'
percentage_capacity_utilized_df.to_excel(percentage_filepath, index=False)

percentage_capacity_utilized_df

```

- **Algorithm no.3 (“eco-friendly” scenario case)**

```python
from scipy.optimize import linprog
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Load the datasets
U = pd.read_csv('./WaterProfiles_Modified.csv').iloc[:, 1:].values
Qd = pd.read_csv('./daily_water_demand_2021.csv')['Demand (m3)'].values

# Define the constants
C = [1.742, 1.522, 1.131, 5.382, 2.05]
E = [12.279, 1.764, 7.775, 10.001, 9.594]
w_c = 10
w_e = 90

min_cost = np.min(C)
max_cost = np.max(C)
C_normalized = (C - min_cost) / (max_cost - min_cost)

min_impact = np.min(E)
max_impact = np.max(E)
E_normalized = (E - min_impact) / (max_impact - min_impact)

total_annual_capacity_per_source = U.sum(axis=0)
yearly_total_demand = Qd.sum()
sources_to_include = total_annual_capacity_per_source >= 0.1 * yearly_total_demand

daily_solutions = []
daily_status = []

# Initialization
rainwater_storage = 0

for day in range(365):
    c_revised = [(w_c * C_normalized[i] + w_e * E_normalized[i]) for i in range(5) if sources_to_include[i]]
    A_ub_revised = [[1 if i == j else 0 for i in range(5) if sources_to_include[i]] for j in range(sum(sources_to_include))]
    b_ub_revised = [U[day, i] for i in range(5) if sources_to_include[i]]
    A_eq_revised = [[1 for i in range(5) if sources_to_include[i]]]
    b_eq_revised = [Qd[day]]
    bounds_revised = [(0, min(U[day, i], Qd[day])) for i in range(5) if sources_to_include[i]]

    if Qd[day] == 0:
        solution = [0 if sources_to_include[i] else None for i in range(5)]
        status = True
    else:
        res = linprog(c_revised, A_ub=A_ub_revised, bounds=bounds_revised, b_ub=b_ub_revised, A_eq=A_eq_revised, b_eq=b_eq_revised, method='highs')
        solution_revised = res.x if res.success else [None]*sum(sources_to_include)
        solution = []
        k = 0
        for i in range(5):
            if sources_to_include[i]:
                solution.append(solution_revised[k])
                k += 1
            else:
                solution.append(None)
        status = res.success

    daily_solutions.append(solution)
    daily_status.append(status)

    # Update the rainwater storage after optimization
    if solution[3] is not None and solution[3] > 0:  # If rainwater is used on this day
        rainwater_storage -= solution[3]
    else:
        rainwater_storage += U[day, 3]  # Add the harvested amount
        rainwater_storage = min(16, rainwater_storage)  # Limit to max capacity

daily_solutions_df = pd.DataFrame(daily_solutions, columns=[f"Source_{i+1}" for i in range(5)])
daily_solutions_df.fillna(0.0, inplace=True)

# Define the source name mapping
source_name_mapping = {
    "Source_1": "Municipal",
    "Source_2": "River",
    "Source_3": "Groundwater",
    "Source_4": "Rainwater",
    "Source_5": "Reuse"
}

# Rename the sources in the dataframe for visualization and saving
daily_solutions_df.rename(columns=source_name_mapping, inplace=True)

daily_solutions_filepath = './daily_water_solutions_2023_v2.xlsx'
daily_solutions_df.to_excel(daily_solutions_filepath, index=True, index_label='Day')

yearly_usage_per_source = daily_solutions_df.sum()
yearly_usage_filepath = './yearly_water_usage_per_source_2023_v2.xlsx'
yearly_usage_per_source.to_excel(yearly_usage_filepath, index=True, index_label='Source')

daily_total_cost = daily_solutions_df.apply(lambda row: sum(row[source_name] * C[i] for i, source_name in enumerate(source_name_mapping.values())), axis=1)
daily_total_env_impact = daily_solutions_df.apply(lambda row: sum(row[source_name] * E[i] for i, source_name in enumerate(source_name_mapping.values())), axis=1)

total_annual_usage = yearly_usage_per_source.sum()
total_annual_cost = sum(daily_total_cost)
total_annual_env_impact = sum(daily_total_env_impact)
new_LCOW = total_annual_cost / total_annual_usage
new_CO2_eq_per_m3 = total_annual_env_impact / total_annual_usage

comparison_df = pd.DataFrame({
    'Metric': ['LCOW (€/m³)', 'Environmental Impact (kg CO₂eq/m³)'],
    'Pre-Optimization': [C[0], E[0]],
    'Post-Optimization': [new_LCOW, new_CO2_eq_per_m3]
})
comparison_df['Percentile Difference (%)'] = ((comparison_df['Post-Optimization'] - comparison_df['Pre-Optimization']) / comparison_df['Pre-Optimization']) * 100

comparison_filepath = './pre_post_optimization_comparison.xlsx'
comparison_df.to_excel(comparison_filepath, index=False)

source_contributions = pd.DataFrame({
    'Source': list(source_name_mapping.values()),
    'Cost Contribution (€)': [sum(daily_solutions_df[source_name] * C[i]) for i, source_name in enumerate(source_name_mapping.values())],
    'Environmental Impact Contribution (kg CO₂eq)': [sum(daily_solutions_df[source_name] * E[i]) for i, source_name in enumerate(source_name_mapping.values())]
})
```

```python
source_contributions_filepath = './source_contributions.xlsx'
source_contributions.to_excel(source_contributions_filepath, index=False)


plt.figure(figsize=(12, 8))
for source_name in source_name_mapping.values():
    plt.plot(daily_solutions_df.index, daily_solutions_df[source_name], label=source_name)
plt.xlabel('Day of the year')
plt.ylabel('Water usage (cubic meters)')
plt.title('Day-to-Day Water Usage Per Source')
plt.legend()
plt.grid(True)
plt.show()

plt.figure(figsize=(8, 6))
yearly_usage_per_source.plot(kind='bar')
plt.xlabel('Water Sources')
plt.ylabel('Total Yearly Usage (cubic meters)')
plt.title('Total Yearly Usage Per Source')
plt.grid(axis='y')
plt.show()

plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
plt.plot(daily_total_cost, label='Daily Total Cost (EUROS)')
plt.xlabel('Day of the year')
plt.ylabel('Total Cost (EUROS)')
plt.title('Daily Total Cost')
plt.grid(True)
plt.subplot(2, 1, 2)
plt.plot(daily_total_env_impact, label='Daily Total Environmental Impact (kg CO2eq)', color='green')
plt.xlabel('Day of the year')
plt.ylabel('Total Environmental Impact (kg CO2eq)')
plt.title('Daily Total Environmental Impact')
plt.grid(True)
plt.tight_layout()
plt.show()

percentage_capacity_utilized = (yearly_usage_per_source / total_annual_capacity_per_source) * 100
plt.figure(figsize=(10, 6))
percentage_capacity_utilized.plot(kind='bar', color='mediumseagreen', edgecolor='black')
plt.xlabel('Water Sources', fontsize=14)
plt.ylabel('Percentage of Capacity Utilized (%)', fontsize=14)
plt.title('Percentage of Each Water Source\'s Capacity Utilized', fontsize=16)
plt.grid(axis='y')
plt.xticks(rotation=0)
plt.tight_layout()
plt.ylim(0, 110)
plt.show()

percentage_capacity_utilized_df = percentage_capacity_utilized.reset_index()
percentage_capacity_utilized_df.columns = ['Water Source', 'Percentage of Capacity Utilized (%)']
percentage_filepath = './percentage_capacity_utilized.xlsx'
percentage_capacity_utilized_df.to_excel(percentage_filepath, index=False)

# Combining "Total Yearly Usage Per Source" and "Percentage of Capacity Utilized" into a single chart
plt.figure(figsize=(10, 6))

# Primary Y-axis: Total Yearly Usage Per Source
ax1 = plt.gca()
yearly_usage_per_source.plot(kind='bar', ax=ax1, position=1, color='mediumblue', width=0.4)
ax1.set_xlabel('Water Sources', fontsize=14)
ax1.set_ylabel('Total Yearly Usage (cubic meters)', fontsize=14)
ax1.set_title('Total Yearly Usage and Percentage Capacity Utilized Per Source- Eco', fontsize=16)
ax1.grid(axis='y')

# Secondary Y-axis: Percentage of Capacity Utilized
ax2 = ax1.twinx()
percentage_capacity_utilized.plot(kind='bar', ax=ax2, position=0, color='lightblue', width=0.4)
ax2.set_ylabel('Percentage of Capacity Utilized (%)', fontsize=14)
ax2.set_ylim(0, 110)

plt.xticks(rotation=0)
plt.tight_layout()
plt.show()

# Pie charts with different shades of blue
blue_shades = ['#003f5c', '#2f4b7c', '#665191', '#a05195', '#d45087']

plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.pie(source_contributions['Cost Contribution (€)'], labels=source_contributions['Source'], autopct='%1.1f%%', startangle=140, colors=blue_shades)
plt.title('Cost Contribution-Eco')

plt.subplot(1, 2, 2)
plt.pie(source_contributions['Environmental Impact Contribution (kg CO₂eq)'], labels=source_contributions['Source'], autopct='%1.1f%%', startangle=140, colors=blue_shades)
plt.title('Environmental Impact Contribution-Eco')
plt.tight_layout()
plt.show()


# Resetting the starting point for the fill
starting_point = np.zeros(365)

# Plotting the corrected area chart
plt.figure(figsize=(14, 8))

colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd']

# Iterating through each source in reverse order to properly stack them
for i, source_name in reversed(list(enumerate(daily_solutions_df.columns))):
    plt.fill_between(daily_solutions_df.index,
                     starting_point,
                     starting_point + daily_solutions_df[source_name],
                     color=colors[i],
                     label=source_name)
    starting_point += daily_solutions_df[source_name]

plt.xlabel('Day of the year', fontsize=14)
plt.ylabel('Water usage (cubic meters)', fontsize=14)
plt.title('Daily Water Usage Per Source (Area Chart)-Eco', fontsize=16)
plt.legend(loc='upper left')
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()
```

- **Sensitivity analysis algorithm -0.25-bounds case**

The simplified version of the code above, set for the 0.25-bounds case in the Sensitivity Analysis section. All cases for the Analysis followed the same pattern.

```python
import pandas as pd
import numpy as np
from scipy.optimize import linprog

# Load the datasets
U = pd.read_csv('./WaterProfiles_Modified.csv').iloc[:, 1:].values
Qd = pd.read_csv('./daily_water_demand_2021.csv')['Demand (m3)'].values

# Define the constants
C = [1.742, 1.522, 1.131, 5.382, 2.05]
E = [12.279, 1.764, 7.775, 10.001, 9.594]
w_c = 65
w_e = 35

source_name_mapping = {
    "Source_1": "Municipal",
    "Source_2": "River",
    "Source_3": "Groundwater",
    "Source_4": "Rainwater",
    "Source_5": "Reuse"
}

min_cost = np.min(C)
max_cost = np.max(C)
C_normalized = (C - min_cost) / (max_cost - min_cost)

min_impact = np.min(E)
max_impact = np.max(E)
E_normalized = (E - min_impact) / (max_impact - min_impact)

total_annual_capacity_per_source = U.sum(axis=0)
yearly_total_demand = Qd.sum()
sources_to_include = total_annual_capacity_per_source >= 0.1 * yearly_total_demand

# Define the maximum contribution for each source
max_contribution_per_source = [float('inf'), 17.26974, 11.25, float('inf'), 6.019737]

# Initialization
rainwater_storage = 0
reuse_storage = 0

# Run the optimization with the limits
daily_solutions_with_limits = []
daily_status_with_limits = []

for day in range(365):
    c_revised = [(w_c * C_normalized[i] + w_e * E_normalized[i]) for i in range(5) if sources_to_include[i]]
    A_ub_revised = [[1 if i == j else 0 for i in range(5) if sources_to_include[i]] for j in range(sum(sources_to_include))]
    b_ub_revised = [U[day, i] for i in range(5) if sources_to_include[i]]
    A_eq_revised = [[1 for i in range(5) if sources_to_include[i]]]
    b_eq_revised = [Qd[day]]
    # Adjust bounds to consider the manually set maximum limits
    bounds_revised = [(0, min(U[day, i], 0.25*Qd[day], max_contribution_per_source[i])) for i in range(5) if sources_to_include[i]]

    if Qd[day] == 0:
        solution = [0 if sources_to_include[i] else None for i in range(5)]
        status = True
    else:
        res = linprog(c_revised, A_ub=A_ub_revised, bounds=bounds_revised, b_ub=b_ub_revised, A_eq=A_eq_revised, b_eq=b_eq_revised, method='highs')
        solution_revised = res.x if res.success else [None]*sum(sources_to_include)
        solution = []
        k = 0
        for i in range(5):
            if sources_to_include[i]:
                solution.append(solution_revised[k])
                k += 1
            else:
                solution.append(None)
        status = res.success

    daily_solutions_with_limits.append(solution)
    daily_status_with_limits.append(status)

    # Update the rainwater storage after optimization
    if solution[3] is not None and solution[3] > 0:  # If rainwater is used on this day
        rainwater_storage -= solution[3]
    else:
        rainwater_storage += U[day, 3]  # Add the harvested amount
        rainwater_storage = min(16, rainwater_storage)  # Limit to max capacity

    # Update the reuse storage after optimization
    if day > 0:
        reuse_storage = 0.7 * Qd[day-1]

# Convert the solutions to a DataFrame for easier visualization
daily_solutions_with_limits_df = pd.DataFrame(daily_solutions_with_limits, columns=[f"Source_{i+1}" for i in range(5)])
daily_solutions_with_limits_df.fillna(0.0, inplace=True)
daily_solutions_with_limits_df.rename(columns=source_name_mapping, inplace=True)


# Save the results
daily_solutions_filepath = './daily_water_solutions_2023_v3_with_limits.xlsx'
daily_solutions_with_limits_df.to_excel(daily_solutions_filepath, index=True, index_label='Day')

# Calculate new LCOW and environmental impact
yearly_usage_per_source = daily_solutions_with_limits_df.sum()
daily_total_cost = daily_solutions_with_limits_df.apply(lambda row: sum(row[source_name] * C[i] for i, source_name in enumerate(source_name_mapping.values())), axis=1)
daily_total_env_impact = daily_solutions_with_limits_df.apply(lambda row: sum(row[source_name] * E[i] for i, source_name in enumerate(source_name_mapping.values())), axis=1)

total_annual_usage = yearly_usage_per_source.sum()
total_annual_cost = sum(daily_total_cost)
total_annual_env_impact = sum(daily_total_env_impact)
new_LCOW = total_annual_cost / total_annual_usage
new_CO2_eq_per_m3 = total_annual_env_impact / total_annual_usage

# Comparison DataFrame
comparison_df = pd.DataFrame({
    'Metric': ['LCOW (€/m³)', 'Environmental Impact (kg CO₂eq/m³)'],
    'Pre-Optimization': [C[0], E[0]],
    'Post-Optimization': [new_LCOW, new_CO2_eq_per_m3]
})
comparison_df['Percentile Difference (%)'] = ((comparison_df['Post-Optimization'] - comparison_df['Pre-Optimization']) / comparison_df['Pre-Optimization']) * 100

# Save the comparison
comparison_filepath = './pre_post_optimization_comparison_with_limits.xlsx'
comparison_df.to_excel(comparison_filepath, index=False)
# Calculate the overall volume of each source used in a year
yearly_volume_per_source = daily_solutions_with_limits_df.sum()

# Aggregate these volumes to find the overall total
total_yearly_volume = yearly_volume_per_source.sum()

print(yearly_volume_per_source)
print("\nTotal yearly volume:", total_yearly_volume)
```