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An integrated framework for stormwater management and life cycle assessment of rainwater harvesting: A comparative study of two underserved communities

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HIGHLIGHTS

- Global warming potential (GWP) decreases with Rain Barrels (RBs) in both study areas.
- Human Toxicity potential (HTP) increases with RBs in both study areas.
- Higher rainfall results in an increased water collection and greater GWP reduction.
- Ecotoxicity and eutrophication in receiving waters is decreased with reduced runoff.
- Regional event mean concentration parameters are effective for pollution estimation.

GRAPHICAL ABSTRACT

ARTICLE INFO

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ABSTRACT

Green infrastructure, which is designed to provide sustainable and resilient stormwater management solutions, inherently supports flood mitigation, pollution reduction, and a decentralized water supply. When proposing this type of infrastructure, it is important to identify environmental trade-offs related to their implementation. Our research focuses on a city-wide rain barrel (RB) deployment in northern and southern California, San Leandro and Imperial Beach, respectively. San Leandro and Imperial Beach are similar in that they are both low-lying coastal areas, containing a high percentage of residential areas with several census tracts listed as disadvantaged. A key difference is that San Leandro receives approximately 2.5 times the annual rainfall as Imperial Beach. This work utilizes PCSWMM for stormwater modeling to quantify captured stormwater, changes in conventional stormwater management (such as ocean outfall stormwater pumping), and reduced pollutant loading for RB deployment. Stormwater modeling is combined with Life Cycle Assessments (LCA) to quantify trade-offs in terms of Global Warming Potential (GWP), Human Toxicity Potential (HTP), Ecotoxicity Potential (EcoP) and Eutrophication Potential (EP). In Imperial Beach, RBs reduce GWP by 2.6×10^6 kg Carbon Dioxide Equivalent (CO_2-Eq) and increase HTP by 3.8×10^6 kg Dichlorobenzene Equivalent (DCB-Eq). In San Leandro, GWP reduces by 1.3×10^7 kg CO_2-Eq, and HTP increases by 4.7×10^6 kg DCB-Eq. In Imperial Beach, a reduction in runoff from captured rainfall results in a 44 % reduction of pollutant loading, while San Leandro sees a 27 % reduction. These reductions are equal to the reductions in EcoP and EP. Normalized per 1 m^3 of collected

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stormwater, there is a lower reduction in GWP for Imperial Beach than San Leandro, and a higher contribution to HTP. This study advances current knowledge by quantifying RB benefits through multiple sustainability metrics, while comparing two underserved coastal California communities with distinct rainfall patterns. It demonstrates that while RBs reduce runoff and pollution, they also present environmental trade-offs, providing key insights for green infrastructure deployment.

1. Introduction

Urban stormwater management is moving away from grey infrastructure, where water is conveyed out of cities rapidly, to green infrastructure, where water is treated or reclaimed to reduce pollution and increase water supply (O'Sullivan et al., 2015; Rodak et al., 2020). An increased water supply is especially important in areas that have limited access to clean freshwater (Sukri et al., 2023). RainWater Harvesting (RWH), which captures rain either in a storage container or larger cistern, is a form of green infrastructure that can accomplish the goals of urban stormwater management (Ghimire et al., 2017; Martins Vaz et al., 2023). These systems are generally for household use, although larger ones can be used for agricultural use (Greco, 2019). These systems can have various benefits from reduced flooding and reduced quantities of urban runoff, to providing a decentralized water supply; however, large scale deployments need to be assessed to quantify the sustainability.

Life cycle assessments (LCA) and life cycle impact assessments (LCIA) are valuable tools to help researchers determine the environmental impacts of materials, and processes. These assessments are utilized to estimate the consumption of resources and emissions associated with the life cycle of a product, process, or infrastructure. The following steps are utilized in a LCA: outlining the goal and scope of the analysis, gathering the data needed to develop a life cycle inventory, quantifying the impacts through a life cycle impact assessment, and interpreting results. In LCA studies investigating water and wastewater treatment plants, a functional unit (FU) of 1 m^3 of treated water is typically utilized (Tavakol-Davani et al., 2018). The FU is a measure of the performance of the functional outputs of the system and is utilized as the comparison basis for all results (ISO, 2006). The goal of this study is to assess the benefits toward stormwater management and a decentralized water supply; therefore, the FU was defined as 1 m^3 of captured stormwater in a rain barrel system. These assessments can provide researchers with quantifiable sustainability metrics, such as Global Warming Potential (GWP), Human Toxicity Potential (HTP), acidification potential, Eutrophication Potential (EP), Ecotoxicity Potential (EcoP), and ozone depletion potential (Baitz et al., 2012). Furthermore, LCA can support hydrologic analysis, enabling more holistic decision-making, and providing sustainability criteria.

Through LCA modeling, researchers have investigated various aspects of water resources. Researchers have shown the life cycle impacts of water infrastructure (Cellura et al., 2018) including water treatment, wastewater treatment (Ando and Netusil, 2018; Buonocore et al., 2018; Corominas et al., 2020; Xue et al., 2016; Zhang et al., 2021), various methods of green infrastructure and low-impact development (dos Santos et al., 2021; Feigl et al., 2018; Kim et al., 2013), conventional urban stormwater management (Brudler et al., 2019; Hengen Tyler et al., 2016; Rodríguez-Sinobas et al., 2018), and conventional stormwater management under climate change (Brudler et al., 2016). However, assessments that include a broad spectrum of benefits (flood reduction, water quality improvements, and a decentralized water supply) are limited. Thus, this research aims to explore the multifaceted benefits of implementing RWH on a city scale.

A contribution of this work is to demonstrate the potential for reduced pollutant loading with large scale Rain Barrel (RB) deployments. Stormwater has been shown to transport pollutants into receiving water bodies (Nguyen et al., 2023; Nguyen and Truong, 2023; Pamuru et al., 2022; Stein et al.). Pollutants carried by stormwater from urbanized areas can enter waterways used for irrigation, potentially impacting food security (Nguyen et al., 2023; Sukri et al., 2023). Characterizing the pollutants in stormwater is critical for quantifying a risk assessment, in order to properly implement protective measures (Nguyen and Truong, 2023). Through the capture of stormwater from roofs and the redirection of this runoff into pervious surfaces, pollutants carried by urban runoff can also be reduced. Researchers have used LCIA to quantify the impacts of stormwater pollution on environmental systems (Brudler et al., 2019; Jeong et al., 2016; Phillips et al., 2018). Researchers that utilize LCIA for stormwater discharges primarily analyze the effects on the receiving waters in terms of ecotoxicity and eutrophication. Ecotoxicity is a measure of the relative harm caused to people or the environment by an emitted substance. Eutrophication is the enrichment of an aquatic ecosystem with nutrients (nitrates, phosphates) that accelerate biological productivity of some plants and an undesirable accumulation of algal biomass (Bare et al., 2012). This research will focus on Total Nitrogen (N) and Total Phosphorus (P) for EP. In urban areas, heavy metal contaminants originate from roof weathering, degradation of vehicle parts, and additives in oil and petrol (O'Sullivan et al., 2015). Due to the ubiquitous nature of heavy metals in the urban environment, this study will focus on Copper (Cu), Lead (Pb) and Zinc (Zn) for determining EcoP. These metals are also selected since Cu and Zn have been shown to contribute to about 90 % of the EcoP for stormwater (Brudler et al., 2019).

The impacts of stormwater and benefits of proposed management strategies can affect a range of sectors; therefore, an assessment framework is required to consolidate the separate but interrelated concepts. As part of our proposed framework, we aim to demonstrate both the sustainability metrics of RB deployments and the environmental benefits from pollution reduction. Our study focuses on the implementation of RBs as a form of RWH to assist with stormwater management in the City of Imperial Beach (IB) and the Lower San Leandro Creek Watershed (SL). Researchers have shown some of the emissions-based costs of developing RB systems (Ghimire et al., 2017). However, direct comparisons of emissions and energy savings compared to existing stormwater infrastructure and urban water supply from large-scale (city-wide) deployments are lacking from the literature. With and without RB deployment, we also analyze the changes in pumping needs for a stormwater pump station, which pumps stormwater for drainage and first-flush stormwater for treatment. Furthermore, we run scenarios with and without RBs to estimate changes in pollutant loads discharged from stormwater outfalls. We accompany the pollutant loading analysis with an assessment of the EP and EcoP of these discharges.

Past research has highlighted the benefits of RWH and RB systems for stormwater management, as well as the impact of stormwater constituents on EcoP and EP. However, there is a gap in the literature when it comes to combining stormwater modeling with LCAs, in order to evaluate the environmental impact of stormwater collection as both a decentralized water source and a method for pollution control. Moreover, few studies have examined a city-wide RB deployment. This study addresses this gap by analyzing stormwater impacts with and without RBs. A key contribution is the evaluation of environmental benefits related to reducing centralized water demand and stormwater pumping, presented in terms of GWP and HTP. In addition to comparing conventional stormwater systems with integrated RWH systems, this work introduces the novelty of examining a large-scale RB deployment in two areas with distinct rainfall patterns. It builds on previous research comparing traditional stormwater and water distribution systems to decentralized RWH but extends it by evaluating the large-scale

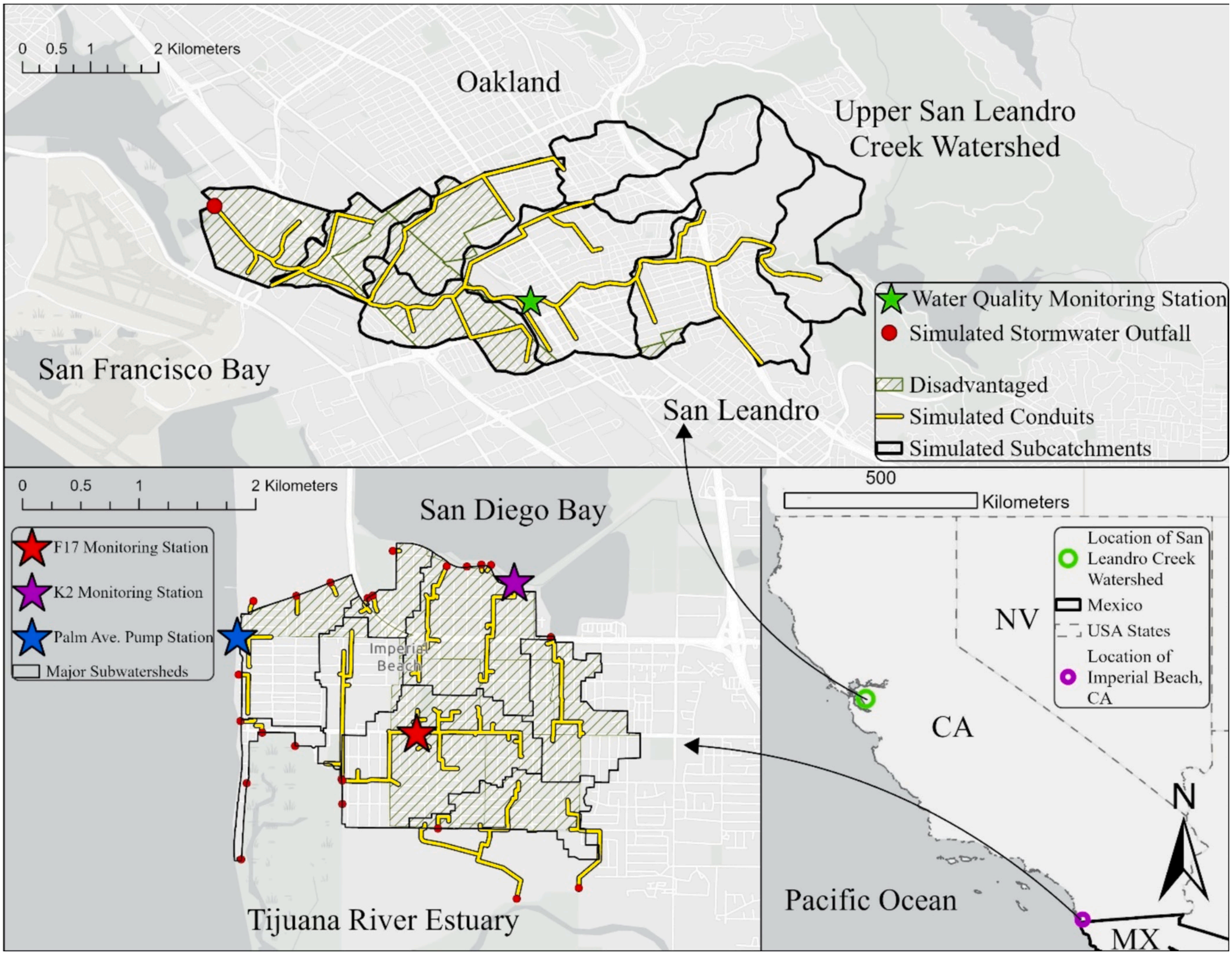


Fig. 1. Imperial Beach (lower left) and San Leandro Creek Watershed (upper panel) study areas, with simulated subcatchments, conduits, outfalls, environmental monitoring stations, and Pump Station. Disadvantaged census tracts are shown with green hatched polygons.

application of RBs, while analyzing environmental benefits from reduced energy costs for watersheds that rely on pump stations for drainage. Other contributions include expanding the limited research on regional water quality parameters for smaller watersheds and integrating stormwater numerical modeling with LCAs to enhance sustainability metrics.

We aim to address the following questions to fill the abovementioned knowledge gaps:

1. How do RBs reduce the energy demands of existing stormwater management in IB?
2. Do the benefits of GWP reduction from decentralized water supply and reduced pumping hours outweigh the cost of construction, and installation of RBs?
3. What is the addition to HTP from a city-wide deployment of RBs?
4. What is the estimated pollutant load reduction and reduction in EP and EcoP with city-wide RB deployment?

The following section demonstrates the data utilized and methods for developing a framework to assess the broad spectrum of sustainability and environmental factors around utilizing RBs. This section is followed by the results section, outlining the key takeaways and tradeoffs for large-scale deployments of RBs. Lastly, the conclusion and discussion sections highlight key findings, identify areas of uncertainty, and emphasize the need for future research.

2. Data and methods

2.1. Study areas

To exemplify the proposed framework, we focus on two low-lying urbanized coastal watersheds. The City of IB (Fig. 1) has faced decades of environmental injustice and in recent years has shown its vulnerability to compound flooding from heavy precipitation combined with sea-level rise driven groundwater table rise and overtopping by waves (Merrifield et al., 2021). IB receives approximately 218 mm of rain annually (U.S. Geological Survey, 2019). The topography is relatively flat with an average slope of 1 % across all Subwatersheds. For proper drainage in certain low areas, IB must pump stormwater into the ocean (Blue Star in Fig. 1). IB also pumps a portion of the first-flush stormwater to the Point Loma WasteWater Treatment Plant (WWTP). IB has stormwater outfalls discharging into the Pacific Ocean, the Tijuana River Estuary, and the San Diego Bay. This work uses a stormwater model previously calibrated and presented in Sangsefidi et al. (2023). Two monitoring stations in Fig. 1 (Yellow and Purple stars) collect flow and water quality data. These stations were used for parameter verification when modeling pollutant loadings into receiving water bodies, and for hydrologic verification in Sangsefidi et al. (2023).

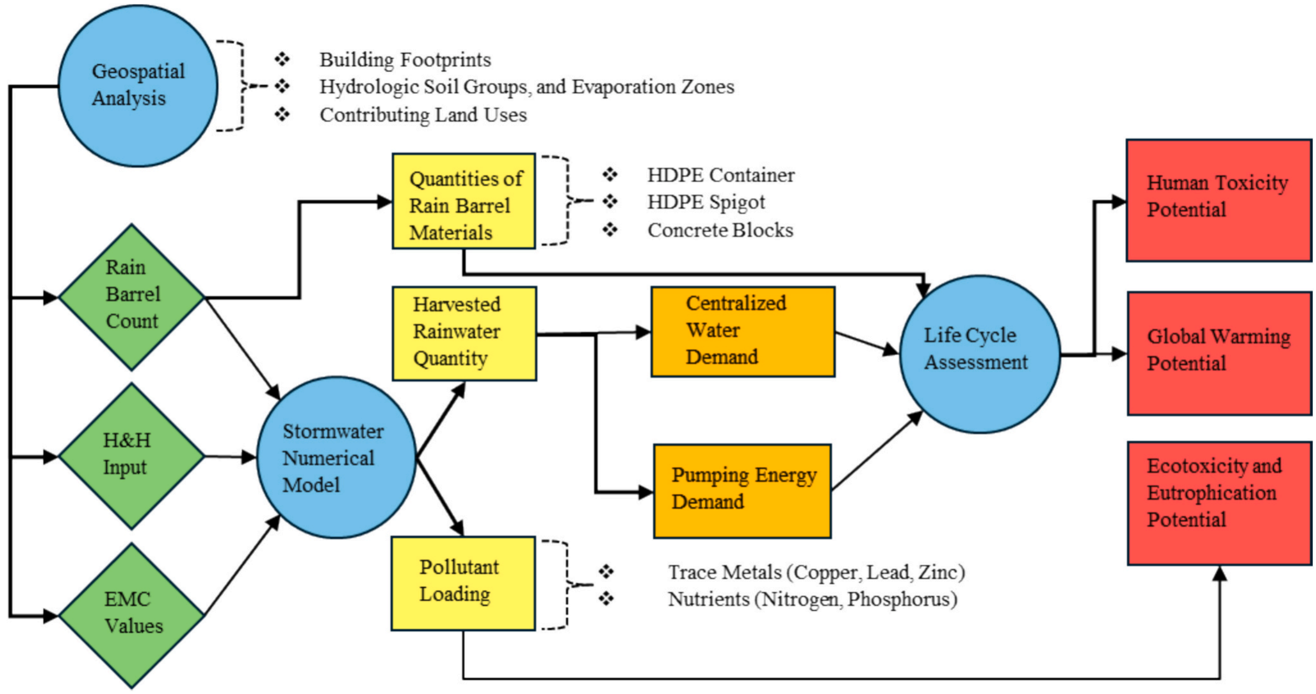


Fig. 2. Framework Process Flow Schematic. Blue symbolizes a process or simulation. Green symbolizes initial input variables determined from geospatial analyses. Yellow symbolizes initial output variables. Orange symbolizes a secondary output. Red symbolizes the final output.

Table 1
Datasets utilized for hydrologic-hydraulic modeling, EMC washoff model, and LCA.

Data	Source	Use
IB Building Footprint	USGS Earth Explorer High Resolution Orthoimagery and ArcGIS Deep Learning Toolbox	RB number determination
Hourly rainfall data	Tijuana River Research Institute Meteorological data NOAA NCEI Local Climatological Data	PCSWMM Continuous Rainfall Simulation
Digital Elevation Model	USGS Earth Explorer Satellite	Watershed Delineation and Characteristics (i. e., slope).
Event Mean Concentrations for various pollutants	National Stormwater Quality Database	PCSWMM Washoff Model
Land use	ArcGIS Open Data Platforms (San Diego Associated Governments, Alameda County, San Leandro)	Contributing Land Use Fractions for Washoff Model
Rain Barrel Materials	Uline, Home Depot	LCA input data

The two study areas have similarities and differences that make them appropriate for comparison. Both the San Leandro Creek Watershed (Fig. 1) and Imperial Beach have approximately 25,000 people listed as disadvantaged, or people who have been marginalized and disproportionately experience economic and or environmental burdens (Council on Environmental Quality, 2024). Additionally, both areas have considerable parts that are low-lying and near coastal waters. The soil in IB is mostly in hydrologic soil group D, which has the lowest infiltration associated with it, with a strip of hydrologic soil group B near the coast, which is two classes higher for infiltration. San Leandro has greater proportions of hydrologic soil group B and C, increasing the infiltration capacity of this watershed (NRCS).The watershed spans 127 square km and is under the jurisdiction of Alameda and Contra Costa Counties (Alameda County, 2024). San Leandro also receives 533.4 mm of rainfall annually (U.S. Geological Survey, 2019), approximately 2.5 times the rainfall that Imperial Beach receives. Similar to IB, water quality monitoring has been conducted in SL. The Green Star in Fig. 1 shows the monitoring station utilized for pollutant load verification. Since the monitoring station is in the center of the watershed, our study is limited to the water quality impacts from the watershed area upstream of this point.

2.2. Data

The following sections present the data utilized in this framework as well as various analyses using geographic information systems (GIS), numerical modeling, and LCIA databases. Fig. 2 depicts a process flow diagram with the data inputs and steps to reach the end goal of determining net emissions (i.e., global warming potential, human toxicity potential, ecotoxicity potential and eutrophication potential). Various datasets and sources were utilized for hydrologic and hydraulic (H&H) modeling, RB quantification, RB material determination, and water quality parameters. Table 1 displays the datasets utilized and sources where datasets were acquired from. We utilize satellite imagery and machine learning to determine the building footprints of the two watersheds using the ArcGIS Deep Learning Toolbox. High-resolution orthoimagery was acquired from the USGS Earth Explorer database (U.S. Geological Survey, 2024). This imagery was imported into ArcGIS where the Deep Learning toolbox was utilized for building footprint extraction. The deep learning toolbox utilizes pretrained models to delineate building footprints. Visual inspections were conducted to determine the accuracy of these delineations, within ArcGIS for the entire modeled area. Polygons were modified if there were non-roof areas included. Building footprints are then utilized to determine the necessary number of RBs to use within each Subwatershed, following the guidelines from the County of San Diego (a 60-gal RB per every 100 ft^2 of roof area). A discussion of the effectiveness of these guidelines for an area that receives higher rainfall is presented in the Discussion Section. The following section presents additional details on the numerical stormwater modeling and life cycle assessment methods and impacts (Tables 3, 9 and 10).

2.3. Surface runoff analysis and RB water collection

PCSWMM, a numerical stormwater model, was used to determine the amount of water collected in the RBs over a seven-year period (from 2016 to 2023). The mean collected values were determined and then scaled up by 20 to represent the total water collection over the RB lifespan. These rainfall years received considerable variability (from 76 mm to 406 mm for IB and 152 mm to 711 mm for SL; therefore, they serve as a good proxy for the variability of rainfall in these areas. For the present research, we modified a model previously developed by Sangsefidi et al. (2023). We utilized the guidelines by the County of San Diego to allocate a single "60-gallon RB per every 100 ft^2 of roof area" (County of San Diego Rain Barrel Tutorial, 2022).

Within PCSWMM, we utilized the Low impact Development (LID) Control Editor to input the barrel height. A 36-in. barrel height (91 cm) is selected to match existing barrel products. For RB drainage the drain coefficient is set to 0.5 in/h (12.7 mm/h). The drain exponent is set to 0.5. The RBs have a surface area of 2.4 ft^2 (0.22 m^2). The above-mentioned parameters are selected so that a 60-gal (227-l) barrel is drained over a 24-h period. This allows for a delay period to be established, since it is unlikely that people will utilize water collected in the RBs for outdoor purposes during or immediately after a rain event. The RBs are set to route all outflow to pervious areas. In the case of overflow, the RB will also drain to pervious areas. Based on the area of building roof surfaces each subcatchment receives a certain number of RBs. Within PCSWMM we designate the percent of impervious area treated by the RBs, which is determined by taking the building roof area and dividing it by the total subcatchment area. We extract results from PCSWMM to estimate the volume of rain that each rain barrel could collect.

The total volume of rainwater captured is calculated by taking the total number of units (# of RBs), multiplying by the surface area/unit (m^2/RB) and the total inflow (m) to get volume in (m^3). The process is repeated to determine the overflow volume with the surface overflow (m). The overflow volume is then subtracted to determine the annual water collection that would be used. The volume of rainwater was also used to determine the changes to GWP and HTP from reduced centralized water demand (Fig. 2).

Through PCSWMM modeling, we were also able to simulate the changes in pumping hours at the Palm Ave. Pump Station (Blue Star Fig. 1), the changes in first-flush stormwater that would require treatment, and the reduction in pollutants from reduced surface runoff. A similar type of Pump Station for SL does not exist; therefore, it was not included in our analysis.

2.4. Stormwater pumping numerical simulations

PCSWMM was also used to simulate a stormwater outfall pump station (Blue Star Fig. 1). The IB Public Works department provided information on the pump station. The pump station has a total storage capacity of 28.31 m^3 and houses three pumps. As water enters the pump station, the "jockey" pump, hereafter "First Flush Pump", is activated and starts pumping stormwater into the sewer system at 16.42 l/s, where it will be sent to the Point Loma WWTP. This pump operates until the Pump Station fills to its maximum depth of 3.66 m. Once this occurs the Main Pumps are activated to drain the stormwater into the ocean, operating at 410.59 l/s. The main pumps operate one at a time. A series of control rules were input into PCSWMM to simulate the pump operation. To estimate Pump Hours run, we use the total volume of water pumped and each pump's average flow rate. To estimate the potential benefits from reduced pumping, we convert the total pumping hours into energy costs of pump operation (Eq. (1)).

$$E_P = V \times Q^{-1} \times P \quad (1)$$

where:

E_P = Energy used by pump (Joules).
V = Volume of Water Pumped (m^3).
Q = Pump Flow Rate (m^3/s)
P = Pump Wattage (Watts)

Table 2
Components used for LCA model and corresponding Units and Quantities.

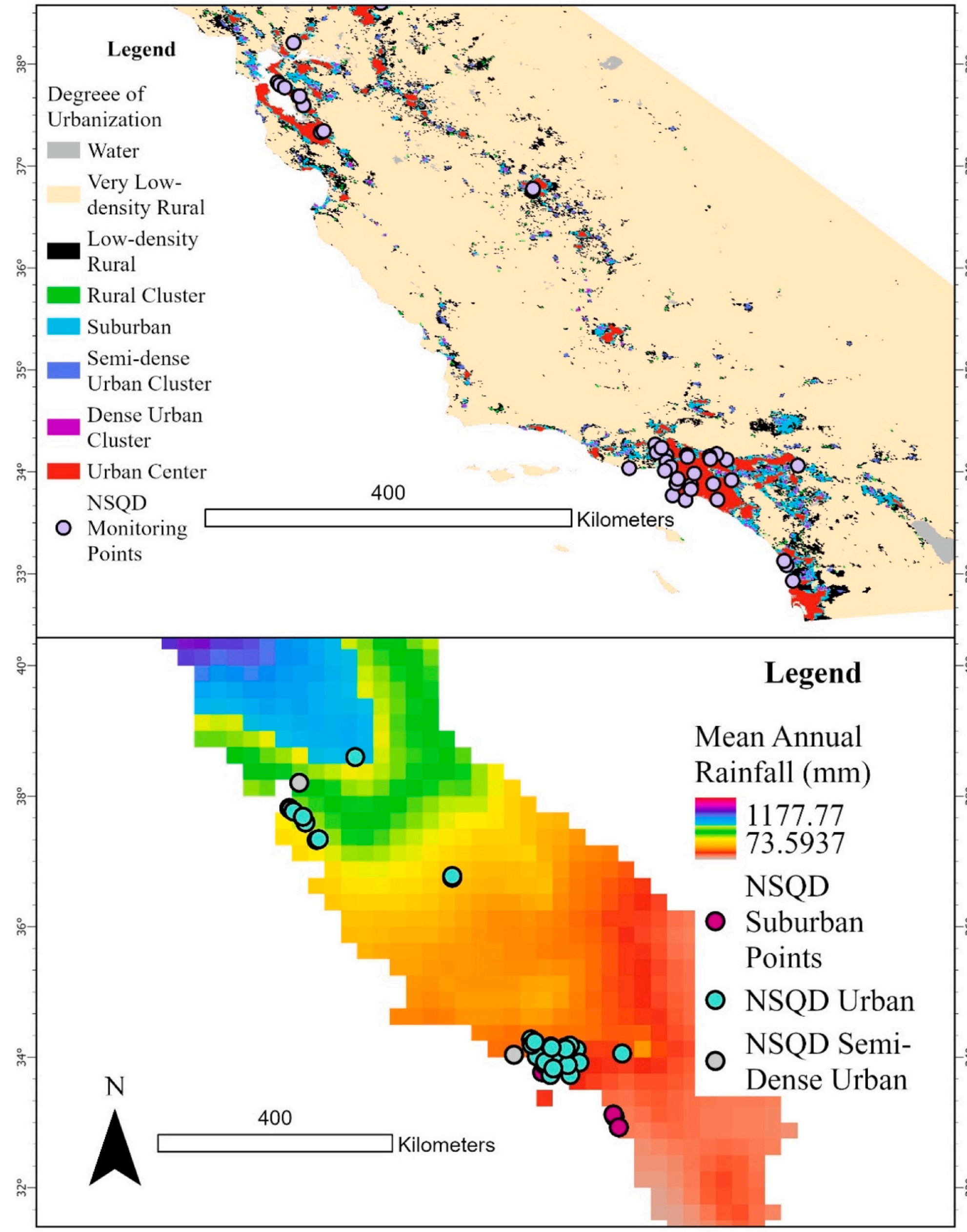
Component	Material or Process	Unit	Quantity
RB container, and RB spigot	HDPE Plastic	1 kg	1 RB and 1 spigot per 9.29 m^2 of roof
RB support blocks	Concrete	1 kg	4 blocks per RB
Domestic Water Use	Water Treatment	1 m^3	0.43 m^3 (113 gal)/capita daily
Stormwater Pumping Energy Usage	Electricity at the Grid	1 MJ	0.31 MJ/ 1 m^3 water for main pump 0.71 MJ/ 1 m^3 water for first-flush pump

Table 3
GWP and HTP characterization factors in LCA model compared with data from literature.

Study	Process/Material	Unit	kg CO_2-Eq / Unit	kg DCB-Eq/ Unit
(Ghimire et al., 2017)	Municipal Drinking Water	1 m^3	0.85	N/A
(Padilla-Rivera et al., 2019)	Wastewater Treatment	1 m^3	0.91	N/A
(Ando and Netusil, 2018)	Urban Water Supply	1 m^3	1.096	N/A
(Buonocore et al., 2018)		1000 m^3	620.64 (0.621/ m^3)	198.70 (0.199/ m^3)
This Study	**Water Treatment**	**1 m^3**	**0.958**	**0.150**
(Racoviceanu et al., 2007)	Energy Production	1 kWh	0.22 (0.06/ MJ)	N/A
(Wang and Sun, 2012)	Coal Fired Energy Production	1 kWh	0.975 (0.27/ MJ)	N/A
(Brizmohun and Ramjeawon, 2015)		1 MWh	N/A	150 (0.04/ MJ)
(Phillips et al., 2018)	Electricity Production	1 kWh	N/A	0.14 (0.38/ MJ)
This Study	**Electricity at the Grid**	**1 MJ**	**0.162**	**0.050**
(Mufarrij et al., 2023)	Plastic Production	1 kg	1.86	N/A
(Benavides et al., 2020)	Plastic Production	1 kg	2.6	N/A
This Study	**Plastic Production (HDPE)**	**1 kg**	**0.189**	**2.53**
(Guo et al., 2018)	Concrete	1 m3	284	N/A
This Study	**Concrete**	**1 m3**	**0.260**	**0.039**

2.5. Life cycle assessment (inventory and impact categories)

The PCSWMM model results were incorporated as input data for Sphera's LCA for Experts (LCA-FE) model to determine the impacts to global warming potential (GWP) and human toxicity potential (HTP) from reduced dependency on centralized potable water and reduced urban runoff. The output of Eq. (1) for the different pumps and different scenarios is also implemented into LCA-FE to assess the GWP and HTP from reduced pumping hours. We compare the existing scenario with the scenario of a city-wide RB deployment, in order to determine if the GWP and HTP of RB materials are outweighed by the avoided emissions from water collection and reduced pumping. Within LCA-FE, we use the CML 2001 method to determine GWP and HTP (Baitz et al., 2012). This method was created by the University of Leiden in Netherlands in 2001. Table 2 summarizes the components, and characterization factors used



(a)

(b)

Fig. 3. (a) Degree of urbanization and sample locations from stormwater monitoring in the NSQD. (b) Mean annual rainfall for California, and subdivided NSQD data points into degree of urbanization categories.

for our assessment. The following units were used for comparison with available characterization factors from the literature, 1 m^3 of treated water, 1 kg of plastic, 1 m^3 of concrete, and 1 MJ of energy. We estimate typical potable water usage reports from the California Water Commission. We then scale this number down by roughly 55 % (based on water usage reports by the San Diego County Water Authority) to estimate how much water would be used for irrigation purposes. Water collected by the RBs is deducted from the existing centralized water treatment amount to provide a new value with avoided emissions. Table 3 presents GWP and HTP characterization factors in LCA model compared with data from literature.

To analyze the benefits of RBs we analyze the Net Emissions (Eq. (2)) from the installation and disposal of RBs, the avoided emissions from reduced pumping and the reduced emissions from a decentralized water source.

$$N_{Em} = \frac{\sum RB_{Em} - \Delta P_{Em} - \Delta W_{Em}}{V_{SW}} \tag{2}$$

where:

N_{EM} = Net Emissions (kg CO_2-Eq).
RB_{EM} = RB Emissions from Installation and Disposal (kg CO_2-Eq).
P_{EM} = Pump Energy Usage Emissions (kg CO_2-Eq).
W_{EM} = Water Treatment Emissions (kg CO_2-Eq)
V_{SW} = Total Captured Stormwater (m^3).

A similar equation is used for determining HTP, however, the units are in kg 1,4 Dichlorobenzene equivalent (kg DCB-Eq.). The FU used for this study is 1 m^3 of collected stormwater in the RB system. Thus, the total water captured over the RB lifetime, which is commonly set at 20 years (Bell et al.; Li et al., 2019; Taguchi & Nakamura; Zhang et al., 2020), can determine the net emissions per FU. This FU is selected to

Table 4
Mean and Median EMC values from the NSQD for Southern California.

Land Use	Copper			Lead			Zinc			Phosphorus			Nitrogen		
	Median	Mean	Count	Median	Mean	Count	Median	Mean	Count	Median	Mean	Count	Median	Mean	Count
Commercial	24.0	22.6	10	12.0	12.75	4	225	246.6	10	0.41	0.45	12	3.3	3.9	12
Industrial	48.0	75.85	7	60.5	97.73	6	429	468	7	0.16	0.49	7	3.1	3.3	7
Residential	19.0	26.7	137	14.75	22.80	60	111.5	163.65	110	0.31	0.41	118	2.54	3.8	132
Open Space	10.5	26.7	48	10.0	23.43	11	77.0	128.31	19	0.10	0.19	47	1.56	2.2	78

Table 5
Mean and Median EMC values from the NSQD for Northern California.

Land Use	Copper			Lead			Zinc			Phosphorus			Nitrogen		
	Median	Mean	Count	Median	Mean	Count	Median	Mean	Count	Median	Mean	Count	Median	Mean	Count
Mixed-Com	24.0	45.2	5	50.0	121	5	200	1062	5	NA	NA	NA	0.96	0.96	2
Industrial	36.0	51.11	9	41.0	46.44	9	280	353.33	9	NA	NA	NA	1.3	1.3	4
Mixed-Res	42.0	60.5	27	110	109.8	5	235	329.04	30	0.39	0.42	19	2.9	1.07	3

ensure comparisons can be made with other LCA studies that analyze rainwater collection methods and green infrastructure.

2.6. PCSWMM EMC Washoff

In addition to the sustainability assessment, we use PCSWMM to estimate surface water pollution from stormwater constituents. We test scenarios with and without RBs to see the reduction in pollutant loading. This analysis is done using event mean concentrations (EMCs) selected from the National Stormwater Quality Database (NSQD). The NSQD contains information for various regions in the United States. When determining EMC values the following equation can be used (Eq. (3)):

$$EMC = \frac{\sum_{i=1}^{n} C_i {*} Q_i}{\sum_{i=1}^{n} Q_i} \tag{3}$$

where:

C_i = individual runoff sample concentration of ith sample
Q_i = instantaneous flow at the time of the ith sample
n = number of samples per event

From the NSQD, sampling locations within California were plotted to determine if areas had same degree of urbanization as IB and the SL (Fig. 3a). Within ArcGIS, the degree of urbanization toolbox combines census tract level population data with a built-up raster layer containing physical building structures. The points were then categorized into dense urban, suburban, and urban. These data were further categorized based on annual rainfall (Fig. 3b). EMCs have been shown to vary with annual rainfall, and storm water intensity (Pitt, 1998). Based on the locations of the datapoints in relation to mean annual rainfall, points were further divided into two categories, hence forth, Northern and Southern California. Northern California data points are in areas with mean annual precipitation between 450 and 700 mm. Southern California data points are in areas with mean annual precipitation between 170 and 370 mm. The separation occurs roughly at the 37° latitude line.

Investigation of the degree of urbanization and corresponding land use designation in the NSQD revealed that dense-urban areas correlated to Freeways (FW), suburban areas correlated to (RE) and FW, and urban centers correlated to Commercial (CO), Industrial (ID), RE, Open Space (OP), Commercial Mix (CO-MIX), Industrial Mix (ID-MIX), Residential Mix (RE-MIX), and Institutional (IS) land uses. The distribution of EMCs for the two different rainfall regions is presented in Fig. S1. All parameters were selected from the NSQD database except Total Nitrogen, which was calculated based on values within the NSQD database. Total Nitrogen was calculated by summing concentrations for Total Kjeldahl Nitrogen, Total Nitrates, and Total Nitrites.

Table 6
Average Median EMC values between Southern California and Northern California.

Land Use	Copper	Lead	Zinc	Phosphorus	Nitrogen
Commercial	24	31	212.50	0.41	2.15
Industrial	42	50.80	354.50	0.16	2.08
Residential	30.50	62.40	173.30	0.35	2.72

Median EMC values were used to overcome any skew in the mean values from outliers. Southern California EMC values (Table 4) were present for each dominant Land Use type (i.e., CO, ID, RE, and OP). For Northern California (Table 5), there were gaps in the database that required additional analyses. Available Land Uses included CO-MIX, ID, and RE-MIX. An average between the Median values for Northern and Southern California were used for SL to ensure that the Mixed-land use types did not skew the EMC value selection (Table 6). Since OP data was lacking for Northern California, Southern California values were used.

EMCs are the most common parameters used to estimate nonpoint water quality loads in SWMM and in most other models (Rossman and Huber, 2016). The EMC washoff function has the form:

$$w = K_w q f_{Lu} A \tag{4}$$

where

w = Washoff Rate mg/s.
K_w = EMC concentration expressed in the same volumetric units as flow rate (mg/m^3).
q = runoff rate (mm/h).
f_{Lu} = Fraction of land use.
A = Subcatchment area (m^2).

Simulated pollutant washoff concentrations were then verified with data from more recent field observations (presented in the Results Section 3.4). Monitoring data was extracted from the California Environmental Data Exchange Network (CEDEN). CEDEN is the State Water Board's data system for surface water quality in California. The monitoring stations can be seen in Fig. 1. Annual discharge loads were verified with available literature and are presented in the results section.

We use the estimated annual pollutant loads to calculate the EP for the scenario with and without RBs. To estimate EcoP and EP of stormwater constituents we use EPA's Tool for the Reduction and Assessment of Chemical and Environmental Impacts 2.2 (TRACI 2.2). TRACI 2.2 utilizes the amount of the chemical emission or resource and the estimated potency of the stressor to determine EcoP and EP in terms of Comparative Toxicity Units (CTUe). Total washoff loads (kg) were multiplied by Ecotoxicity and Eutrophication characterization factors (CFs). CFs (Table 7) are expressed in terms of the relevant impact per kg

Table 7
Characterization factors (CFs) for Ecotoxicity and Eutrophication potential.

Constituent	Ecotoxicity CF (CTUe/kg of emitted substance)		Eutrophication CF for IB (kg N or kg P equivalent)		Eutrophication CF for SL (kg N or kg P equivalent)	
	Freshwater	Seawater	Freshwater	Seawater	Freshwater	Seawater
Total N	N/A	N/A	0.061	0.303	0.090	0.191
Total P	N/A	N/A	0.326	N/A	0.111	N/A
Copper	5.52×10^{4}	1.03×10^{-16}	N/A	N/A	N/A	N/A
Lead	3.75×10^{2}	1.39×10^{-19}	N/A	N/A	N/A	N/A
Zinc	3.86×10^{4}	3.27×10^{-15}	N/A	N/A	N/A	N/A

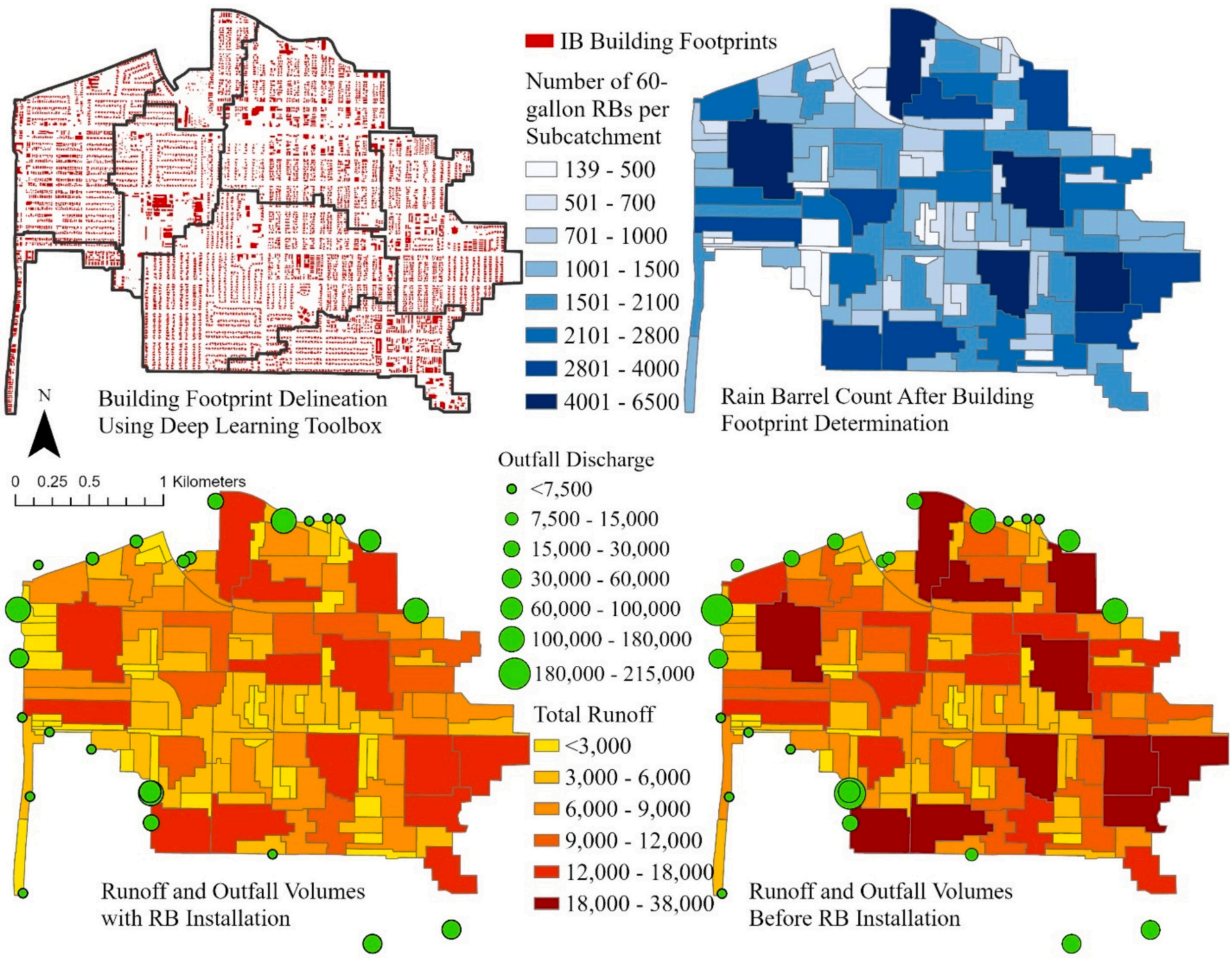


Fig. 4. Process workflow for determining quantities of RBs to deploy in one of the two study areas and the changes in flow quantities with RB implementation (workflow starts from top left, then top right, then bottom right, and lastly bottom left). Changes in outfall discharge volumes (m^3) are shown with green circles at outfall discharge locations. Changes in subcatchment runoff (m^3) are shown with a gradient of red orange and yellow.

of emission (CTUe/kg). Regional (county-level) Eutrophication CFs (Table 7) were utilized from Henderson et al. (2021).

Since a portion of IB's stormwater drains directly to seawater, a weighted sum was using to determine the EcoP and EP. For SL, all stormwater was considered to drain to the San Leandro Creek before entering the San Francisco Bay, so only the freshwater CFs were utilized.

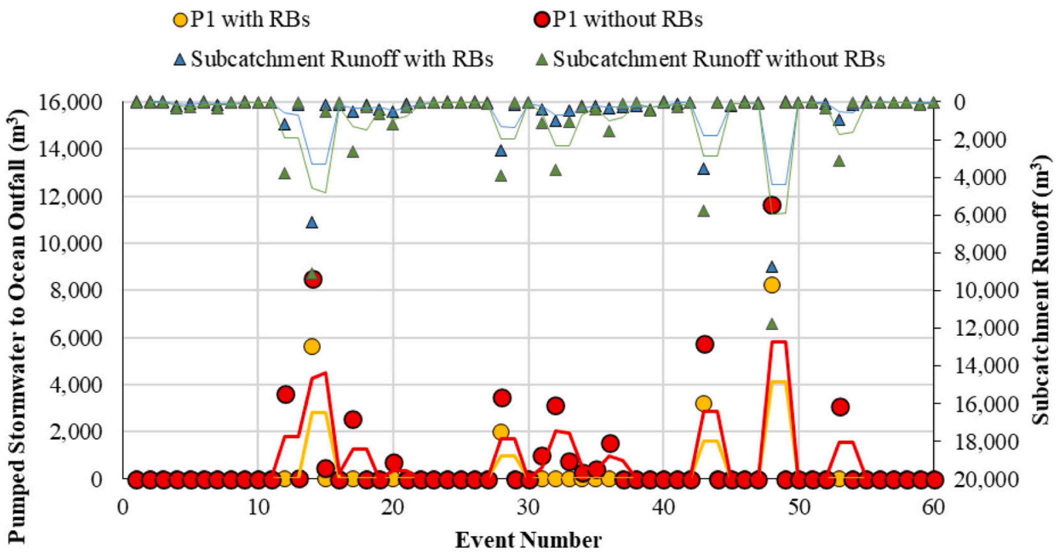
3. Results

3.1. RB water collection and reduction in pumping

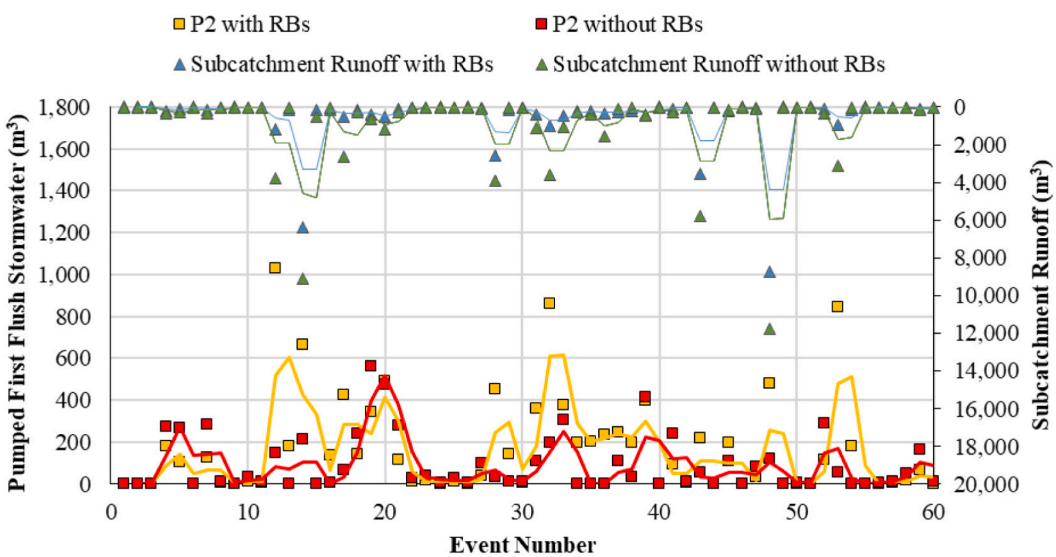
Results from PCSWMM estimate the total water collected by the RBs, reduced runoff quantities, and changes to pumping needs. The total water collected by RBs over the simulation period was determined to have a mean value of 3.1×10^5 m^3/yr in IB and 9.5×10^5 m^3/yr in SL. This value is scaled up by 20 to estimate the water collection over the RB lifetime, 6.2×10^6 m^3 in IB and 1.9×10^7 m^3 in SL. Over the RB lifetime, each RB collects approximately 36 m^3 in IB, and 69 m^3 in SL. Fig. 4 provides a visual representation of RB implementation in the PCSWMM model. The GWP and HTP associated with these collection amounts are presented in the following Results Section 3.2.

By design, the areas with the greatest building density receive more rain barrels. Implementing rain barrels in larger subcatchments that also have a greater percentage of impervious area results in the greatest reduction of runoff.

Over the lifespan of the RBs (20 years), and in the IB study area, the reduced runoff led to the following changes in stormwater pumping: 216,000 m^3 reduction for stormwater pumping to the ocean outfall,



(a)



(b)

Fig. 5. (a) Total pumped stormwater volume by the Main Pump (P1) with trendline showing the moving average value for stormwater pumped to the ocean with and without rain barrels (RBs). (b) Total pumped first flush stormwater by the First Flush Pump (P2) with trendline showing the moving average value for first flush stormwater pumped for treatment with and without RBs.

36,800 m^3 increase of first-flush stormwater pumping to the WWTP, 1217-h reduction in Main Pump (P1) operation, 1640-h increase in First Flush Pump (P2) operation. The reduction in P1 pumping usage led to 1.46×10^5 MJ energy savings. Fig. 5 depicts pump operation across 60 consecutive events. The inverted top axis demonstrates how RBs can reduce peak flows, thus improving stormwater management. Fig. 5a depicts the reduced stormwater pumping to the ocean outfall with the implementation of RBs, while Fig. 5b depicts the increase in first flush stormwater pumping to the WWTP with RBs.

Fig. 5 demonstrates the difference in pump operation with the two scenarios (with and without rain barrels). The moving average shows that pumping for P1 is consistently lower when rain barrels are implemented. On the contrary, for P2, the reduction in runoff from harvested rain has a variable effect. With smaller storm events, the RBs can retain a large portion of the potential runoff, this can lead to less first flush stormwater sent to the WWTP. For larger storm events, the reduction in peak flow allows P2 to operate for a longer period, sending more first flush stormwater to the WWTP. Supplemental Fig. S4 displays a closer examination of the pump operation with two different storm size scenarios with and without RBs.

3.2. *Global warming potential and human toxicity potential*

Life Cycle Impact Assessments reveal the environmental trade-offs of

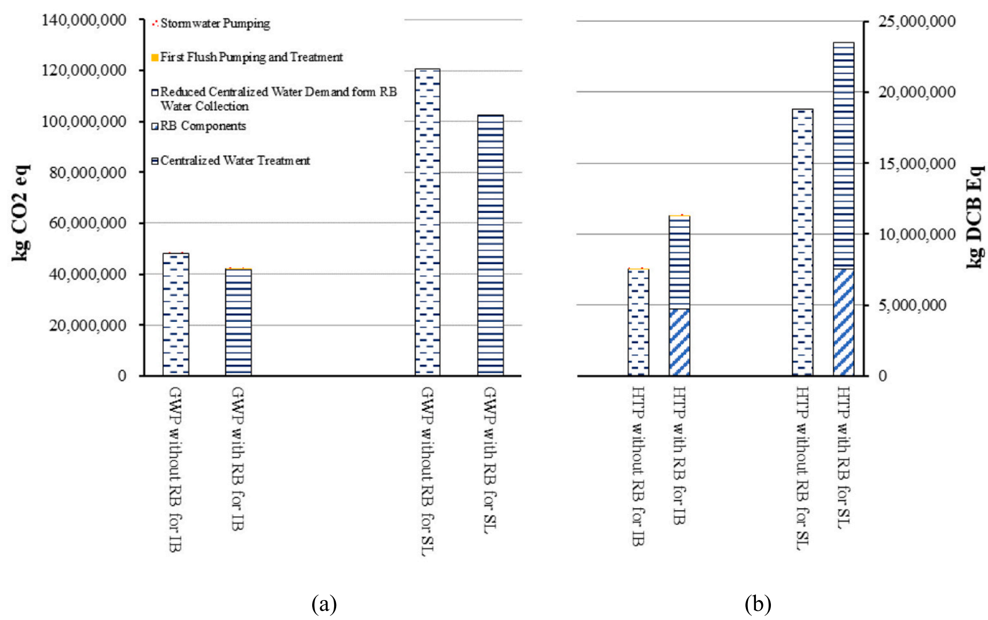


Fig. 6. (a) GWP and HTP (b) with and without RBs for Imperial Beach and San Leandro. For each subplot totals for Imperial Beach (IB) are on the left and values for the San Leandro Creek Watershed (SL) are on the right.

RB implementation. Although RBs can positively impact GWP there is a contribution to HTP (Fig. 6). With our selected life cycle inventory, the materials produce roughly 19 kg CO_2-Eq/RB. The RB materials produced a total of 3.3×10^6 kg CO_2-Eq in IB and 5.3×10^6 kg CO_2-Eq in the SL, where the difference in emitted kg CO_2-Eq comes from the different RB quantities in each study area. Considering the total water volume collected over the RB lifespan (i.e., 20 years), the emissions per FU, 1 m3 of collected, stormwater are greater in IB than SL. The emissions in IB are 0.53 kg CO_2-Eq/m^3 and in SL are 0.28 kg CO_2-Eq/m^3. The Net Emissions, determined using (Eq. (2)), show a Net Positive benefit, in other words the emissions per m^3 of collected stormwater are offset by the emissions saved from reduced need on the centralized water demand and reduced pumping. Therefore, there is a reduction of 0.47 kg/m^3 for IB, and 0.68 kg/m^3 for the SL. Results show that implementing RBs in Imperial Beach and the SL can significantly reduce global warming potential by 2.6×10^6 and 1.3×10^7 kg of CO_2-Eq. The avoided emissions from RB water collection are 6.0×10^6 kg CO_2-Eq in IB and in SL 1.8×10^7 kg of CO_2-Eq. The difference in avoided emissions is due to the number of RBs and annual rainfall.

Although RBs can clearly positively impact reductions in GWP, the reduced need for centralized water demand is not sufficient to overcome the contributions to HTP. The RB materials produce 27.3 kg DCB-Eq/RB. Considering the FU, there are 0.75 and 0.39 kg DCB-Eq/m^3 of collected stormwater, in IB and SL. Reusing Eq. (2) but replacing the units and values with kg DCB-Eq, there is a Net Emission of 0.58 kg DCB-Eq/m^3 in IB, and 0.25 kg DCB-Eq/m^3 in SL. Total HTP increases by 3.8×10^6 kg DCB-Eq in IB and 4.7×10^6 kg DCB-Eq in SL. The increased HTP mainly comes from the HDPE RB container, which has a CF of 2.54 kg DCB-Eq/kg. An analysis of alternate materials to use for this component could improve the HTP and the GWP for these systems. The use of alternative materials is further presented in the Discussion Section.

The difference in GWP between avoided emissions in IB compared with SL comes from the rainfall volumes, and projected captured rainfall. Considering that the RBs would emit the same amount of kg CO_2-Eq, RBs that are able to collect more rainwater during their lifetime, such as those in SL, would be able to have a reduced amount of GWP per FU. Furthermore, in IB, the capital energy investment into RBs would take 11 years to be surpassed by the emission reductions from water collection alone, but roughly 6 years in SL. To surpass the emitted HTP it would take 100 years in IB and 50 years in SL. Jeong et al. (2016) reports emissions of 0.403 of kg CO_2-Eq per 1 m^3 of harvested rainwater. Their reported values for toxic effects to humans is reported in Comparative Toxicity Units for human health, which is not directly comparable to kg DCB-Eq. Ghimire et al. (2017) reports a value of 0.33 kg CO_2-Eq/m^3 for a commercial rainwater harvesting system. This study also reports human health criteria in a different impact factor, kg Particulate Matter 2.5 equivalent, which again is different than what is used in our study, making direct comparisons difficult. Both Jeong et al. (2016) and Ghimire et al. (2017) report a decrease in human health impacts when implementing decentralized water collection methods. Each of these studies used a service life of 50 years which would bring the emitted values per m^3 of collected rainwater down and improve the toxic effects to humans.

3.3. Water quality

Washoff results provide estimates for pollutant loading from all IB Subwatersheds. Tables 8, 9 and 10 show the average washoff loads in kg/ha for a seven-year simulation. CFs reveal the EcoP and EP for the estimated washoff loads. From modeling EMCs of stormwater pollutants, a city-wide RB deployment can result in approximately 44 % reduction in annual pollutant washoff loading, EcoP, and EP. For SL there is approximately a 27 % reduction. Pollutant loading varies in different subcatchments based on subcatchment size, land use, land cover (Fig. 7 and Fig. 8). The percentages of each washed off pollutant between subcatchments are similar due to the distribution of land uses; therefore, Fig. S4 shows a single pie chart for the relative loading of each pollutant with respect to the other constituents, per unit area. Figs. 9 and 10 show the calculated EcoP of heavy metals, and the EP for nutrients.

When considering pollutant loading, it is important to analyze the relative toxicity of each constituent to better understand the impact on the environment. For example, an analysis of the heavy metal loading and toxicity for SL reveals Pb loading is 1.66 times greater than Cu; however, the ecotoxicity from Cu is about two orders of magnitude greater than Pb. This reveals the importance of not only understanding the loading from stormwater constituents but also the relative toxicity

Table 8
Error analysis for pollutants in IB. Percent error values show differences relative to observed values. Concentrations for metals are in (ug/L) and nutrients in (mg/L). Negative error values indicate that observed values were greater than simulated values.

Day	Cu Simulated	Cu Observed	Error (%)	Pb Simulated	Pb Observed	Error (%)	Zn Simulated	Zn Observed	Error (%)	N Simulated	N observed	Error (%)	P Simulated	P Observed	Error (%)
F12															
11/21/2016	ND	ND	**ND**	ND	ND	**ND**	67	110	**−39.09**	ND	ND	**ND**	ND	ND	**ND**
1/9/2018	18.5	22	**−15.91**	13.9	4.1	**239.02**	ND	ND	**ND**	2.48	2.6	**−4.62**	0.3	0.41	**−26.83**
11/29/2018	19.4	19	**2.11**	14.5	2.6	**457.69**	ND	ND	**ND**	2.5	1.5	**66.67**	0.31	0.26	**19.23**
1/24/2021	8.05	12	**−32.92**	5.9	3.3	**78.79**	57.2	60	**−4.67**	ND	ND	**ND**	0.12	1.03	**−88.35**
12/15/2021	8.8	11	**−20.00**	6.85	3.2	**114.06**	90.6	52	**74.23**	1.5	1.7	**−11.76**	ND	ND	**ND**
11/9/2022	13.1	10	**31.00**	8	2.2	**263.64**	92.9	59	**57.46**	1.28	1.3	**−1.54**	0.16	0.25	**−36.00**
K2															
11/21/2016	19.5	36	**−45.83**	14.76	7.5	**96.80**	121.5	270	**−55.00**	2.6	10.8	**−75.93**	0.32	0.94	**−65.96**
1/10/2018	ND	ND	**ND**	13.55	6	**125.83**	108.8	160	**−32.00**	2.4	4	**−40.00**	0.29	0.58	**−50.00**
11/30/2018	19.4	15	**29.33**	14.7	2.6	**465.38**	118.7	96	**23.65**	2.58	2.6	**−0.77**	0.31	0.5	**−38.00**
1/23/2021	10.1	12	**−15.83**	13.2	3.5	**277.14**	63.7	83	**−23.25**	1.34	2.4	**−44.17**	0.16	0.38	**−57.89**
12/9/2021	ND	ND	**ND**	8.45	2.2	**284.09**	75.7	110	**−31.18**	1.49	6.1	**−75.57**	0.2	0.72	**−72.22**
11/9/2022	ND	ND	**ND**	9.3	2.8	**232.14**	78.1	81	**−3.58**	1.65	2.2	**−25.00**	0.2	0.37	**−45.95**

Table 9
Error analysis for pollutants in SL. Percent error values show differences relative to observed values. Concentrations for Cu are in (ug/L) and nutrients in (mg/L). Negative error values indicate that observed values were greater than simulated values.

Date	Time	Constituent	Simulated Value	Observed Value	Error (%)
1/20/2012	18:00	P	0.29	0.35	−17.14
	23:40	P	0.08	0.62	−87.10
	20:13	P	0.34	0.38	−10.53
	1:42	P	0.015	0.41	−96.34
3/16/2012	22:30	Cu	10.9	39.5	−72.41
	22:30	P	0.23	0.49	−53.06
	20:40	P	0.11	0.67	−83.58
	22:17	P	0.07	0.76	−90.79
4/13/2012	1:20	Cu	15.4	17.1	−9.94
11/21/2012	6:30	Cu	24	11	118.18
	6:30	P	0.34	0.25	36.00
	1:37	P	0.27	0.23	17.39
	2:55	P	0.26	0.21	23.81
	4:02	P	0.3	0.25	20.00
11/30/2012	3:32	N	0.12	0.14	−14.29
	9:46	P	0.29	0.61	−52.46
	9:50	N	1.55	0.77	101.30
	1:40	N	0.25	1	−75.00
	19:38	N	0.24	2.8	−91.43
	3:27	P	0.014	0.16	−91.25
	7:25	P	0.27	0.21	28.57
	13:33	P	0.32	0.2	60.00
12/1/2012	10:17	Cu	0.05	28	−99.82

Table 10
Outfall loading (kg/ha-yr) for simulated stormwater constituents from our study for the existing condition compared with reports from the literature.

Study	Location	N	P	Cu	Pb	Zn
This Study	San Leandro, CA	5.46	0.70	0.06	0.10	0.38
This Study	Imperial Beach, CA	3.35	0.41	0.03	0.02	0.16
Alamdari et al. (2017)	Virgina	5.9 to 14.7	0.24 to 2.80	N/A	N/A	N/A
Simpson et al. (2023)	Ohio	3.2 to 11.5	0.41 to 1.53	N/A	N/A	0.1 to 0.7
Järveläinen et al. (2015)	Finland	1.6 to 10.3	0.08 to 6.07	0.01 to 0.89	0.001 to 2.01	0.04 to 2.10
Lee and Bang (2000)	Korea	N/A	5.5–14.8	N/A	0.15 to 0.40	N/A

from different stormwater constituents.

Reductions in pollutant loading directly align with reductions in EcoP and EP. Reductions in pollutant loading and thus the toxic and eutrophic effects in receiving water bodies is an added benefit of RBs. Long term implications of the reduction in EcoP and EP serve as a trade-off, when considering the contribution of RBs to toxic effects for humans. Through the reduction of urban runoff, we show an average reduction in pollutant loading of 44 % in IB and 28 % in SL. This percent reduction reflects the total reduced loading for the simulation period of 7 years. Values for reduction reflect the reduced total load from the entire system. In the results section there is also a comparison of the EcoP and EP per unit volume to allow for comparisons with available literature.

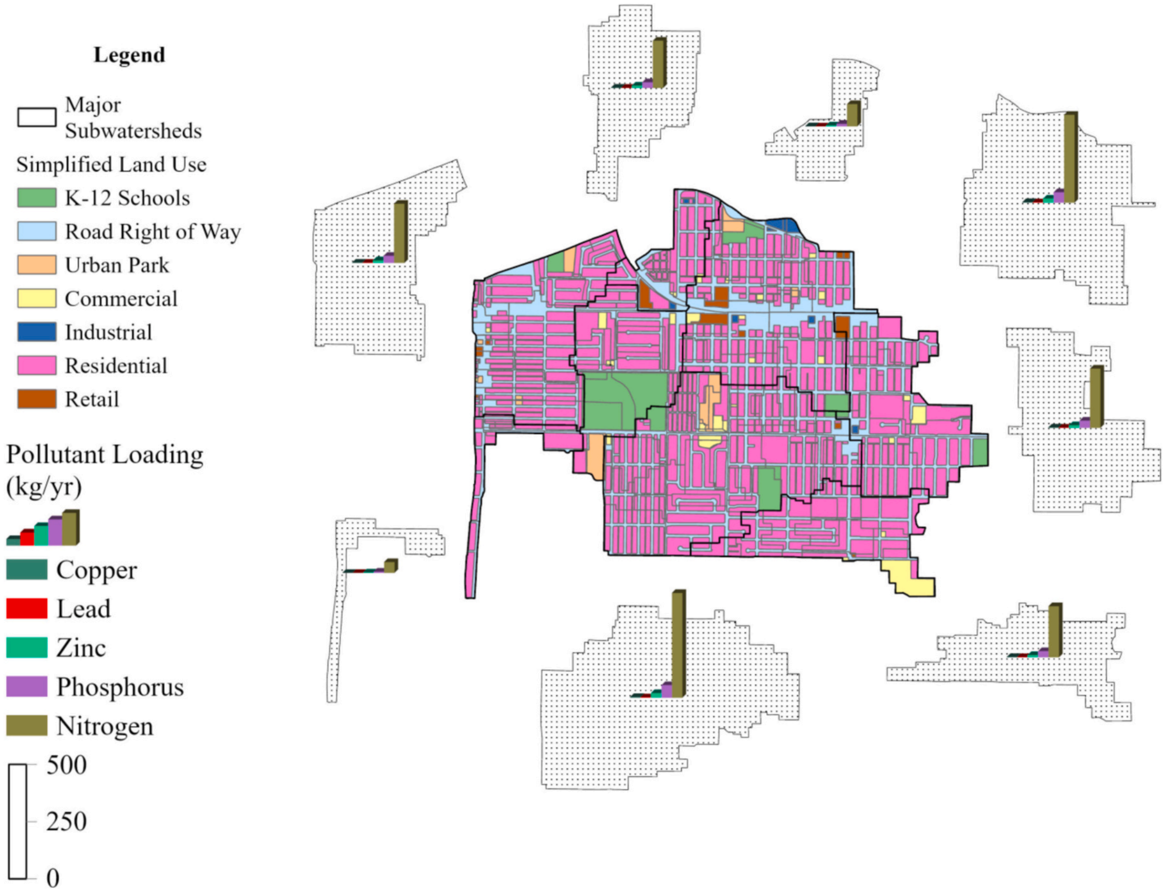


Fig. 7. Results from water quality simulations for Imperial Beach. The map shows the prefiltered land uses in each of the major subcatchments, as well as the total pollutant loading for each constituent (kg/yr). Total loading is reflected as the amount of the constituent produced by the entire Subwatershed. This figure represents the scenario without RB implementation.

3.4. Verification of parameters and results

Simulated pollutant washoff concentrations were plotted against observed pollutant concentrations, for verification of developed parameters. In IB, the EMC values for Pb were outside the range of the upper quartile and outliers from the collected field monitoring data. The values for Cu, Zn, N, and P were all in the range of the upper and lower quartile range of values from field measurements. For SL, observations for Zn and Pb were missing from the CEDEN database. The values selected for modeling N and P were within the upper and lower quartile range of the reported measured values. The selected values for Cu loading were within the upper and lower quartile range for measured values, except for the industrial land use which was slightly greater than the selected EMC value. The variable replication of observed values with simulated results is shown in Figs. 11, 12, and 13 as well as Supplemental Figs. S6, S7, and S8.

Water quality verification depicts that selected EMC values do not consistently match observed pollutant loading in the selected watersheds. These parameters result in a range of accuracy when matching with the timestamp of collected samples, both in magnitude and time.

Since the simulated washoff values were able to match observed values for some storms it is seen as a potentially viable estimation of pollutant loading. Generally, for Imperial Beach, Pb was overestimated in the simulations with differences ranging from 79 % to 465 %. In Imperial Beach observed values for Cu, Zn, N and P were within 100 % of simulated values and as close as a 5 % error. In San Leandro, the timing of peak concentrations was missed for some observation points (such as the 03/13/2012 and 12/01/2012 storm events). Other events had elevated concentrations without the presence of rain (03/14/2012). The observed values for P were generally greater than simulated value, with some simulated storm events more closely following observed values (e.g., Fig. 13, storm on 11/11/12, and 11/30/12).

More accurate estimates of pollutant loading would require additional calibration and more validation datasets, which do not exist for these study areas. Future research could implement more sampling in these areas during wet weather events to better calibrate models. The current modeling results serve as a baseline, revealing how regional parameters could be developed for study areas. The simulated annual loading per unit area (kg/ha-yr) are within range of reported values in the literature (Table 8, 9 and 10). Since the primary goal is to determine relative changes to pollutant loads from implementing rain barrels, developing more accurate pollutant washoff parameters was not the focus of this work. A secondary objective was to assess the performance of regional parameters at a local scale, which in this case revealed the need for additional field measurements to optimize regional parameters. These estimates provide the basis for ecotoxicity impacts and determining overall reductions in loading from RB installation.

The EcoP of stormwater is estimated to be 8.10 CTUe/m^3 in SL and 2.5 CTUe/m^3 in IB. These value are on the same order of magnitude as reports from Jeong et al. (2016) where there is 3.71 CTUe/m^3 from water pollutants discharged with stormwater runoff. Tavakol-Davani et al. (2018) determined the CTUe/m^3 of combined sewer overflows (CSOs) to be 25.9 CTUe/m^3. This value shows that CSOs could be three times more toxic than direct stormwater discharges in SL, and about ten times more than stormwater discharges in IB. Brudler et al. (2019) reports values of 0.72 and 0.82 CTUe/l (720 and 820 CTUe/m^3) for freshwater and marine ecotoxicity impacts from stormwater discharges. These values are two orders of magnitude greater than the reported

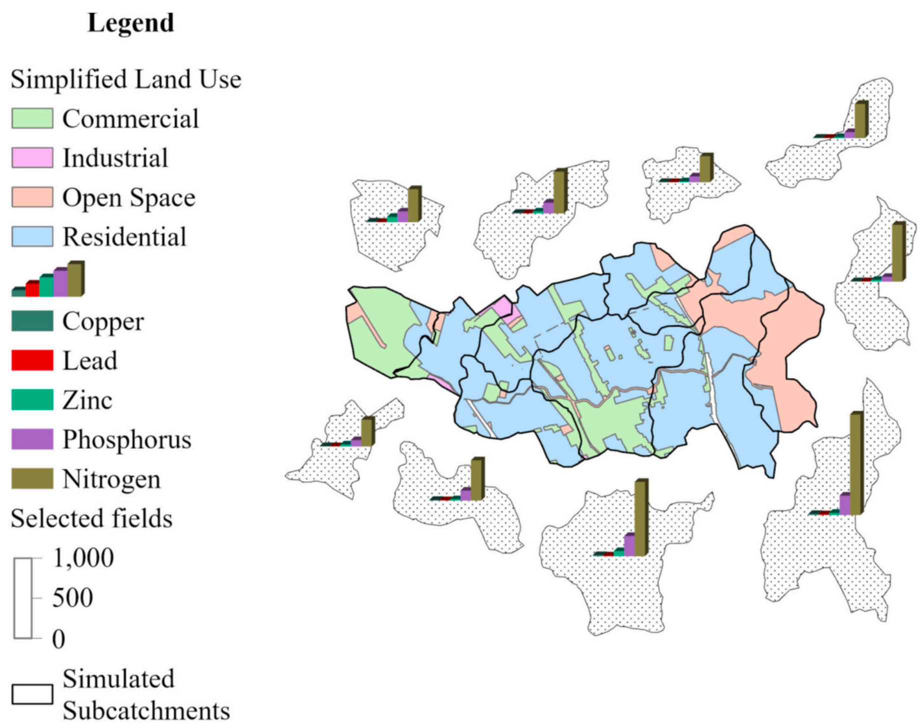


Fig. 8. Results from water quality simulations for San Leandro. The map shows the simplified land uses in each of the major subcatchments, as well as the total pollutant loading for each constituent (kg/yr). Total loading is reflected as the amount of the constituent produced by the entire Subwatershed. This figure represents the scenario without RB implementation. This figure represents the scenario without RB implementation.

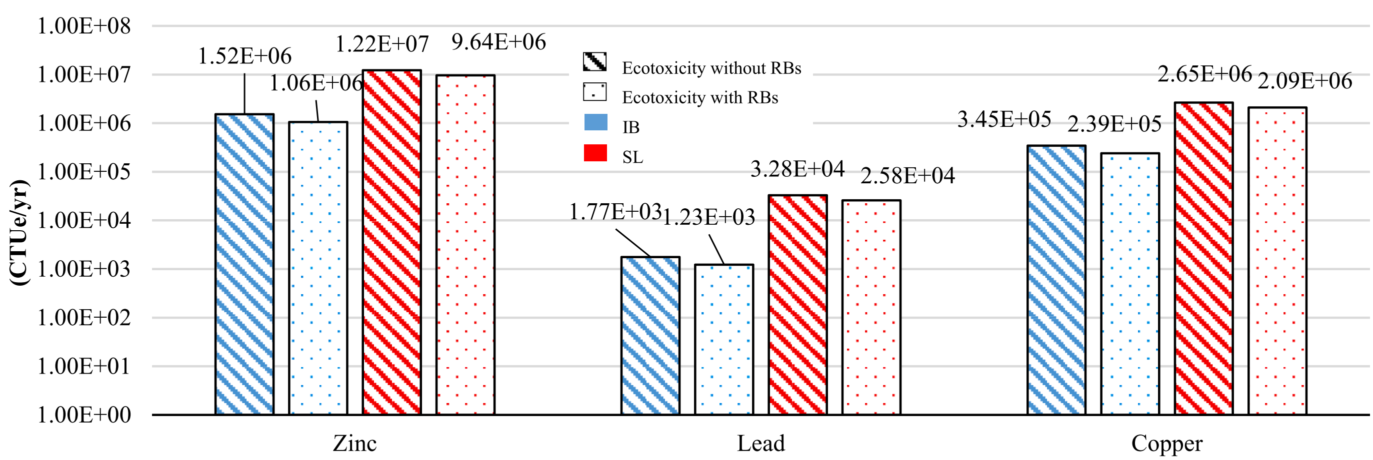


Fig. 9. Annual Ecotoxicity Potential, in terms of Comparative Toxicity Units for Ecotoxicity (CTUe) for Metals in Imperial Beach, presented on a logarithmic scale.

values from our study and the above-mentioned studies. One difference stems from the difference in Ecotoxicity CFs. They used CFs from the USEtox model for freshwater (Rosenbaum et al., 2008) and marine water (Dong et al., 2017). They report that Cu and Zn made up 90 % of the toxicity impact score (81 % Copper and 9 % Zinc). Their reported values for CFs for Cu are 3.6×10^7 CTUe/kg in freshwater and 1.2×10^4 CTUe/kg for marine water. This means that the CF values used by Brudler et al. (2019) for freshwater are three orders of magnitude greater than those used in our study. The values for marine water are 15 orders of magnitude greater than Cu. This highlights that there is uncertainty in the calculated CTUe values due to the range of CFs present in the literature.

4. Discussion

The proposed framework of this study demonstrates the utilization of stormwater numerical modeling with life cycle assessments to determine environmental trade-offs, from large scale RB deployments. When considering the production of a single rain barrel it was determined the initial emissions related to GWP could be offset by the reduced need for centralized water at varying timelines between the two study areas (6 years for SL, and 11 years for IB). The reduced need for centralized water provided less of an offset for reducing the initial emissions related to HTP, taking approximately 50 years in SL and 100 years in IB. Beyond HTP, there are environmental benefits to reducing stormwater runoff, which come from the reduced pollutant loading into the aquatic ecosystem.

There is a clear trade-off between reducing GWP and increasing Human Toxicity Potential HTP with the implementation of rain barrels (RBs). While alternative materials for RBs could result in similar greenhouse gas emissions, they may offer improvements in emissions that impact human health. In the case of comparing fossil-based plastics

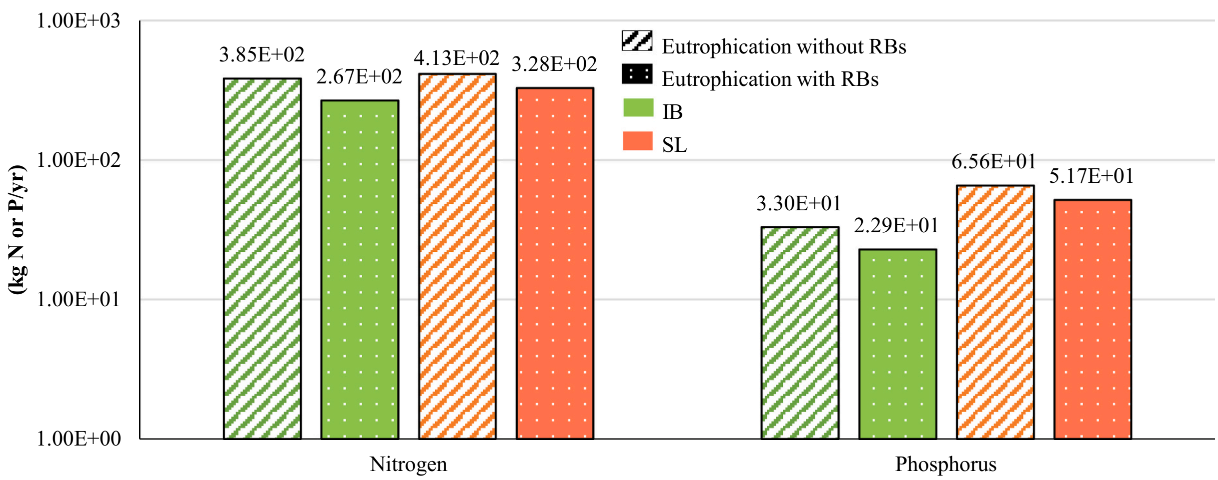


Fig. 10. Annual Eutrophication Potential for Metals in Imperial Beach, presented on a logarithmic scale.

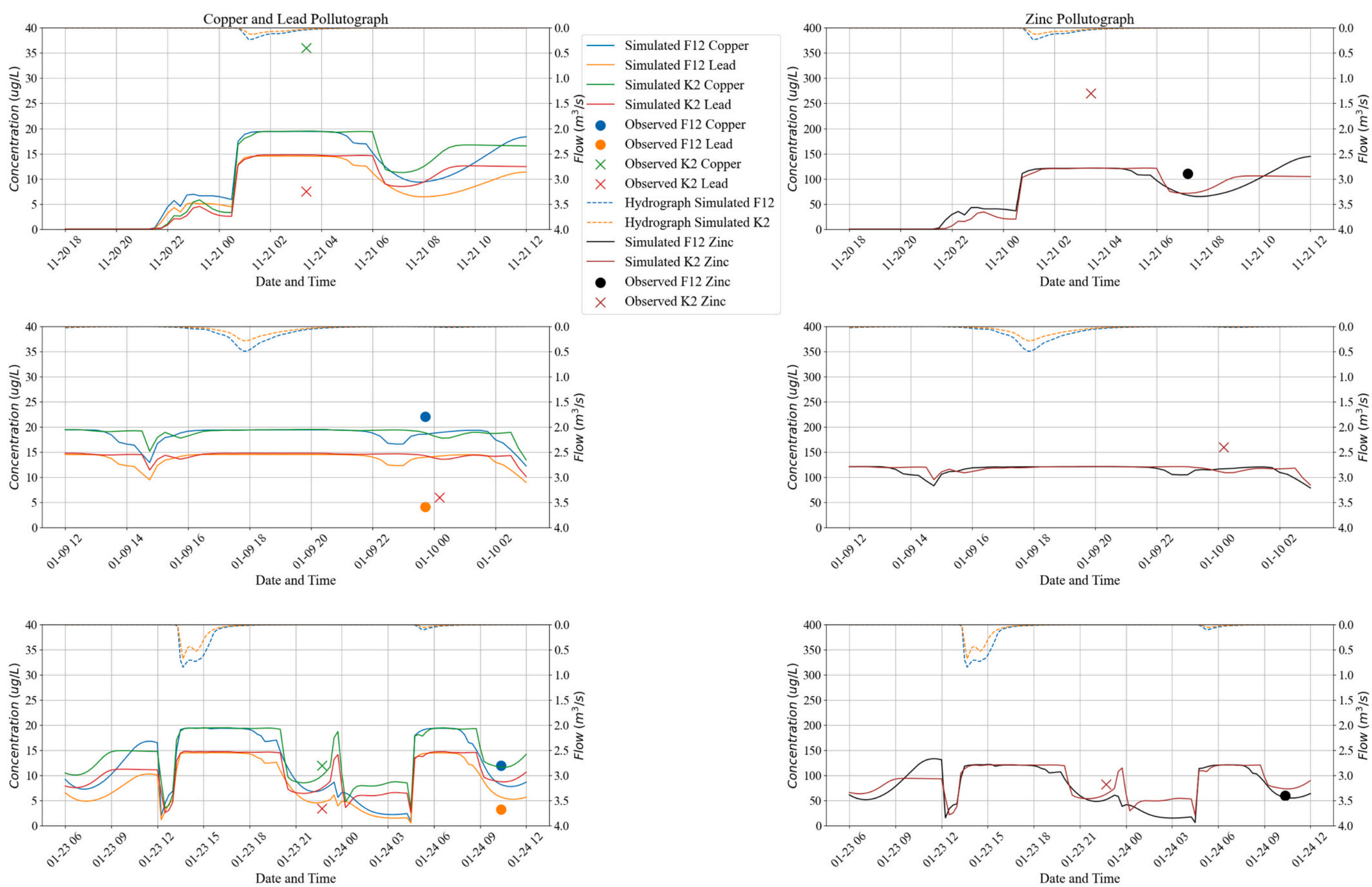


Fig. 11. Validation Results for Metals in Imperial Beach using data from CEDEN.

with bio-based plastics, significant improvements have been shown in the reduction of greenhouse gas emissions (Vink et al., 2003). On the other hand, some reports show a higher contribution to global carbon emissions from bio-plastics, like polylactide, but an improvement to human toxicity (Bałdowska-Witos et al., 2021). There are also reports of bio-based polymers contributing greater percentages to global warming potential and human toxicity than fossil-based production (Nessi et al., 2021). Thus, the study of alternative materials needs to be further pursued to determine the potential for using plastic alternatives.

Rather than using plastic alternatives to produce additional barrels, a possible solution could come from reusing existing materials. The County of San Diego, for example, suggests reusing barrels from restaurants that were previously used for food-related products. This option could be the best alternative, reducing the production costs and environmental impact of new RB materials. In any case, proper recycling of RBs is critical. Without recycling, RBs would have a higher GWP. In our study, recycling reduces the emitted kg CO_2 equivalent by 1.18 per kg of plastic.

The benefits from RBs depend on the proper utilization and maintenance of the system. This study conservatively estimates a 20-year

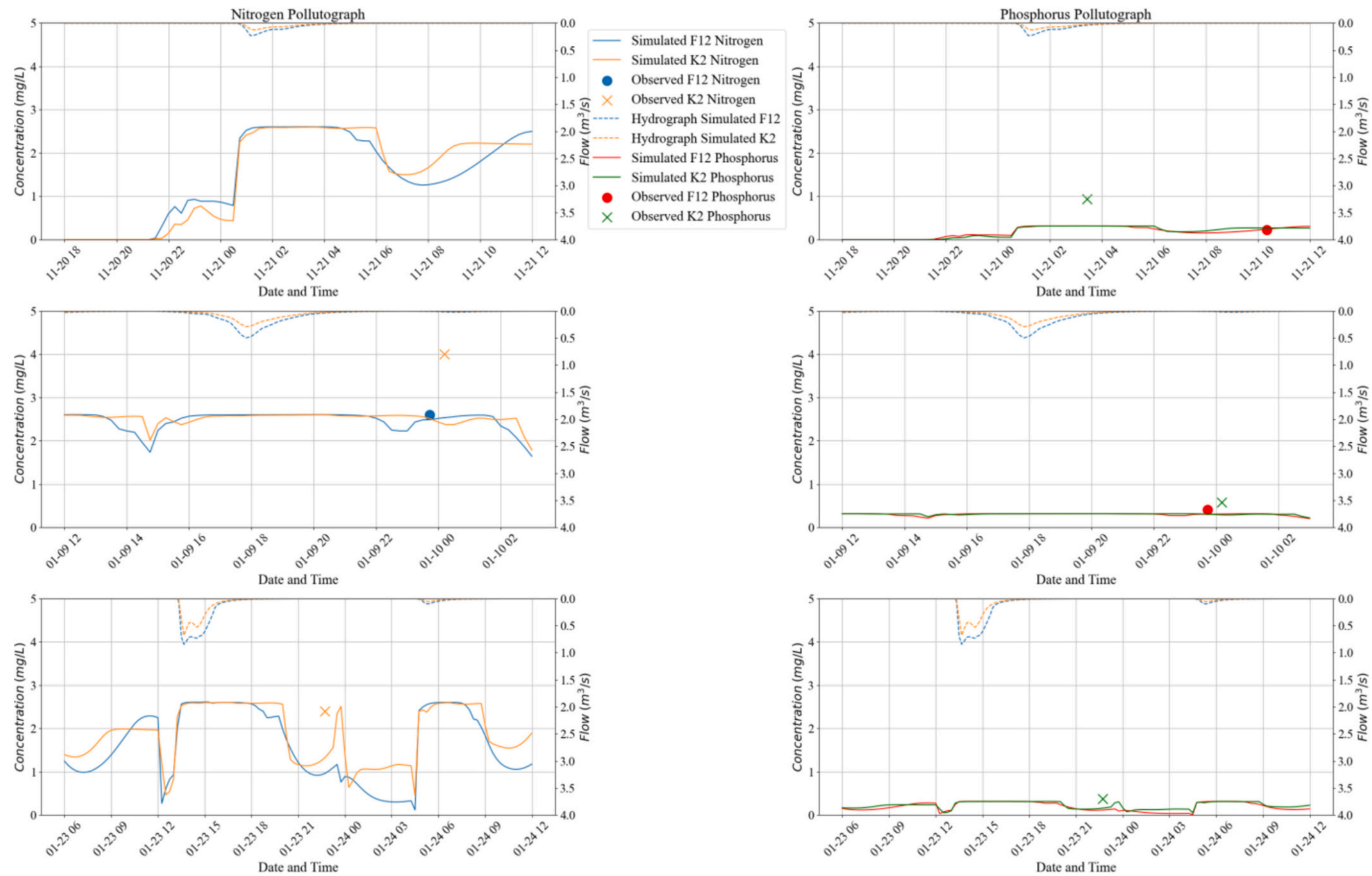


Fig. 12. Validation Results for Nutrients in Imperial Beach, using data from CEDEN.

lifespan for RBs, though with proper maintenance, the actual lifespan could be extended, reducing emissions per cubic meter of collected water. If consecutive or prolonged rain events occur, or if water is not used, overflow can negate the runoff reduction benefits. In areas like SL, with the current design of one 60-gal RB per 100 ft^2 of roof area, overflows could result in the loss of 8.0 m^3 of water over the RB lifespan (1.3 m^3 in Imperial Beach). This emphasizes the importance of allocating an appropriate number of RBs per building, while also taking into consideration annual rainfall. The Bay Area Stormwater Management Association, of which SL is a part of, recommends four RBs for every 500–1000 ft^2 of roof (Bay Area Stormwater Management Agencies Association, 2012). Our results suggest this should be increased to at least a 1:1 ratio (1 RB per 100 ft^2) or more, due to the high rainwater volume in the area. Our approach assumes residents will properly use the collected water and direct it to pervious areas, which could require educational outreach and city oversight to ensure the system is used as designed. We also assume a maximum adoption rate—if the adoption is lower, the benefits in runoff reduction, pollutant reduction, and GWP would be diminished, though the benefits per FU would remain.

We deepen our analysis with an assessment of the toxicity and eutrophic aspects of stormwater constituents. One challenge with determining EcoP of stormwater is the data intensive nature of determining characterization factors and accurately quantifying pollutant loads, leading to limited literature that both determines pollutant loads and CFs to provide EcoP in terms of CTUe/volume of stormwater. Brudler et al. (2019) provides a thorough analysis of stormwater pollutant loading based on event mean concentration, EcoP characterization factors, and EP characterization factors; however, the characterization factors used for EcoP and EP (selected from values within the USEtox database) varied by several orders of magnitude greater than those available in the TRACI 2.2 database. Brudler et al., 2019 compares the CTUe/unit volume of stormwater to the average impact per person per year in Europe, which is estimated to be 8940 CTUe. Their findings show that 12 m^3 of stormwater has the same toxicity impacts as the normalization reference. Our results suggest that between 1100 and 3600 m^3 (correlating to the CTUe/m^3 for SL and IB, respectively) can produce the same toxicity impacts as the normalization reference. EP is also determined using open-source databases, where regional CFs show differences in EP. This is apparent for the EP of IB stormwater loads compared to SL, since the EP CFs are approximately 3 times greater in San Diego County compared with Alameda County. It's important to note that CFs across other impact categories (i.e., GWP and HTP) from different databases can introduce uncertainty in results. Studies have shown that uncertainty in GWP estimates is limited (Table 2). However, CFs for stormwater pollutants carry greater uncertainty, as discussed in the relevant section. Global CFs for Ecotoxicity Potential (EcoP) and Eutrophication Potential (EP) can be several orders of magnitude lower than those used in the United States, making region-specific CFs crucial for accuracy.

These results enhance the assessment of RBs in terms of the feasibility and effectiveness framework of the Intergovernmental Panel on Climate Change (Pörtner et al., 2023). The IPCC provides information on how to determine a viable solution for a target community. Along with the benefits described in this paper, the feasibility of this proposed solution can be further strengthened through the administration of social surveys to determine the public's perceptions. The present research shows how this solution can aid in reducing GWP and aligns with responses from past social survey responses, where community members were in favor of having RBs and Rain Gardens for the environmental and water savings benefits.

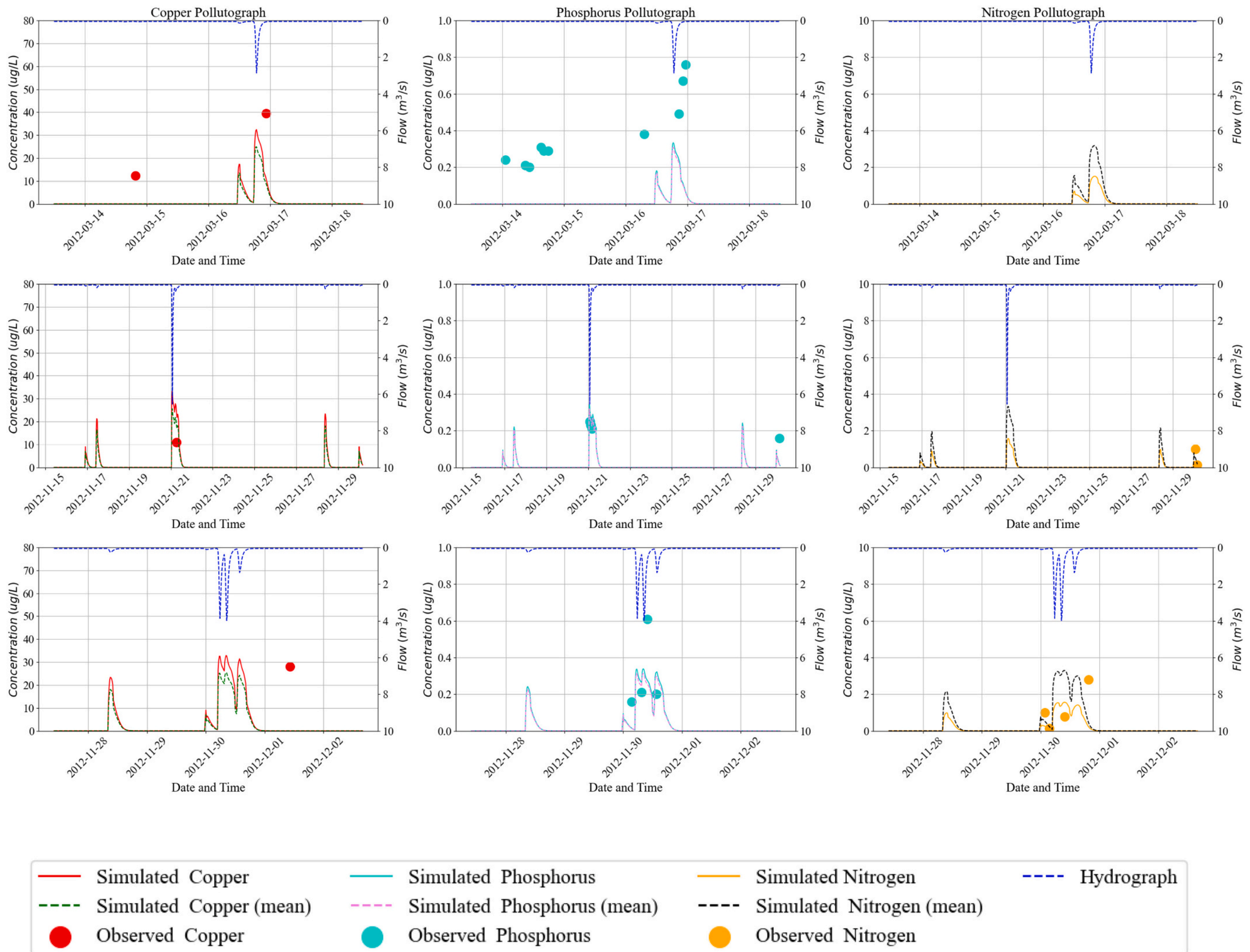


Fig. 13. Validation Results for Metals and Nutrients in the San Leandro Creek Watershed, using data from CEDEN.

5. Conclusion

This study quantifies the multifaceted benefits of rain barrels (RBs) across three sectors: centralized water treatment and distribution, stormwater pumping, and stormwater pollution control, illustrating that RBs can positively impact each of these areas. Results also suggest that RB implementation can reduce global warming potential (GWP), though it may increase human toxicity potential (HTP).

Our work combines multiple criteria to estimate a broad spectrum of benefits and trade-offs for rainwater harvesting (RWH). Unlike similar studies, we include a life cycle analysis (LCA) of how one type of green infrastructure (GI) performs across two regions with differing rainfall patterns. The results show that regions with more rainfall, like San Leandro, experience greater benefits in reducing GWP, while mitigating the increased HTP. However, when rainfall exceeds the storage capacity of RBs, overflow occurs, limiting the improvements in Ecotoxicity and Eutrophication Potential. This underscores the need to adjust GI recommendations based on the unique characteristics of each watershed. Current recommendations for the two study areas are similar, but our results indicate that a higher allocation of RBs in San Leandro would be more effective in reducing urban runoff and promoting sustainability through decentralized water systems.

The sustainability of these systems improves in areas with more available rainfall, where the benefits of reducing strain on centralized water infrastructure outweigh the HTP costs of RB materials. This trade-off aligns with the goal of reducing pollutant discharges through decreased urban runoff, which can in turn lower Ecotoxicity and Eutrophication Potential for receiving water bodies. RB implementation is just one method of green infrastructure and combining multiple strategies can lead to even greater benefits. However, LCA studies must accompany large-scale designs to account for the material and emissions costs of any proposed applications of green infrastructure. Additionally, LCA investigations are essential for developing runoff-reduction techniques, allowing researchers and decision-makers to anticipate and address potential challenges from these solutions. This allows for protection against unforeseen consequences and ensures a more sustainable future.

CRediT authorship contribution statement

K. Bagheri: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **H. Davani:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.177220.

Data availability

Data will be made available on request.

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