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ARTICLE

Design of rainwater harvesting tanks in different climate types modeled under SSP scenarios

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ABSTRACT

Rainwater harvesting (RWH) is an adaptation strategy for managing rainfall variability, but changing rainfall patterns make standardized RWH designs difficult, and few studies have related changing climate conditions in different climate types to RWH designs optimized for runoff generation.This study designed RWH tanks for four Philippine climate types, using the Personal Computer Storm Water Management Model (PCSWMM) with rainfall projected under climate-change scenarios.Daily rainfall for 1985-2014 was collected for one city in each of the four Philippine climate types and projected to 2015-2044 using global climate models (GCMs) under Shared Socioeconomic Pathways (SSP2-4.5, SSP3-7.0, SSP4-3.4, and SSP4-7.0, and served as modeling input to depict runoff reduction performance and design sizing. Results show that runoff reduction generated by rainfall tanks can peak at nearly 80-90% across three climate types (II, III, and IV) from the largest tank size (1200 L), although the roof runoff reduction decreases as rainfall increases. Tanks were then sized for 50%, 75%, and 99% runoff reduction at each site. The relationship between rainfall depth and the ratio of storage volume to catchment area (SV/CA) was mostly linear in Type I and IV climates, nonlinear in Type II, and mixed in Type III. These findings suggest that RWH design requirements differ among climate types and rainfall conditions. The relationships may serve as a starting point for climate-responsive RWH sizing and for site-specific planning in the Philippines.

INTRODUCTION

Climate change has made rainfall patterns less predictable and more variable, so the standard methods used to project rainfall for hydraulic design need to be reevaluated. Climate-related events such as storms, floods, droughts, and unexpected rainfall involve water, so the link between water and climate is critical in addressing climate change (Karimi et al., 2024). Many studies report that climate change is increasing precipitation intensity and event frequency and shortening return periods, which raises the risk of flooding (Singh et al., 2016; Prathna and Shrivastava 2025). Changes in rainfall distribution can also bring intense downpours followed by dry spells (Prathna and Shrivastava 2025). The harm that climate change does to agriculture, and the growing demand from urbanizing regions, make water supply a major concern, especially in areas far from water sources and on islands without large watersheds (Aquino et al., 2023). Sustainable, climate-resilient planning and implementation have therefore been recommended (Maralapalle et al., 2026).

In recent years, various sustainable approaches have been studied to address the environmental and socioeconomic risks of climate change (Samadder and Lal 2025). Low impact development (LID) techniques have recently gained traction because they reduce runoff (Frias and Maniquiz-Redillas 2021; Edra et al., 2023; Co et al., 2023; Garbanzos and Maniquiz-Redillas 2022a, 2022b). Among these controls, harvesting stormwater from roofs is also attracting attention because it addresses sustainability and water demand (Bañas et al., 2023). Rainwater harvesting (RWH) has re-emerged as a sustainable stormwater solution because it reduces environmental footprints, decentralizes water supply, and promotes sustainable water use, which helps mitigate the effects of climate change (Upreti et al., 2025). RWH systems also provide a cost-effective source of water and reduce reliance on contaminated sources (Samadder and Lal 2025). Countries with limited technological and institutional capacity are also more vulnerable to climate change. This has led to recommendations to adapt rainwater management to water scarcity (Kiggundu et al., 2018). RWH addresses the growing concerns of flood management and water supply, which remain major issues in vulnerable communities.

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KEYWORDS

climate change; rainfall; rainwater harvesting; stormwater modeling; tropical

However, intense events and highly variable rainfall make it difficult to design standardized rainwater tank sizes, particularly where climate variability is greatest. Carleton et al. (2024) noted that standard empirical approaches may not clearly capture weather variability. These uncertainties have led researchers to use estimation and modeling methods to project ranges of future rainfall. Previous studies have modeled the performance of RWH systems. Kc et al. (2021) used PCSWMM to model the effects of urbanization and climate change in Kathmandu under current urbanization, extreme urbanization, and a management scenario with rainwater harvesting. Climate-induced rainfall increased flood volume by 75% (current) and 90% (extreme), while the management scenario reduced it by 20-35%. Rajbhandari et al. (2026) used PCSWMM to evaluate configurations of greywater reuse, rainwater harvesting, and efficient fixtures in a residential area under increasing precipitation and sea level rise. Applying all the circular-water strategies together gave the greatest reductions in combined sewer overflows and flood volume, of up to 11%. Ben-Daoud et al. (2022) built a PCSWMM model that included permeable pavement and rainwater harvesting and found that the two together could reduce flood volume by up to 37%.

To account for climate-change uncertainty, some studies have supplemented rainfall analysis with climate models that project future values. One example is the Coupled Model Intercomparison Project (CMIP), which provides standardized multi-model climate simulations that are vital for understanding historical, present, and future climate (Engida et al., 2025). The Shared Socioeconomic Pathways (SSPs) are used with these models to explore five plausible futures, defined by socioeconomic development and the level of greenhouse-gas emissions (Mausen et al., 2020). Many studies have used CMIP6 models and SSP scenarios to investigate changes in precipitation. Hejazizadeh et al. (2022) used 12 CMIP6 global climate models (GCMs) under three scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5) to examine changes in precipitation extremes over the Middle East and North Africa, and concluded that extremes and intensities are expected to increase. Norgate et al. (2024) used three scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) and 12 GCMs to study present and future monsoon precipitation in six precipitation regions of India and reported increases of up to 1.4 mm per day, with extremes further intensified under fossil-fuel-intensive development These methods can be combined to account for rainfall uncertainty in RWH design.

However, the combined use of hydrologic modeling, climate projections, and RWH design remains underexplored in regions with highly variable climates. Tropical regions such as Southeast Asia experience strong climatic extremes (Hong et al., 2022), which complicates the design of hydrologic infrastructure (Akhter et al., 2018). High urban density limits the space and structural capacity for large rainwater tanks, making it impractical to install tanks large enough for high rainfall volumes. Environmental, economic, and operational constraints make design and implementation harder still. Despite the high potential of RWH in this region (Yuan et al., 2025), region-specific research on rooftop RWH design remains sparse.Existing Philippine studies mainly examine volume reduction and water-saving efficiency at single sites (Borgonia and Fornis 2020); only recent studies, such as Co et al. (2023), have begun to consider climate variability and its design implications." To address these gaps, this study designs RWH tanks for four Philippine climate types using PCSWMM and rainfall projected under climate-change scenarios. The tanks are designed for storage volume sizing, with climate type, rainfall pattern, and climate projections taken into account. The results may contribute to standardized RWH design guidance for different climate conditions, for use in policy and national implementation.

MATERIALS AND METHODS

Study Sites

This study focused on four sites, one for each of the four Philippine climate types. Climate change affects the Philippines mainly through droughts and extreme rainfall, which threaten the country's water supplies and economic resilience (Sabino et al., 2025). The Philippines generally has two distinct seasons, dry and rainy, but its climate is divided into four types according to the distribution of rainfall (Philippine Institute for Development Studies 2005). Quezon City, the most populous city in Metro Manila, represents the Type I climate, which has two pronounced seasons: dry from November to April and wet from May to October. Guiuan, a first-class municipality in Eastern Samar, represents the Type II climate, which has no dry season and a pronounced rainfall maximum from December to January. Tuguegarao City, the capital of Cagayan, represents the Type III climate, which has no pronounced rainfall maximum and a short dry season from November to April. Lastly, Butuan City, a highly urbanized city in Agusan del Norte, represents the Type IV climate, in which rainfall is distributed approximately evenly throughout the year. The sites are labelled S1-QC, S2-GC, S3-TC, and S4-BC, for Types I to IV respectively. Figure 1 shows the location and climate type of each site. The sites were selected because an automated weather station (AWS) or rain gauge is nearby, which gives better rainfall data, and because they are urbanized areas with a medium to high density of roofs that could host RWH.

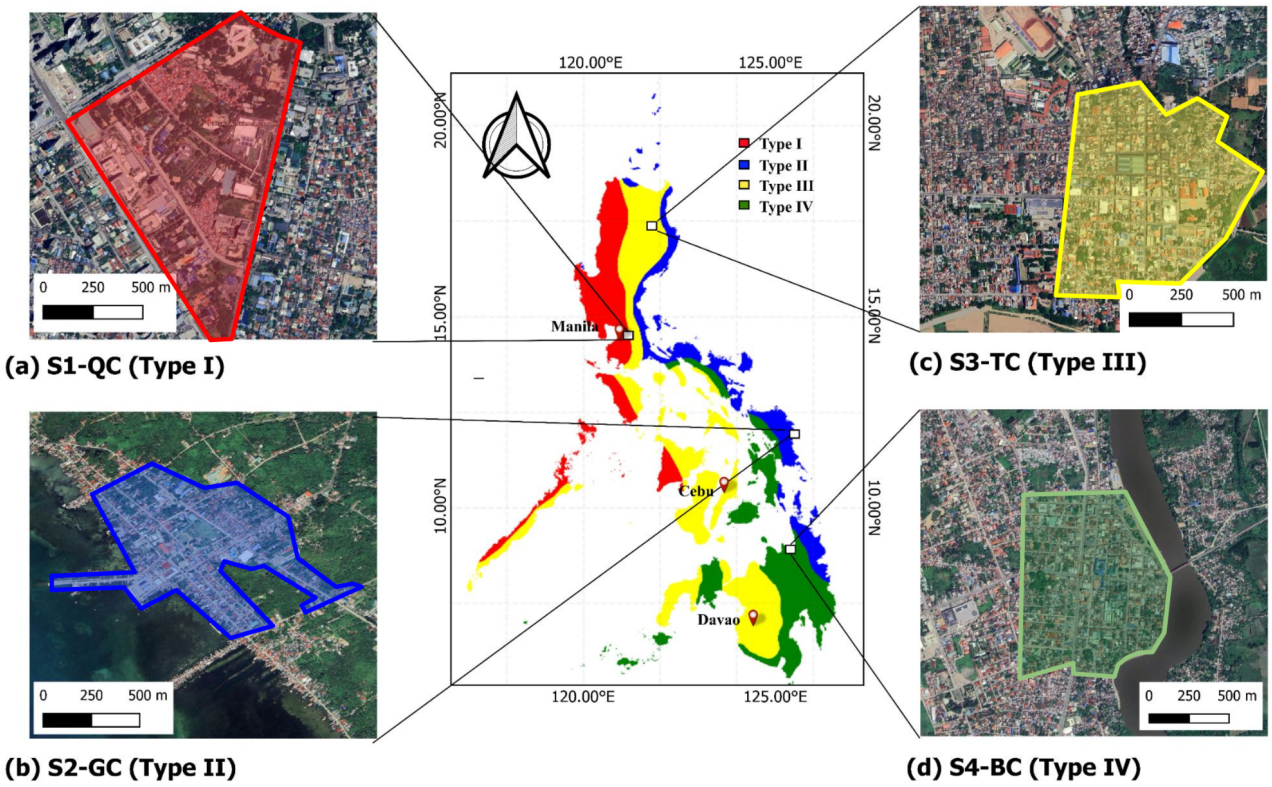


Figure 1: Locations of the four study sites and the climate types of the Philippines.

QGIS (version 3.34; Open Source Geospatial Foundation) was used to locate each city. Building-footprint polygons for each site were imported from OpenStreetMap (OSM) into QGIS to obtain roof areas. Roof area and width were then calculated with the QGIS Field Calculator. Table 1 shows that small roofs dominate, particularly at S1-QC and S2-GC, where more than half of the roofs (76% and 59%) are smaller than 50 m². Small roofs may limit RWH implementation by restricting both rooftop mounting and ground-level installation of larger tanks.

Table 1: Number of roofs in each area class at each study site.

Roof Area (m^2)	S1-QC	S2-GC	S3-TC	S4-BC
< 50	1394	1551	375	570
50 - 100	198	612	576	717
100 - 150	40	204	374	483
150 - 200	27	104	205	313
> 200	177	139	365	577
Total	1836	2610	1895	2660

Rainfall data and climate projections

Daily rainfall data for 1985-2014 (30 years) were obtained from the rain gauge station nearest to each site. The data came from stations of the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA): Science Garden, Quezon City (14.64°N, 121.04°E) for Type I; Guiuan, Eastern Samar AWS (11.03°N, 125.73°E) for Type II; Tuguegarao Synoptic Station (17.65°N, 121.76°E) for Type III; and Butuan, Agusan del Norte AWS (8.95°N, 125.54°E) for Type IV. The rainfall data for each site were analyzed for trends, and the probability of non-exceedance was estimated with the Weibull plotting position (Equation 1) [state the data used: all days, wet days, or annual maxima].. The Weibull plotting position was chosen because it is less likely than other plotting positions to underestimate high percentiles, which would lead to undersized controls (Garbanzos and Maniquiz-Redillas 2022a). This method was also used by Frias and Maniquiz-Redillas (2021), Edra et al. (2023), Co et al. (2023) and Garbanzos and Maniquiz-Redillas (2022a, 2022b). The 90th, 95th, and 99th percentiles were evaluated to represent rainfall from moderate to extreme events. The resulting daily depths were disaggregated into hourly values using the triangular distribution of the Hydrological Simulation Program-FORTRAN (HSPF) as input to the hydrologic model by proportioning the daily depth according to the distribution pattern.

$$1P = \frac{m}{n+1} \quad (1)$$

where P is the probability of non-exceedance, m is the rank of the observation (in ascending order), and n is the number of observations.

Projected rainfall data were obtained from the Earth System Grid Federation (ESGF) for four Shared Socioeconomic Pathways (SSPs). We used ten CMIP6 models from ESGF.Table 2 lists the ten modeling groups and models used. GCM projections for four scenarios (SSP2-4.5, SSP3-7.0, SSP4-3.4, and SSP4-7.0) were processed to obtain projected rainfall for 2015-2044. The projected rainfall fields were regridded to a common grid by bilinear interpolation in Python, and values at each site were then taken from the nearest grid cell.. Interpolation methods of this kind have been used for rainfall data (Nobrega and Filho 2025), but they do not improve the resolution of the underlying model.

Four (4) statistical metrics were incorporated in the spatial performance assessment to conduct a comparison between the projected rainfall data from ESGF and the historical rainfall data from PAGASA: Cramer's V, the Spatial Efficiency Metric (SPAEF), the Kling-Gupta Efficiency (KGE), and the Relative Mean Error (RME). Cramer's V was used to evaluate the association of each of the GCM gridded projected rainfall data with the historical rainfall dataset, where values ranging from 0 to 1 indicate increasing association strength. Cramér's V is calculated

by Equation 2. SPAEF combines the Pearson correlation coefficient, the ratio of coefficients of variation, and the histogram overlap to compare spatial patterns (Koch et al. 2018). Equations 3-5 show the SPAEF formula and the computation of its variables. KGE combines three components: correlation, the ratio of means (bias), and the ratio of standard deviations (variability). Equations 6-9 indicate the KGE formula and their respective variables. RME is the mean of the relative errors between simulated and observed values Equation 10 depicts the RME formula. The GCMs were then ranked to identify the model that best reproduced the observed rainfall at the study sites. The rating metric was defined in Equation 11. Ranking allows attention to be focused on the best-performing models and excludes poor ones, which makes adaptation planning more reliable (Bastola et al. 2025). The Quantile Mapping bias adjustment is then conducted using the Climate Data Bias Corrector (CDBC) software to the regridded historical and project rainfall data from the top performing GCMs to align their distributions with the observed historical rainfall data to generate an adjusted projected rainfall dataset.

Table 2: Climate modeling groups and models evaluated

No.	Dataset	Name	Description
1	MRI	Meteorological Research Institute	MRI conducts research for the improvement of information issued by JMA on weather, earthquakes, volcanic activity, climatic conditions and other phenomena.
2	CCCMa	Canadian Centre for Climate Modelling and Analysis	CCCMa develops and applies computer models of the climate system to simulate global and Canadian climate, and to predict changes on seasonal to centennial timescales
3	MPI	Max Planck Institute	MPI is composed of 86 institutes focused on basic research in natural sciences, life sciences, and the humanities. Known for high-impact science, these independent institutes cover diverse fields from astrophysics and AI to biology and art history.
4	KIOST	Korean Institute of Ocean Science and Technology	South Korea's premier, state-run research institution dedicated to comprehensive marine science, oceanography, and technology development
5	NASA-GISS	Goddard Institute for Space Studies	Conducts broad study of global change, an interdisciplinary initiative addressing natural and man-made changes in our environment that occur on various time scales
6	BCC	Beijing Climate Center	BCC focuses on operational and research climate activities, climate monitoring and diagnosis, climate prediction, climate impact assessment and climate change.
7	IPSL	Institut Pierre Simon Laplace	Eight laboratories and two associated teams specialising in one or more aspects of the climate and environmental sciences and the exploration of the solar system.
8	NUIST	Nanjing University of Information of Science and Technology	A public university in Nanjing, Jiangsu, China. It is affiliated with the province of Jiangsu.
9	NOAA-GFDL	National Oceanic and Atmospheric Administration, Geophysical Fluid Dynamics Laboratory	A laboratory in the National Oceanic and Atmospheric Administration (NOAA) Office of Oceanic and Atmospheric Research (OAR).
10	NCC	NorESM Climate modeling Consortium	A collaborative Norwegian network that produces advanced climate simulations for IPCC assessments and research, with a focus on high-latitude processes

$$V = \sqrt{\frac{x^2 n^{-1}}{min(c-1, r-1)}} \quad (2)$$

Where V is Cramer's V, x^2 is the chi-square value, n is the number of data, c is the columns, and r is the rows.

$$SPAEF = 1 - \sqrt{(\alpha_s - 1)^2 + (\beta_s - 1)^2 + (\gamma_s - 1)^2} \quad (3)$$

$$\beta_s = \frac{\sigma_g / u_g}{\sigma_o / u_o} \quad (4)$$

$$\gamma_s = \frac{\Sigma_{j-1}^{b} min(H_j, L_j)}{\Sigma_{j-1}^{b} H_j} \quad (5)$$

Where *SPAEF* is the Spatial Efficiency Metric, α_s is the spatial correlation coefficients (Pearson's correlation coefficient), β_s is the coefficient of variation for spatial variability, σ_o is the standard deviation of simulated rainfall, σ_g is the standard deviation of observed rainfall, u_g is the mean of simulated rainfall, u_o is the mean of observed rainfall, and γ_s is the histogram overlap, H is the histogram value of observed rainfall, L is the histogram value of simulated rainfall, and b is the number of bins.

$$KGE = 1 - \sqrt{(\alpha_k - 1)^2 + (\beta_k - 1)^2 + (\gamma_k - 1)^2} \quad (6)$$

$$\alpha_k = (obs, sim) = \frac{\Sigma(x_i - u_g)(y_i - u_o)}{\sqrt{\Sigma(x_i - u_g)^2 \Sigma(y_i - u_o)^2}} \quad (7)$$

$$\beta_k = \frac{u_g}{u_o} \quad (8)$$

$$\gamma_k = \frac{\sigma_g}{\sigma_o} \quad (9)$$

Where *KGE* is the Kling-Gupta efficiency, α_k is the spatial correlation coefficients, β_k is the relative variability, x_i is the

simulated rainfall value, u_g is the mean of simulated rainfall, y_i is the observed rainfall value, u_o is the mean of observed rainfall, γ_k is the ratio between σ_o and σ_g, σ_o is the standard deviation of simulated rainfall, and σ_g is the standard deviation of observed rainfall.

$$RME = \frac{1}{n}\Sigma_{i=1}^{n}\left|\frac{x_i - y_i}{y_i}\right| \quad (10)$$

Where *RME* is the Relative Mean Error, x_i is the simulated rainfall value, y_i is the observed rainfall value, and n is the total number of observations.

$$RM = 1 - \frac{1}{ab}(rank_i) \quad (11)$$

Where *RM* is the ranking metric, a is the number of metrics, b is the number of models, and $rank_i$ is the rank of the model based on each index.

Figure 2 shows the methodological framework of the study. The study used a simulation-based approach to assess how rainfall and roof catchment characteristics affect the sizing of RWH tanks, in four phases. Phase 1 characterized rainfall: site climate and rainfall data were collected. Phase 2 analyzed the rainfall data and the climate projections. Phase 3 simulated catchment response to the processed rainfall at each site with a stormwater model (PCSWMM). Phase 4 designed the RWH tanks from the simulation results and identified the best sizing scenarios. he framework could be transferred to other regions because it combines climate projections with site-specific rainfall and catchment data to size RWH systems for future conditions. The approach may also help countries with high rainfall and an interest in RWH, such as Germany, the United Kingdom, Brazil, the United States, and New Zealand (Raimondi et al. 2023), to consider design criteria that take rainfall and space constraints into account.

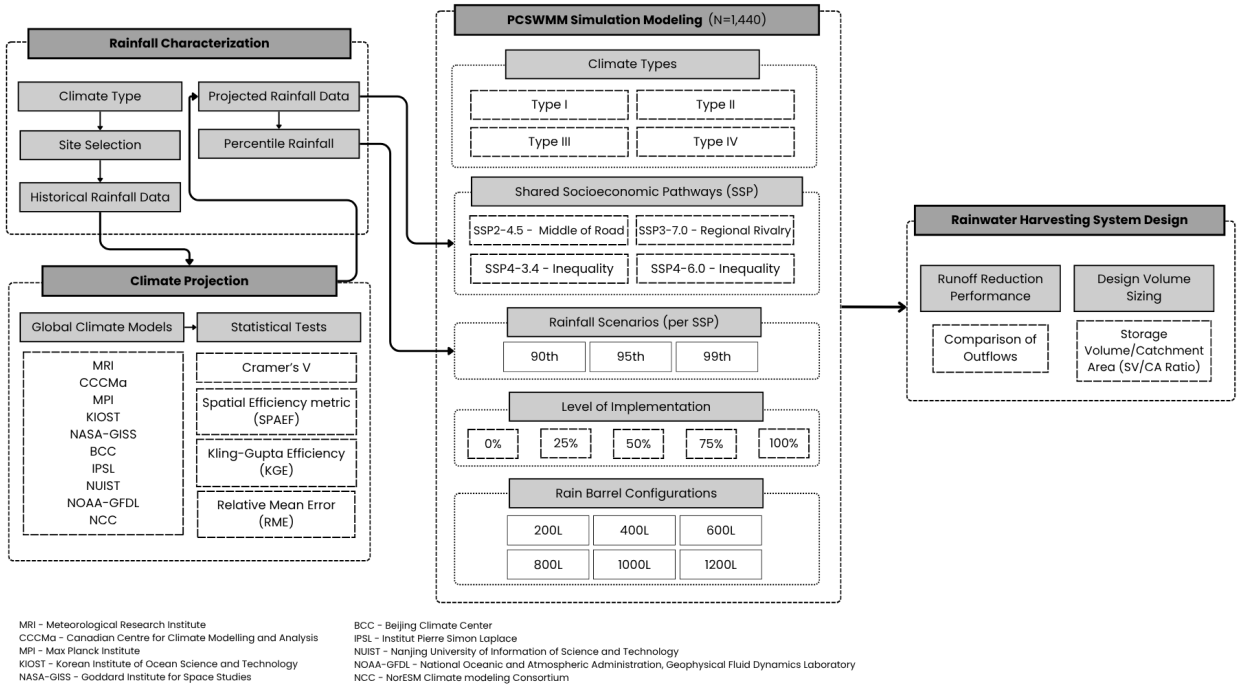


Figure 2: Flowchart of the of the study

Hydrologic modeling

PCSWMM was used to model the hydrology of the RWH systems in each city PCSWMM is software that couples hydrologic and hydrodynamic modeling with a geographic information system (GIS) to simulate hydrologic processes and stormwater movement in urban areas t is a commercial interface and extension of the US EPA Stormwater Management Model (SWMM5), with 1D and overland 2D flow and continuous simulation. It has a built-in Low Impact Development (LID) module for hydrologic, hydraulic, and water-quality analysis (Kc et al., 2021; Rajbhandari et al., 2026; Zhou et al., 2026), and the rain barrel was selected for simulation. Because of this module and its use in previous studies, PCSWMM was selected. Table 3 lists the sub-catchment parameters.

Table 3: Roof sub-catchment parameters

Sub-catchment Parameters	Unit	Climate Type			
		S1-QC (Type I)	S2-GC (Type II)	S3-TC (Type III)	S4-BC (Type IV)
Area	ha	1.05	0.08	0.20	0.21
Width	m	77.6	23.2	46.5	39.9
Flow Length	m	134.97	35.57	43.62	52.22
Slope	%	0.25	0.25	0.25	0.25
Imperviousness	%	100	100	100	100

N Imperv	-	0.015	0.015	0.015	0.015
N Perv	-	0.41	0.41	0.41	0.41
D_{store} Imperv	mm	0.015	0.015	0.015	0.015
D_{store} Perv	mm	0.41	0.41	0.41	0.41

A total of 1,440 simulation runs were conducted for all four selected sites considering four (4) SSP scenarios, three (3) rainfall percentiles, utilizing six (6) RWH tank sizes and five (5) implementation levels. Table 4 shows the scenarios used in the study. RWH sizes were set based on commercially available sizes including 200 L, 400 L, 600 L, 800 L, 1000 L, and 1200L tanks. Varying implementation levels (0%, 25%, 50%, 75%, 100%) were also applied to the model for comparison.

Table 4: Simulation scenarios

Climate types	Type I, Type II, Type III, Type IV
SSP scenarios	SSP 2.45, SSP 3.70, SSP 4.34, SSP 4.70
Rainfall percentiles	90th, 95th, 99th
Rainwater harvesting tank sizes	200 L, 400 L, 600 L, 800 L, 1000 L, 1200L
Implementation levels	0%, 25%, 50%, 75%, 100%
Total Simulation Runs (N) = 1,440	

RESULTS AND DISCUSSION

Rainfall characterization

Figures 3a and 3b show the annual and monthly rainfall at each site. Annual rainfall varies from year to year; the Type II site has the highest peaks and the Type I site the lowest annual values. The mean annual rainfall was 1,739.55m m (Type I), 2,962.45 mm (Type II), 1,524.99 mm (Type III), and 2,945.65m mm (Type IV). Rainfall at the Type I and Type III sites peaks in the middle of the year (June to October), whereas the Type II and Type IV sites peak at the end and start of the year (November to February). This suggests that the Type IV climate representative site exhibits signs of a transitional behavior between the two climate types, leading to variances in observations. This is supported by the geographical standpoint of the site is near the classified boundary of Type II climate classified areas. Monthly rainfall is much higher at the Type II and Type IV sites, reaching 600-1,000 mm, than at the other two, where peaks are about 600 mm. The high rainfall at the Type II and Type IV sites is probably due to the northeast monsoon and Pacific easterlies Figure 3c shows the Weibull plotting positions of the rainfall data. The computed values are tabulated in Table 5.

Table 5. Simulation scenarios

	Rainfall (mm)		
Climate Type	90^{th} Percentile	95^{th} Percentile	99^{th} Percentile
S1-QC (Type I)	23.4	35.1	95.6
S2-GC (Type II)	26.6	45.4	93.5
S3-TC (Type III)	12.5	29	78.6
S4-BC (Type IV)	18.8	32.6	72.2

These percentiles are similar to or higher than those reported in some other studies, but lower than others. For a Type I climate, Frias and Maniquiz-Redillas (2021) estimated 4.80 mm at the 90th percentile and 15.10 mm at the 95th percentile, which are much lower than the present values, probably because of a different record or definition of the population Garbanzos and Maniquiz-Redillas (2022a) obtained 16.64, 35.44, and 99.44 mm for the 90th, 95th, and 99th percentiles in a Type I climate, closer to the present estimates (23.4, 35.1, and 95.6 mm). For a Type IV climate, Edra et al. (2023) estimated 22.2 mm and Campos et al. (2025) 23.07 mm for the 90th percentile, both higher than the present 18.8 mm. The differences probably reflect the choice of rain gauge, its location, and the length and completeness of the record, which shows the need for site-specific observations.

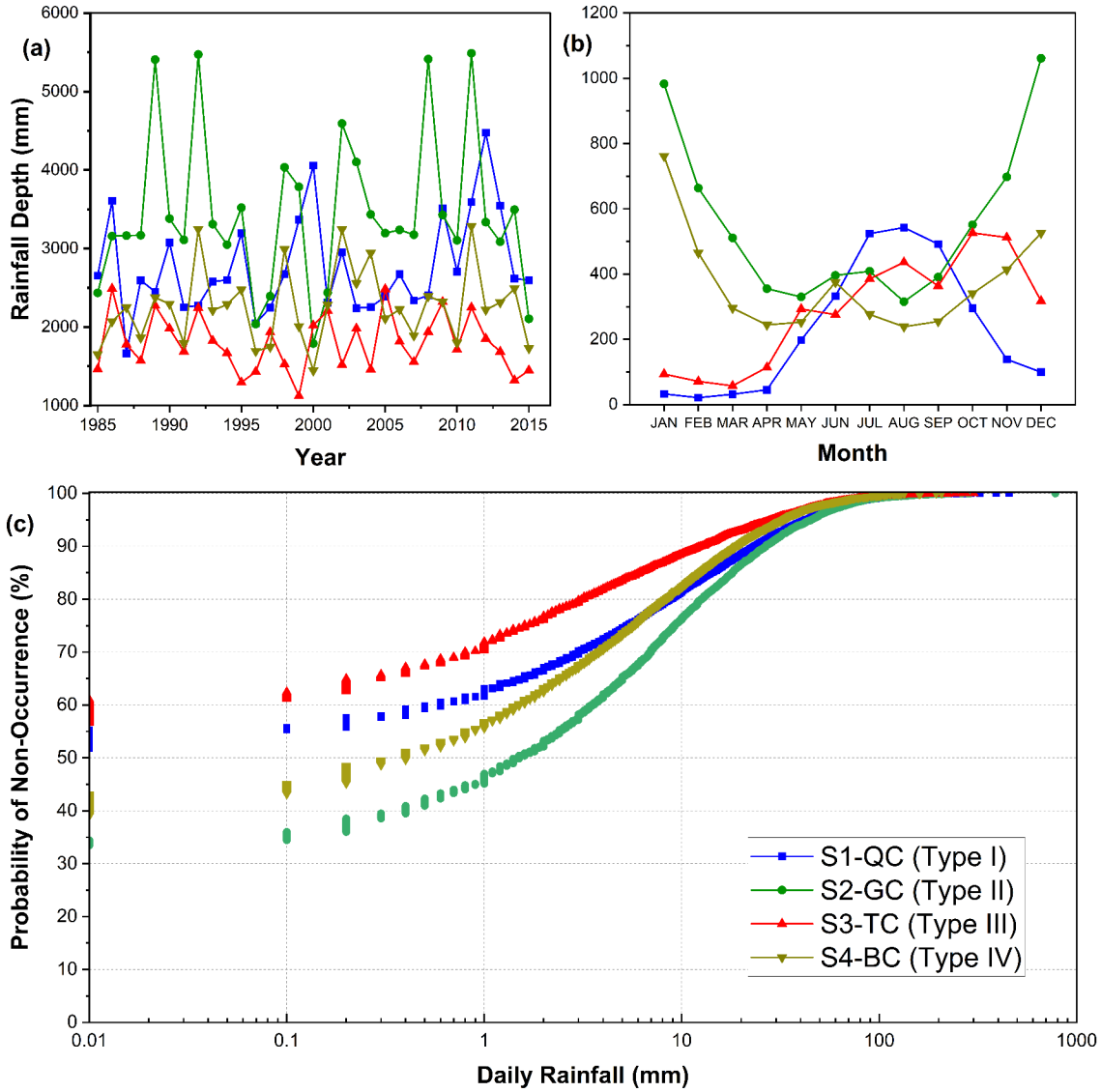


Figure 3: (a) Annual rainfall, (b) monthly rainfall, and (c) probability of non-exceedance of daily rainfall at each study site (1985-2015).

Projected rainfall changes based on climate change scenarios

Figure 4 summarizes the performance of each GCM on the four metrics at each site. On all four metrics (KGE, Cramér's V, SPAEF, and RME), the MRI, CCCma, and IPSL are the top GCMs,with historical simulations closest to the PAGASA values Rainfall for 2015-2044 was then projected with this model for the four SSP scenarios (Figure 5)). With the projections, the percentile values increase by up to 73.16% or decrease by up to 80.66%. above the baseline values in Table 5.This increase seems large because it concerns high percentiles and extreme values, but other studies also project more intense rainfall in the western Pacific region. Tangang et al. (2020) estimated a 10-20% increase in mean rainfall over Indochina and the Philippines, and Hong et al. (2022) projected increases in annual maximum daily precipitation of 8.5%, 11.6%, and 17% under SSP2-4.5, SSP3-7.0, and SSP5-8.5. Percentiles estimated from historical data alone may therefore be unreliable for design, consistent with Haque et al. (2016), who state that RWH development should incorporate climate-change projections. However, it should be noted that not all values are expected to increase, as seen in the results of Hong et al. (2022) who indicated that return periods are expected to decrease by around 18-30% by the year 2100 in the country using other models. The projected values were used as input to simulations.

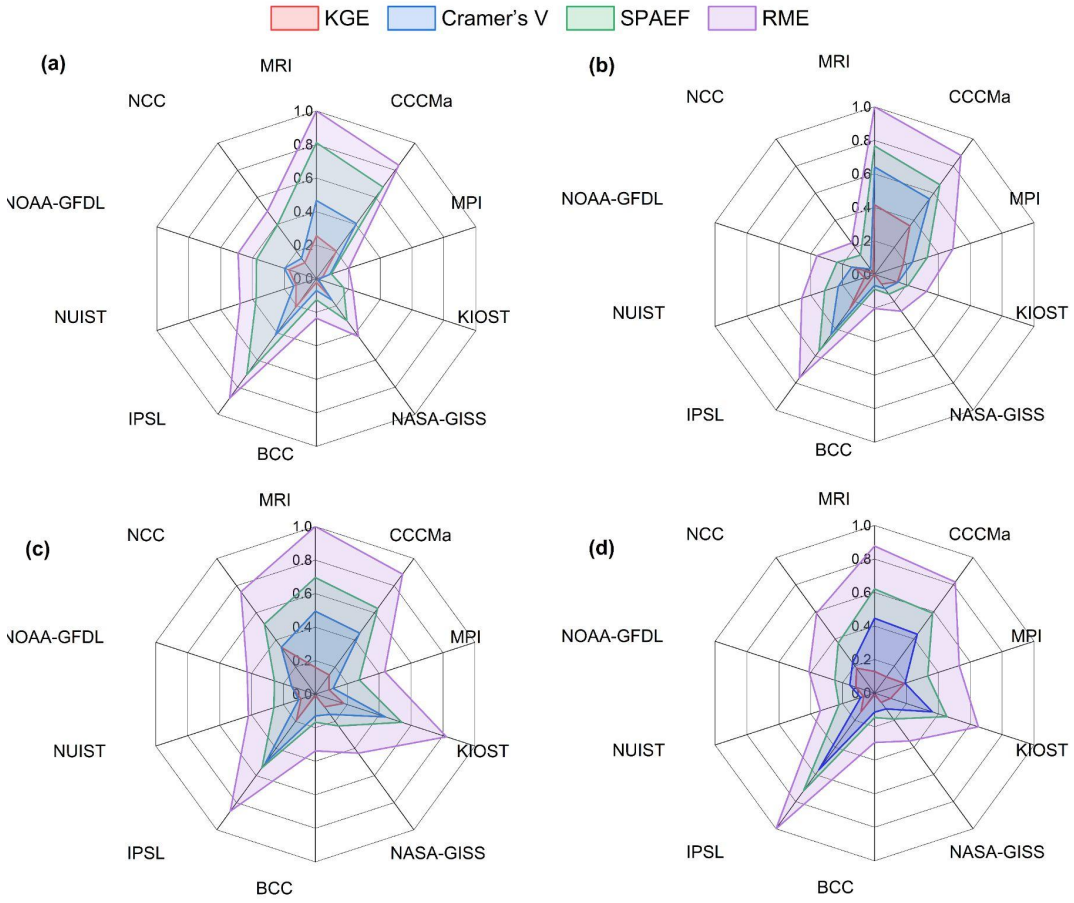


Figure 4: Polar plot of the cumulative ranking of the ten climate models on the four metrics at each study site.

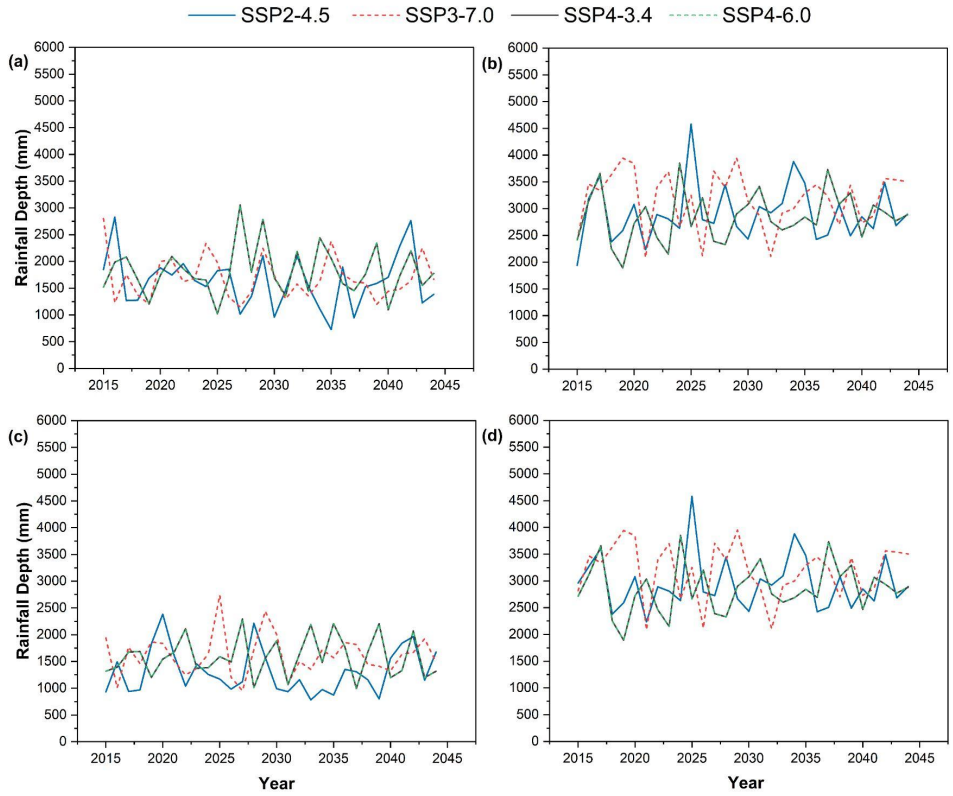


Figure 5: Rainfall percentiles projected for 2015-2045 [or 2044] by the MRI model under four SSPs, relative to the baseline

Roof runoff reduction performance of RWH systems across the four climate types

Figure 6a-d shows the roof runoff reduction of RWH tanks of six commercially available sizes at each site, for each rainfall percentile. Although RWH systems are not expected to give the greatest flood reduction (Walsh et al., 2014), they contribute to volume reduction at the roof scale. Runoff reduction was higher for lower rainfall percentiles and lower for higher ones. Rainfall below 30 mm can be largely captured by the tanks, giving runoff reductions of up to 90%. Larger depths are harder to accommodate because the storage is limited. These reductions are higher than those reported in earlier studies (Basinger et al., 2010; Steffen et al., 2013; Rashid et al., 2022), probably because small roof catchments were modeled at each site. Roofs smaller than 50 m² make up 76% of the Type I roofs, against 59% (Type II), 20% (Type III), and 21% (Type IV) at the other sites. Volumetric runoff reduction is reported to increase linearly with storage capacity (Walsh et al., 2014), although local factors such as rainfall pattern, roof area, and indoor and outdoor water demand should also be considered (Alamdari et al., 2018). The importance of roof size is shown by the ratio of storage volume to catchment area (SV/CA), which must be at least 0.05 for the 90th percentile and 0.10 for the 95th to reach at least 40% runoff reduction at every site.

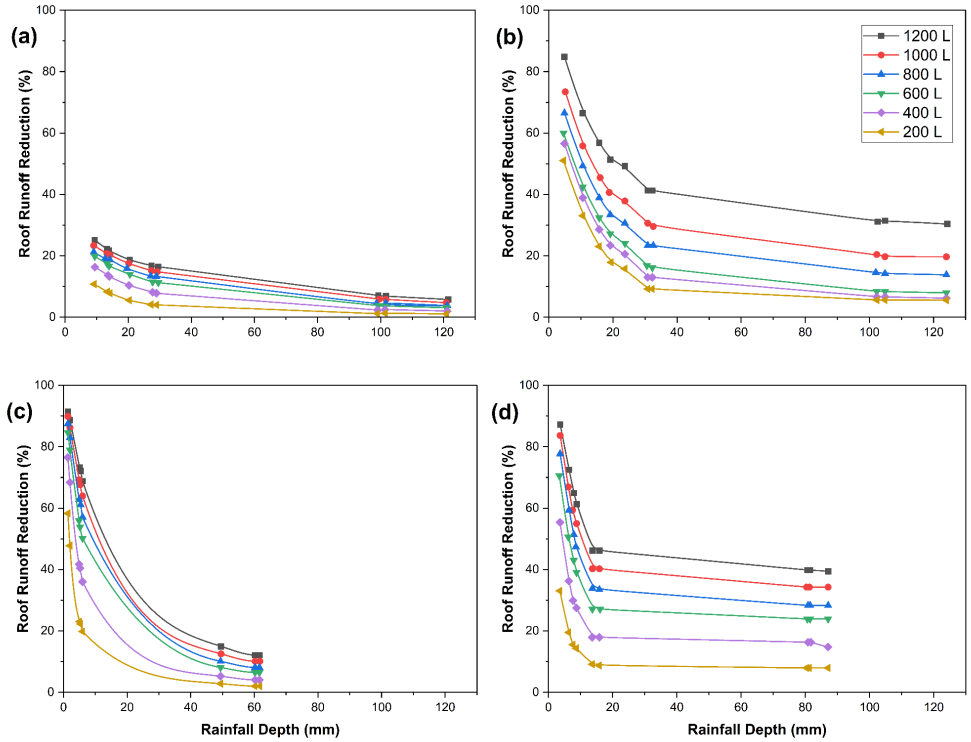


Figure 6: Runoff reduction as a function of tank volume for the rainfall percentile scenarios at (a) S1-QC (Type I), (b) S2-GC (Type II), (c) S3-TC (Type III), and (d) S4-BC (Type IV).

Design sizing of RWH systems for each climate type

Figure 7 shows the SV/CA needed for each rainfall depth at the three target runoff reductions. Three target runoff reductions (50%, 75%, and 99%) were used to identify trends with rainfall depth, to assess the role of catchment size, and to simplify the selection of tank volume for each climate type. The Type I site follows linear trends for the 90th, 95th, and 99th percentiles. The Type IV site is also mostly linear, except for the 99th percentile, which is logarithmic. Type III is mixed: the 90th percentile is linear at the 50% and 75% targets but concave-down at 99%, the 95th percentile is accelerating and nonlinear, and the 99th percentile is more nearly linear. The Type II site was the most distinctive, with a logarithmic-like trend for the 90th percentile, a nonlinear trend for the 95th, and a power trend for the 99th. The Type II and Type IV sites receive the most frequent rainfall (Corporal-Lodangco and Leslie 2017), but the results presented do not show that they are more volatile or harder to manage. However, these results depend strongly on the roof size at each site, so the differences among sites cannot be attributed to climate alone.

The required SV/CA increases with rainfall depth, as expected, because deeper rainfall needs more storage per unit roof area. Tobio et al. (2015) found a similar result for the ratio of storage volume to surface area (SV/SA): a ratio adequate for small events becomes insufficient as rainfall depth increases. However, the SV/CA ratio needed for a given runoff reduction differs with climate type. The nonlinear behavior at higher rainfall shows that more storage does not give a proportional gain in runoff reduction, which highlights the importance of climate- and site-specific sizing.

Additional simulations were run to relate SV/CA to rainfall depth at all four sites. The regression equations were then used to extrapolate to hypothetical storage volumes of up to 78,500 L. Figure 8 shows the tank volumes required for each climate type as a function of SV/CA and rainfall depth. Higher rainfall depths require larger storage volumes, in proportion to the catchment area. Because rainfall is greater at the Type II and Type IV sites, larger storage volumes are needed there. This agrees with Co et al. (2023), where the Type II and Type IV climates required the largest tank volume (930 L) on the basis of rainfall monitoring and recalibration of the tank size. In Co et al., the Type I and Type III tank sizes were 75% and 50% of this volume, respectively. Hong et al. (2022) also expect heavy rainfall to increase in northwestern and central-western Luzon (Type I climate) and along the eastern coast (Type II climate) of the Philippines.

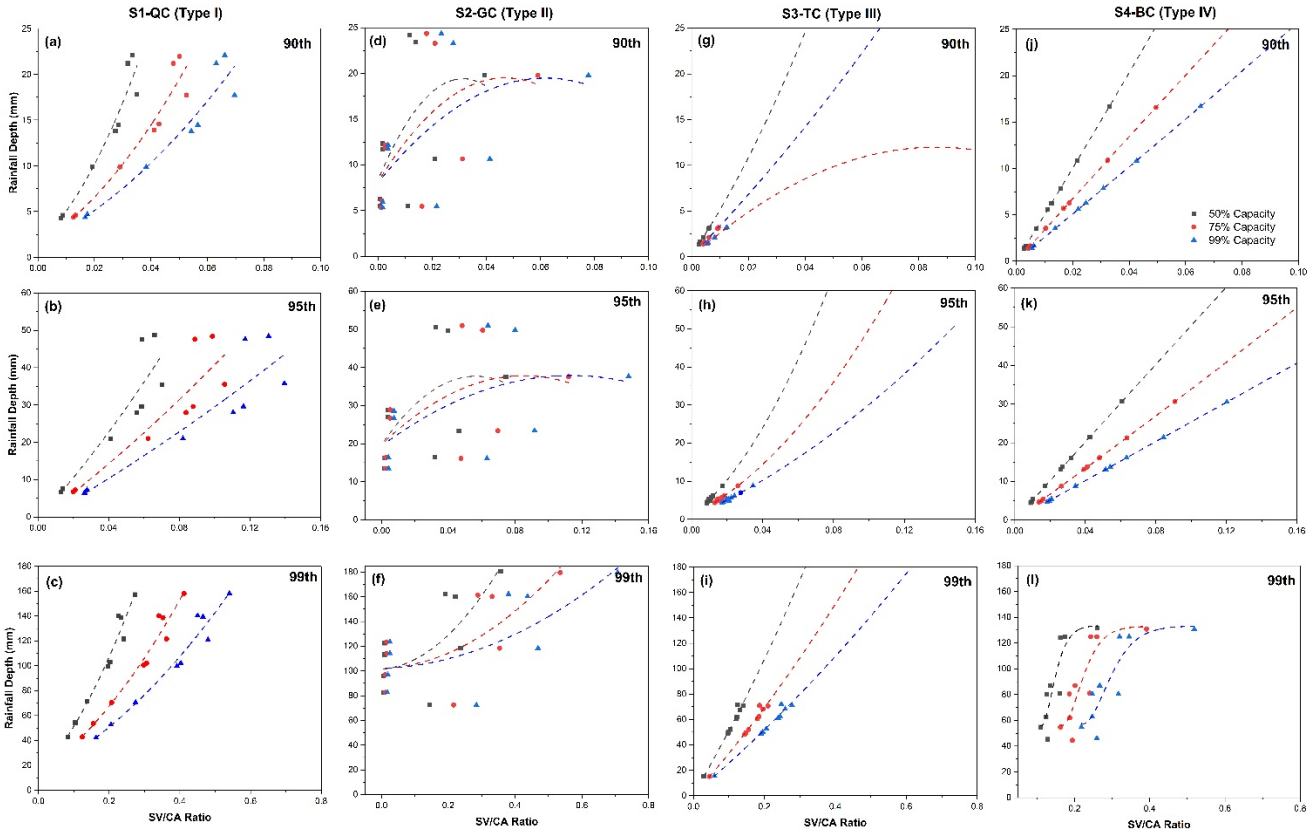


Figure 7: SV/CA required to reach the target runoff reductions (50%, 75%, and 99%) as a function of rainfall depth at (a-c) S1-QC (Type I), (d-f) S2-GC (Type II), (g-i) S3-TC (Type III), and (j-l) S4-BC (Type IV), for the 90th, 95th, and 99th percentile scenarios

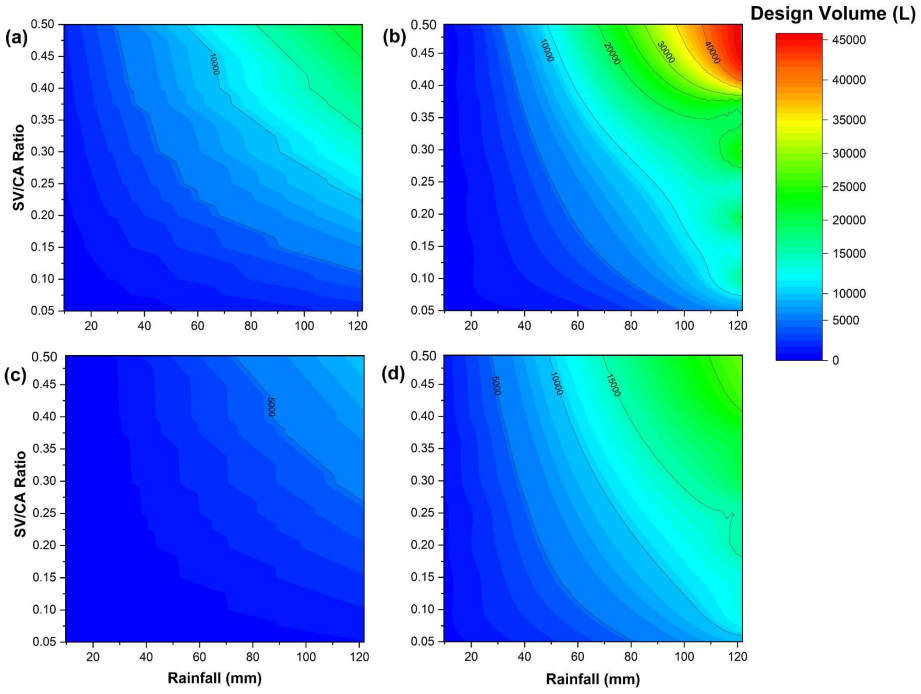


Figure 8: Tank volume required at each study site as a function of rainfall depth and SV/CA.

CONCLUSION

This study designed RWH tanks for projected rainfall in four Philippine climate types. Rainfall differs among the four representative cities, with the highest mean annual rainfall at the Type II site and the lowest at the Type I site. The Type II and IV sites had the highest rainfall, probably because of the northeast monsoon and easterlies. Projections from the ten climate models differed, and the MRI model gave the best fit to the observed rainfall at all four sites. Compared with the historical percentiles, the projected percentiles could increase by up to 73.16% or decrease by up to 80.66%. In the models, runoff reduction was high only for small rainfall depths below30 mm. Roof size is an important parameter in reaching the target runoff reduction and in sizing RWH tanks in urban areas. Sizing relationships were mostly linear at the Type I and IV sites and nonlinear or mixed at the Type II and III sites, in line with the different projected rainfall. Larger tanks are expected for the Type II and Type IV sites, which receive more rainfall.

The study makes several recommendations for estimating future rainfall, to improve research, and support wider use of RWH. Standardizing rainfall percentiles is hampered by the uneven distribution, siting, and monitoring of rain gauges in the Philippines; the gauge network should be reviewed to improve forecasting and data management. Because variability in precipitation can lead to over- or underestimating potential rainfall volumes, further studies using other methods and scenarios are needed Finally, pilot RWH installations in different climate types should be monitored to refine the design. Collecting, calibrating, and validating observed rainfall data would give a reliable baseline for site-specific tank design. Long-term monitoring would also allow the model to be recalibrated for extreme events that were underestimated in the initial sizing. The study is also limited to historical design storms, and a wide range of projections, which could be resolved with additional analysis on validated models and uncertainty analysis.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

CONTRIBUTIONS OF INDIVIDUAL AUTHORS

J.R.M.: Formal Analysis, Methodology, Validation, Visualization, Writing – Original Draft, Writing – Review & Editing. S.G.: Formal Analysis, Methodology, Validation, Visualization, Writing – Original Draft, Writing – Review & Editing. J.P.A.: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Visualization, Writing – Original Draft. C.L.D.: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – Original Draft. S.N.P.: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – Original Draft. R.C.T.: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – Original Draft. M.D.L.: Supervision, Validation. R.M.T.: Supervision, Validation. R.D.: Supervision, Validation. M.M.-R.: Conceptualization, Investigation, Funding acquisition, Methodology, Project administration, Supervision, Validation, Writing – Review & Editing. All authors have read and approved the manuscript.

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