# WeatherShift™ Water Tools: Risk-based Resiliency Planning for Drainage Infrastructure Design and Rainfall Harvesting

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## Abstract

Infrastructure and buildings constructed today will experience significantly different weather patterns over the course of their lifetime due to the impacts of climate change. In order for utility agencies and property developers to plan for these changes, localized data on the projected changes in rainfall patterns is needed. For stormwater management, this data would include changes in rainfall intensity, duration, and frequency, along with correlating updates to existing hydrologic design standards. The WeatherShift flooding tool uses data from 21 global climate models to generate projected rainfall statistics for a range of emission scenarios and future time frames. This data is presented in the form of localized climate change-shifted rainfall Intensity-Duration-Frequency (IDF) curves for use in drainage infrastructure design, such as for sizing storm drain networks, pump stations, and treatment plants.

In this paper we discuss how we use data from global climate models and an Argos Analytics-developed tool to construct distributions of future rainfall intensity as a function of rainfall duration and return time, which can then be applied in engineering practice for risk-based resiliency planning of drainage infrastructure. Optimizing infrastructure capacity design enables planning for risk-based adaptations while minimizing lifecycle costs. We also discuss a proposed tool for morphing daily rainfall time series to reflect future climate conditions, which can be used by the TopUp™ rainfall harvesting tool to predict future rainfall harvesting scenarios.

## 1. Introduction

Commonly, drainage infrastructure design makes use of historical rainfall data to size stormwater systems and manage flood risk using a rate of recurrence approach. However, historical data is likely insufficient to provide adequate risk mitigation given the predicted changes in climate over the coming decades. Design storms having a rate of recurrence at 1 in 100 years today may shift to more frequent recurrences, e.g. 1 in 50 or less before the end of the century. This shift will have a significant impact on infrastructure with a design life exceeding the historical recurrence rate to which it was sized, especially those systems serving critical functions such as dams, levees, and pump stations.

Our strategy is to analyze changes in rainfall patterns projected by the latest global climate models used for the Fifth Assessment (AR5) conducted by the Intergovernmental Panel on Climate Change (IPCC)[1] to produce a set of projected IDF curves.

The TopUp tool is a GIS-based platform created to evaluate and optimize rain harvesting tank sizes based on daily rainfall time series coupled with building and site demands for rainfall reuse at a building or campus scale. In this paper we compare tank size optimization using both historical and climate shifted daily rainfall data, generated using one of the widely accepted morphing techniques introduced by Belcher et al (Belcher)[2], to illustrate the impact of future climate conditions on this type of planned infrastructure.

## 2. Constructing Projected Future IDF Curves

Although the general course of future changes to the climate is well understood, specific outcomes are uncertain, especially for precipitation and those at spatial scales relevant to infrastructure planning. There are three sources of uncertainty that affect projections of the future climate. One is the path of future emissions. This is generally modeled by running projections for several emission scenarios. In AR5, the Special Report on Emissions Scenarios (SRES) scenarios used for AR4 were replaced by the Representative Concentration Pathways (RCPs)[3], which are four different possible future emissions trajectories labeled in terms of the increase in radiative forcing (heating due to greenhouse gases in the atmosphere) in 2100 relative to pre-industrial times. Two of the four, RCP 4.5 and 8.5, were mandatory for all modeling centers and are the two that we chose to use for this work. RCP 8.5 represents a business as usual scenario, and RCP 4.5 represents a moderately aggressive emissions reduction scenario.

A second source of uncertainty stems from the fact that climate models are not exact representations of the real climate system. In particular, each model has its own implicit value of equilibrium climate sensitivity (ECS), which is the long term mean global temperature rise that results from doubling the concentration of atmospheric CO2 and other equivalent greenhouse gases.

The third source of uncertainty is the natural variability of the climate, also referred to as internal variability. Natural variability is due to the chaotic nature of the climate system, such that small differences in initial conditions can lead to large differences in outcomes. Recently, there has been a growing recognition that much of what has been interpreted as differences in model structure is actually the result of natural variability[4].

A broadly accepted way to account for the second and third sources of uncertainty is to use an ensemble of projections in order to consider a range of possible future climates for a given emissions scenario[5]. In some cases, an ensemble consists of projections from multiple models, often referred to as an ensemble of opportunity. In other cases, an ensemble consists of projections from a single model with slightly different initial conditions. One advantage of a multimodel ensemble is that it includes projections based on different assumptions about ECS, while using a large ensemble provides greater insight into the range of possible climate outcomes due to natural variability.

IDF curves are a widely used graphical representation of precipitation statistics[6]. Figure 1 shows a subset of the IDF curves for the SAN FRANCISCO DWTN station based on NOAA data[7]. The vertical line on the figure is an example of the distribution of precipitation intensity for a fixed duration, in this case 6 hours, expressed in terms of return time, rather than frequency. To construct a corresponding projected future distribution based on a single climate model, we need to compute the difference in intensity for each return time for that duration between the future time period of interest and a baseline period that is generally consistent with the period during which the data for the historical IDF curves were collected and then add it to the historical value. This involves fitting generalized extreme value (GEV) functions to the intensity values for that duration, for both the future period and the baseline period, based on the output of that model.

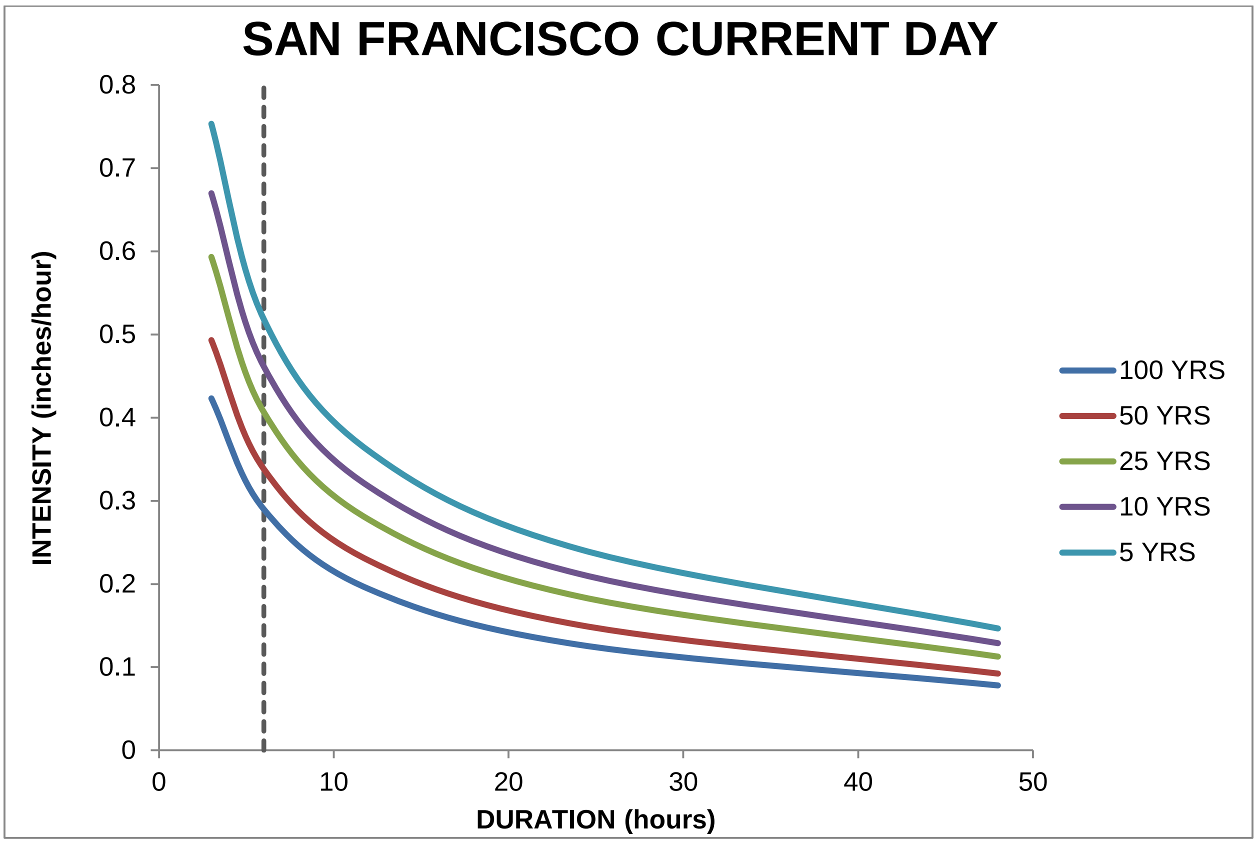


*Figure 1: IDF Curves for the San Francisco Downtown Station at Present Day*

There are 21 models in the CMIP5[8] ensemble that archived from their projections 3-hourly precipitation data for 2026-2045 and 2081-2100 for both RCP 4.5 and 8.5. They also have simulated output for 1960-2005, which we have taken as the baseline period. For each of the models and RCPs, we calculate projected intensity change distributions for each duration for the two future periods. Then for each combination of duration and return time, we construct a cumulative distribution function (CDF) of intensity changes between each of the future periods and the baseline period across the 21 models. From the CDFs we extract values for the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles by linear interpolation between the two nearest model values.

Figure 2 shows the 5th, 50th, and 95th percentile IDF curves at the end of the century under RCP 8.5 for a 100 year return time compared to the corresponding current historical 100-year curve.

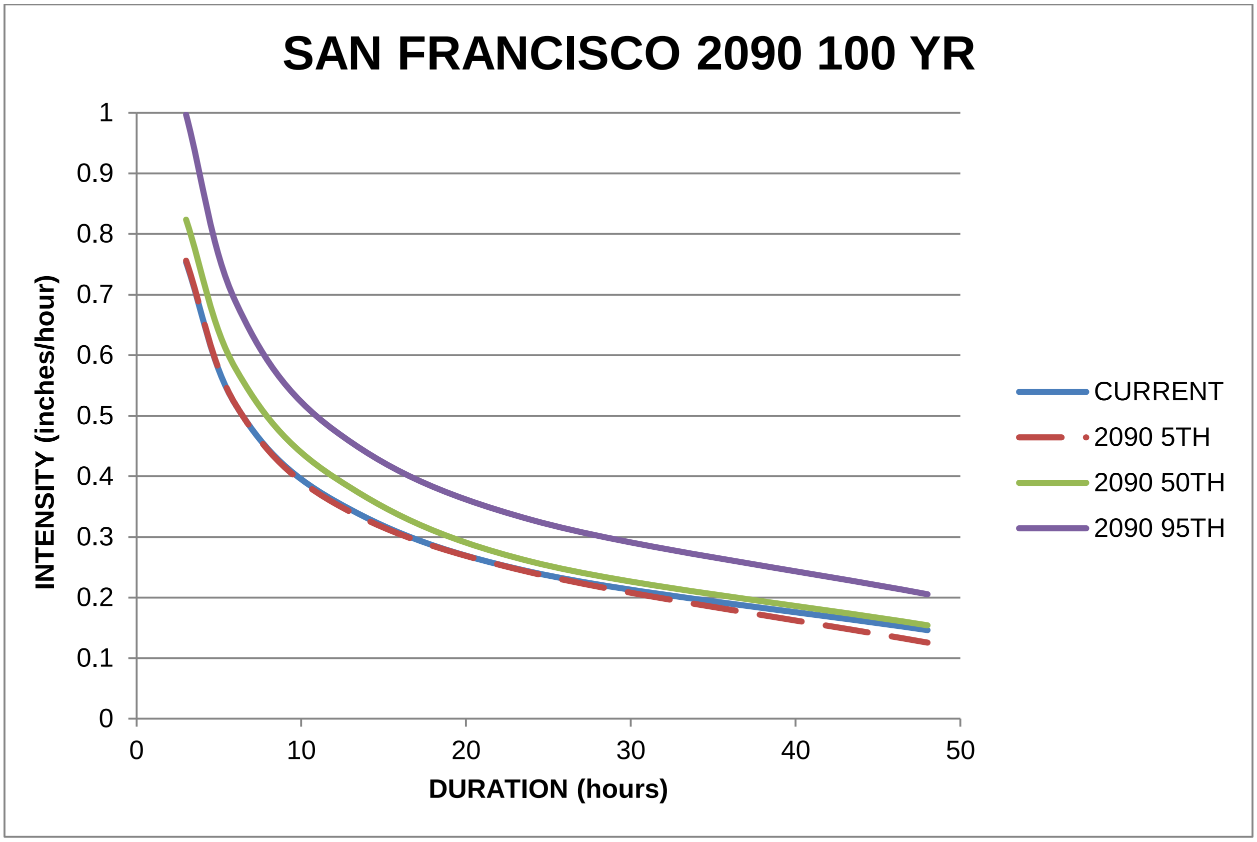


*Figure 2: IDF Curves for San Francisco at the End of the Century under RCP 8.5*

A similar approach has been used with statistically downscaled AR4 climate projections[9]. However, using statistically downscaled projections has two major limitations. The first is intrinsic to all statistical downscaling techniques, which is that the underlying assumption that historical statistical relationships between large scale and finer scale weather will continue to be valid in the future is unverifiable. The second is that, so far at least, the temporal resolution of the downscaled projections has been limited to daily data, which is too long for analyzing flooding risks for many catchments that have times of concentration measured in hours.

Our method is also subject to limitations. One is that analysis of current models has indicated that they tend to underestimate future precipitation extremes and do not represent convective precipitation well (important primarily in the summertime)[10]. The other is due to the relatively coarse spatial resolution of current GCMs (~100 km). Consequently, variations in the spatial distribution of precipitation due to topography, such as orographic rainfall and rain shadows, are not well represented. We are currently investigating the use of historical spatial distributions to improve our IDF projections on a local scale.

## 3. Morphing Rainfall Times Series

As described above, the TopUp tool uses historical daily rainfall time series data to analyze the effectiveness of rainfall harvesting designs. However, as with historical IDF data, this does not reflect future changes in rainfall patterns due to climate change. To address this need, we chose to use a morphing technique similar to those in use for generating future typical weather data for building energy analysis. The fundamental premise is to preserve the historical variability of the time series while transforming its monthly mean value in a manner consistent with future climate projections.

With respect to precipitation, the most appropriate transformation is a simple scaling operation. If $r_i$ is the historical rainfall amount on the $i^{th}$ day of the month and $r_i'$ is the projected future value, then:

$$r_i' = r_i(1 + \delta_r)/\langle r_i \rangle \qquad (1)$$

where $\delta_r$ is the difference between the mean daily rainfall in the future period of interest and a baseline period generally consistent with the time period in which the historical data was collected and:

$$\langle r_i \rangle = \Sigma\, r_i/N \qquad (2)$$

is the mean monthly value of the historical rainfall where N is the number of days in the month. The use of a scaling transformation, rather than an additive transformation, eliminates the possibility of projected daily values being negative and means that days in a month with no rain historically will also have no rain in the projected time series.

We calculate the monthly values of $\delta_r$ for projections from 27 CMIP5 models and construct CDFs based on the changes in annual rainfall for each of the models. We extract values for each month for the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles by linear interpolation between the two nearest model values. Because our method preserves the historical day-to-day variability, it does not represent changes in the shape of the daily rainfall distribution well. Since rainfall harvesting is by its nature an integrative process, we believe this limitation is a reasonable one.

## 4. Risk Tolerance, Economic Tradeoffs, and Design Implications

Historical rainfall data is used to size stormwater systems and manage flood risks using a rate of recurrence design approach. Government agencies typically set standards for the level of service provided by infrastructure systems within their jurisdiction based on a particular design return period, e.g. 1 in 100 years. This means that the infrastructure system is designed to convey or store runoff generated by a rainfall event with recurrence rate of 1 in 100 years. Mitigating risks with extremely low recurrence rates, e.g. 1 in 1000 years, is often extremely expensive and brings into question whether the likelihood of the event occurring during the system's design life justifies the added investment. The design return period ultimately balances the anticipated design life of the infrastructure system, the capital cost of investment, and a reasonable acceptance of risk (either anticipated or mitigated in some other form) due to capacity exceedance beyond the design return period.

The weakness in the rate of recurrence design approach based on historical data is that changes in climate will cause shifts in the recurrence rates over the coming decades. Heavy rainfall events are expected to become more frequent, therefore infrastructure built by today's standard will not provide the same level of service in the future[11]. To mitigate this emerging risk, designers may size infrastructure systems based on a greater return period, intuitively providing a higher level of service. However, doing so may also incur substantially greater capital and operational costs without really knowing how much additional service is being added. Improving performance, optimizing use of materials, and minimizing costs while increasing resilience are common goals that need to be achieved together.

Due to uncertainties in changing rainfall patterns, a range of possible outcomes enables the designer to consider multiple future rainfall scenarios and to quantify the tradeoffs between them. This way the owner may balance investment costs with a preferred level of service (or risk mitigation) based on a quantitative assessment of future performance. Infrastructure systems are first designed using baseline historical rainfall data, then tested using a range of shifted data to evaluate the performance of the baseline design. The system can then be resized to accommodate the shifted data under the various future scenarios and/or time periods. New risks and mitigation opportunities may become apparent. Cost comparisons can be made to guide decisions around the level of risk an owner is willing to mitigate with respect to changing rainfall patterns.

As an example, consider a stormwater pump station designed to expel collected runoff from a low-lying area in order to mitigate flood risk to an adjacent new building. Using historic rainfall data, the designer sizes the pump station to expel the 100-year design storm which, for this catchment, amounts to 500 gallons per minute (gpm) with a capital cost of $50,000. Using projected IDF curves, the shifted 100-year design storm is tested for three future time periods under RCP4.5 and RCP8.5 emission scenarios at the 5th, 50th, and 95th percentiles (covering the median, upper, and lower tails of the 21 climate models). Figure 2 illustrates the resulting pump capacities required to expel the estimated stormwater flow rates under each design scenario.

Each tested scenario has an associated capital investment cost as shown in Figure 2. The owner now has the opportunity to choose an appropriate level of risk mitigation suited for the unique project conditions, e.g. building design life and project budget. If the building design life is 75 years, the owner may decide to invest $65,000 to mitigate the risk of changes in rainfall pattern under emission scenario RCP4.5 5th Percentile. While RCP4.5 assumes a moderate reduction in global emissions, and the 5th Percentile generally represents a lesser increase in projected rainfall, this combination may provide a reasonable level of mitigation for the owner to accept. Alternatively, the owner may invest up to $85,000 to provide more robust mitigation under emission scenario RCP8.5 50th Percentile. This would mitigate a larger risk due to a lesser reduction in emissions (under RCP8.5) and the median percentile of increased rainfall, but serve a building design life of only 50 years. It is this level of granularity that allows the owner to weigh risks against costs in order to reasonably mitigate future impacts on their infrastructure investment today.

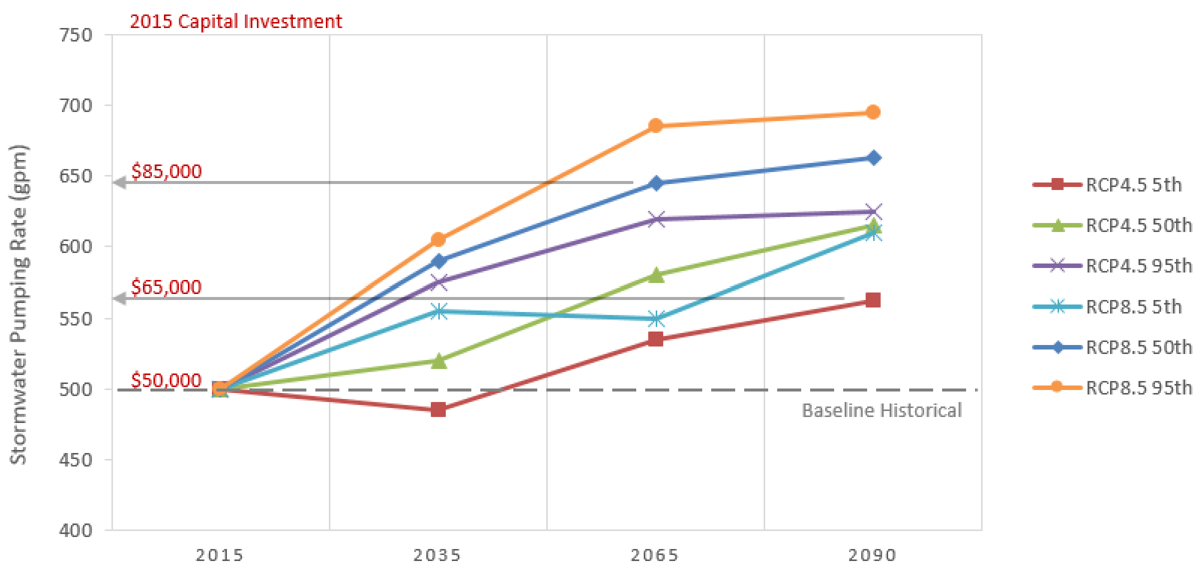


*Figure 3: Capital Investment Costs vs. Risk Mitigations, Scenario Tradeoffs*

As another example, consider a rain harvesting cistern for a corporate campus near San Francisco Airport designed to store rainwater during the wet season to irrigate landscaping throughout the year. Making use of the TopUp tool, the designer constructs a mass balance calculation that uses time series historical rainfall to determine the daily supply of runoff coming into the tank from pedestrian surfaces and the demand for irrigation in landscaped areas being withdrawn from the tank (also based on rainfall). The tool performs a regression analysis, testing several cistern sizes over the daily time series to plot the actual amount of rainfall used in a given year for each size tested. Referring to Figure 4 below, the optimal cistern size is located where the slope of the curve is 1:1, the point at which the maximum amount of rain is used per gallon of cistern storage.

The same analysis is then performed for future time periods at the 50th percentile for the 21 climate models under emission scenario RCP 8.5. The WeatherShift data is extracted for this project location and the TopUp model reflects the project specific mass balance calculation. The WeatherShift data adjusts the historical daily time series rainfall used by TopUp to reflect the projected daily rainfall during three future time periods: 2026-2045, 2056-2075, and 2080-2099.

As shown in Figure 4, TopUp estimates the optimal cistern size for this project in 2056-2075 (mid-century) to be 12% smaller than the baseline optimal cistern size. Thus a cistern built at optimal size today using historical rainfall data would use an average of 50 fewer gallons per day in 40 years. Based on this RCP 8.5 50th Percentile comparison, the owner may realize a 12% capital cost savings today to offset the loss in rainfall usage due to changing rainfall patterns occurring by mid-century. However testing this tank at the 5th and 95th Percentiles may also be appropriate since they represented drier and wetter rainfall patterns respectively. These results may show an optimal tank size in future to be much larger (or smaller).

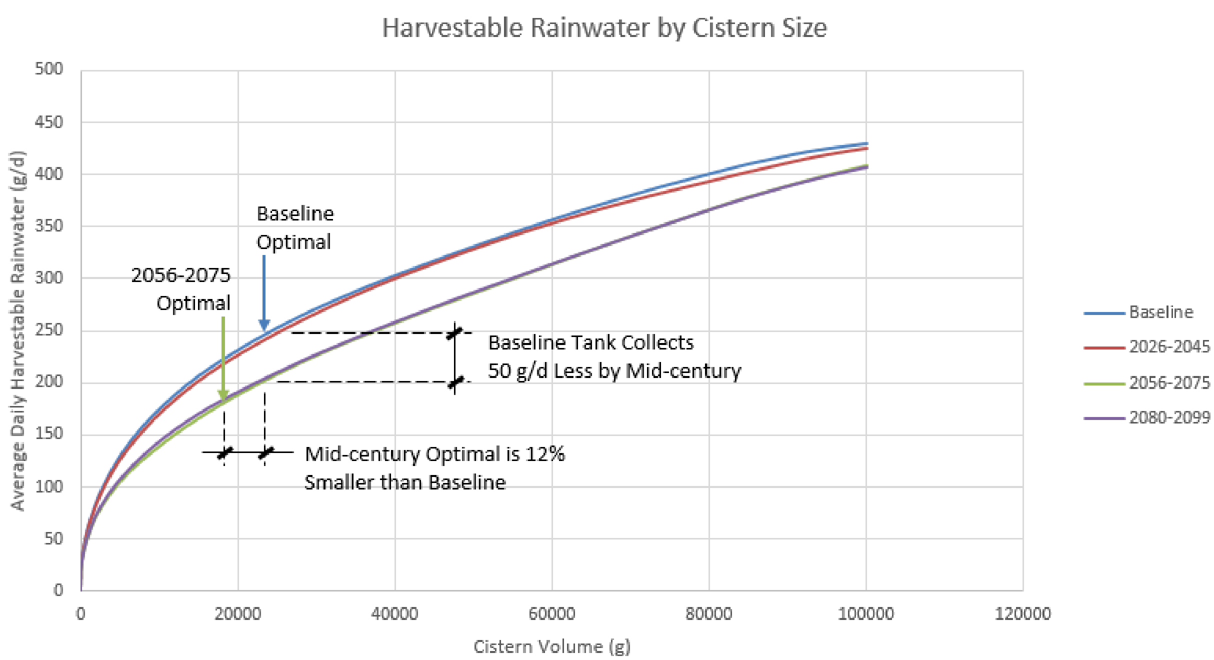


*Figure 4: TopUp Estimates for the Optimal Cistern Size at Mid-Century*

The same assessment could also be performed for RCP 4.5, which assumes a moderate reduction in emissions and will generally show a lesser variation in performance. By considering both emission scenarios and more than one point on the percentile distribution for each, several scenarios can be studied to quantitatively evaluate the future value of capital investments made today. Tradeoffs can then be made as to the cost of capital investment the owner is willing to make now to offset a measurable amount of anticipated risk in the future.

## 5. Conclusions

The use of historical rainfall data for designing new infrastructure, such as drainage and rainfall harvesting systems, creates a substantial risk that the systems may not meet their design objectives over their useful life due to climate change. The tools we have described for constructing future IDF curves and daily rainfall time series based on the latest IPCC climate projections offer the designer an alternative approach that explicitly addresses the uncertainty in the degree of those changes. Because of this, the designer can explore the tradeoff between the cost of the design mitigation and the point on the distribution of rainfall changes where the system will fail to meet its design objectives. By considering an array of future climate scenarios over several time periods, the designer can offer measurable solutions to combat the risks of future changes in rainfall patterns on infrastructure built today.

## 6. Acknowledgements

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## 7. References

[1] Fifth Assessment Report (AR5), Intergovernmental Panel on Climate Change, 2013-2014.

[2] Belcher, S. E., J. N. Hacker and D. S. Powell, "Constructing design weather data for future climates," Building Services Engineering Research & Technology, pp. 49-61, 2005.

[3] Moss, Richard et al, *Towards New Scenarios for Analysis of Emissions, Climate Change, Impacts, and Response Strategies*, Intergovernmental Panel on Climate Change, Geneva, 2008.

[4] Trenberth, Kevin E. et al, Attribution of climate extreme events, Nature Climate Change, 5, doi:10.1038/NCLIMATE2657.

[5] Pierce, David W. et al, Probabilistic estimates of California climate change by the 2060s using statistical and dynamical downscaling, Climate Dynamics, 38, doi:10.1007/s00382-012-1337-9.

[6] Lindeburg, Michael R. "Civil Engineering Reference Manual for the PE Exam." 13th ed. Belmont, CA: Professional Publications, Inc. 2012.

[7] US Department of Commerce (DOC), National Oceanic and Atmospheric Administration (NOAA), National Weather Service (NWS), Office of Water Prediction (OWP). "Precipitation Frequency Data Server (PFDS)." http://hdsc.nws.noaa.gov/hdsc/pfds/

[8] Program For Climate Model Diagnosis and Intercomparison (PCMDI). "CMIP5 - Coupled Model Intercomparison Project Phase 5." http://cmip-pcmdi.llnl.gov/cmip5/

[9] US Environmental Protection Agency (EPA). "SWMM CAT 2.0 - SWMM CAT User's Guide." EPA/600/R-14/428, September 2014.

[10] Fischer, E. M., and R. Knutti (2014), Detection of spatially aggregated changes in temperature and precipitation extremes, *Geophysical Research Letters*, 41, 547–554, doi:10.1002/2013GL058499.

[11] Trenberth, Kevin E. et al, The Changing Character of Precipitation, *Bulletin of the American Meteorological Society, 84*, doi:10.1175/BAMS-84-9-1205.