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OPTIMAL GREEN INFRASTRUCTURE

Reducing Stormwater Runoff Pollution in Maunalua Bay, O‘ahu, Hawai‘i

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The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

Dr. Samantha Stevenson

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Abstract

High runoff from impervious surfaces of the urbanized environment can have negative impacts on receiving water bodies. In Hawai‘i, this problem is exacerbated by drastic gradients in elevation, where the landscape rapidly changes from steep ridges to relatively low-lying valleys. These steep slope gradients increase runoff during rain events. Maunalua Bay, O‘ahu, Hawai‘i, a region located on the southeastern coast, has been declared an impaired water body by the Hawai‘i Department of Health due to high levels of nutrients and pollutants. Nine highly urbanized watersheds feed into Maunalua Bay. Runoff from these watersheds brings harmful sediment and pollutants directly into Maunalua Bay's waters. This project aims to provide insight into remediating Maunalua Bay's waters by combining hydrologic modeling and analyses on the runoff-reduction potential of green infrastructure with region-specific climate change projections. The Environmental Protection Agency's Stormwater Management Model 5.1 (SWMM) was used to create hydrologic models of the nine watersheds that feed into Maunalua Bay. The goal in developing such models is to identify stormwater runoff hotspots in the Maunalua Bay region so that stakeholders can determine where to prioritize remediation efforts on land. The runoff reduction potential of strategically-placed green infrastructure elements was modeled for the Wailupe watershed. Simulations indicate that green infrastructure constructed at a large enough scale can have significant reductions on stormwater runoff from a given location This analysis serves as the starting point for green infrastructure recommendations for the Maunalua Bay region. Additionally, this project explores a variety of climate change scenarios specific to the Maunalua Bay region and analyzes how climate change may influence regional runoff patterns in the future. We conducted an analysis of a climate change-representative storm event using a multiplicative change factor (MCF), allowing us to quantify simulated differences in runoff coefficients and peak flow. We identified 20 subcatchment hotspots with the highest runoff coefficient and peak runoff (cfs) values under climate change conditions. These results aid in informing management practices that prioritize future green infrastructure placement in top ranking peak flow and runoff coefficient subcatchments that will ultimately aid in reducing runoff that feeds into the Maunalua Bay.

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Project Objectives

1. Create reproducible hydrologic models for the watersheds of Maunalua Bay, O‘ahu, Hawai‘i for future teams to identify areas of high stormwater runoff once more precipitation and stream gauge data becomes available.

2. Provide recommendations and cost estimates for optimal green infrastructure placement to reduce stormwater runoff from the Wailupe watershed.

3. Use Coupled Model Intercomparison Project (CMIP6) climate data to determine how shifts in precipitation due to climate change influence stormwater runoff from the Wailupe watershed.

4. Develop a region-wide ArcGIS model to identify suitable locations for rain gardens within areas of high stormwater runoff to reduce sediment entering Maunalua Bay, O’ahu, Hawai’i.

Background

Land Acknowledgement

We acknowledge that the land in which our project takes place was home to and is still home to *kānaka maoli* (“Native Hawaiians”), who were the original stewards of the land, and many of whom were displaced from their unceded ancestral lands.

The Maunalua Bay Region

The Maunalua Bay region is located on the southeastern shore of O‘ahu, Hawai‘i. The 28 mi^2 region encompasses Maunalua Bay and the surrounding *āpana* (“watersheds”). Nine different *āpana*, with a total contributing area of 57 km^2, drain water from the region into Maunalua Bay. Average rainfall within the Maunalua Bay region varies dramatically over short distances due to the interactions between the mountainous terrain, trade winds, and heating and cooling of the land, amongst other factors (Stevens et al., 2017). Heavy rain and high winds, associated with strong storms during *ho'oilo* (November to April), are often the cause of regional flooding. However, these storms vary annually, occurring up to five times per year in some years, to being absent in others (Miller et al., 2009).

Maunalua Bay lies between the geologic features of Koko Head (*Kuamo‘okäne*) and Black Point (*Kūpikipiki‘ō*). The Bay contains 6.3 mi^2 of ocean waters and nearly 8 miles of shoreline, providing surrounding communities with numerous important biological and social resources (Atkinson, 2007). Within the Bay, broad reef flats extend 3,000 feet from the shoreline before dropping 15 feet to 20 feet in depth. The corals that make up the fringing reef flats, along with the Bay’s unique mixture of fresh and saltwater, provide habitat and food for a diversity of aquatic organisms (Dept. of Planning and Permitting, 2019; Miller, 2009). Additionally, the

Bay's attractive beaches give rise to a variety of recreational opportunities including surfing, scuba diving, parasailing, boating, and fishing (Miller, 2009).

Cultural Significance

Prior to Western settlement, Native Hawaiians carefully managed the resources of the Maunalua Bay region. The Ancient Hawaiian land division system divided the Islands into districts called *moku,* which were then subdivided into smaller areas called *ahupua'a. Ahupuaʻa* extended vertically from the mountains down to the waters of the fringing reef. The vertical arrangement allowed for maximization of biodiversity over short distances (Mueller-Dombois, 2007). *Ahupuaʻa* contained a range of resources from the uplands, plains, and the sea, providing everything the people needed to survive (Blaisdell et al., 2005). The health of the mountain-to-sea ecosystems, and of the people and their livelihoods, remain connected today; activities in the upland region affect life downstream (Blaisdell et al., 2005). Degradation of the *ahupuaʻa* of the Maunalua Bay region through increased urbanization is directly causing damage to the Bay.

Maunalua Bay was once an extremely productive ecosystem, supporting a fishery that supplied fish, *limu* ("seaweed"), and invertebrates to the region (Mālama Maunalua, 2006). However, development and urbanization of the Maunalua Bay region over the last 70 years has had significant negative impacts on the Bay. Prior to the 1950s, the Maunalua Bay region consisted mainly of small ranches, dairies, farms, and homes. Now, around 45% of the region is urbanized, 42% is non-urban (mostly steep slopes in the upper watersheds), and less than 1% is used for agriculture (Miller et al., 2009). The region boasts a population of 60,000 people and features a dozen neighborhoods, 8 shopping malls, and other large, commercial sites. The Bay is directly linked to employment and economic benefits of community stakeholders, who rely on the region for their livelihoods (Kittinger et al., 2016).

Ecological and Community Health Problem

The rapid and recent development of the region has led to the replacement of large, natural areas with impervious surfaces such as roads, parking lots, and roofs. These impervious surfaces prevent the natural landscape from performing water retention and filtering functions (Miller et al., 2009). The natural streams in the region have also been degraded through straightening and concrete lining, which increases the rate of runoff flow into the Bay. Infrastructure such as Kalanianāole Highway and other roads along the Bay have destroyed estuaries and shoreland wetlands—features that have been shown to counteract increased rates and volume of surface and stormwater runoff from impervious surfaces (EPA, 2021). Additionally, a significant portion of base flow that normally would provide freshwater to lower streams, shoreline wetlands, and inshore habitats of the Bay, is now diverted into storm drains via culverts, roads, and drains, preventing groundwater recharge (Miller et al., 2009). Urbanization in the region has ultimately led to a drastic increase in the volume of polluted runoff and land-based sediment flowing into the Bay (Takesue & Storlazzi, 2017). In 2009, the average annual suspended sediment concentration measured 9.6 mg/L, just in the Wailupe watershed alone (Storlazzi, et al., 2010). Previous studies have suggested that chronic concentrations above 10 mg/L are considered high, resulting in damaging impacts to coral reefs and reef organisms (Rogers, 1990).

Field studies have shown that modification of terrestrial ecosystems resulting in sedimentation, nutrient enrichment, and turbidity into receiving waters can have detrimental effects on coral reef ecosystems at local scales (Fabricius, 2005; Wolanksi et al., 2009). Coral reefs play an integral role in the Maunalua Bay ecosystem. They provide habitat for fish life, support the local food web, and act as a buffer along the coastline against natural hazards such as hurricanes. The coral reef ecosystem has ecological, economic, and cultural value to the community.

In Maunalua Bay, urbanization has led to increased polluted runoff, sediment exposure, and subsequent coral decline. Historically, coral reef cover consisted of 25-meter to 33-meter wide patches covering up to 50% of the reef (Pollock, 1925). However, in 2009, there was less than 5% coral cover in the same area over most of the reef slope (Wolanski et al., 2009). Sediment composition and water flow magnitude greatly influence sediment yield, causing varying levels of stress in the corals (Weber et al., 2006; Waters et al., 2015). The increase in polluted runoff leads to a decline in corals, which leads to an increase in invasive algae, which leads to a decline in fish. Fish communities of the Maunalua reef have some of the lowest populations in the Hawaiian Islands (Williams, et al., 2009, Minton et al., 2014).

Numerous nutrients have the potential to affect coral reefs, but the most prevalent are excess nitrogen and phosphorus (Hallock and Schalger, 1986). Inputs of such nutrients feed algae which can suffocate the coral and inhibit recruitment of coral larvae (Wolanski et al., 2009). Sediment exposure also diminishes the photosynthetic efficiency of corals and increases respiration, causing bleaching and necrosis (Weber et al., 2006). The composition of the sediment and the water flow magnitude across the land surface are the main influences on sediment yield entering the Bay; since water flow varies over time, the corals experience varying levels of stress (Weber et al., 2006; Waters et al., 2015). This has increased the incidence of waves breaking along the coast, and consequently, has increased coastal erosion (Wolanski et al., 2009).

The Hawaiʻi Department of Health (DOH) has declared Maunalua Bay an impaired water body for recreation, aquatic habitat, and wildlife habitat, due to high levels of bacteria, suspended solids, and nutrients (USDA NRCS, 2004). This impairment has consequential implications for the health, economic well-being, and cultural integrity of the region's residents (Miller et al., 2009). The most critical threats to the Bay are polluted runoff and sediment input, invasive alien algae, and unsustainable harvesting practices. We have established that the Maunalua Bay region is an important area of focus due to the high runoff's detrimental impact on the Bay. However, there is still uncertainty on where the runoff rates are highest and, therefore, where the optimal places are within the watershed to intervene. Our project will determine high runoff locations, which will inform intervention actions.

Green Infrastructure

Green Infrastructure (GI) refers to a "range of measures that use plant or soil systems, permeable pavement or other permeable surfaces or substrates, stormwater harvest and reuse, or landscaping to store, infiltrate, or evapotranspirate stormwater and reduce flows to sewer systems or surface waters" (Water Infrastructure Improvement Act, 2019). Examples of green infrastructure include rain gardens, bioswales, green roofs, and permeable pavement. By filtering and absorbing stormwater where it falls, or close to it, green infrastructure provides cleaner water and runoff. It can also provide cleaner air, flood protection, diverse habitat, and visually appealing green spaces (EPA, 2021).

Green infrastructure is an effective tool for reducing and filtering stormwater runoff and associated pollutants from urban areas (Sparkman et al., 2017). The soil media and plant components of green infrastructure elements, such as rain gardens, play an important role in the pollutant removal process. Plant mechanisms and chemical processes are particularly effective at removing stormwater contaminants (Sharma and Malaviya, 2021). Watersheds equipped with LID elements have been found to remove significantly higher amounts of nitrogen, phosphorus, and sediment on an annual basis compared to traditional watersheds (Sparkman et al., 2017).

Green infrastructure elements can be implemented in the community at several scales, including urban and residential scales (USEPA). Implementing green infrastructure in optimal locations across the Maunalua Bay region has the potential to significantly reduce pollutant loads flowing into the Bay. When placed in locations of high stormwater runoff and flow volume, green infrastructure will serve as a stormwater management tool, reducing the impacts of urbanization and associated reduction in natural vegetation. Green infrastructure activities, such as implementation of rain gardens and rain barrels, are already ongoing in the region. Our client Mālama Maunalua, is part of the "CPR Campaign", which is currently focused on addressing flooding in the Maunalua Bay watersheds by offering free rainwater assessments and promoting rain barrels to the community.

Often used interchangeably with green infrastructure is the term low impact development (LID). Low impact development is a "management approach and set of practices that can reduce runoff and pollutant loadings by managing runoff as close to its source(s) as possible, including overall site design approaches and individual small-scale stormwater management practices that promote the use of natural systems for infiltration, evapotranspiration and the harvesting and use of rainwater" (USEPA, 2012). Green infrastructure is considered to be an umbrella term under which LID resides.

Climate Change Impacts

Earth has been undergoing an unprecedented warming process since the Industrial Revolution. The Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) reports the change in global mean surface temperature (GMST) is assessed to be 0.69 (0.52-0.82)°C from the 1850-1900 baseline to 1986-2005 reference period. Projected increases in temperature are expected to cause a general increase in precipitation extremes, leading to more intense drought periods and heavy rainfall events associated with increased storm intensities (Chu et al., 2010).

Climate change is also expected to have impacts on the El Niño-Southern Oscillation (ENSO). ENSO is a recurring climate pattern involving changes in the temperature of waters in the central and eastern tropical Pacific Ocean, related to changes in the easterly trade winds. Additionally, El Niño tends to increase the number of tropical cyclones (TC) in the eastern and central North Pacific regions. This makes for increased risk of TC activity in Hawaiʻi during the TC season of El Niño years (NOAA, 2015). These expected increases in storm intensity (Norton et al., 2011 &

Murakami et al., 2013) are expected to influence future storm runoff, ultimately affecting the communities, ecosystems, and economic revenues associated with the Maunalua Bay region.

Project Significance

Mālama Maunalua is a community-based, non-profit organization dedicated to the environmental stewardship of Maunalua Bay, Hawai‘i. To ensure the health of the Bay, Mālama Maunalua conducts restoration and conservation efforts, ensuring a foundation of scientific evidence and cultural and local knowledge. Mālama Maunalua addresses three critical threats to Maunalua Bay: land-based sources of pollution, overfishing, and invasive alien algae. The objectives of this project aim to address the first threat—sources of pollution flowing from land into the Bay.

Community members, especially fishers and *kupuna* (“elders”), who depend upon a healthy Bay for their livelihoods and cultural practices, would significantly benefit from additional research focused on land-based sources of pollution. However, capacity and expertise limit the ability of Mālama Maunalua to conduct a region-wide watershed assessment to prevent high runoff entering Maunalua Bay. The combined efforts of our group and Mālama Maunalua will aid in the management of the watersheds feeding Maunalua Bay.

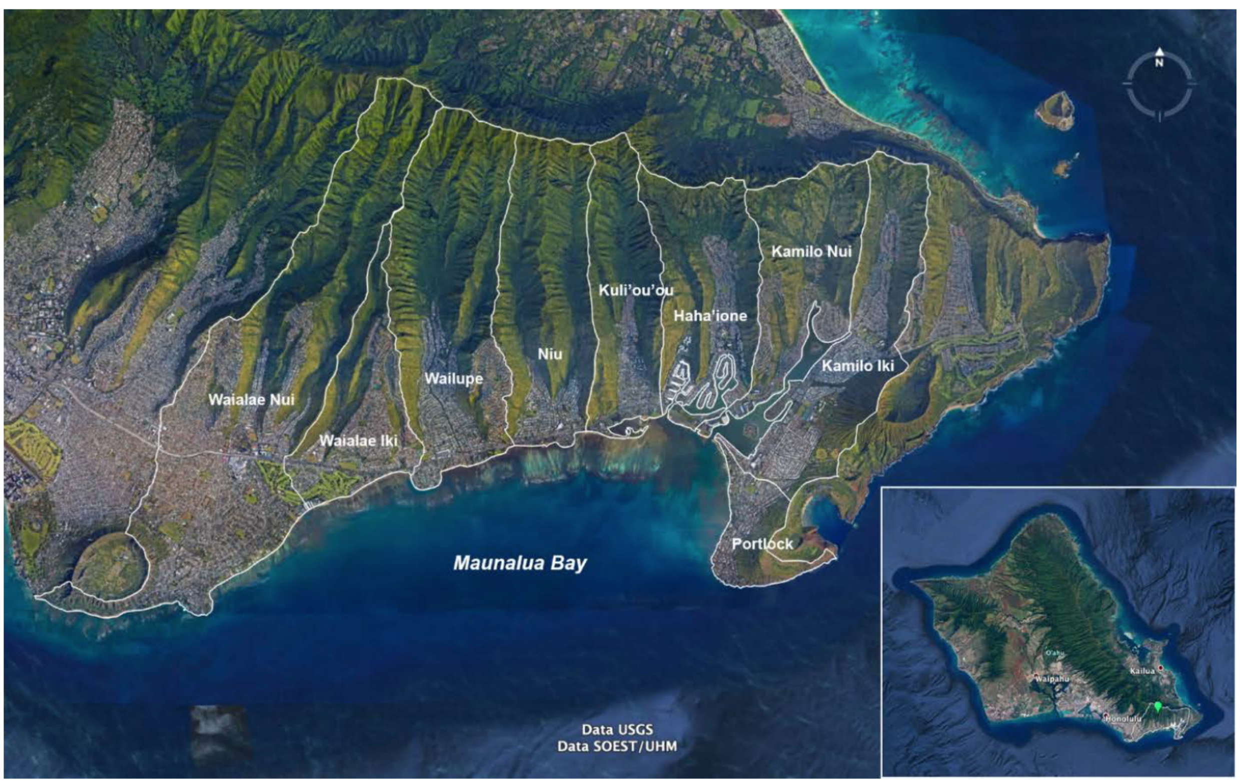

Figure 1. The Maunalua Bay Region, Oʻahu, Hawaiian Islands, U.S.A. Data provided by the U.S. Geological Survey and the University of Hawaiʻi at Mānoa School of Ocean, Earth, Science, and Technology (SOEST). (Credit: Dornan et al., 2020).

A previous group project of The Bren School of Environmental Science & Management developed protocols to identify runoff hotspots (areas within a watershed that produce the greatest runoff quantity) within the Wailupe watershed. The protocols require utilizing a hydrologic modeling tool, the Environmental Protection Agency's Stormwater Management Model 5.1 (SWMM). Mālama Maunalua is interested in expanding this hydrologic analysis to the entire region, but this project has been delayed due to a lack of precipitation and stream gauge data in the region. However, Mālama Maunalua has begun placing rain gauges throughout Maunalua Bay, which makes creating a SWMM model for each watershed more possible. The new precipitation data collection began in 2019, and could be useful for calibrating SWMM models in the future. For this reason, we created SWMM models for the region that will be prepared for future calibration. To test and maintain reproducibility, we utilized the previous group's protocol to create SWMM input files for the 8 other watersheds in the region. These watersheds are Kuliʻouʻou, Hahaione, Kamilo Iki, Kamilo Nui, Niu, Portlock, Waialae Iki, and Waialae Nui (Figure 1). Furthermore, we build on the previous group's project by determining the impact of green infrastructure and climate change on runoff hotspots in the Wailupe watershed.

Methods and Results

SWMM Model Setup

We used the U.S. Environmental Protection Agency's (EPA) Storm Water Management Model 5.1 (SWMM)—an open source tool that can be downloaded from the EPA website. SWMM simulates hydrologic processes, taking into account impervious surfaces, to estimate stormwater runoff and pollutant loading, and can represent both natural and urbanized watersheds. This model is ideal for the Maunalua Bay region, which is urbanized in the lower watershed and natural in the upper watershed. SWMM requires precipitation data, subcatchment delineation, subcatchment characteristic data, stormwater network data, and stream gauge data. When setting up SWMM to model runoff hotspots, we followed protocols developed by a previous Bren Group Project (Dornan et al., 2020) during their runoff hotspot analysis of Wailupe. We started setting up the Kuliʻouʻou SWMM model first because, after Wailupe, it is the watershed with the most precipitation data. We also created SWMM models for Hahaione, Kamilo Iki, Kamilo Nui, Niu, Portlock, Waialae Iki, and Waialae Nui watersheds. We will use the Kuliʻouʻou watershed as an example here as we lay out our methods.

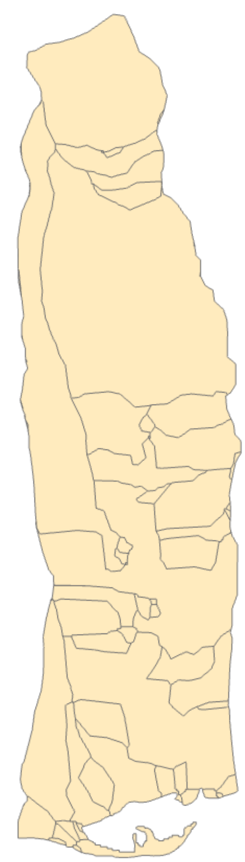

Figure 2. Kuliʻouʻou Subcatchments

Stormwater Network

The stormwater network was created by merging the stormwater conduits ArcGIS layer with the streams. For the ArcGIS model used to create the stormwater network, see Appendix A.

Subcatchment Delineation

Subcatchment delineation is a process in which watersheds are broken down into smaller flow areas based on the digital elevation model (DEM). Subcatchment delineation is helpful in determining runoff hotspots, or subcatchments within the watershed that contribute higher runoff flow and volume than surrounding subcatchments. This allows runoff intervention on a smaller scale. Subcatchment delineation is particularly important in urbanized watersheds because waterflow has been changed by stormwater systems and leveling. Subcatchments can be delineated in such a way that the urban stormwater network is also taken into account when determining water flow over the surface. This is done by lowering elevations where stormwater drains are located so that water flows in those areas during simulations. We performed the subcatchment delineation in ArcGIS Pro, utilizing the Kuliʻouʻou watershed outline, streams, and the stormwater network (Figure 2). For more details on the methods, see Appendix B.

Subcatchment Characteristics

SWMM requires several characteristics for each watershed subcatchment to be input in order to simulate runoff. We calculated percent impervious cover, soil curve number, and slope for each subcatchment in the 8 watersheds using ArcGIS Pro. These characteristics affect the volume or velocity of runoff. For more details on the methods, see Appendix C. For all SWMM inputs for subcatchment characteristics, see Appendix D.

Impervious Surface Cover

Percent impervious cover is calculated using data layers for existing bike lanes, buildings and rooftops, and roads. The spatial layer for roads was buffered by 6 feet to account for sidewalks. All streets were assumed to have sidewalks. This layer was then combined with the buildings footprints layer and bike facilities layer, using the ArcGIS ʻUnionʼ tool, to take into account impervious buildings, rooftops, and bike paths into a single layer.

The resulting layer was then compared to Google Earth images of the watersheds to ensure that no major impervious surfaces were missed, such as parking lots and roads. The few surfaces that were missed were then drawn manually into the layer (Figure 3).

The percent of impervious cover in each subcatchment was then calculated using the ʻTabulate Area Intersectionʼ tool in ArcGIS. These results can be found in Appendix D.

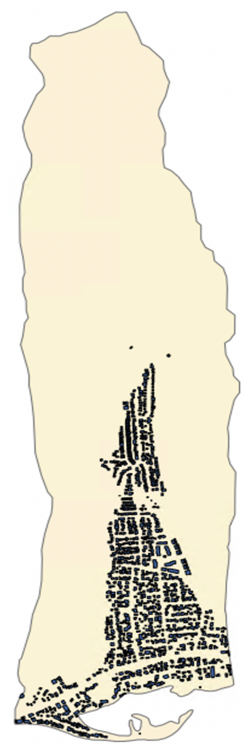

Figure 3. Kuliʻouʻou Impervious Cover

Soil Curve Numbers

SWMM can take into account the infiltration of stormwater into soils using curve numbers. A soil curve number is a metric that represents the amount of runoff that infiltrates the soil. It is based on the area's hydrologic soil group, land use, treatment and hydrologic conditions. Curve numbers range from 0 to 100, with 0 representing completely saturated wet surfaces (such as lakes or oceans), and 100 representing completely impervious surfaces (USDA, Soil Conservation Service).

We utilized the previous Bren group project's soil curve data, which combines both soil hydrologic group and land use data. Hydrologic Soil Groups are broken into groups A, B, C, and D, representing different soil types and infiltration levels. A soil curve number is produced by jointly assigning scores to the different combinations of hydrologic soil groups and land uses (Figure 4). A table listing the soil curve numbers by land cover and hydrologic groups found in the region can be found in Appendix E.

The 'Tabulate Area Intersection' tool in ArcGIS was then used to calculate the percent area of each curve number within each subcatchment. The resulting attribute table was exported to R to create a new column with an average curve number per subcatchment using a weighted average method. This resulted in a final shapefile with the curve numbers for the Maunalua Bay region.

Figure 4. Kuliʻouʻou Soil Curve Numbers

Percent Slope

SWMM also requires a percent slope for each subcatchment. To calculate this, the 10 meter DEM layer used in the Subcatchments Delineation method was used to calculate the area percentage of different slopes in each subcatchment in ArcGIS. The resulting table was then exported to R to calculate the weighted mean slope for each subcatchment.

SWMM Preparation

To prepare our SWMM input file, we utilized the code produced by the previous Bren Group Project. This code is available on GitHub at https://github.com/nataliedornan/Kahuwai. We reformatted their code so it could all be run at once, which is easier for users unfamiliar with R. This code can be found at our GitHub account https://github.com/aloha-aina/Aloha-Aina. The data needed to run this code include stormwater system, subcatchment delineation, and subcatchment characteristics.

Kuliʻouʻou Model Calibration

SWMM requires precipitation data from the region of interest to simulate runoff from storm events. Precipitation data was provided by the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information (NCEI) for the Wailupe Valley School 723.6, HI US COOP:519500 (WVS) and Paiko Drive 723.4, HI US COOP:517540 (Paiko Drive) stations between the years 1977 and 2014 (NOAA NCEI, 2021). WVS is located in the Wailupe watershed, while Paiko Drive is located in the Kuliʻouʻou watershed. The two watersheds are separated by the Niu watershed.The R code can be found in the Aloha-Aina GitHub project.

Due to the lack of data availability for the Kuli‘ou‘ou watershed at a time interval necessary for SWMM, we conducted a time series analysis comparing Wailupe and Kuli‘ou‘ou rainfall. This was done to determine whether the watersheds received similar enough rainfall to use rainfall data from Wailupe as a proxy for Kuli‘ou‘ou rainfall.

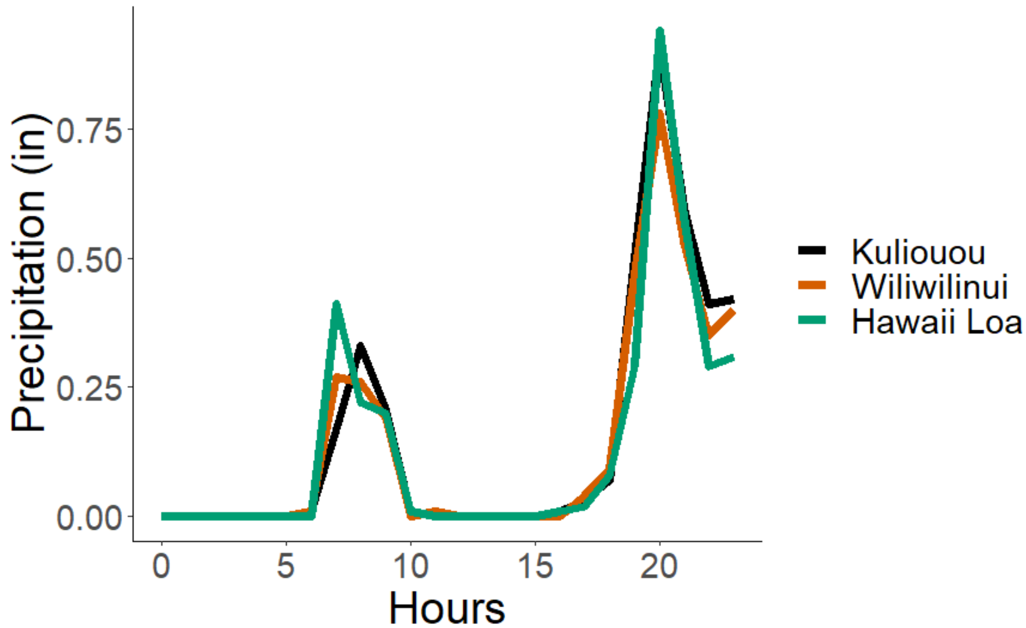

Figure 5. Ridgeline Precipitation data across watersheds for January 18, 2021.

Because precipitation varies with elevation, we compared both upper watershed and lower watershed precipitation in Wailupe and Kuli‘ou‘ou. First, we compared the ridgeline precipitation gauges, which had uniform rainfall over a 2021 storm event (Figure 5).

Next, we compared the lower watershed WVS precipitation to Paiko Drive precipitation. We found a relationship between WVS and Paiko Drive daily total precipitation across multiple storm events (Figure 6, Appendix F), confirming that WVS precipitation data for the Wailupe watershed could potentially be used as a proxy for Paiko Drive precipitation data in the Kuli‘ou‘ou watershed for our Kuli‘ou‘ou SWMM model.

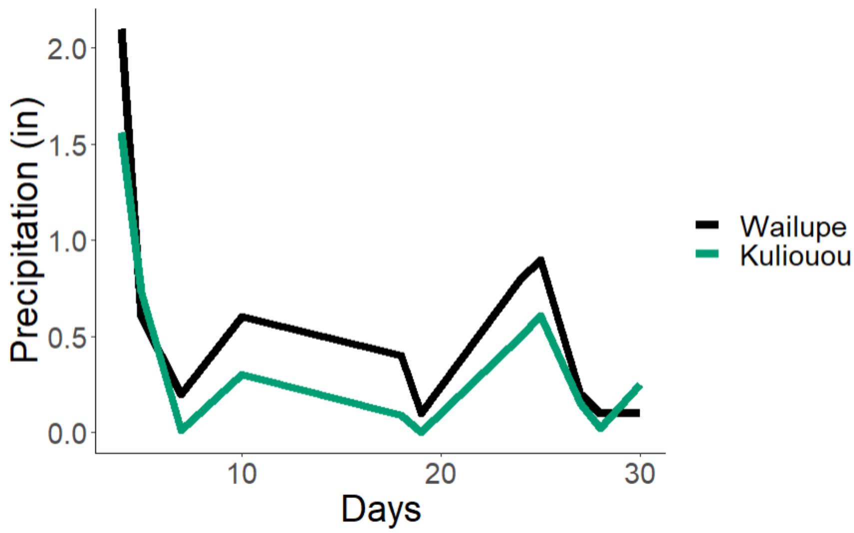

Figure 6. Wailupe Valley School and Paiko Drive NOAA precipitation data comparison for the January 4-10, 1996 storm.

However, an additional factor when choosing storm events to run in SWMM is that the precipitation data needs to be paired with stream gauge data to facilitate in-model calibration, comparing observed and simulated streamflow. For this project, we utilized stream discharge data from the USGS station 16247900 (Kuliʻouʻou Valley at Kuliʻouʻou, Oʻahu, HI). The data for this stream gauge was downloaded from the USGS National Water Information System. This data was available from 2009-07-09 to 2010-10-03, and thus limited our available window of precipitation data to pair with stream gauge data for model calibration.

We found two storms that overlapped with the stream gauge data, however they were unable to be used for model calibration. The first storm (November-December 2009) had an overall similar precipitation pattern between Wailupe and Kuliʻouʻou, but had too few data points for SWMM to generate runoff (Figure 7). Most storms had similar rainfall for both watersheds; however, the storm on October 11, 2009 had precipitation that differed between the watersheds, and therefore, would not accurately produce stream flow for the Kuliʻouʻou watershed (Figure 7). Due to the data limitations, we were unable to calibrate the SWMM model we produced for the Kuliʻouʻou watershed.

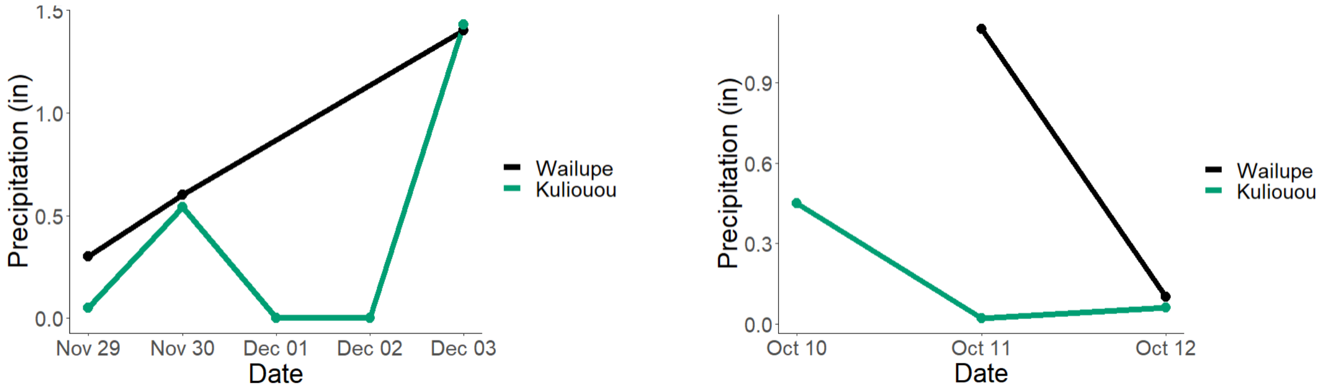

Figure 7. Wailupe Valley School and Paiko Drive NOAA precipitation data comparison for November-December, 2009 storm (left). December 3, 2009 only had six data points. October 11, 2009 had uneven precipitation between the watersheds (right).

SWMM Results

Because we were unable to calibrate our model due to data limitations, we instead focused on creating SWMM input files for the remaining watersheds in the Maunalua Bay region. These input files provide Mālama Maunalua with hydrologic models for the entire region, and will be ready for calibration once the necessary precipitation and stream gauge data becomes available.

We created SWMM input files for the 8 remaining watersheds in the Maunalua Bay region, including Kuliʻouʻou.To create the input files, we designed multiple ArcGIS models that streamline the process for delineating subcatchments, creating subcatchment characteristics layers, and creating the stormwater network layers. These models allowed us to more effectively reproduce the previous group's protocols. An example of one of the SWMM hydrologic models created through this process is shown in Figure 8.

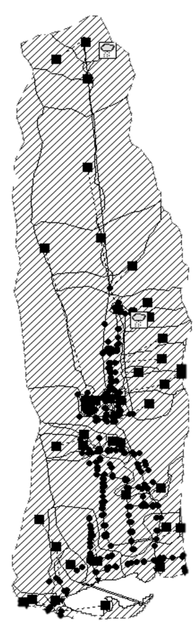

Figure 8. Diagram of the EPA Storm Water Management Model 5.1 Setup for the Kuliʻouʻou Watershed.

At this time, we are unable to calibrate the models due to a lack of data availability. However, these models will be useful for identifying stormwater runoff hotspots in the future when calibration data becomes available. Malama Maunalua has placed two rain gauges in the Kuliʻouʻou watershed, one at the ridge line and one at mid-watershed, approximately 350 meters above sea level. This precipitation data collection began in 2019. There is currently no stream gauge data published by USGS for this time period. Therefore, we recommend the installment of additional stream gauges in the Kuliʻouʻou watershed. Furthermore, aside from Wailupe and Kuliʻouʻou, the other watersheds in the region lack precipitation and steam gauge data. In order to expand this SWMM analysis to the entire region, more precipitation and stream gauges need to be placed throughout the region in each watershed.

Green Infrastructure – Wailupe Watershed

In SWMM, green infrastructure options are modeled through eight different types of 'low impact development' (LID) controls. LID controls available to model in SWMM include: bioretention cells, rain gardens, green roofs, permeable pavement, infiltration trenches, rain barrels, rooftop disconnections, and vegetative swales. Each LID control is represented by a combination of vertical layers whose properties are defined on a per-unit-area basis, meaning that differently-sized LIDs of the same design can be placed in various subcatchments of a single study area. During a simulation, SWMM performs a moisture balance that keeps track of how water moves between and is stored within each LID layer, accounting for infiltration, evapotranspiration, and any overflow that may occur from larger storm events.

Selection of LID Control Type and Location

For this project, green infrastructure recommendations and analysis are focused in the Wailupe watershed. Wailupe was chosen for GI analysis because it is the only watershed within the Maunalua Bay region for which a SWMM 5.1 hydrological model has been both developed and calibrated (Dornan et al., 2020). Calibration for this model was previously completed using the NOAA precipitation gauge for the Wailupe watershed: COOP:519500 Wailupe Valley School 723.6 HI US (WVS), located at 21.2918º N, -157.7534º W (NOAA NCEI, 2020) paired with observed stream discharge data from the USGS station 16247550 (Wailupe Gulch at E. Hind Dr. Bridge) located at 21.2853º N, -157.7542º W.

The previous Bren group project that completed and calibrated the Wailupe hydrologic model used a 2.8-inch, 11 hour storm event that occurred on March 14, 2009 to identify the top 19 subcatchments in Wailupe with the highest runoff coefficient values (Figure 9). A runoff coefficient is a ratio of the total volume of runoff flowing from a subcatchment relative to the total volume of rainfall that the subcatchment receives across its area (Ratzlaff, 1994). For the purposes of this project, the 19 subcatchments with the highest runoff coefficient values in Wailupe are classified as runoff hotspots. The runoff coefficient hotspots in the Wailupe watershed were used as an initial starting point for guiding optimal green infrastructure placement. The primary goal of implementing green infrastructure in the Maunalua Bay region is to reduce stormwater runoff and pollutants (such as suspended solids (dirt), nutrients (nitrogen and phosphorous), and heavy metals (lead, copper, and zinc)) originating from the highly impervious, urbanized environment.

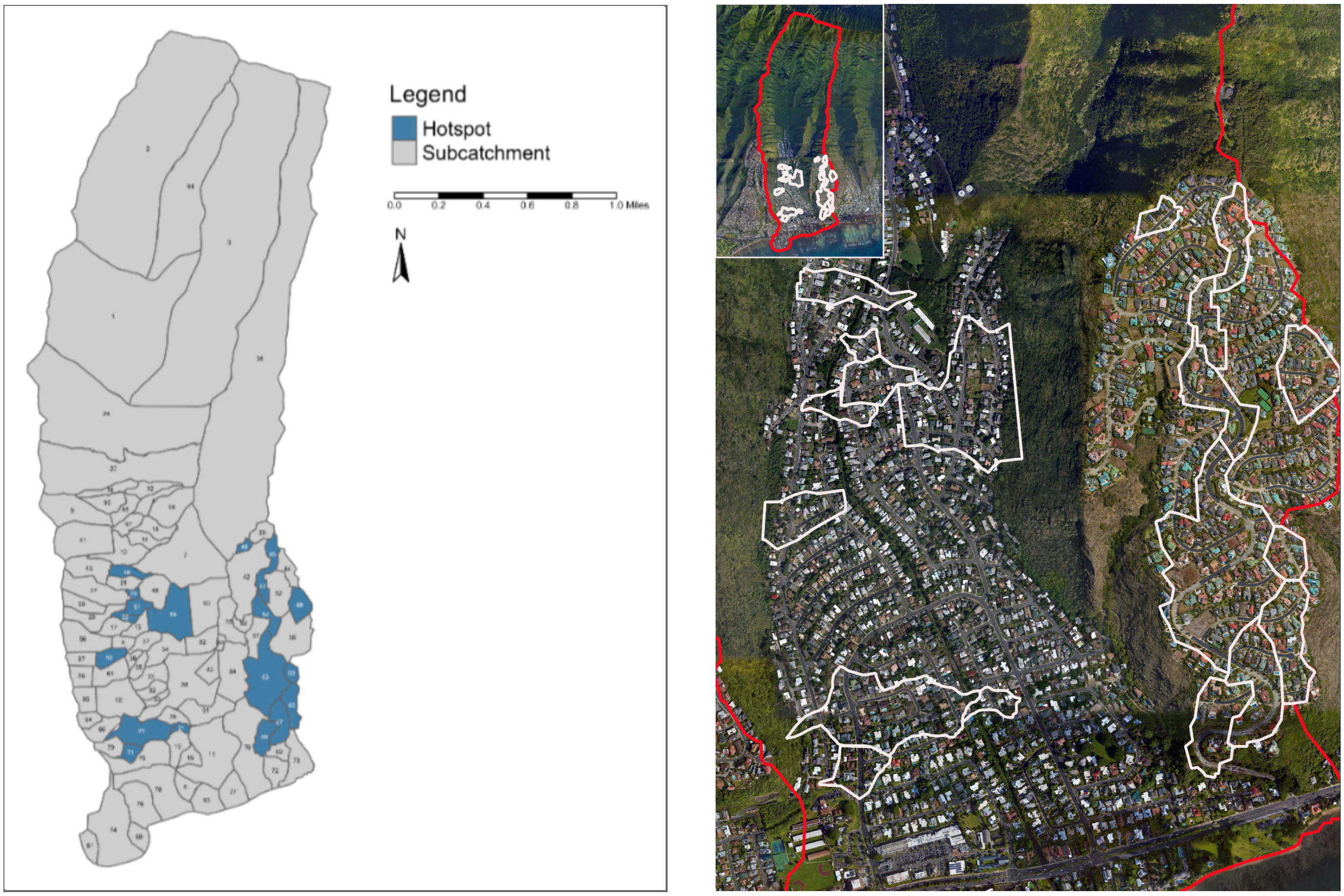

Figure 9. Wailupe Watershed Runoff Hotspots. Left: Blue polygons represent the top 19 hotspots in Wailupe watershed based on runoff coefficient values (Credit: Dornan et al., 2020). Right: Wailupe hotspot areas overlaid onto most recent Google satellite imagery.

We observed each of the Wailupe runoff coefficient hotspots via Google Earth, finding that all 19 of the subcatchments consist of residential areas containing predominantly single-family homes (Figure 9). The fact that every hotspot contains only residential areas significantly limited the size and LID control-type that could be implemented for this study. Given the size of each subcatchment and total volume of stormwater flowing from each subcatchment hotspot, the addition of smaller-sized LID controls that are normally implemented at the residential scale (such as a rain barrel, rain garden, or rooftop disconnection) will not reduce runoff enough to be reflected in the SWMM simulation.

Malama Maunalua has produced a variety of outreach materials that provide recommendations for residential-scale LID measures that homeowners can implement to reduce stormwater runoff from their properties. Primarily, these recommendations focus on rain gardens and rain barrels.

Given the size limitations and the relatively small storage capacity of these LID measures, we chose to instead focus our residential-scale analysis on green roofs. A green roof is a layer of vegetation planted over a waterproof liner that is installed on top of a flat or slightly-sloped roof (National park Service, 2021). Green roofing provides a larger-scale LID option with greater potential for reducing the total volume of runoff flowing from a residential property, and therefore, from a subcatchment overall.

Green Roofing Scenarios in Runoff Hotspots

For each of the runoff hotspots in the Wailupe watershed, we modeled three different green roofing scenarios: 1) 20% of houses in each hotspot contain a green roof, 2) 30% of houses in each hotspot contain a green roof, and 3) 50% of houses in each hotspot contain a green roof.

We used ArcGIS to calculate the total surface area (sq. ft) of buildings in each of the hotspot subcatchments. We then multiplied each hotspot's total building surface area by 0.2, 0.3, and 0.5 to obtain the appropriate total green roof area that should be applied to each hotspot for the three different green roofing scenarios.

Non-residential LID Scenarios

As previously mentioned, the land area contained in each of the Wailupe runoff coefficient hotspots is strictly residential. However, because Mālama Maunalua has experienced past difficulty encouraging individual homeowners to implement GI features on their properties, they specifically expressed interest in also exploring how GI elements placed in non-residential locations can reduce stormwater runoff. Therefore we expanded the analysis outside of the runoff coefficient hotspots, to quantify the runoff-reduction potential of large-scale GI features located in public or commercial properties.

To find suitable locations for non-residential GI placement, we observed each of the Wailupe subcatchments via Google Earth. A number of those that contained public and/or commercial property were identified and chosen for LID modeling in SWMM. Suitable public or commercial areas within each of the selected subcatchments, identified through satellite imagery, were used to guide which type of LID control could realistically be added to a particular location in a subcatchment. We considered appropriate LID options for public spaces, taking into consideration area, aesthetics, and feasibility. We considered green roofs and permeable pavements where subcatchments contained commercial buildings and/or public parking lots. Conversely, we considered bioretention cells or rain gardens as appropriate capture solutions for public park spaces.

Specific GI best practices were followed when determining the potential placement of certain LID controls. Rain gardens and bioretention cells were not considered for any subcatchment hotspot with an average slope gradient greater than 10%. These same controls were also not added to a subcatchment if, in a real-world scenario, they could not be placed at least 10 feet from a building or at least four feet from a sidewalk, concrete slab, or retaining wall (Hawai'i DOH, 2013). The 'Measure' tool on Google Earth was used to verify that such criteria could be met in a real-world setting within a given subcatchment.

Modeling LID Scenarios in SWMM

After determining the appropriate types and locations of green infrastructure scenarios for the Wailupe watershed, based on previously determined runoff hotspots and satellite imagery, we then determined appropriate parameter measures and sizes for LID controls before manually adding them to the Wailupe SWMM hydrologic model and running simulations with LIDs in place.

Parameterization

In SWMM, LID controls are modeled through a combination of vertical layers. SWMM LID layers include a surface layer, pavement layer, soil layer, storage layer, and/or drain system. There is also a drainage mat layer that is unique to green roof LID controls. A drainage mat is a multi-layer fabric mat that combines soil separation, drainage and protection functions; they are often used for residential green roofs (Conservation Technology, 2008). The LID layer combinations differ depending on the type of LID, but are representative of an LID control's real-world function and design. For example, a rain barrel in SWMM only contains a storage layer and a drain layer, whereas a bioretention cell contains a surface, soil, storage, and drain layer.

Each vertical layer has a set of parameters that ultimately determines the LID control's capacity to infiltrate, store, and filter runoff. Parameter values were determined based on information found in the SWMM manual, literature, and resources provided by Mālama Maunalua. Because Hawaiʻi contains unique soil and vegetation types relative to other places in the U.S., and to many places referenced in the literature, we primarily referred to Hawaiʻi-specific sources when determining sensitive LID model parameters such as Surface Roughness, Conductivity, and Seepage Rate. This is because green infrastructure features in the real-world should ideally contain native vegetation and soil types (Wagner et al., 2013). We wanted the modeled LID controls in this study to represent Hawaiian soil and vegetation as closely as possible in order to more accurately model the runoff-reduction potential introduced through GI. The parameters used for the different LID types modeled in this study are shown in Appendix G.

Sizing

When adding LID controls to a subcatchment in SWMM, a user must define the area of each LID unit (in ft^2). For the green roofing analyses in hotspot subcatchments, green roofs were capped at 3000 ft^2. The values for 20%, 30%, and 50% of the total building area previously calculated for each subcatchment were divided by 3000 to determine the number of green roofs that should be applied to each hotspot (the number of houses was rounded up when necessary to keep each green roof surface area at or below 3000 ft^2).

For non-residential areas, we used the 'Measure' tool on Google Earth to determine the approximate size of any LID control that corresponds to a specific building or feature.

For example, if a green roof were considered for placement on top of a mall strip, then we used the 'Measure' tool to determine the approximate size of the mall strip's roof area. This value was then used for the LID unit area in SWMM. Similar measurement methods were used for other LID controls relating to specific areas, such as permeable pavement systems. For any LID control that did not correspond to a specific building or feature (rain garden, bioretention swale, vegetative swale), we based sizing on available space and standard LID measurements found in the literature.

Running the Simulation

After LID control scenarios were added to a hotspot subcatchment, the subcatchment's percent imperviousness and percent perviousness were recalculated to account for any impervious area replaced by a green infrastructure element. Next, we ran the model under the March 2009 storm event to quantify the reduction in total runoff and peak flow values as a result of green infrastructure implementation. Peak flow is a measure of the maximum discharge value measured during a storm event and can have implications for the volume of pollutants flowing from a subcatchment.

Results: Runoff Reduction from Green Roofing

The addition of green roofing to runoff hotspots significantly reduced the total runoff volume, peak runoff values, and runoff coefficients for every hotspot subcatchment across all three green roof scenarios. Figure 10 depicts a time series of stormwater discharge (runoff) in cubic-feet-per-second (cfs) for the five hotspots with the highest initial runoff coefficients. As shown in the figure, the primary reduction in stormwater runoff from the addition of green roofing occurs during the period of peak runoff, occurring between hours 5 and 6.

Across the three scenarios, reductions in total runoff volume, peak runoff, and the runoff coefficients increased as the percentage of green roofs applied to each subcatchment increased. The following sections outline the results for each green roofing scenario in more detail.

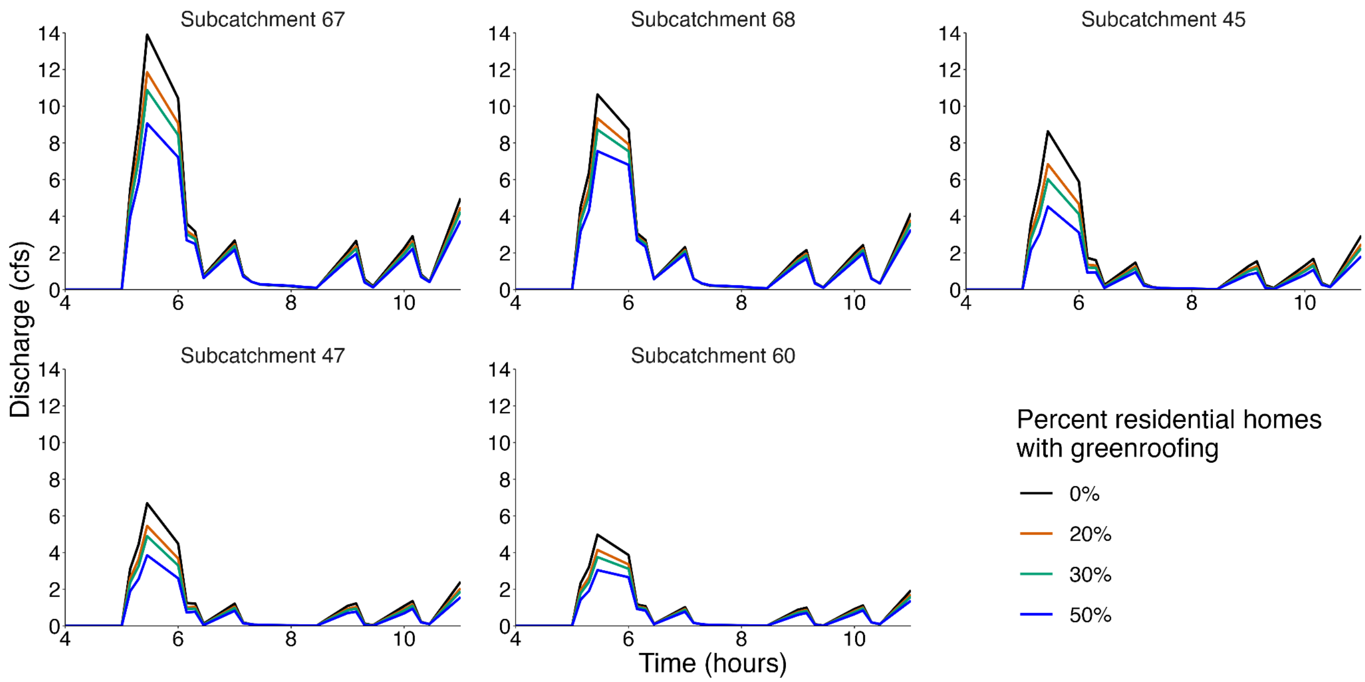

Figure 10. Time series of observed simulated discharges from the top five runoff coefficient hotspots for the March 14, 2009 storm event, starting at hour 4. Colored lines represent simulated discharge for each hotspot under different green roof scenarios (Black: Simulated discharge when 0% of homes have green roofs, Orange: Simulated discharge when 20% of homes have green roofs, Green: simulated discharge when 30% of homes have green roofs, Blue: Simulated discharge when 50% of homes have green roofs).

20% Green Roofing in Hotspots

Adding green roofs to 20% of homes located in the Wailupe hotspots reduced peak runoff from the hotspots by an average of 15.8%. The greatest peak runoff reduction simulated in the 20% scenario was a 21.5% reduction in subcatchment 40. The smallest peak runoff reduction for this scenario was a 7.5% reduction observed in subcatchment 65. Prior to the addition of LIDs, the 19 runoff hotspots produced a total of 6,290,000 gallons of runoff. With 20% of houses in the hotpots converted to green roofing, total runoff decreased to 5,710,000 gallons (a 9.2% decrease). Table 1 contains more detailed results of runoff parameters for each hotspot subcatchment under this scenario.

Table 1. Summary Output Table of Significant Runoff Parameters For the 20% Green Roofing Scenario (20% of houses in runoff hotspots retrofit with green roofing).

Subcatchment	Total Runoff (10^6 gal)	Peak Runoff (cfs)	Runoff Coefficient
68	0.31	9.34	0.609
60	0.13	4.14	0.608
67	0.38	11.85	0.601
47	0.16	5.45	0.588
46	0.21	6.21	0.586
45	0.20	6.84	0.585
65	0.30	9.04	0.575
71	0.15	4.71	0.567
54	0.28	9.47	0.555
59	0.23	6.87	0.554
89	0.85	25.07	0.542
51	0.18	5.92	0.541
29	0.06	1.83	0.540
23	0.64	19.81	0.536
63	1.13	35.59	0.534
40	0.07	2.23	0.532
21	0.07	2.29	0.512
22	0.09	2.70	0.511
49	0.27	8.97	0.508

30% Green Roofing in Hotposts

Adding green roofs to 30% of homes located in the Wailupe hotspots reduced peak runoff from the hotspots by an average of 23.4%. The greatest peak runoff reduction simulated in the 30% scenario was a 30.9% reduction also occurring in Subcatchment 40. The smallest peak runoff reduction for this scenario was a 17.1% reduction observed in Subcatchment 89. With 30% of houses in the hotspots converted to green roofing, total runoff decreased from the initial value of 6,290,000 gallons to 5,330,000 gallons (a 15.3% decrease). Table 2 contains more detailed results of runoff parameters for each hotspot subcatchment under this scenario.

Table 2. Summary Output Table of Significant Runoff Parameters For the 30% Green Roofing Scenario (30% of houses in runoff hotspots retrofit with green roofing).

Subcatchment	Total Runoff (10^6 gal)	Peak Runoff (cfs)	Runoff Coefficient
68	0.30	8.72	0.579
59	0.23	7.30	0.574
60	0.12	3.75	0.564
67	0.36	10.88	0.563
46	0.19	5.73	0.551
51	0.18	5.92	0.541
47	0.15	4.89	0.533
45	0.18	6.02	0.523
71	0.14	4.23	0.522
54	0.26	8.75	0.518
89	0.81	23.50	0.517
63	1.06	32.89	0.501
23	0.60	18.16	0.500
29	0.05	1.72	0.498
65	0.25	6.90	0.483
40	0.06	1.96	0.476
49	0.25	8.11	0.466
21	0.06	2.05	0.463
22	0.08	2.37	0.463

50% Green Roofing in Hotposts

Adding green roofs to 50% of homes located in the Wailupe hotspots reduced peak runoff from the hotspots by an average of 38.4%. The greatest peak runoff reduction simulated in the 40% scenario was a 48.6% reduction which again occurred in subcatchment 40. The smallest peak runoff reduction for this scenario was a 27.8% reduction observed in subcatchment 89. With 50% of houses in the hotspots converted to green roofing, total runoff decreased to 4,610,000 gallons (a 26.7% decrease). Table 3 contains more detailed results of runoff parameters for each hotspot subcatchment under this scenario.

Table 3. Summary Output Table of Significant Runoff Parameters For the 50% Green Roofings Scenario (50% of houses in runoff hotspots retrofit with green roofing).

Subcatchment	Total Runoff (10^6 gal)	Peak Runoff (cfs)	Runoff Coefficient
68	0.27	7.55	0.522
67	0.31	9.06	0.491
46	0.17	4.83	0.486
60	0.11	3.04	0.479
89	0.73	20.48	0.467
59	0.19	5.49	0.466
54	0.23	7.39	0.447
71	0.12	3.35	0.439
63	0.93	27.75	0.438
47	0.12	3.85	0.431
23	0.52	15.02	0.431
29	0.04	1.34	0.414
51	0.14	4.37	0.414
45	0.14	4.53	0.408
65	0.21	5.24	0.400
49	0.21	6.52	0.386
22	0.07	1.78	0.374
40	0.05	1.46	0.372
21	0.05	1.60	0.371

LID Runoff Reduction Results: Non-Residential Areas

Subcatchment 78: LID Controls in a Commercial Shopping Center

Subcatchment 78 is one of the few subcatchments in the Wailupe watershed that contains non-residential areas. We added two LID controls to public spaces in this subcatchment: a green roof scaled to the size of the ‘Āina Haina Shopping Center roof and a permeable pavement system scaled to the size of the ‘Āina Haina Shopping Center parking lot. The green roof totaled 49,100 ft^2 and the permeable pavement totaled 55,295 ft^2 (Figure 11).

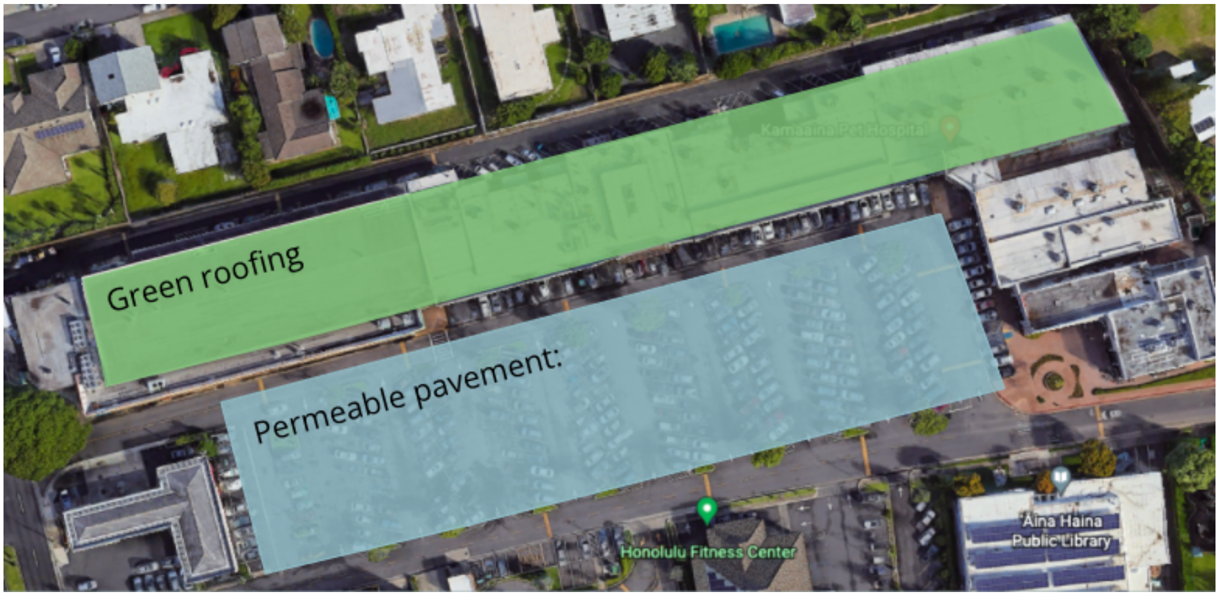

Figure 11. Theoretical placement of a green roof and permeable pavement system in subcatchment 78. The green rectangle represents a green roof along the ʻĀina Haina Shopping Center and the blue rectangle represents a permeable pavement system in the ʻĀina Haina Shopping Center parking lot.

Without the addition of LID controls, subcatchment 78 produced 860,000 gallons of runoff and a peak runoff value of 28.6 cubic-feet-per-second (cfs) during the March 2009 storm event. Individually adding the green roof and permeable pavement LID controls reduced the total runoff values to 760,000 gallons and 730,0000 gallons, respectively. Simulated peak flow under the green roof and permeable pavement scenarios was 25.5 cfs and 24.6 cfs, respectively (an ~11% reduction created by each LID control). Under a combined LID scenario, where the green roof and permeable pavement were both added to subcatchment 78, total runoff decreased to 640,000 gallons (a 26% reduction). Under this same scenario, peak flow decreased to 21.9 cfs (a 23% reduction) (Figure 12).

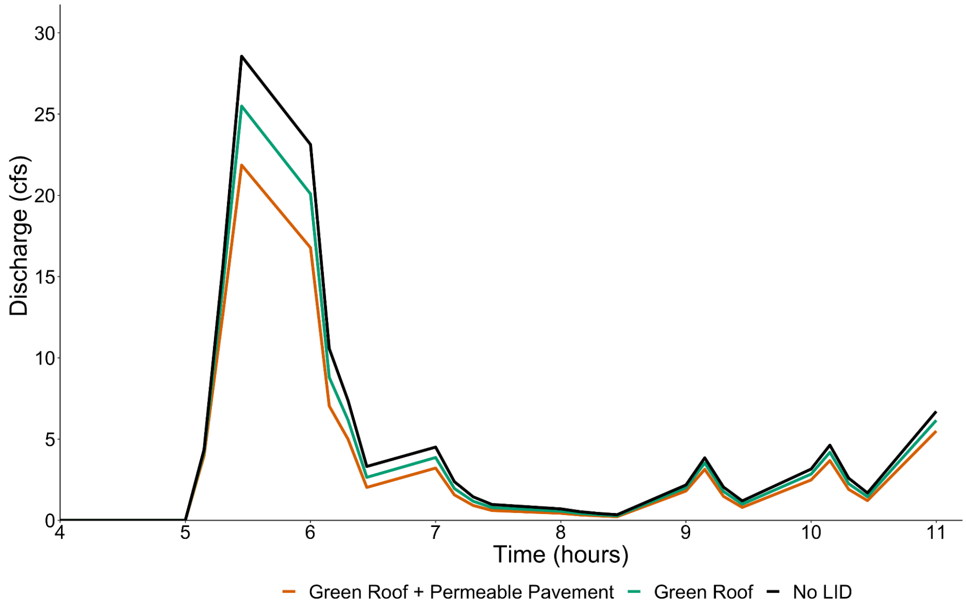

Figure 12. Time Series of simulated discharges from subcatchment 78 for the March 14, 2009 precipitation event under different LID Scenarios, starting at hour 4 of the storm event. Observed data provided by NOAA NCEI precipitation gauge COOP:519500 (WAILUPE VALLEY SCHOOL 723.6 HI US). (Black: Simulated discharge (cfs) with no LIDs in place, Green: Simulated discharge (cfs) for green roof only, Orange: Simulated discharge (cfs) for green roof and permeable pavement combination scenario).

Subcatchment 11: LID Controls in a Public Park

Subcatchment 11 is one of the largest subcatchments in the Wailupe watershed. Subcatchment 11 also has one of the highest peak runoff values simulated during the March 14, 2009 storm event, implying that this portion of the watershed contributes a significant amount of runoff into Wailupe Stream and ultimately, into Maunalua Bay. Subcatchment 78 is also one of the few subcatchments in the Wailupe watershed that contains a public park area– Nehu Park. The park consists of a few trees, and a large, grassy area. It is located in the middle of a neighborhood and surrounded by houses from which a well-placed rain garden has potential to capture runoff. We modeled the

Figure 13. Theoretical placement of 900 ft^2 rain garden in Nehu Park, located in the Wailupe watershed. The rain garden is shaded yellow.

runoff-reduction potential of adding a 900 ft^2 rain garden area to Nehu Park (Figure 13). Under the March 14 storm event simulation, we did not see a significant reduction in simulated runoff from subcatchment 11 with the rain garden area in place (Table 4). The 900 ft^2 rain garden decreased the runoff coefficient value by only 0.3% and the peak runoff value by 1.5%. Total runoff decreased by 1,000 gallons.

Table 4. Summary Output Table of Subcatchment 11 Significant Runoff Parameters.

LID Scenario	Total Runoff (10^6 gal)	Peak Runoff (cfs)	Runoff Coefficient
No LIDs	1.36	40.87	0.553
900 sq.ft Rain garden	1.35	40.26	0.550

LID Cost Estimates

The costs of green infrastructure vary widely across geographic regions and can be quite substantial when implemented at large-scales. However, it is likely that the prices associated with green infrastructure in the U.S. will decline as market demand increases (USEPA, 2008). In the following sections we will outline the potential monetary costs of the various LID controls modeled in this study, including capital and maintenance costs. Given the scope of this project, a full cost-benefit analysis of green infrastructure implementation was not feasible and therefore social and environmental costs and/or benefits are not included in our calculations.

Green Roof Costs

The cost of green roofing is variable, ranging in price from \$18-\$64 per cubic foot of storage (a cubic foot of storage is about 7.5 gallons of water). Difference in price depends on construction materials. Such as filter membranes, drainage layers, support panels, and thermal insulation (NOAA, 2015). To ensure proper use and efficiency, annual maintenance costs include frequent watering and tending for plant survival, invasive species control, and yearly inspections for structural integrity and leak reduction. This cost could range from \$0.75-\$1.50 per ft^2 (Green Values National Stormwater Calculator).

The potential cost of installing green roofing on 20% of the homes in the Wailupe hotspots (equaling approximately 370,637 ft^2 of green roofing) ranges from approximately \$6,671,000 to \$23,721,000. The average price per house ranges from \$8,952 to \$31,828 for the green roofings itself, and from \$1,956 to \$3,912 for yearly maintenance.

The total cost of installing green roofing on 30% of the homes in the Wailupe hotspots (equaling 555,955 ft^2 of green roofing) ranges from approximately \$10,007,000 to \$35,581,000. The total price of installing green roofing to 50% of homes in the hotspot areas (equalling 926,591 ft^2 of green roofing) ranges from approximately \$16,679,000 to \$59,302,000.

The price for 49,100 ft^2 of green roofing on top of the Aina Haina Shopping center ranges from $883,800 to $3,142,400, with yearly maintenance costs between $36,825 and $73,650.

Permeable Pavement Costs

Permeable pavement costs range depending on the material chosen for implementation. Permeable pavement systems are often composed of a combination of asphalt and concrete, or other porous materials. However, individual materials such as porous asphalt, pervious concrete, and permeable interlocking concrete can range from; $1-$1.50, $3-$9, and $7-$14, per square foot, respectively. Annual maintenance costs range from $400-$500 per acre which include regular inspections for clogging, cracks, and potholes in order to ensure the most efficient water infiltration (Green Values National Stormwater Calculator; USEPA, 2013).

Most maintenance costs are attributed to areas in colder climates that demand snow plowing, salting, and de-icing that alter the state of the permeable pavements. For Hawai'i, maintenance costs would fall in the lower cost range since there would be little to no complications due to freeze-thaw stress.

Although permeable pavement options cost more than traditional pavement to construct initially, low maintenance and stormwater management costs can contribute to economic savings, long term (USEPA, 2013).

Rain Garden Costs

Rain garden installation costs $7-$60 per cubic foot of storage. Rain gardens require annual maintenance costs of about $0.70 per ft^2 for regular landscaping and upkeep to ensure that the green infrastructure practice is functioning properly (NOAA, 2015; Green Values National Stormwater Calculator). Initially, rain gardens may require more labor for maintenance, but generally it will decrease over time if they contain appropriate vegetation. Traditional use of endemic, low maintenance Hawaiian plant species such as Carex (*Carex wahuensis),* Ihiihilauakea (*Marsilea villosa), and* Ma'o (*Gossypium tomentosum)* would demand less water consumption and regular landscaping maintenance.

The price of installing a 400 ft^2 rain garden in Nehu Park ranges from $2,800 to $24,000. This estimate does not include construction costs. The installation of rain gardens in public parks could be turned into a community project, where members of the community have the opportunity to volunteer and work together to build rain gardens in their local parks.

Climate Change – Wailupe Watershed

We determined the impacts of future climate change scenarios on the runoff coefficients and peak flow values of the subcatchments in Wailupe. The runoff coefficient is a ratio of the total volume of runoff relative to the total number of rainfall that a subcatchment receives across its area (Ratzlaff, 1994). Peak flow is a measure of the maximum discharge value measured during the storm event. We used projected precipitation data to view differences in runoff coefficients and peak flow under extreme climate change scaled conditions.

To understand the impact of future climate change on the Maunalua Bay region, we have utilized climate data provided by the PanGeo Gallery, utilizing Jupyter Notebooks with Python 3. This data server contains global climate data from the Coupled Model Intercomparison Projects (CMIP6). CMIP6 are coordinated general circulation model (GCM) simulations, constituting climate projections used in the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6). Specifically, this CMIP6 dataset contains historic and projected precipitation fluxes up to 2100 with four Shared Socioeconomic Pathways (SSPs) based on different possible concentrations of greenhouse gas (GHG) emissions and climate policies.

For this analysis, we confine our assessment of precipitation impacts on the island of O‘ahu to concentration-driven simulations, focusing on four SSPs that include: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, which result in end-of-century approximate total radiative forcing levels of 2.6, 4.5, 7.0, and 8.5 W m^{-2}, respectively. The SSPs describe alternative evolutions of future society in the absence of climate change or climate policy. SSP1 is a pathway of sustainability, which assumes climate protection measures are being taken and global commons are being preserved; SSP2 is a middle of the road pathway, which assumes Intermediate GHG emissions around current levels until 2050 then falling but not reaching net zero by 2100; SSP3 is a pathway of regional rivalry, which assumes increased future economic and social development, fast-growing population and increasing inequalities; SSP5 is a pathway of fossil-fueled development, which assumes intensified exploitation of fossil fuel resources with a high percentage of coal and an energy-intensive lifestyle worldwide. Generally, the SSPs have a higher associated accumulated concentration of atmospheric CO_2 (Figure 14).

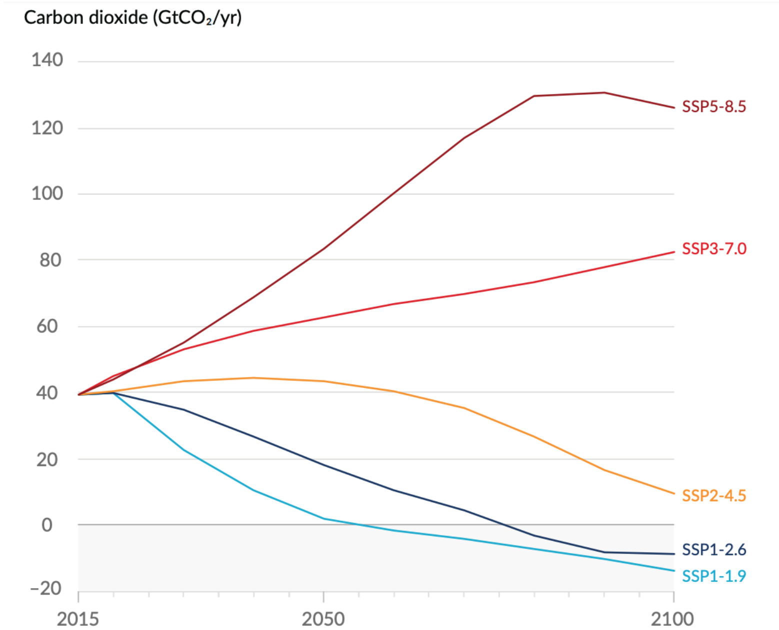

Figure 14. Future annual emissions of CO_2 from the IPCC AR6. Future annual emission of CO_2 ($GtCO_2$/yr) from 2015-2100 where colored lines represent SSPs. (IPCC, Box SPM.1)

To determine how climate change-driven shifts in precipitation influence differences in stormwater runoff in the Wailupe watershed, we extracted daily total precipitation for the island of O‘ahu from historical periods and projected periods: 1984-2014 and 2020-2050, respectively. See Appendix H for the code used to extract these values. Precipitation data was filtered for March 14 for each year to align with the Wailupe storm events used as SWMM input. The March 14 daily total precipitation was then averaged across 2020-2050 for each SSP and separately for the 1984-2014 historical precipitation. We then took the ratio of daily total precipitation averaged across 2020-2050 for each SSP divided by historical daily total precipitation across 1984-2014 to serve as the multiplicative change factor (MCF), as depicted below.

$$MCF_{SSP,\ March\ 14} = \frac{Projected\ daily\ total\ precip\ avg\ from\ 2020-2050}{Historical\ daily\ total\ precip\ avg\ from\ 1984-2014}$$

This methodology was deployed for three separate CMIP6 models (Figure 15). We multiplied each time step in the SWMM model input by the maximum (2.20) and minimum (0.40) MCF across all SSPs and CMIP6 models. This was applied to the Wailupe watershed for the March 14, 2009 storm event to serve as the extreme scenarios associated with climate change impacts (Figure 15).

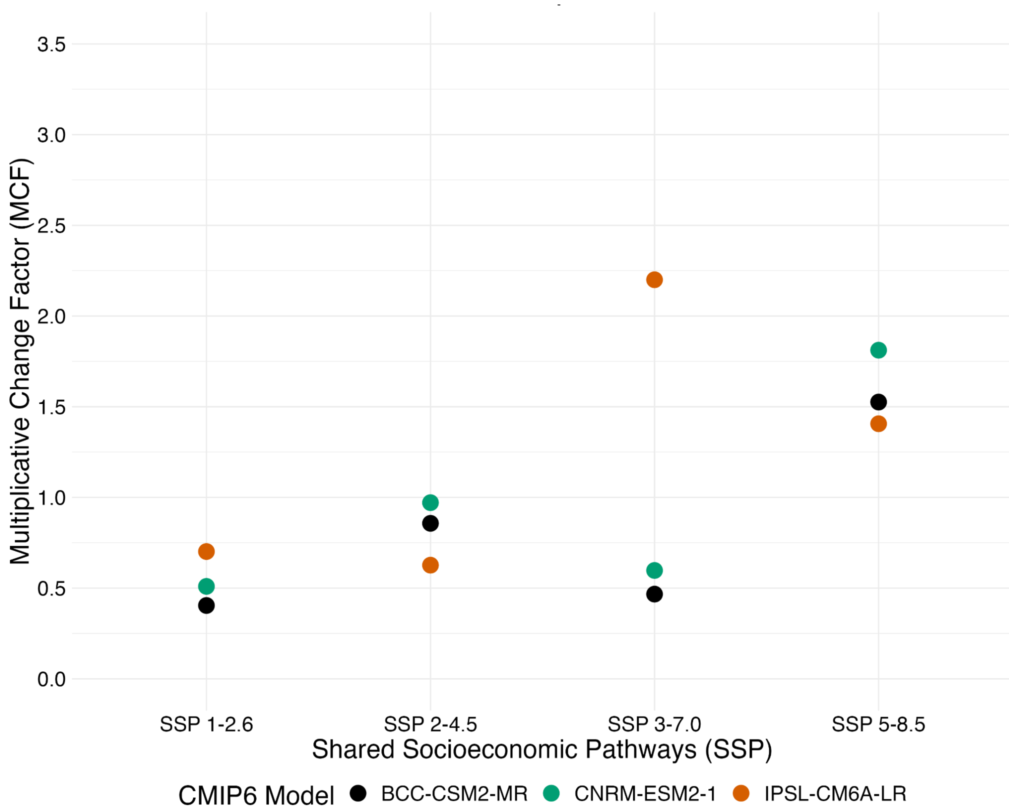

Figure 15. Multiplicative Change Factors for the March 14 Storm Event. Multiplicative change factors (MCF) by Shared Socioeconomic Pathways (SSPs) for the Wailupe March 14 storm event. Points indicate CMIP6 models (Black: BCC-CSM2-MR, Green: CNRM-ESM2-1, Orange: IPSL-CM6A-LR).

Minimum and Maximum MCF

SWMM output provides total precipitation (inches), total runoff (inches), total infiltration (inches), impervious runoff (inches), pervious runoff (inches), total runoff (inches, gallons), peak runoff (cfs), and runoff coefficient by subcatchment in the watershed. Over the course of the 11-hour storm on March 14, 2009, the maximum MCF model simulated discharge of 11,059.47 cfs and the minimum MCF model simulated discharge of 344.66 cfs, whereas the stream discharge gauge observed a total of 3,617.86 cfs. There was a 194% increase in peak discharge with the max MCF applied and a 78% decrease in peak discharge with the min MCF applied at hour 5:45 as compared to the observed peak discharge that occurred on March 14, 2009 (Figure 16).

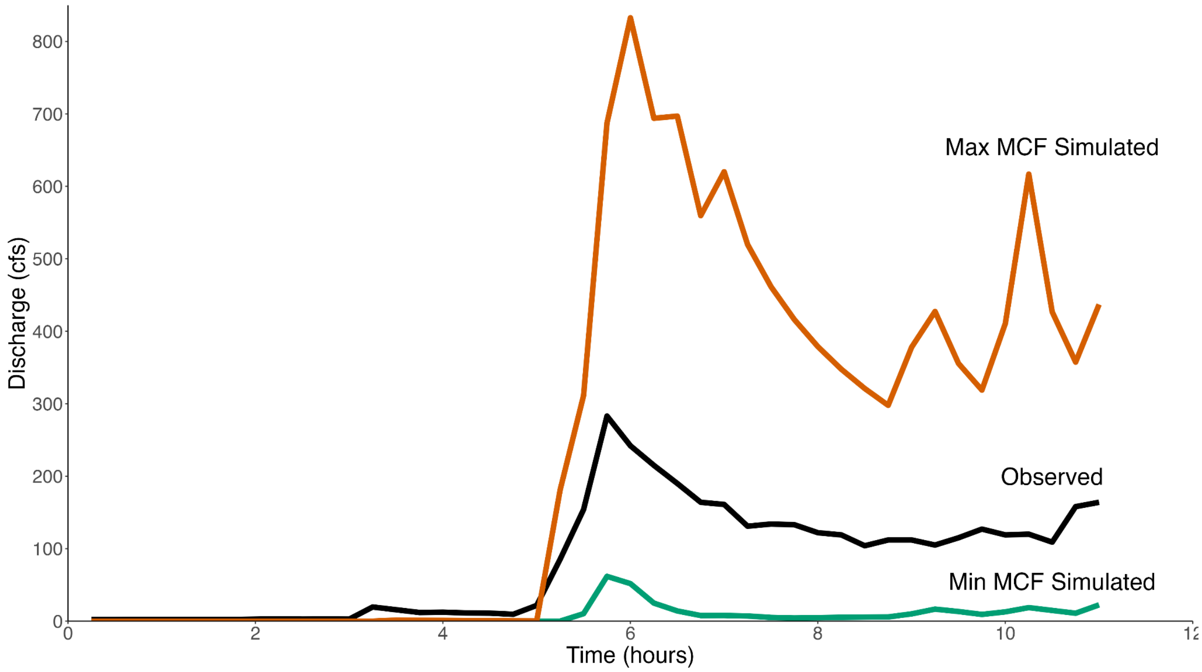

Figure 16. Time Series of Observed, Maximum and Minimum Multiplicative Change Factor (MCF) Simulated Discharge for the March 14, 2009 Precipitation event. Observed data provided by NOAA NCEI precipitation gauge COOP:519500 (WAILUPE VALLEY SCHOOL 723.6 HI US). (Black: Observed, Green: Minimum MCF simulated, Orange: Maximum MCF Simulated).

Runoff Coefficients

For the March 14, 2009 storm, runoff coefficients range from 0 to 0.82 with the max MCF applied and from 0 to 0.60 with the min MCF applied. See Appendix I for code used to view differences in runoff coefficients for each subcatchment.The spatial distribution of runoff coefficients for both can be observed in Figure 17. Hotspots here were defined as the top 20 highest runoff coefficient subcatchments in the lower, urbanized watershed (Table 5). Knowing changes in runoff coefficients related to climate change impacts will aid in management practices that prioritize future placement of green infrastructure in top ranking runoff coefficient subcatchments which will ultimately help reduce runoff that feeds into the Maunalua Bay. When comparing runoff coefficients from a previous study for the March 14, 2009 storm event (Dornan et al., 2020), we found that subcatchments 89, 14, 65, 23, and 63 are the top 5 subcatchments that experienced the greatest difference between max MCF scaled runoff coefficients and historically simulated March 14, 2009 runoff coefficients. Future concentration on these specific subcatchments as target areas for green infrastructure placement will ultimately aid in reducing runoff that will feed into the Maunalua Bay.

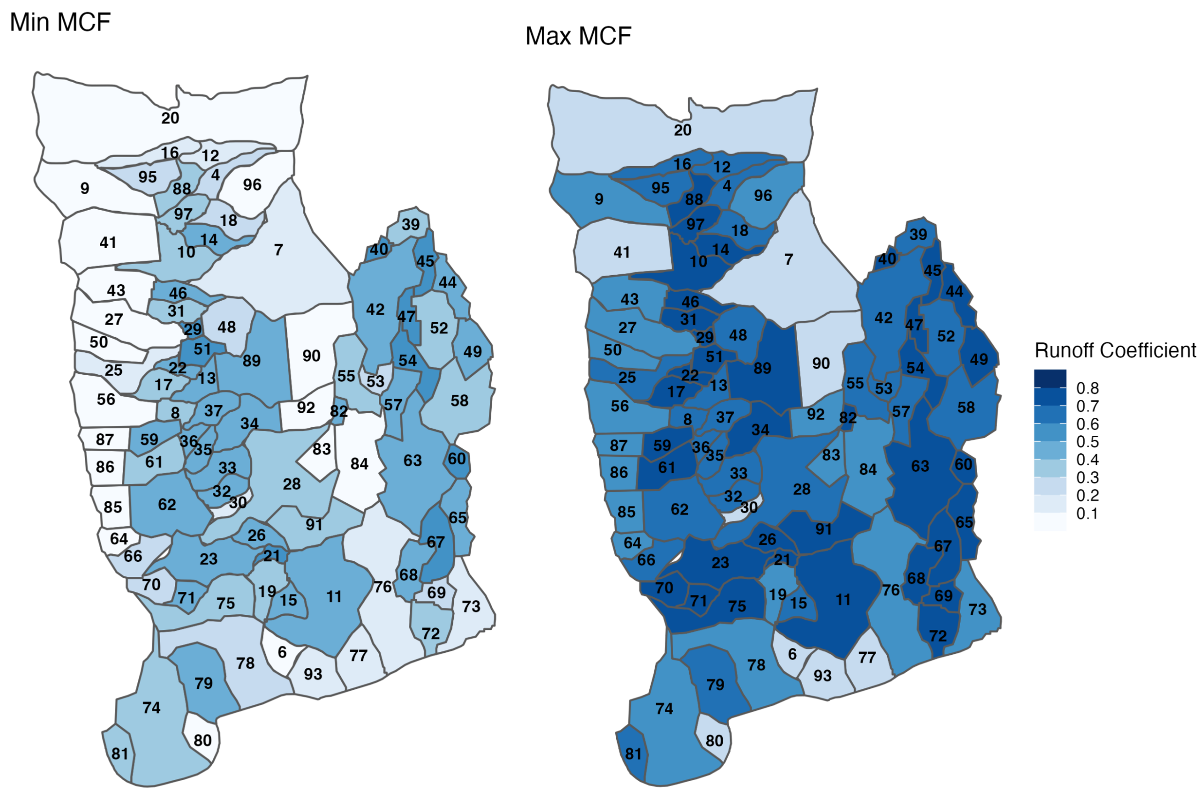

Figure 17. Modeled Runoff Coefficient Results for Wailupe Watershed. Left: March 14, 2009 storm with the min MCF applied. Right: March 14, 2009 storm with the max MCF applied. Higher runoff coefficients indicate areas where more precipitation becomes stormwater runoff.

Table 5. Summary Output Table of Top 20 Runoff Coefficient Subcatchment with Min and Max MCF Results and Significant Parameters.

Subcatchment	Slope	Percent Impervious	Area (sqft)	Runoff Coefficient, Min MCF	Runoff Coefficient, Max MCF
45	10.837372	75.81188	205273.48	0.594	0.815
47	9.017865	73.67874	163180.85	0.586	0.799
60	10.200056	66.27512	130703.86	0.531	0.821
40	7.774446	65.26444	78272.63	0.528	0.762
51	3.205696	65.70618	194382.01	0.516	0.746
54	11.985041	65.90850	301206.44	0.514	0.748
21	2.133592	64.38962	78832.74	0.511	NA
29	4.303893	63.75090	62214.52	0.510	0.747
67	13.094514	65.31544	376961.02	0.509	0.809
71	1.229756	63.33945	161251.17	0.493	0.793
5	4.973908	59.22529	42008.07	0.489	0.809
49	11.626618	61.33458	317060.05	0.484	NA
46	9.180995	59.97949	209977.29	0.481	0.789
13	2.801558	60.72206	210147.80	0.473	NA
59	9.355130	58.61615	241399.55	0.465	0.751
22	5.224538	57.36459	106889.43	0.463	0.745
35	2.502320	58.10591	163977.29	0.461	NA
36	3.413503	57.37835	103198.24	0.458	NA
63	11.350848	59.59508	1260905.98	0.454	0.746
23	2.091764	60.15849	712111.05	0.452	0.759
68	16.778001	56.40240	306366.86	NA	0.813
65	12.285943	54.98557	309782.87	NA	0.770
14	10.062202	51.97367	244581.39	NA	0.764
91	7.225773	49.19777	543493.09	NA	0.755
89	12.267217	54.37988	929708.78	NA	0.748

Peak Flow

Peak flow is a measure of the maximum discharge value measured during the storm event. Peak flow ranges from 0 to 106.39 cfs for the March 14, 2009 storm with the max MCF applied and 0 to 15.29 cfs for the March 14, 2009 storm with the min MCF applied (Appendix I). Figure 18 shows the spatial distribution of the peak flows for both MCF values applied to the March 14, 2009 storm event. Hotspots here were defined as the top 20 highest peak flow (cfs) subcatchments in the lower, urbanized watershed (Table 6). To determine the influence of subcatchment area on peak discharge, we normalized peak discharge by dividing each subcatchments peak discharge value by its total area. The subcatchments with the highest normalized peak flow values were defined as hotspots (Appendix J). Viewing differences in peak flow under the min and max MCF applied will help inform management practices that prioritize future placement of green infrastructure in top ranking peak discharge subcatchments which will ultimately help reduce runoff that feeds into the Maunalua Bay. When comparing peak flow from a previous study (Dornan et al., 2020), we found that subcatchments 63, 11, 28, 74, and 89 are the top 5 subcatchments that experienced the greatest difference between max MCF scaled peak discharge and historically simulated March 14, 2009 peak discharge. Future implementation of green infrastructure in these subcatchments specifically will ultimately aid in reducing runoff that feeds into the Maunalua Bay.

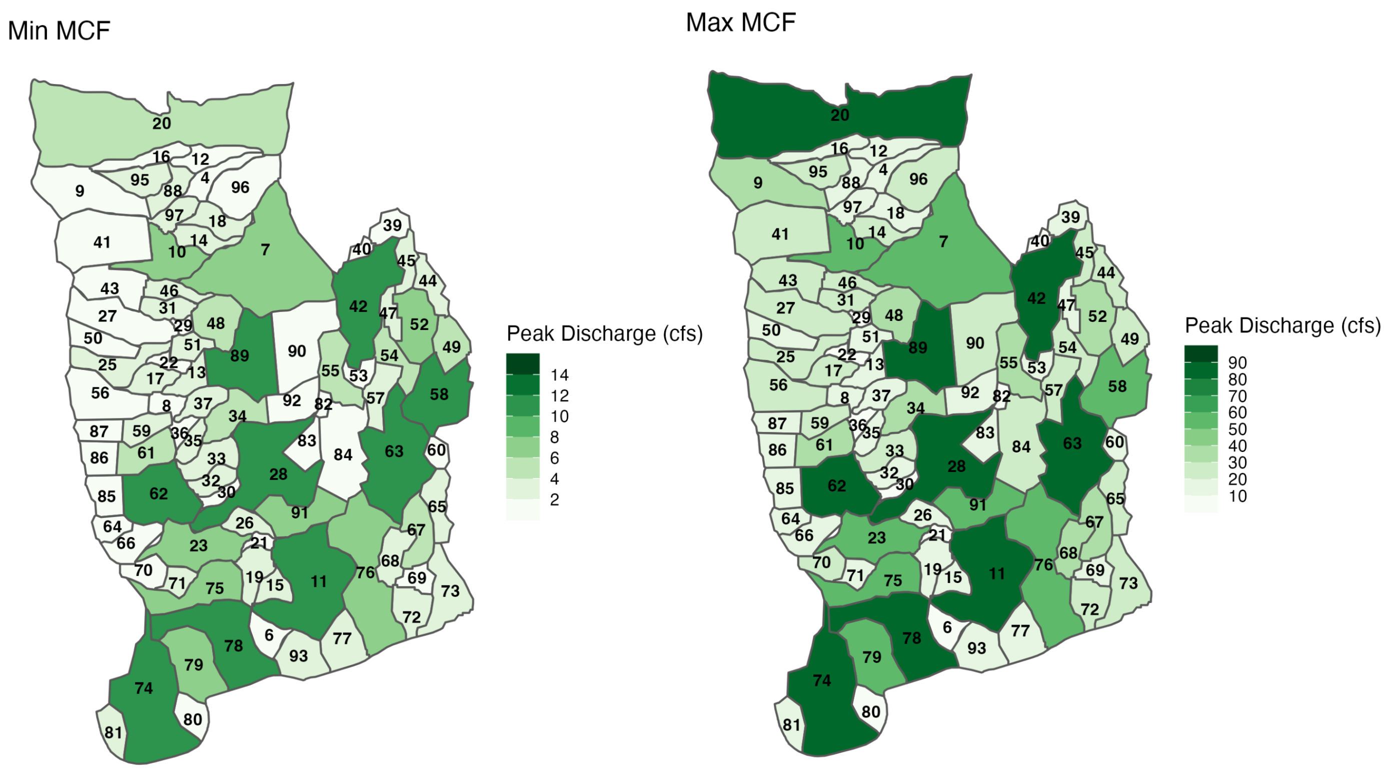

Figure 18. Modeled Peak Flow Results for Wailupe Watershed. Left: March 14, 2009 storm used with the min MCF applied. Right: March 14, 2009 storm used with the max MCF applied.

Table 6. Summary Output Table of Top 20 Highest Peak Flow Subcatchment with Min and Max MCF Results and Significant Parameters

Subcatchment	Slope	Percent Impervious	Area (sqft)	Peak Runoff (cfs), Min MCF	Peak Runoff (cfs), Max MCF
63	11.3508475	59.595082	1260906.0	15.29	106.39
28	9.6951530	45.648739	1400355.0	13.56	99.65
42	12.7741916	52.075244	1097149.0	12.15	80.56
11	0.9475857	60.176841	1461121.3	11.91	105.54
89	12.2672167	54.379880	929708.8	10.85	79.13
74	0.5130342	49.951879	1593473.1	10.07	90.09
62	4.9693069	57.621143	816823.7	9.66	62.88
58	13.4737125	50.489651	794612.3	8.76	57.25
78	0.6625196	45.869531	1272102.3	8.38	69.55
23	2.0917640	60.158489	712111.1	8.09	59.82
76	12.6689327	21.946154	1533842.8	7.40	52.96
7	24.3708501	14.101788	2174275.2	6.79	56.98
75	3.1037990	49.969260	646779.6	6.65	47.57
79	0.7809627	55.674414	703208.6	6.63	48.58
91	7.2257735	49.197766	543493.1	5.86	47.33
52	14.2092259	49.068201	521285.7	5.66	38.27
10	13.0349991	46.827316	527259.5	5.46	38.42
67	13.0945141	65.315445	376961.0	5.35	37.74
34	6.5716791	55.845327	439337.8	5.31	35.34
55	14.0124563	43.238717	456026.8	4.37	NA
20	28.7382083	5.926749	3260351.4	NA	64.99

Probability of Extreme Climate Change Events

Another important factor to consider with extreme climate change events is the probability of those events occurring today. We conducted a density distribution analysis of present-day Wailupe precipitation from 1996-2013 to determine if the MCF-scaled precipitation amounts associated with the March 14, 2009 storm are unlikely to occur by the standards of today's climate. We summed the sub hourly Wailupe precipitation data to obtain a dataframe with daily total precipitation across the time series, where the average was 0.35 inches. We then applied the *dnorm* function in baseR to the dataframe of daily total precipitation (in) (Appendix K). In Figure 19, the vertical orange line represents the max MCF (2.20) multiplied by the average precipitation of the March 14, 2009 storm (0.20 inches) and the green line represents the min MCF (0.40) also multiplied by the average precipitation of the March 14, 2009 storm (0.20 inches). The intersections of the vertical lines with the density distribution black line represent the likelihood of a max or min MCF equivalent storm occurrence. The likelihood of a min MCF scaled storm event is 69% and the likelihood of a max MCF scaled storm event is 77%. These results indicate that the max scaled March 14, 2009 event is 0.09 inches more than the density distribution mean, suggesting climate change impacts are unlikely to alter the types of green infrastructure that would be necessary in the future.

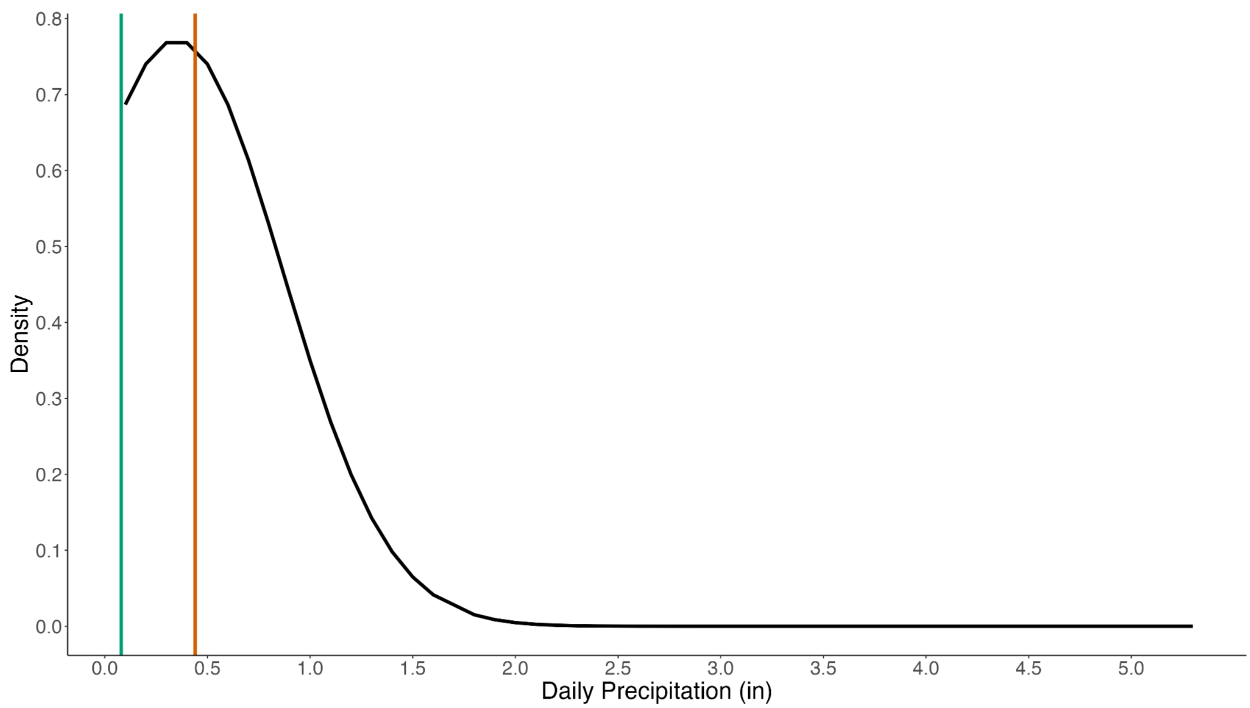

Figure 19. Density Distribution of Wailupe precipitation events. Black line indicates the density distribution of the Wailupe daily total precipitation time series from 1996-2013. Orange line depicts the max MCF multiplied by the March 14, 2009 average precipitation (0.2 inches). Green line depicts the min MCF multiplied by the March 14, 2009 average precipitation.

Wailupe LID Effectiveness Under Climate Change Scenarios

One factor to consider prior to the implementation of green infrastructure elements is their effectiveness under the potential impacts of climate change and larger storm events. The costs associated with large-scale green infrastructure projects can come with substantial costs, and their long-term effectiveness and benefits must justify the necessary expenditures. To explore the effectiveness of LIDs under climate change scenarios, we applied the MCFs to subcatchment 78 within the Wailupe watershed.

Methods

The same LID controls as modeled in subcatchment 78 previously (a green roof and permeable pavement parking lot scaled to the ʻĀina Haina Shopping Center) were modeled under two climate change scenarios– one that represents a average wetter climate across the Maunalua Bay region and one that represents an average drier climate across the region. For the wetter climate scenario, we modeled subcatchment 78 runoff with the Max MCF applied to the March 14, 2009 storm event. To represent a drier climate change scenario, we applied the Min MCF values to the March 14 storm event. Both scenarios were modeled in SWMM and runoff parameters for subcatchment 78 were used to illustrate how LID controls might function under realistic climate change scenarios.

Results – Max MCF

With the Max MCF applied, peak flow from subcatchment 78 increased to 69.6 cfs (compared to 21.7 cfs when the Max MCF was not applied). This represents a 220.7% increase in the peak flow value. Adding the 49,100 ft^2 green roof and the 55,295 ft^2 of permeable pavement and simulating the Max MCF scenario decreased peak flow to 54.1 cfs (Figure 20).

In the initial LID analysis for subcatchment 78 (with no MCF applied), the addition of the green roof and permeable pavement reduced the subcatchment's peak flow by 23%. Under the Max MCF scenario, which represents average wetter conditions across the region, the addition of the two LID controls resulted in a 22.3% reduction in peak flow and a 19.5% reduction in the overall volume of runoff from subcatchment 78. These results show that the LIDs retain 97% of their effectiveness in reducing peak flow under the larger storm event.

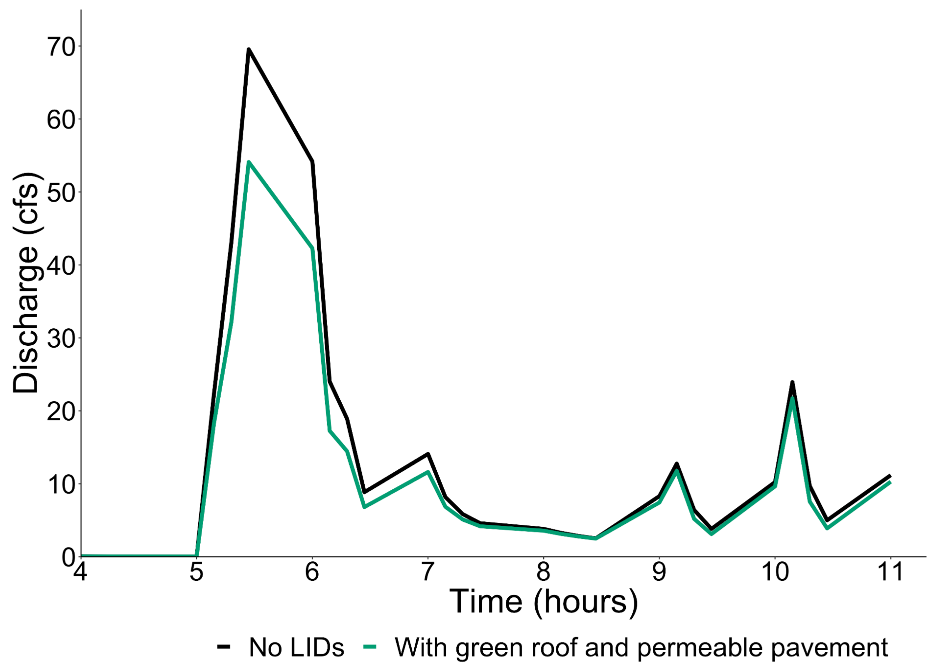

Figure 20. Time series of simulated LID scenario discharges from subcatchment 78 for the March 14, 2009 precipitation event with the Max MCF applied, starting at hour 4 of the storm. (Black: Simulated discharge (cfs) with no LIDs, Green: Simulated discharge (cfs) with the addition of a green roof and permeable pavement).

Results – Min MCF

When the Min MCF was applied to the March 14, 2009 storm event (representing average regional drier conditions), peak flow from subcatchment 78 decreased from 28.6 cfs to 8.4 cfs (a 70.6% decrease). With the addition of the green roof and permeable pavement LID controls, peak runoff decreased from 8.4 cfs to 6.3 cfs (Figure 21). This is a 25% reduction in peak runoff with the two LIDs in place compared with no LIDs. With the decrease in precipitation, the LIDs became slightly more effective at reducing the peak flow from subcatchment 78 (25% under the Min MCF scenario compared to 23% under normal conditions).

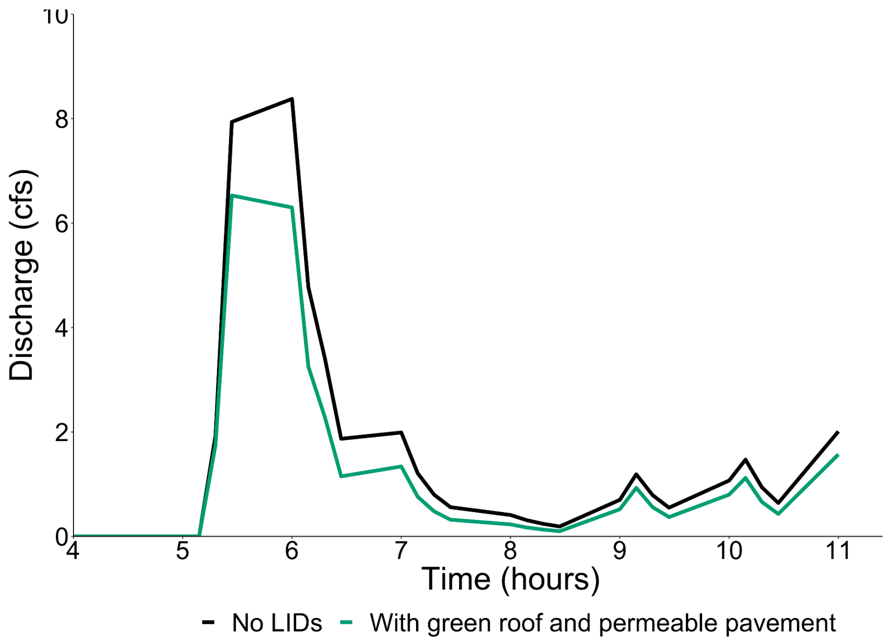

Figure 21. Time series of simulated LID scenario discharges from subcatchment 78 for the March 14, 2009 precipitation event with the Min MCF applied, starting at hour 4 of the storm. (Black: Simulated discharge (cfs) with no LIDs, Green: Simulated discharge (cfs) with the addition of a green roof and permeable pavement).

Optimal Locations for Green Infrastructure in Maunalua Bay

Rain gardens, in particular, are aesthetically pleasing, ideal for implementation at the residential scale, and capable of removing much of the sediment in runoff. Rain gardens are built depressions planted with vegetation that collects and treats stormwater runoff from impervious surfaces such as rooftops, driveways, parking lots, and roads (Figure 22). They are designed to capture runoff and filter the water through the plants and soils—reducing the amount of sediment and pollution entering storm drains, streams, and the ocean. Small, multiple rain gardens that are incorporated uphill and downhill of a given site or runoff hotspot would be the most effective (Cahill, et al., 2018). Ideally, rain gardens implemented in Maunalua Bay would serve to reduce the flow of sediment and pollutants into the Bay, decreasing harm inflicted on the coral reef habitat.

Figure 22. Community Rain Garden. Image from University of Minnesota.

Community rain garden programs already exist in Hawai'i such as the Koʻolaupoko Rain Garden Co-op and Cost Share Program, which provides grant funds for residents and communities who are interested in installing a rain garden on their property. The project grant funds come from the U.S. Environmental Protection Agency and the State of Hawaiʻi, Clean Water Branch, Polluted Control Runoff.

In order to identify optimal locations for rain garden placement throughout the entire Maunalua Bay region, different methods and data were utilized from the previous analyses. Instead of using SWMM and precipitation data from USGS, ArcGIS and rainfall data from the Rainfall Atlas of Hawaiʻi were used. Rainfall data was needed for the entire region, which was not available through USGS.

We created a ModelBuilder model in ArcGIS that consists of three models: Site Locator, Runoff Hotspot, and Optimal Rain Garden Location. The Site Locator model determines suitable locations for rain garden placement based on proximity to impervious surfaces, buildings, streams, sidewalks, wetlands, stormwater drains, flood zones, and parks, as well as the location's slope and soil curve number. Next, the Runoff model utilizes hydrologic tools in ArcGIS and rainfall data from the Rainfall Atlas of Hawaiʻi to determine areas of high runoff. Then, the

Optimal Rain Garden Location model takes into account the results from both aforementioned models to determine optimal rain garden intervention locations across the Maunalua Bay region. Lastly, we calculated the yearly volume of sediment reduction that results from rain garden implementation.

Site Locator Model

The suitable locations for rain gardens are mostly in the lower parts of the watersheds due to the slope restriction of a 6% grade or less (Figure 23). This is also due to the fact that the upper watershed is mostly natural habitat and our model focuses on locating rain gardens near impervious surfaces.

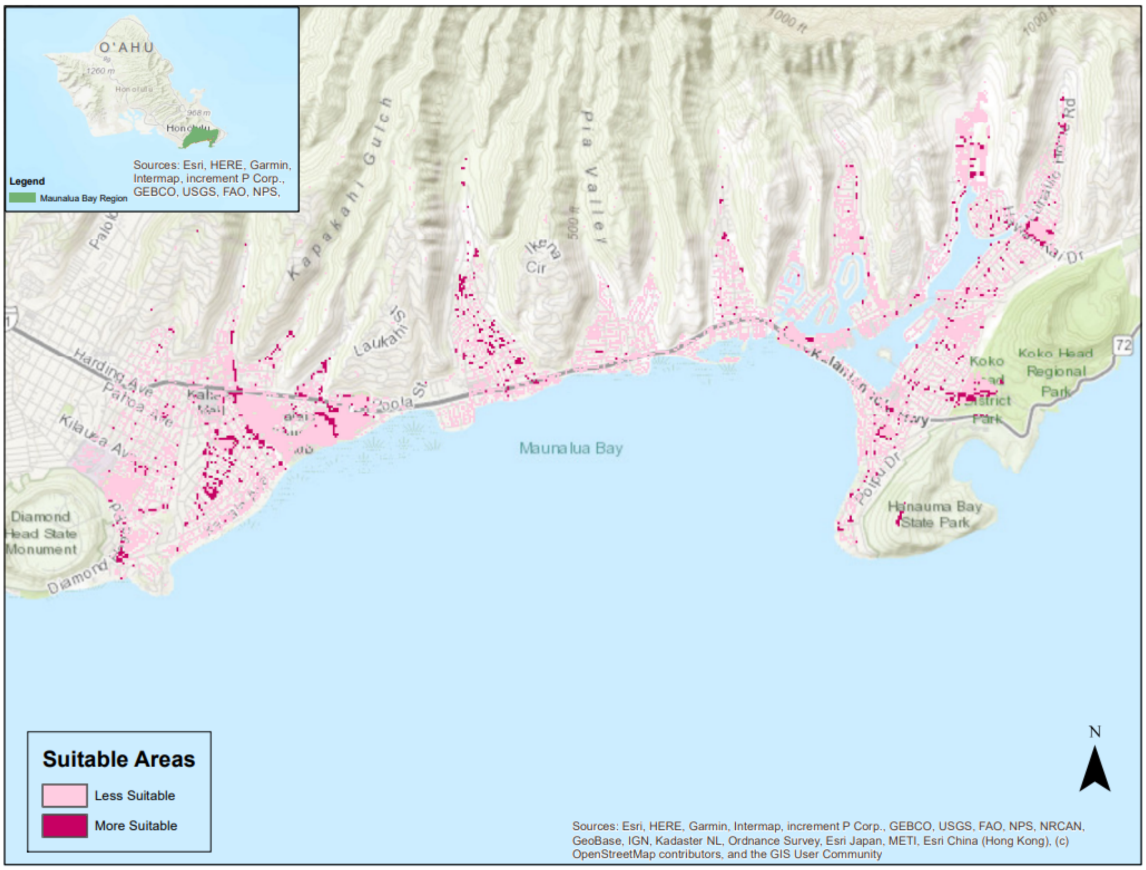

Figure 23. Site Locator Model Results. All of the suitable locations for rain gardens are in pink. The darker pink indicates the upper quantile of the data, where rain gardens are most suitable due to proximity to streams, stormwater drains, flood zones, impervious surfaces, parks, and wetlands. Data from the City and County of Honolulu, the Hawaii Statewide GIS Program, and The University of Hawaii, among other sources listed in the metadata in Appendix L.

Runoff Hotspot Model

To determine a rainfall hotspot, the ArcGIS 'Flow Accumulation' tool was used, which calculates accumulated flow as the accumulated weight of all cells flowing into each downslope cell in the output raster. A rainfall hotspot should be an area that receives a large amount of water from surrounding cells at a higher elevation. The runoff hotspots map below is at a less fine scale resolution than our site suitability output map due to the resolution of the rain data available from the Rainfall Atlas of Hawai'i.

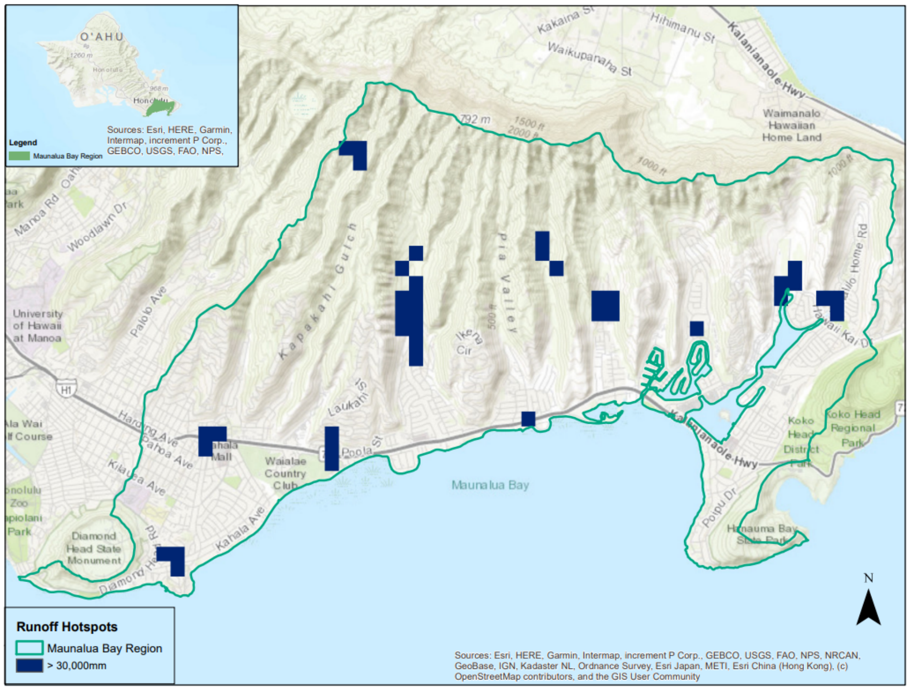

Figure 24. Runoff Hotspot Model Results. The areas of annual average flow accumulation of greater than 30,000 mm (the upper quantile) are shown in dark blue. Rainfall data from the Rainfall Atlas of Hawai'i.

Results in Figure 24 show there are runoff hotspots in both the urbanized and natural environment. The runoff hotspots in the urbanized lower watershed are expected since stormwater must flow through those areas to reach the ocean. However, the runoff hotspots in the natural upper watershed are unexpected. They appear to be pinch points in the landscape, where water must flow through a tight space. As the upper watershed tends to receive more rain, these areas have a large amount of rain water flowing through them in the tight valleys before the valleys widen. After the valleys widen, this water would then flow across a wider surface area, resulting in lower flow accumulation values.

For a future analysis on optimal rain garden placement, the flow accumulation values could be first constrained by the slope before taking the highest values. This would enable us to have more runoff hotspots within the area of interest. Rain garden placement in the upper watershed would ruin the natural habitat, and would limit the amount of water that could naturally flow over the surface and evaporate from the landscape before reaching the urbanized area.

Optimal Rain Garden Location Model

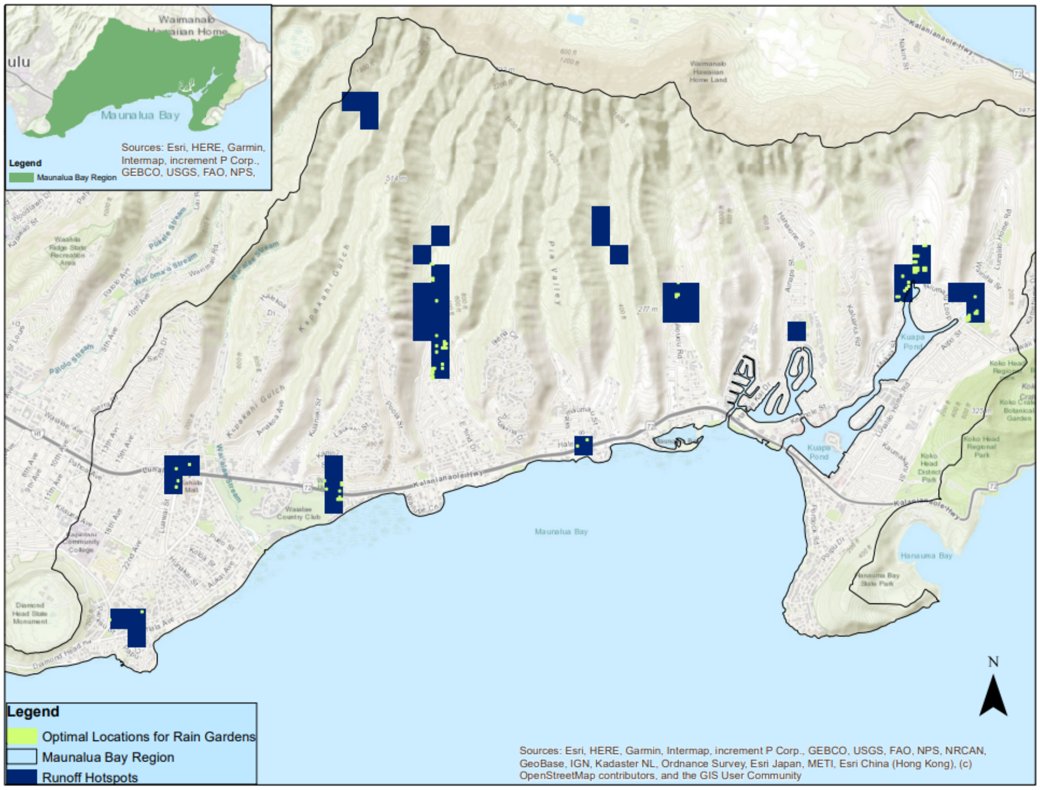

Figure 25. Optimal Locations for Rain Gardens. The runoff hotspots are in dark blue and the rain gardens are in green. The optimal locations for rain garden placement are areas where runoff hotspots are greatest and rain garden suitability is highest.

The runoff hotspots layer has a larger cell size (62,500 m^2) than the rain garden suitable locations layer (625 m^2). For this reason, we clipped the runoff hotspots by the rain garden suitable locations layer, resulting in a layer with the optimal locations for rain gardens that had cell areas of 625 m^2. We conservatively assumed that one 25 m^2 rain garden could fit within each optimal location cell, although theoretically 25 could fit. This allows for variability in placement of the rain garden. If the optimal location overlaps both public and private property, the one rain garden could be implemented in either location within the optimal cell depending on who is building it. However, stakeholders could decide to place more rain gardens within the optimal location cell.

Sediment Calculation

In order to calculate the amount of sediment removed by rain gardens, we first needed to identify the amount of sediment that would flow when it rains. The amount of sediment that would flow per mm of rainfall (0.6 kg/mm) was calculated using the below equation. The average annual suspended sediment concentration, taken at a stream gauge in Maunalua Bay in 2009, measured 9.6 mg/L (USGS 16247550 Wailupe Gulch at E. Hind Dr. Bridge, Oʻahu, HI) (Storlazzi, et al., 2010). Using the USGS Rainfall Calculator, we found that 1 mm of rainfall on an area of 62,500 m^2 is equal to 62,500 L of water. We multiplied these two numbers to determine the amount of sediment per mm of rainfall.

$$\frac{9.6\,mg}{L} * \frac{62{,}500\,L}{1\,mm} = 0.6\,\frac{sediment\,(kg)}{rainfall\,(mm)}$$

Next, we created an equation to calculate the per year sediment reduction that results from rain garden implementation in a particular hotspot. We divided the annual flow accumulation per cell (found in the Runoff model) by the runoff hotspot cell area (62,500 m^2) to get the flow accumulation per m^2. We then multiplied this by the rain garden area (25 m^2) to determine how much rain would flow through each rain garden. Next, we multiplied the flow through the rain garden by the number of rain gardens within the hotspot. Then, we multiplied by the amount of sediment that would flow per mm of rainfall (0.6 kg/mm) to get the amount of sediment that flows through the hotspot per year. This number was then multiplied by 0.56 to determine the amount of sediment that each rain garden would be able to remove from runoff per year, as it is recommended that rain gardens aim to reach a target of sediment reduction by 56% to be effective (Cahill, et al., 2018).

$$\frac{annual\,flow\,accum.\,per\,cell\,(mm/year)}{62{,}500\,(m^2)} * 25\,(m^2) * number\,of\,rain\,gardens * 0.6\,\frac{sediment\,(kg)}{rainfall\,(mm)} * 0.56 = \frac{sediment\,(kg)}{year}$$

Implementing all 81 rain gardens could reduce the amount of sediment by 6,408 kg per year. To put this into context, the annual suspended sediment discharge from the same stream gauge in 2009 (USGS 16247550 Wailupe Gulch at E. Hind Dr. Bridge, Oʻahu, HI) discharged 286,089.78 kg of sediment into the Bay. As this sediment reduction is not significant compared to how much sediment is annually discharged from one stream gage, rather than focusing on implementing many rain gardens, capture solutions which will capture sediment high in the watershed at the source, may be a more effective option.

Table 6. The amount of sediment reduction by implementing rain gardens in runoff hotspots in Maunalua Bay, given flow accumulation, assuming that sediment flow is 0.6 kg/mm of rainfall.

Hotspot #	Rain Gardens	Flow Accumulation (mm rain)	Sediment Reduction (kg/yr)
1	4	9,193,579	4,942
2	8	32,000	34
3	1	38,900	5
4	18	80,000	194
5	2	36,262	10
6	3	2,051,482	827
7	33	45,000	200
8	8	22,830	25
9	4	318,000	171
Total	**81**	**11,764,053**	**6,408**

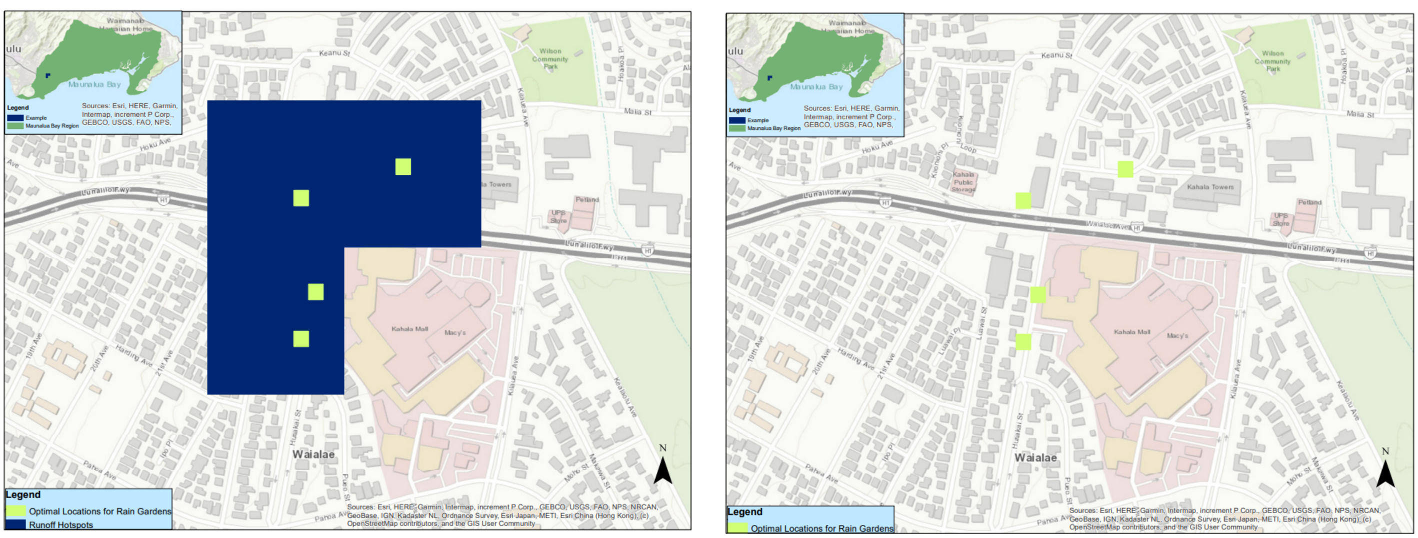

Figure 26. Kahala Mall Runoff Hotspot. Here is a zoomed-in example of one hotspot in the region. Runoff hotspot (blue) surrounding Kahala Mall in Maunalua Bay. The optimal locations for rain gardens are shown in green.

Kahala Mall Case Study

Kahala Mall is the only mall in the Maunalua Bay region and a known runoff hotspot. In March 2006, the mall was shut down due to flooding after a powerful thunderstorm (Hawaii News Now, 2006). This area had the highest flow accumulation in the region based on the DEM, which is compounded by the presence of a mall, a major impervious surface. 9,193,479 mm of rainfall flows through this hotspot each year and there are 4 optimal locations for rain gardens. Using these numbers and the equations above, we calculated that implementation of these 4 rain gardens can reduce the amount of sediment flowing into Maunalua Bay by 4,942 kg per year.

Cost Calculation

Rain gardens are estimated to cost \$1,230 per 100 ft^2, which equates to \$132 per m^2 (Cullison). Each 25 m^2 rain garden would cost \$3,310, and the total cost of all 81 rain gardens is \$268,110. These costs do not take into account upkeep for the rain gardens over time, as excess sediment will need to be removed in order for the rain garden to continue to effectively function. Also, the plants will need to be watered and tended to.

Rain Garden Recommendations

We recommend that the local government implement the 4 rain gardens outside Kahala Mall as a priority, before then focusing on building rain gardens in the 77 other optimal locations. Based on flow accumulation and ease of installation, these 4 rain gardens are responsible for 77% of the total estimated sediment reduction. In addition to the City and County of Honolulu installing the rain gardens, the City should also encourage property owners to install rain gardens on their land. Although rain gardens may not be the most effective type of green infrastructure for the region, given its low cost and effort to build, rain gardens may be an easy step towards implementing more green infrastructure. If implementing only 4 rain gardens outside Kahala Mall can reduce 4,942 kg per year, although it may not be significant compared to the annual amount of sediment discharge into the Bay, this reduction in sediment can still contribute to a healthier Bay.

Discussion

Our objective is to provide recommendations on green infrastructure selection and placement for runoff capture based on the results of our comprehensive hotspot identification within the Maunalua region. Determining optimal placement of green infrastructure is a complex task that must consider hydrologic factors, placement feasibility, and climate change effects to maximize both management benefits and successful capture. With the available data, we explored different LID strategies to show how we could provide the most effective green infrastructure for cost effectiveness and aesthetic consideration within the Wailupe watershed. Different green infrastructure design and placement results may be preferential, depending upon stakeholder engagement and feasibility.

Main Findings

The expansion of hydrologic models in the region has been hindered by the lack of available data. In order to obtain runoff hotspot findings and intervene with green infrastructure, more precipitation and stream gauges need to be placed in the Maunalua Bay region. Furthermore, implementation of green infrastructure at optimal locations such as Kahala Mall to reduce runoff, including sediment and pollutants, can have a significant impact on the heath of Maunalua Bay.

According to climate change projections and SWMM results, climate change could either increase or decrease storm intensity and runoff in the Maunalua Bay Region. We found that climate change projections can affect future stormwater runoff into the Bay, but under either future storm intensity scenario, green infrastructure elements will still provide significant stormwater runoff reductions.

Study Limitations

Our study was limited by the amount of precipitation and stream gauge data in the region. In order to calibrate the SWMM models, stream gauges will need to be placed within each watershed in the Maunalua Bay region. These stream gauges can be paired with the precipitation gauges that Mālama Maunalua recently installed for model calibration; however, based on our results, at least one paired precipitation gauge and stream gauge measurement at an hourly resolution, located above the stream gage in each watershed, is critical for a complete characterization of Maunalua Bay hydrology.

This study was also limited in its ability to model changes to pollutant loads as a result of LID control placement in the Wailupe watershed. In the absence of available pollutant data, overall runoff and peak flow were used as a proxy for pollutant loading from a subcatchment. In our analysis determining the optimal locations for rain garden placement in Kuliʻouʻou, annual average rainfall data was used, instead of storm data.

Green Infrastructure

Our results imply that green infrastructure can be an effective mechanism for reducing stormwater runoff flowing into Maunalua Bay from the urbanized environment.
Modeling of green infrastructure elements within the Wailupe watershed hotspots revealed significant reductions in total runoff volume and peak flow when implemented at a large enough scale. In order to have a significant impact on runoff reduction, appropriate forms of GI must be chosen. Small-scale GI features, such as rain gardens and rain barrels, are often lauded for their stormwater capture capabilities. However, this project has found that smaller-scale GI types are much less effective at reducing runoff in comparison to larger forms of GI incorporated at a level that is scaled to a roof, parking lot, or other large feature. Efforts to implement and encourage green infrastructure construction across the Maunalua Bay region should first focus on larger GI features, such as green roofing and permeable pavement. This is not to say that rain gardens and other small-scale green infrastructure options should be ignored, but rather designed, constructed, and placed in the most strategic manner possible in order to fully maximize their effectiveness. Targeting identified stormwater runoff hotspots within a watershed would be one strategic method when considering placement of any GI features, especially those of a smaller-size.

For the Wailupe watershed in particular, stormwater runoff hotspots have been found to be located primarily in residential areas. The costs associated with adding a highly effective GI feature to a residential property (e.g. a green roof or permeable driveway) are likely to deter many residents from wanting to make an investment in GI on their property. Government subsidies or rebate programs should be explored as one option for reducing the financial burden associated with adding GI features to residents' properties. The additional benefits outside of stormwater management should also be communicated to homeowners whenever possible. For example, green roofs can reduce a homeowner's energy costs related to heating and cooling; reduce air pollution and greenhouse gas emissions that would otherwise be emitted during energy production; and improve human health by reducing heat stress (USEPA, 2008).

Given the proven ability of green infrastructure to filter pollutants, it can also be inferred that green infrastructure elements will not only be effective at reducing the amount of runoff flowing from the urbanized environment, but that it will also be effective at improving runoff quality before it reaches the Bay's waters. When implemented across urbanized areas of the Maunalua Bay region, green infrastructure can serve as a stormwater management tool that intercepts chemical and sediment pollutants before it reaches the Maunalua Bay. However, it is important to note that an overwhelming majority of the sediment pollution that reaches Maunalua Bay originates in the upper watersheds and as a result, there are limitations on the potential of our recommended green infrastructure improving the overall health of Maunalua Bay.

Climate Change

Results show that the top ranking runoff coefficient and peak flow subcatchment hotspots in lower Wailupe watershed are similar across the minimum and maximum MCF applied. This is likely due to the influence of large areas (sqft) and high percent imperviousness from the urbanized lower watershed subcatchments (Tables 4 & 5). However, the ranking of peak flow hotspots were more variable when the minimum and maximum was MCF applied (Table 5). This can be attributed to the influence of subcatchment area (sqft), slope, and percent imperviousness. A previous Bren group project found peak flow can be attributed to high percept impervious cover (~45% or more) for peak flow hotspots in the lower Wailupe watershed region (Dornan et al., 2020). We identified specific subcatchments that experienced the greatest difference between max MCF scaled values and historical March 14, 2009 values associated with runoff coefficients and peak flow (subcatchement 63 and 89, for example). Therefore, strategic implementation of green infrastructure in the lower Wailupe watershed hotspots will ultimately help reduce runoff that feeds into the Maunalua Bay as climate change continues to impact the watershed.

The green roof and permeable pavement controls in subcatchment 78, scaled to the ʻĀina Haina Shopping Center, resulted in a 22.2% and 25% decrease of discharge with the Max and Min MCF applied, respectively, compared to a 23% decrease under the normal March 14, 2009 storm conditions. These results indicate that green infrastructure features have the ability to remain effective in the face of climate change, retaining their ability to reduce (and filter) stormwater runoff during larger storm events.

Our results also indicate that the probability of extreme climate change scaled events are likely to occur today. Therefore, strategic implementation of green infrastructure in the lower Wailupe watershed will aid in the preparation of extreme climate change events occurring today as well as in the future.

Conclusions

Currently, Maunalua Bay is experiencing an overwhelming amount of sediment buildup that is smothering corals. Reducing the flow of sediment into Maunalua Bay will help conserve biodiversity by protecting species that rely on the coral reef for habitat. Implementing green infrastructure targeted to reduce the flow of sediment can help promote a healthier environment for marine life, the coral reef community, and the community members. Furthermore, many community members depend on the Bay for their livelihoods and cultural practices, and protecting the coral reef will help to improve fishing and water quality. A main part of Hawaii's economy is reliant on tourism, which depends on maintaining the local environment. Coral reefs are valuable snorkeling sites for tourists. The implementation of green infrastructure throughout the Maunalua Bay region will bring economic and cultural benefits.

Study Relevance

This project contributes to the understanding of the hydrologic dynamics in the Maunalua Bay region that are connected to the health of Maunalua Bay. Our evaluation of the Bay has successfully created hydrological models for all of the watersheds, which provides complete coverage when combined with the pre-existing Wailupe model. Once the appropriate precipitation and stream gauge data is available, these models can be calibrated and used to identify effective management areas for both total runoff and peak flow (sediment hotspots) in the whole Bay. Identification of these hotspots assists Mālama Maunalua in prioritizing areas that are optimal for green infrastructure, reducing stormwater pollution into the Bay.

Furthermore, we have identified within the Wailupe watershed hotspot areas that are suitable for green roofs and permeable pavement, and how climate change is projected to impact these areas. Within the Kuliʻouʻou watershed, we have identified optimal locations for rain gardens which can significantly reduce sediment flowing into the Bay.

Recommendations for Future Work

Our SWMM models are the basic SWMM models with the stormwater network, slope, impervious surfaces, and soil curve numbers. These models could be improved to more accurately reflect reality by including other data such as temperature and evaporation data, which SMWM is able to take into account. In order to make the SWMM models more comprehensive, we recommend that temperature and evaporation data be included. Including temperature data could produce a more accurate model that considers how much water did not enter the stream due to evaporation throughout the time series.

Additionally, we recommend the placement of capture solutions in the upper watershed, such as sediment traps or basins, to address the significant sedimentation contributions originating in the upper watershed. Sediment traps and basins are often used at the inflow of green infrastructure features to assist with the removal of accumulated sediment and ensure the green infrastructure does not get clogged, but are often used on their own (USEPA, 2017). Green infrastructure placement is not feasible in the upper watershed due to the steep slopes and inaccessible terrain.

A coupled approach of upper watershed intervention and green infrastructure placement in the lower watershed could increase the effective capability of stormwater and sediment capture.

LIDs could be placed within SWMM to determine optimal placement in additional watersheds. Once calibrated, LID placement and parameter manipulation could reveal the highest capture impact on runoff reduction. A region-wide approach to green infrastructure placement would need more specific considerations of cost and aesthetic use.

Our findings will further aid Mālama Maunalua in their scientific analysis and community efforts through the Maunalua Bay region. The cumulative region-wide SWMM input files will identify hotspots that Mālama Maunalua can prioritize as they work to determine green infrastructure placement in the future. Our findings can provide the basis for Mālama Maunalua to pursue external grant funding or projects necessary for collaborative work with community partners and stakeholders to address continued ruoff issues with climate change implications.

References

Alsobrooks, A.D. Rain garden fact sheet. Prince George's County Department of the Environment. https://cbtrust.org/wp-content/uploads/Fact-Sheet-and-Guidelines_Rain-Garden_042120.pdf

Arcos-Aguilar, R., Favoretto, F., Kumagai, J.A., Jimenez-Esquivel, V., Martinez-Cruz, A.L., Aburto-Oropeza, O. Diving tourism in Mexico – Economic and conservation importance. (2021). Marine Policy, 126. https://www.sciencedirect.com/science/article/pii/S0308597X21000208?via%3Dihub#sec0115

Arlington Echo, Rain gardens. (2010). Environmental Literacy and Outdoor Education. https://www.arlingtonecho.org/restoration-projects/rain-gardens.html

Atkinson, Anne. (2007). A Natural and Cultural History of Maunalua Bay and Its Watershed. [Unpublished master's thesis, San Francisco State University]. http://www.imuamaunalua.org/wp-content/uploads/A-Natural-Cultural-History-of-Maunalua-Bay.pdf

Bessell-Browne, P., A. P. Negri, R. Fisher, P.L. Clode, A. Duckworth, R. Jones. (2017). Impacts of turbidity on corals: The relative importance of light limitation and suspended sediments. *Marine Pollution Bulletin.* 117: 161-170. https://doi.org/10.1016/j.marpolbul.2017.01.050

Blaisdell, R.K., Lake, J.K. & Chang, H.K. (2005). Cover Essay: Ka Ahupuaʻa. EcoHealth, 2, 373–375. https://doi.org/10.1007/s10393-005-8932-8

Cahill, M., Godwin, D., & Tilt, J.H. (2018). Rain gardens: low-impact development fact sheet. Oregon State University. https://extension.oregonstate.edu/sites/default/files/documents/12281/rain-gardens-fact-sheet.pdf

Chu, P., Chen, Y. R., & Schroeder, T. A. (2010). Changes in Precipitation Extremes in the Hawaiian Islands in a Warming Climate, Journal of Climate, 23(18), 4881-4900. Retrieved Mar 14, 2022, from https://journals.ametsoc.org/view/journals/clim/23/18/2010jcli3484.1

Cullison, Todd. Hawaii residential rain garden manual. Hui o Koʻolaupoko. https://www.huihawaii.org/uploads/1/6/6/3/16632890/raingardenmanual-web-res-smaller.pdf

Department of Planning and Permitting. (2019). Public Review Draft – East Honolulu Sustainable Communities Plan. http://www.honoluludpp.org/Portals/0/pdfs/planning/EastHonolulu/2019%20EHSCP%20PRD%20Feb%20Web.pdf

Dornan N., Durand, E., Jagadeesh, T., and Johnson, E. (2020). From Mauka to Makai: Reducing Stormwater Runoff Pollution in Maunalua Bay, Oʻahu, Hawaii. UC Santa Barbara Bren School of Environmental Science & Management. https://bren.ucsb.edu/projects/creating-region-wide-green-infrastructure-strategic-plan-maunalua-bay

Fabricius, K. E. (2005). Effects of terrestrial runoff on the ecology of corals and coral reefs: review and synthesis. Marine Pollution Bulletin, 50(2), 125-156. https://doi.org/10.1016/j.marpolbul.2004.11.028

Fletcher, C. (2010). Hawai'i's Changing Climate. School of Ocean and Earth Science and Technology, University of Hawai'i at Manoa. https://www.soest.hawaii.edu/coasts/publications/ClimateBrief_low.pdf

Giambelluca, T. W., Diaz, H. F., & Luke, M. S. A. (2008). Secular temperature changes in Hawaiʻi. *Geophysical Research Letters*, *35*(12). https://doi.org/10.1029/2008GL034377

Hallock, P. & Schlager, W. (1986). Nutrient excess and the demise of coral reefs and carbonate platforms. PALAIOS, 1(4), 389. https://doi.org/10.2307/3514476

Hawaiʻi Clean Water Branch, Polluted Runoff Control. (2008). Annual Report Fiscal Year 2008. Hawaiʻi State Department of Health. https://health.hawaii.gov/cwb/files/2013/05/PRC_EndOfYearReport2008.pdf

IPCC, 2021: Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [MassonDelmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press. In Press.

Katsifarakis, K.L., Vafeiadis, M., & Theodossiou, N. (2015). Sustainable drainage and urban landscape upgrading using rain gardens, site selection in Thessaloniki, Greece. Agriculture and Agricultural Science Procedia, 4, 338-347. https://www.sciencedirect.com/science/article/pii/S2210784315001011

Kittinger, J. N., Bambico, T. M., Minton, D., Miller, A., Mejia, M., Kalei, N., Wong, B., & Glazier, E. W. (2016). Restoring ecosystems, restoring community: Socioeconomic and cultural dimensions of a community-based coral reef restoration project. Regional Environmental Change, 16(2), 301–313. https://doi.org/10.1007/s10113-013-0572-x

Luo, Q.L., Hillock, D., & Holmes, M. (2017). Sustainable landscapes: designing a rain garden for residential property. Oklahoma State University. https://extension.okstate.edu/fact-sheets/sustainable-landscapes-designing-a-rain-garden-for-residential-property.html

Mālama Maunalua. (2006). Maunalua Bay conservation action plan. https://www.conservationgateway.org/Documents/Maunalua-Bay-CAP.pdf

Malaviya, P., Sharma, R., & Sharma, P.K. (2019). Rain gardens as stormwater management tool. Sustainable Green Technologies for Environmental Management, 141-166. https://link.springer.com/chapter/10.1007/978-981-13-2772-8_7

Miller, A., Wilcox, C., Davis, G., Oram, R., Chaston, K., Co, E., Salz, R. (2009). Maunalua Bay Regional Watershed Strategy: A Community Approach. Mālama Maunalua. http://www.malamamaunalua.org/wp-content/uploads/Maunalua-Regional-Watershed-Strategy-2009.pdf

Mueller-Dombois, D. (2007). The Hawaiian Ahupua'a Land Use System: Its Biological Resource Zones and the Challenge for Silvicultural Restoration, Bishop Museum Bulletin in Cultural and Environmental Studies, 3, 23–33. http://hbs.bishopmuseum.org/pubs-online/strm/04-Mueller-Domboisr.pdf

National Oceanic and Atmospheric Administration (NOAA). (2015). El Niño and its Impacts on The Hawaiian Islands. https://www.pacificrisa.org/wp-content/uploads/2015/11/Pacific-Region-EL-NINO-Fact-Sheet_Hawaii_2015-FINAL.pdf

Murakami, H., Wang, B., Li, T., & Kitoh, A. (2013). Projected increase in tropical cyclones near Hawaii. Nature Climate Change, 3(8), 749–754. https://doi.org/10.1038/nclimate1890

National Oceanic and Atmospheric Administration, National Centers for Environmental Information. 2020. Data Tools: Find a Station – Precipitation 15 Minute. https://www.ncdc.noaa.gov/cdo-web/datatools/findstation.

National Oceanic and Atmospheric Administration, Office for Coastal Management. (2015). Green Infrastructure Options to Reduce Flooding https://coast.noaa.gov/data/digitalcoast/pdf/gi-reduce-flooding.pdf.

National Park Service. What is a Green Roof? (2021). https://www.nps.gov/tps/sustainability/new-technology/green-roofs/define.htm.

Norton, C. W., Chu, P.-S., & Schroeder, T. A. (2011). Projecting changes in future heavy rainfall events for Oʻahu, Hawaii: A statistical downscaling approach. Journal of Geophysical Research: Atmospheres, 116(D17). https://doi.org/10.1029/2011JD015641

O'Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., et al. (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. Geoscientific Model Development, 9(9), 3461–3482. https://doi.org/10.5194/gmd-9-3461-2016

Ratzlaff, J. R. (1994). Mean Annual Precipitation, Runoff, and Runoff Ratio for Kansas, 1971-1990. Transactions of the Kansas Academy of Science (1903-), 97(3/4), 94–101. https://doi.org/10.2307/3627776

Rogers, Caroline S. "Responses of Coral Reefs and Reef Organisms to Sedimentation." Marine Ecology Progress Series, vol. 62, 1990, pp. 185–202. DOI.org (Crossref), https://doi.org/10.3354/meps062185.

Sharma, R. & Malaviya, P. (2021). Management of stormwater pollution using green infrastructure: The role of rain gardens. *WIREs Water, 8*(2), https://doi.org/10.1002/wat2.1507.

Sparkman, S.A., Hogan, D.M., Hopkins, K.G., and Loperfido, J.V. (2017). Modeling watershed-scale impacts of stormwater management with traditional versus low impact development design. *Journal of the American Water Resources Association, 53*(8), http://dx.doi.org/10.1111/1752-1688.12559.

State of Hawaiʽi Department of Transportation. Sidewalks and walkways. https://hidot.hawaii.gov/highways/files/2013/07/Pedest-Tbox-Toolbox_4-Sidewalks-and-Walkways.pdf

Stevens, L., R. Frankson, K. Kunkel, P-S. Shin, and W. Sweet. (2017). Hawaii State Climate Summary. NOAA Technical Report NESDIS 149-HI, 4 pp. https://statesummaries.ncics.org/chapter/hi/

Storlazzi, C.D., Presto, M.K., Logan, J.B., and Field, M.E. (2010) Coastal circulation and sediment dynamics in Maunalua Bay, Oahu, Hawaii; measurements of waves, currents, temperature, salinity, and turbidity; November 2008-February 2009: U.S. Geological Survey Open-File Report 2010-1217. http://pubs.usgs.gov/of/2010/1217/

SUNY College of Environmental Science and Forestry. Runoff calculator page 2: curve number. Stormwater Management. https://www.esf.edu/ere/endreny/GICalculator/CurveNumberInstruct.html?0

Takesue, R., & Storlazzi, C. (2017). Sources and dispersal of land-based runoff from small Hawaiian drainages to a coral reef: Insights from geochemical signatures. Estuarine, Coastal and Shelf Science, 188, 69-80. https://doi.org/10.1016/j.ecss.2017.02.013

US Congress. (2019). Public Law 115-436 Water infrastructure improvement act. https://www.congress.gov/115/plaws/publ436/PLAW-115publ436.pdf

USDA Natural Resource Conservation Service. (2004). Water Technical Note - No. 12, Final 2004 List of Impaired Waters in Hawaii. USDA. https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs142p2_036828.pdf.

USDA Natural Resources Conservation Service. Rain garden fact sheet. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/null/?cid=nrcs142p2_008528

USEPA. NPDES: Stormwater Best Management Practice, Permeable Pavements (2013). https://www.epa.gov/system/files/documents/2021-11/bmp-permeable-pavements.pdf

USEPA. NPDES: Stormwater Best Management Practice, Bioretention (Rain Gardens) (2013). https://www.epa.gov/system/files/documents/2021-11/bmp-bioretention-rain-gardens.pdf

USEPA. Reducing Urban Heat Islands: Compendium of Strategies- Green Roofs. (2008). https://www.epa.gov/sites/default/files/2017-05/documents/reducing_urban_heat_islands_ch_3.pdf.

USEPA 2012 Green Infrastructure Technical Assistance Program. (2014). Addressing green infrastructure design challenges in the Pittsburgh region. USEPA. https://www.epa.gov/sites/default/files/2015-10/documents/pittsburgh-united-steep-slopes-508.pdf

USEPA. Green Infrastructure Design and Implementation. (2017). Green Infrastructure. https://19january2017snapshot.epa.gov/green-infrastructure/green-infrastructure-design-and-implementation_.html

USEPA. Terminology of Low Impact Development. (2012). LID Barrier Busters Fact Sheet Series. https://www.epa.gov/sites/default/files/2015-09/documents/bbfs2terms.pdf

USEPA. What is green infrastructure? (2021). https://www.epa.gov/green-infrastructure/what-green-infrastructure

Waters, K. A., & Curran, J. C. (2015). Linking bed morphology changes of two sediment mixtures to sediment transport predictions in unsteady flows. Water Resources Research, 51(4), 2724–2741. https://doi.org/10.1002/2014WR016083

Watershed/Mauka Watch. (2011). Watershed management, Mālama Maunalua., 18 Jan. 2011.

Weber, M., Lott, C., & Fabricius, K. E. (2006). Sedimentation stress in a scleractinian coral exposed to terrestrial and marine sediments with contrasting physical, organic and geochemical properties. Journal of Experimental Marine Biology and Ecology, 336(1), 18–32. https://doi.org/10.1016/j.jembe.2006.04.007

Webber, J.L., Fletcher, T.D., Cunningham, L., Fu, G., Butler, D., & Burns, M.J. (2019). Is green infrastructure a viable strategy for managing urban surface water flooding? Urban Water Journal, 17(7), 598-608. https://doi.org/10.1080/1573062X.2019.1700286

Williams, I.D., et al. Meijia, M., Caldwell, Z.R., Pollock, K.S., & Conklin, E.J., (2009). Nature Conservancy of Hawaii Maunalua Marine Survey Report. The Nature Conservancy of Hawaii. http://www.malamamaunalua.org/wp-content/uploads/TNC-2009-1.pdf

Wolanski, E., Martinez, J. A. & Richmond, R. H. (2009). Quantifying the impact of watershed urbanization on a coral reef: Maunalua Bay, Hawaii. Estuarine, Coastal and Shelf Science, 84(2), 259-268. https://doi.org/10.1016/j.ecss.2009.06.02

Appendices

Appendix A

Stormwater Network Model

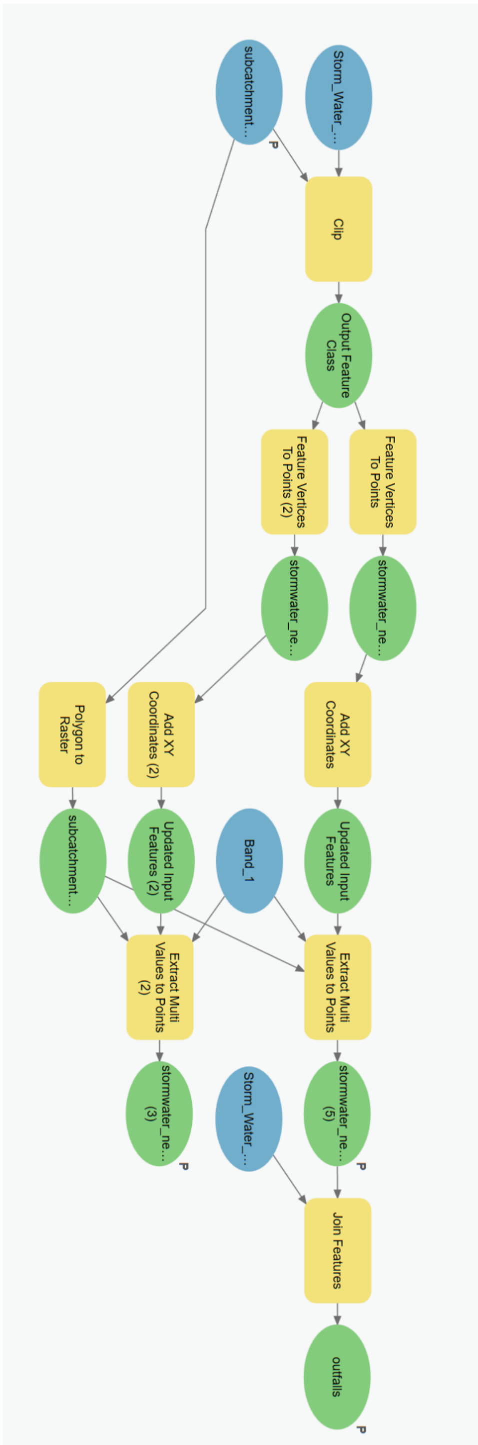

Figure A.1 Stormwater Network ArcGIS Model.

Appendix B

Subcatchment Delineation Methods and Models

We created an ArcGIS model that did the following. We reprojected all data into WGS 84 (Data Management Toolbox - Project and Project Raster). From the watershed outlines of the Maunalua Bay region, we selected only Kuliʻouʻou (Select Layer by Attribute). Then, we clipped the stormwater network and stream data to the Kuliʻouʻou watershed (Clip and Clip Raster). We next connected disconnect lines in the stormwater network by extending the lines to within 15 meters (Extend Line). After, we merged the conduits with the streams, repaired the geometry, and extended lines again to ensure they were connected (Merge, Repair Geometry, and Extend Line). We also filled the sinks in the DEM (Fill). We converted the stream and conduit layer to raster to recondition the DEM (Polyline to Raster). The DEM was reconditioned by the stormwater network – consisting of pipes, outfalls, and streams (DEM reconditioning). Finally, we ran the standard delineation tools: generate a flow direction raster (ArcHydro- Flow Direction), create basins from the flow direction raster (Spatial Analyst - Basins), and create the watershed boundaries from the basins raster (Raster To Polygon). Then, the subcatchment boundaries were converted to points with XY coordinates and exported as a .csv suitable for the SWMM input file.

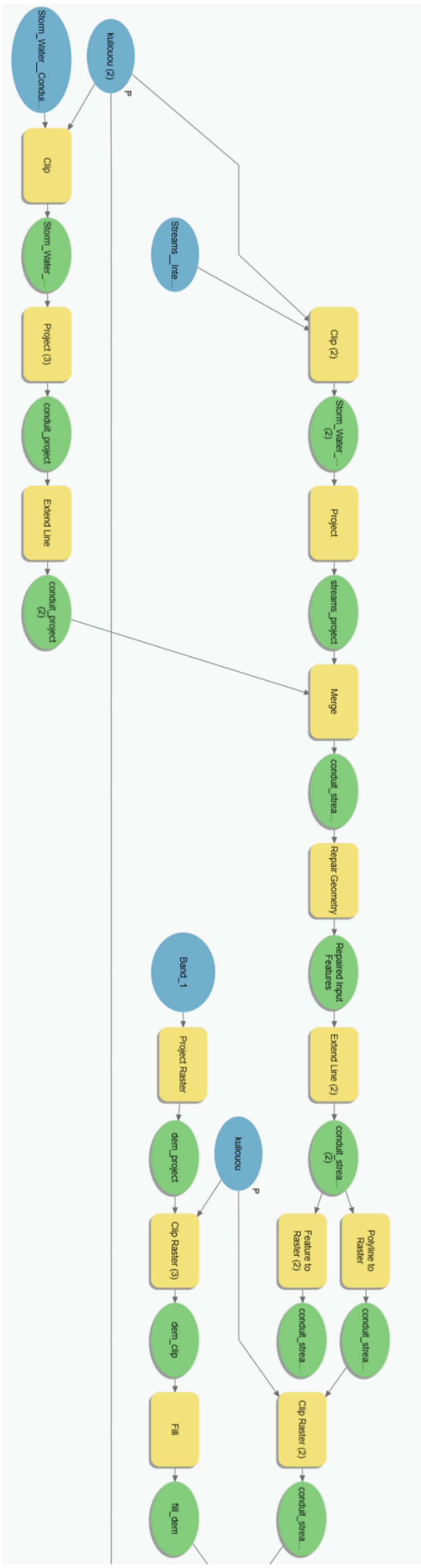

Figure B.1. Subcatchment Delineation ArcGIS Model Part 1.

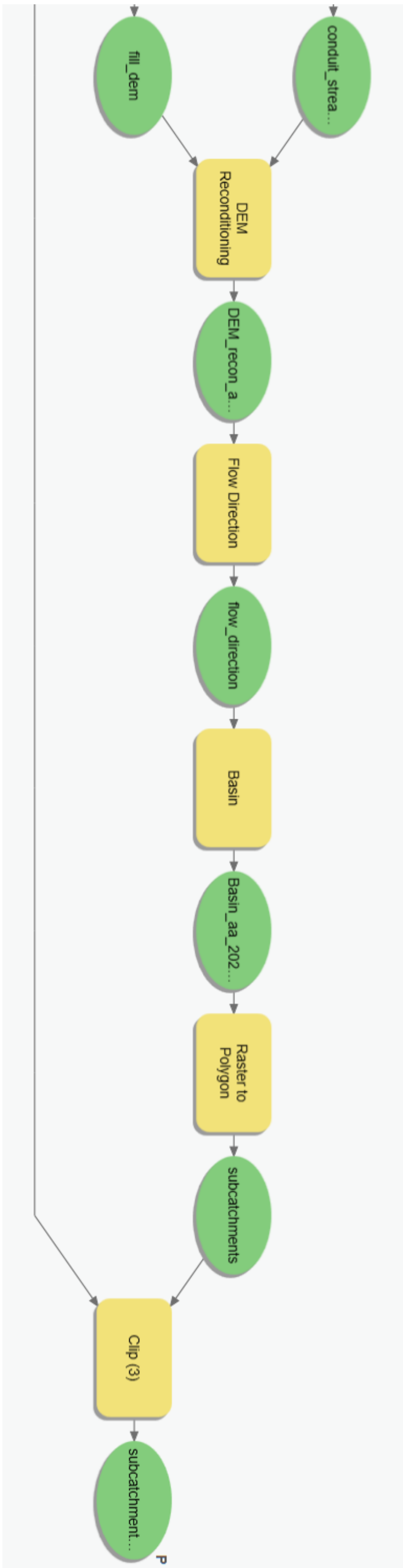

Figure B.2. Subcatchment Delineation ArcGIS Model Part 2.

Appendix C

Subcatchment Characteristics Methods and Models

We created an ArcGIS model that calculated percent impervious cover and slope for each subcatchment in the Kuliʻouʻou watershed. Percent impervious cover is calculated using data layers for existing bike lanes, buildings and rooftops, and roads. The spatial layer for roads was buffered by 6 feet to account for sidewalks (Buffer). All streets were assumed to have sidewalks. This layer was then unioned with the buildings footprints layer and bike facilities layer to take into account impervious buildings, rooftops, and bike paths (Union).

The resulting layer was then compared to Google Earth images of Kuliʻouʻou watershed to ensure that no major impervious surfaces were missed, such as parking lots and roads. The few surfaces that were missed were then drawn manually into the layer. The percent of impervious cover in each subcatchment was then calculated using the "Tabulate Area Intersection" tool in ArcGIS.

For slope, the DEM layer for Maunalua Bay was projected into WGS 84 (Data Management Toolbox - Project and Project Raster). Next, the slope for the whole region was calculated and then each cell value of the raster was converted to an integer by truncation (Slope; Int). The slope raster was then converted to a polygon (Raster to Polygon). The percent of slope in each subcatchment was then calculated using the "Tabulate Area Intersection" tool.

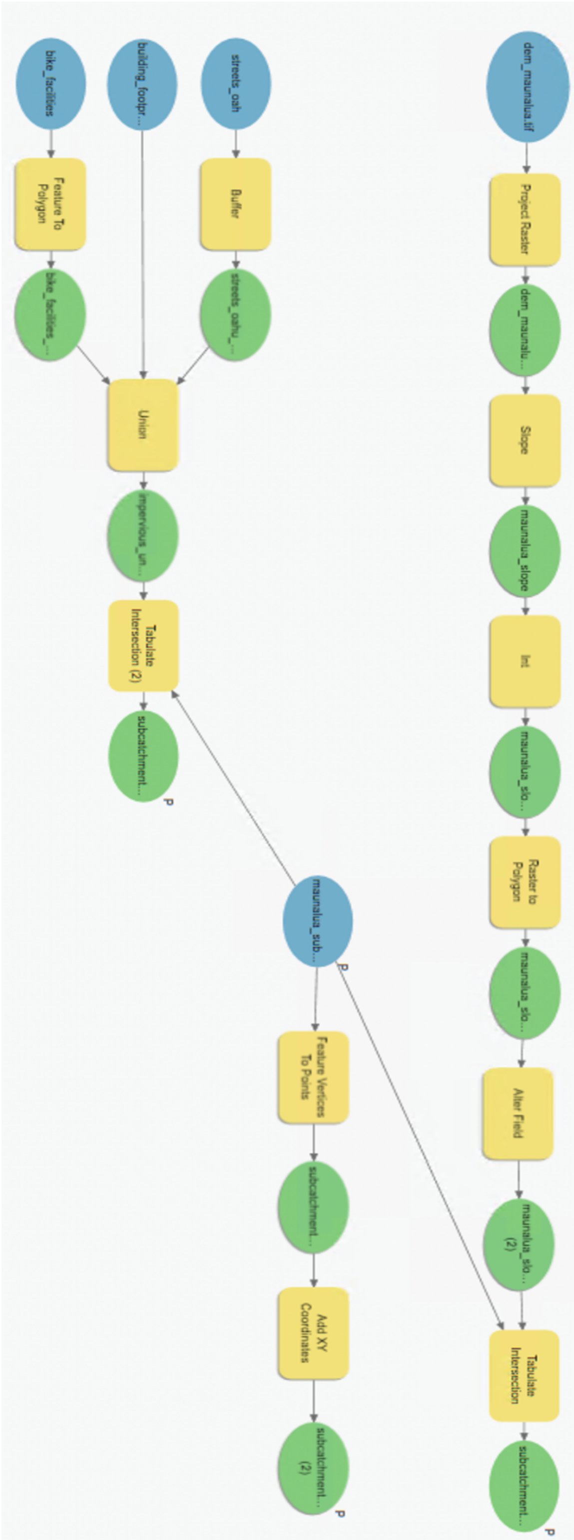

Figure C.1 Subcatchment Characteristics ArcGIS Model.

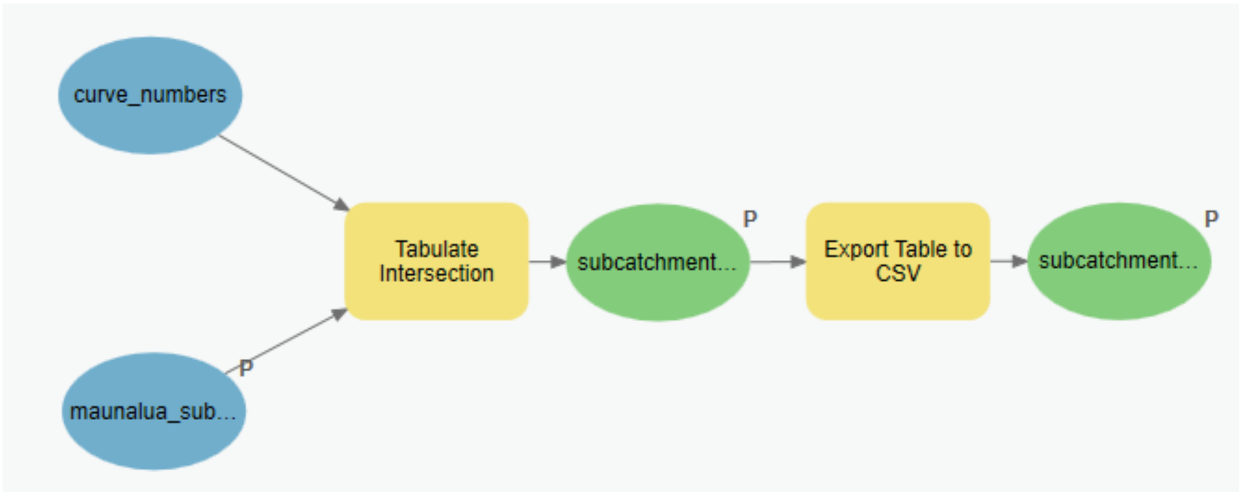

Figure C.2 Curve Number ArcGIS Model.

Appendix D

Subcatchment Characteristics SWMM Inputs

```
[SUBCATCHMENTS]
;;Name           Rain Gage        Outlet           Area     %Imperv  Width    %Slope
;;-------------- ---------------- ---------------- -------- -------- -------- --------
1                R1               J28              24.19730286 0           400         39.1670099
2                R1               J28              28.02701288 0           400         40.03444124
4                R1               J28              61.36141722 0           400         42.26163313
5                R1               6                182.4095206 0           400         35.17776052
6                R1               7                82.54138257 0           400         26.65275257
7                R1               J153             64.59418544 0.65179986  400         26.43150238
9                R1               J204             1.503889658 31.8259591  133.0135518 11.08344224
10               R1               J261             19.44408823 4.704323194 400         24.80948632
11               R1               J212             15.80270455 1.977154214 400         24.55093604
12               R1               J207             20.32994323 0.096263372 400         24.30728808
14               R1               J188             18.62584262 0.022137958 400         25.98126211
18               R1               21               0.254760948 0           16.35438205 8.410732214
19               R1               J191             4.239338295 0.209930589 9.790041963 20.97102443
20               R1               21               0.319184774 0           21.26014693 5.865671419
21               R1               J214             16.07947238 0.631095375 400         24.87200184
27               R1               J153             137.8810382 0.439998296 300         28.18444499
28               R1               J68              0.885211 27.75916462   15.30186809 6.635215605
29               R1               J33              1.467963649 19.87951785 55.89268185 6.212734453
30               R1               J175             1.780428067 31.24775051 200         7.343252298
31               R1               J35              2.6355038 24.81529291  38.32211664 10.20984243
32               R1               J177             184.7741424 13.10253318 400         19.84290028
33               R1               J256             16.80044739 1.593483141 400         26.98650018
37               R1               J218             0.929276535 54.01730979 258.4462782 1.050916937
38               R1               J193             1.914448825 43.41958948 300         1.656374265
39               R1               J77              7.581719689 21.82160771 400         12.97960356
40               R1               J26              12.04433663 0           400         29.34109871
41               R1               J41              15.6252043 20.35907081  400         17.79208429
42               R1               J271             107.9757733 25.23290066 400         10.04769159
44               R1               J293             3.646546106 4.049436877 200         21.83246032
45               R1               J310             0.868133864 22.53818108 400         7.952872095
50               R1               J295             27.97197097 29.6564504  400         0.042753398
55               R1               J292             13.43872471 27.27890511 400         4.993677116
62               R1               J22              9.398419019 9.857653023 400         13.02126595
97               R1               J85              40.91635444 20.14527434 400         12.07699991
122              R1               J14              9.908515044 2.551149353 400         12.02171351
127              R1               J17              21.98572423 13.80571742 400         2.504237553
136              R1               122              59.10523394 3.829467667 400         14.63815312
139              R1               J3               3.645018968 35.10937671 200         2.372113202
232              R1               J10              2.680079306 26.01336487 200         0
242              R1               J7               5.048323783 38.02624955 400         2.118329265
```

```
[SUBAREAS]
;;Subcatchment   N-Imperv   N-Perv     S-Imperv   S-Perv     PctZero    RouteTo
;;-------------- ---------- ---------- ---------- ---------- ---------- ----------
1                0.01       0.4        0.2        0.3        0          OUTLET
2                0.01       0.4        0.2        0.3        0          OUTLET
4                0.01       0.4        0.2        0.3        0          OUTLET
5                0.01       0.4        0.2        0.3        0          OUTLET
6                0.01       0.4        0.2        0.3        0          OUTLET
7                0.01       0.4        0.2        0.3        0          OUTLET
9                0.01       0.15       0.2        0.3        0          OUTLET
10               0.01       0.4        0.2        0.3        0          OUTLET
11               0.01       0.4        0.2        0.3        0          OUTLET
12               0.01       0.4        0.2        0.3        0          OUTLET
14               0.01       0.4        0.2        0.3        0          OUTLET
18               0.01       0.4        0.2        0.3        0          OUTLET
19               0.01       0.4        0.2        0.3        0          OUTLET
20               0.01       0.4        0.2        0.3        0          OUTLET
21               0.01       0.4        0.2        0.3        0          OUTLET
27               0.01       0.4        0.2        0.3        0          OUTLET
28               0.01       0.15       0.2        0.3        0          OUTLET
29               0.01       0.15       0.2        0.3        0          OUTLET
30               0.01       0.15       0.2        0.3        0          OUTLET
31               0.01       0.15       0.2        0.3        0          OUTLET
32               0.01       0.4        0.2        0.3        0          OUTLET
33               0.01       0.4        0.2        0.3        0          OUTLET
37               0.01       0.15       0.2        0.3        0          OUTLET
38               0.01       0.15       0.2        0.3        0          OUTLET
39               0.01       0.15       0.2        0.3        0          OUTLET
40               0.01       0.4        0.2        0.3        0          OUTLET
41               0.01       0.15       0.2        0.3        0          OUTLET
42               0.01       0.15       0.2        0.3        0          OUTLET
44               0.01       0.15       0.2        0.3        0          OUTLET
45               0.01       0.15       0.2        0.3        0          OUTLET
50               0.01       0.15       0.2        0.3        0          OUTLET
55               0.01       0.15       0.2        0.3        0          OUTLET
62               0.01       0.15       0.2        0.3        0          OUTLET
97               0.01       0.15       0.2        0.3        0          OUTLET
122              0.01       0.4        0.2        0.3        0          OUTLET
127              0.01       0.15       0.2        0.3        0          OUTLET
136              0.01       0.4        0.2        0.3        0          OUTLET
139              0.01       0.15       0.2        0.3        0          OUTLET
232              0.01       0.15       0.2        0.3        0          OUTLET
242              0.01       0.15       0.2        0.3        0          OUTLET
```

Appendix E

Maunalua Bay Region Soil Curve Numbers by Land Cover and Hydrologic Group

Table E.1 Soil Curve Numbers by Land Cover and Hydrologic Groups found in the Maunalua Bay Region, O'ahu. Data from Dornan et al., 2020.

Land Cover	Hydrologic Group A	Hydrologic Group B	Hydrologic Group C	Hydrologic Group D
Grassland: poor condition	68	79	86	89
Unconsolidated shore	0	0	0	0
Bare Land/Bare soil	77	86	91	94
Open Space Developed- good	39	61	74	80
Evergreen forest- fair	36	60	73	79
Scrub Shrub	36	42	55	62
Open Water	0	0	0	0
Impervious surface- like shrubland	36	42	55	62
Palustrine Scrub Shrub wetland (woody wetland)	86	86	86	86
Palustrine Forested wetland (woody wetland)	86	86	86	86
Palustrine Aquatic Bed	NA	NA	NA	NA
Estuarine Emergent wetland	80	80	80	80
Palustrine emergent wetland	80	80	80	80
Pasture/Hay	40	61	73	79
Unclassified - here: open water	0	0	0	0
Cultivated Land	62	74	82	86

Appendix F

Kuliʻouʻou Precipitation Data Analyses

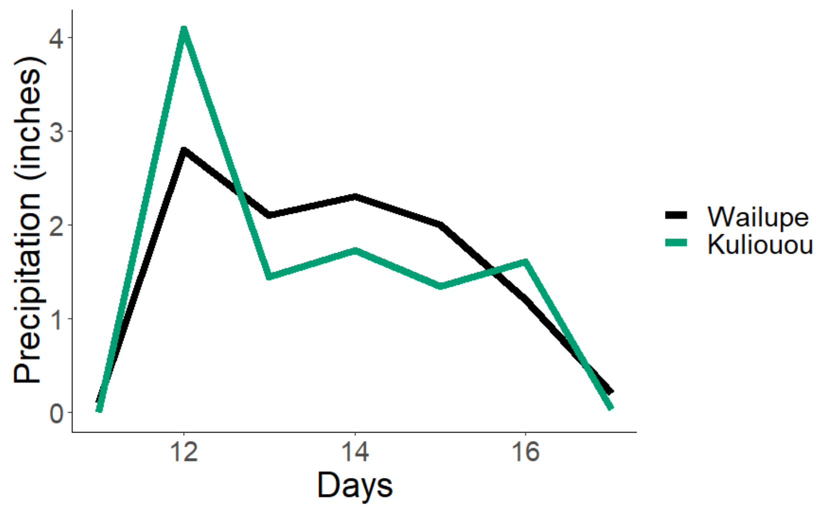

Figure F.1 Wailupe Valley School and Paiko Drive NOAA precipitation data comparison for November 12-16, 1996 storm.

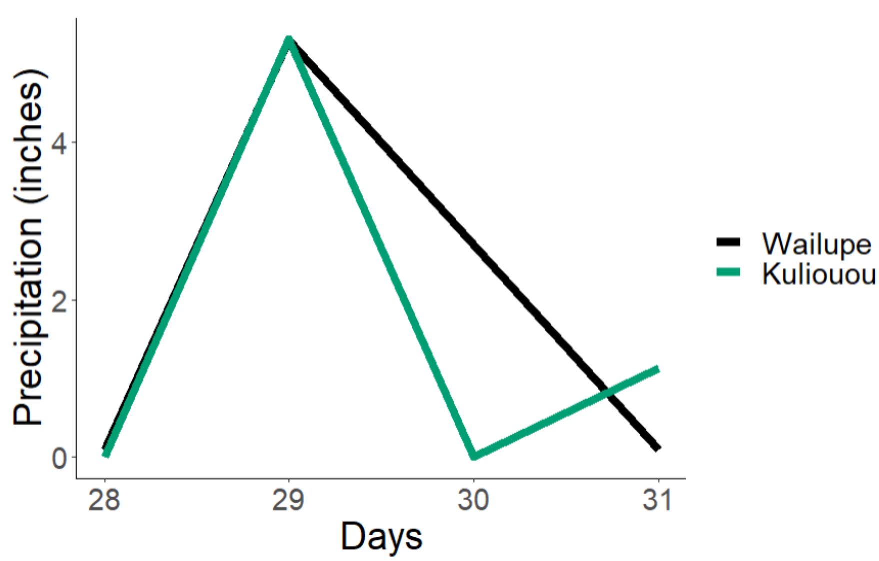

Figure F.2 Wailupe Valley School and Paiko Drive NOAA precipitation data comparison for January 28-31, 2005 storm.

Appendix G

Parameters for Relevant LID Controls

The following section lists the parameters used for the relevant LID controls modeled in this project: Green roofs, permeable pavement, and rain gardens. Each LID control is associated with a different combination of layers.

*layer is optional and was not included in LID design

GREEN ROOF:

SURFACE LAYER
- Berm Height = 2
- Vegetation Volume Fraction = 0.2
- Surface Roughness = 0.19
- Surface Slope = 1

SOIL LAYER
- Thickness = 6
- Porosity = 0.42
- Field Capacity = 0.3
- Wilting Point = 0.08
- Conductivity = 0.5
- Conductivity Slope = 5
- Suction Head = 3

DRAINAGE MAT
- Thickness = 1
- Void Fraction = 0.45
- Roughness = 0.02

PERMEABLE PAVEMENT:

SURFACE LAYER
- Berm Height = .05
- Vegetation Volume Fraction = 0
- Surface Roughness = 0.12
- Surface Slope (percent) = 1.0

PAVEMENT LAYER
- Thickness = 5
- Void Ratio = 0.15
- Impervious Surface Fraction = 0
- Permeability = 100
- Clogging Factor = 0
- Regeneration Interval = 0
- Regeneration Fraction = 0

*SOIL LAYER
- Thickness = 0
- Porosity = n/a
- Field capacity = n/a
- Wilting Point = n/a
- Conductivity = n/a
- Conductivity Slope = n/a
- Suction Head = n/a

STORAGE LAYER
- Thickness = 12
- Void Ratio = 0.63
- Seepage Rate = 2
- Clogging Factor = 0

*DRAIN LAYER
- Flow Coefficient = 0
- Flow Exponent = n/a
- Offset = n/a

RAIN GARDEN:

SURFACE LAYER
- Berm Height = 6
- Vegetation Volume Fraction = 0.4
- Surface Roughness = 0.2
- Surface Slope (percent) = 0.95

SOIL LAYER
- Thickness = 25
- Porosity = 0.3
- Field capacity = 0.2
- Wilting Point = 0.1
- Conductivity = 0.5
- Conductivity Slope = 30
- Suction Head = 3.5

*STORAGE LAYER
- Thickness = 0
- Void Ratio = n/a
- Seepage Rate = n/a
- Clogging Factor = n/a

Appendix H

Code for CMIP6 Historical and Projected Precipitation

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CNRM_Oahu_Projection

February 23, 2022

1 Climate Change Exploration: Maunalua Bay, Oahu, Hawai'i

1.1 Fall 2021

1.1.1 Elmera Azadpour

1.1.2 2021-12-08

All scripts and data can be accessed from Aloha Aina Repo

Code derived from CMIP6 PanGeo Gallery

Note: This analysis pulls data from CNRM-ESM2-1 only, you will find two other notebook files (BCC_Oahu_Projection.ipynb & IPSL_Oahu_Projection.ipynb) that will pull from other climate model sources (BCC-CSM2-MR & IPSL-CM6A-LR).

[2]:
```
## import libraries:
from matplotlib import pyplot as plt
import numpy as np
import pandas as pd
import xarray as xr
import zarr
import fsspec
import gcsfs
import s3fs
import kedro
import nc_time_axis
import plotly.express as px
import metpy
from metpy.units import units

%matplotlib inline
%config InlineBackend.figure_format = 'retina'
plt.rcParams['figure.figsize'] = 12, 6
```

[4]:
```
## CMIP6 Public Data
df = pd.read_csv('https://storage.googleapis.com/cmip6/
↪cmip6-zarr-consolidated-stores.csv')
df.head(10)
```

[4]:
```
  activity_id institution_id     source_id       experiment_id member_id  \
0  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
1  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
2  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
3  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
4  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
5  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
6  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
7  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
8  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1
9  HighResMIP           CMCC  CMCC-CM2-HR4  highresSST-present  r1i1p1f1

  table_id variable_id grid_label  \
0     Amon          ps         gn
1     Amon        rsds         gn
2     Amon        rlus         gn
3     Amon        rlds         gn
4     Amon         psl         gn
5     Amon         prw         gn
6     Amon        hurs         gn
7     Amon        huss         gn
8     Amon         hus         gn
9     Amon        hfss         gn

                                              zstore  dcpp_init_year   version
0  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
1  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
2  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
3  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
4  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
5  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
6  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
7  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
8  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
9  gs://cmip6/CMIP6/HighResMIP/CMCC/CMCC-CM2-HR4/…             NaN  20170706
```

[5]:
```python
## Query for projection CMIP6 data
df_3hr_pr = df[(df.table_id == '3hr') & (df.variable_id == 'pr')]
len(df_3hr_pr)

run_counts = df_3hr_pr.groupby(['source_id', 'experiment_id'])['zstore'].count()
run_counts
```

[5]:
```
source_id         experiment_id
BCC-CSM2-MR       historical             1
                  ssp126                 1
                  ssp245                 1
```

```
                  ssp370                1
                  ssp585                1
CNRM-CM6-1        highresSST-present    1
                  historical            3
                  ssp126                1
                  ssp245                1
                  ssp370                1
                  ssp585                1
CNRM-CM6-1-HR     highresSST-present    1
CNRM-ESM2-1       historical            1
                  ssp126                1
                  ssp245                1
                  ssp370                1
                  ssp585                1
GFDL-CM4          1pctCO2               2
                  abrupt-4xCO2          2
                  amip                  2
                  historical            2
                  piControl             2
GFDL-CM4C192      highresSST-future     1
                  highresSST-present    1
GFDL-ESM4         1pctCO2               1
                  abrupt-4xCO2          1
                  esm-hist              1
                  historical            1
                  ssp119                1
                  ssp126                1
                  ssp370                1
GISS-E2-1-G       historical            2
HadGEM3-GC31-HM   highresSST-present    1
HadGEM3-GC31-LM   highresSST-present    1
HadGEM3-GC31-MM   highresSST-present    1
IPSL-CM6A-ATM-HR  highresSST-present    1
IPSL-CM6A-LR      highresSST-present    1
                  historical           15
                  piControl             1
                  ssp126                3
                  ssp245                2
                  ssp370               10
                  ssp585                1
MRI-ESM2-0        historical            1
Name: zstore, dtype: int64
```

Fig. 1: Future and historical CO2 emissions scenarios featured in CMIP6 Source: https://www.carbonbrief.org/cmip6-the-next-generation-of-climate-models-explained

1.1.3 Pulling CNRM-ESM2-1, ssp2-4.5 Projection

[6]:
```
## querty for 3hr, precipitaion for ssp 2-4.5 projection from CNRM-ESM2-1
df_3hr_ssp245_CNRM_pr = df[(df.table_id == '3hr') & (df.variable_id == 'pr') &␣
↪(df.experiment_id== 'ssp245') & (df.source_id== 'CNRM-ESM2-1') ]
len(df_3hr_ssp245_CNRM_pr)
df_3hr_ssp245_CNRM_pr
```

[6]:
```
      activity_id institution_id    source_id experiment_id member_id  \
68835  ScenarioMIP    CNRM-CERFACS  CNRM-ESM2-1        ssp245  r1i1p1f2

      table_id variable_id grid_label  \
68835      3hr          pr         gr

                                                  zstore  dcpp_init_year  \
68835  gs://cmip6/CMIP6/ScenarioMIP/CNRM-CERFACS/CNRM…             NaN

        version
68835  20190328
```

[7]:
```
## pull data
# get the path to a specific zarr store (the first one from the dataframe above)
zstore = df_3hr_ssp245_CNRM_pr.zstore.values[-1]
print(zstore)

# create a mutable-mapping-style interface to the store
mapper = fsspec.get_mapper(zstore)

# open it using xarray and zarr
ds_proj = xr.open_zarr(mapper, consolidated=True)
ds_proj
```

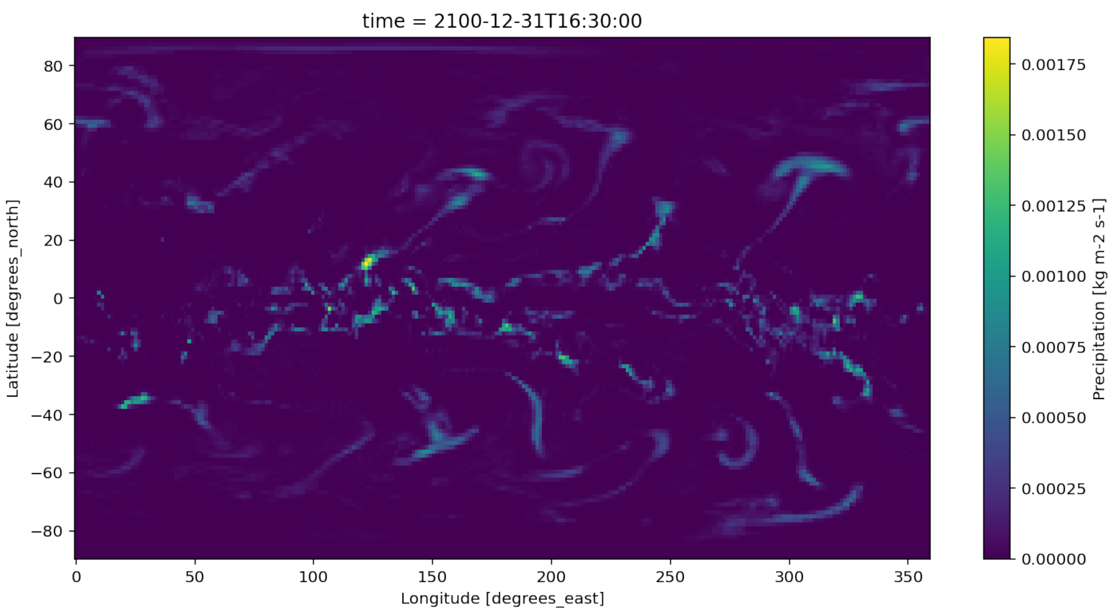
```
gs://cmip6/CMIP6/ScenarioMIP/CNRM-CERFACS/CNRM-
ESM2-1/ssp245/r1i1p1f2/3hr/pr/gr/v20190328/
```

[7]:
```
<xarray.Dataset>
Dimensions:      (lat: 128, lon: 256, time: 251288, axis_nbounds: 2)
Coordinates:
  * lat          (lat) float64 -88.93 -87.54 -86.14 -84.74 … 86.14 87.54 88.93
  * lon          (lon) float64 0.0 1.406 2.812 4.219 … 354.4 355.8 357.2 358.6
  * time         (time) datetime64[ns] 2015-01-01T01:30:00 … 2100-12-31T22:…
    time_bounds  (time, axis_nbounds) datetime64[ns]
dask.array<chunksize=(62822, 1), meta=np.ndarray>
Dimensions without coordinates: axis_nbounds
Data variables:
    pr           (time, lat, lon) float32 dask.array<chunksize=(600, 128, 256),
meta=np.ndarray>
Attributes: (12/55)
```

```
CMIP6_CV_version:         cv=6.2.3.0-7-g2019642
Conventions:              CF-1.7 CMIP-6.2
EXPID:                    CNRM-ESM2-1_ssp245_r1i1p1f2
activity_id:              ScenarioMIP
arpege_minor_version:     6.3.2
branch_method:            standard
…                       …
variable_id:              pr
variant_label:            r1i1p1f2
xios_commit:              1442-shuffle
status:                   2019-10-25;created;by nhn2@columbia.edu
netcdf_tracking_ids:      hdl:21.14100/215d187a-7fa5-41cd-a59b-7fe164306a61…
version_id:               v20190328
```

[8]:
```
## Plot a map from a specific date: global coverage
ds_proj.pr.sel(time='2100-12-31T16:30:00.000000000').squeeze().plot()
```

[8]:
```
<matplotlib.collections.QuadMesh at 0x7ff244b0e4f0>
```



[9]:
```
# # Create logical masks for lat and lon variables for oahu
# bouding box: -158.5698,20.9057,-157.406,22.0022
mask_lon = (ds_proj.pr.lon >= 201.43) & (ds_proj.pr.lon <= 202.59)
mask_lat = (ds_proj.pr.lat >= 20.91) & (ds_proj.pr.lat <= 22.00)
```

[7]:
```
# Apply lat/lon masks to the field, then calculate averages over the lat and␣
↪lon dimensions
oahu_pr_proj=ds_proj.pr.where(mask_lon & mask_lat, drop = True)
```

```
## remove times associated with leap years (remove feb 29 from all recorded␣
↪years)
oahu_pr_proj = oahu_pr_proj.sel(time=~((oahu_pr_proj.time.dt.month == 2) &␣
↪(oahu_pr_proj.time.dt.day == 29)))
oahu_pr_proj

## group by day of year and avg by day
oahu_pr_proj['dayofyear'] = xr.DataArray(oahu_pr_proj.indexes['time'].
↪strftime('%Y-%m-%d'), coords=oahu_pr_proj.time.coords)
oahu_pr_proj_avg = oahu_pr_proj.groupby('dayofyear').mean('time',␣
↪keep_attrs=True) #retain attributes for metpy conversion in nxt step
oahu_pr_proj_avg
```

[7]:
```
<xarray.DataArray 'pr' (dayofyear: 31390, lat: 1, lon: 1)>
dask.array<stack, shape=(31390, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[8]:
```
## daily sum of precip ssp3-7.0 Projection
oahu_pr_proj_sum_245 = oahu_pr_proj.groupby('dayofyear').sum('time',␣
↪keep_attrs=True) #retain attributes for metpy conversion in nxt step
oahu_pr_proj_sum_245
```

[8]:
```
<xarray.DataArray 'pr' (dayofyear: 31390, lat: 1, lon: 1)>
dask.array<stack, shape=(31390, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
Attributes:
    cell_measures:       area: areacella
```

```
    cell_methods:         area: time: mean
    description:          at surface; includes both liquid and solid phases.  …
    history:              none
    interval_operation:   900 s
    interval_write:       3 h
    long_name:            Precipitation
    online_operation:     average
    standard_name:        precipitation_flux
    units:                kg m-2 s-1
```

[9]:
```
# Make metpy recognize the units
oahu_pr_proj_sum_245 = oahu_pr_proj_sum_245.metpy.quantify()

# convert kg/m2/sec to in/day
density_water = units('kg / m^3') * 1000
oahu_pr_proj_converted_int_ssp245_sum = (oahu_pr_proj_sum_245 / density_water)
oahu_pr_proj_converted_int_ssp245_sum = oahu_pr_proj_converted_int_ssp245_sum.
 ↪metpy.convert_units('inches / day')
oahu_pr_proj_converted_int_ssp245_sum = oahu_pr_proj_converted_int_ssp245_sum.
 ↪mean("lon").mean("lat")
oahu_pr_proj_converted_int_ssp245_sum
```

[9]:
```
<xarray.DataArray 'pr' (dayofyear: 31390)>
<Quantity(dask.array<mean_agg-aggregate, shape=(31390,), dtype=float32,
chunksize=(1,), chunktype=numpy.ndarray>, 'inch / day')>
Coordinates:
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
```

Fig. 2: Bouding box coordinates used for projection analysis Source: https://boundingbox.klokantech.com/

[49]:
```
# Cast our xarray to dataframe -- daily averages
oahu_pr_proj_df = oahu_pr_proj_converted_int.to_dataframe().reset_index()
oahu_pr_proj_df.head(20)
```

[49]:

	dayofyear	pr
0	2015-01-01	0.000390
1	2015-01-02	0.001306
2	2015-01-03	0.022132
3	2015-01-04	0.196844
4	2015-01-05	0.441790
5	2015-01-06	0.076026
6	2015-01-07	0.059438
7	2015-01-08	0.060714
8	2015-01-09	0.026974
9	2015-01-10	0.005410
10	2015-01-11	0.001053

```
11  2015-01-12  0.009215
12  2015-01-13  0.644469
13  2015-01-14  0.055369
14  2015-01-15  0.019334
15  2015-01-16  0.442971
16  2015-01-17  0.001024
17  2015-01-18  0.054217
18  2015-01-19  0.481935
19  2015-01-20  0.000166
```

[10]:
```
# Cast our xarray to dataframe for daily sums
oahu_pr_proj_converted_int_ssp245_sum_df =␣
↪oahu_pr_proj_converted_int_ssp245_sum.to_dataframe().reset_index()
oahu_pr_proj_converted_int_ssp245_sum_df.head(20)
```

[10]:
```
     dayofyear        pr
0   2015-01-01  0.003117
1   2015-01-02  0.010450
2   2015-01-03  0.177055
3   2015-01-04  1.574751
4   2015-01-05  3.534323
5   2015-01-06  0.608212
6   2015-01-07  0.475508
7   2015-01-08  0.485709
8   2015-01-09  0.215790
9   2015-01-10  0.043283
10  2015-01-11  0.008423
11  2015-01-12  0.073718
12  2015-01-13  5.155749
13  2015-01-14  0.442954
14  2015-01-15  0.154673
15  2015-01-16  3.543765
16  2015-01-17  0.008195
17  2015-01-18  0.433738
18  2015-01-19  3.855481
19  2015-01-20  0.001325
```

[66]:
```
## to export df,daily avg
## oahu_pr_proj_df.to_csv('oahu_ssp245_2015_2100_avg.csv', index = False)
```

[11]:
```
## to export df, daily sum
oahu_pr_proj_converted_int_ssp245_sum_df.to_csv('oahu_ssp245_2015_2100_total.
↪csv', index = False)
```

1.1.4 Exploring CNRM-ESM2-1, ssp3-7.0 Projection

[19]:
```
## querty for 3hr, precipitaion for ssp 3-7.0 projection from CNRM-ESM2-1
df_3hr_ssp370_CNRM_pr = df[(df.table_id == '3hr') & (df.variable_id == 'pr') &␣
↪(df.experiment_id== 'ssp370') & (df.source_id== 'CNRM-ESM2-1') ]
len(df_3hr_ssp370_CNRM_pr)
df_3hr_ssp370_CNRM_pr
```

[19]:
```
      activity_id institution_id    source_id experiment_id member_id  \
69219  ScenarioMIP   CNRM-CERFACS  CNRM-ESM2-1        ssp370  r1i1p1f2

     table_id variable_id grid_label  \
69219      3hr          pr         gr

                                                  zstore  dcpp_init_year  \
69219  gs://cmip6/CMIP6/ScenarioMIP/CNRM-CERFACS/CNRM…             NaN

       version
69219  20190328
```

[20]:
```
## pull data
# get the path to a specific zarr store (the first one from the dataframe above)
zstore2 = df_3hr_ssp370_CNRM_pr.zstore.values[-1]
print(zstore2)

# create a mutable-mapping-style interface to the store
mapper2 = fsspec.get_mapper(zstore2)

# open it using xarray and zarr
ds_proj_ssp370 = xr.open_zarr(mapper2, consolidated=True)
ds_proj_ssp370
```

```
gs://cmip6/CMIP6/ScenarioMIP/CNRM-CERFACS/CNRM-
ESM2-1/ssp370/r1i1p1f2/3hr/pr/gr/v20190328/
```

[20]:
```
<xarray.Dataset>
Dimensions:      (lat: 128, lon: 256, time: 251288, axis_nbounds: 2)
Coordinates:
  * lat          (lat) float64 -88.93 -87.54 -86.14 -84.74 … 86.14 87.54 88.93
  * lon          (lon) float64 0.0 1.406 2.812 4.219 … 354.4 355.8 357.2 358.6
  * time         (time) datetime64[ns] 2015-01-01T01:30:00 … 2100-12-31T22:…
    time_bounds  (time, axis_nbounds) datetime64[ns]
dask.array<chunksize=(62822, 1), meta=np.ndarray>
Dimensions without coordinates: axis_nbounds
Data variables:
    pr           (time, lat, lon) float32 dask.array<chunksize=(449, 128, 256),
meta=np.ndarray>
Attributes: (12/55)
```

```
    CMIP6_CV_version:       cv=6.2.3.0-7-g2019642
    Conventions:            CF-1.7 CMIP-6.2
    EXPID:                  CNRM-ESM2-1_ssp370_r1i1p1f2
    activity_id:            ScenarioMIP AerChemMIP
    arpege_minor_version:   6.3.2
    branch_method:          standard
    …                     …
    variable_id:            pr
    variant_label:          r1i1p1f2
    xios_commit:            1442-shuffle
    status:                 2019-11-03;created;by nhn2@columbia.edu
    netcdf_tracking_ids:    hdl:21.14100/2a291f7e-b9c9-4c68-b33b-cbfc153a587f…
    version_id:             v20190328
```

[21]:
```python
# Apply lat/lon masks to the field, then calculate averages over the lat and␣
↪lon dimensions
oahu_pr_proj_ssp370=ds_proj_ssp370.pr.where(mask_lon & mask_lat, drop = True)

## remove times associated with leap years (remove feb 29 from all recorded␣
↪years)
oahu_pr_proj_ssp370 = oahu_pr_proj_ssp370.sel(time=~((oahu_pr_proj_ssp370.time.
↪dt.month == 2) & (oahu_pr_proj_ssp370.time.dt.day == 29)))
oahu_pr_proj_ssp370

## group by day of year and avg by day
oahu_pr_proj_ssp370['dayofyear'] = xr.DataArray(oahu_pr_proj_ssp370.
↪indexes['time'].strftime('%Y-%m-%d'), coords=oahu_pr_proj_ssp370.time.coords)
oahu_pr_proj_ssp370_avg = oahu_pr_proj_ssp370.groupby('dayofyear').mean('time',␣
↪keep_attrs=True) #retain attributes for metpy conversion in nxt step
oahu_pr_proj_ssp370_avg
```

[21]:
```
<xarray.DataArray 'pr' (dayofyear: 31390, lat: 1, lon: 1)>
dask.array<stack, shape=(31390, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
```

```
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[22]:
```
## daily sum of precip ssp3-7.0 projection
oahu_pr_proj_sum_370 = oahu_pr_proj_ssp370.groupby('dayofyear').sum('time',␣
 ↪keep_attrs=True) #retain attributes for metpy conversion in nxt step
oahu_pr_proj_sum_370
```

[22]:
```
<xarray.DataArray 'pr' (dayofyear: 31390, lat: 1, lon: 1)>
dask.array<stack, shape=(31390, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[23]:
```
# Make metpy recognize the units
oahu_pr_proj_ssp370_sum = oahu_pr_proj_sum_370.metpy.quantify()

# convert kg/m2/sec to in/day
density_water = units('kg / m^3') * 1000
oahu_pr_proj_ssp370_converted_int_sum = (oahu_pr_proj_ssp370_sum /␣
 ↪density_water)
oahu_pr_proj_ssp370_converted_int_sum = oahu_pr_proj_ssp370_converted_int_sum.
 ↪metpy.convert_units('inches / day')
oahu_pr_proj_ssp370_converted_int_sum = oahu_pr_proj_ssp370_converted_int_sum.
 ↪mean("lon").mean("lat")
oahu_pr_proj_ssp370_converted_int_sum
```

[23]:
```
<xarray.DataArray 'pr' (dayofyear: 31390)>
<Quantity(dask.array<mean_agg-aggregate, shape=(31390,), dtype=float32,
chunksize=(1,), chunktype=numpy.ndarray>, 'inch / day')>
Coordinates:
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
```

[16]:

```
# Cast our xarray to dataframe -- daily avg
oahu_pr_proj_ssp370_df = oahu_pr_proj_ssp370_converted_int.to_dataframe().
↪reset_index()
oahu_pr_proj_ssp370_df.head(20)
```

[16]:

	dayofyear	pr
0	2015-01-01	3.701659e-04
1	2015-01-02	2.282345e-03
2	2015-01-03	1.025546e-02
3	2015-01-04	3.492512e-01
4	2015-01-05	9.594570e-01
5	2015-01-06	2.072181e-01
6	2015-01-07	1.574929e-01
7	2015-01-08	5.034250e-02
8	2015-01-09	4.010621e-02
9	2015-01-10	2.340790e-02
10	2015-01-11	3.337233e-03
11	2015-01-12	5.087506e-03
12	2015-01-13	4.717490e-02
13	2015-01-14	1.209491e+00
14	2015-01-15	9.867913e-03
15	2015-01-16	1.273414e-01
16	2015-01-17	1.849313e+00
17	2015-01-18	4.772992e-03
18	2015-01-19	5.384365e-22
19	2015-01-20	1.341719e-05

[24]:

```
# Cast our xarray to dataframe -- daily sum
oahu_pr_proj_ssp370_df_sum = oahu_pr_proj_ssp370_converted_int_sum.
↪to_dataframe().reset_index()
oahu_pr_proj_ssp370_df_sum.head(20)
```

[24]:

	dayofyear	pr
0	2015-01-01	2.961327e-03
1	2015-01-02	1.825876e-02
2	2015-01-03	8.204365e-02
3	2015-01-04	2.794009e+00
4	2015-01-05	7.675656e+00
5	2015-01-06	1.657745e+00
6	2015-01-07	1.259943e+00
7	2015-01-08	4.027400e-01
8	2015-01-09	3.208497e-01
9	2015-01-10	1.872632e-01
10	2015-01-11	2.669786e-02
11	2015-01-12	4.070005e-02
12	2015-01-13	3.773992e-01
13	2015-01-14	9.675924e+00

```
14   2015-01-15   7.894330e-02
15   2015-01-16   1.018731e+00
16   2015-01-17   1.479451e+01
17   2015-01-18   3.818394e-02
18   2015-01-19   4.307492e-21
19   2015-01-20   1.073375e-04
```

[23]:
```
## to export df
# oahu_pr_proj_ssp370_df.to_csv('oahu_ssp370_2015_2100.csv', index = False)
```

[25]:
```
## to export df, daily total ssp370
oahu_pr_proj_ssp370_df_sum.to_csv('oahu_ssp370_2015_2100_total.csv', index =␣
↪False)
```

1.1.5 Exploring CNRM-ESM2-1, ssp5-8.5 Projection

[26]:
```
## querty for 3hr, precipitaion for ssp 5-8.5 projection from CNRM-ESM2-1
df_3hr_ssp585_CNRM_pr = df[(df.table_id == '3hr') & (df.variable_id == 'pr') &␣
↪(df.experiment_id== 'ssp585') & (df.source_id== 'CNRM-ESM2-1') ]
len(df_3hr_ssp585_CNRM_pr)
df_3hr_ssp585_CNRM_pr
```

[26]:
```
      activity_id institution_id    source_id experiment_id member_id  \
69200  ScenarioMIP   CNRM-CERFACS  CNRM-ESM2-1        ssp585  r1i1p1f2

      table_id variable_id grid_label  \
69200      3hr          pr         gr

                                                 zstore  dcpp_init_year  \
69200  gs://cmip6/CMIP6/ScenarioMIP/CNRM-CERFACS/CNRM…             NaN

        version
69200  20190328
```

[27]:
```
## pull data
# get the path to a specific zarr store (the first one from the dataframe above)
zstore3 = df_3hr_ssp585_CNRM_pr.zstore.values[-1]
print(zstore3)

# create a mutable-mapping-style interface to the store
mapper3 = fsspec.get_mapper(zstore3)

# open it using xarray and zarr
ds_proj_ssp585 = xr.open_zarr(mapper3, consolidated=True)
ds_proj_ssp585
```

```
gs://cmip6/CMIP6/ScenarioMIP/CNRM-CERFACS/CNRM-
```

```
ESM2-1/ssp585/r1i1p1f2/3hr/pr/gr/v20190328/
```

[27]:
```
<xarray.Dataset>
Dimensions:       (lat: 128, lon: 256, time: 251288, axis_nbounds: 2)
Coordinates:
  * lat           (lat) float64 -88.93 -87.54 -86.14 -84.74 … 86.14 87.54 88.93
  * lon           (lon) float64 0.0 1.406 2.812 4.219 … 354.4 355.8 357.2 358.6
  * time          (time) datetime64[ns] 2015-01-01T01:30:00 … 2100-12-31T22:…
    time_bounds   (time, axis_nbounds) datetime64[ns]
dask.array<chunksize=(62822, 1), meta=np.ndarray>
Dimensions without coordinates: axis_nbounds
Data variables:
    pr            (time, lat, lon) float32 dask.array<chunksize=(600, 128, 256),
meta=np.ndarray>
Attributes: (12/55)
    CMIP6_CV_version:       cv=6.2.3.0-7-g2019642
    Conventions:            CF-1.7 CMIP-6.2
    EXPID:                  CNRM-ESM2-1_ssp585_r1i1p1f2
    activity_id:            ScenarioMIP
    arpege_minor_version:   6.3.2
    branch_method:          standard
    …                      …
    variable_id:            pr
    variant_label:          r1i1p1f2
    xios_commit:            1442-shuffle
    status:                 2019-08-26;created;by nhn2@columbia.edu
    netcdf_tracking_ids:    hdl:21.14100/6fb366f9-6ed1-47fe-918c-08fa5ca8baa3…
    version_id:             v20190328
```

[28]:
```
# Apply lat/lon masks to the field, then calculate averages over the lat and␣
 ↪lon dimensions
oahu_pr_proj_ssp585=ds_proj_ssp585.pr.where(mask_lon & mask_lat, drop = True)

## remove times associated with leap years (remove feb 29 from all recorded␣
 ↪years )
oahu_pr_proj_ssp585 = oahu_pr_proj_ssp585.sel(time=~((oahu_pr_proj_ssp585.time.
 ↪dt.month == 2) & (oahu_pr_proj_ssp585.time.dt.day == 29)))
oahu_pr_proj_ssp585

## group by day of year and avg by day
oahu_pr_proj_ssp585['dayofyear'] = xr.DataArray(oahu_pr_proj_ssp585.
 ↪indexes['time'].strftime('%Y-%m-%d'), coords=oahu_pr_proj_ssp585.time.coords)
oahu_pr_proj_ssp585_avg = oahu_pr_proj_ssp585.groupby('dayofyear').mean('time',␣
 ↪keep_attrs=True) #retain attributes for metpy conversion in nxt step
oahu_pr_proj_ssp585_avg
```

[28]:
```
<xarray.DataArray 'pr' (dayofyear: 31390, lat: 1, lon: 1)>
dask.array<stack, shape=(31390, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[29]:
```
## daily sum of precip ssp5-8.5 Projection
oahu_pr_proj_sum_585 = oahu_pr_proj_ssp585.groupby('dayofyear').sum('time',␣
↪keep_attrs=True) #retain attributes for metpy conversion in nxt step
oahu_pr_proj_sum_585
```

[29]:
```
<xarray.DataArray 'pr' (dayofyear: 31390, lat: 1, lon: 1)>
dask.array<stack, shape=(31390, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[30]:
```
# Make metpy recognize the units
oahu_pr_proj_ssp585_sum = oahu_pr_proj_sum_585.metpy.quantify()

# convert kg/m2/sec to in/day
```

```
density_water = units('kg / m^3') * 1000
oahu_pr_proj_ssp585_converted_int_sum = (oahu_pr_proj_ssp585_sum /␣
 ↪density_water)
oahu_pr_proj_ssp585_converted_int_sum = oahu_pr_proj_ssp585_converted_int_sum.
 ↪metpy.convert_units('inches / day')
oahu_pr_proj_ssp585_converted_int_sum = oahu_pr_proj_ssp585_converted_int_sum.
 ↪mean("lon").mean("lat")
oahu_pr_proj_ssp585_converted_int_sum
```

[30]:

```
<xarray.DataArray 'pr' (dayofyear: 31390)>
<Quantity(dask.array<mean_agg-aggregate, shape=(31390,), dtype=float32,
chunksize=(1,), chunktype=numpy.ndarray>, 'inch / day')>
Coordinates:
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
```

[29]:

```
# Cast our xarray to dataframe
oahu_pr_proj_ssp585_df = oahu_pr_proj_ssp585_converted_int.to_dataframe().
 ↪reset_index()
oahu_pr_proj_ssp585_df.head(20)
```

[29]:

	dayofyear	pr
0	2015-01-01	0.000311
1	2015-01-02	0.001061
2	2015-01-03	0.019240
3	2015-01-04	0.289843
4	2015-01-05	0.766865
5	2015-01-06	0.173856
6	2015-01-07	0.088689
7	2015-01-08	0.044970
8	2015-01-09	0.023198
9	2015-01-10	0.016240
10	2015-01-11	0.005077
11	2015-01-12	0.207648
12	2015-01-13	0.277482
13	2015-01-14	0.007074
14	2015-01-15	0.011796
15	2015-01-16	0.483247
16	2015-01-17	0.000010
17	2015-01-18	0.009342
18	2015-01-19	0.069012
19	2015-01-20	0.005040

[31]:

```
# Cast our xarray to dataframe
oahu_pr_proj_ssp585_df_sum = oahu_pr_proj_ssp585_converted_int_sum.
 ↪to_dataframe().reset_index()
oahu_pr_proj_ssp585_df_sum.head(20)
```

[31]:
```
     dayofyear        pr
0   2015-01-01  0.002490
1   2015-01-02  0.008486
2   2015-01-03  0.153917
3   2015-01-04  2.318743
4   2015-01-05  6.134923
5   2015-01-06  1.390850
6   2015-01-07  0.709511
7   2015-01-08  0.359761
8   2015-01-09  0.185582
9   2015-01-10  0.129921
10  2015-01-11  0.040615
11  2015-01-12  1.661184
12  2015-01-13  2.219857
13  2015-01-14  0.056589
14  2015-01-15  0.094369
15  2015-01-16  3.865978
16  2015-01-17  0.000081
17  2015-01-18  0.074732
18  2015-01-19  0.552095
19  2015-01-20  0.040323
```

[30]:
```
## to export df
# oahu_pr_proj_ssp585_df.to_csv('oahu_ssp585_2015_2100.csv', index = False)
```

[32]:
```
## to export df, daily total ssp585
oahu_pr_proj_ssp585_df_sum.to_csv('oahu_ssp585_2015_2100_total.csv', index =␣
↪False)
```

1.1.6 Exploring CNRM-ESM2-1, ssp1-2.6 Projection

[33]:
```
## querty for 3hr, precipitaion for ssp 1-2.6 from CNRM-ESM2-1
df_3hr_ssp126_CNRM_pr = df[(df.table_id == '3hr') & (df.variable_id == 'pr') &␣
↪(df.experiment_id== 'ssp126') & (df.source_id== 'CNRM-ESM2-1') ]
len(df_3hr_ssp126_CNRM_pr)
df_3hr_ssp126_CNRM_pr
```

[33]:
```
      activity_id institution_id    source_id experiment_id member_id  \
69045  ScenarioMIP   CNRM-CERFACS  CNRM-ESM2-1        ssp126  r1i1p1f2

      table_id variable_id grid_label  \
69045      3hr          pr         gr

                                                  zstore  dcpp_init_year  \
69045  gs://cmip6/CMIP6/ScenarioMIP/CNRM-CERFACS/CNRM…             NaN

       version
```

```
69045  20190328
```

[34]:
```python
## pull data
# get the path to a specific zarr store (the first one from the dataframe above)
zstore4 = df_3hr_ssp126_CNRM_pr.zstore.values[-1]
print(zstore4)

# create a mutable-mapping-style interface to the store
mapper4 = fsspec.get_mapper(zstore4)

# open it using xarray and zarr
ds_proj_ssp126 = xr.open_zarr(mapper4, consolidated=True)
ds_proj_ssp126
```

```
gs://cmip6/CMIP6/ScenarioMIP/CNRM-CERFACS/CNRM-
ESM2-1/ssp126/r1i1p1f2/3hr/pr/gr/v20190328/
```

[34]:
```
<xarray.Dataset>
Dimensions:      (lat: 128, lon: 256, time: 251288, axis_nbounds: 2)
Coordinates:
  * lat          (lat) float64 -88.93 -87.54 -86.14 -84.74 … 86.14 87.54 88.93
  * lon          (lon) float64 0.0 1.406 2.812 4.219 … 354.4 355.8 357.2 358.6
  * time         (time) datetime64[ns] 2015-01-01T01:30:00 … 2100-12-31T22:…
    time_bounds  (time, axis_nbounds) datetime64[ns]
dask.array<chunksize=(62822, 1), meta=np.ndarray>
Dimensions without coordinates: axis_nbounds
Data variables:
    pr           (time, lat, lon) float32 dask.array<chunksize=(449, 128, 256),
meta=np.ndarray>
Attributes: (12/55)
    CMIP6_CV_version:       cv=6.2.3.0-7-g2019642
    Conventions:            CF-1.7 CMIP-6.2
    EXPID:                  CNRM-ESM2-1_ssp126_r1i1p1f2
    activity_id:            ScenarioMIP
    arpege_minor_version:   6.3.2
    branch_method:          standard
    …                      …
    variable_id:            pr
    variant_label:          r1i1p1f2
    xios_commit:            1442-shuffle
    status:                 2019-11-03;created;by nhn2@columbia.edu
    netcdf_tracking_ids:    hdl:21.14100/6255501d-a196-47b5-be0f-7d61a687e6e1…
    version_id:             v20190328
```

[35]:
```python
# Apply lat/lon masks to the field, then calculate averages over the lat and␣
↪lon dimensions
oahu_pr_proj_ssp126=ds_proj_ssp126.pr.where(mask_lon & mask_lat, drop = True)
```

```
## remove times associated with leap years (remove feb 29 from records)
oahu_pr_proj_ssp126 = oahu_pr_proj_ssp126.sel(time=~((oahu_pr_proj_ssp126.time.
↪dt.month == 2) & (oahu_pr_proj_ssp126.time.dt.day == 29)))
oahu_pr_proj_ssp126

## group by day of year and avg by day
oahu_pr_proj_ssp126['dayofyear'] = xr.DataArray(oahu_pr_proj_ssp126.
↪indexes['time'].strftime('%Y-%m-%d'), coords=oahu_pr_proj_ssp126.time.coords)
oahu_pr_proj_ssp126_avg = oahu_pr_proj_ssp126.groupby('dayofyear').mean('time',␣
↪keep_attrs=True) #retain attributes for metpy conversion in nxt step
oahu_pr_proj_ssp126_avg
```

[35]:
```
<xarray.DataArray 'pr' (dayofyear: 31390, lat: 1, lon: 1)>
dask.array<stack, shape=(31390, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[36]:
```
## daily sum of precip ssp126
oahu_pr_proj_sum_126 = oahu_pr_proj_ssp126.groupby('dayofyear').sum('time',␣
↪keep_attrs=True) #retain attributes for metpy conversion in nxt step
oahu_pr_proj_sum_126
```

[36]:
```
<xarray.DataArray 'pr' (dayofyear: 31390, lat: 1, lon: 1)>
dask.array<stack, shape=(31390, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
```

```
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[37]:
```
# Make metpy recognize the units
oahu_pr_proj_ssp126_sum = oahu_pr_proj_sum_126.metpy.quantify()

# convert kg/m2/sec to in/day
density_water = units('kg / m^3') * 1000
oahu_pr_proj_ssp126_converted_int_sum = (oahu_pr_proj_ssp126_sum /␣
↪density_water)
oahu_pr_proj_ssp126_converted_int_sum = oahu_pr_proj_ssp126_converted_int_sum.
↪metpy.convert_units('inches / day')
oahu_pr_proj_ssp126_converted_int_sum = oahu_pr_proj_ssp126_converted_int_sum.
↪mean("lon").mean("lat")
oahu_pr_proj_ssp126_converted_int_sum
```

[37]:
```
<xarray.DataArray 'pr' (dayofyear: 31390)>
<Quantity(dask.array<mean_agg-aggregate, shape=(31390,), dtype=float32,
chunksize=(1,), chunktype=numpy.ndarray>, 'inch / day')>
Coordinates:
  * dayofyear  (dayofyear) object '2015-01-01' '2015-01-02' … '2100-12-31'
```

[14]:
```
# Cast our xarray to dataframe -- daily average
oahu_pr_proj_ssp126_df = oahu_pr_proj_ssp126_converted_int.to_dataframe().
↪reset_index()
oahu_pr_proj_ssp126_df.head(20)
```

[14]:

	dayofyear	pr
0	2015-01-01	0.001504
1	2015-01-02	0.001572
2	2015-01-03	0.015226
3	2015-01-04	0.296919
4	2015-01-05	0.762305
5	2015-01-06	0.135178
6	2015-01-07	0.150985
7	2015-01-08	0.028382
8	2015-01-09	0.016181
9	2015-01-10	0.011141
10	2015-01-11	0.001719
11	2015-01-12	0.156439
12	2015-01-13	0.533256

```
13  2015-01-14  0.029845
14  2015-01-15  0.002761
15  2015-01-16  1.747228
16  2015-01-17  0.000391
17  2015-01-18  0.092346
18  2015-01-19  0.001736
19  2015-01-20  0.000678
```

[38]:
```
# Cast our xarray to dataframe -- daily sum
oahu_pr_proj_ssp126_df_sum = oahu_pr_proj_ssp126_converted_int_sum.
 ↪to_dataframe().reset_index()
oahu_pr_proj_ssp126_df_sum.head(20)
```

[38]:

	dayofyear	pr
0	2015-01-01	0.012032
1	2015-01-02	0.012579
2	2015-01-03	0.121809
3	2015-01-04	2.375351
4	2015-01-05	6.098441
5	2015-01-06	1.081423
6	2015-01-07	1.207878
7	2015-01-08	0.227057
8	2015-01-09	0.129448
9	2015-01-10	0.089130
10	2015-01-11	0.013749
11	2015-01-12	1.251516
12	2015-01-13	4.266051
13	2015-01-14	0.238757
14	2015-01-15	0.022086
15	2015-01-16	13.977824
16	2015-01-17	0.003131
17	2015-01-18	0.738765
18	2015-01-19	0.013890
19	2015-01-20	0.005426

[15]:
```
## to export df
#oahu_pr_proj_ssp126_df.to_csv('oahu_ssp126_2015_2100.csv', index = False)
```

[39]:
```
## to export df, daily total ssp1-2.6 Projection
oahu_pr_proj_ssp126_df_sum.to_csv('oahu_ssp126_2015_2100_total.csv', index =␣
 ↪False)
```

1.1.7 Exploring CNRM-ESM2-1, historical

[42]:
```
## querty for 3hr, precipitaion for historical from CNRM-ESM2-1
df_3hr_historical_CNRM_pr = df[(df.table_id == '3hr') & (df.variable_id ==␣
↪'pr') & (df.experiment_id== 'historical') & (df.source_id== 'CNRM-ESM2-1') ]
len(df_3hr_historical_CNRM_pr)
df_3hr_historical_CNRM_pr
```

[42]:
```
      activity_id institution_id    source_id experiment_id member_id  \
44063        CMIP   CNRM-CERFACS  CNRM-ESM2-1    historical  r1i1p1f2

      table_id variable_id grid_label  \
44063      3hr          pr         gr

                                                  zstore  dcpp_init_year  \
44063  gs://cmip6/CMIP6/CMIP/CNRM-CERFACS/CNRM-ESM2-1…             NaN

        version
44063  20181206
```

[43]:
```
## pull data
# get the path to a specific zarr store (the first one from the dataframe above)
zstore5 = df_3hr_historical_CNRM_pr.zstore.values[-1]
print(zstore5)

# create a mutable-mapping-style interface to the store
mapper5 = fsspec.get_mapper(zstore5)

# open it using xarray and zarr
ds_proj_historical = xr.open_zarr(mapper5, consolidated=True)
ds_proj_historical
```

```
gs://cmip6/CMIP6/CMIP/CNRM-CERFACS/CNRM-
ESM2-1/historical/r1i1p1f2/3hr/pr/gr/v20181206/
```

[43]:
```
<xarray.Dataset>
Dimensions:      (lat: 128, lon: 256, time: 482120, axis_nbounds: 2)
Coordinates:
  * lat          (lat) float64 -88.93 -87.54 -86.14 -84.74 … 86.14 87.54 88.93
  * lon          (lon) float64 0.0 1.406 2.812 4.219 … 354.4 355.8 357.2 358.6
  * time         (time) datetime64[ns] 1850-01-01T01:30:00 … 2014-12-31T22:…
    time_bounds  (time, axis_nbounds) datetime64[ns]
dask.array<chunksize=(60265, 1), meta=np.ndarray>
Dimensions without coordinates: axis_nbounds
Data variables:
    pr           (time, lat, lon) float32 dask.array<chunksize=(600, 128, 256),
meta=np.ndarray>
Attributes: (12/55)
```

```
    CMIP6_CV_version:       cv=6.2.3.0-7-g2019642
    Conventions:            CF-1.7 CMIP-6.2
    EXPID:                  CNRM-ESM2-1_historical_r1i1p1f2_v2
    activity_id:            CMIP
    arpege_minor_version:   6.3.2
    branch_method:          standard
    …                     …
    variable_id:            pr
    variant_label:          r1i1p1f2
    xios_commit:            1442-shuffle
    status:                 2019-10-25;created;by nhn2@columbia.edu
    netcdf_tracking_ids:    hdl:21.14100/f1e5c10f-c895-46b1-a771-05e33c7947b6…
    version_id:             v20181206
```

[44]:
```
# Apply lat/lon masks to the field, then calculate averages over the lat and
 ↪lon dimensions
oahu_pr_proj_historical=ds_proj_historical.pr.where(mask_lon & mask_lat, drop =
 ↪True)

## remove times associated with leap years (remove feb 29 from records)
oahu_pr_proj_historical = oahu_pr_proj_historical.
 ↪sel(time=~((oahu_pr_proj_historical.time.dt.month == 2) &
 ↪(oahu_pr_proj_historical.time.dt.day == 29)))
oahu_pr_proj_historical

## group by day of year and avg by day
oahu_pr_proj_historical['dayofyear'] = xr.DataArray(oahu_pr_proj_historical.
 ↪indexes['time'].strftime('%Y-%m-%d'), coords=oahu_pr_proj_historical.time.
 ↪coords)
oahu_pr_proj_historical_avg = oahu_pr_proj_historical.groupby('dayofyear').
 ↪mean('time', keep_attrs=True) #retain attributes for metpy conversion in nxt
 ↪step
oahu_pr_proj_historical_avg
```

[44]:
```
<xarray.DataArray 'pr' (dayofyear: 60225, lat: 1, lon: 1)>
dask.array<stack, shape=(60225, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '1850-01-01' '1850-01-02' … '2014-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
```

```
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[45]:
```
## daily sum of precip historical
oahu_pr_proj_sum_historical = oahu_pr_proj_historical.groupby('dayofyear').
 ↪sum('time', keep_attrs=True) #retain attributes for metpy conversion in nxt␣
 ↪step
oahu_pr_proj_sum_historical
```

[45]:
```
<xarray.DataArray 'pr' (dayofyear: 60225, lat: 1, lon: 1)>
dask.array<stack, shape=(60225, 1, 1), dtype=float32, chunksize=(1, 1, 1),
chunktype=numpy.ndarray>
Coordinates:
  * lat        (lat) float64 21.71
  * lon        (lon) float64 202.5
  * dayofyear  (dayofyear) object '1850-01-01' '1850-01-02' … '2014-12-31'
Attributes:
    cell_measures:       area: areacella
    cell_methods:        area: time: mean
    description:         at surface; includes both liquid and solid phases.  …
    history:             none
    interval_operation:  900 s
    interval_write:      3 h
    long_name:           Precipitation
    online_operation:    average
    standard_name:       precipitation_flux
    units:               kg m-2 s-1
```

[47]:
```
# Make metpy recognize the units
oahu_pr_proj_historical_sum = oahu_pr_proj_sum_historical.metpy.quantify()

# convert kg/m2/sec to in/day
density_water = units('kg / m^3') * 1000
oahu_pr_proj_historical_converted_int_sum = (oahu_pr_proj_historical_sum /␣
 ↪density_water)
oahu_pr_proj_historical_converted_int_sum =␣
 ↪oahu_pr_proj_historical_converted_int_sum.metpy.convert_units('inches / day')
oahu_pr_proj_historical_converted_int_sum =␣
 ↪oahu_pr_proj_historical_converted_int_sum.mean("lon").mean("lat")
oahu_pr_proj_historical_converted_int_sum
```

[47]:
```
<xarray.DataArray 'pr' (dayofyear: 60225)>
<Quantity(dask.array<mean_agg-aggregate, shape=(60225,), dtype=float32,
chunksize=(1,), chunktype=numpy.ndarray>, 'inch / day')>
```

```
Coordinates:
  * dayofyear  (dayofyear) object '1850-01-01' '1850-01-02' … '2014-12-31'
```

[22]:
```python
# Cast our xarray to dataframe -- daily avg
oahu_pr_proj_historical_df = oahu_pr_proj_historical_converted_int.
 ↪to_dataframe().reset_index()
oahu_pr_proj_historical_df.head(20)
```

[22]:

	dayofyear	pr
0	1850-01-01	7.431174e-04
1	1850-01-02	5.950664e-02
2	1850-01-03	3.129180e-01
3	1850-01-04	4.294988e-04
4	1850-01-05	1.384215e-03
5	1850-01-06	4.975918e-03
6	1850-01-07	9.406500e-05
7	1850-01-08	9.380140e-23
8	1850-01-09	2.022306e-05
9	1850-01-10	2.199838e-22
10	1850-01-11	5.801964e-04
11	1850-01-12	1.061206e-01
12	1850-01-13	4.339770e-02
13	1850-01-14	2.547624e-02
14	1850-01-15	2.540510e-01
15	1850-01-16	1.818833e-05
16	1850-01-17	2.309185e-03
17	1850-01-18	1.173254e-01
18	1850-01-19	1.011662e-01
19	1850-01-20	7.681608e-05

[48]:
```python
# Cast our xarray to dataframe --  daily sum historical
oahu_pr_proj_historical_df_sum = oahu_pr_proj_historical_converted_int_sum.
 ↪to_dataframe().reset_index()
oahu_pr_proj_historical_df_sum.head(20)
```

[48]:

	dayofyear	pr
0	1850-01-01	5.944939e-03
1	1850-01-02	4.760531e-01
2	1850-01-03	2.503344e+00
3	1850-01-04	3.435990e-03
4	1850-01-05	1.107372e-02
5	1850-01-06	3.980734e-02
6	1850-01-07	7.525200e-04
7	1850-01-08	7.504112e-22
8	1850-01-09	1.617845e-04
9	1850-01-10	1.759870e-21
10	1850-01-11	4.641572e-03

```
11  1850-01-12  8.489646e-01
12  1850-01-13  3.471816e-01
13  1850-01-14  2.038099e-01
14  1850-01-15  2.032408e+00
15  1850-01-16  1.455066e-04
16  1850-01-17  1.847348e-02
17  1850-01-18  9.386032e-01
18  1850-01-19  8.093297e-01
19  1850-01-20  6.145286e-04
```

[23]:
```
## to export df
#oahu_pr_proj_historical_df.to_csv('oahu_historical_2015_2100.csv', index =␣
↪False)
```

[49]:
```
## to export df, daily total historical
oahu_pr_proj_historical_df_sum.to_csv('oahu_historical_1850_2014_total.csv',␣
↪index = False)
```

Appendix I

Code for Runoff Coefficient and Peak Flow Values with Maximum and Minimum MCF Applied

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Graphs of Climate Change SWMM Results

This is code to analyze the climate change scaled results from SWMM and create figures

Elmera Azadpour

1/24/2022

NOTE: Figures will be be hidden from knitted markdown.

Analysis of simulated vs observed runoff

```
#Graph observed vs simulated runoff for Max Multiplicative Change Factor (MCF)

observed<- read.csv(here("climate_change_data","SWMM_results", "Mar14_observed.csv"))
simulated_max_march14 <- read.csv(here("climate_change_data","SWMM_results", "MCF_max_Mar14_simulated.cs
simulated_min_march14 <- read.csv(here("climate_change_data","SWMM_results", "MCF_min_Mar14_simulated.cs

# merge MCF max with observed
discharge_MCF_max<- merge(observed, simulated_max_march14, by = "time_step")

#merge MCF min with observed
discharge_MCF_min<- merge(observed, simulated_min_march14, by = "time_step")


summary(discharge_MCF_max)

graph_max<- ggplot(discharge_MCF_max, aes(x=discharge_obs_cfs, simulated_flow_cfs))+
  geom_point()

graph_max
```

```
graph_min<- ggplot(discharge_MCF_min, aes(x=discharge_obs_cfs, simulated_flow_cfs))+
  geom_point()

graph_min
```

```
calibrate_graph_max<- discharge_MCF_max %>%
  ggplot()+
  geom_line(aes(x=time_step, y=discharge_obs_cfs), color="#000000", size = 2.5)+
  geom_line(aes(x=time_step, y=simulated_flow_cfs), color= "#009E73", size = 2.5)+
  theme_classic()+
  labs(x="Time (hours)", y="Discharge (cfs)")+
  scale_y_continuous(limits= c(0,850), breaks= seq(0,850, by= 100),expand= c(0,0))+
  scale_x_continuous(limits= c(0,12), breaks= seq(0,12, by= 2),expand= c(0,0))+
  annotate("text", label= "Observed", x=10.5, y=85, size=8)+
  annotate("text", label= "Simulated", x=10.5, y=300, size=8) +
  theme(text = element_text(size=22))
```

```
calibrate_graph_max
```

```
calibrate_graph_min<- discharge_MCF_min %>%
  ggplot()+
  geom_line(aes(x=time_step, y=discharge_obs_cfs), color="#000000", size =2.5) +
  geom_line(aes(x=time_step, y=simulated_flow_cfs), color= "#009E73", size =2.5)+
  theme_classic()+
  labs(x="Time (hours)", y="Discharge (cfs)")+
  scale_y_continuous(limits= c(0,400), breaks= seq(0,350, by= 50),expand= c(0,0))+
  scale_x_continuous(limits= c(0,12), breaks= seq(0,12, by= 2),expand= c(0,0))+
  annotate("text", label= "Simulated", x=10.5, y=45, size=8)+
  annotate("text", label= "Observed", x=10.5, y=185, size=8) +
    theme(text = element_text(size=22))


calibrate_graph_min
```

```
# save graphs
 # ggsave('discharge_mar14_max_MCF.png', calibrate_graph_max, width = 16, height = 9, units = "in")

# ggsave('discharge_mar14_min_MCF.png', calibrate_graph_min, width = 16, height = 9, units = "in")


## combine all three lines onto one graph for easabilty
calibrate_graph <- ggplot()+
  geom_line(data = discharge_MCF_min, aes(x=time_step, y=discharge_obs_cfs), color="#000000", size =2.5
  geom_line(data= discharge_MCF_min, aes(x=time_step, y=simulated_flow_cfs), color= "#009E73", size =2.
  geom_line(data= discharge_MCF_max, aes(x=time_step, y=simulated_flow_cfs), color= "#D55E00", size = 2
  theme_classic()+
  labs(x="Time (hours)", y="Discharge (cfs)")+
  scale_y_continuous(limits= c(0,850), breaks= seq(0,850, by= 100),expand= c(0,0))+
  scale_x_continuous(limits= c(0,12), breaks= seq(0,12, by= 2),expand= c(0,0))+
  annotate("text", label= "Observed", x=10.5, y=200, size=8)+
  annotate("text", label= "Max MCF Simulated", x=10.5, y=655, size=8) +
   annotate("text", label= "Min MCF Simulated", x=10.5, y=55, size=8) +
  theme(text = element_text(size=22))

calibrate_graph
```

```
# ggsave('discharge_mar14_MCF.png', calibrate_graph, width = 16, height = 9, units = "in")
```

Analysis of MCF max storm results

```
subcatch_max_mcf<- read_csv("subcatchments_all.csv") %>%
  mutate(subcatchment= OBJECTID_1) %>%
  select(subcatchment, Curve_Number, Slope, percent_imp, Area_sqft)

swm_results_max_mcf<-read_csv("Wailupe_MCF_Max_Mar14.csv")

#Characterize results by urbanization level
results_max_mcf<- merge(subcatch_max_mcf, swm_results_max_mcf, by = "subcatchment") %>%
  mutate(runoff_normalized=
           total_runoff_in/Area_sqft) %>%
```

```
  mutate(Urbanization_level=
           case_when(
             percent_imp <15 |percent_imp == 15 ~ "Natural (less than 15 % Impervious)",
             percent_imp >15 & percent_imp <45 ~ "Urbanized (Between 15 and 45 % Impervious)",
             percent_imp >44.9999 ~ "Very urbanized (More than 45 % Impervious)"
             )
           )

write.csv(results_max_mcf, file = "results_max_mcf.csv") ##Export as .csv for use with graph maps

## normalize peak discharge (cfs) for max MCF by dividing by subcatchment area
results_max_mcf_normalized <- results_max_mcf %>%
  mutate(peak_runoff_cfs_norm = peak_runoff_cfs/Area_sqft)

results_maxmcf_peakflow_table <- results_max_mcf %>%
  select(subcatchment, peak_runoff_cfs, Curve_Number, Slope, percent_imp, Area_sqft) %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(peak_runoff_cfs)) %>%
  top_n(20,peak_runoff_cfs) %>%
  kable(col.names=c("Subcatchment","Peak Runoff (cfs), Max MCF",
                               "Curve Number", "Slope",
                               "Percent Impervious", "Area (sqft)")) %>%
  kable_styling(bootstrap_options = "striped")

results_maxmcf_peakflow_table

results_maxmcf_peakflow_table_normalized <- results_max_mcf_normalized %>%
  select(subcatchment, peak_runoff_cfs, Curve_Number, Slope, percent_imp, Area_sqft,peak_runoff_cfs_norm
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(peak_runoff_cfs_norm)) %>%
  top_n(20,peak_runoff_cfs_norm) %>%
  kable(col.names=c("Subcatchment","Peak Runoff (cfs), Max MCF",
                               "Curve Number", "Slope",
                               "Percent Impervious", "Area (sqft)", "Normalized Peak Runoff (cfs/sqft)
  kable_styling(bootstrap_options = "striped")

results_maxmcf_peakflow_table_normalized

results_maxmcf_runoffcoef_table <- results_max_mcf %>%
  select(subcatchment, runoff_coeff, Curve_Number, Slope, percent_imp, Area_sqft) %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(runoff_coeff)) %>%
  top_n(20,runoff_coeff) %>%
  kable(col.names=c("Subcatchment","Runoff Coefficient, Max MCF",
                               "Curve Number", "Slope",
                               "Percent Impervious", "Area (sqft)")) %>%
  kable_styling(bootstrap_options = "striped")

results_maxmcf_runoffcoef_table

#Perform a linear regression for the SWMM max MCF storm results
results_max_mcf_regression<- lm(total_runoff_in ~Curve_Number + Slope + percent_imp +
                              Area_sqft, data = results_max_mcf)
```

```r
#Graph the relationship bw simulated runoff and impervious cover by urbanization level
runoff_imp_graph_max_mcf<- results_max_mcf %>%
  ggplot(aes(x=percent_imp, y=total_runoff_in))+
  geom_point(aes(color=Urbanization_level))+
  labs(x= "Percent Impervious of Subcatchment", y= "Total Simulated Runoff (inches)")+
  scale_y_continuous(limits= c(0,8), breaks= seq(0,8, by= 1),expand= c(0,0.08))+
  scale_x_continuous(limits= c(0,80), breaks= seq(0,80, by= 10),expand= c(0,0))+
  scale_color_manual(name= "Urbanization Level", values= c("darkgreen", "darkseagreen",
                                                           "darkgoldenrod1"))+
  theme_classic()

runoff_imp_graph_max_mcf
```

```r
#Save runoff vs. impervious graph
# ggsave("runoff_imp_max_mcf.pdf", width = 8, height =4)
# ggsave("runoff_imp_max_mcf.png", width = 8, height =4)

#Create a table for the regression results for max mcf storm
regress_table_max_mcf<- stargazer(results_max_mcf_regression, type ="html", digits= 2,
                          dep.var.labels = "Total Runoff (Inches)",
                       covariate.labels = c("Curve Number", "Slope", "Percent Impervious",
                                            "Area (sqft)", "Y-Intercept"),
                       omit.stat = c("rsq"))
regress_table_max_mcf
```

Analysis of MCF min storm results

```r
subcatch_min_mcf<- read_csv("subcatchments_all.csv") %>%
  mutate(subcatchment= OBJECTID_1) %>%
  select(subcatchment, Curve_Number, Slope, percent_imp, Area_sqft)

swm_results_min_mcf<-read_csv("Wailupe_MCF_Min_Mar14.csv")

#Characterize results by urbanization level
results_min_mcf<- merge(subcatch_min_mcf, swm_results_min_mcf, by = "subcatchment") %>%
  mutate(runoff_normalized=
           total_runoff_in/Area_sqft) %>%
  mutate(Urbanization_level=
           case_when(
             percent_imp <15 |percent_imp == 15 ~ "Natural (less than 15 % Impervious)",
             percent_imp >15 & percent_imp <45 ~ "Urbanized (Between 15 and 45 % Impervious)",
             percent_imp >44.9999 ~ "Very urbanized (More than 45 % Impervious)"
             )
           )

write.csv(results_min_mcf, file = "results_min_mcf.csv") ##Export as .csv for use with graph maps


## normalize peak discharge (cfs) for min MCF by dividing by subcatchment area
results_min_mcf_normalized <- results_min_mcf %>%
  mutate(peak_runoff_cfs_norm = peak_runoff_cfs/Area_sqft)

results_minmcf_peakflow_table <- results_min_mcf %>%
```

```r
  select(subcatchment, peak_runoff_cfs, Curve_Number, Slope, percent_imp, Area_sqft) %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(peak_runoff_cfs)) %>%
  top_n(20,peak_runoff_cfs) %>%
  kable(col.names=c("Subcatchment","Peak Runoff (cfs), Min MCF",
                              "Curve Number", "Slope",
                              "Percent Impervious", "Area (sqft)")) %>%
  kable_styling(bootstrap_options = "striped")

results_minmcf_peakflow_table

results_minmcf_peakflow_normalized_table <- results_min_mcf_normalized %>%
  select(subcatchment, peak_runoff_cfs, Curve_Number, Slope, percent_imp, Area_sqft,peak_runoff_cfs_norm
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(peak_runoff_cfs_norm)) %>%
  top_n(20,peak_runoff_cfs_norm) %>%
  kable(col.names=c("Subcatchment","Peak Runoff (cfs), Min MCF",
                              "Curve Number", "Slope",
                              "Percent Impervious", "Area (sqft)", "Normalized Peak Runoff (cfs/sqft)
  kable_styling(bootstrap_options = "striped")

results_minmcf_peakflow_normalized_table

results_minmcf_runoffcoef_table <- results_min_mcf %>%
  select(subcatchment, runoff_coeff, Curve_Number, Slope, percent_imp, Area_sqft) %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(runoff_coeff)) %>%
  top_n(20,runoff_coeff) %>%
  kable(col.names=c("Subcatchment","Runoff Coefficient, Min MCF",
                              "Curve Number", "Slope",
                              "Percent Impervious", "Area (sqft)")) %>%
  kable_styling(bootstrap_options = "striped")

results_minmcf_runoffcoef_table


#Perform a linear regression for the SWMM max MCF storm results
results_min_mcf_regression<- lm(total_runoff_in ~Curve_Number + Slope + percent_imp +
                              Area_sqft, data = results_min_mcf)

#Graph the relationship bw simulated runoff and impervious cover by urbanization level
runoff_imp_graph_min_mcf<- results_min_mcf %>%
  ggplot(aes(x=percent_imp, y=total_runoff_in))+
  geom_point(aes(color=Urbanization_level))+
  labs(x= "Percent Impervious of Subcatchment", y= "Total Simulated Runoff (inches)")+
  scale_y_continuous(limits= c(0,7), breaks= seq(0,7, by= 1),expand= c(0,0.08))+
  scale_x_continuous(limits= c(0,80), breaks= seq(0,80, by= 10),expand= c(0,0))+
  scale_color_manual(name= "Urbanization Level", values= c("darkgreen", "darkseagreen",
                                                        "darkgoldenrod1"))+
  theme_classic()

runoff_imp_graph_min_mcf
```

```r
#Save runoff vs. impervious graph
# ggsave("runoff_imp_min_mcf.pdf", width = 8, height =4)
# ggsave("runoff_imp_min_mcf.png", width = 8, height =4)

#Create a table for the regression results
regress_table_min_mcf<- stargazer(results_min_mcf_regression, type ="html", digits= 2,
                           dep.var.labels = "Total Runoff (Inches)",
                        covariate.labels = c("Curve Number", "Slope", "Percent Impervious",
                                             "Area (sqft)", "Y-Intercept"),
                        omit.stat = c("rsq"))
regress_table_min_mcf
```

Maps of SWMM Results

Maps for MCF max storm hotspots

```r
results_max_mcf<- read_csv("results_max_mcf.csv") ##read in file from code above

#Combine subcatchments outline with wet storm results
subcatch_max <- read_sf(dsn = here("climate_change_data", "SWMM_results","shapefiles"), layer = "subcat
  st_transform(st_crs(4326)) %>%
  clean_names() %>%
  select(subcatchment = objectid_1) %>%
  merge(results_max_mcf) %>%
   filter(subcatchment != "5")

#  Total volume hotspots
hotspots_max_mcf_total <- tm_basemap("OpenStreetMap.Mapnik") +
  tm_shape(subcatch_max, unit = "Miles") +
  tm_polygons("runoff_coeff", alpha = 0.8, palette = "Blues", style = "cont", n=8,
             legend.hist = TRUE, title = "Runoff Coefficient") +
  tm_layout(title = "March 2009 Max MCF storm", inner.margins=c(.05, .05, 0.1, .53),
            legend.position =  c(.6,.32), legend.title.size = 1.4, legend.text.size = 1) +
  tm_text("subcatchment", size = 0.3) +
  tm_scale_bar(position = c(.6,.59), breaks = c(0, 0.2, 0.4, 0.6, 0.8,1)) +
  tm_compass(position = c(.58,.52))

# tmap_save(hotspots_max_mcf_total, here("climate_change_data", "output_maps","hotspots_mcf_max.png"))


#  Peak flow hotspots
hotspots_max_mcf_peak <- tm_basemap("OpenStreetMap.Mapnik") +
  tm_shape(subcatch_max, unit = "Miles") +
  tm_polygons("peak_runoff_cfs", alpha = 0.75, palette = "Greens", style = "cont", n=8,
             legend.hist = TRUE, title = "Peak Discharge (cfs)") +
  tm_layout(title = "March 2009 Max MCF storm", inner.margins=c(.05, .05, 0.1, .53),
            legend.position =  c(.6,.27), legend.title.size = 1.4, legend.text.size = 1) +
  tm_text("subcatchment", size = 0.3) +
  tm_scale_bar(position = c(.6,.54), breaks = c(0, 0.2, 0.4, 0.6, 0.8,1)) +
  tm_compass(position = c(.58,.47))
#tmap_save(hotspots_max_mcf_peak, here("climate_change_data", "output_maps","hotspots_max_mcf_peak.png"

subcatch_max_peak <- subcatch_max %>%
```

```
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  ggplot() +
  geom_sf(aes(fill = peak_runoff_cfs)) +
  theme_bw() +
  scale_fill_gradient(low = "#D1F2EB", high = "#148F77", name = "Peak Discharge (cfs)",
                      breaks = c(0, 25, 50, 75, 100 )) +
  labs(title = "Max MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 1.8) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90))+
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
        panel.border=element_blank()) +
  theme_void() # for faculty presentation, remove lines and axis elements

subcatch_max_peak
```

```
# ggsave('subcatch_max_peak_removedsubs_themevoid.png', subcatch_max_peak, width = 5, height = 7, units

subcatch_max_total <- subcatch_max %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  ggplot() +
  geom_sf(aes(fill = runoff_coeff)) +
  theme_bw() +
  scale_fill_gradient(low = "#D6EAF8", high = "#2874A6", name = "Runoff Coefficient",
                      breaks = c(0, 0.2, 0.4, 0.6, 0.8, 1.0),
                      limits = c(0,1.0)) +
  labs(title = "Max MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 1.8) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90)) +
    theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
        panel.border=element_blank()) +
  theme_void()

subcatch_max_total
```

```
  #  ggsave('subcatch_max_total.png', subcatch_max_total, width = 5, height = 7, units = "in")
```

Maps for MCF min storm hotspots

```
results_min_mcf<- read_csv("results_min_mcf.csv") ##read in file from code above

#Combine subcatchments outline with wet storm results
```

```
subcatch_min <- read_sf(dsn = here("climate_change_data", "SWMM_results","shapefiles"), layer = "subcat
  st_transform(st_crs(4326)) %>%
  clean_names() %>%
  select(subcatchment = objectid_1) %>%
  merge(results_min_mcf) %>%
   filter(subcatchment != "5")

#  Total volume hotspots
hotspots_min_mcf_total <- tm_basemap("OpenStreetMap.Mapnik") +
  tm_shape(subcatch_min, unit = "Miles") +
  tm_polygons("runoff_coeff", alpha = 0.8, palette = "Blues", style = "cont", n=8,
              legend.hist = TRUE, title = "Runoff Coefficient") +
  tm_layout(title = "March 2009 Min MCF storm", inner.margins=c(.05, .05, 0.1, .53),
            legend.position =  c(.6,.32), legend.title.size = 1.4, legend.text.size = 1) +
  tm_text("subcatchment", size = 0.3) +
  tm_scale_bar(position = c(.6,.59), breaks = c(0, 0.2, 0.4, 0.6, 0.8,1)) +
  tm_compass(position = c(.58,.52))
##tmap_save(hotspots_wet_total, here("5.Results_Maps", "output_maps","hotspots_wet_total.png"))


#  Peak flow hotspots
hotspots_min_mcf_peak <- tm_basemap("OpenStreetMap.Mapnik") +
  tm_shape(subcatch_min, unit = "Miles") +
  tm_polygons("peak_runoff_cfs", alpha = 0.75, palette = "Greens", style = "cont", n=8,
              legend.hist = TRUE, title = "Peak Discharge (cfs)") +
  tm_layout(title = "March 2009 Min MCF storm", inner.margins=c(.05, .05, 0.1, .53),
            legend.position =  c(.6,.27), legend.title.size = 1.4, legend.text.size = 1) +
  tm_text("subcatchment", size = 0.3) +
  tm_scale_bar(position = c(.6,.54), breaks = c(0, 0.2, 0.4, 0.6, 0.8,1)) +
  tm_compass(position = c(.58,.47))
##tmap_save(hotspots_wet_peak, here("5.Results_Maps", "output_maps","hotspots_wet_peak.png"))

subcatch_min_peak <- subcatch_min %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24))  %>%
  ggplot() +
  geom_sf(aes(fill = peak_runoff_cfs)) +
  theme_classic()+
  scale_fill_gradient(low = "#D1F2EB", high = "#148F77", name = "Peak Discharge (cfs)",
                      breaks = c(0, 3, 6, 9, 12, 15)) +
  labs(title = "Min MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 1.8) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90)) +
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
        panel.border=element_blank()) +
  theme_void() # for facily presentation, remove lines and axis elements

subcatch_min_peak
```

```
# ggsave('subcatch_min_peak_removedsub_themevoid.png', subcatch_min_peak, width = 5, height = 7, units

subcatch_min_total <- subcatch_min %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  ggplot() +
  geom_sf(aes(fill = runoff_coeff)) +
  theme_bw() +
  scale_fill_gradient(low = "#D6EAF8", high = "#2874A6", name = "Runoff Coefficient",
                      breaks = c(0, 0.2, 0.4, 0.6, 0.8, 1.0),
                      limits = c(0,1.0)) +
  labs(title = "Min MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 1.8) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90)) +
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
        panel.border=element_blank()) +
  theme_void()

subcatch_min_total
```

```
# ggsave('subcatch_min_total.png', subcatch_min_total, width = 5, height = 7, units = "in")
```

Normalized Peak Discharge Maps

```
subcatch_max_normalized <- read_sf(dsn = here("climate_change_data", "SWMM_results","shapefiles"), laye
  st_transform(st_crs(4326)) %>%
  clean_names() %>%
  select(subcatchment = objectid_1) %>%
  merge(results_max_mcf_normalized) %>%
   filter(subcatchment != "5")

## normalized Max MCF Peak Discharge
subcatch_max_peak_normalized <- subcatch_max_normalized %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  ggplot() +
  geom_sf(aes(fill = peak_runoff_cfs_norm)) +
  theme_bw() +
  scale_fill_gradient(low = "#D1F2EB", high = "#148F77", name = "Normalized Peak Discharge (cfs/sqft)")
  labs(title = "Max MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 1.8) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90))+
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
```

```
        panel.border=element_blank()) +
  theme_void() # for faculty presentation, remove lines and axis elements

subcatch_max_peak_normalized
```

```
# ggsave('subcatch_max_peak_removedsubs_themevoid_norm.png', subcatch_max_peak_normalized, width = 5, h

subcatch_min_normalized <- read_sf(dsn = here("climate_change_data", "SWMM_results","shapefiles"), laye
  st_transform(st_crs(4326)) %>%
  clean_names() %>%
  select(subcatchment = objectid_1) %>%
  merge(results_min_mcf_normalized) %>%
   filter(subcatchment != "5")

## normalized Min MCF Peak Discharge
subcatch_min_peak_normalized <- subcatch_min_normalized %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24))  %>%
  ggplot() +
  geom_sf(aes(fill = peak_runoff_cfs_norm)) +
  theme_classic()+
  scale_fill_gradient(low = "#D1F2EB", high = "#148F77", name = "Normalized Peak Discharge (cfs/sqft)")
  labs(title = "Min MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 1.8) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90)) +
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
        panel.border=element_blank()) +
  theme_void() # for facily presentation, remove lines and axis elements

subcatch_min_peak_normalized
```

```
 # ggsave('subcatch_min_peak_removedsub_themevoid_norm.png', subcatch_min_peak_normalized, width = 5, h
```

binned runoff coefficient maps for min and max MCF

```
# View a single RColorBrewer palette by specifying its name
display.brewer.pal(n = 7, name = 'Blues')
```

```
# Hexadecimal color specification
brewer.pal(n = 7, name = "Blues")


mycols <- brewer.pal(n = 11, name = "Blues")
mybreaks_max<- c(0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9)

subcatch_min_total <- subcatch_min %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  mutate(runoff_coeff_cut = cut_number(runoff_coeff, n = 10)) %>%
  ggplot() +
```

```r
  geom_sf(aes(fill = runoff_coeff_cut)) +
  theme_bw()  +
  scale_fill_gradientn(colours = mycols,
                       breaks= mybreaks_max,
    super = metR::ScaleDiscretised,
    name = "Runoff Coefficient") +
  theme(legend.position = "bottom") +
  labs(title = "Min MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 3.1) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90)) +
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
        panel.border=element_blank()) +
  theme_void()

subcatch_min_total
```

```r
  # ggsave('subcatch_min_total_binned.png', subcatch_min_total, width = 5, height = 7, units = "in")

mycols <- brewer.pal(n = 11, name = "Blues")
mybreaks_max<- c(0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9)

subcatch_max_total <- subcatch_max %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  mutate(runoff_coeff_cut = cut_number(runoff_coeff, n = 10)) %>%
  ggplot() +
  geom_sf(aes(fill = runoff_coeff_cut)) +
  theme_bw()  +
  scale_fill_gradientn(colours = mycols,
                       breaks= mybreaks_max,
    super = metR::ScaleDiscretised,
    name = "Runoff Coefficient") +
  labs(title = "Max MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 3.1) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90)) +
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
        panel.border=element_blank()) +
  theme_void()

subcatch_max_total
```

```r
 # ggsave('subcatch_max_total_binned.png', subcatch_max_total, width = 5, height = 7, units = "in")
```

binned peak flow maps for min and max MCF

```
mycols2 <- brewer.pal(n = 11, name = "Greens")
mybreaks2_min<- c(0.0, 2.0, 4.0, 6.0, 8.0, 10.0, 12.0, 14.0, 16.0)

subcatch_min_peak <- subcatch_min %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24))  %>%
  mutate(peak_runoff_cfs_cut = cut_number(peak_runoff_cfs, n = 11)) %>%
  ggplot() +
  geom_sf(aes(fill = peak_runoff_cfs_cut)) +
  theme_classic()+
  scale_fill_gradientn(colours = mycols2,
                       breaks= mybreaks2_min,
    super = metR::ScaleDiscretised,
    name = "Peak Discharge (cfs)") +
  labs(title = "Min MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 3.1) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90)) +
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
        rect = element_blank(),
        panel.border=element_blank()) +
  theme_void() # for facily presentation, remove lines and axis elements

subcatch_min_peak
```

```
 # ggsave('subcatch_min_peak_removedsub_themevoid_binned.png', subcatch_min_peak, width = 5, height = 7

mycols3 <- brewer.pal(n = 11, name = "Greens")
mybreaks3_max<- c(0.0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100)

subcatch_max_peak <- subcatch_max %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  mutate(peak_runoff_cfs_cut = cut_number(peak_runoff_cfs, n = 11)) %>%
  ggplot() +
  geom_sf(aes(fill = peak_runoff_cfs_cut)) +
  theme_classic()+
  scale_fill_gradientn(colours = mycols3,
                       breaks= mybreaks3_max,
    super = metR::ScaleDiscretised,
    name = "Peak Discharge (cfs)") +
  labs(title = "Max MCF") +
  geom_sf_text(aes(label = subcatchment), colour = "black", fontface = "bold", size = 3.1) +
  # geom_sf_label(aes(label = subcatchment), size = 1.5) +
  theme(axis.title.x = element_blank(),
        axis.title.y = element_blank()) +
theme(axis.text.x = element_text(angle = 90))+
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.ticks = element_blank(),
```

```
       rect = element_blank(),
       panel.border=element_blank()) +
  theme_void() # for faculty presentation, remove lines and axis elements

subcatch_max_peak
```

```
# ggsave('subcatch_max_peak_removedsubs_themevoid_binned.png', subcatch_max_peak, width = 5, height = 7
```

combine max and min runoff coefficient results into single table showing the catchment #, min, and max runoff coefficient, slope, percent impervious, and area (sqft)

```
results_min_mcf_rc <- results_min_mcf %>%
  select(subcatchment, Slope, percent_imp, Area_sqft, runoff_coeff) %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(runoff_coeff)) %>%
  top_n(20,runoff_coeff)

results_max_mcf_rc <- results_max_mcf %>%
  select(subcatchment, Slope, percent_imp, Area_sqft, runoff_coeff) %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(runoff_coeff)) %>%
  top_n(20,runoff_coeff)

results_runoffcoef_table <- results_min_mcf_rc %>%
  full_join(results_max_mcf_rc, by=c("subcatchment", "Slope", "percent_imp", "Area_sqft")) %>%
  kable(col.names=c("Subcatchment","Slope", "Percent Impervious", "Area (sqft)", "Runoff Coefficient, Mi
                              "Runoff Coefficient, Max MCF")) %>%
  kable_styling(bootstrap_options = "striped")

results_runoffcoef_table
```

combine max and min peak runoff (cfs) results into single table showing the catchment #, min, and max peak runoff (cfs)

```
results_min_mcf_peak <- results_min_mcf %>%
  select(subcatchment, Slope, percent_imp, Area_sqft, peak_runoff_cfs) %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(peak_runoff_cfs)) %>%
  top_n(20,peak_runoff_cfs)

results_max_mcf_peak <- results_max_mcf %>%
  select(subcatchment, Slope, percent_imp, Area_sqft, peak_runoff_cfs) %>%
  filter(!subcatchment %in% c(1, 2,94,3,38, 24)) %>%
  arrange(desc(peak_runoff_cfs)) %>%
  top_n(20,peak_runoff_cfs)

results_peakflow_table <- results_min_mcf_peak %>%
  full_join(results_max_mcf_peak, by=c("subcatchment", "Slope", "percent_imp", "Area_sqft")) %>%
  kable(col.names=c("Subcatchment","Slope", "Percent Impervious", "Area (sqft)","Peak Runoff (cfs), Min
                              "Peak Runoff (cfs), Max MCF")) %>%
  kable_styling(bootstrap_options = "striped")
```

```
results_peakflow_table
```

comparing historical vs Max MCF runoff coeffiecients from Dornan et al., 2020

```
## runoff coefficients differences
dornan_results_top20_rc <- read_csv("~/Desktop/Aloha-Aina-Master/climate_change_data/SWMM_results/dornan
  select(subcatchment, runoff_coeff) # read in dorana et al RC results

results_max_mcf_rc_summary <- results_max_mcf_rc %>%  select(subcatchment, runoff_coeff) # select just

combined_rc_results <- dornan_results_top20_rc %>%  right_join(results_max_mcf_rc_summary, by = c("subca

combined_rc_results = combined_rc_results %>%  mutate(subtract = runoff_coeff.y-runoff_coeff.x) # add c

## peak flow differences
dornan_results_top20_peakflow <- read_csv("~/Desktop/Aloha-Aina-Master/climate_change_data/SWMM_results/
  select(subcatchment, peak_runoff_cfs) # read in Team Kahuawais peak flow results

results_max_mcf_peak_summary <- results_max_mcf_peak %>%  select(subcatchment, peak_runoff_cfs) # selec

combined_peak_results <- dornan_results_top20_peakflow %>%  right_join(results_max_mcf_peak_summary, by

combined_peak_results = combined_peak_results %>%  mutate(subtract = peak_runoff_cfs.y-peak_runoff_cfs.
```

Appendix J

Wailupe Normalized Peak Discharge

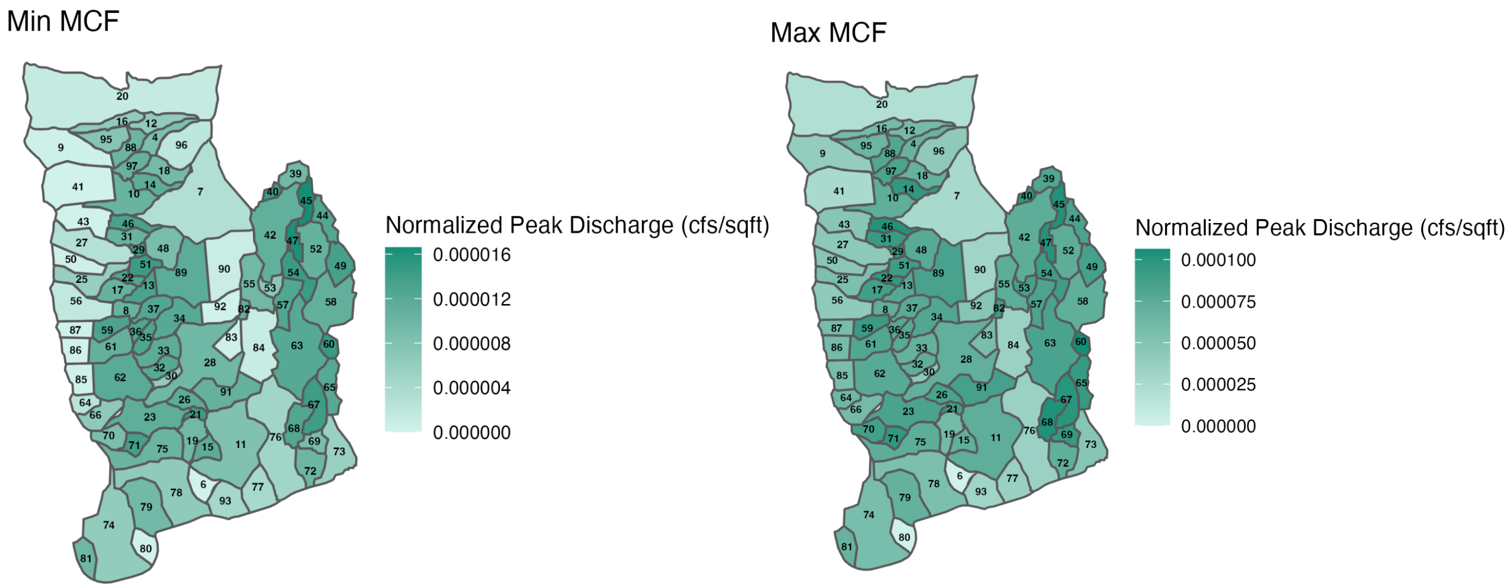

Figure J.1. Modeled Normalized Peak Flow Results for Wailupe Watershed. Left: March 14th, 2009 storm with the min MCF applied. Right: March 14th, 2009 storm used with the max MCF applied.

Table J.1. Summary Output Table of Normalized Peak Flow with Max MCF Results and Significant Parameters

Subcatchment	Peak Runoff (cfs), Max MCF	Curve Number	Slope	Percent Impervious	Area (sqft)	Normalized Peak Runoff (cfs/sqft)
5	4.51	59.94459	4.973908	59.22529	42008.07	0.0001074
60	13.90	58.26651	10.200056	66.27512	130703.86	0.0001063
68	31.68	64.12348	16.778001	56.40240	306366.86	0.0001034
45	21.10	46.68192	10.837372	75.81188	205273.48	0.0001028
46	21.33	57.85258	9.180995	59.97949	209977.29	0.0001016
47	16.51	44.12992	9.017865	73.67874	163180.85	0.0001012
67	37.74	59.21465	13.094514	65.31544	376961.02	0.0001001
40	7.68	46.96258	7.774446	65.26444	78272.63	0.0000981
71	15.57	58.22480	1.229756	63.33945	161251.17	0.0000966
14	23.52	59.93120	10.062202	51.97367	244581.39	0.0000962
22	10.23	52.60335	5.224538	57.36459	106889.43	0.0000957
69	16.14	61.92279	23.710094	39.74707	171176.11	0.0000943
65	29.11	59.79150	12.285943	54.98557	309782.87	0.0000940
29	5.84	46.60531	4.303893	63.75090	62214.52	0.0000939
31	21.49	58.70699	10.270774	47.00970	229731.45	0.0000935
59	22.41	53.74048	9.355130	58.61615	241399.55	0.0000928
82	5.99	52.36590	12.984541	50.03241	65510.58	0.0000914
51	17.68	45.48179	3.205696	65.70618	194382.01	0.0000910
54	27.29	46.30916	11.985041	65.90850	301206.44	0.0000906
21	7.00	41.71682	2.133592	64.38962	78832.74	0.0000888

Table J.2. Summary Output Table of Normalized Peak Flow with Min MCF Results and Significant Parameters.

Subcatchment	Peak Runoff (cfs), Min MCF	Curve Number	Slope	Percent Impervious	Area (sqft)	Normalized Peak Runoff (cfs/sqft)
45	3.41	46.68192	10.837372	75.81188	205273.48	0.0000166
47	2.66	44.12992	9.017865	73.67874	163180.85	0.0000163
60	1.92	58.26651	10.200056	66.27512	130703.86	0.0000147
40	1.13	46.96258	7.774446	65.26444	78272.63	0.0000144
51	2.80	45.48179	3.205696	65.70618	194382.01	0.0000144
54	4.32	46.30916	11.985041	65.90850	301206.44	0.0000143
21	1.12	41.71682	2.133592	64.38962	78832.74	0.0000142
67	5.35	59.21465	13.094514	65.31544	376961.02	0.0000142
29	0.88	46.60531	4.303893	63.75090	62214.52	0.0000141
71	2.21	58.22480	1.229756	63.33945	161251.17	0.0000137
49	4.29	44.95489	11.626618	61.33458	317060.05	0.0000135
46	2.80	57.85258	9.180995	59.97949	209977.29	0.0000133
13	2.77	37.24907	2.801558	60.72206	210147.80	0.0000132
5	0.55	59.94459	4.973908	59.22529	42008.07	0.0000131
59	3.13	53.74048	9.355130	58.61615	241399.55	0.0000130
35	2.11	36.38429	2.502320	58.10591	163977.29	0.0000129
22	1.36	52.60335	5.224538	57.36459	106889.43	0.0000127
36	1.31	36.48504	3.413503	57.37835	103198.24	0.0000127
44	3.09	46.81877	9.792575	56.58471	246676.73	0.0000125
68	3.83	64.12348	16.778001	56.40240	306366.86	0.0000125

Appendix K

Code for Probability of Extreme Climate Change Events

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Probabilty Distribution Function: Climate Change Analysis

This is code to create probability distribution figure

Elmera Azadpour

1/30/2022

NOTE: Figures will be be hidden from knitted markdown.

```
## read in wailupe precip data from NOAA
wailupe_77_rain <- read.csv(here("climate_change_data", "probabilty_distribution", "NOAA_WailupeHawaiiKa

##Use lubridate to clean up the dates and times
wailupe_77_rain$DATE <- ymd(wailupe_77_rain$DATE)
```

```
## for wailupe 1977-2014
wailupe_tidy_77 <- wailupe_77_rain %>%
  rename(station = STATION, station_name = STATION_NAME, elevation = ELEVATION,
         lat = LATITUDE, lon = LONGITUDE, date = DATE, time = TIME, qgag = QGAG,
         qgag_flag = Measurement.Flag, qgag_qual = Quality.Flag, qgag_units = Units,
         qpcp = QPCP, qpcp_flag = Measurement.Flag.1, qpcp_qual = Quality.Flag.1,
         qpcp_units = Units.1) %>% #renames columns
  filter(station_name == "WAILUPE VALLEY SCHOOL 723.6 HI US") %>% #filter to Wailupe gauge only
  filter(qpcp != "-9999",
         qpcp != "999",
         qpcp != "999.99",
         qpcp_flag != "g",
         qpcp_flag != "{",
         qpcp_flag != "}",
         qpcp_flag != "[",
         qpcp_flag != "]",
         qgag != "-9999.00",
         qgag != "-9999",
         qgag_flag != "g",
         qgag_flag != "V",
         qgag_flag != "P",
         qgag_flag != "{",
         qgag_flag != "}",
         qgag_flag != "[",
         qgag_flag != "]") ## removes all flagged data


## daily total precip
wailupe_daily_77 <- wailupe_tidy_77 %>%
  group_by(date) %>%
  summarize(
    daily_pcp = sum(qpcp),
    daily_vol = sum(qgag)) ## gives total summed precip data per day. HT is given in inches.
```

```
wailupe_daily_77$date <- ymd(wailupe_daily_77$date)
wailupe_tidy_77$date <- ymd(wailupe_tidy_77$date)
```

PDF with the scaled march 14, 2009 storm (PDF code sourced from: https://rstudio-pubs-static.s3.amazonaws.com/100906_8e3a32dd11c14b839468db756cee7400.html)

```
z=wailupe_daily_77$daily_pcp

dStandardNormal <- data.frame(daily_pcp=z,
                              Density=dnorm(z, mean=0.3498252, sd=0.5167536),
                              Distribution=pnorm(z, mean=0.3498252, sd=0.5167536),
                             Quantile = qnorm(z, mean=0.3498252, sd=0.5167536))
## add color pallete
cbp2 <- c("#000000", "#009E73",
           "#D55E00")

## take average of March 14, 2009
wailupe_tidy_77_march14 <- wailupe_tidy_77 %>%
  filter(date >= as.Date("2009-03-14") & date <= as.Date("2009-03-14"))

mean(wailupe_tidy_77_march14$qpcp) # mean of March 14, 2009 storm = 0.2

## plot density distribution plot
pdf_plot_density <- ggplot(data=dStandardNormal, aes(x=daily_pcp, y= Density)) +
  geom_line(size=1.5) +
  theme_classic() +
  labs(x= "Daily Precipitation (in)") +
  geom_vline(xintercept = 0.44, linetype="solid",  ## 2.20 (Max MCF) * 0.2 = 0.44
              color = "#D55E00", size=1.5) +
  geom_vline(xintercept = 0.08, linetype="solid",  ## 0.40 (Min MCF) * 0.2 = 0.08
              color = "#009E73", size=1.5) +
  # annotate("text", x = 4.75, y = 0.75, label = "Max MCF * avg pcp", color = "#D55E00", size =5) +
  # annotate("text", x = 4.75, y = 0.70, label = "Min MCF * avg pcp", color = "#009E73",size =5) +
    theme(text = element_text(size=22)) +
scale_x_continuous(breaks=seq(0,5,0.5)) +
scale_y_continuous(breaks=seq(0,0.8,0.1))

pdf_plot_density
```

```
#  ggsave('pdf_MCF_mar14.png', pdf_plot_density_corrected2, width = 16, height = 9, units = "in")
```

Appendix L

Methods, Models, and Metadata for Optimal GI Placement in Maunalua Bay

Site Locator Model

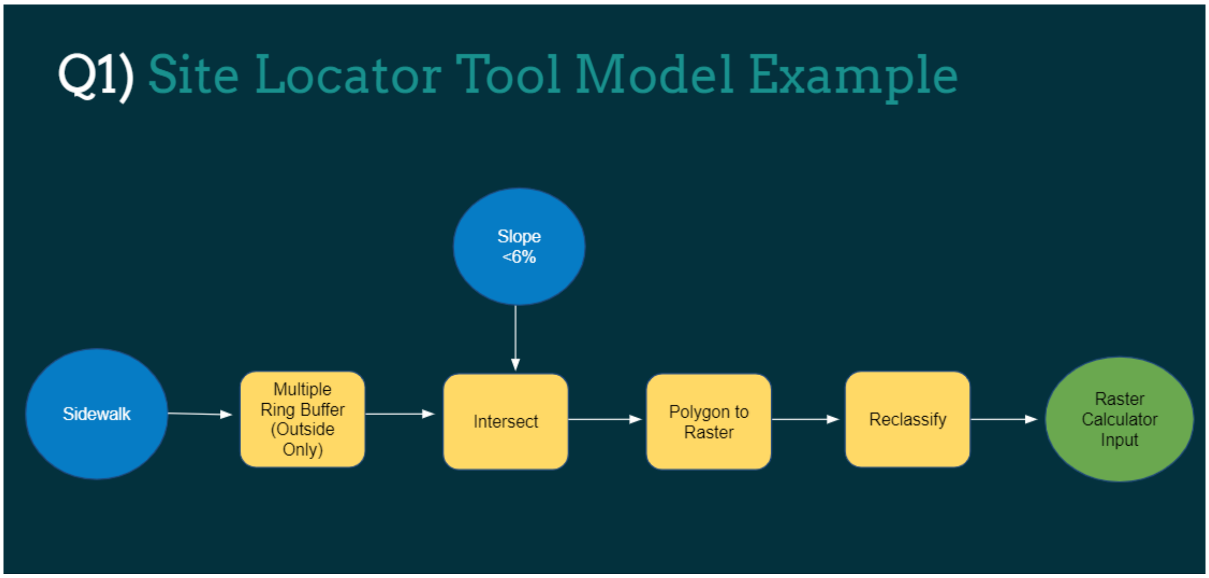

Figure L.1. This is an example of our Site Locator Model. We added data layers to the map, buffered them using the Multiple Ring Buffer Tool, intersected them with the slope layer to only include areas with a grade less than 6%, converted them to raster, and reclassified them so that increasing distance from them had decreasing value. We used a variation of this methodology for each layer.

The Site Locator Model final output is a raster layer with higher cell values indicating more suitable areas for rain garden implementation. The following methods are for a raster layer suitability analysis. In order to utilize the raster calculator tool at the end, each layer needed to cover the entire region. This is the case because the raster calculator tool will eliminate cells if one of the layers added does not have data in those cells. For this reason, we added an additional large buffer of no value to the layers that needed to be expanded. For example, the parks layer initially only has a couple of small parks within the region. After adding the buffer, the park raster covers the entire region, with higher values for areas closer to or within parks and no value everywhere else in the region.

Clip to ROI and Project to WGS 84

Before beginning our analysis, we clipped each layer to the Maunalua Bay region (Extract Toolbox - Clip) and projected each layer into WGS 84 (Data Management Toolbox - Project).

Calculate Slope

In the ArcMap project, we loaded the digital elevation model (DEM) layer for the Bay and then calculated the slope to give an output measurement in degrees (Analysis Toolbox - Slope). Next, we used the Extract by Mask tool (Spatial Analyst Toolbox) to mask the slope layer with the projected Maunalua layer (WGS 84). The slope layer was then reclassified so that values from 0-6% were given a value of 1, and all other values were given a 2 (Analysis Toolbox - Reclassify). Next, we used Extract by Attributes to extract all rasters where value = 1 and converted the layer to polygon (Conversion Toolbox - Raster to Polygon), to produce a final slope polygon layer. This was done because according to the Environmental Protection Agency (EPA), most green infrastructure types must be implemented on slope grades of 6% or lower (USEPA, 2014).

Create Roads

In the ArcMap project, we loaded the roads data layer. Since the roads data we downloaded was line data, we buffered (Analysis Toolbox - Buffer) the roads by 13.5ft to make them polygons the size of actual roads. We chose to buffer by 13.5ft because the average road size in Oʻahu is about 27ft (measured using Google Earth and ArcMap). We set the dissolve type to “All” to merge the buffered polygons.

Create Sidewalks

We buffered (Analysis Toolbox - Buffer) the “roads” polygon by 6ft. We chose 6ft because it is the recommended sidewalk size for Oʻahu (State of Hawaiʻi Department of Transportation). We set the dissolve type to all to merge the buffered polygons.

Create Flood Zones

To only include areas of intense flooding, we loaded the flood zones data layer and used the "Select Layer by Attribute" tool three times with "Selection type = NEW_SELECTION" for each one. We selected ZONE_SUBTY = 'RIVERINE FLOODWAY SHOWN IN COASTAL ZONE', ZONE_SUBTY = 'FLOODWAY', and ZONE_SUBTY = '0.2 PCT ANNUAL CHANCE FLOOD HAZARD' (Data Management Toolbox - Select Layer by Attribute). The “Select Layer by Attribute” tool does not create a new layer, it simply highlights the selection within the current layer. Therefore, we needed to copy the selected features to layers three separate times (Data Management Toolbox - Copy Features). These three layers were then merged so that only one flood zone layer remained that included all three selections of high flood risk areas (Data Management Toolbox - Merge).

Create Rasters - Wetlands, Stormwater Drains, Streams, and Flood Zones

The site suitability raster analysis requires creating buffers of increasing distance at decreasing values. We followed the example of a site suitability analysis performed by the Aburto Lab at the Scripps Institution of Oceanography (Arcos-Aguilar et al., 2021). In their suitability analysis, Arcos-Aguilar et al. assigned decreasing values to buffers of increasing distance from desired locations to create a raster layer where each piece of land had a suitability value associated with it.

Multiple Ring Buffer Layer

We utilized the multiple ring buffer tool to create 10 meter, 20 meter, 30 meter, and 2000 meter buffers around the sidewalks, wetlands, stormwater drains, streams, and flood zones (Analysis Toolbox - Multiple Ring Buffer). For the wetlands, we clicked “Outside Only” to include only the buffered area, since rain gardens should not be placed on pre-existing wetlands to leave wetlands intact (Cullison; Malaviya et al., 2019). For stormwater drains, streams, and flood zones, we *did not* click “Outside Only” so that the inner polygons would be included as suitable locations for rain gardens (Katsifarakis et al., 2015; Webber et al., 2019).

Slope Less than 6%

We intersected the buffered layers with the slope layer to only include areas with a slope at or below a 6% grade (Analysis Toolbox - Intersect).

Reclassify Raster

After, we converted the polygons to rasters (Conversion Toolbox - Polygon to Raster) and reclassified the rasters (Analysis Toolbox - Reclassify), so that areas within 10 meters of the desired locations have a value of 3, areas between 10 meters and 20 meters have a value of 2, and areas between 20 meters and 30 meters have a value of 1. Areas that were greater than 30 meters away from the desired location were given a value of 0.

Create Parks Raster

We loaded the parks data and utilized the multiple ring buffer tool to create 5 meter and 2000 meter buffers around the parks (Analysis Toolbox - Multiple Ring Buffer). We included the parks by not clicking “Outside Only” on the “Multiple Ring Buffer Tool” because rain gardens can be implemented inside of parks (Katsifarakis et al., 2015). We intersected the buffered layer with the slope layer to only include areas with a slope at or below a 6% grade (Analysis Toolbox - Intersect). After, we converted the polygon to raster (Conversion Toolbox - Polygon to Raster) and reclassified the raster (Analysis Toolbox - Reclassify), so that areas within 5 meters of the park were given a value of 3 and areas between 5 meters and 2000 meters were given value = 0.

Create Sidewalks Raster

We utilized the multiple ring buffer tool to create 1.2m, 10 meter, 20 meter, 30 meter, and 2000 meter buffers around the sidewalks (Analysis Toolbox - Multiple Ring Buffer). We intersected the buffered layer with the slope layer to only include areas with a slope at or below a 6% grade (Analysis Toolbox - Intersect). After, we converted the polygons to rasters (Conversion Toolbox - Polygon to Raster) and reclassified the rasters (Analysis Toolbox - Reclassify), so that areas within 1.2 meters of the desired location have a value of 0, between 1.2 meters and 10 meters have a value of 3, areas between 10 meters and 20 meters have a value of 2, areas between 20 meters and 30 meters have a value of 1, and areas greater than 30 meters away have a value of 0. We gave the areas within 1.2m of sidewalks a value of 0 because rain gardens could harm the sidewalk if placed too close (Cullison).

Create Soil Curve Number Raster

We utilized the soil curve numbers produced by the previous Bren group project. They created the soil curve numbers by intersecting the Soil Hydrologic Group and Land Use data. They then assigned the curve numbers based on both the types of soil and the types of land use in a subcatchment. We added the curve number data to ArcMap and converted it from polygon to raster (Conversion Toolbox - Polygon to Raster). Next, we reclassified the soil curve numbers so that a 0 curve number had a value of 1 whereas a 91 curve number has a value of 10. Higher curve numbers indicate more impervious surfaces and rain gardens should be placed near impervious surfaces (SUNY; USDA).

Raster Calculation - Adding the Layers Together

We used the raster calculator to sum up the raster layers we created, such as sidewalks, parks, wetlands, streams, stormwater structures, flood zones, and soil curve numbers (Spatial Analyst - Raster Calculator). This resulted in a raster layer overlay with higher value cells displaying areas that are better for rain garden implementation. For example, if a cell had a 3 for being near a park and a 0 value for every other layer, the resultant layer would have a value of 3 for that cell.

Create Buildings Layer

We buffered the buildings layer by 10 feet (Analysis Toolbox - Buffer), as rain gardens should not be placed within 10 feet of buildings to protect the foundation (Luo et al., 2017). We then erased the buildings layer from our final raster calculator layer (Analysis Toolbox - Erase). To use the erase tool, both layers needed to be polygons so we converted our raster calculator layer to polygon before using the “Erase Tool” (Conversion Toolbox - Raster to Polygon).

Final Output

After erasing the buildings from our suitable areas, we converted the output layer back to a raster for use in our next model (Conversion Toolbox - Polygon to Raster). We also extracted the upper quantile of the data to only include the best locations for rain gardens; this included cells with values from 12-18 (Spatial Analyst Toolbox - Extract by Attributes).

Table L.1. Data layers, parameters, and reasoning used in the Site Locator Model to determine the suitable locations for rain gardens. The citation is for the reasoning behind each parameter. The data layer citations can be found in the Metadata in the Appendix.

Layer	Parameters	Reasoning/Citation for Parameters
Slope	0-6% grade	US EPA 2014
Roads	27ft width	Measured on Google Earth and ArcMap
Sidewalks	6ft width	State of Hawaiʻi Department of Transportation
Sidewalk Buffer	4ft/1.2m: value = 0 10m: value = 3 20m: value = 2	Rain gardens should be located near impervious surfaces like sidewalks (Arlington Echo, 2010; USDA). Rain gardens should not

	30m: value = 1 2000m: value = 0	be placed within 4ft/1.2m of sidewalks to prevent damage to them (Cullison).
Wetland Buffer	Within 10m: value = 3 10m - 20m: value = 2 20m - 2000m: value = 0	Polluted runoff harms wetlands (Malaviya et al., 2019).
Park Buffer	Within+5m buffer: value = 3 5m - 2000m buffer: value = 0	Rain gardens can be implemented within parks and green spaces (Katsifarakis et al., 2015).
Stream Buffer	10m: value = 3 20m: value = 2 30m: value = 1 2000m: value = 0	Rain gardens can be implemented within stream zones (Katsifarakis et al., 2015) and can decrease the magnitude of pollution entering waterways (Cullison).
Building Buffer	Not within 10ft, eliminated	Rain gardens should not be placed within 10ft of buildings, to protect the foundation (Luo et al., 2017). We buffered by 10ft and then erased the buildings from our raster layer.
Stormwater Drain Buffer	10m: value = 3 20m: value = 2 30m: value = 1 2000m: value = 0	Rain gardens can decrease the amount of water entering storm drains (Alsobroooks).
Flood Zone Buffer	Within 10m: value = 3 20m: value = 2 30m: value = 1 2000m: value = 0	Implementing green infrastructure in multiple areas within a watershed can decrease flood risk; it is a desirable method for increasing resilience in urban areas (Webber et al., 2019).
Soil Curve Number Reclassify	0 = 1 36 - 40 = 4 41 - 50 = 5 51 - 60 = 6 61 - 70 = 7 71 - 80 = 8 81 - 90 = 9 91 - 100 = 10	A higher soil curve number indicates that the soil is less permeable and more runoff occurs there. Rain gardens can help to lower soil curve numbers (SUNY).

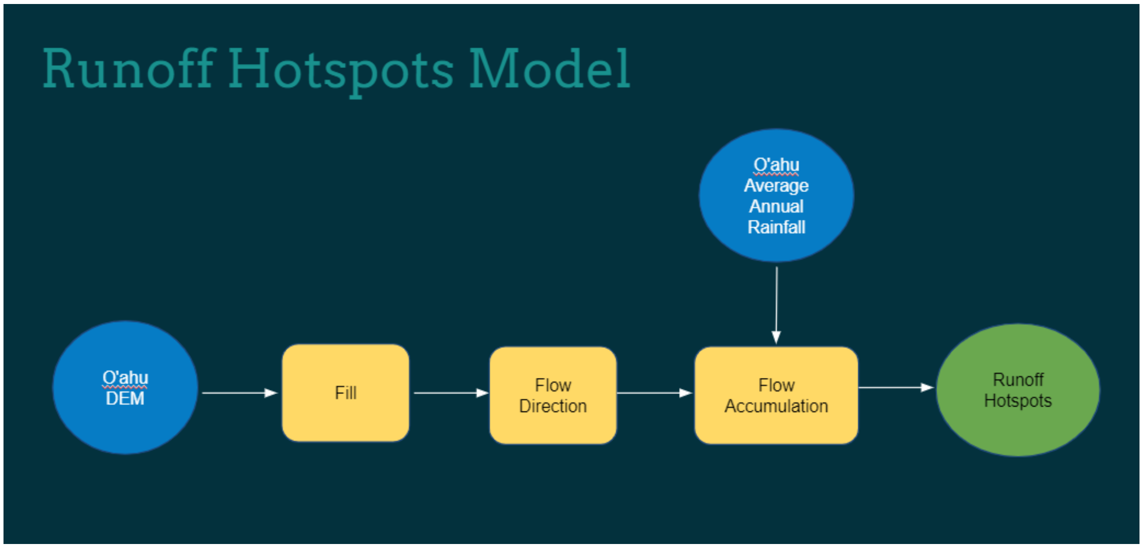

Figure L.2. This is the Runoff Hotspot model. We filled the DEM and found the flow direction of water over the surface of the DEM. Then, we found the flow accumulation, weighted by the average annual rainfall for the state of O'ahu. The output of this tool is our runoff hotspots map. For more detail on our Runoff model, see our methods in the appendix and the attached ArcMap Project.

Fill Sinks

We loaded the DEM layer for all of O'ahu. We filled the sinks in the DEM, so that water flow does not unnaturally stop in one cell where it would in reality flow to the next (Spatial Analysis Toolbox > Hydrology - Fill).

Flow Direction

We created a flow direction raster, showing the direction that water would flow through the watersheds based on elevation (Spatial Analysis Toolbox > Hydrology - Flow Direction).

Download Rainfall Data

We downloaded a GIS precipitation data layer in mm (rainfall grids in ESRI Grid Format) from the Hawaii Rainfall Atlas (Downloads > GIS Layers > ESRI Grid Format > OahuRFGrids_mm.zip). The raster files are available at 250 m resolution (0.00225 x 0.00225 cell size). Files of this type must be saved to the local C Drive (C:) for ArcGIS to access them.

Flow Accumulation

From the flow direction output, we created a flow accumulation raster, determining how much water would flow into each cell (Spatial Analysis Toolbox > Hydrology - Flow Accumulation). For the "Flow Accumulation Tool," we used the precipitation raster layer from the Hawaii Rainfall Atlas as the input weight raster.

Final Output

We clipped the output to the Maunalua Bay region (Extract Toolbox - Clip). We decided to do this at the end of the runoff model instead of clipping the DEM in the beginning, in case the Maunalua Bay region had water running in or out of it. Next, we extracted the upper quantile of the data to only include the areas of highest flow accumulation, which was over 30,000mm (Spatial Analyst Toolbox - Extract by Attributes). Lastly, we converted from raster to polygon using the "Int Tool" (Conversion Toolbox - Raster to Polygon; Spatial Analyst Toolbox - Int).

Optimal Locations of Rain Gardens Model

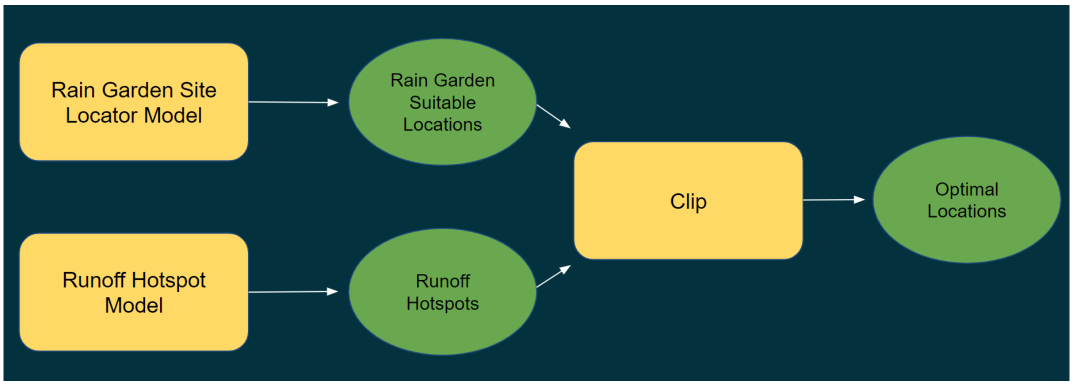

Figure L.3. This is the Optimal Locations for Rain Gardens model. This model combines our Site Locator Model and our Runoff Hotspot Model. We clipped the runoff hotspots by the suitable locations for rain gardens to get the optimal locations for rain gardens.

We then created the Optimal Locations of Rain Gardens model by combining the Rain Garden Site Locator model and the Runoff Hotspot model to determine the optimal locations for rain gardens, taking into consideration runoff hotspots. Taking the highest quantile from both models, we clipped the outputs from the Runoff Hotspot model by the Rain Garden Suitable Locations model, which left us with the optimal locations for rain gardens (Extract Toolbox - Clip). Both models needed to be polygons to use the "Clip Tool" (Conversion Toolbox - Raster to Polygon).

Data Description and Metadata

To determine optimal rain garden placement locations in the Maunalua Bay region, we created three ArcGIS models analyzing site suitability for rain gardens and runoff hotspots. The data is broken down into these different categories below. Click on the links below to go to the specified data table. We downloaded the data and projected each layer into the coordinate system WGS 84.

Site Locator Model

Table L.2. Data for the Site Locator Tool, including parks, roads, sidewalks, and parking lots. This analysis determines the best locations for rain gardens.

Data	Data Source	Data Type	Date Created	Description
Elevation (DEM)	The University of Hawai'i, Mānoa	.shp		Raster elevation data for the main 8 Hawaiian Islands. The datasets were derived from USGS 7.5' DEM Quads, individual DEM quads were converted to a common datum and mosaicked in ArcGIS 9.x. The DEM for Hawaii has a coordinate system of NAD83 UTM5N, the DEM for Maui, Kahoolawe, Lanai, Molokai, Oʻahu, Kauai and Niihau have a coordinate system of NAD83 UTM4N. All rasters have a spatial resolution of 10 meters and are in the ESRI grid format. More metadata can be found here.
Parks	City and County of Honolulu	.shp	2016-03-23 Updated: 2021-09-24	This layer contains data on parks, open spaces, and outdoor recreational facilities on the island of Oʻahu. These are spaces maintained by the City and County of Honolulu. The attribute table identifies the different types of parks and there are 429 records. The park types include: mini park, neighborhood park, community park, district park, urban, regional park, beach park, nature/preserve, botanical garden, zoo, pedestrian mall, other (airplane field, campground, dog park, senior citizens center, nursery), golf course, community park/garden, slide areas. More metadata can be found here. Use: Parks are potential locations for green infrastructure implementation.
Roads – C&C of Honolulu	Hawaiʻi Statewide GIS Program	.shp	2014-02-27 Updated: 2020-10-31	Streets for the island of Oʻahu in Line format. Includes freeways, highways, county arterial, city street, jeep trail, special roads, and other roads. The data is exported in NAD 83 coordinates. View more metadata here. Use: We converted the line data to polygon data (a requirement for this tool) by buffering the roads by 13.5 feet on each side. We had measured the roads on ArcGIS and determined that the average road size in the Maunalua Bay region was 27 feet.
Sidewalks	Hawaiʻi Statewide	.shp	2021-10-12	We created sidewalk data by buffering the roads polygon (created from the roads line data provided by the Hawaiʻi Statewide GIS Program) by 6 feet on each side.

	GIS Program			The minimum sidewalk width suggested for Hawai‘i is 6 feet. Use: Rain gardens should be implemented near impervious surfaces.
Maunalua Bay Region	Hawai‘i Statewide GIS Program	.shp	2014-04-09 Updated: 2020-10-31	Watershed boundaries for the Hawaiian Islands. Polygonal data projected in UTM NAD 83. For more metadata see here. Use: To create the Maunalua Bay region, a previous Bren group project (Dornan et al., 2020) joined and dissolved the watersheds that fed into Maunalua Bay. This layer is used as the region of interest for the study.
Soil Hydrologic Group and Draining Conditions	Natural Resources Conservation Service’s SSURGO	.shp		To download the data, click on the link and then click on “Island of O‘ahu.” Follow the directions on the bottom of the following page, after clicking on “Start Web Soil Survey (WSS).” The soil map provides information on different types of soils in the defined area of interest (AOI). Use: 2020 Bren Group Project (Dornan et al., 2020) used the Soil Hydrologic Group data along with the land use data to create the soil curve number data.
Land Use and Land Cover	Hawaii Statewide GIS Program	.shp	2016-12-30 Updated: 2020-11-02	As of 1976, polygonal land use and land cover data of O‘ahu. The data is projected in UTM NAD 83. Land use includes urban, agricultural, rangeland, forest land, water, wetland, and barren land. More metadata can be found here. Use: The land use data was used by the 2020 Bren Group Project (Dornan et al., 2020), alongside soil hydrologic group data, to create the soil curve number data.
Soil Curve Numbers	2020 Bren Group Project (Dornan et al., 2020)	.shp	2020-06-06	2020 Bren Group Project (Dornan et al., 2020) created the soil curve numbers by intersecting the Soil Hydrologic Group (soil classifications determined by the Natural Resources Conservation Service's National Water and Climate Center based on a soil's infiltration and runoff potential as well as measured rainfall) and Land Use data. They then assigned the curve numbers based on both the types of soil and the types of land use in a subcatchment. Use: Higher curve numbers indicate more impervious surfaces and rain gardens should be placed near

				impervious surfaces (SUNY; USDA).
Wetlands	Hawaii Statewide GIS Program	.shp	2018-05-01 Updated: 2020-10-31	This layer contains data on the extent, approximate location, and type of wetlands and deepwater habitats in Hawaii, delineated as defined by Cowardin et al. (1979). Certain habitats were excluded, such as seagrass, submerged aquatic vegetation found in the intertidal and sbutidal zones of estuaries and near shore coastal waters, and some deepwater reef communities. More metadata can be found here. Use: Proximity to wetlands is beneficial for green infrastructure placement to avoid sending large amounts of polluted runoff into the wetland while also being able to direct the outflow of some green infrastructure types to the wetland.
Flood Zones	City and County of Honolulu	.csv, .shp	2016-03-23 Updated: 2020-10-26	This data layer contains flood zones that were designated by the Federal Emergency Management Agency. Special flood hazard areas are those that may experience the 100-year flood (1% annual chance flood). More metadata can be found here. Use: Areas of known flooding are potential locations for green infrastructure implementation.
Building Footprints	City and County of Honolulu	.csv, .shp	2016-03-23 Updated: 2020-11-05	The Hawaii Statewide GIS Program created this data layer by compiling data from different sources, including LIDAR data collected in 2005 and 2009, an aerial data collection from 2004, and a pictometry data collection from 2010, as well as new building plans (maintained by the City and County of Honolulu). This data includes polygon data of building location and size. More metadata can be found here. Use: Removing buildings from the analysis, as these green infrastructure types are not compatible with rooftops.
Stream Flowline	USGS National Hydrography Dataset	.csv, .shp	2017-01-26 Updated: 2020-10-31	This data layer displays the streams and rivers in Niihau, Kauai, O'ahu, Maui, Molokai, Lanai, Kahoolawe, and Hawaii. The data layer contains Point, Line, and Polygon features. More metadata can be found here.
Coral Reef	Hawaii Statewide GIS Program	.shp	2014-02-07 Updated: 2020-11-01	This data layer shows all of the coral reefs that are located in marine waters off the coast of Hawaii. The data is in polygon format. For more metadata, click here.

Runoff Hotspots Model

Table L.3. Data for determining the location of runoff hotspots using the ArcHydro Tool.

Data	Data Source	Data Type	Date Created	Description
O'ahu Annual Average Rainfall	Hawaii Rainfall Atlas	.adf (ESR Grid)		GIS precipitation data layer in mm of the average annual rainfall in O'ahu in millimeters (rainfall grids in ESRI Grid Format) from the Hawaii Rainfall Atlas (Downloads > GIS Layers > ESRI Grid Format > OahuRFGrids_mm.zip). The raster files are available at 250 m resolution (0.00225 x 0.00225 cell size). Files of this type must be saved to the local C Drive (C:) for ArcGIS to access them.
Elevation (DEM)	The University of Hawai'i, Mānoa	.shp		Raster elevation data for the main 8 Hawaiian Islands. The datasets were derived from USGS 7.5' DEM Quads, individual DEM quads were converted to a common datum and mosaicked in ArcGIS 9.x. The DEM for Hawaii has a coordinate system of NAD83 UTM5N, the DEM for Maui, Kahoolawe, Lanai, Molokai, O'ahu, Kauai and Niihau have a coordinate system of NAD83 UTM4N. All rasters have a spatial resolution of 10 meters and are in the ESRI grid format. More metadata can be found here.

Calculations

Table L.4. Discharge/Sediment Data. This data was used to calculate the amount of sediment flowing through each runoff hotspot. This enabled us to find the reduction in sediment flowing into Maunalua Bay by implementing rain gardens in major runoff hotspots. This data was also used to calculate the average annual amount of sediment discharge into the Bay.

Data	Data Source	Data Type	Date Created	Description
Suspended sediment concentration (mg/L) at USGS 16247550	USGS National Water Information System 2009 Annual Suspended Sediment Concentration	.csv		This data contains information on streamflow in the Wailupe Gulch. There is a dataset for 1958 to 2009 at Aina Haina and another dataset for 2008 to 2020 at E. Hind Dr. Bridge. At Aina Haina, the Hydrologic Unit Code is 20060000, Latitude 21°17'33.4", Longitude 157°45'19.9". The data is projected in NAD83. The drainage area is 2.36 square miles and the gage datum is 110 feet above LMSL. At E. Hind Dr. Bridge, the Hydrologic Unit Code is 20060000, Latitude 21°17'07.2", Longitude 157°45'14.6". The data is

				projected in NAD83. The drainage area is 2.84 square miles and the gage datum is 50 feet above LMSL.
Suspended sediment discharge (short tons/day) at USGS 16247550	2009 Annual Suspended Sediment Discharge	.csv		