EVALUATING THE ROLE OF LOW IMPACT DEVELOPMENT RECHARGE FOR SUSTAINABLE GROUNDWATER RESOURCES

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CERTIFICATION OF APPROVAL

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EVALUATING THE ROLE OF LOW IMPACT DEVELOPMENT RECHARGE FOR SUSTAINABLE GROUNDWATER RESOURCES

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Low impact development (LID) is an innovative ecological and landscaped based design framework that is used in urban planning to imitate pre-development hydrologic systems. LID is a new concept in stormwater management that is replacing conventional stormwater systems in urban environments due to its effectiveness in retaining large volume of stormwater runoff and treatment of water quality. Cities around the world are actively installing hundreds of LID Best Managed Practices (BMPs) without underdrains, which can enhance groundwater recharge to underlying aquifers. Previous research on LID recharge has focused on local and neighborhood scales and only a few studies have quantified LID recharge beneath individual BMPs. Given the widespread installation of LID, I hypothesized that the cumulative LID recharge at the watershed scale could have a significant effect on the groundwater budget, potentially increasing groundwater storage in urban aquifers. To test this hypothesis, I analyzed the discharge and LID recharge in the Lake Merced watershed. For this study, I used PCSWMM, a GIS based hydraulic model created by Computational Hydraulics International (CHI) that integrates the *U.S EPA Storm Water Management Model* (SWMM). Using PCSWMM, four models of the study area with different area coverage of LID (0%, 0.5%, 1% & 2% LID coverage) were created, compared and analyzed. Model outputs of discharge, stormwater inflow into LID, infiltration beneath LID (recharge), and recharge efficiency were created and analyzed. Results showed that despite 0.5% LID coverage model having the largest infiltration beneath the LID, it had the lowest recharge efficiency of all models and had the largest stormwater inflow and discharge. These results show that by increasing the %LID coverage, there is lower volume of stormwater flowing into LID, which ultimately increases the recharge efficiency.

I certify that the Abstract is a correct representation of the content of this thesis.

12-17-2019

Chair, Thesis Committee   Date

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1.0 INTRODUCTION

Urbanization and the associated increase in impervious surfaces alters hydrological processes and contributes to pressing environmental and water resources challenges, including flooding, nonpoint-source pollution, and freshwater scarcity. Impervious surfaces, such are pavement, buildings, and compacted soils greatly reduce or prevent the infiltration of stormwater and accelerates runoff, which reduces the lag time between storm events and flooding and increases flood discharge and frequency (USEPA, 2000; Burns et al., 2012; Ahiablame et al., 2012; Bhaskar et al., 2016; Chen et al., 2016; Eckart et al., 2017). The reduction in infiltration and increased runoff also increases nonpoint-source contaminant loads in stormwater, which have well-documented, negative effects on the water quality and aquatic ecosystems of receiving water bodies, including rivers, lakes and coastal marine systems (USEPA, 1996; Walsh et al., 2012). For example, in 1996, the United States Environmental Protection Agency (USEPA) reported that urban stormwater impaired 5,000 square miles of estuaries, 20,000 miles of rivers, and 1.4 million acres of lakes in U.S. (USEPA, 1996). Today, the concern over urban stormwater pollution continue because urban populations are expected to increase to 5 billion by 2030 (Riche et al., 2012).

Impervious surfaces that reduce or prevent infiltration may also exacerbate freshwater scarcity by limiting recharge to urban aquifers and contribute to groundwater sustainability challenges. For example, in California, like many western States, where severe and multi-year droughts are common, the over-abstraction and unsustainable use of groundwater, particularly during droughts, is a widespread problem. To address this problem, California adopted in 2014 the Sustainable Groundwater Management Act

(SGMA), which are regulations for sustainable groundwater management. As part of SGMA, some urban Groundwater Sustainability Agencies (GSAs) may evaluate and implement plans to increase urban recharge by means of stormwater collection and managed aquifer recharge (MAR). As explored here in my thesis, MAR using low impact development (LID) may be a viable plan for some GSAs or for groundwater management more broadly.

LID is an innovative ecological and landscape-based stormwater management and design framework that is increasingly being used in urban planning to imitate pre-development hydrologic systems by increasing retention, detention, and treatment of the quality of stormwater (USEPA, 2000; Burns et al., 2012; Ahiablame et al., 2012; Eckart et al., 2017). LID Best Management Practices (BMPs) includes porous pavement, roof garden, bioretention, detention ponds, constructed wetlands, rain gardens, swales, and infiltration trenches. Since the first development in the 1990's from Prince George's County, Maryland, LID BMPs have shown positive results in retaining large volumes of storm runoff and removing harmful contaminants such as motor oil, copper, lead, zinc, ammonia, and phosphorus (USEPA, 1996; Brattebo and Booth, 2003; Riche et al., 2012; Walsh et al., 2012; Niu et al., 2016; Bhaskar et al., 2016; Chen et al., 2016).

Studies have shown that LID has improved urban ecosystems by providing habitat for existing wildlife and enhancing social benefits, such as urban aesthetics and improved community and livability (CNT, 2010; Riche et al., 2012; SFPUC, 2016). LID has also shown to be economically beneficial due to the various types of BMP designs, which can easily retrofit existing infrastructure such as parking lots, roads, sidewalks, and buildings without compromising their primary function in a wide range of lot sizes (USEPA, 2000; Ahiablame et al., 2012; Eckart et al., 2017). LID is generally less expensive than traditional stormwater approach in terms of development cost and maintenance cost (Montalto et al., 2007; USEPA, 2007; CNT, 2010). In 2012, USEPA released 17 LID case studies that showed total capital cost saving ranging from 15 to 80% (USEPA, 2012). For the reasons stated above, LID is quickly replacing conventional stormwater systems, including impervious/impermeable surfaces such as roads, sewer systems, gutters, regional facility and other grey infrastructure (Chen et al., 2016).

Because of these ecological and cost benefits, cities across the world are actively transforming their urban landscape with LID BMPs. China has developed 30 sponge cities, which are entire cities filled with LID BMPs and designed to absorb, store, infiltrate, and purify rainwater and release for reuse (Li et al., 2017). In Australia, LID is referred to as water-sensitive urban design (WSUD) and is being used for its potential in harvesting rainwater as a water resource (Chang et al., 2018). European countries such as Germany and the United Kingdom (UK) are also implementing LID (referred to as sustainable urban drainage system or SuDS in UK) for improving ecological quality and flood prevention (Chang et al., 2018). LID is quickly gaining popularity in the United States as cities such as Chicago, Seattle, St. Paul, and Tampa are using various LID BMP designs (SFPUC, 2017; Chang et al., 2018). In San Francisco, 142 LID projects have been approved and 114 more are in progress (SFPUC, 2017).

Previous hydrologic research surrounding LID has largely focused on urban stormwater runoff quantity and quality that impact local surface-water receiving bodies, and relatively fewer studies have explored how LID BMPs affect groundwater recharge and quality (Newcomer et al., 2014; Danfoura and Gurdak, 2016). Newcomer et al. (2014) summarizes the recharge rates and mechanisms that control recharge beneath individual LID BMPs, including precipitation intensity and duration, runoff characteristics of the impervious cover connected to the BMP, soil properties, and storage capacity of the BMP. The important finding from these previous site-specific studies is that recharge beneath LID BMPs can be an order-of-magnitude larger than diffuse recharge in natural (non-LID) areas of the aquifer (Newcomer et al., 2014). However, these previous studies have been limited to either one or several LID BMPs at a pilot-scale, and only one study to my knowledge has quantified recharge beneath individual LID BMPs at a watershed scale and evaluated the cumulative effects of LID groundwater recharge (Zheng et al., 2018). Zheng et al. (2018) simulated 7.5% and 15% conversion of an urban area to LID and found that simulated recharge increased substantially and groundwater heads could increase by 0.9 m and 1.7 m, respectively. While these results are promising, many urban centers such as San Francisco, do not have the available space or resources to convert such relatively large percentage (>5%) of urban landscape into LID.

Given that San Francisco and many other U.S. cities are actively installed hundreds of LID BMPs at coverages <5% of the urban landscape, an important yet unexplored question is how the city-scale implementation of LID may be altering the recharge regime to urban aquifers. The city-scale installation of LID BMPs could be changing recharge rates and processes, and cumulatively altering groundwater storage within urban aquifers. Although the total volume of recharge beneath individual LID BMPs are orders-of-magnitude smaller than conventional large-scale MAR facilities (Newcomer et al., 2014), I hypothesize that the cumulative effect of a city-scale LID implementation program could have a significant effect on groundwater recharge and storage. Conventional MAR and artificial storage and recovery (ASR) is the intentional recharge and storage of water in an aquifer for subsequent recovery for environmental benefits, which are often large-scale bodies of water such as dams, infiltration or spreading basins, and injection and recovery wells (Tuinhof et al., 2005; Gale et al., 2006; Damigos et al., 2017). Here, I conceptualize LID BMPs as small-scale, decentralized MAR. My research is motivated by the lack of studies addressing LID BMPs as decentralized MAR recharge and the potential management approach of using cumulative LID recharge to help meet groundwater sustainability goals. LID recharge from decentralized MAR could be one of many viable projects that groundwater managers use to meet sustainability targets. A conceptual model of LID recharge is shown in Figure 1.

Therefore, the overall objective of my thesis is to characterize and analyze cumulative LID recharge on a city scale, which can be used to better understand and manage urban stormwater effects on groundwater recharge and sustainability. Here, I use a suite of hypothetical, yet realistic LID implementation plans (%LID coverage of the city) to simulate the potential changes to recharge across a watershed in San Francisco. This study addresses the following research question: What is the relationship between the %LID coverage of a city and changes to the water budget, including groundwater recharge? Addressing this research question will provide important insight into how policy and management choices for LID programs and engineering design considerations for BMPs may help simultaneously meet urban stormwater and groundwater sustainability goals.

2.0 METHODOLOGY

I used PCSWMM (Computational Hydraulics International (CHI), 2019), which is a geographic information system (GIS)-based hydraulic modeling software and graphical user interface (GUI) that integrates the *U.S EPA Storm Water Management Model* (SWMM) (Rossman, 2015). SWMM is a well-documented and dynamic rainfall-runoff simulation model that can be used for single event or continuous simulation of runoff quantity and quality from urban areas. SWMM can simulate runoff based on user-defined sub-catchments and precipitation, and the routing portion of SWMM transports the runoff through user defined pipes, channels, or storage and treatment devices such as LID (Rossman, 2015). I used PCSWMM to address the research question and simulate how a suite of hypothetical LID implementation plans would alter the water budget to the Lake Merced watershed in San Francisco, California (Figure 2a). Beneath the Lake Merced watershed is the Westside Basin aquifer, which is part of the regionally extensive California Coastal aquifer system (Figure 2b). The following sections describe the study area; suite of hypothetical LID implementation plans; model development, calibration, and validation; and subsequent statistical tests to evaluate the research question.

2.1. Lake Merced Watershed Study Area

Lake Merced is a coastal and predominantly urban watershed (2,794 acres) on the western side of San Francisco and overlies the Westside Basin aquifer (28,800 acres) (Figure 2a) (SFPUC, 2005). A prominent feature of the watershed is Lake Merced (650 acres), which is a freshwater lake on the western side of the watershed (Figure 2a). The Westside Basin aquifer near Lake Merced is shallow and generally unconfined (SFPUC, 2005). At approximately 100 ft below sea level, there is a clay layer that separates the shallow aquifer from the underlying confined primary production aquifer in the Lake Merced area (SFPUC, 2005). Primary land use type of the Lake Merced watershed is urban (Figure 2a).

2.2. Regional Calibration

The Lake Merced watershed currently does not have a publicly available stream discharge data to calibrate the PCSWMM model. Therefore, I used a regional calibration approach to calibrate the un-gauged Lake Merced watershed model following the methods outlined by Fry and Maxwell (2017). Fry and Maxwell (2017) demonstrate that the use of regional parameters that are developed from calibrated models for similar land-surfaces can be effective during the parameterization of ungauged stormwater models. To develop the regional model parameters, I chose the nearby San Jose watershed (Figure 2a) because it has publicly available USGS stream discharge data and similar urban land use and percent impervious surface as the Lake Merced watershed.

To calibrate the San Jose Watershed PCSWWM model, I used manual trial and error approach for history matching the data collected from 2011 to 2017, including stream discharge data from USGS stream gauge site number 11169025 and daily precipitation data from NOAA station ID: USW00023293. I used a 10-digit hydrologic unit code (HUC) watershed boundary shapefile from the USGS Watershed Boundary Dataset (WBD) and made sure that USGS stream gauge site:11169025 was located inside the watershed. I used the 2011 impervious surface raster data from the National Land Cover Database (NLCD) (NLCD, 2019). The model calibration was finished before early 2019 when the new 2016 NLCD impervious data became available and thus was not incorporated into this study. I used ESRI's ArcGIS Desktop 10.6 to clip the raster image and used the Raster data statistics to calculate the average impervious surface value of the San Jose watershed boundary, which is 69% (Table 1). Using the NLCD data, I also calculated the average land-surface slope as 1% (Table 1).

During the manual history matching for model calibration, I used qualitative and quantitative methods to compare simulated stream discharge to observed stream discharge at USGS gage 11169025. The qualitative evaluation involved visually comparing the simulated and observed hydrograph. In general, the calibrate model provides a reasonable simulation of the winter and spring high-flow events and the baseflow during the summer and fall seasons (Figure 3). However, the simulated discharge tends to under-estimate observed discharge throughout much of the calibration period (Figure 3). For the quantitative evaluation, I relied on summary statistics that are commonly used to evaluate the goodness of fit for hydrologic models, including the R^2 value and Nash-Sutcliffe coefficient of efficiency (NSE):

$$NSE = \frac{\sum_{i=1}^{n} |(Q_m - Q_s)|_i^2}{\sum_{i=1}^{n} |(Q_m - \bar{Q}_m)|_i^2} \qquad \text{Equation 1}$$

where Q_m is the measured (observed) stream discharge, Q_s is the simulated stream discharge, and $\bar{Q}_m$ is the mean of the measured stream discharge. NSE values range from $-\infty$ to 1, where values close to 1 indicate a good fit (Anderson et al., 2015). For NSE values of 0, the mean of the data is as good a predictor as the simulated values; and for a value less than 0, the mean of the data would be a better predictor (Anderson et al., 2015). The resulting $R^2 = 0.85$ indicates that 85% of the variability in the observed stream discharge can be explained by the simulated discharge. Additionally, the NSE = 0.736 indicates a reasonably good fit between the simulated and observed stream discharge for the San Jose watershed PCSWMM model. Following the method of Fry and Maxwell (2017), the model parameters from the calibrated San Jose watershed PCSWMM model were used in the Lake Merced PCSWMM models, as described next.

2.3. Lake Merced watershed models

All model parameters, except impervious surface percentage and precipitation, from the calibrated San Jose watershed model were used as input parameters for all the Lake Merced watershed models (Table 2). The average impervious percentage for the Lake Merced watershed models was calculated as 49% (Table 2) using the 2011 NLCD data and following the same method as for the San Jose watershed model. I used precipitation data from 1921 to 2017 that were downloaded from NOAA station ID: USW00023272 (Table 2). By using the complete historical record (96 years) of precipitation, my simulations will account for the complete range of historical variability in precipitation.

Using the same model parameters, I created a total of four models, each with a different %LID coverage (ranging from 0 to 2%) of the watershed to represent a suite of hypothetical, yet realistic LID implementation plans within San Francisco to simulate the potential changes to recharge across the watershed. The first model was simulated with no LID (0% coverage) and represents the null hypothesis. Three additional models were simulated with the following %LID coverage: 0.5% (16 acres), 1% (28 acres), and 2% (56 acres). Given the previously described SFPUC (2017) plans for approximately 256 LID BMPs to be implemented across San Francisco and the average surface area of LID BMPs, the range of %LID coverage from 0.5 to 2% represents a much more reasonable and realistic suite of simulations as compared to previous studies that simulated 5 to 15% increases in LID coverage (Fry and Maxwell, 2017; Zheng et al., 2018).

PCSWMM is limited to simulating only one type of LID BMP per watershed (subcatchment). Therefore, I used bio-retention to represent all simulated LID BMPs in the four models. Bio-retention is a very common type of LID BMP that is used in San Francisco and other regions. Bio-retention is a treatment area that consists of plants, ponding area and soil layer that collects and removes contaminants from stormwater runoff (SFPUC, 2016). The model parameters used to simulate the bio-retentions BMPs are described in Table 3 and were taken from the CHI support site user manual for PCSWMM (James, 2005). Since the objective of my study was to simulate infiltration beneath the

LID, no underdrains were used as parameters in the LID control setting (Table 3). The area of a single unit of bio-retention was 1,076 ft^2. The model takes the area of one unit and replicates for the desired %LID coverage: 510 units represents 16 acres (0.5%), 1,100 units represents 28 acres (1%), and 2,207 units represents 56 acres (2%) (Table 3).

The PCSWMM models simulated a large number of hydrologic parameters, including time series of discharge, soil moisture, infiltration, total evaporation, total inflow to the LID, rate of percolation, and many others. To address my research question, I focused the analysis on total discharge from the watershed (cfs), stormwater inflow to the LID (in/hr), and infiltration beneath the LID (in/hr), which represents recharge. I also calculated the percent of inflow to the LID that infiltrated beneath the LID by dividing the infiltration beneath the LID (recharge) by stormwater inflow to the LID, which I define as recharge efficiency (%). Recharge efficiency is the percentage of stormwater entering the system (i.e, inflow to the LID) that becomes recharge for each year (i.e., infiltration beneath the LID).

2.4. Statistical Tests

I analyzed the simulated total annual discharge from the four models using JMP (JMP, 2009) to evaluate if the suite of hypothetical LID implementation plans (0.5% LID, 1% LID, and 2% LID) has a statistical effect on the hydrologic parameters compared to the null hypothesis (0% LID). Because I ran the PCSWMM models with a daily timestep, I first converted the 96 years of daily simulated discharge to annual values to remove the large number of zero discharge values before running statistical tests. Next, I ran the

Shapiro-Wilk test (α-level = 0.05) and determined that the simulated discharge was from a non-normal distributed (p-value < 0.05). Therefore, used the non-parametric Kruskal-Wallis test (α-level = 0.05) and Steel-Dwass test (α-level = 0.05) to determine if the median annual discharges from the four models were statistically different and come from different distributions (JMP, 2009).

I also analyzed the output from the 0.5% LID, 1% LID and 2% LID models using JMP to evaluate if these LID implementation plans have a statistical effect on infiltration beneath the LID (recharge) and recharge efficiency (%). I used the Kruskal-Wallis test (α-level = 0.05) and Steel-Dwass test (α-level = 0.05) to determine if the median annual recharge and recharge efficiency from the three models were statistically different.

3.0. RESULTS & DISCUSSION

I present results from the analysis of simulated discharge from the four models (0% LID, 0.5% LID ,1% LID & 2% LID) to address the research question and evaluate the relationship between %LID and changes to the water budget. I also present results from the analysis of simulated infiltration beneath LID (recharge) and recharge efficiency from the three models (0.5% LID, 1% LID, and 2% LID).

3.1. Discharge Response to LID Implementation

The simulated timeseries of discharge out of the Lake Merced watershed using the suite of hypothetical LID implementation plans (0.5% LID, 1% LID, and 2% LID) are shown in Figure 4a, b, and c, respectively. In each of these figures, the simulated discharge from each of the 0.5–2% LID implementation plan models are compared to the simulated discharge from the null hypothesis (0% LID coverage). Discharge from the 0% LID model has an average of 263 cfs. (Figures 4a,b,c). The largest simulated discharge occurs in 1998 and 1983 (Figures 4a,b,c), which are associated with the strong El Niño conditions and above average rainfall to the watershed.

The simulated discharge from the 0.5% LID model generally captures the same temporal variability as the 0% LID model (Figure 4a). However, in most years, the 0.5% LID model tends to simulate less discharge compared to the 0% LID (Figure 4a). A similar pattern of less discharge as compared to the 0% LID is found for the 1% and 2% LID models, but the difference between 0% and 1% and between 0% and 2% LID models is progressively greater (Figure 4b,c). For example, during many years of average to below average simulated discharge from the 0% LID model, the corresponding discharge from the 2% model approaches 0 cfs (Figure 4c). To summarize, these results indicate an inverse relation between discharge and %LID coverage; the discharge from the 0.5% LID is most similar to the 0% LID, but an increase in simulated %LID coverage tends to decrease discharge out of the watershed. These findings indicate that potential implementation plans of 0.5 to 2% LID coverage across the watershed would decrease discharge associated with stormwater compared to the null hypothesis (0% LID).

The visual observations of difference in simulated discharge from Figures 4a,b,c were confirmed using the Kruskal-Wallis and Steel-Dwass tests (Figure 5). Figure 5 shows the distribution of discharge from the 0%, 0.5%, 1%, and 2% models. The median and variance in simulated discharge is largest from the 0% model and smallest from the 2% model (Figure 5). Results from the Kruskal-Wallis test (p-value<0.0001, α-level = 0.05) confirm that there are statistical differences among the median values of discharge from the four models. Results from the Steel-Dwass test (p-value<0.0001, α-level = 0.05) confirm that each combination of the four models has statistically different median values of discharge. These test results confirm that simulated implementation of LID at 0.5%, 1%, and 2% coverage produce statistically lower discharge out of the Lake Merced watershed that is associated with stormwater. The findings of a statistically significant inverse relation between %LID coverage and stormwater discharge is generally consistent with previous studies that have demonstrated the effectiveness of LID in terms of increasing the infiltration and decreasing the runoff of stormwater in urban watershed. Results from my study would support the use of LID to decrease stormwater and associated non-point contaminant loads to Lake Merced in the watershed and to the Pacific Ocean, which is the outlet of the Lake Merced watershed.

A statistically significant reduction in stormwater discharge out of the watershed under the LID implementation plans indicates that there is a fundamental change in the water budget of the Lake Merced watershed. The next section of results explores how the LID reduction in discharge affects changes to recharge to the underlying Westside Basin aquifer.

3.2. Recharge Response to LID Implementation

The simulated timeseries of inflow to the LID (in/yr) and infiltration beneath the LID (in/yr) within the Lake Merced watershed using the suite of hypothetical LID implementation plans (0.5% LID, 1% LID, and 2% LID) are shown in Figure 6a, b, and c, respectively. Because the LID were simulated without underdrains, the infiltration beneath the LID approximates recharge (in/yr) to the underlying Westside Basin aquifer.

The results presented in Figure 6a,b,c indicate an inverse relation between %LID coverage and inflow to the LID; the 0.5% LID model generates the greatest inflow to the LID and the 2% LID model generates the least inflow to the LID. The average inflows to the LID were 24.6 in/yr, 11.8 in/yr, and 6.3 in/yr for the 0.5%, 1%, and 2% LID models, respectively. The inverse relation between %LID coverage and the inflow to the LID can be explained by the differences in the impervious surfaces and stormwater generation among the three models. The 0.5% LID (16 acres) model has approximately 40 acres more impervious surface than the 2% LID (56 acres) model. Based on my simulations, the difference of 40 acres generates, on average, 18.3 in/yr more (24.6 – 6.3 in/yr) inflow to the LID from the 0.5% LID model compared to the 2% LID model. In addition to the reduction in average inflow to the LID, the larger %LID models generate less variable inflow to the LID (Figure 6a,b,c). In general, the year-to-year variability in inflow to the LID is much larger for the 0.5% LID model compared to the 2% LID model (Figure 6a,b,c). The findings of an inverse relation between %LID coverage and inflow to the LID fits the conceptual model of the previous findings of an inverse relation between %LID coverage and discharge out of the Lake Merced watershed. By increasing the %LID, less stormwater runoff is generated, which means relatively less stormwater flows into LID BMPs at progressively higher percentages of LID coverage across the Lake Merced watershed.

Figure 6a,b,c also shows the simulated infiltration beneath the LID (recharge) (in/yr) within the Lake Merced watershed using the suite of hypothetical LID implementation plans (0.5% LID, 1% LID, and 2% LID). The average annual infiltration beneath the LID (recharge) were 14.2 in/yr, 9.5 in/yr, and 5.5 in/yr for the 0.5%, 1%, and 2% LID models, respectively. Based on my simulations, the difference of 40 acres generates, on average, 8.7 in/yr more (14.2 – 5.5 in/yr) infiltration beneath the LID from the 0.5% LID model compared to the 2% LID model. Under each %LID coverage, the infiltration beneath the LID (recharge) generally follows the same temporal variability as the inflow to the LID (Figure 6a,b,c). However, there are some important differences between the relative increase in %LID and the corresponding differences between simulated inflow to the LID and infiltration beneath the LID. Results of the 0.5% LID model indicate relatively large differences between the inflow to the LID and infiltration beneath the LID (recharge) (Figure 6a), as compared to simulated results from the 2% LID model (Figure 6c). The difference in magnitude between the inflow to the LID and infiltration beneath the LID (recharge) decreases as the %LID coverage across the watershed increases. This apparent trend could be explained because of a decline in the LID performance and efficiency to capture and infiltrate the stormwater at relatively low %LID coverage where relatively more stormwater is generated that overflows the storage capacity of the LID BMPs.

Statistical analysis of the infiltration beneath the LID (recharge) for the 0.5%, 1%, and 2% models, using the Kruskal-Wallis test (p-value<0.0001, α-level = 0.05) and the Steel-Dwass test (p-value<0.0001, α-level = 0.05) show that each combination of the median values of infiltration from three models is statistically different from each other (Figure 7). Also, the statistical analysis show that each combination of the three models has statistically different median values of infiltration beneath the LID. This analysis shows that recharge is greater under the 0.5% LID model than the 2% LID model (Figure 7). This pattern is similar to the findings from Figure 6 where infiltration occurs more in 0.5% LID as compared with the 2% LID.

Figure 8a,b,c shows the simulated recharge efficiency (%) beneath the LID within the Lake Merced watershed using the suite of hypothetical LID implementation plans (0.5% LID, 1% LID, and 2% LID), respectively. Two important trends are apparent from Figure 8a,b,c. First, the average recharge efficiency increases as %LID coverage increases; average recharge efficiencies increase from 60%, 81%, and 87% for 0.5%, 1%, and 2% LID coverage, respectively. Second, the year-to-year variability in recharge efficiency decreases as %LID coverage increases; standard deviation of recharge efficiencies decreases from 11%, 9.2%, and 7.8%, for 0.5%, 1%, and 2% LID coverage, respectively. These two trends are explained again by the relatively greater stormwater that is generated under the 0.5% LID coverage that in turn creates more conditions where the storage capacity of the LID exceeded and relatively less water is able to infiltrate and recharge beneath the LID. Results of the Kruskal-Wallis test (p-value<0.0001, α-level = 0.05) and the Steel-Dwass test (p-value<0.0001, α-level = 0.05) for the simulated recharge efficiency indicate that there is a statistically significant difference between the 0.5%, 1% and 2% LID coverage models (Figure 9). The 0.5% LID has the lowest mean recharge efficiency and the 2% LID has the highest mean, which indicates that the 2% LID coverage promotes the most efficient LID recharge of the three models. This is consistent with the previous results that shows that lower %LID have low recharge efficiently due to more stormwater generated that overflows the storage capacity and maximizes the infiltration beneath the LID.

Figure 10 summarizes the results for average annual inflow to the LID, infiltration beneath the LID (recharge), and recharge efficiency for the 0.5%, 1%, and 2% LID coverage models. The inverse relation between inflow and infiltration beneath the LID (recharge) to %LID coverage is shown in Figure 10a, and the positive relation between recharge efficiency and %LID coverage is shown in Figure 10b. Although, models were not run for <0.5% or >2% LID coverage, the general monotonic relations in Figure 10 may be useful in extrapolation conditions to relatively lower (<0.5%) or higher (>2%) LID coverage. Extrapolating the data from Figure 10a indicates that infiltration rates (i.e., recharge rates) greater than about 14 in/yr are possible as %LID decreases below 0.5%. However, this relationship will not extend indefinitely because as %LID coverage approaches zero, there will be no LID features to collect and create LID enhanced recharge. Conversely, by extrapolating the data from Figure 10b indicates a reduction in recharge efficiency below 60% as %LID coverage decreases below 0.5%. Figure 10b indicates that there is a sharp ~20% increase in recharge efficiency when increasing the %LID coverage from 0.5% to 1%. However, doubling of the %LID coverage area from 1% to 2% results in only a ~10% increase in recharge efficiency. This shows that recharge efficiency and increasing %LID coverage is not a linear relationship. The relationships in Figure 10 could be used by stormwater and groundwater resource managers to help identify the optimal %LID coverage of the Lake Merced watershed, depending on stormwater reduction targets, groundwater sustainability goals, and the costs associated with installation and maintenance of LID coverage across the watershed.

4.0. ASSUMPTIONS & LIMITATIONS

The assumptions and limitations of this project are associated with both the data used and from the PCSWMM models. The following sections describe the assumptions and limitations of this study.

4.1. Data Assumptions

I used the 2011 NLDC land cover data, which is not the current land cover data. As mentioned earlier, the 2016 NLDC data was released in early 2019 after I had completed the model simulations using the 2011 data, and thus the 2016 data were not incorporated into this study. Also, the population of San Jose, CA has increased since 2011 (City of San Jose, 2019). Therefore, the current impervious percentage is likely greater than in the 2011 NLDC data that was used in the models. Finally, the resolution of NLDC land cover data is 30 m, which may inaccurately represent the percent imperviousness due to its large resolution.

The assumptions of the using the USGS stream discharge data is that the recorded discharge data may not necessary reflect just the stormwater runoff. The data could be influenced by human activity, groundwater discharge and/or other factors. Also, I used a 10-digit HU in creating the San Jose watershed model. However, there were watershed boundary bigger than 10-digit HU that could have been used for this project. The relationship between the watershed boundary chosen and the USGS stream site number: 11169025 is unclear and would need to be researched more. Also, there were no other publicly available stream discharge data to calibrate the model with to compare with.

For the NOAA precipitation data, there were a few data values missing from the precipitation data. The few missing values could change the output results of all models.

4.2. Model Assumptions & Limitations

As with any hydrologic model, there are inherent uncertainties and limitation in the conceptual model and how the resulting PCSWMM model simulates the real watershed. In PCSWMM, the user must delineate each subcatchment, which are hydrologic units of land topography and drainage system elements that direct surface runoff to a single discharge point (James, 2005). The user can divide a study area into multiple number of subcatchments and assign parameter attributes to each subcatchment. However, in this study, I used a single subcatchment to represent the entire watershed. Therefore, I generalized my watershed under one parameter set, rather than using different attributes with multiple subcatchments. If I were to divide my study area into multiple subcatchment, it would have required more extensive knowledge of the Lake Merced Watershed far beyond the scope of this project. I would have to know where to draw the boundary lines each of my subcatchments and gather principal attribute parameters for each subcatchments.

As mentioned in the methodology section, the parameters used to build the PCSWWM models were taken from a manual from CHI support. However, field-derived LID inputs parameters from the Lake Merced watershed were not available, and may have improved the simulations results.

Finally, the infiltration model used in all models was the widely used Green-Ampt Method. The Green-Ampt infiltration model assumes that a sharp wetting front exists in the soil column and separates the unsaturated soil below (James, 2005). It also assumes that the wetting surface and water table are horizontal and the water flux are traveling vertically (James, 2005). Since no field samples of the soil column were collected for either San Jose watershed or Lake Merced Watershed, the Green-Ampt infiltration model is a reasonable approximation of the actual infiltration processes in this study.

5.0 CONCLUSION

I used PCSWMM to create a model for the San Jose Watershed to calibrate my study area, Lake Merced Watershed. After creating my Lake Merced Watershed model, I created four models of the study area to represent the suite of hypothetical LID implementation plans (0% LID coverage, 0.5% LID coverage, 1% LID coverage and 2% LID coverage). Using the four models, I have simulated and statistically analyzed using JMP for the annual discharge, annual inflow to LID and annual infiltration beneath the

LID. I also calculated the recharge efficiency from the outputs of my models and ran statistical analysis.

Results from discharge outputs confirmed that simulated implementation of LID at 0.5%, 1%, and 2% coverage produce statistically lower discharge out of the Lake Merced watershed compared with the null hypothesis (0% LID coverage). This showed that LID can indeed increase infiltration, decrease stormwater runoff and that there is a fundamental change in the water budget of Lake Merced watershed between all implementation plans (0.5%, 1% and 2% LID coverage).

Results from inflow into LID showed that the difference of 40 acres generated on average 18.3 in/yr more inflow when comparing the 0.5% LID model to the 2% LID model. The models also generated less variable inflow to the LID as the % LID coverage increased.

Results from infiltration beneath LID (recharge) and recharge efficiency show that the difference of 40 acres generated on average 8.7 in/yr more infiltration when comparing the 0.5% LID model to the 2% LID model. There are statistical differences among all % LID models and recharge is greater under 0.5% LID model than 2% LID model.

Analyzing recharge efficiency showed efficiency increased as %LID coverage increased but the % efficiency was not a linear relationship. Efficiency % increases by ~20% from 0.5% LID to 1% LID but only increases by ~10% from 1% LID to 2% LID despite doubling the area coverage. Running a statistical analysis on recharge efficiency, there are statistical differences among all models. Results show that 2% LID coverage is the most efficient of the three models.

The results of discharge, inflow into LID, infiltration beneath the LID and recharge efficiency show that despite 0.5% LID model having the greatest infiltration beneath the LID, it has the lowest recharge efficiency of all the models due to having the largest stormwater inflow and largest discharge. This finding regarding the relationship between % LID coverage and its effect on the water budget (including groundwater recharge) could help support groundwater resource managers find the optimal % LID coverage in an urban system. Groundwater resource managers could use similar processes conducted in this study to apply to their own city.

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6.0 FIGURES

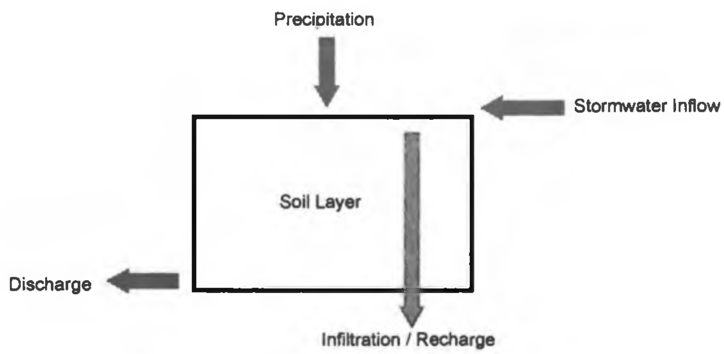


Figure 1. Conceptual model of LID recharge in relation to stormwater inflow, precipitation and discharge.

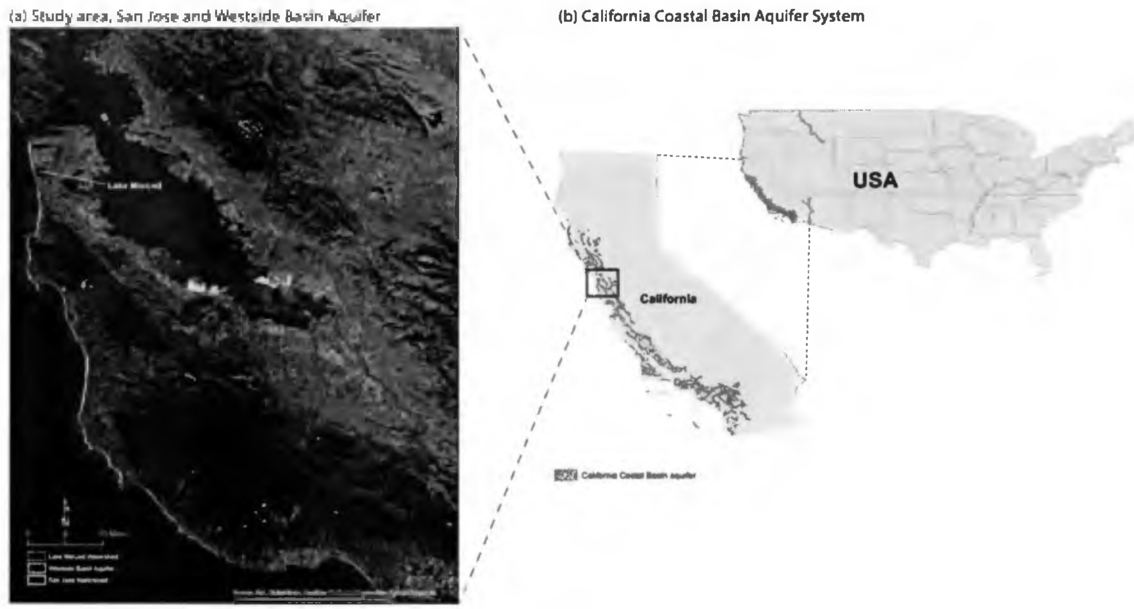


Figure 2. Study area map showing (a) the Lake Merced and San Jose watersheds and the extent of the Westside Basin aquifer, and (b) the location of the California Coastal Basin aquifer system. The aquifer locations are modified from data collected from USGS.

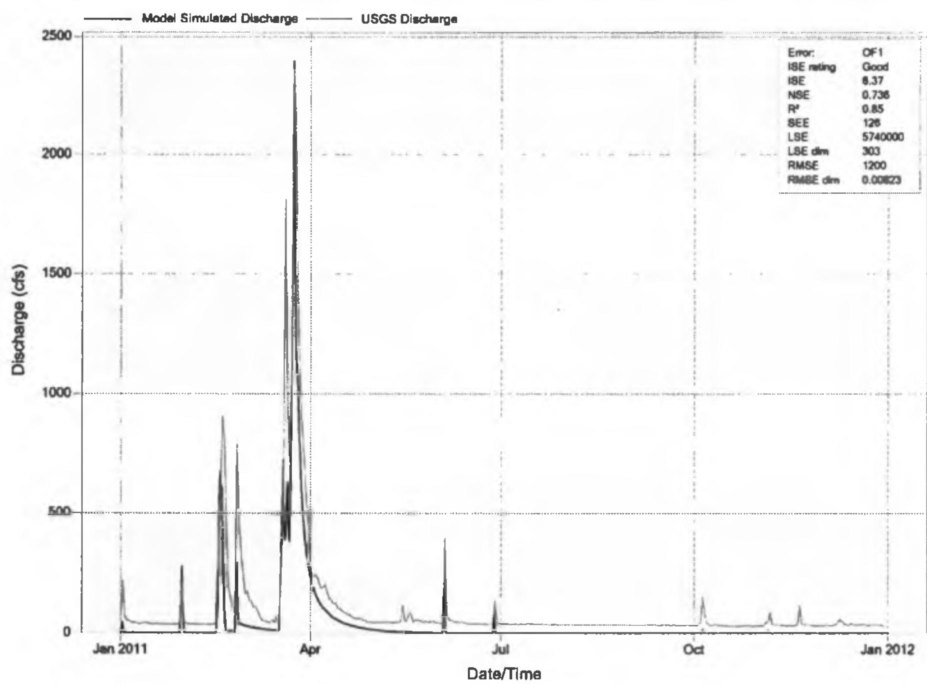


Figure 3. Graph of PCSWMM model simulated discharge compared with USGS discharge (observed data). The top right corner indicates NSE value of 0.736 and $R^2 = 0.85$ which both indicates that the data is a good predictor and good fit.

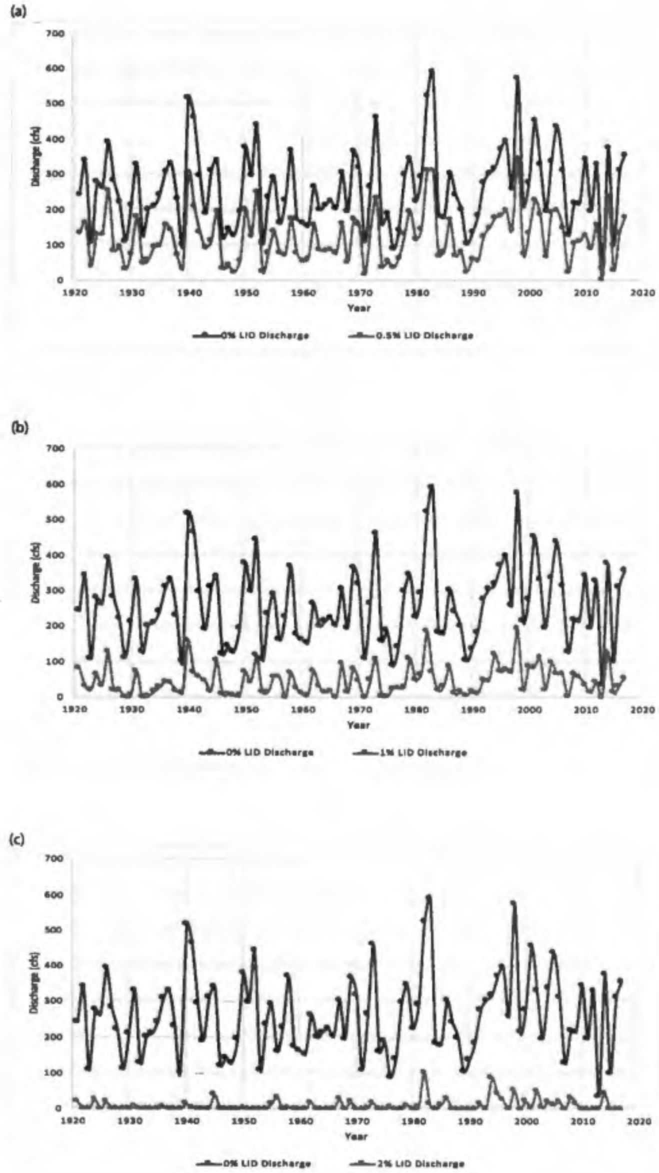


Figure 4. Simulated timeseries of discharge out of the three Lake Merced watershed models for the three hypothetical LID implementation plans (a) 0.5% LID (b) 1% LID, and (c) 2% LID.

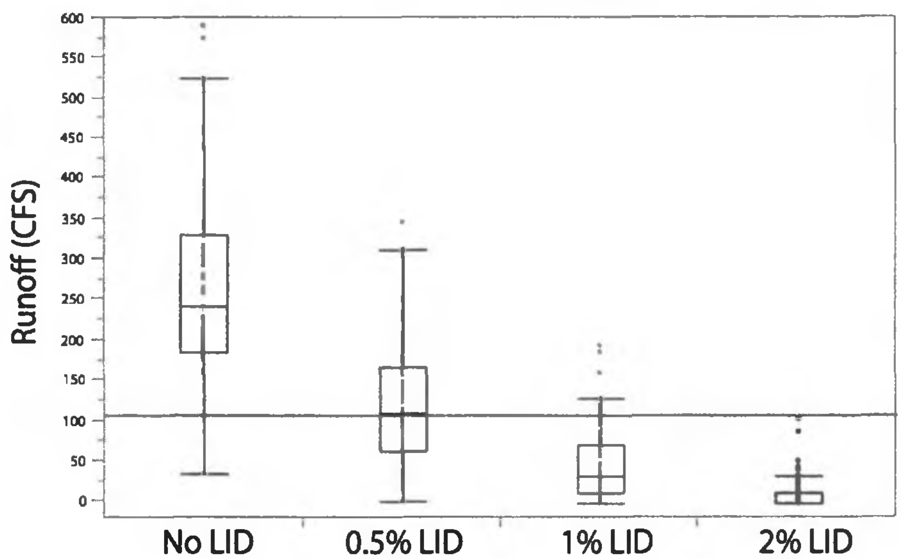


Figure 5. Boxplot and visual observation of difference in simulated discharge of all four models created (0%, 0.5%, 1%, 2% LID coverage).

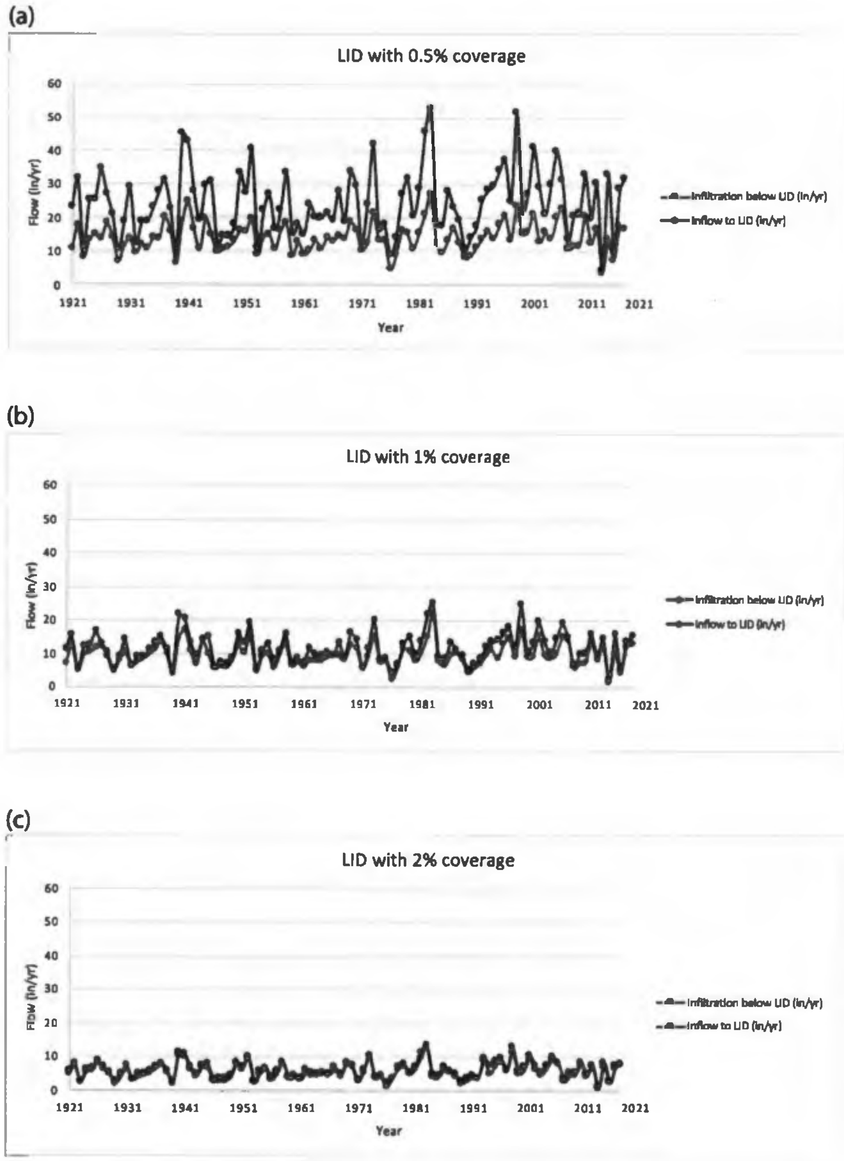


Figure 6. Timeseries of inflow to LID (in/yr) and infiltration beneath the LID (in/yr) for three LID implementation plans (a) 0.5% LID, (b) 1% LID and (c) 2% LID.

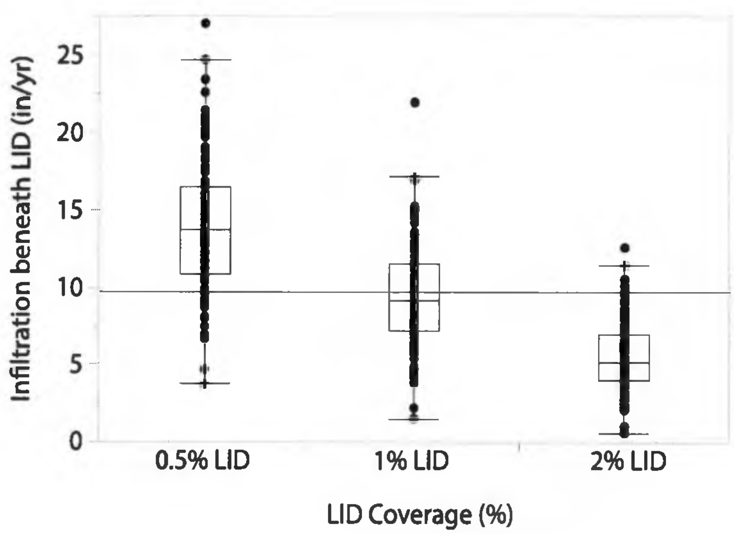
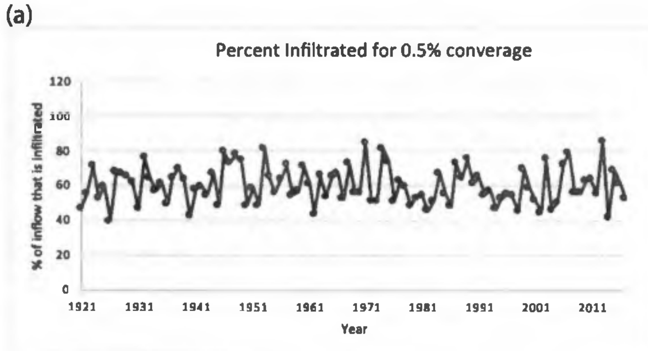
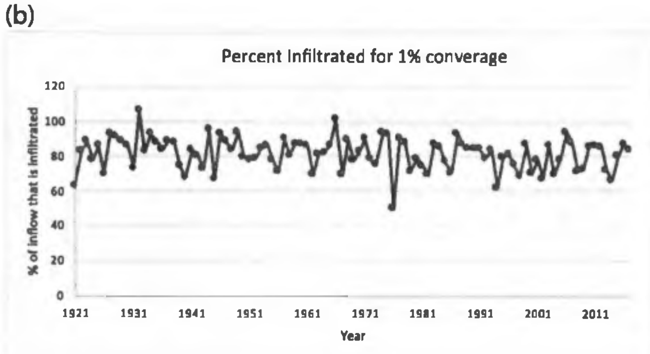


Figure 7. Boxplot and visual observation of difference in simulated infiltration beneath LID for the models created (0.5%, 1%, 2% LID coverage).

(a)



(b)



(c)

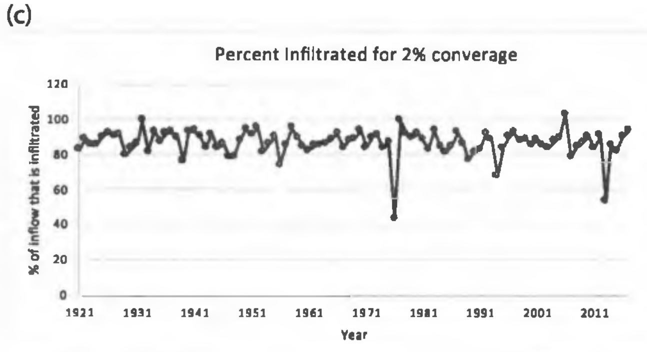


Figure 8. Graphs of simulated recharge efficiency beneath the LID (in/yr) from the three models, (a) 0.5% LID, (b) 1% LID, (c) 2% LID.

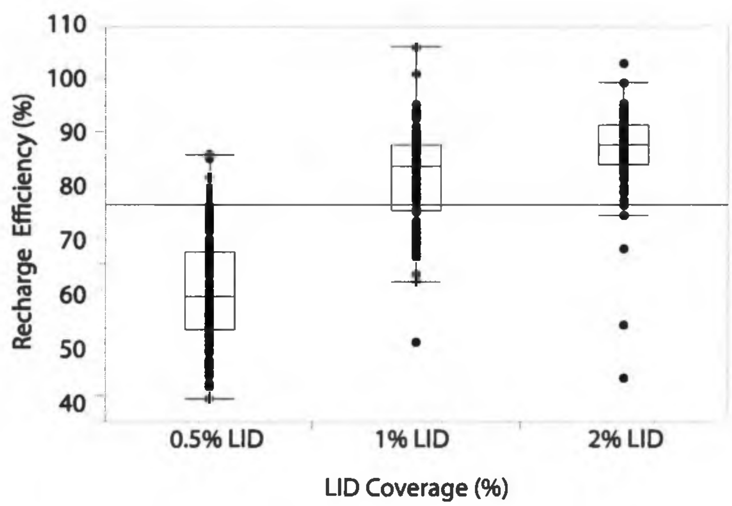
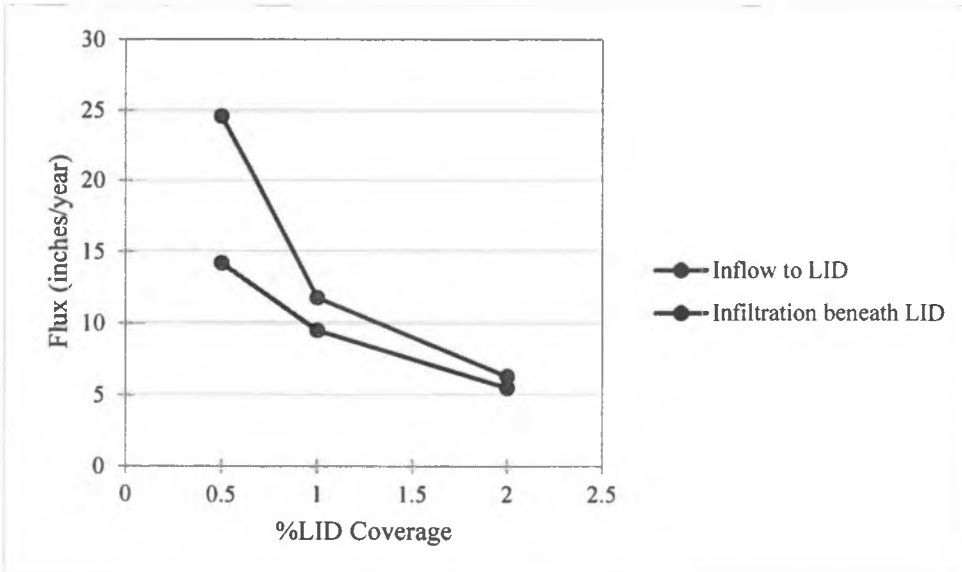


Figure 9. Boxplot and visual observation of difference in recharge efficiency % for the models created (0.5%, 1%, 2% LID coverage).

(a)



(b)

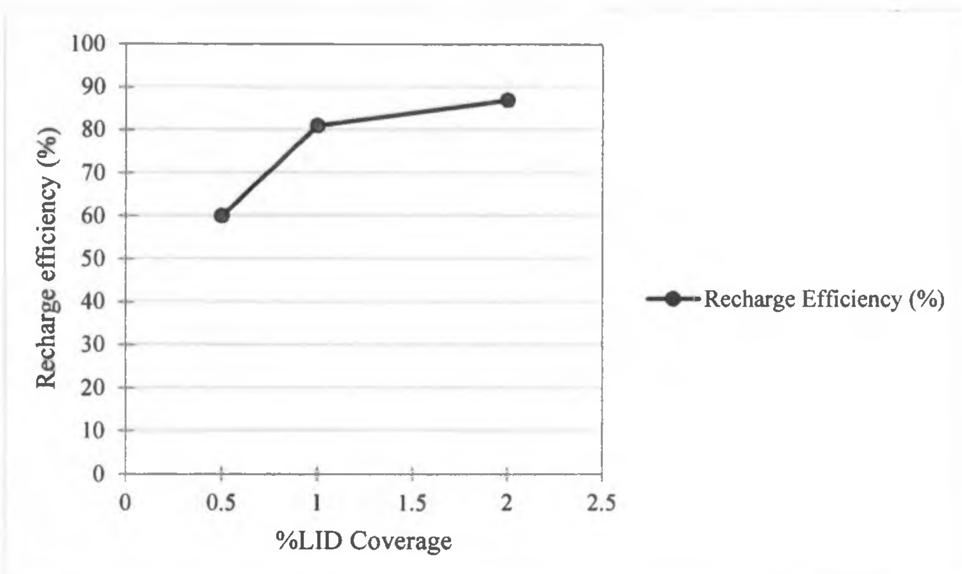


Figure 10. Summary of (a) average annual inflow to the LID (in/yr), infiltration beneath the LID (in/yr), and (b) recharge efficiency (%) for model simulations of 0.5%, 1%, and 2% LID coverage across the Lake Merced watershed.

7.0 TABLES

Table 1. Select model parameters for the calibrated San Jose PCSWMM model.

Parameters	Source or value	Station ID	Period of record
Precipitation (in/hour)	NOAA	USW00023293	2011-2017
Stream discharge (ft^3/s)	USGS	11169025	2011 - 2017
Impervious surface/land use	NLDC	--	2011
Watershed boundary dataset	USGS	--	2016
Infiltration model	Green-Ampt	--	--
Impervious (% of area)	69	--	--
Slope (%)	1	--	--

Table 2. Select model parameters for the calibrated Lake Merced PCSWMM models.

Parameters	Source or value	Station ID	Period of record
Precipitation (in/hour)	NOAA	USW00023272	1921-2017
Impervious surface/land use	NLDC	--	2011
Infiltration model	Green-Ampt	--	--
Impervious (% of area)	49	--	--
Slope (%)	1	--	--

Table 3. Bio-retention parameters used in all hypothetical LID implementation plans.

Surface	
Bern Height (m)	4
Vegetation volume (fraction)	0.1
Surface roughness (Manning's n)	0.3
Surface slope (percent)	0.25
Soil	
Thickness (in)	35
Porosity (volume fraction)	0.44
Field Capacity (volume fraction)	0.11
Wilting point (volume fraction)	0.05
Conductivity (in/hr)	1
Conductivity slope	7.5
Suction head (in)	3.5
Storage	
Thickness (in)	18
Void Ratio (voids/solids)	0.75
Seepage rate (in/hr)	0.24
Clogging factor	0
Underdrain	
Drain Coefficient (in/hr)	0
Drain exponent	0
Drain offset height (in)	0
Area of each unit (square feet)	1,076
Surface width per u nit (feet)	10.8
% Initially saturated	0
% of impervious area treated	100
% of pervious area treated	0