**Modeling the hydrologic effects of watershed-scale green roof implementation using VELMA, a spatially explicit ecohydrological watershed model**

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**Abstract**

Environmental watershed models are widely used to simulate the impacts of infrastructure development on environmental outcomes, including water quantity and quality. In this study, we utilize a spatially explicit (i.e., gridded) ecohydrological watershed model called Visualizing Ecosystem Land Management Assessments (VELMA) to simulate watershed-scale hydrologic discharge for four urban watersheds in Seattle, Washington, USA. In particular, we simulate four scenarios of green roof implementations where 25%, 50%, 75%, and 100% of existing buildings hypothetically adopt green roofs. Intensive and extensive green roof types are tested separately and produce approximately 20-25% and 10-15% mean annual runoff reductions, respectively, over a 28-year simulation. We also show that stormwater runoff reductions are proportionately smaller during higher flow regimes caused by increased precipitation, likely due to the limited storage capacity of saturated green roofs. In general, the results suggest that wide-scale implementation of green roofs can be effective at reducing stormwater runoff but are limited by their areal extent and storage capacity. Also, grid-based watershed models can facilitate the prioritization of urban water infrastructure to improve water retention in urban streams and receiving waters such as Puget Sound, and our approach is likely applicable in other metropolitan areas.

Keywords: Green roofs, urban watershed modeling, VELMA, stormwater

**1. Introduction**

Watershed models have been widely used to simulate the combined effects of topography, soil type, land use, and management on water quantity and quality (Aksoy and Kavvas, 2005; Borah and Bera, 2003) and aid decision making (Barnhart et al., 2018). In particular, numerous studies have examined the impacts of alternative land use scenarios on various hydrologic and biogeochemical components throughout urban, suburban, rural as well as mixed-use regions (Hoghooghi et al., 2018; Lee et al., 2018). Mechanistic or processed-based watershed models typically represent an environmental system as a series of equations that evolve a set of state variables. These models produce outputs that range temporally from minutes (e.g., Hydrologic Simulation Program in Fortran [HSPF; (Bicknell et al., 1997)], Stormwater Management Model [SWMM; (Rossman, 2010)]) to hours (e.g., Soil and Water Assessment Tool [SWAT; (Gassman et al., 2007)]) to days, years, and decades (e.g., Visualizing Ecosystem Land Management Assessments [VELMA; (Abdelnour et al., 2011)], Regional Hydro-Ecological Simulation System [RHESSys; (Tague and Band, 2004)]). Additionally, these models are generally classified as either semi-distributed, for example, models that utilize sub-basins (e.g., HSPF, SWAT), or spatially explicit, which simulate interrelated voxels within a gridded matrix (e.g., VELMA, RHESSYs). While each type of watershed model serves to aid decision making in different contexts, spatially explicit models are particularly advantageous because they enable explicit placement of management actions on the landscape and can simulate subsequent environmental impacts.

In cities throughout the United States (Hoghooghi et al., 2018; Sarkar et al., 2018) and the world (Tzoulas et al., 2007), green infrastructure (GI) has gained attention as an urban management option that can potentially reduce and delay storm runoff and provide a host of other ecosystem services including heat reduction, habitat de-fragmentation, nutrient management, green space, recreation and others (Berardi et al., 2014; Golden and Hoghooghi, 2018; Passeport et al., 2013; Woznicki et al., 2018). The term ‘green infrastructure’ typically includes a suite of practices that can be installed and implemented in urban and/or semi-urban systems, including green roofs, permeable pavement, bioswales, and riparian buffers, among others. Green roofs, in particular, are among the most popular GI type implemented in highly urbanized watersheds due to their low cost and efficient utilization of unused or under-used space (Carter and Jackson, 2007). Studies have investigated the water retention and delay impacts of green roofs in urban watersheds. For example, Sarkar et al. (2018) used the RHESSys model to simulate various GI practices and showed that GI caused water yields to decrease and evapotranspiration to increase. Green roofs, in particular, provided a 33% (median) reduction in annual water yields. In addition, experimental studies have shown that green roof retention times vary from minutes to hours and can help to slow storm flow (Speak et al., 2013).

There remains a disconnect between experimental studies that provide green roof efficacy results in various contexts and watershed modeling results that extrapolate these findings to large scales. In this paper, we model watershed-scale hydrologic discharge for four urban watersheds in Seattle, Washington, USA. We use a spatially explicit (i.e., gridded) watershed model called VELMA to explicitly account for spatially distributed urbanized land cover. VELMA is a watershed model that can assess green infrastructure options for controlling the fate and transport of water, nutrients, and toxics across multiple spatial and temporal scales for different ecoregions and present and future climates (McKane et al., 2014b). We employ a 1-m land use/land cover (LULC) data layer, resampled to 10 m, to differentiate buildings, roads and other impermeable surfaces (e.g., parking lots, sidewalks), trees, and grass. After initial calibration and validation of a baseline model with no green roof implementations using observed hydrologic discharge data, we construct four scenarios of green roof implementation (25%, 50%, 75%, 100% coverage) that randomly distribute green roof parameterizations to existing buildings in each of the watersheds. We run two sets of scenarios to test the effects of installing intensive vs. extensive green roofs and compare the resulting hydrologic discharge with the baseline simulations.

Our study makes two major contributions. First, our results provide an upper limit on the possible peak stormflow reductions that can be expected by employing green roofs in a metropolitan system. By simulating the impacts of 100% green roof implementation, we provide an upper limit on the possible peak stormflow reductions that can be expected for these Seattle watersheds. Therefore, these results can inform decision makers when crafting programs to support the adoption of urban GI including green roofs and identify the maximum benefit of green roofs for stormwater management. Second, we employ VELMA, a heretofore unutilized watershed model for simulating green roofs. VELMA has been used to model natural and engineered green infrastructure for water quality protection in other systems to compare the effects of GI and climate scenarios on water quality and associated co-benefits and trade-offs for other ecosystem services (Abdelnour et al., 2013; Abdelnour et al., 2011; Golden et al., 2012; Golden et al., 2014; Knightes et al., 2014). Our parameterizations and model improvements of VELMA provide another application of this model that can be useful for future studies to simulate the impacts of green roofs and to compare other green and traditional stormwater infrastructure. Our approach is intended to be useful to assess effectiveness of green roof implementation in other large metropolitan areas.

**2. Materials and Methods**

**2.1. Study Areas**

We focused on four watersheds in four distinct urban watersheds within the greater Seattle metropolitan area: Taylor Creek, Thornton Creek, Longfellow Creek, and Pipers Creek. Figure 1 shows Seattle, Washington and the four watershed areas along with their respective stream networks. Note that two of the watersheds drain west into Puget Sound, and two drain into Lake Washington.

**<Insert Figure 1 Here>**

Table 1 shows the percentage distribution of land use for each of the four watersheds, as derived from the 1-m land use/ land cover data obtained from the University of Washington’s Remote Sensing & Geospatial Analysis Laboratory (Styers et al., 2014). Note that the 1-m data were resampled to 10 m to match the digital elevation data (see Input Data section).

**<Insert Table 1 Here>**

The four watersheds vary in size from approximately 3 km2 to 31 km2, yet the land use classification characteristics are remarkably similar (Table 1). For example, the percentages of buildings were 10%, 10%, 10%, and 11% in Taylor, Thornton, Longfellow, and Pipers watersheds, respectively.

Longfellow Creek is located in the southwestern corner of Seattle, Washington and is the most urbanized watershed among the four based on its percentage of buildings and impervious surfaces (e.g., roads, parking lots, and sidewalks). The High Point neighborhood, accounting for approximately 10% of the Longfellow Creek watershed, has worked with Seattle Public Utilities since the 1980s to adopt green infrastructure practices such as grass and vegetated swales, porous pavement, and a large storm-water pond to slow runoff and filter contaminants before reaching the creek and ultimately heading to the Puget Sound (Seattle Public Utilities, 2018).

Thornton Creek, the largest of the four watersheds (31 km2), is located in northeastern Seattle, Washington. The watershed is heavily urbanized and is intersected by Interstate 5, which cuts through the western portion of the watershed. Numerous GI and low-impact design studies have been implemented in Thornton Creek, including the Thornton Creek Water Quality Channel (US EPA, 2016).

Pipers Creek, located on the western side of Seattle, Washington, flows directly into Puget Sound. The watershed holds the highest percentage of forests (46%) of all the watersheds included in this study, and approximately 11% of the watershed area is covered by buildings.

Taylor Creek, located in the southeastern region of Seattle, Washington, flows into Lake Washington. Taylor is the smallest watershed in our sample (3 km2), and the total areal percentage of buildings within the watershed is 10%. Numerous restoration efforts led by the Seattle Public Utilities have been conducted throughout the watershed since 1971, yet, as with the other watersheds included in this study, the large-scale potential of green roof implementations have not been investigated.

**2.2. Watershed Model**

**2.2.1. *Model Overview***

To simulate the effects of green roof implementation scenarios on hydrologic discharge, we used the Visualizing Ecosystem and Land Management Assessments (VELMA v2019-07-22) model (Abdelnour et al., 2011). VELMA is a spatially explicit (i.e., gridded) watershed model that integrates hydrologic and biogeochemical (C and N) sub-models to simulate numerous environmental attributes, including watershed-scale discharge. A complete description of the model and its sub-components can be found in Abdelnour et al. (2011), Abdelnour et al. (2013), and in the VELMA user manual (McKane et al., 2014b). The model has been tested in a variety of ecosystem types, including grassland prairie ecosystems (Barnhart et al., 2015), forests in the Pacific Northwest (Abdelnour et al., 2013; Abdelnour et al., 2011; McKane et al., 2014a), and urbanized mixed-use ecosystems (Hoghooghi et al., 2018).

**2.2.2. *Model Improvements***

VELMA has only recently been used to model semi-urbanized environments for implementation of GI (Hoghooghi et al., 2018) and has not yet been used in fully urbanized watersheds or to explicitly model green roofs. Figure 2 depicts a single VELMA voxel that describes how VELMA models the environment. The left panel designates a traditional VELMA voxel that includes an optional impermeable layer, as implementable in VELMA 2.0. This optional impermeable layer limits the percentage of water that can infiltrate from the surface to the first soil layer and allows VELMA to simulate increased surface runoff and less infiltration caused by the increased impermeability of urbanized surfaces (e.g., buildings, roads, parking lots, sidewalks).

In addition to utilizing the optional permeable layer to better represent urbanized surfaces such as roads and parking lots, we manually parameterized a new soil type to represent green roofs. Figure 2 shows how the traditional VELMA voxel representation (Figure 2, left panel) was altered to accommodate green roofs (Figure 2, right panel). The first layer of the green roof soil type is characterized by the soil properties of the green roof, whereas the remaining three soil layers are characterized by the soil properties of soil under the building. Lateral flow is allowed both in and out of the first soil layer (i.e., the green roof) and in and out of the lower soil layers, but vertical flow is limited between soil layers 1 and 2 by manually setting the first-layer value of *setSoilLayerKsLateralValues* to a small but non-zero quantity. This essentially limits flow between soil layers 1 and 2 to a negligible quantity while also preventing model crashes due to divisions by 0. We note that the allowance of lateral flow into the green roof is a model simplification that is not reflected in the real world. However, the digital elevation model did not include buildings, and preventing lateral flow between cells via parameterization caused unrealistic flow patterns and model crashes. Therefore, we chose to adopt this model simplification to reflect an approximate mechanistic representation of green roofs in urban environments (Figure 2).

**<Insert Figure 2 Here>**

**2.3. Input Data**

A number of standard, spatially distributed inputs are required to construct watershed models including VELMA. These include a digital elevation model, soil and land use/land cover maps, a stream network, and weather drivers including daily temperature and precipitation (Table 2).

**<Insert Table 2 Here>**

A 10-m digital elevation model (DEM) was acquired from the USGS (Table 2). This product was chosen over lidar-based digital terrain models, which provide higher spatial resolution, for two main reasons. First, higher resolutions require more voxels to be simulated within VELMA, which in turn increase the total simulation time. Second, lidar products are data-intensive and require complex processing to ensure reliable outputs; therefore, we chose a 10-m DEM that would be more widely applicable and used by state agencies and municipalities. The 10-m DEM was flat-processed using the JPDEM-Dredge processing tool (McKane et al., 2014b; Pan et al., 2012). A hand-digitized stream network obtained from the City of Seattle was used to aid the JPDEM-Dredge processing tool that enforces pre-determined flow routing within the DEM. Municipal sewers and pipes were ignored and may be incorporated in further studies.

A single soil type was initially used for all four watersheds, which was characterized as sandy loam. An additional soil type was then created for cells that implemented green roofs and were characterized by intensive and extensive green roof media characteristics, as described in a subsequent section.

Land use data were acquired from the University of Washington’s Remote Sensing & Geospatial Analysis Laboratory (Styers et al., 2014) and consisted of 1-m land use land cover data across the Seattle metropolitan area (Tables 1-2). These data were resampled to 10-m cells via majority rule, resulting in an average increase of 0.58% in building area for the four watersheds. For these and other geospatial and statistical techniques used in this analysis, scripts were written using R 3.1.2 statistical software (R Core Team, 2013) and Python 2.7.12 (Python Software Foundation, 2016) programming language. Visualizations, sampling location analysis, and basic map editing were made with ArcGIS 10.3 (ESRI, 2014)

Three NOAA-referenced weather stations (Sand Point, Portage Bay, and Boeing Field) and Daymet modeled data were used to compile daily mean temperature and precipitation estimates for the duration of our model runs(NOAA, 2016; Thornton et al., 2017). All three stations were within the municipal boundaries of the City of Seattle and were located between 2-21.5 km of either Thornton or Pipers creeks. The Sand Point weather station had 10,076 recorded daily weather observations between 1986 and 2015, including 526 missing daily observations, 13 precipitation NA’s, and 1 average temperature NA observations. Between 1986-1-1 and 1998-4-30, Sand Point had 151 missing daily observations, 4 precipitation NA’s, and 1 average temperature NA, which were gap filled with Portage Bay recorded weather. Boeing Field weather observations were used to gap fill 153 days of missing Sand Point daily data between 1998-12-5 and 2015-12-31 as well as being used to replace the 9 remaining precipitation NA’s. From 1998-5-1 through 1998-12-4, there were no recorded weather observations at Sand Point, Portage Bay, or Boeing Field, so these days were completely gap filled with Daymet modeled data (Thornton et al., 2017). Daymet model output data were acquired for the 1-km cell at the Sand Point station latitude and longitude. R 3.1.2 statistical software (R Core Team, 2013) was used for gap filling observed NOAA weather station data with Daymet daily gridded modeled weather parameters, using the “daymetr” package (Hufkens et al., 2018) for single cell sampling.

**2.4. Baseline Calibration and Validation**

A semi-automatic calibration tool called MOEA-VELMA was used to tune VELMA’s calibration parameters in order to match simulated discharge with observed streamflow for a baseline model of Taylor Creek including buildings with no green roofs. A full description of the MOEA-VELMA framework will be provided in the forthcoming VELMA 2.1 user manual (McKane et al., In Preparation). Taylor Creek was chosen because it was the smallest watershed and therefore produced the fastest computational runtime, and it also had the longest period of observed hydrologic data available.

The goal of calibration was to adequately represent the hydrologic storage throughout the watershed without overfitting the model. MOEA-VELMA utilizes the MOEA Framework (McKane et al., 2014b) to implement evolutionary algorithms in order to calibrate chosen model parameters. In particular, the nondominated sorting genetic algorithm II (NSGA-II; (Deb et al., 2002)) was used to choose the optimal set of input parameters to minimize an objective function. The Nash Sutcliffe efficiency (NSE; Nash and Sutcliffe [1970]) criterion (Equation 1) was used as the sole objective function:

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|  |  | (1) |

where O is the observed value, S is the simulated value, and is the mean of the observed values. NSE values range from -∞ to 1.0 where one represents a perfect fit with the observed data.

Observed discharge data from the mainstem of Taylor Creek near the outlet was obtained from Seattle Public Utilities (station 401), which consisted of daily discharge data between January 2004 and July 2016 (Seattle Public Utilities, 2016). Calibration was performed with daily data from 2004-2009 and tuned the parameters shown in Table 3.

**<Insert Table 3 Here>**

The *petparam1* parameters for both conifer and grass cover types determine the allowable potential evapotranspiration using the Hamon equation (Hamon, 1960), and the parameter *be* adjusts the fraction of actual evapotranspiration compared with the potential values. Meanwhile, the parameter *surfaceKs* is the surface saturated hydraulic conductivity (mm-day-1), and the parameters *ksLat* and *ksVert* are unitless multipliers that determine the respective rates of decrease in lateral and vertical flow with depth.

The calibration algorithm tested approximately 3,500 parameter sets, and the NSE values between daily observed and simulated discharge were maximized. By visual inspection, all parameter sets that produced simulations with NSE > 0.6 were retained, from which a single parameter set was chosen and applied to each of the four watersheds to serve as baseline models. These baseline models were compared with the scenarios.

**2.5. Green Roof Scenarios**

Green roofs are generally categorized as either intensive or extensive (McIntosh, 2010). Intensive green roofs (IGRs) are characterized by thicker soil columns (e.g., >15 cm) and larger vegetation and can include landscaped gardens, mixtures of trees, bushes and grass. They require substantial structural support and are typically installed on larger, commercial buildings that may allow pedestrian access. Extensive green roofs (EGRs) are characterized by shallow soil depths (e.g., 5-15 cm) and low-level vegetation that typically covers a large proportion of the roof. EGRs can be implemented on buildings with less structural support than IGRs, and typically do not require maintenance such as irrigation, fertilization (McIntosh, 2010).

To parameterize green roofs in VELMA, both the cover and soil characteristics were changed to match those of intensive or extensive green roofs. Table 4 shows the soil characteristic parameterizations for green roofs in VELMA.

**<Insert Table 4 Here>**

The values for the general soil type were chosen to match a sandy loam soil type and were taken from McKane et al. (2014b). The intensive and extensive green roof soil characteristics were taken from the technical specifications of a proprietary source of green roof media (Rooflite Extensive 600 Media and Rooflite Intensive 700 Media; (Rooflite, 2020) that was designated as an approved media source to obtain stormwater reduction credit by the City of Seattle (Magnusson Klemencic Associates and Seattle Public Utilities, 2008)

In addition to the soil characteristics, we also changed the land cover from a traditional building (i.e., no vegetation biomass) to cover characteristics of grass that match either extensive or intensive green roofs. VELMA input parameters were manually parameterized to ensure that the simulated maximum annual aboveground biomass values reached approximately 240 and 1000 gC m-2 yr-1, which match data from experiments conducted by Getter et al. (2009).

Four green roof scenarios were tested using intensive and extensive green roofs separately. Figures 3-6 show the four scenarios for each of the four watersheds.

**<Insert Figure 3 Here>**

**<Insert Figure 4 Here>**

**<Insert Figure 5 Here >**

**<Insert Figure 6 Here>**

Each of the four panels in Figures 3-6 show varying proportions of existing buildings converted to green roofs (25%, 50%, 75%, and 100%). The land use types of trees, grass, and roads, parking lots, and sidewalks are all in gray, and the spatial distribution of buildings and green roofs are shown in red and green, respectively. The spatial designations of green roofs were performed randomly.

**3. Results and Discussion**

**3.1. Calibration and Validation Results**

We used the automatic calibration algorithm MOEA-VELMA to calibrate VELMA for the Taylor Creek watershed. The algorithm resulted in 848 out of 3,500 parameter sets that gave NSE values >0.6 (see Table 3).

As shown in Table 3, the automatic calibration procedure found solutions with a wide range of parameter values because different combinations of parameters (e.g., a high *be* value combined with a low *Petparam1* value compared with a low *be* value combined with a high *Petparam1* value) can produce similar discharge simulations. Fully addressing parameter redundancy is beyond the scope of this investigation. Therefore, we chose one parameter set and applied that set to each of the four watersheds to serve as the baseline models, which will then be compared with the scenario results.

**3.2. Scenario Results**

Four green roof scenarios (25%, 50%, 75%, and 100% of buildings converted to green roofs) in addition to the baseline scenario (0%) were run for each of the four watersheds and for extensive and intensive green roof types (Figure 7). Figure 7 shows the percentage change in total annual runoff between each of the scenarios and the baseline simulations. Simulations were run for 29 years (1987-2015), and the first year was designated as a spin-up year and not included in the results. The gray and white boxplots therefore denote the annual extensive and intensive green roof simulation results, respectively, across a 28-year period (1988-2015).

As the total percentage of buildings converted to green roofs increases, the total runoff reductions increase among the scenarios. Also, intensive green roof scenarios have higher storage capacity and are therefore able to reduce total annual runoff values more effectively that the extensive green roofs. The simulated runoff reductions are 10-15% for extensive green roofs and 20-25% for intensive green roofs. While these reductions may appear moderate, note that only approximately 10% of the watershed areas were converted from building rooftops to green roofs in the 100% scenarios. This forms a realistic upper bound on the runoff reductions that would be feasible within these four watersheds by employing green roofs alone as a stormwater management tool.

Note that the 75% and 100% extensive green roof simulations for Pipers Creek appear to be anomalous outliers. These simulations give runoff reductions that are less than the 50% scenarios, which is counterintuitive, and the runoff simulations for the 100% green roof scenarios even stretch above the baseline (0%) simulations. One reason for these anomalous results may be due to the improper characterization of flow in Pipers Creek using calibration parameters from Taylor Creek. Alternatively, the presence and function of storm drains and sewer networks were not included within the model, nor in any of the models used in this study, and this lack of realism may have contributed to these anomalous results. Therefore, these model results should be viewed with caution, and further work should be done to evaluate and amend these inconsistencies.

**3.3. Hydrologic discharge reductions impacted by rainfall amounts**

Figure 8 shows the annual runoff reductions achieved by the 100% green roof scenarios for all four watersheds and for extensive (filled circles) and intensive (unfilled circles) green roofs plotted against total annual precipitation (mm). Intensive green roofs have larger storage capacity and therefore cause greater annual runoff reductions compared with extensive green roofs. Also, all runoff reductions exhibit an increasing trend with annual precipitation, as shown by the linear regression lines in Figure 7. These trends are slightly more pronounced in the extensive green roof scenarios compared with the intensive green roofs, but overall, they indicate that wetter years decrease the annual effectiveness of green roofs. The green roofs simply become saturated more often throughout the year and cannot retain water beyond their capacity.

**4. Conclusions**

We examined the hydrologic impacts of large-scale green roof implementations in four heavily urbanized watersheds in Seattle, Washington. We found that 20-25% and 10-15% median annual runoff reductions were achievable when all of the buildings within the watersheds were converted to green roofs when using intensive and extensive green roof varieties, respectively. The land use percentages were remarkably similar among the four watersheds, even though the watersheds varied in size from 3 to 31 km2 and were located in four distinct regions of the greater Seattle metropolitan area. For all watersheds, approximately 10% of the watershed area was covered by buildings. Therefore, implementing green roofs on only 10% of the watershed area resulted in up to 25% reductions in the annual flow volume at 100% implementation of extensive green roofs. This result may help guide city planners who seek to mitigate excessive stormwater runoff in highly urbanized watersheds using green infrastructure approaches. Because converting all roof area to green roofs may not be feasible in most metropolitan areas, spatially explicit approaches for placing green roofs non-randomly in urban watersheds can optimize GI effectiveness (Martin-Mikle et al., 2015).

One of the advantages of using VELMA, a spatially explicit (i.e., gridded) watershed model, is the ability to test spatially precise implementations of GI and management. Therefore, future research should investigate the impacts of different spatial configurations of green roofs to determine whether prioritizing particular watershed areas can increase their effectiveness.

Further work could also compare the results of these scenarios to other hydrologic and watershed models (e.g., SWMM or WWHM). Also, these could be coupled with an instream model such as the Water Assessment Simulation Program (WASP) to simulate the upland contributions to instream water quality.

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