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Incorporating Green Infrastructure into Water Management Plans using Multi-Objective Optimization

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Abstract: Sustainable management of water resources is challenged by numerous conflicting interests and objectives. Decision support tools (DSTs) are evolving to incorporate multiple objectives (e.g. economic, social, and environmental) into the development of water management plans, rather than focus only on minimizing cost. A recent version of the DST known as WMOST (Watershed Management Optimization Support Tool) uses a multi-objective evolutionary algorithm to generate management plan options that specify the location, quantity, and types of green infrastructure (GI) to implement in a watershed. In this study, we applied WMOST to a watershed in southern Massachusetts to develop management plan options that minimize cost, nutrient loads, and runoff. The resultant set of options are indicative of tradeoffs between these objectives, which were visualized multi-dimensionally to help inform the decision-making processes of stakeholders. Preliminary takeaways include: (1) implementing GI with small storage capacity on higher permeability soils leads to stronger performance in the objectives than implementing GI with large storage capacity on lower permeability soils and (2) implementing more units of GI on the categories of land use with low nutrient loads is more cost-effective than implementing fewer units of GI on the categories of land use with high nutrient loads.

Keywords: multi-objective optimization; decision support; green infrastructure; evolutionary algorithms

1 MOTIVATION

Mounting pressures on water resources, such as population growth and changes in extreme weather, are having numerous, compounding impacts affecting the quality and availability of our water resources (Grimm et al. 2008, Westra et al. 2013). Increases in the frequency and magnitude of stormwater runoff is one such effect of these pressures, which has subsequent impacts on water quantity (e.g. flooding and related infrastructure damage) and water quality (e.g. overland transport and direct discharge of nonpoint source pollutants to lakes and streams) (Schueler et al. 2009). Green infrastructure (GI), that is, decentralized control measures designed to mimic the hydrology of the predeveloped landscape (Shuster et al. 2008), is more commonly being used in urban areas to alleviate these water quantity and quality issues (Villareal et al. 2004). Many types of GI provide retention of runoff during storm events which leads to increased infiltration and subsequently, increased water supply as groundwater storage (Roy et al. 2008). GI can also provide treatment of pollutants, such as filtration of the particulate forms of pollutants through the media layers of the GI, plant uptake of the bioavailable forms of pollutants, or biogeochemical processes such as denitrification (Lee et al. 2012).

To have a meaningful impact on water quantity and quality, GI should be implemented at the watershed scale (Roy et al. 2008). This is consistent with foundational concepts in restoration ecology in which the scale of the management action should match the scale of the disturbance (Engstrom et al. 1999). However, determining where to locate GI within a watershed and how much to implement is not a straightforward process. Ideally, the success of any management plan under consideration should be evaluated by the degree to which the goals that matter to stakeholders are satisfied, for example, minimizing implementation cost, mitigating flooding risk, and meeting regulatory nutrient targets. Furthermore, each plan should not be considered in isolation; it is better to evaluate plans as a complete set to understand where differences, and perhaps tipping points among options exist. For example, at what threshold of GI implementation does the reduction in nutrient load per unit cost of GI increase? Designing and assessing plans for GI implementation one plan at a time (i.e. scenario by scenario) is possible, but it is also tedious and does not guarantee an optimal solution to stakeholders' goals. In this study, we used multi-objective optimization to strategically develop a set of Pareto optimal management plans, each of which specifies where to locate GI within a watershed and how much to implement to meet management goals. These plans reflect tradeoffs among the objectives, which for this study include minimizing costs (capital and operations & maintenance) while also mitigating issues related to both water quantity and quality, specifically, maximizing reductions in cumulative runoff volume and maximizing reductions in cumulative nitrogen and phosphorus loads. This research was conducted for an urban watershed in southern Massachusetts, the Taunton River watershed, which is experiencing rapid development and facing issues related to point and nonpoint source nutrients (Barbaro and Sorenson 2013). By employing multi-objective optimization, this research provides stakeholders with a comprehensive understanding of the extents to which different GI management options can address the water quality and quantity problems in the watershed.

2 CASE STUDY DATA

2.1 Watershed Data

The Taunton River watershed is a 113.3 km^2 area that has been described by the nine land use categories given in Table 1 (Barbaro and Sorenson 2013). The surficial geology of the watershed has been categorized as either sand and gravel or till and fines (Barbaro and Sorenson 2013). Together, a land use type and a surficial geology type comprise a hydrologic response unit (HRU). Hourly runoff rates for each HRU were obtained from a calibrated Stormwater Management Model (SWMM; U.S. EPA 2015) developed for the watershed by U.S. EPA Region 1, based on historic temperature and precipitation records from the Local Climatological Data records from the National Climatic Data Center station WBAN14765. Throughout this paper, we refer to this historic data as baseline data. SWMM was also used to estimate hourly pollutant loading rates for pervious and impervious HRUs based on pollutant build-up and wash-off processes (Tetra Tech 2015a, 2015b). The pollutants considered in this study were nutrients: nitrogen and phosphorus. Excess nutrients are a common cause of water pollution, often resulting in eutrophication of lakes and streams (Carpenter et al. 1998). The nutrient-specific parameter values used in the empirical build-up and wash-off equations of SWMM were obtained from a regional SWMM model calibrated by U.S. EPA Region 1 based on New England data from the National Urban Runoff Program.

2.2 Climate Data

Predicted changes in mean annual temperature and mean annual precipitation in Taunton were obtained from the general circulation models (GCMs) included in the 5th Coupled Model Intercomparison Project (CMIP5) for two of the representative concentration pathways (rcp-4.5 and rcp-8.5) adopted by the Intergovernmental Panel on Climate Change (IPCC) in its 5th Assessment Report (IPCC 2014). The pathways in this report correspond to changes in radiative forcing relative to pre-industrial values (i.e. +2.6, +4.5, +6.0, +8.5 W/m^2) that are possible in year 2100 based on projections of greenhouse gas emissions (IPCC 2014). These data were corrected for bias and statistically downscaled to a regional scale (Sheffield et al. 2013). Four combinations of changes in temperature and precipitation (ΔT, ΔP) were selected for this study to roughly bound the extremes of ΔT and ΔP reflected by the collection of GCMs (Table 2), thereby representing a range of possible future climate scenarios. A new set of hourly temperature and precipitation data was generated for each scenario by uniformly adjusting the baseline temperature and precipitation records by the corresponding ΔT and ΔP values (Table 2), respectively. Using the adjusted temperature and precipitation data, hourly runoff rates were generated for each scenario using SWMM. Similarly, the temperature, precipitation, and runoff data were used in SWMM to generate four new sets of hourly nitrogen and phosphorus loading rates. Note that the runoff and loading data were generated for each HRU in the watershed.

3 OPTIMIZATION AND MODELING METHODS

3.1 Multi-Objective Optimization

This research used multi-objective optimization to investigate how GI can be incorporated in water resource management plans. Multi-objective optimization yields a set of Pareto optimal solutions, meaning that for any given solution in the set, its performance in one objective cannot be improved without degrading the performance in another objective (Cohen and Marks 1975). In general, all multi-objective optimization problems are structured in terms of decision variables, objectives, and constraints. Decision variables represent a solution to a design problem in the form of a set of parameter values. In this study, the decision variables described the GI implementation plan; more specifically, on each developed HRU (2-5, 8-11 from Table 1), we allowed implementation of small- or large-capacity bioretention basins (or both) to treat 0 acres (0 hectares) to 50 acres (20.234 hectares) of runoff (for 0.6” (1.52 cm) and 1.0” (2.54 cm) storms, respectively), resulting in 16 decision variables total. The 50-acre (20.234-hectare) limit was selected arbitrarily to allow for a straightforward comparison of GI implementation on different HRUs. In optimization, objectives are used to evaluate the performance of any given solution, and represent the goals of stakeholders. In this study, a candidate solution, that is management plan, was evaluated based on its cost (implementation cost plus operation and maintenance costs) and the amounts of reduction in runoff and nitrogen and phosphorus loads it achieved. The cost of implementation depended on the HRU; more urbanized HRUs have higher costs due to the greater value of the space and complexity of installation. The costs used in this study were default values from the EPA’s System for Urban Stormwater Treatment and Analysis Integration SUSTAIN tool (U.S. EPA 2009). Constraints are used in optimization as criteria to define whether a solution is acceptable. Other than the limits on bioretention basin implementation per HRU, we did not apply any constraints in this case study.

We used a multi-objective evolutionary algorithm (MOEA) to conduct the optimization. With MOEAs, information on the performance of each solution (i.e. its objective function values) is provided to the MOEA via a simulation model. In our case study, the simulation model was SWMM, as described above, which we used to calculate the cost, runoff reduction, and nutrient reduction objective functions for each candidate solution. This information was used by the MOEA, which retains ‘fit’ solutions in a population that progresses over generations until the Pareto optimal set is achieved, assuming the analyst has allowed for sufficient run time. The specific MOEA used in this case study is the Borg MOEA (Hadka and Reed 2013), which has been shown to have strong performance relative to other comparable MOEAs (Zheng 2016).

3.2 Green Infrastructure Modeling

The bioretention basin was selected for this study as a representative type of green infrastructure. Two sizes of bioretention basins were considered, designed to capture stormwater volumes equivalent to either 0.6” or 1.0” (1.52 cm or 2.54 cm) of rainfall on one acre (0.405 hectare) of HRU. For simplicity, this paper refers to these sizes of bioretention basin as small-capacity and large-capacity, respectively. The basin depth (e.g. depth of the soil and storage layers) is the same for both sizes of basin. Given that the basin depth is fixed, the difference between the design volumes of the small-capacity and large-capacity basins is due to different design areas of each basin. Calculation of the design area also accounts for the porosities of the soil and storage layers since the stormwater can only occupy the voids of these media. The values for the depths and porosity of the different bioretention layers were obtained from U.S. EPA’s Opti-Tool (Tetra Tech 2015a, 2015b); these BMP parameters were based on the performance of BMPs at the University of New Hampshire’s Stormwater Center. Parameter values were assumed to be regionally specific to the northeast. The LID module in SWMM was used to determine changes in runoff and loading rates associated with different impervious HRUs based on implementation of one of the above mentioned small- or large-capacity bioretention basins.

Table 1. Hydrologic response units (HRUs) in the Taunton River watershed and associated costs of implementation and operation & maintenance for small-capacity and large-capacity bioretention basins, designed to capture either 0.6” or 1.0” (1.52 cm or 2.54 cm) of rainfall on one acre (0.405 hectare) of HRU, respectively

HRU	Land use type	Soil type	Cost to implement bioretention basin (small / large capacity, respectively)	Operations & maintenance cost per year for basins (small / large capacity, respectively)
1	Forest	Sand & gravel	n/a	n/a
2	Open nonresidential	Sand & gravel	$2,742 / $4,571	$137 / $228
3	Medium to low density residential	Sand & gravel	$2,831 / $4,718	$141 / $235
4	High density residential	Sand & gravel	$9,851 / $16, 418	$493 / $820
5	Commercial, industrial, transportation	Sand & gravel	$42,283 / $ 70, 471	$2,114 / $3,523
6	Agriculture	Sand & gravel	n/a	n/a
7	Forest	Till & fines	n/a	n/a
8	Open nonresidential	Till & fines	$2,793 / $4,655	$139 / $233
9	Medium to low density residential	Till & fines	$2,832 / $4,720	$141 / $236
10	High density residential	Till & fines	$9,605 / $16,009	$480 / $300
11	Commercial, industrial, transportation	Till & fines	$42,329 / $70,548	$2,116 / $3,527
12	Agriculture	Till & fines	n/a	n/a
13	Cranberry bogs	Combined	n/a	n/a
14	Forested wetlands	Combined	n/a	n/a
15	Nonforested wetlands	Combined	n/a	n/a

Table 2. Results from four Coupled Model Intercomparison Project (CMIP5) climate models representing the extremes of possible changes in temperature and precipitation selected for use in this study

CMIP5 model	Representative Concentration Pathway of greenhouse gases	Mean annual change in precipitation (%), ΔP	Mean annual change in temperature (°F), ΔT
GCM 6	rcp-4.5	4.84	16.1
GCM 32	rcp-4.5	5.87	0.8
GCM 12	rcp-8.5	4.05	16.2
GCM 13	rcp-8.5	3.86	0.3

4 OPTIMIZATION SCENARIOS

The optimization was conducted for two cases, which we refer to as (i) baseline and (ii) climate change. For the baseline case, the baseline watershed data (hourly runoff and nutrient loading rates from SWMM) served as inputs to the simulation model to determine the changes in runoff and recharge associated with implementing different amounts of small- and large-capacity bioretention basins on the various developed HRUs. A set of Pareto optimal solutions, that is, GI management plans, was generated based on the five-year time frame from January 2000 to December 2004, which had a range of wet and dry periods. For the climate change case, the same approach was taken using each of the four datasets described in section 2.2. Consequently, four sets of GI management plans were generated corresponding to each of the climate change scenarios.

5 RESULTS

5.1 Baseline

The Pareto optimal set of GI management plans demonstrate the tradeoffs among minimizing cost while maximizing reductions in runoff volume and nutrient loads (Figure 1). Within the set of plans, the most expensive plans involve as much GI as possible, approaching the 50-acre (20.234-hectare) limit on all developed HRUs of small- and large-capacity bioretention basins. Consequently, these plans achieve the greatest reductions in runoff volume and nutrient load. However, for these "high reduction" plans, the per unit cost of GI implementation is high relative to plans that achieve moderate to low reductions, because the plans implement bioretention basins on the commercial HRUs, which are the most expensive due to the value of the space and the complexity of implementation. The commercial HRUs also contribute the highest pollutant loads to stormwater runoff. Plans that achieve low to moderate amounts of reduction do not implement GI on the commercial HRUs; these plans locate GI primarily on the open nonresidential, medium to low density residential, and high density residential HRUs, which are less expensive and contribute lower pollutant loads to stormwater runoff. It is noteworthy that none of the plans in the set implement small amounts of GI on only the commercial HRU. This indicates that targeting treatment of the high pollutant loads of the commercial HRU is not a cost-effective strategy.

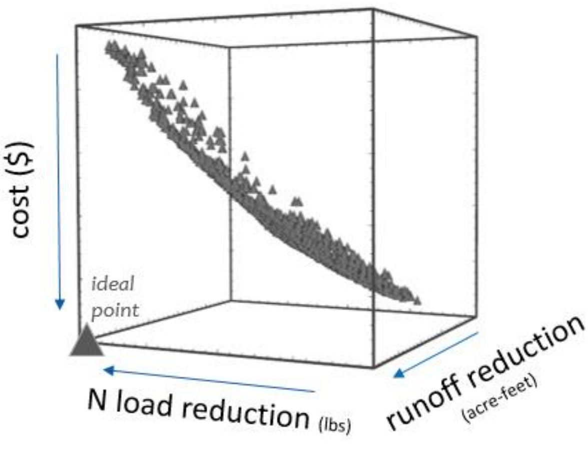

Figure 1. Pareto optimal solutions generated for the baseline case. Arrows indicate the preferred direction for each objective, that is minimizing cost, maximizing reductions in runoff, and maximizing reductions in nitrogen load. The ideal point shown in the front, left corner of the objective space represents the solution with the best performance in each of the objectives; however, this solution cannot feasibly be obtained because of tradeoffs among the objectives.

Across the set of management plans, there is more GI located on sand and gravel than on till and fines, especially for implementation of small-capacity GI. Because sand and gravel allows for faster infiltration from the bioretention basin into the subsurface, less basin storage capacity is needed, which is preferable in terms of cost. Furthermore, because most pollutants are transported in the stormwater volume at the storm onset (the "first-flush" effect), the benefit of implementing larger-capacity bioretention is diminished in terms of reducing nutrient loads.

5.2 Climate Scenarios

The general tradeoffs between minimizing cost and maximizing reductions in runoff and nutrient loads is the same for each of the four climate scenarios discussed in section 2.2. The two scenarios with the greater predicted changes in precipitation (GCM 12 and GCM 32, Table 2) yielded larger volumes of stormwater due to the increased intensity of storm events under wetter climates. Consequently, the per unit cost of GI implementation was lower for these scenarios, because the implemented GI was "put to use" more often. Therefore, we can intuit that the value of investing in GI has greater returns under wetter future climates.

6 CONCLUSIONS

This research investigated how green infrastructure can be incorporated into water resource management plans to address issues related to both water quantity and quality while minimizing management plan costs. To account for these competing goals, we took a multi-objective approach to optimization: we used a MOEA to generate a set of solutions, or management options, that reflect the tradeoffs between these conflicting goals. Analysis of the results suggests that (1) implementing more GI on HRUs contributing low nutrient loads is more cost-effective than implementing less GI on HRUs contributing high nutrient loads, (2) implementing GI on sand and gravel essentially augments the storage volume of the GI due to the faster drainage from the basin into the subsurface, and (3) investing in GI has greater returns under wetter possible future climates.

The views expressed in this (article/presentation/poster) are those of the authors and do not necessarily reflect the views or policies of the U.S. Environmental Protection Agency.

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