



# Effectiveness of BMP plans in different land covers, with random, targeted, and optimized allocation



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## ABSTRACT

The ability of 5 Best Management Practice (BMP) allocation methods that consider 8 pre-selected BMPs, to control 4 Nonpoint Source (NPS) constituents in 4 watersheds with contrasting land covers, is investigated. The methods range from random selection of BMPs on randomly selected sites, to optimized selection of BMPs at optimized locations, and the land covers range from natural to ultra-urban. The optimization methods rely on Genetic Algorithms (GA), and a method that uses expert systems is also applied. Watershed hydrologic and water quality response models are developed, using the Soil Water Assessment Tool (SWAT), to compute baseline outputs from the 4 study watersheds without BMPs, and to obtain predicted reductions in NPS constituent outputs when BMPs are implemented in accordance with the 5 allocation plans. Methods used to represent BMPs in SWAT and to speed up optimization processes are also presented. Results indicate that the most computationally intensive methods produce the best results across landscape types. Results also show that opportunities exist for less intensive methods, particularly in less-built environments. For these, however, siting BMPs to hotspots remains an important requirement. The need to select the most appropriate BMP for each implementation site is observed to increase with the level of urbanization of the landscape. Results indicate that optimized selection of BMPs, sited at optimized locations, results in the highest-performing BMP allocation plans across landscape types. Also, the focus on hotspots has the advantage of resulting in BMP plans requiring involvement of fewer stakeholders than when BMPs are located in non-hotspot zones. This targeted hotspot approach could help reduce cost and increase efficiency of implementation.

## 1. Introduction

Nonpoint source (NPS) pollution is an important environmental problem worldwide (Lian et al., 2019; McCoy et al., 2015), responsible for approximately 60 % of water quality impairments in the U.S. (Liu et al., 2014). It arises from spatially extended areas within landscapes and is difficult to capture and treat (McCoy et al., 2015). Agricultural landscapes, where excess fertilizers, herbicides, and insecticides are common causes of water quality degradation, account for approximately 60 % of total NPS pollution loads (USEPA, 2017). Urban and suburban areas are, however, also major sources of NPS pollution due to the large amount of runoff per unit area they produce. The USEPA estimates, for example, that urban runoff (including storm sewer outfall) is the second leading cause of impairment in estuaries, third in lakes, and fourth in rivers (USEPA, 2002).

The control of NPS pollution is commonly approached through the implementation of Best Management Practices (BMPs) (Benedict and McMahon, 2002; Eckart et al., 2017), which may function by reducing or delaying the volume of stormwater entering the sewer system, lengthening

the discharge hydrograph duration while reducing peak flow rate, and improving water quality by volume reduction. They may further perform physical filtering of runoff water, and promote biological processes that extract pollutants from the water, or convert them to innocuous forms (Ahiablame et al., 2013; Ahiablame et al., 2012; Drake et al., 2014; Hamel et al., 2013; Liu et al., 2015; Mao et al., 2017). BMPs, such as rain gardens, rain barrels, downspout disconnections, and native landscaping, among others, are potentially less expensive and better integrated into the landscape than large-scale stormwater treatment plants (Debo and Reese, 2002). They also help control NPS pollution by reducing overflow events from aging combined sewer infrastructure (green retrofitting) and have the advantage of spatially-variable target-specificity, whereby each implemented measure can be designed to address specific impairment agents, that are of concern at precisely identified landscape positions (e.g., hotspots, or Critical Source Areas, CSAs) (Djodjic et al., 2002; Shore et al., 2014; Liu et al., 2016; Wang et al., 2016; Ice, 2004).

A widespread and non-specific approach to BMP implementation may be cost-prohibitive and socially-challenging (O'Donnell et al., 2008; Srinivasan and McDowell, 2007; White et al., 2009). Relatively random implementation of non-specific BMPs often occurs when stakeholders are broadly encouraged to adopt BMPs, leading to sub-par pollutant control,

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relative to costs (Liu et al., 2016; Wang et al., 2016; Ice, 2004). The development of BMP allocation plans is aimed to overcome these issues by focusing on the geographical implementation of BMPs in areas that generate higher concentrations of pollutants (i.e., hotspots, CSAs) that are specifically suited to the environmental conditions and specific pollutants of the areas (Zhang and Chui, 2018). This targeted approach commonly uses a hydrologic model to identify hotspots within impaired watersheds, followed by decision tools that find appropriate BMPs for each hotspot (Wang et al., 2017). This approach is most efficient in watersheds where hotspots are clearly identifiable, such as in natural and agricultural areas rather than built environments where the original variability of the landscape has been altered by construction.

In urban zones, a optimization approach that considers BMP types and locations beyond hotspot targets (unconstrained) may provide additional cost reductions and exploit synergies between BMPs and landscape features (Zhang and Chui, 2018). Optimization methods can treat the BMP selection process as a multiobjective optimization problem and consider several NPS pollutants simultaneously more readily than expert system-oriented methods. They can also readily incorporate socioeconomic and institutional constraints (Chen et al., 2015; Coello et al., 2007; Kumar et al., 2022; Liu et al., 2019; Liu et al., 2013; Oraei Zare et al., 2012; Wang et al., 2020). For example, the USEPA SUSTAIN and Opti-Tool software illustrate some of these features (Mao et al., 2017; Lee et al., 2012; Tech, 2016). However, the main disadvantage of optimization approaches is their computational cost, which is substantially larger than that of targeting methods (itself greater than that of random allocation). The effectiveness of targeting and optimization approaches to BMP allocation has been demonstrated in several research studies, but they have mainly focused on single land covers like urban or agricultural land (Kumar et al., 2022; Liu et al., 2019; Geng et al., 2019; Gitau et al., 1923; Veith et al., 2003; Srivastava et al., 2002; Veith et al., 2004).

The current knowledge regarding the generalizability and efficacy of BMP allocation methods across various land cover types, ranging from natural to ultra-urban, is limited. There is a lack of understanding of the degree to which optimization methods outperform targeting approaches in generating BMP plans with lower costs. Additionally, the potential suitability of random allocation for BMP allocation across diverse land covers has yet to be evaluated. The overall objective of this paper is to analyze the applicability of BMP allocation methods in different land covers and determine if any of them is more suitable across landscape types. Five methods are investigated, from random BMPs at random locations, through random, expert-selected, and optimized BMPs on hotspots, to optimized BMPs at optimized sites. The investigation is carried out on two real-world and two synthetic watersheds, representing landscapes ranging from natural to ultra-urban.

The research primarily focuses on controlling four environmentally-significant NPS constituent pollutants: total surface runoff (SurfQ), total sediment (Sed), total nitrogen (TN), and total phosphorus (TP). Results are expected to help researchers, watershed stewards, and policymakers better understand trade-offs between BMP implementation strategies and choose allocation methods most suited to various land cover types. This should help to address the hydrologic and water quality impacts of climate variability in cost-effective ways and further help to adapt BMP-adoption social intervention strategies to different types of watersheds.

## 2. Materials and methods

### 2.1. Study watersheds

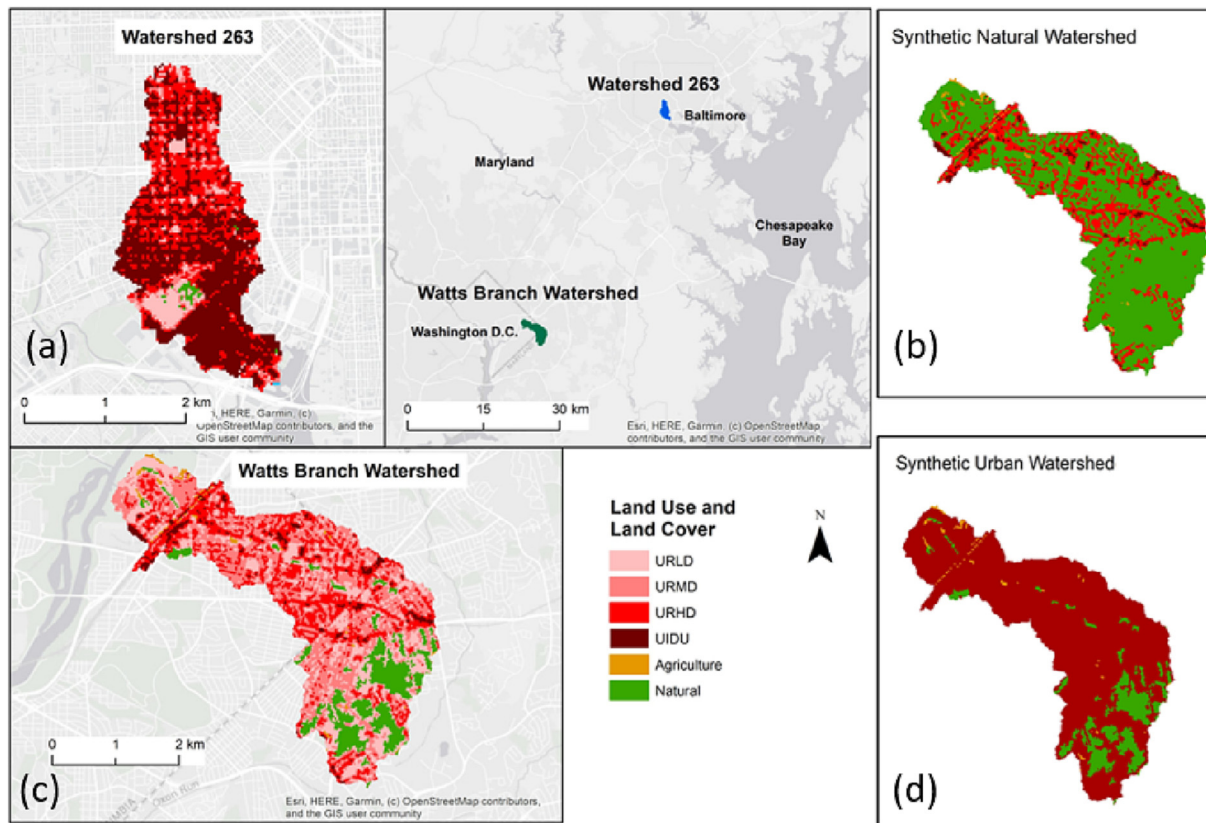
Two existing watersheds (Watts Branch and Watershed 263) and two synthetic watersheds were used in this study (Fig. 1). Watts Branch is located partly in Washington, D.C., and partly in Prince George's County, Maryland. It has a suburban land cover and spans an area of 10.4 km<sup>2</sup>, with a moderate average slope of 7.8 %. The landscape in Watts Branch consists of 24.2 % of high-density residential areas (URHD), 37.2 % of medium-density residential areas (URMD), 22.1 % of low-density

residential areas (URLD), and 12.9 % of natural regions. The watershed is monitored for streamflow at USGS gauging station No. 01651800, where water samples are also occasionally obtained for sediment and nutrient content analyses. Watershed 263 is located in Baltimore City, Maryland, and has an urban landscape, an area of 4.63 km<sup>2</sup>, and a moderate slope that averages 5.3 %. Its land cover includes 51.2 % of industrial urban areas (UIDU) and 33 % of high-density residential areas. The watershed is ungauged, but the USDA Forest Service and Cary Institute of Ecosystem Studies (CIES) monitored two of its sub-catchments, for flow and nutrients, over a 7-year period (Belt et al., 2012). These two real-world watersheds are approximately 56 km from each other and are, therefore, subject to the same climate patterns. Two synthetic watersheds were designed to extend the range of land covers of the BMP allocation analysis. The Watts Branch watershed was used as a base (topography, hydrography, soils), and its land cover was modified to produce a synthetic natural watershed and a synthetic ultra-urban watershed. The synthetic natural watershed was developed by changing medium-density residential and low-density residential areas of Watts Branch to a natural land cover (e.g., forest). This resulted in a landscape with 73 % of natural or forested areas and 27 % of residential land (URHD). The synthetic ultra-urban watershed was constructed by changing residential areas of low-density, medium, and high-density residential areas to industrial urban land use. The landscape of the resulting synthetic ultra-urban watershed is 86 % industrial (UIDU).

### 2.2. Watershed response models

The SWAT (Soil Water Assessment Tool) modeling software was used to develop computational models of the study watersheds and to simulate their response to local weather time series, with and without implemented BMPs (Arnold et al., 1998). The computational models produced by SWAT represent watersheds as collections of multiple subwatersheds, that are further subdivided into Hydrologic Response Units (HRUs), consisting of homogeneous land use, soil type, slope, and management characteristics. SWAT uses physically-based formulas to compute the hydrologic and water quality response of HRUs to weather, combine these responses among subwatersheds, and route the results to the outlet of the modeled watershed. The parameters of interest of the model formulas are specified separately for each HRU (spatially-distributed), and are derived from physical characteristics of the landscape, obtained from spatial databases. These parameters include the surface slope (HRU\_SLP), SCS runoff curve number (CN2), soil available water capacity (SOL\_AWC), soil saturated hydraulic conductivity (SOL\_K), soil erodibility (USLE\_K), Manning's roughness coefficient for surface flow (OV\_N), and maximum canopy storage (CANMX), among others. The spatial input data used in this study to derive SWAT parameters included 10 m resolution (1/3 arc/s) USGS Digital Elevation Models (DEM), USDA SSURGO soils data, and NLCD land cover data. These spatial data were stored in ArcGIS and converted to SWAT parameters by the ArcSWAT software (Arnold et al., 2012; Srinivasan et al., 2010). Weather time series of daily temperature and precipitation, used to drive the simulations, were obtained from NWS databases and complemented with solar radiation, wind speed, and relative humidity generated by the CLIGEN weather generator (Nicks, 1985) available in SWAT (Williams et al., 1996).

Computational models of the two real-world watersheds were built for this study using ArcSWAT/Version 2012. The resulting Watts Branch model consisted of 2148 HRUs grouped into 23 subwatersheds, while Watershed 263 was represented as 566 HRUs distributed among 21 subwatersheds (Zhang et al., 2023). Models of the two synthetic watersheds were derived from that of Watts Branch, by reassigning its land use layer, resulting in 1293 HRUs for the natural landscape and 1007 HRUs for the ultra-urban model. The computational models of the real-world watersheds were calibrated and validated against observed data using the SUFI-2 algorithm in the SWAT-CUP software (Abbaspour, 2013). Ten years of USGS gauge data (2002–2011), and up to 7 years of sediment and nutrient data, were used for this purpose in Watts Branch, and in Watershed 263,



**Fig. 1.** Location and land cover of the study watersheds: (a) real-world urban watershed 263, (b) synthetic natural watershed, (c) real-world suburban Watts Branch watershed, (d) synthetic ultra-urban watershed. URLD, URMD, and URHD: urban residential low-, medium-, and high-density, respectively. UIDU: industrial ultra-urban.

respectively. Total Surface runoff (SurfQ, mm), total sediment (Sed, T/ha), total nitrogen (TN, kg/ha), and total phosphorus (TP, kg/ha) were chosen sequentially for calibration and validation. Diagnostic statistics (Moriassi et al., 2007) indicated good results for both watersheds, with correlation coefficient ( $r$ ), Nash-Sutcliffe coefficient (NSE), and bias (PBIAS) values of  $r = 0.88$ ,  $NSE = 0.64$ , and  $PBIAS = 30\%$  at daily step for Watts Branch, and  $r = 0.82$ ,  $NSE = 0.50$ , and  $PBIAS = 5.3\%$  at annual step for Watershed 263 (Zhang et al., 2023). The calibrated models were then used to identify NPS hotspots, and to simulate and compare the response of these watersheds with different BMP allocation methods. For the two synthetic watersheds, calibration was not performed as no observed data exists for them, and simulations were performed with the ArcSWAT default spatially-variable parameters derived by ArcSWAT from the spatial input data of these watersheds. This approach has been successfully demonstrated in the study where the focus is on relative changes in watershed behavior (with and without BMPs) rather than absolute values, and it was found that calibration has little effect on nutrients distribution and hotspot locations (Liu et al., 2016; Srinivasan et al., 2010).

### 2.3. Study BMPs

Eight commonly used BMPs applicable to the control of at least one target NPS constituent (runoff, sediment, nitrogen, phosphorus) and characterized by different costs and modes of action were selected for this research: porous pavement (PP), vegetated filter strip (VFS), rain barrel (RB), green roof (GR), native landscaping (NL), rain garden (RG), infiltration trench (IT), and downspout disconnection (DD). The fact sheets of these BMPs are summarized in “Guidance for Federal Land Management in the Chesapeake Bay Watershed” (USEPA, 2010). Some of these BMPs reduce runoff volume by intercepting rainfall (RB, GR, NL, RG), and all of them also reduce it by increasing opportunities for infiltration (to varying degrees). A few BMPs also reduce peak runoff rate by increasing surface

roughness (PP, GR, NL), and those with increased vegetation help to control sediment and nutrients (VFS, GR, RG). NL reduces nutrients by decreasing fertilizer input (switching from lawns to less-demanding native plants).

The construction costs of the selected BMPs (King and Hagan, 2011) were estimated from the guidance document for the Maryland Department of the Environment Science Services Administration, from University of Maryland Center for Environmental Science (UMCES), and from discussions with local professionals. Maintenance costs or differences in functional lifespans were not considered in this study due to a lack of appropriate data. The obtained cost figures were expressed as an overall value in terms of either dollar per house or dollar per square meter, as appropriate for each individual BMP. In most cases, the implementation of BMPs could not cover throughout the hotspots, an Area Factor was defined to represent the fraction of the area of an HRU to be covered by the specific BMP (for cost computation). The cost figures and area factors retained for the selected BMPs are presented in Table 1. These costs range from a low of \$25 per house for DD to a high of \$160/m<sup>2</sup> for a GR (the area of which would be 10 % of the destination HRU).

A step-wise procedure (Arabi et al., 2008; Waidler et al., 2011) was used to determine quantitative adjustments of model parameter values that accurately represent the effects of the selected BMPs on HRU response. The process started with identification of the working mechanisms of each BMP, as listed above, followed by selection of those SWAT parameters most related to these modes of action, and sensitivity analysis of the model to those parameters (using the one-at-a-time method, applied to calibrated watershed models) (Arnold et al., 2012). The most sensitive parameters, relative to SurfQ, Sed, TN, and TP outputs, were identified, analyzed at the HRU level, and adjusted in accordance with individual modes of action, to replicate values of BMP effectiveness reported in the literature (Waidler et al., 2011). Results of this analysis are presented in Table 1 for the eight study BMPs. As expected, rainfall interception by BMPs is mostly represented by increasing CANMX. Reductions in runoff volume are characterized



**Table 1**  
BMP costs and representative parameter changes in SWAT.

| BMPs                          | Costs (\$/m2) | Area Factor | Representation |       |       |         |        |        |        |            |                    |
|-------------------------------|---------------|-------------|----------------|-------|-------|---------|--------|--------|--------|------------|--------------------|
|                               |               |             | SOL_AWC        | CN2   | CANMX | FILTERW | OV_N   | SOL_K  | USLE_K | FIMP/FCIMP | AUTO_NAPP/AUTO_NYR |
| Porous Pavement (PP)          | 107.64        | 0.1         |                | ↓20 % |       | 0.5     | ↑100 % | ↑100 % |        | ↓80 %      |                    |
| Filter Strip (VFS)            | 7.53          | 0.25        | ↑50 %          | ↓20 % | 5 mm  | 4       |        |        |        |            |                    |
| Rain Barrel (RB)              | 150/house     |             |                | ↓20 % | 10 mm |         |        |        |        |            |                    |
| Green Roof (GR)               | 161.46        | 0.1         | ↑100 %         | ↓20 % | 8 mm  | 1       | ↑100 % |        |        | ↓30 %      |                    |
| Native Landscaping (NL)       | 5.38          | 0.1         | ↑100 %         |       | 10 mm | 1       | ↑50 %  |        |        |            | 10 %               |
| Rain Garden (RG)              | 86.11         | 0.1         | ↑100 %         | ↓30 % | 10 mm | 1       |        | ↑100 % | ↓50 %  | ↓30 %      |                    |
| Infiltration Trench (IT)      | 53.82         | 0.1         |                | ↓30 % | 5 mm  |         |        | ↑900 % |        | ↓30 %      |                    |
| Downspouts Disconnection (DD) | 25/house      |             | ↑50 %          | ↓20 % | 5 mm  | 0.5     |        |        |        |            |                    |

SOL\_AWC: soil available water capacity; CN2: SCS runoff curve number; CANMX: maximum canopy storage; FILTERW: filter strip width; OV\_N: Manning's roughness coefficient; SOL\_K: soil saturated hydraulic conductivity; USLE\_K: soil erodibility; FIMP: fraction of impervious land; AUTO\_NAPP: max. N to apply.

mostly by decreases in CN2, increases in SOL\_K and SOL\_AWC, and also reductions of SWAT's fraction of impervious land parameters (FIMP and FCIMP). Reductions in peak runoff rate are reflected by increased OV\_N values. Sediment and nutrient filtering by vegetation are specified by non-zero values of the FILTERW parameter. Native Landscaping leads to a reduction in nitrogen fertilizer input as represented by lowered values of the parameters AUTO\_NAPP and AUTO\_NYR.

#### 2.4. BMP allocation methods

In this study, the BMP allocation process assigned one of 9 control measures (either one of the 8 selected BMPs, or no BMP) to each of the  $m$  HRUs in a given watershed (where  $m = 2148$  for Watts Branch,  $m = 1293$  for the natural watershed,  $m = 1007$  for the ultra-urban basin, and  $m = 566$  for Watershed 263). BMP allocation methods are summarized in Table 2. Three categories of BMP selection methods were investigated: 1) random, 2) targeted, and 3) optimized. These methods were applied to BMP selection over NPS hotspots, in which case they were labeled with a suffix of HS (i.e., Random\_HS, DDSS\_HS, and GA\_HS), and the random approach was also applied to random HRUs (labeled Random), while the optimization method was further applied to unconstrained HRUs (labeled GA), for a total of 5 different allocation techniques. For hotspot-centered allocations, the target CSAs were identified by, first, simulating the response of the study watersheds to observed weather time series without BMPs. The hotspots were then defined as those HRUs that contribute the most of each constituent (runoff, sediments, nitrogen, and phosphorus) on a per-area basis, selected such that their cumulative area corresponds to 40 % of the area of each study watershed. The 40 % was chosen as we found that these areas could account for more than 60 % of the total NPS constituents output in Watts Branch watershed (Zhang et al., 2023; Wang, 2015). HRUs that were hotspots for a given constituent are frequently hotspots for other constituents as well, such that the total area targeted for BMP implementation in HS methods was of the order of 40 % of the watershed area.

For each study watershed, the Random and unconstrained GA allocations were designed to target the same percentage of the watershed area as the corresponding HS method. The two random approaches to BMP selection were meant to represent a baseline of what may occur when stakeholders are broadly encouraged to implement BMPs on the most impaired area of their land without the knowledge of which specific NPS constituent(s) such BMP should seek to control (Random\_HS), nor

information on whether any BMP would actually be useful at any particular location (Random). Either situation was likely to arise in real life as relatively few watersheds have been analyzed to locate their hotspots, and lack of widespread availability of the knowledge and skills needed to select appropriate BMPs for specific topographic, soil, and land cover conditions. Still, random implementation of control measures is expected to be more beneficial than no BMP at all, especially if those BMPs were located at hotspots. This was because several BMPs reduce surface runoff, which in turn leads to reductions in sediment generation and downgradient transport of plant nutrients. These benefits may, however, vary with land cover. In this study, the random allocation of BMPs was performed based on uniform distributions of the chosen BMPs (no individual preference by stakeholders) and of HRUs where they were located (except for Random\_HS, which targets hotspots). Randomization was, however, limited by local landscape conditions; for example, green roofs and porous pavements were not part of the set of BMPs considered for random allocation in forested HRUs.

The targeted approach to BMP allocation, labeled DDSS\_HS, is a method that leverages both information and knowledge to produce better NPS control at lower cost than random methods. This approach focuses BMP implementation to hotspots that have been previously located by hydrologic modeling, and for which the NPS constituents to be controlled are known as a result of this modeling. BMP selection knowledge, encoded as rules and implemented in expert systems, is then applied to each hotspot to choose the most appropriate BMP for it, based on local conditions and on the constituent(s) to be controlled. The approach is exemplified by the work of Wang et al. (Wang et al., 2016; Wang et al., 2017), in which BMP selection was split into a diagnosis phase, aimed at identifying the reasons for which a hotspot generated excessive constituents, and a prescription phase, aimed at choosing the proper corrective measure based on diagnosis and local conditions. Diagnosis and prescription were implemented as separate expert systems, and the overall framework, including the SWAT software and spatial databases, was referred to as a Diagnostic Decision Support System (or DDSS). This approach was followed in this study for targeted BMP allocation in the four investigated watersheds.

The two optimized BMP allocation approaches applied in this study rely on the use of Genetic Algorithms (GAs) (Sivanandam and Deepa, 2008) to select control measures (method labeled GA\_HS), and to additionally position them in the watershed (method labeled GA) in ways that maximize NPS control and minimize costs. GAs are a set of multiobjective search algorithms inspired by the mechanics of natural selection and evolutionary genetics (Kumar et al., 2010). They are particularly suited to nonlinear problems with discontinuous or discrete search spaces, where gradient-based techniques are not applicable. A typical GA computation process is shown in Fig. 2. It starts with an initial population of different types of chromosomes, and then produces a new generation of offspring from it, with altered chromosomes, resulting from random crossovers and mutations. An evaluation function quantifying desired characteristics is computed over each offspring, and those that best satisfy it are selected for the next iteration of the process, taking care not to over-represent any overly similar sub-group of offsprings. The process continues until either the value of

**Table 2**  
Lists of BMP allocation methods.

| Category     | Description                                                             | Symbol    |
|--------------|-------------------------------------------------------------------------|-----------|
| 1) Random    | Random BMP selection on whole watershed (same areal extent as hotspots) | Random    |
|              | Random BMP selection on hotspots                                        | Random_HS |
| 2) Targeted  | DDSS method for BMP selection on hotspots                               | DDSS_HS   |
| 3) Optimized | Genetic algorithm on hotspots                                           | GA_HS     |
|              | Genetic algorithm on whole watershed (same areal extent as hotspots)    | GA        |

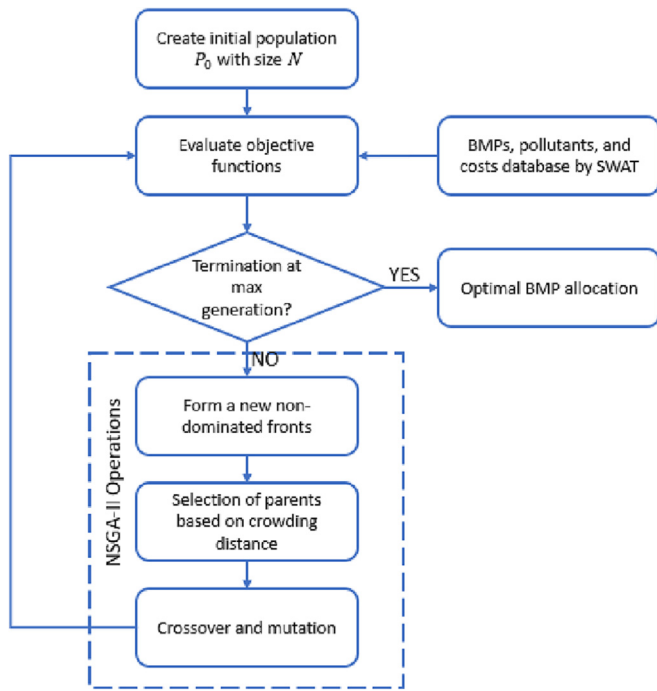


Fig. 2. Typical GA computational process.

the evaluation function reaches a pre-selected threshold of acceptability on at least one offspring (successful solution), or a pre-set maximum number of generations has been reached. In the context of BMP allocation, a chromosome consists of as many genes as there are either hotspots (GA\_HS) or HRUs (GA) in a watershed, and each gene represents the specific BMP selected for that HRU (including cases of no BMP in the unconstrained GA method). In other words, each chromosome represents a potential allocation of BMPs to HRUs, and the algorithm seeks to improve these allocations in terms of NPS control and costs. Mutations lead to testing of alternative untested BMPs for a given HRU, and crossovers swap an HRU's BMPs between two different allocations (or chromosomes) that both survived evolutionary competition thus far. To address the simultaneous, yet conflicting, objectives of the lowest generation of runoff, sediment, nitrogen, and phosphorus and of the lowest cost, a composite evaluation function is used in the GA:

$$\text{Argmin}F(x) = \text{Argmin}\{f_1(x), f_2(x), \dots, f_m(x)\} \quad (1)$$

where the individual functions ( $f_1, f_2, \dots$ ) correspond to each of the simultaneous goals. Here, they are the predictions of watershed models for outlet values of runoff, sediment, nitrogen, and phosphorus, and the computed cost of the corresponding BMP allocation. The solution to such a multiobjective problem is, however, no longer a single “best” solution, but a Pareto-optimal set of solutions consisting of the optimal trade-offs achievable between the  $m$  simultaneous objectives (Maringanti et al., 2009; Vrugt, n.d.). The Pareto-optimal set of solutions forms the Pareto front from which specific BMP allocations can be picked, corresponding, for example, to the least-cost solution that provides a pre-selected level of runoff reduction or to that which provides the highest runoff reduction at a fixed cost.

The use of the optimization approach to BMP allocation is computationally intensive, not just because of the iterative nature of the algorithm, but also because of the potential need to simulate watershed response for each of the chromosomes generated during this process. To reduce this significant computational burden, we pre-computed a database of watershed responses to individual BMPs, implemented in individual HRUs, assuming independence of BMP effects, and linearity of routing processes. The database for a watershed with  $n$  HRUs contains a total of  $5 \times n \times 9$  entries

which are stored as five tables (corresponding to the four NPS constituents and total cost) of  $n \times 9$  values. The rows of these tables represent HRUs, and their columns BMPs (including the base case with no BMP). If we denote by  $\alpha_{ij}$ , the value found in row  $i$  and column  $j$  of a given table, and consider the table related to total surface flow at the watershed outlet (SurfQ), then  $\alpha_{4,3}$  will contain the value of the reduction in SurfQ predicted to occur by the watershed model when BMP number 3 (e.g., Rain Barrel) is implemented in HRU number 4 of the watershed, and no other BMP is installed. With this representation, during GA optimization, the yield of NPS constituents of a watershed where several BMPs are allocated (chromosome) can be calculated efficiently as a summation process of properly selected rows and columns of the database tables, rather than re-simulating the watershed's response; essentially:

$$\Sigma \text{Target}_i = \Sigma \text{Target}_i(\text{HRUs}, \text{BMPs}) = \begin{pmatrix} \alpha_{1,1} & \cdots & \alpha_{1,m} \\ \vdots & \ddots & \vdots \\ \alpha_{n,1} & \cdots & \alpha_{n,m} \end{pmatrix} \quad (2)$$

where the symbol  $\text{Target}_i$  can refer to total surface flow (SurfQ), total sediment (Sed), total nitrogen (TN), total phosphorus (TP), or total cost of implementation (Cost).

The GA optimization process is regulated by a set of hyperparameters, including population size, the number of generations, crossover rate, and mutation probability that should be fine-tuned for each specific problem to ensure that Pareto-optimal fronts are reached efficiently. We analyzed the behavior of the algorithm for the BMP allocation problem in Watts Branch, and in Watershed 263, using a sensitivity approach that varied a single hyperparameter at a time, with other parameters fixed at default values. The investigated ranges of population size, number of generations, crossover rate, and mutation probability, were 100 to 5000, 100 to 5000, 0.5 to 0.9, and 0.0001 to 0.1, respectively. Both this analysis, and the ensuing application of GAs to optimized BMP allocation, were performed using the NSGA-II algorithm implemented in the Pymoo software, which is a Python toolkit for GA optimization (Blank and Deb, 2020). Results of the hyperparameter analysis are presented in Fig. 3 for the trade-offs between total outflow and BMP cost. With respect to population size, the Pareto front for this pair of variables is reached with a minimum of 500 chromosomes in Watershed 263, while 1000 chromosomes appear to be needed in Watts Branch. For both watersheds, 1000 generations are observed to be sufficient to identify the optimal trade-off curve. GA solutions are less sensitive to crossover rate (in the investigated range), but higher values are observed to provide slightly better fronts. Finally, mutation probabilities of 0.01 and lower are found to be needed for the convergence of the optimization process. Based on these results, the GA hyperparameters for population, generation, crossover, and mutation were given values of 1000, 1000, 0.9, 0.001, respectively, for the Watts Branch Watershed, and 500, 1000, 0.9, 0.001, respectively, for Watershed 263. Synthetic watersheds having a similar structure to Watts Branch, their hyperparameters were selected to be the same as those of that watershed.

### 3. Results and discussions

#### 3.1. BMP allocation maps

BMP allocation maps produced by the five selected allocation methods in the four study watersheds are presented in Fig. 4. Percentage of area covered by BMPs in all these scenarios are summarized in Supplementary Fig. 1. The first column of the figure shows the results of random BMP allocation to random HRUs (Random). The three central columns display the results of allocations targeted to hotspots using random (Random\_HS), expert system (DDSS\_HS), and optimization (GA\_HS) methods, respectively. The last column shows the results of unconstrained optimization (GA) where BMPs could be placed on non-hotspot HRUs. The computational effort required to produce these plans increases from left to right in the figure, being the least (less than 1 s) for the fully random approach, intermediate for hotspot-oriented methods, and greatest (larger than 15 min) for the

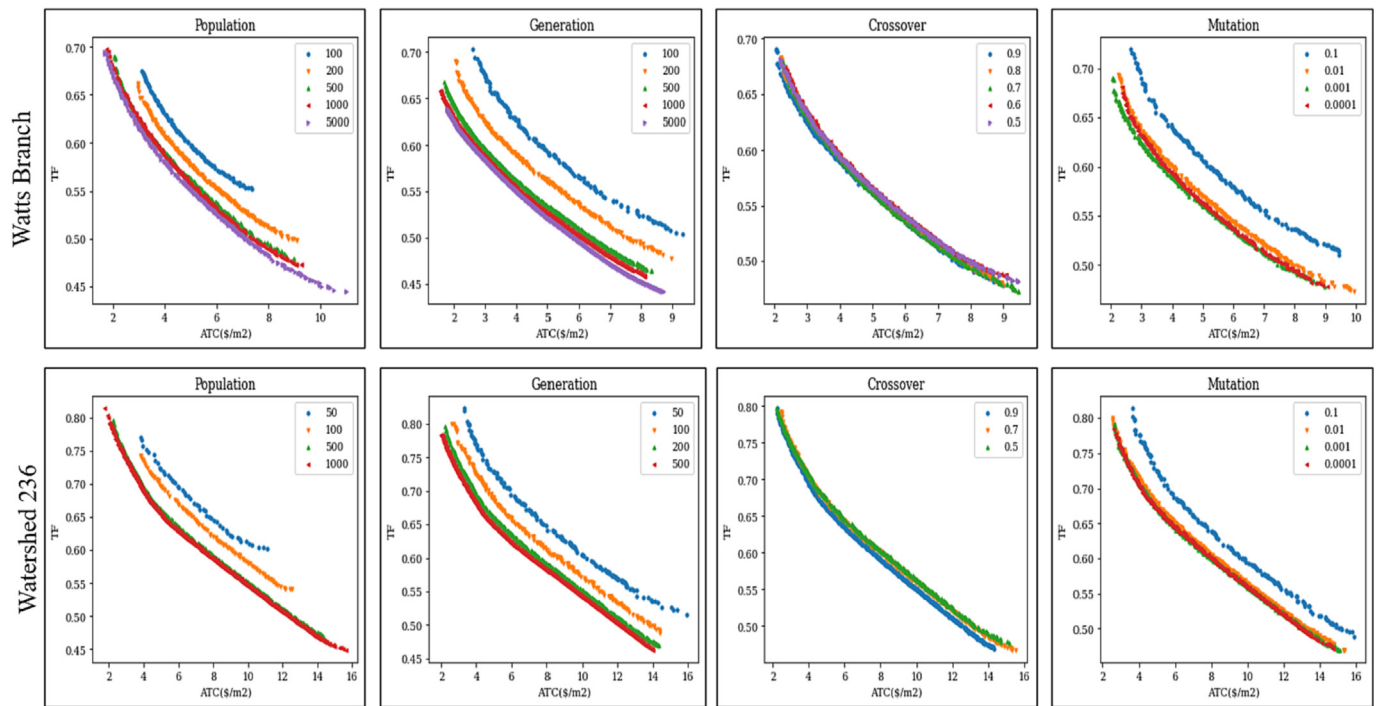


Fig. 3. Sensitivity analysis of Genetic Algorithm (GA) hyperparameters in two watersheds: population size, number of generations, crossover rate, and mutation rate.

unconstrained optimization technique. The first and second rows of maps on the figure are for the real-world Watts Branch watershed, and Watershed 263, respectively. The two bottom rows are for the synthetic natural and synthetic ultra-urban watersheds. The least built-up landscape is accordingly found in the third row, and the level of urbanization then increases as one moves through to the first, second, and then fourth row of the figure.

We first considered the results for the synthetic natural watershed (Fig. 4, third row) as they were somewhat atypical. The watershed was under a mostly natural land cover (73 %) for which the only applicable BMP, out of the eight selected for this study, was the vegetated filter strip (VFS). Accordingly, the five allocation methods agreed that VFS should be the prevalent BMP for this watershed, especially as more hotspots occur in its natural areas, due to adverse combinations of slope and soil, than in its residential zones. It was quite noticeable, however, that hotspots were somewhat spatially localized in this synthetic watershed, with a wide and visible band that runs from southwest to northeast in its eastern half. Hotspot allocation methods (\_HS) and the unconstrained GA method agree that this zone was where BMPs should be concentrated, but the random method with random locations (Fig. 4, first column) allocated BMPs (of the correct VFS type) more uniformly throughout the watershed. Accordingly, irrespective of its cost, we expected this random allocation to result in significantly smaller improvements in NPS control than that provided by the other four methods in this watershed. Similarly, despite its simple nature, we expected the method of random BMP selection on hotspots (Random\_HS) to produce NPS control that was like that of the more computationally expensive methods, since (through lack of choice) it resulted in allocation of the right BMP, at the suitable locations. Confirmation of such expectations will be discussed in Section 3.3.

Hotspots in the suburban Watts Branch watershed (Fig. 4, first row) were more spatially spread-out than in the synthetic natural watershed (Fig. 4, third row), which was especially visible in the northwest section of the watershed. Hotspots were distributed over a broader variety of land covers, for which several BMPs were applicable, and this better highlighted the differences between the BMP selection methods. We first noted, similar to in the synthetic natural watershed (Fig. 4, third row), BMP allocation to random HRUs resulted in a BMP allocation that was still more spatially spread-out than the distribution of hotspots, and this was expected to lower the effectiveness of this approach for NPS control.

The hotspot-oriented expert system and optimization approaches (DDSS\_HS and GA\_HS) agreed with each other on the use of native landscaping (NL) and VFS in most of the southern half of the watershed but differed in BMP selection in its upper portion where infiltration trench (IT) and green roofs (GR) were favored by DDSS\_HS method, while porous pavement (PP) was preferred in GA\_HS method, for the same total cost. BMPs selected at random (Random\_HS) were much less similar to those of the expert and optimized methods than in the synthetic natural watershed (Fig. 4, third row) because of the broader choices of applicable BMPs in this more typical landscape. This dissimilarity was expected to lead to a lower performance of the random method relative to that of these two more computationally advanced approaches in NPS control. The unconstrained GA method produced a BMP allocation map that generally resembles that of GA\_HS, with VFS, NL, and PP as dominant BMPs, but it was notable that it abandoned allocation of some of the northern hotspots in favor of placing BMPs in non-hotspot areas located near the central band of NPS CSAs. The initial population of BMP implementation locations used in this method coincided with hotspots and the allocation results, therefore, indicated that the optimization process succeeded in finding alternate HRUs, where BMP implementation could be more beneficial to the control of NPS constituents than when all BMPs are sited on hotspots.

Pollution hotspots in the urban Watershed 263 (Fig. 4, second row) were more spatially distributed than those of the suburban watershed, Watts Branch (Fig. 4, first row), continuing the trend also observed with the synthetic natural watershed (Fig. 4, third row). A consequence of a more dispersed hotspots in the ultra-urban Watershed 263 was that the performance of random BMP allocation at random locations was expected to be more similar to that of Random\_HS in this watershed than the other, less urban, watersheds. Since hotspots were nearly evenly distributed in space in Watershed 263, a selection of random BMPs may provide nearly the same NPS control level whether they were located at hotspots, or at evenly distributed random locations. BMPs allocated by expert systems and by optimization were more similar to one another in this watershed than in the suburban Watts Branch watershed, with only slight differences in localized selection of IT, NL, and rain barrel (RB), resulting in similar NPS control performances. Random BMP selection on hotspots, however, led to quite different (and more varied) choices, which should, unfortunately lead to a lower performance for this simpler technique. As with Watts Branch,



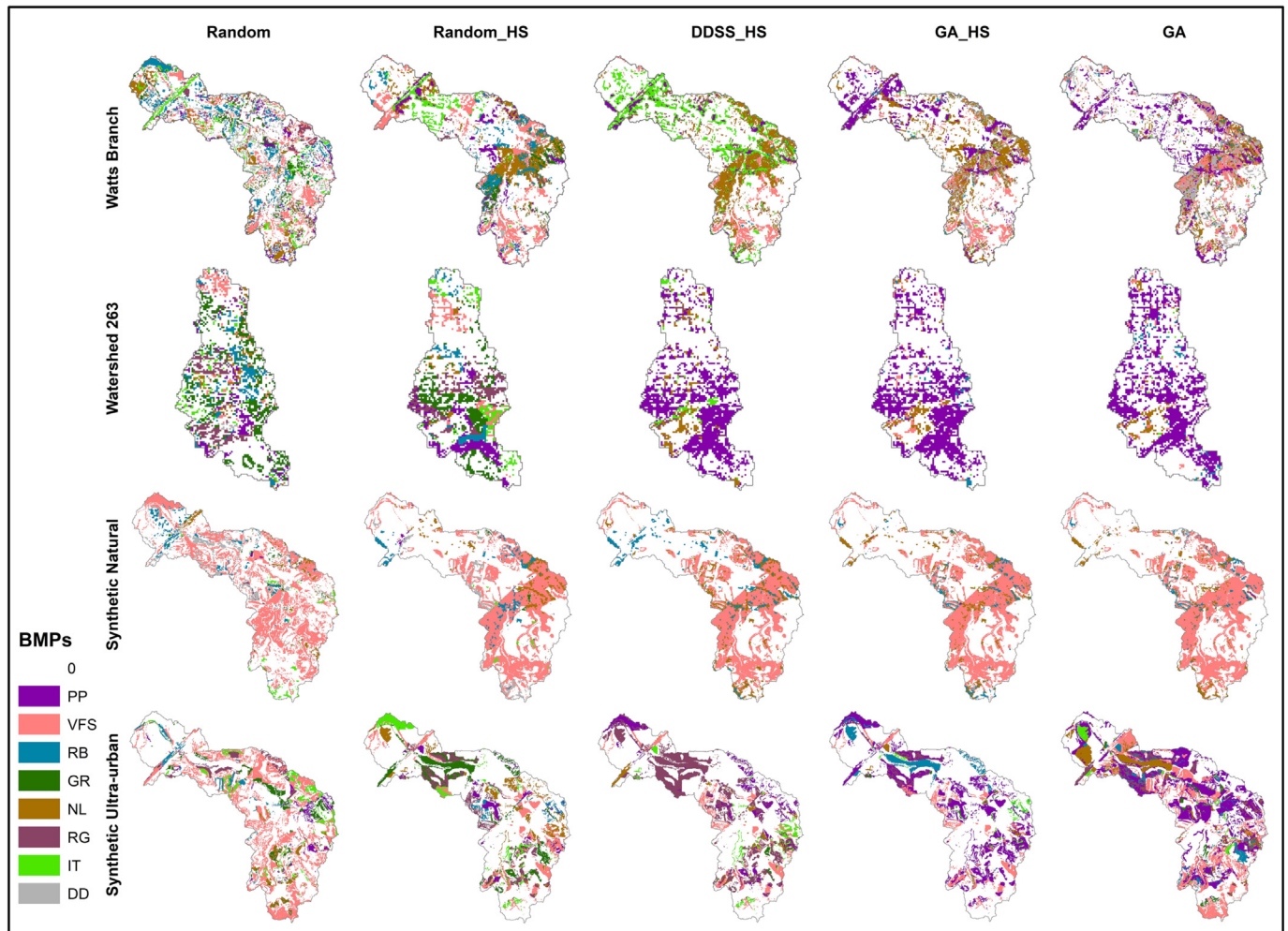


Fig. 4. BMP (0: no BMPs; PP: porous pavement; VFS: vegetated filter strip; RB: rain barrel; GR: green roof; NL: native landscaping; RG: rain garden; IT: infiltration trench; DD: downspouts disconnection) allocation maps produced by five methods (Random, Random\_HS, DDSS\_HS, GA\_HS, and GA) in four watersheds (suburban Watts Branch, urban Watershed 263, synthetic natural, and synthetic urban watersheds).

the unconstrained GA approach also abandoned some hotspots, this time in the southern half of the watershed, in favor of BMP allocation to non-hotspot HRUs located in the northern portion of Watershed 263. This modified spatial allocation presumably leveraged hidden synergies that result in higher constituent control performance, at a given cost level, than when BMPs are targeted only to hotspots.

The BMP allocation maps for the synthetic ultra-urban watershed (Fig. 4, bottom row) shared some characteristics with those of the urban Watershed 263 (Fig. 4, second row). In the synthetic ultra-urban watershed, hotspots (as seen on \_HS maps) were observed to be more spatially spread-out than in the suburban (Watts Branch, Fig. 4, top row) and natural (synthetic natural, Fig. 4, third row) watersheds, especially as the southwest to the northeast band of congregated hotspots was no longer present. This suggested, here again, in this heavily built environment, that random allocation of BMPs to random locations (Random) may result in a level of NPS constituent control that was similar to that of random BMPs placed on hotspots (Random\_HS). These random BMPs, however, seldom agreed with those selected by the DDSS\_HS and GA\_HS methods, leading to reduced performance. The expert and optimized methods mostly agreed on BMP selection in the southern half of the watershed, with more disagreement in the choice between rain garden (RG), RB, and PP, in the north. The degree to which optimized BMPs (on hotspots) perform better than expert-selected ones was discussed in Section 3.3. The BMP allocation map produced by unconstrained optimization (GA) differed more from those of hotspot methods in this heavily built watershed than in the less

urban ones. The unconstrained GA abandoned some hotspots where PP and RB were selected by GA\_HS, and introduced NL and VFS in selected non-hotspot HRUs. It also converted some of the RB selected by GA\_HS to NL, and some PP to RB. By design of the method, these changes were expected to improve NPS control performance, with the same implementation cost as DDSS\_HS and GA\_HS.

### 3.2. Coincidence of hotspots and optimized implementation sites

The unconstrained optimization approach (GA), in which both the type and location of BMPs were determined by the allocation algorithm, was the most computationally demanding of those selected for this study, and was expected to provide a boost in NPS constituent control performance relative to the other approaches. In the analysis of BMP allocation plans presented above, it was noted, qualitatively, that the degree to which optimized implementation sites differ from hotspots varies in relation to landscape type. In particular, the optimized locations of BMPs were observed to be quite similar to those of hotspots in the synthetic natural watershed, and most different from hotspots in the synthetic ultra-urban landscape. Deviations between optimized sites and hotspots were intermediate in the suburban and urban environments. Fig. 5 quantified this spatial coincidence of optimized BMP implementation sites and hotspots in the four study watersheds, which represent landscapes that progress from natural to heavily-built. In the synthetic natural watershed, 95 % of optimized implementation sites were found to also be NPS constituent hotspots. This coincidence

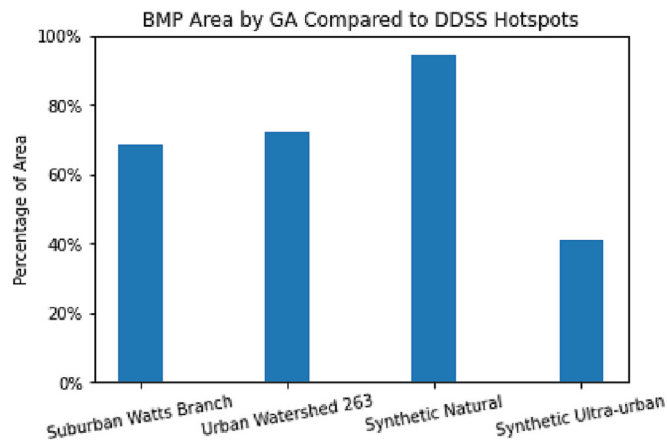


Fig. 5. Coincidence of optimized BMP implementation sites and hotspots in relation to land cover.

decreased to approximately 70 % in the suburban and urban landscapes, and eventually reached a low of 45 % in the synthetic ultra-urban watershed. This trend in coincidence indicates that the potential benefits of optimized BMP siting were landscape-dependent and increased with its degree of urbanization. Accordingly, the extra effort required by unconstrained optimization may be increasingly justified as the environment for which a BMP allocation plan was designed becomes more heavily built. This justification eventually depended also on the actual improvement in NPS constituent control performance that resulted from optimized siting of BMPs to non-hotspot HRUs.

The trend in coincidence with land cover type was likely a result of the spatial characteristics of hotspots, which were also observed to vary with increasing urbanization. In this study, and in prior analyses, hotspots were observed to be more spatially concentrated in natural and agricultural landscapes, and more spread-out in constructed urban environments. The denser hotspots of the less-built landscapes typically produced higher levels of NPS constituents per unit area (relative to non-hotspot areas of the landscape) than found in urban watersheds, and were consequently more important targets for BMP implementation than the less well-differentiated hotspots of urban land. In built-environments, where the differentiation between hotspot and non-hotspot areas was not as evident (e.g., as a result of the homogenizing effect of construction; esp. pavement), more opportunities arise to replace higher-cost BMPs, targeted to hotspots with lower-cost BMPs implemented in other HRUs. Such substitutions were observed in the BMP allocation maps presented earlier for the ultra-urban watershed, where unconstrained GA swapped the porous pavement (PP) selected by GA\_HS for some hotspots, with native landscaping and vegetated filter strips (NL and VFS) in other non-hotspot areas. This type of substitution resulted in equal control of NPS constituents at lower cost than a purely hotspot-oriented allocation, or better control at the same cost. It, however, also increased the percentage of watershed areas where BMPs were to be implemented. Hence, it eventually required a higher level of stakeholder participation to successfully realize the design plan.

In some cases, unconstrained optimization may also resulted in allocation plans that swapped BMPs from hotspots to other HRUs while maintaining the percentage of the targeted watershed area. Such an outcome would result from the identification and exploitation of spatial synergies by the optimization process, whereby hydromodifications positioned in the vicinity of a hotspot would have a higher impact on NPS control than operating directly on the hotspot itself. An example of this would be the positioning of runoff control measures upland of a sediment-generating hotspot to reduce the velocity of surface inflows to the hotspot, thereby reducing soil detachment in this CSA. Another example may be to reduce infiltration upgradient of a nitrogen-producing hotspot to reduce its subsurface lateral inflow and ensuing transport of the pollutant. This type of synergies, and others, may

be at play in the allocation plans produced by the unconstrained optimization method and will need to be studied in future investigations. Their practical advantage is that the realization of the resulting BMP plan does not require involvement of additional stakeholders relative to a hotspot-focused allocation. Suppose it can be determined that unconstrained GA did exploit such synergies. In that case, it should be valuable to identify the conditions leading to their existence and possibly define expert system rules, or other analytical tools, that can be used to take advantage of them in hotspot-based methods as well, without the extra computational burden of spatial optimization. One could imagine, for example, the development of a GA\_HS method that selects optimal BMPs for hotspots and specific HRUs, with pre-identified synergistic potential, located in their vicinity. Expert systems that integrate spatial reasoning subsystems could similarly be used for this purpose, with reduced computational requirements relative to optimization approaches.

### 3.3. Performance of BMP allocation plans

The predicted reductions in the four target NPS constituents (runoff, sediments, nitrogen, and phosphorus), at the outlet of the four study watersheds (natural to ultra-urban), in response to the five investigated BMP allocation methods (random to unconstrained optimization), were presented in Fig. 6. These results were obtained by simulating the response of these watersheds to a 10-year long time-series of observed weather, with HRU parameters adjusted in accordance with Table 1 to represent the allocated BMPs. The outputs of these simulations were then compared to the baseline responses of the study watersheds when no BMPs were implemented, such that the corresponding percentage reductions in NPS constituents could be calculated. In Fig. 6, results for the synthetic natural watershed are displayed in subplot (c), and those for the other watersheds, with increasingly urban landscapes, follow in clockwise order, ending with the synthetic ultra-urban watershed at subplot (d). The leftmost set of bars in each plot represents the reductions in total surface runoff (SurfQ) obtained with BMPs allocated in accordance to plans produced by each of the five studied methods, as shown in the maps of Fig. 4. The second and third sets of bars represent reductions in total sediments (TS) and total nitrogen (TN), respectively, and the rightmost set shows the reductions in total phosphorus (TP). In all cases, taller bars represent better control of the corresponding NPS constituent.

In 78 of the 80 presented cases, the degree of NPS constituent control (quantified by the percentage reductions) either remained the same or increased, as the computational effort required by the BMP allocation method increased, which was as expected. In other words, in almost all studied situations, unconstrained GA produced equal to, or better, control than GA\_HS, which provided greater or equal control to DDSS\_HS, which was itself better or similar to Random\_HS, that bested or equaled fully Random BMP allocation. The two exceptions were for sediment control in Watts Branch and runoff control in the ultra-urban watershed. In the first case, Random\_HS produced a reduction in sediment yield that is 2 % greater than that resulting from DDSS\_HS, and in the second case, fully Random allocation resulted in a reduction of runoff volume that is 1.5 % larger than random allocation on hotspots (Random\_HS). We interpreted these outliers as being the result of chance, since they both involve at least one random allocation method, and considered them to be of minimal significance because of the small magnitude of the non-monotonic disruption that they represent.

To address the goal of determining the applicability of the selected BMP allocation methods across land covers, we divided our analysis of the results of Fig. 6 into three parts. We first compared NPS reductions produced by the simplest and less computationally intensive fully random method (Random) to those of random BMP selection on hotspots (Random\_HS), across watersheds and NPS constituents. We then evaluated how proper selection of BMPs improved NPS control by comparing the Random\_HS results to those of the DDSS\_HS method. Thirdly, we evaluated the NPS control benefits resulting from optimization by comparing results of DDSS\_HS with those of GA\_HS and unconstrained GA.



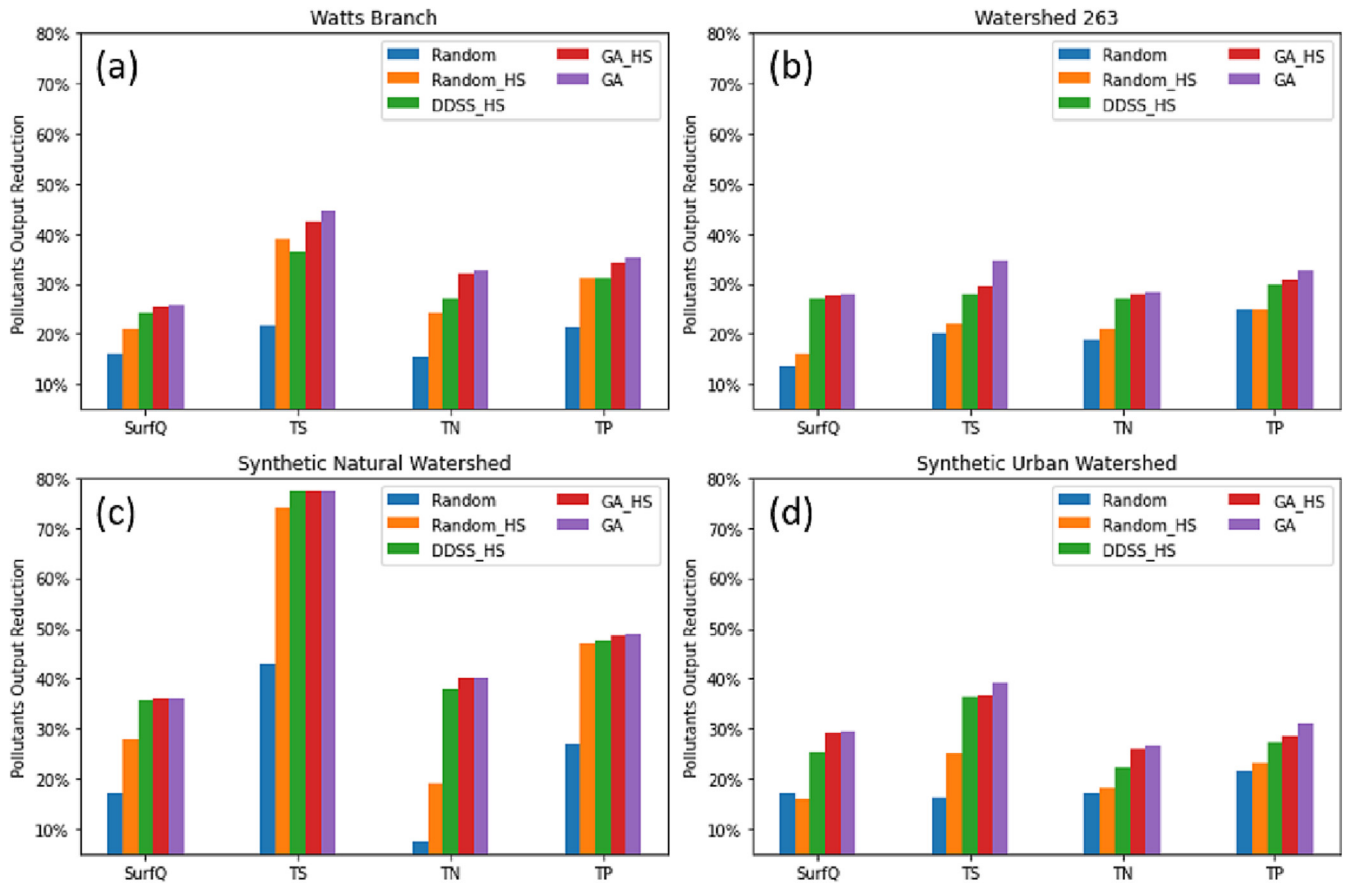


Fig. 6. Reduction of NPS constituents (surface runoff: SurfQ; total sediment: TS; total nitrogen: TN; total phosphorus: TP) for five allocation methods (Random, Random\_HS, DDSS\_HS, GA\_HS, and GA) in four watersheds: (a) Watts Branch watershed, (b) Watershed 263, (c) synthetic natural watershed, and (d) synthetic urban watershed.

Random allocation of BMPs at random locations was meant to represent the undirected behavior of stakeholders in their adoption of BMPs, resulting potentially from a broad, untargeted sensitization or publicity campaign for such measures, and contrasted with Random\_HS where the corresponding social interventions may instead have been focused specifically in the vicinity of pre-identified hotspots. The difference in NPS control performance between these two methods was observed to be largest in the synthetic natural watershed (Fig. 6(c)), where random BMPs sited at hotspots reduce NPS constituents nearly twice as much as random siting (e.g., reductions of 28 %, 74 %, 19 % and 47 % in runoff, sediments, nitrogen, and phosphorus, respectively, for Random\_HS, versus 17 %, 42 %, 7 %, and 26 % for Random). The difference between these allocation methods was also significant in the suburban landscape of Watts Branch (Fig. 6(a)), where hotspot targeting reduces NPS constituents approximately 1.5 times better than random siting (e.g., 26 % vs. 16 % reduction in nitrogen, and 31 % vs. 21 % reduction in phosphorus). The difference in control performance between these random approaches was however observed to mostly disappear in the urban and ultra-urban landscapes, where hotspot siting was at most 2 % better than the fully random approach in 7 out of 8 comparisons (the exception being sediments in the synthetic ultra-urban catchment). The observed trend, with changing land cover, of the comparative performance between these random methods, agreed with our earlier observations of the trend in the spatial distribution of CSAs with landscape type (cf. discussion of Fig. 4). Hotspots were observed to become more evenly spatially spread-out as the landscape became increasingly built-up, and the NPS control results confirmed that this spatial spreading led to a lesser need to specifically target hotspots, at least when BMPs were selected randomly. In other words, our results indicated that random siting of random BMPs (non-targeted, broad encouragements of stakeholders) was as valid as random selection of BMPs sited on hotspots, in the more highly urbanized landscapes. Random siting

of random BMPs was, however, much less effective than hotspots sitting in suburban and natural landscapes.

The degree to which proper selection of BMPs in hotspots (DDSS\_HS) improved the control of NPS constituents relative to random selection (Random\_HS) followed a trend that was largely the opposite of that between fully random and random-hotspot allocations. For 6 out of 8 cases in the natural and suburban watersheds, expert allocation of BMPs to hotspots improved NPS reductions by just 3 % or less when compared to random BMPs sited at hotspots. The two outliers were for runoff and nitrogen control in the synthetic natural watershed where proper BMPs provide additional reductions of 8 % and 20 %, respectively (i.e., from 27 % and 18 % reductions in SurfQ and TN, respectively, by Random\_HS, to 35 % and 38 % by DDSS\_HS). Conversely, in the urban and ultra-urban landscapes, appropriate selection of BMPs always (8 out of 8 cases) provided a 5 % or better increase in NPS constituent reductions compared to random BMPs (the observed maximum is 13 % for sediments in the ultra-urban watershed, that Random\_HS reduces by 22 %, and DDSS\_HS reduces by 35 %). These results suggest that, in landscapes where hotspots are well-differentiated and localized, the choice of which BMP to apply to them was not as critical as it was in environments with spatially spread-out CSAs. In other words, the key analytical step for the less-built landscapes was probably the localization of hotspots, such that BMPs can be sited on them, and the key step for more heavily built environments was the selection of appropriate BMPs, for the NPS constituents of concern, identified at their siting location. Whereas the NPS control performance of BMPs that were randomly located and selected was found, above, to be similar to that of random BMPs sited on hotspots in urban and ultra-urban zones, the greater impact of proper BMP selection in these landscapes implied that random methods should not be favored there, particularly when cost and performance of the allocation plan were important considerations.

The improvements in the control of NPS constituents resulting from optimization approaches (GA\_HS and GA), as compared to expert selection of BMPs on hotspots (DDSS\_HS) were not observed to follow a simple trend with land cover. In the synthetic natural watershed, optimization provided up to a 2 % greater reduction in NPS control than expert selection and this relatively small improvement in performance reflected the greater importance that targeting BMPs to hotspots plays in such landscapes, relative to the selection of specific BMPs. In the other 3 watersheds, just under half of cases (5 out of 12) showed a greater than 5 % decrease in NPS constituent production when optimized allocation was applied, and in most of these cases (4 out of 5) it was the transition from expert BMP selection to optimized selection on hotspots (DDSS\_HS to GA\_HS) that provided most of the performance improvement. More specifically, in the suburban watershed, the reduction of NPS outputs produced by GA\_HS was 6 % and 5 % larger than that of DDSS\_HS for sediments and nitrogen, respectively, and in the ultra-urban catchment it was 4 % and 6 % larger than DDSS\_HS for runoff and nitrogen, respectively. On the other hand, unconstrained optimization (GA) was found to produce its largest control improvement, of 7 % when compared to GA\_HS, for the case of sediments in the urban watershed. The largest increase provided by GA, in comparison to DDSS\_HS was 8 %, which occurs for sediment control in both Watts Branch (35 % to 43 %), and Watershed 263 (26 % to 34 %). In other cases, optimization improved NPS reductions by 1 % to 3 % between DDSS\_HS and GA\_HS, and also between GA\_HS and GA, but with a total that was less than 5 % from DDSS\_HS to unconstrained GA. Overall, our results indicated that NPS control benefits resulting from optimized allocation varied with both land cover type and specific constituents, without specific trends, and can provide 8 % of additional reductions compared to expert selection of BMPs on hotspots.

Combining results from the three parts of this analysis leads to the following perspective on the applicability of the studied BMP allocation methods to landscapes with different land covers. Optimized selection of BMPs, sited at optimized locations, results in the highest performing BMP allocation plans across landscape types. It is not particularly beneficial in natural environments, and its substantial computational burden can be alleviated by focusing it on hotspots, with frequently similar results. The focus on hotspots has the advantage of resulting in BMP plans requiring involvement of fewer stakeholders than when BMPs are also sited in non-hotspot zones. Expert selection of BMPs targeted to hotspots is also broadly applicable, across land cover types, and results in reductions of NPS constituents that are slightly smaller than with optimization (up to 8 % here), but at lower computational cost, which can be particularly valuable when planning is performed for a large watershed or region. These methods, where specific appropriate BMPs are selected for each implementation site, are required for the production of allocation plans with good performance in built-environments, from urban to ultra-urban. Targeting BMP implementation to hotspots, without selection of the most appropriate such measures (as in the Random\_HS approach), is acceptable in the less-built landscapes only, where precise localization of hotspots is the most important activity, and may be useful in the most computationally-challenged environments. Random siting of randomly selected BMPs is generally not advisable in any landscape, except possibly as a last resort approach that is “better than nothing”. Because this method yields fewer NPS control benefits at higher costs than the others, it has greater potential for eventually discouraging stakeholders from further participation as they wonder why so few improvements in environmental quality have resulted from such large and long-term efforts, and resource investments.

#### 4. Summary and conclusions

This study explored the effectiveness of five BMP allocation methods in managing four NPS constituents (runoff, sediments, nitrogen, and phosphorus) across different land covers (natural, suburban, urban, and ultra-urban). Eight BMPs were considered, including porous pavement, filter strip, rain barrel, green roof, native landscaping, rain garden, infiltration trench, and downspout disconnection. Real-world and synthetic watersheds

were analyzed using watershed response models calibrated against observed data. BMP implementation costs were determined based on literature and BMPs were represented by modifying SWAT parameters. Rule-based expert systems and Genetic Algorithms were used to select appropriate BMPs and optimize their location. The study assessed the percentage reduction in NPS constituents achieved through each method, presenting results as maps of BMP allocation and bar plots of percentage reductions.

Results indicated that implementing BMPs on hotspots is particularly important in less-built landscapes, and that the selection of specific BMPs becomes more important as urbanization increases. The most computationally demanding optimized allocation methods work well across all land cover types. They are not particularly needed in natural landscapes and can be simplified slightly by sitting BMPs on hotspots without substantial performance reductions. The less computationally demanding method of expert selection of BMPs on hotspots also applies across land covers but may result in slightly reduced performance for some constituents when compared to optimization. Random selection of BMPs sited on hotspots is acceptable in less-built environments, but random selection of randomly located BMPs is mostly unacceptable.

Results also showed that different BMPs may be suitable for different environments and financial constraints. For natural areas, the vegetated filter strip is recommended as it is effective in reducing nonpoint source pollution while maintaining the natural aesthetic. Porous pavement, on the other hand, is recommended for urban environments due to its ability to reduce stormwater runoff and alleviate urban flooding. However, rain gardens are a good choice for any environment if there are enough financial resources available to support their implementation. When resources are limited, the rain barrel can be a reasonable choice as it is a low-cost BMP that can still contribute to reducing stormwater runoff. Additionally, downspout disconnection can be a good choice for reducing stormwater runoff and preventing flooding at a lower cost, if the conditions for implementation are met.

An implication of the results obtained in this study is that broad campaigns aimed at increasing BMP adoption by stakeholders may not produce the desired control of NPS constituents, and may simultaneously consume more human and financial resources than necessary. For natural and suburban landscapes, hotspot identification efforts, and the targeting of social interventions to their vicinity, should produce much higher NPS control returns on stakeholder investments. For urban and ultra-urban landscapes, adoption campaigns should further focus on fostering the adoption of the “right BMP”, as required by site characteristics, and by the specific NPS constituent(s) of concern.

To ensure the success of BMP allocation plans, it is important to consider social factors in addition to hydrological, physical, and chemical considerations. Variations in the socioeconomic characteristics of watershed stakeholders can affect their willingness to adopt BMPs, potentially impacting the efficacy of the physical BMP allocation plan. Spatial analysis can help identify areas where positive and negative correlations exist between physical and social factors, allowing for targeted social interventions that maximize the return on investment. This can be facilitated through the use of behavioral models, such as Bayesian Belief Networks or Agent-Based Modeling, informed by survey data and BMP implementation databases (Bonabeau, 2002; Kavak et al., 2018; Montalto et al., 2013). Incorporating social components into BMP planning systems can help target educational and promotional programs, financial incentives, and other interventions to areas where they are most needed to improve NPS constituent control while keeping costs low. Such socio-hydrologic analysis should be a focus of future research in this field.

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## Credit authorship contribution statement

Conceptualization, Z.Z., H.M. and A.S.; methodology, Z.Z. and H.M.; software, Z.Z.; validation, Z.Z., H.M., and A.S.; formal analysis, Z.Z.; investigation, Z.Z.; resources, H.M., A.S., and P.L.; writing original draft preparation, Z.Z. and H.M.; writing review and editing, H.M., A.S., P.L., and M.N.A.; visualization, Z.Z.; supervision, H.M. and A.S.; project administration, P.L.; funding acquisition, H.M. A.S. and P.L. All authors have read and agreed to the published version of the manuscript.

## Data availability

Data will be made available on request.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

- Abbaspour, K.C., 2013. Swat-cup 2012: SWAT Calibration and Uncertainty Program—A User Manual.
- Ahiablame, L.M., Engel, B.A., Chaubey, I., 2012. Effectiveness of low impact development practices: literature review and suggestions for future research. *Water Air Soil Pollut.* 223, 4253–4273.
- Ahiablame, L.M., Engel, B.A., Chaubey, I., 2013. Effectiveness of low impact development practices in two urbanized watersheds: retrofitting with rain barrel/cistern and porous pavement. *J. Environ. Manag.* 119, 151–161.
- Arabi, M., Frankenberger, J.R., Engel, B.A., Arnold, J.G., 2008. Representation of agricultural conservation practices with SWAT. *Hydrol. Process. Int. J.* 22, 3042–3055.
- Arnold, J.G., Srinivasan, R., Mutiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development 1. *JAWRA J. Am. Water Resour. Assoc.* 34, 73–89.
- Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., Griensven, A.V., Liew, M.W.V., et al., 2012. SWAT: model use, calibration, and validation. *Trans. ASABE* 55, 1491–1508. <https://doi.org/10.13031/2013.42256>.
- Belt, K.T., Stack, W.P., Pouyat, R.V., Burgess, K., Groffman, P.M., Frost, W.M., Kaushal, S.S., Hager, G., 2012. Ultra-urban baseflow and stormflow concentrations and fluxes in a watershed undergoing restoration (WS263). *Proceedings of the Water Environment Federation, Stormwater 2012*, 5, pp. 262–276 (2014, 2012, 262–276).
- Benedict, M.A., McMahon, E.T., 2002. Green infrastructure: smart conservation for the 21st century. *Renew. Resour. J.* 20, 12–17.
- Blank, J., Deb, K., 2020. pymoo: multi-objective optimization in python. *IEEE Access* 8, 89497–89509.
- Bonabeau, E., 2002. Agent-based modeling: methods and techniques for simulating human systems. *Proc. Natl. Acad. Sci.* 99, 7280–7287.
- Chen, L., Qiu, J., Wei, G., Shen, Z., 2015. A preference-based multi-objective model for the optimization of best management practices. *J. Hydrol.* 520, 356–366.
- Coello, C.A.C., Lamont, G.B., Van Veldhuizen, D.A., 2007. *Evolutionary Algorithms for Solving Multi-objective Problems*. volume 5. Springer.
- Debo, T.N., Reese, A., 2002. *Municipal Stormwater Management*. CRC Press.
- Djordje, F., Montas, H., Shirmohammadi, A., Bergström, L., Ulén, B., 2002. A decision support system for phosphorus management at a watershed scale. *J. Environ. Qual.* 31, 937–945.
- Drake, J., Bradford, A., Van Setters, T., 2014. Hydrologic Performance of Three Partial-infiltration Permeable Pavements in a Cold Climate over Low Permeability Soil.
- Eckart, K., McPhee, Z., Bolisetti, T., 2017. Performance and implementation of low impact development—a review. *Sci. Total Environ.* 607, 413–432.
- Geng, R., Yin, P., Sharpley, A.N., 2019. A coupled model system to optimize the best management practices for nonpoint source pollution control. *J. Clean. Prod.* 220, 581–592.
- Gitau, M., Veith, T.L., Gburek, W., 1923. Farm-level optimization of BMP placement for cost-effective pollution reduction. *Trans. ASAE* 2004, 47.
- Hamel, P., Daly, E., Fletcher, T.D., 2013. Source-control stormwater management for mitigating the impacts of urbanisation on baseflow: a review. *J. Hydrol.* 485, 201–211.
- Ice, G., 2004. History of innovative best management practice development and its role in addressing water quality limited waterbodies. *J. Environ. Eng.* 130, 684–689.
- Kavak, H., Padilla, J.J., Lynch, C.J., Diallo, S.Y., 2018. Big data, agents, and machine learning: towards a data-driven agent-based modeling approach. *Proceedings of the Proceedings of the Annual Simulation Symposium*, pp. 1–12.
- King, D., Hagan, P., 2011. *Costs of Stormwater Management Practices in Maryland Counties*. Kumar, M., Husain, M., Upreti, N., Gupta, D., 2010. Genetic Algorithm: Review and Application. Available at SSRN 3529843.
- Kumar, S., Guntu, R.K., Agarwal, A., Villuri, V.G.K., Pasupuleti, S., Kaushal, D.R., Gosian, A.K., Bronstert, A., 2022. Multi-objective optimization for stormwater management by green-roofs and infiltration trenches to reduce urban flooding in central Delhi. *J. Hydrol.* 127455.
- Lee, J.G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J.X., Shoemaker, L., Lai, F.-H., 2012. A watershed-scale design optimization model for stormwater best management practices. *Environ. Model Softw.* 37, 6–18.
- Lian, Q., Yao, L., Uddin Ahmad, Z., Lei, X., Islam, F., Zappi, M.E., Gang, D.D., 2019. Nonpoint source pollution. *Water Environ. Res.* 91, 1114–1128.
- Liu, Y., Shen, H., Yang, W., Yang, J., 2013. Optimization of agricultural BMPs using a parallel computing based multi-objective optimization algorithm. *Environ. Resour. Res.* 1, 39–50.
- Liu, R., Wang, J., Shi, J., Chen, Y., Sun, C., Zhang, P., Shen, Z., 2014. Runoff characteristics and nutrient loss mechanism from plain farmland under simulated rainfall conditions. *Sci. Total Environ.* 468, 1069–1077.
- Liu, Y., Bralts, V.F., Engel, B.A., 2015. Evaluating the effectiveness of management practices on hydrology and water quality at watershed scale with a rainfall-runoff model. *Sci. Total Environ.* 511, 298–308.
- Liu, R., Xu, F., Zhang, P., Yu, W., Men, C., 2016. Identifying non-point source critical source areas based on multi-factors at a basin scale with SWAT. *J. Hydrol.* 533, 379–388.
- Liu, Y., Wang, R., Guo, T., Engel, B.A., Flanagan, D.C., Lee, J.G., Li, S., Pijanowski, B.C., Collingsworth, P.D., Wallace, C.W., 2019. Evaluating efficiencies and cost-effectiveness of best management practices in improving agricultural water quality using integrated SWAT and cost evaluation tool. *J. Hydrol.* 577. <https://doi.org/10.1016/j.jhydrol.2019.123965>.
- Mao, X., Jia, H., Shaw, L.Y., 2017. Assessing the ecological benefits of aggregate LID-BMPs through modelling. *Ecol. Model.* 353, 139–149.
- Maringanti, C., Chaubey, I., Popp, J., 2009. Development of a multiobjective optimization tool for the selection and placement of best management practices for nonpoint source pollution control. *Water Resour. Res.* 45.
- McCoy, N., Chao, B., Gang, D.D., 2015. Nonpoint source pollution. *Water Environ. Res.* 87, 1576–1594.
- Montalto, F.A., Bartrand, T.A., Waldman, A.M., Travalline, K.A., Loomis, C.H., McAfee, C., Geldi, J.M., Riggall, G.J., Boles, L.M., 2013. Decentralised green infrastructure: the importance of stakeholder behaviour in determining spatial and temporal outcomes. *Struct. Infrastruct. Eng.* 9, 1187–1205.
- Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans. ASABE* 50, 885–900.
- Nicks, A., 1985. Generation of climate data. *Proceedings of the Proceedings of the Natural Resources Management Symposium*, pp. 297–300 USDA-ARS-30.
- O'Donnell, T.K., Baffaut, C., Galat, D.L., 2008. Predicting effects of best management practices on sediment loads to improve watershed management in the Midwest, USA. *Int. J. River Basin Manag.* 6, 243–256.
- Oraci Zare, S., Saghaian, B., Shamsai, A., 2012. Multi-objective optimization for combined quality–quantity urban runoff control. *Hydrol. Earth Syst. Sci.* 16, 4531–4542.
- Shore, M., Jordan, P., Mellander, P.-E., Kelly-Quinn, M., Wall, D., Murphy, P., Melland, A., 2014. Evaluating the critical source area concept of phosphorus loss from soils to water-bodies in agricultural catchments. *Sci. Total Environ.* 490, 405–415.
- Sivanandam, S., Deepa, S., 2008. Genetic algorithms. *Introduction to Genetic Algorithms*. Springer, pp. 15–37.
- Srinivasan, M., McDowell, R., 2007. Hydrological approaches to the delineation of critical-source areas of runoff. *N. Z. J. Agric. Res.* 50, 249–265.
- Srinivasan, R., Zhang, X., Arnold, J., 2010. SWAT ungauged: hydrological budget and crop yield predictions in the Upper Mississippi River Basin. *Trans. ASABE* 53, 1533–1546.
- Srivastava, P., Hamlett, J., Robillard, P., Day, R., 2002. Watershed optimization of best management practices using AnnAGNPS and a genetic algorithm. *Water Resour. Res.* 38 (3-1-3-14).
- Tech, T., 2016. Opti-tool for Stormwater and Nutrient Management (User's Guide). Prepared for United States Environmental Protection Agency-Region 1.
- USEPA, 2002. 2000 National Water Quality Inventory. US Environmental Protection Agency, Office of Water, Washington DC.
- USEPA, 2010. Guidance for Federal Land Management in the Chesapeake Bay Watershed.
- USEPA, 2017. National Water Quality Inventory: Report to Congress. US Environmental Protection Agency, Office of Water, Washington DC.
- Veith, T.L., Wolfe, M.L., Heatwole, C.D., 2003. Optimization procedure for cost effective bmp placement at a watershed scale 1. *JAWRA J. Am. Water Resour. Assoc.* 39, 1331–1343.
- Veith, T.L., Wolfe, M.L., Heatwole, C.D., 2004. Cost-effective BMP placement: optimization versus targeting. *Trans. ASAE* 47, 1585.
- Vrugt, J. Multi-criteria Optimization Using the AMALGAM Software Package: Theory, Concepts, and MATLAB Implementation. Manual, Version 2015, 1, 1–53.
- Waidler, D., White, M., Steglich, E., Wang, S., Williams, J., Jones, C., Srinivasan, R., 2011. *Conservation Practice Modeling Guide for SWAT and APEX*. Texas Water Resources Institute.
- Wang, Y., 2015. A Diagnostic Decision Support System for Selecting Best Management Practices in Urban/Suburban Watersheds. University of Maryland, College Park.
- Wang, Y., Montas, H.J., Brubaker, K.L., Leisnham, P.T., Shirmohammadi, A., Chanse, V., Rockler, A.K., 2016. Impact of spatial discretization of hydrologic models on spatial distribution of nonpoint source pollution hotspots. *J. Hydrol. Eng.* 21, 04016047.
- Wang, Y., Montas, H.J., Brubaker, K.L., Leisnham, P.T., Shirmohammadi, A., Chanse, V., Rockler, A.K., 2017. A diagnostic decision support system for BMP selection in small urban watershed. *Water Resour. Manag.* 31, 1649–1664. <https://doi.org/10.1007/s11269-017-1605-x>.
- Wang, J., Liu, J., Wang, H., Mei, C., 2020. Approaches to multi-objective optimization and assessment of green infrastructure and their multi-functional effectiveness: a review. *Water* 12, 2714.
- White, M.J., Storm, D.E., Busested, P.R., Stoodley, S.H., Phillips, S.J., 2009. Evaluating non-point source critical source area contributions at the watershed scale. *J. Environ. Qual.* 38, 1654–1663.
- Williams, J., Nearing, M., Nicks, A., Skidmore, E., Valentin, C., King, K., Savabi, R., 1996. Using soil erosion models for global change studies. *J. Soil Water Conserv.* 51, 381–385.
- Zhang, K., Chui, T.F.M., 2018. A comprehensive review of spatial allocation of LID-BMP-GI practices: strategies and optimization tools. *Sci. Total Environ.* 621, 915–929.
- Zhang, Z., Montas, H., Shirmohammadi, A., Leisnham, P.T., Negahban-Azar, M., 2023. Impacts of land cover change on the spatial distribution of nonpoint source pollution based on SWAT model. *Water* 15, 1174.