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Advances in Total Maximum Daily Load Implementation Planning by Modeling Best Management Practices and Green Infrastructures

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Abstract: In this paper, a review of advances in total maximum daily load (TMDL) implementation planning by modeling best management practices (BMPs) and green infrastructure (GI) practices along with enhanced (hybrid/streamlining) approaches is presented. The review emanates from Chapter 12 of the recent ASCE Manual of Practice on TMDLs. The latest models and modeling tools, specifically the United States Environmental Protection Agency's (USEPA's) GI Modeling Toolkit and the Landscape and Green Infrastructure Design (L-GrID) model for formulating GI strategies with flexibility to support stakeholder engagement, are reviewed. In addition, other decision support tools that can help advance the state-of-the-practice of TMDL implementation are included in the synthesis. Advances in incorporating model uncertainties related to BMPs and GI practices in TMDL analysis are briefly discussed. Furthermore, enhanced approaches to cost-effective TMDL implementation measures are discussed, which can be combined with other watershed management strategies for greater synergy between TMDL modelers and other watershed stakeholders. Some emerging technologies such as remote sensing can be useful for monitoring the effectiveness of the TMDL implementation measures over time. Several emerging technologies are discussed through an example illustrating the long-term efficacy of implementation practices. Finally, an enhanced approach to the full TMDL life cycle that explicitly incorporates BMPs and GI practices in the TMDL is proposed, and expected benefits of this approach are demonstrated with conceptual diagrams. **DOI:** 10.1061/JOEEDU.EEENG-7578. © *2024 American Society of Civil Engineers.*

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Introduction

Although total maximum daily loads (TMDLs) set the waste load allocations (WLAs) and load allocations (LAs) at the time of regulatory approval, they do not always lead to the establishment of feasible management plans to guide the TMDL implementation process. A major technical challenge is how to associate explicit modeling of individual best management practices (BMPs) and green infrastructure (GI) practices with assessments of watershed-scale and receiving water quality impacts. TMDL regulatory approval includes a requirement for "reasonable assurance" of success that depends upon watershed stakeholders developing a TMDL implementation plan and demonstrating pollutant reductions through effective monitoring. However, minimal guidance is available from state and federal regulatory agencies on what modeling and management tools could be useful in support of TMDL implementation, leading watershed stakeholders to fall back upon 'trial and error' procedures to conduct the TMDL implementation phase. There are many reasons for such actions including stakeholders' wide variety of choices, technical expertise, and knowledge gaps. Modeling tools, particularly those that can explicitly model management practices, are potentially valuable for predicting the effectiveness of the BMPs and GI practices for managing stormwater at the watershed-scale and for making sure TMDL implementation is consistent with water quality goals (Zhang and Albertin 2012). An adaptive TMDL implementation process can be designed to develop stakeholder confidence that can lead to the attainment of water quality standards over time provided it is accompanied by rigorous water quality monitoring and providing timely feedback on project performance to those responsible for TMDL implementation.

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USEPA Regions and state environmental agencies have used various analytical methods in TMDL development and implementation planning over the past two decades for TMDLs related to stormwater sources. This includes TMDLs and water quality impairments due to sewer overflows such as combined sewer overflows (CSO) or sanitary sewer overflows (SSO). The National Pollution Discharge Elimination System (NPDES) program was expanded to include the Stormwater Phase II MS4s (Municipal Separate Storm Sewer Systems) Final Rule for small municipalities and for minor construction activity. With that expansion, demand for detailed quantification of stormwater pollutant load allocations in the overall TMDLs according to NPDES permit requirements (USEPA 2007) has increased. TMDL implementation should be planned to identify and consider all Clean Water Act (CWA) requirements, enabling a community to address high priority water quality needs (USEPA 2022b). In addition to an NPDES program, a Section 319 Nonpoint Source Management Program can be used to support nonpoint sources pollution reduction (which are generally less regulated) at a watershed level during TMDL implementation.

The USEPA promotes integrated planning, BMPs, and GI practices in water quality improvement practices using integrated modeling tools as also accomplished in the TMDL implementation phase. The USEPA (2022a) GI Modeling Toolkit provides decision support tools capable of supporting the planning during the implementation phase. For example, among eight tools in the GI Modeling Toolkit, the Community-Enabled Lifecycle Analysis of Stormwater Infrastructure Costs (CLASIC) tool [WRF (The Water Research Foundation) 2021] produces a publicly accessible model output that can satisfy the community needs for stormwater and wet weather management across different scales around the United States. User-based design with stakeholder inputs is the core component of CLASIC that integrates the performance, life cycle cost, and cobenefits of green and gray infrastructure along with the projected impacts of climate scenarios into a web-based single cohesive platform (Zhang et al. 2021). CLASIC can help communities make informed decisions on holistic wet weather management including climate resilience planning. The System for Urban Stormwater Treatment and Analysis IntegratioN (SUSTAIN) is another USEPA tool (Shoemaker et al. 2009; Lee et al. 2012) that allows for the optimization of BMP design and sitting and estimation of the potential benefits and implementation cost. SUSTAIN can be deployed from a specific site- to the watershed-scale to optimize a single BMP to a collection of distributed BMPs. Although SUSTAIN (public domain version) was developed more than 10 years ago using an older version of the Geographic Information System (GIS), the underlying concept in the tool remains the same in newer (proprietary) versions that could be used to simulate the impact of BMPs for achieving ambient water quality goals and supporting TMDL implementation planning. Consideration of using tools such as CLASIC and SUSTAIN in support of TMDL implementation could be emphasized early on during the TMDL development phase for a robust reasonable assurance, a requirement for an approved TMDL, and to help meet stakeholder expectations and inspire confidence in the process.

In Chapter 12 (Frost et al. 2022) of the recent ASCE Manual of Practice (ASCE-EWRI TMDL Analysis and Modeling Task Committee 2022), not only are the state-of-the practices for various models in TMDL implementation planning up to 2020 discussed, but several knowledge gaps are also identified. The objective of this paper is to address these deficiencies together with a state-of-the-art review of available models and decision support tools using BMPs and GI practices to support TMDL implementation planning. In addition, enhanced (hybrid/streamlining) modeling approaches for cost-effective and successful TMDL implementation can engender greater synergy in the goals of modelers and watershed stakeholders' beneficiaries. Furthermore, novel technologies such as remote sensing to evaluate long-term effectiveness of BMP and GI practices are covered. An advanced holistic approach in TMDL development and implementation planning is proposed where some of the traditional implementation steps such as using BMP and GI tools and close stakeholder engagement beyond public comments take place early in the development phase. The anticipated benefits of the advanced approach over the traditional approach are demonstrated using conceptual diagrams.

Advances in Best Management Practice and Green Infrastructure Modeling for TMDL Implementation

There are multiple options for selecting and placing BMPs and GI practices that can help reduce pollutants in urban waterbodies, which can also serve as TMDL implementation practices. Example practices include porous pavements, ponds, green roofs, vegetated swales, and bioretention cells. These practices can remove various pollutants such as nutrients, metals, suspended solids, and microplastics (Rossman and Huber 2016; Golden and Hoghooghi 2018; Sharma and Malaviya 2021; Smyth et al. 2021). The removal efficiencies of these practices depend on their characteristics (e.g., vegetation, soil, and underdrains), target pollutants, and rainfall properties (volume, intensity, duration, temporal pattern, etc.) that entrain accumulated pollutants in surface runoff (Ahmadisharaf et al. 2021; Zeng et al. 2021; Wang et al. 2023; Liu et al. 2016; Cook et al. 2021; Giese et al. 2019). Given the wide range of BMPs and GI and their different removal efficiencies, these practices can be simulated using algorithms applied to simple spreadsheets or recognized more explicitly in more complex watershed models. However, most urban watershed models do not feature algorithms or modules that represent BMPs and GI. A nonexhaustive list of example models that facilitate simulation of BMPs and GI are the Storm Water Management Model (SWMM; Rossman 2015), the Hydrological Simulation Program—FORTRAN (HSPF; Bicknell et al. 2005), and MIKE URBAN+ (DHI 2023). As will be shown conceptually later in this paper, attention to simulating the BMP and GI measures during the TMDL development has the potential to foster robust and holistic watershed management outcomes.

Although there are deficiencies in easy-to-use, flexible optimization tools that are applied to identify the best combinations of GI practices for water quality benefits across a watershed, they may nonetheless provide enough information for decision-making. Current practices rely on trial-and-error procedures in the process of developing an optimal management outcome (Alamdari et al. 2017; Alamdari and Sample 2019; Macro et al. 2019; Zhu et al. 2023). The selection and setup of a suitable optimization–simulation model for generating better scenarios of spatially distributed GI practices in each watershed is complex and depends on the pollutant(s) of interest, study area, GI options, and climate conditions. These are elaborated below.

1. Pollutant(s) of interest: while GI practices can remove various pollutants, studies have focused mainly on nutrients, suspended solids, and metals (Pennino et al. 2016; Jacklin et al. 2021; Sharma and Malaviya 2021). Research is limited as to the efficiency of GI for removing emerging contaminants such as microplastics and both per- and polyfluorinated substances (PFAS) as well as bacteria (Rahman et al. 2019; Gould 2021). In addition, existing watershed models (e.g., SWMM) with the capability of simulating GI are limited in the number of pollutants whose removal rates can be simulated. Another limitation of

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these models is that they cannot simulate the interactions among different pollutants such as bacteria and suspended solids through resuspension–deposition processes and, as such, the estimates of removal efficiency from these models may be compromised. Additionally, bacteria behave as nonconservative pollutants, and it is therefore more difficult to predict the water quality responses to certain GI and BMP options. Also, some GI practices or BMPs for pollutants such as nutrients and sediment have been known to become a suitable habitat for wildlife, which can lead to an increase in the abundance of bacteria associated with wildlife waste. Therefore, care should be taken to assess whether there is data on the removal efficiency of GI practices and if models exist to simulate GI practices for the target pollutants. When data on the removal of multiple pollutants is necessary, the GI practices and associated models that can simulate all the targeted pollutants may be limited. In those cases, more than one model may be needed.

2. Study area: past research has focused on the removal efficiency of GI in inland watersheds. There are fewer studies on the removal efficiency of GI in coastal watersheds (Sohn et al. 2021; Bae et al. 2021). Further, researchers (e.g., Zhang and Chui 2019) have questioned the efficiency of GI in these watersheds because of potential groundwater contamination. In coastal watersheds, GI practices should be proposed carefully with consideration given to differences between expected and optimal performance, commitments to maintenance, and diminishing pollutant removal efficiency curves. Further research is recommended to confirm the pollutant removal efficiency from these watersheds. An additional complexity in coastal and karst watersheds is that surface water and groundwater are hydraulically connected; thus, integrated catchment simulations are needed to evaluate the efficiency of GI practices. The existing literature about GI efficiency has also focused more on watersheds with wet climate, but arid and semiarid watersheds have received less attention (Jiang et al. 2015; Meerow et al. 2021; Alamdari and Hogue 2022b).
3. GI options: information about feasible GI practices and suitable locations to place the practices for a given watershed should be derived based on feedback from local stakeholders, prior site selection studies, and scientific knowledge. Site selection studies typically consider multiple factors such as soil permeability rate, land cover, drainage area, water table, distance to roadways, ground slope, and surface imperviousness (Young 2006; Young et al. 2009; Ahmadisharaf et al. 2016; Wu et al. 2019; Shojaeizadeh et al. 2021). Example site selection tools include SUSTAIN (Lee et al. 2012) and the GI Placement tool coupled with SWMM (GIP-SWMM; Shojaeizadeh et al. 2021). Selecting an individual GI option is less complicated than selecting multiple GI practices from a wide range of GI types to establish watershed-scale GI solutions. In the case of multiple GI, the location, surface area, and characteristics (vegetation, soil, etc.) of each GI option in a network of practices across the watershed landscape should be determined. There is a dearth of suitable tools, which utilize optimization algorithms to enhance existing watershed-scale simulation models toward the design of a network of GI practices across an entire watershed landscape. Examples of these simulation-optimization tools include SUSTAIN (Lee et al. 2012), OSTRICH-SWMM (Macro et al. 2019), RSWMM-Cost (Alamdari and Sample 2019), GIP-SWMM (Shojaeizadeh et al. 2021), and SWMM-MOPSO (Taghizadeh et al. 2021). However, these tools are not without their limitations in the integration of community criteria that constrain the simulation of the physical attributes of GI during optimization-based simulation.
4. Climate conditions: studies on the effectiveness of BMP and GI practices have been mainly limited to historical climate considerations. Research on how effective these practices are under climate change has increased in recent years (Hathaway et al. 2014; Alamdari et al. 2017, 2018, 2020, 2022; Tirpak et al. 2021; Alamdari and Hogue 2022a; Butcher et al. 2023; Weathers et al. 2023); however, our understanding about their effectiveness under climate change is still limited.

In summary, although the engineering applications of BMPs and GI have increased for TMDL implementation, a thorough evaluation of existing models and tools is needed for their applicability under various hydrologic, environmental, and socioeconomic conditions (Zhang and Chui 2018). In the following sections, descriptions of a GI-specific modeling toolkit and a GI planning model are provided, followed by a brief update on determining uncertainties involved with any natural process simulation model, not simply GI models. Among the modeling toolkit, a more detailed description of a stormwater life cycle cost tool is provided, together with state-of-the-art examples using the USEPA GI modeling toolkit. These reflect some of the latest advancements in this field.

USEPA Green Infrastructure Modeling Toolkit

Over the years, the USEPA has developed multiple tools for communities to support runoff management in urban and other environments. This includes the GI Modeling Toolkit. The toolkit includes resources that incorporate both green or a combination of gray and green infrastructure to promote sustainable community water resources management and increase community resilience to future changes (USEPA 2022a). There are eight available modeling tools included in the GI Modeling Toolkit, with a variety of complexities intended to address different application objectives. Below are descriptions of the three selected stormwater-related modeling tools. A more detailed description is provided of the CLASIC tool, which is the most recent tool included in the toolkit.

SWMM

The Storm Water Management Model (SWMM) is used worldwide for large-scale planning, analyses, and designs that feature runoff, combined and sanitary sewers, and other drainage systems in urban environments. SWMM allows users to perform analysis of various combinations of GI to determine their effectiveness of each in managing runoff and water quality. SWMM was developed to help support stormwater management objectives to reduce runoff through BMPs such as infiltration and retention enhancing practices (USEPA 2022a). This model can explicitly simulate the hydrologic performance of various GI practices, such as bioretention cells, permeable pavement systems, rainwater harvesting, rain gardens, and green roofs. As an example, when applied to the simulation of bioretention, the model utilizes a conceptual representation, which features four soil layers: surface, soil, storage, and underdrains (Zhang and Albertin 2012).

SWC

The Storm Water Calculator tool estimates the annual runoff from a given location in the United States based on local soil conditions, land cover, and historical rainfall. It is used to inform site developers on how well they can meet a desired stormwater retention target with the use of GI. A cost estimation module for low impact development (LID) within the tool allows planners and managers to evaluate LID controls based on comparison of regional and national project planning level cost estimates and predicted LID control performance (USEPA 2022a).

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CLASIC

The CLASIC tool was developed by WRF (2021) with support from the USEPA through its National Priorities program titled "Life Cycle Costs of Water Infrastructure Alternatives." The tool development takes a holistic stormwater management approach providing a comprehensive view of stormwater and wet weather flows throughout the hydrologic cycle, from its source and ending with the receiving water (Zhang et al. 2021). The CLASIC tool is an online decision support system (DSS) that includes a life cycle cost framework to support stormwater infrastructure planning. The tool can help assess the estimated costs, calculate reductions in runoff and pollutant loads, and determine potential cobenefits of various planning scenarios as stormwater professionals, community planners, and local decision-makers consider stormwater management projects. The tool can assess green and gray infrastructure scenarios to inform robust decision-making based on preferences to estimate capital and maintenance costs over the planning horizon (USEPA 2022a). The model also leverages the capabilities of the International Stormwater BMP Database (WRF 2020), SWC, and other studies by WRF. It is hosted on a cloud-based GIS modeling platform that provides access to several national geospatial, hydrologic, and water quality databases (Dell et al. 2021). Users can upload data—either their own data sets or automatically from national databases that include more site-specific or higher-resolution information. Users can select from various green and/or gray stormwater management practices. The practices/technologies in the CLASIC tool are categorized according to implementation strategy and the following primary technology functions:

1. Filtration technologies (volume-based) (e.g., rain gardens, infiltration trenches, sand filters, and bioswales);
2. Detention technologies (volume based) (e.g., extended detention basins and wet ponds);
3. Reclamation/storage technologies (volume-based) (e.g., stormwater harvesting and storage vaults/tunnels); and
4. Area-based volume reduction or filtration technologies (e.g., green roofs and permeable pavements).

The triple bottom line (TBL) analysis module in the CLASIC tool assigns cobenefit scores from (1) environmental, (2) social, and (3) financial aspects of GI applications. The user assigns weights according to a multicriteria decision analysis process. This analysis process provides quantitative outputs to compare cobenefits across scenarios of selection of BMPs and GI practices.

Stakeholder input and user-based design are the core components of the CLASIC system. The goal is to produce an open access tool that can be readily used to meet community needs of various spatial scales (small to large) throughout the United States and across different climate regions. It is worth noting that the CLASIC tool does not provide site-specific designs for GI or gray infrastructure, or optimization of a particular design. Therefore, it is a planning-level decision support tool. The CLASIC DSS encourages users to compare various stormwater infrastructure options that incorporate the simulation of climate scenarios through use of a "multivariate adaptive constructed analog method." The CLASIC tool and supporting materials have provided case studies for communities of different sizes, covering all climate regions across the United States, and incorporating multiple climate scenarios. These examples apply to a range of hydrologic conditions, traditional BMPs and GI, cost, performance, and cobenefit combinations and climate scenarios that together should lead to help more informed community decisions about future stormwater management investments (Zhang et al. 2021).

In summary, the CLASIC tool architecture comprises three integrated components and outputs that assess (1) hydrologic and water quality performance; (2) TBL benefits; and (3) life cycle costs. The life cycle cost component encompasses GI and gray infrastructure selected by the user. The TBL multicriteria decision analysis provides quantitative outputs that compare cobenefits across various scenarios of BMPs and GI selected (Zhang et al. 2021). All three integrated components from the CLASIC tool work synergistically to inform decisions on scenarios for holistic stormwater management at the community level.

Landscape Green Infrastructure Design (L-GrID) Model

The usefulness of established modeling tools is tightly dependent upon their purpose; established models thus become less reliable if they are used to derive generalizable principles of GI design at the urban neighborhood scale (i.e., beyond an individual site, but within a subwatershed) for a range of landscape and rainfall conditions. The policies promoting the use of GI for stormwater management often require site-level performance standards that may not even be attainable, or that while effective at the site-level they may not be at the neighborhood level due to spatial interactions during storm events. The Landscape Green Infrastructure Design (L-GrID) model (Zellner et al. 2016) was developed to help policymakers derive neighborhood-level GI strategies to alleviate urban flooding under diverse neighborhood and storm conditions. The development of L-GrID evolved from initial recommendations for the inclusion of GI approaches by planning agencies for stormwater management (Jaffe et al. 2010) and associated pollution control (Montalto et al. 2007). The benefits of mimicking natural systems to collect, treat, and infiltrate rain where it falls are often assumed but remain untested, ignoring important interactions with other hydrological aspects of the system, such as roads and sewers (or their trenches/ditch lines), and their cumulative impact on urban stormwater hydrology.

The L-GrID model facilitates the evaluation of several different GI scenarios for various landscape characteristics under different rainfall conditions and produces outputs that include estimates of the extent of the flooded area and runoff volume. L-GrID is a cellular process-based model developed in Netlogo (Wilensky 1999). The hydrologic processes included in the model are, in order of execution, precipitation, infiltration, sewer intake and treatment, evapotranspiration, surface flow, and watershed export downstream. The algorithms for these processes were derived from established hydrologic models and local data as well as expert knowledge from water managers and engineers. Model users can customize rainfall duration (which is shaped following a hyetograph), landscape size, GI and sewer placement, and land use cover ratios. The user can run scenario simulations with different system configurations and compare the outcomes across several metrics, namely flooded area and runoff volume directed to sewers, GI, and areas downstream. Rather than focusing on prediction, L-GriD allows users to engage in systematic scenario exploration to support the design of generalizable GI strategies for a particular neighborhood or region. If prediction is the goal, established hydrological models should be used instead.

Simulations with L-GrID can be evaluated across multiple dimensions, thus providing a richer understanding of the flooding problem and how each GI strategy might address it. The scenario results are meaningful only relative to a baseline scenario without GI. Model outputs include volume of water infiltrated by GI, volume of runoff captured by the storm sewer system ("sewer runoff"), volume of runoff flowing downstream through the neighborhood lowest point or outlet ("outlet runoff"), and the maximum flooded area. Inclusion of other outputs relevant to key stakeholders is underway, including the percent capacity of GI used in each storm, the present value of installation and maintenance costs over the lifecycle of the GI, the dollar cost per unit volume of water captured, and an estimate of property damages per storm.

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L-GrID has replicated observed flooding patterns in urban neighborhoods of Chicago, Illinois (Zellner and Massey 2024), as well as those modeled in the Boston, Massachusetts, region (Moira Zellner, personal communication, 2023). The model can inform the design of field experiments to generate the data needed for extensive empirical validation. In the meantime, parsimonious process-based and spatially explicit models such as L-GrID can support GI design with the expert knowledge and opinion that informed model development (Yang et al. 2015). Simulations with L-GrID show that GI can effectively divert stormwater from storm sewer systems, and thus prevent flooding and water pollution. Moreover, better than clustered GI layouts, dispersed layout designs built on curb cuts set a solid foundation to gradually build out designs that follow the runoff flow paths, with even greater potential to alleviate flooding. Such findings, facilitated by the rapid and flexible explorations with L-GrID, may be used as principles for GI planning.

The L-GrID model is currently being enhanced to include water quality aspects of runoff through the representation of proxy pollutants, total nitrogen (TN), and total suspended solids (TSS). The model includes mechanisms for pollutant diffusion facilitated by water flow, and algorithms that simulate the settlement of particulates when runoff rates diminish. This extension can provide users with a better understanding of why GI spatial layouts and amounts perform differently in various settings—i.e., some may be better for runoff reduction, while others may better capture pollutants. Preliminary findings confirm the benefits of curb cuts to also reduce pollution but suggest that there may also be tradeoffs among GI layouts that will require stakeholder input to determine which GI function to prioritize, by how much, and where (Moira Zellner, personal communication, 2023).

The results in Zellner et al. (2016) and preliminary pollution control simulations suggest that at a minimum threshold of GI coverage, benefits become observable and increase with greater GI coverage, but taper off after a certain percentage cover. Where this point is depends on the characteristics of each landscape and the magnitude of the storm events simulated. Further simulation and empirical research are needed to confirm what these GI thresholds are in any specific application and landscape. The GI design principles derived should be assessed under various climate and landscape conditions, given the occurrence of 100-year rainfall events and the likely evolution of policy toward requiring higher levels of enforcement of pollution control as a consequence. To ensure that the GI strategies are robust to a variety of storm events and landscape conditions, configurations should ideally conform to landscape heterogeneity, but if that were not possible, simpler approaches, e.g., installing curb cuts close to storm sewer inlets, would be an effective strategy to reduce runoff conveyed into the sewer system and downstream in a variety of rainfall conditions. With greater rainfall volumes and more spatial distribution, a strategy that follows the water flow and ponding in the landscape may be more effective, reinforcing spatial strategies proposed in other studies (Yang et al. 2015). While effective, such spatial strategies may be limited by the location of utilities or by neighbors' opposition. In such cases, random GI placement would still alleviate flooding more than large GI clusters. If GI clustering were the only option, downstream placements of GI impacting larger drainage areas should be favored over upstream placements.

Addressing Uncertainties Inherent to Modeling Including BMPs and GI Practices

The models for simulating BMPs and GI practices in support of TMDL implementation are subject to various uncertainties arising from parameterization, spatiotemporal resolution of the model and forcing data, and calibration strategy, among others (Shirmohammadi et al. 2006; Ahmadisharaf et al. 2019; Hantush et al. 2022). In one nutrient TMDL study (Zhang and Yu 2004), results from testing different TMDL allocation scenarios demonstrated that increased nonpoint sources load reduction (e.g., by using BMPs and GI practices) relative to total load reduction caused the overall uncertainty to increase and required an increase in the TMDL margin of safety. In addition, based on a simulated water quality trading and TMDL implementation study (Zhang 2008), results show that a greater relative portion of overall TMDL load reduction associated with nonpoint source load reduction correlates with greater uncertainty and thus requires a greater water quality trading ratio. The trading ratio typically refers to a ratio developed to either discount or normalize the value of pollutant credits between a buyer and seller in a trade or between a source and a downstream waterbody, including consideration of uncertainty. Therefore, it is important to pay special attention to uncertainties associated with nonpoint source load reduction strategies and the use of BMPs and GI practices in the TMDL implementation. For water quality trading and its related TMDL implementation program, the rigorous quantification of the trading ratio could enhance the scientific knowledge base and thus improve public perception for more informed decision-making in a watershed-based pollutant trading program for a state, tribe, or territory (Zhang 2008).

Past research (Liang et al. 2016; Mishra et al. 2018, 2019; Ahmadisharaf and Benham 2020; Mallya et al. 2020) has shown the value of probabilistic modeling to quantify these uncertainties and support risk-based decision-making, including applicability in simulating BMPs and GI practices. Probabilistic models can be used to evaluate BMPs, GI practices, and other alternative measures during TMDL implementation studies by acknowledging uncertainties. However, applying probabilistic models in practice is challenging because of the conceptual complexity of such models and the difficulties in communicating these concepts and the results of model outputs to stakeholders (Reckhow 2003). Interdisciplinary research study is needed to enhance existing communication that can facilitate the use of probabilistic models in TMDL implementation practice and simulation of BMPs and GI practices. Especially needed are more effective synergistic activities and collaborations among TMDL practitioners, modelers, sociologists, cooperative extension specialists, and communication specialists.

TMDL Implementation Advances through Hybrid and Optimization Programs with Extensive Stakeholder Engagement

Incorporating BMPs and GI practices in models that support TMDL implementation is an enhancement in the overall TMDL process. However, in some applications, the standard TMDL methodology can be a blunt instrument and can yield suboptimal outcomes. TMDLs can sometimes be in direct conflict where best practices to address contamination supported by one TMDL can aggravate a problem addressed by another and lead to a suboptimal outcome. A notable example is from the lower San Joaquin River in California where TMDLs were simultaneously developed for both salinity and dissolved oxygen in the lower reach of the river upstream of the Sacramento–San Joaquin River Delta (California Environmental Protection Agency 2002). A TMDL was developed to limit salinity impairment of the river that advocated reducing salt loads from contributing subwatersheds to the river upstream of the monitoring compliance points. Most of the salt load was contributed

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from agriculture and managed wetlands on the west side of the river basin. However, using the usual TMDL approach of adopting a 10% low flow hydrology based on historical averages as a design flow and selecting a typical factor of safety, monthly salt load allocations required severe cutbacks in agricultural and seasonal wetland return flows during summer months with significant likely economic impacts to agriculture and to the sustainability of the seasonal wetland habitat (California Environmental Protection Agency 2002; Quinn 2011, 2020). The dissolved oxygen TMDL resulted from low dissolved levels that impaired salmon migration and the viability of two important annual migrations of these anadromous fish. The lower San Joaquin River discharges to the Delta through a deep-water ship channel within the port of Stockton—the transition from a shallow, levee-confined river to a deep, wide ship channel resulted in stagnation, decay of algae, and a large drop in dissolved oxygen levels. Modeling studies suggested that the most cost-effective strategy to reduce this annual occurrence was to significantly increase flow through the ship channel, most easily brought about by increased return flow from upstream watersheds in the San Joaquin River Basin. The myopic nature of single-issue TMDL development that mitigates against a more holistic view of environmental management often leads to similar suboptimal outcomes. In these instances, it is not the inherent limitations of the modeling tools, but rather the mandate for the application of these tools, that we are forced to follow. In the example (above), the WARMF watershed simulation model [reviewed by Borah et al. (2022)] was capable of simulating both pollutants and BMPs but was used independently to arrive at TMDLs and recommended management strategies for each pollutant.

A successful strategy to avoid this practical challenge of dual and conflicting TMDL prescriptions has been the adoption of a real-time water quality management program, which substitutes a strictly load-based salinity control program with a hybrid program that relies upon monthly salinity concentration limits at three river compliance monitoring stations (Quinn and Karkoski 1998). Moreover, by organizing stakeholders for each distinct subwatershed, this approach avoided excessive regulatory oversight while maintaining stakeholder operational flexibility and encouraging local innovative pollutant management solutions. The approach encouraged stakeholders within each subwatershed to establish internal accounting systems and, if needed, collaborate with other subwatersheds through mechanisms such as load trading or salt load curtailment.

Options for salt load control include agricultural drainage reuse and recirculation, temporary agricultural drainage storage in surface ponds or the shallow groundwater, and irrigation water conservation and source control practices (Gardner and Young 1988; Quinn 2011). By replacing the more restrictive traditional TMDL salt load allocations with loads based on the real-time assimilative capacity of the river- allowable salt load export was increased substantially (the new policy based on compliance with downstream salinity objectives assumed that stakeholders could use up to 85% of the available River assimilative capacity). Hence, this more resource efficient approach allowed agricultural and seasonal wetland entities to export greater salt loads to the ocean improving salt balance within the basin while enhancing compliance with state-mandated river water quality objectives. This approach brought about enhanced collaboration and coordination of activities and embracing innovations in sensor web-based data dissemination, simulation model-based forecasting, and the use of social media (Quinn and Hanna 2003; Herr and Chen 2006). All of these collaborative efforts collectively have helped to maximize the success of the TMDL-based pollutant control program by encouraging watershed water quality management innovations.

The formulation of TMDL implementation measures (e.g., traditional BMPs for agricultural lands and GI in urban landscapes) can be viewed as a multicriteria decision problem, one where the decision variables may include the location, type, and characteristics of the recommended practices. TMDL implementers may encounter a number of constraints (Li 2015; Sage et al. 2015) that include (1) site constraints such as unsuitable land cover and soil characteristics for installing a measure or practice; (2) difficulties with the incorporation of existing stormwater control measures; (3) lack of accessible requisite data; and (4) aspects related to the nature of the development (e.g., linear development projects often place limits on siting stormwater management measures). Further, the implementation process often involves consideration of multiple cobenefits related to certain practices as well as some cost–benefit tradeoffs. The complexity of this process may require computational methods to explore an extensive feasible solution space, typical of these problems, if the process cannot be resolved through less complex analysis. Optimization techniques can be used to arrive upon decisions that maximize (or minimize) one or more objective functions (i.e., the numerical representation of goals) in the presence or absence of resource constraints (Walters and Hilborn 1978; Wossink et al. 1999; Srivastava et al. 2002). Simulation models, that contain hydrologic and economic models of BMPs, and GI practices (discussed in the earlier section) are often employed to provide the resource constraints allowing analysis of unique scenarios for multiple decision variables embedded in the optimization algorithm (Groot et al. 2007; van Wenum et al. 2004; Bekele and Nicklow 2005; Arabi et al. 2007; Piemonti et al. 2013; Babbar-Sebens et al. 2013).

While optimization provides an effective computational approach to choose between BMP scenarios developed at different spatial scales, acceptable choices may also depend on local conditions (e.g., farm scale operations) and watershed-scale performance of enterprises such as local restoration strategies. Thus, successful manipulation watershed hydrology via BMPs requires a thorough understanding of people and ecological processes unique to the watershed system to apply this understanding to formulate successful management strategies. To improve the decision-making process, approaches must integrate explicit community participation of diverse stakeholder groups in modeling and decision processes, to identify and include diverse community objectives and local information. This can be effectively facilitated by including the expected benefits of incorporating management options such as BMPs and GI early in the model development, which build trust in the stakeholders concerning the implementation process and actions they may be asked to make on their lands and impacted communities. As a result, research on analytical participatory modeling and design methods that directly engage with humans to better characterize the diversity in stakeholder opinions, knowledge, preferences, and biases when decision alternatives are being generated have recently become popular (Reed 2008; Zellner et al. 2020). In such approaches, stakeholders are involved in all stages of modeling and planning, thereby requiring the need for better understanding of social and cognitive processes that can affect the design and planning of BMP alternatives. Toward that end, newer place-based digital tools (Babbar-Sebens et al. 2015; Møller et al. 2019) have emerged that leverage graphical user interfaces (GUIs) to engage community members to visualize relevant design data and solicit feedback on proposed alternatives. For example, Watershed REstoration using Spatio-Temporal Optimization of Resources (WRESTORE; Babbar-Sebens et al. 2015) is a web-based platform that empowers users to optimize the placement and configuration of new conservation practices, not only based on measurable objectives derived from dynamic simulation models, but also by incorporating their own subjective and potentially unquantifiable criteria. This allows users to consider personal preferences and factors that may not be easily quantified when determining the location and implementation of these practices. Although many of these digital tools are relatively novel in their approaches to involving stakeholders in the design and planning phases, they offer promising prospects for enhancing engagement and collaboration between the public and experts. As a result, they facilitate cooperation and the joint development of potential solutions through a process of coproduction.

Advances in Emerging Technologies to Evaluate TMDL Implementation Measures

The advances in emerging technologies have provided potential opportunities to enhance TMDL implementation, especially for BMPs and GI practices that connect to nonpoint source pollution. Extensive resources have been dedicated to addressing nonpoint sources in watersheds and developing effective BMPs and GI (Dosskey 2001; Lintern et al. 2020). For instance, the estimated costs of BMP implementation associated with nutrient and sediment reduction from agricultural stakeholders in the Chesapeake Bay Watershed were estimated to be 3.6 USD billion during 2011–2025 and 900 USD million annually in later years (Birch et al. 2011). Despite these efforts, many watersheds have yet to substantially improve water quality (Hansen et al. 2021; Lintern et al. 2020; Tomer and Locke 2011; Vitousek et al. 1997). Numerical modeling studies consistently predict water quality improvements with BMP implementation (Almendinger and Ulrich 2017; Kalcic et al. 2015; Mohamoud et al. 2010; Srivastava et al. 2002). However, many of these modeling outcomes have yet to be realized in subsequent monitoring (Ator et al. 2020; Sohn et al. 2019). One cause of this failure is an unrealistic representation of BMPs and GI in numerical modeling (Liu et al. 2018). This is expected because most water quality models are developed with the assumption that BMPs and GI practices retain or degrade pollutants in the long term without due consideration of BMP and GI maintenance practices. This erroneous expectation of continuous static BMP performance is based on limited short-term studies at the local scale. Extrapolation of findings from onsite or local scale sources to the watershed or larger scales can lead to a divergence between expectations of water quality improvement and reality (Ator et al. 2020). A review of Chesapeake Bay Program Modeling by a scientific and technical advisory committee (Hood et al. 2019) found that tracking the dynamic behavior of BMP implementation is needed to improve the realization of nutrient management targets and water quality goals.

The advent of high-resolution remote sensing has allowed better estimates of the performance and sustainability of BMPs and GI that can be used to assess an expected efficacy (Fig. 1). For example, the estimated performance of two dry swales in Virginia, shown in Fig. 1, was 40%–60% for runoff volume, 52%–76% TP (loading), and 55%–74% TN (loading) (VADEQ 2013). The grass strip's seasonal morphology and effectiveness are different between years due to variations in environmental conditions and/or maintenance, which leads to different pollutant reductions associated with the adoption of the dry swale practice. Models such as Bayesian networks can integrate expert knowledge developed for BMP maintenance activities based upon remotely sensed data—leading to a reduction in predicted effectiveness. Tracking individual BMPs distributed within a watershed can be tedious if performed without the benefit of remote sensing technologies. Integrated tools are needed to simultaneously track changes in several BMPs throughout the watershed of interest and changes benchmarked against assumed maintenance activities. Remotely sensed monitoring of BMPs postimplementation using high-resolution satellite imagery may be applied to track the maintenance and performance of BMPs and GIs.

Enhanced Approach to TMDL by Modeling BMPS and GI Practices in the Development Phase

As alluded throughout the paper, a reordering of TMDL implementation to development steps is necessary to facilitate more meaningful stakeholder engagement and understand likely implementation outcomes. Fig. 2 compares the traditional modeling approach [Fig. 2(a)] in TMDL development and implementation planning with a more desirable enhanced modeling approach [Fig. 2(b)]. With careful consideration of BMP and GI modeling tools (including optimization) during TMDL development, better holistic watershed management [Fig. 2(b)] can be achieved compared to traditional TMDL approaches [Fig. 2(a)]. The traditional approach [Fig. 2(a)] assumes that the implementation of BMPs happens outside of the TMDL development process. However, in the enhanced approach [Fig. 2(b)], BMPs and GI practices are planned and implemented along with the TMDL.

For better illustration, a traditional TMDL life cycle is shown in Fig. 3(a), in which a TMDL model is first developed (i.e., first circle and computing icon), followed by load reduction allocations developed by studying alternate scenarios. The level of stakeholder engagement in this approach is limited to public comment periods where a full understanding of the implementation of the TMDL may not be appreciated. This has subsequent ramifications, including potential lack of trust in the approach in certain cases

Fig. 1. Satellite image of the same grass swale in April of (a) 2014; and (b) 2013. Dry swales need a pretreatment area (e.g., grassed filter strips) to catch coarse sediment and prevent clogging of the engineered soil mix. Fig. 1(b) shows signs of degradation of the filter strip, pointing to the degradation of BMP efficacy. (Images © Google Earth Pro.)

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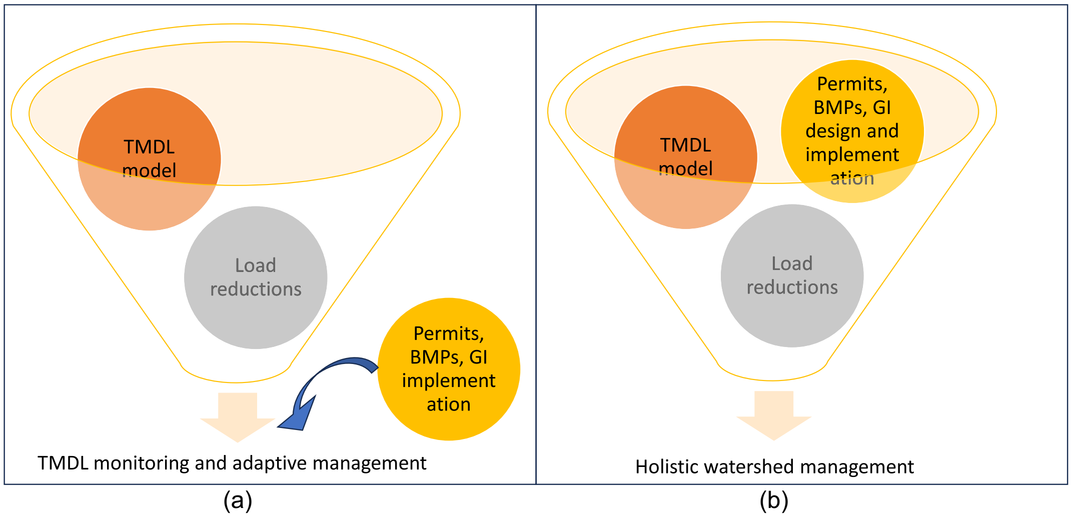

Fig. 2. (a) Traditional versus (b) enhanced modeling approach to TMDL development and implementation.

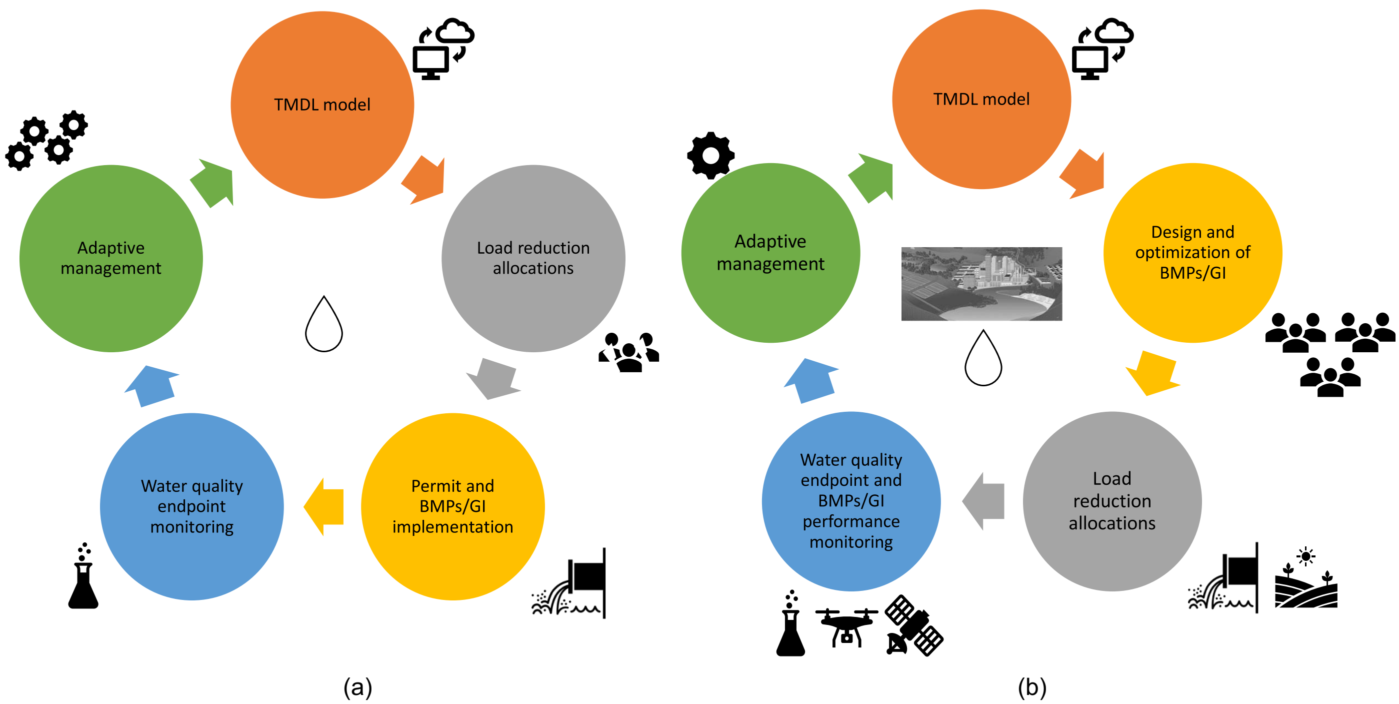

Fig. 3. (a) Traditional versus (b) enhanced modeling approach to TMDL development and implementation in a life cycle diagram.

(i.e., second circle and icon showing minimal stakeholder engagement). After TMDL approval, BMP and GI practice implementation may be carried out with limited information on their likely outcomes (focused primarily on point sources as shown by the third circle and storm sewer outfall icon). Water quality endpoints are then monitored to study the performance of TMDL implementation (i.e., fourth circle and Erlenmeyer flask icon), and an adaptive management approach is used with limited control over many uncertain variables (i.e., fifth circle and multiple turning gears icon).

On the other hand, with a single reordering within the TMDL life cycle [Fig. 3(b)], and with the use of appropriate modeling tools such as SWMM, CLASIC, SUSTAIN, and L-GrID. substantial benefits can potentially be realized by reordering the yellow and gray circles. In this approach, by coupling the simulation and even optimization of BMPs and GI practices with realistic load reductions achievable in the modeling process, the TMDL model can perform double duty as a decision support tool. Stakeholders can be more meaningfully engaged with realistic expectations of the expected performance of the TMDL implementation (i.e., second circle and strong stakeholder engagement icon). Both load and waste load reductions can be projected with expected outcomes shown in the modeling (i.e., third circle and storm sewer outfall and agricultural field icons). Since there are expected performance targets associated with the BMPs and GIs being implemented, along with water quality endpoints, BMP and GI practice performance can be monitored using emerging technologies such as

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remote sensing and Internet-of-things based sensor networks (i.e., fourth circle and Erlenmeyer flask, drone, and satellite icons). Compared with the traditional approach, the enhanced approach is likely to be more effective, as there are now priori expectations to track performance in the TMDL implementation. In addition, uncertainty in the implementation outcomes can be better quantified so that the adaptive management can focus on facilitating the advances that would help fill knowledge gaps. The impact from more uncertain variables can be mitigated so that more sound management decisions can be made (i.e., fifth circle and single gear icon).

Summary and Conclusions

This paper emanating from Frost et al. (2022) summarizes state-of-the-practice uses of enhanced modeling approaches specifically simulating BMPs and GI practices in TMDL implementation. The use of advanced models during the TMDL development and implementation provides an added benefit for estimating and tracking watershed-level BMP and GI practice performance facilitating adaptive management of the TMDL process. The decision-support aspects of the modeling approach can be substantially enhanced using the models discussed in this paper to support TMDL implementation.

An extensive review of literature is presented on advances in BMP and GI practice modeling for TMDL implementation. Two specific GI model resources are reviewed and presented: (1) USEPA's GI Modeling Toolkit, with a focus on the CLASIC tool as an example, and (2) the L-GrlD model in detail. These modeling tools can facilitate the implementation of BMPs and GI with flexibility to promote stakeholder engagement and the use of DSSs to advance TMDL implementation practices. Advances in estimating BMP and GI model uncertainties are also discussed as it is an inseparable modeling issue.

Advances in TMDL implementation are presented through alternate enhanced strategies (hybrid/streamlining) for cost-effective implementation while broadening the scope of TMDLs to combine with other related watershed management efforts for greater synergy. Optimization of TMDL implementation measures (BMPs and GI), including engaging stakeholders and managing multiple cobenefits and diverse costs, are discussed as those are crucial steps in the successful implementation of TMDLs. Advances in emerging technologies such as advanced modeling and remote sensing are discussed, the latter with an example focusing on the long-term efficacy of the implementation measures.

Finally, an advanced holistic approach to TMDL development and implementation is proposed and demonstrated with conceptual diagrams. In this approach, by coupling the simulations, even optimization, of BMPs and GI practices with realistic load reductions achievable in the TMDL modeling process (step), the models serve as a decision-support tool doubling up its benefits. Stakeholders can be more meaningfully engaged with realistic expectations about the anticipated performance of the implemented TMDL. Both load and waste load reductions can be projected with the expected outcomes demonstrated through modeling.

In conclusion, the use of models and modeling tools such as those reviewed here can not only help quantify anticipated water quality improvement from pollutant load reductions but also serve to keep the TMDL load reductions reasonable within the long-term performance of standard BMP and GI technologies. These advanced models can help evaluate spatial and temporal responses from watershed-level BMP and/or GI implementation to achieve TMDL endpoints and water quality targets. In addition, the sensitivity of the TMDL endpoint to the anticipated effectiveness of the different BMPs and GI practices can be analyzed through a sensitivity analysis using the model. This type of analysis is typically cost-effective and beneficial in evaluating different types and placement strategies of BMPs and GI practices within the watershed for a successful TMDL implementation. The adaptive TMDL implementation process through the performance monitoring of BMPs and GI practices provides a measure of reasonable assurance, given the uncertainties that exist in any modeling tools used during TMDL development, and an effective mechanism for developing public support for TMDL implementation (Zhang 2012). A thorough evaluation of existing models and tools is still needed to improve their applicability with respect to various geographic, hydrologic, environmental, and socio-economic conditions (Zhang and Chui 2018).

Modeling tools, particularly those that can explicitly simulate BMPs, and GI can be useful tools for linking with TMDL implementation planning. It is expected that the incorporation of climate change into TMDL development and implementation planning will become standard practice in the future. Water management professionals would be wise to adopt more innovative approaches to assessing TMDL implementation and the effectiveness of BMPs and GI practices under projected climate scenarios and related management responses—leading to more holistic, long-term watershed management planning.

Data Availability Statement

All data, models, and code generated or used during the study appear in the published article.

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