Green infrastructure and its catchment-scale effects: an emerging science

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Urbanizing environments alter the hydrological cycle by redirecting stream networks for stormwater and wastewater transmission and increasing impermeable surfaces. These changes thereby accelerate the runoff of water and its constituents following precipitation events, alter evapotranspiration processes, and indirectly modify surface precipitation patterns. Green infrastructure, or low-impact development (LID), can be used as a standalone practice or in concert with gray infrastructure (traditional stormwater management approaches) for cost-efficient, decentralized stormwater management. The growth in LID over the past several decades has resulted in a concomitant increase in research evaluating LID efficiency and effectiveness, but mostly at localized scales. There is a clear research need to quantify how LID practices affect water quantity (i.e., runoff and discharge) and quality at the scale of catchments. In this overview, we present the state of the science of LID research at the local scale, considerations for scaling this research to catchments, recent advances and findings in scaling the effects of LID practices on water quality and quantity at catchment scales, and the use of models as novel tools for these scaling efforts. © 2017 The Authors. WIREs Water published by Wiley Periodicals, Inc.

INTRODUCTION

Urban and suburban growth modifies the water cycle by expanding impermeable surfaces, changing the spatial patterns of stream networks (e.g., via ditching, culverting, channelizing), and rerouting original water flow paths for stormwater and wastewater treatment.¹,² These modifications to the hydrological cycle create a network of engineered and natural hydrological flow paths,³ often resulting in decreased capacity for water storage on the landscape, increased potential for rapid postevent runoff and ‘flashy’ hydrological systems, and decreased precipitation or snowmelt infiltration into the soil system. Such changes may therefore compromise a catchment’s intrinsic capacity to process water inputs (via precipitation, snowmelt, and runoff) and lead to adversarial effects, such as flooding, erosion, and high-concentration pollutant (e.g., nutrients⁴, metals, and other pollutants) delivery.⁵

Green Infrastructure (GI), hereafter referred to as Low-Impact Development (LID), includes decentralized (i.e., distributed throughout the landscape) approaches aimed at sustainable urban stormwater management. LID, a term most often used in North America and New Zealand, is also discussed globally as sensitive urban design (WSUD), integrated urban water management (IUWM), sustainable urban drainage systems (SUDS), and urban best management practices (BMPs), among other terminology.⁶
The goal of LID is to use plants, soils, and landscape design to control nonpoint sources of water and materials in built environments (Figure 1; Table 1), an approach that has become increasingly popular across communities worldwide as a cost-effective way of managing stormwater pollution (e.g., runoff volumes and nutrient pollution) in urbanizing landscapes. For example, many municipalities across the mid-Atlantic region of the United States (US) have a goal that 10–20% of the landscape drains through LID by 2030. The increased interest in LID practices has led to a corresponding ascent in LID-related...
research. This is evidenced by a number of recent reviews synthesizing these studies9–12 and includes research on the potential societal benefits gained from the use of LID.13

A goal of LID is to promote catchment and stormwater resilience, restore predevelopment flow regimes, and increase watershed, or catchment, capacitance. Catchment capacitance is the extent to which rainwater, snowmelt, and runoff onto and in transport from impervious surfaces to previous areas can be infiltrated, stored, and released as catchment baseflow or evapotranspiration.14 The idea arises from the urban variable source area (UVSA) concept,14,15 a specialized form of variable source area hydrology16–18 which describes locations in a catchment that rapidly saturate and produce runoff following precipitation or snowmelt events. Ultimately, catchment capacitance is a function of the built environment and the underlying natural physiographical conditions of the catchment, such as soils, geology, climate, geomorphology, and vegetation. A key objective of increasing catchment capacity using LID is to enhance chemical transformations and storage of pollutants via longer soil residence times to attenuate entrained constituent and particulate matter transport to a stream, river, or other water body.

Within the past decade, numerous studies have been published on the local-scale (i.e., plot, parcel, small drainage areas <0.1 km²) effects of LID practices. Several literature reviews have synthesized these local-scale studies, summarizing the water quantity and water quality impacts of LID in various forms, such as rain gardens, bioretention and vegetation swales, permeable pavements, green roofs, and downspout (rooftop) disconnections.9–12 Additional reviews focus on literature associated with local-scale model simulations of the hydrological and water quality effects of LID approaches.19,20 These syntheses explicitly highlight the emerging scientific need to develop research that scales the effects of LID practices from those measured and modeled at local scales to catchments of multiple spatial scales9,11 (Figure 2). This is of considerable importance for managing catchments for targeted outcomes, such as maintenance of baseflow or minimizing peak flow conditions, and to reduce rapid pulses of pollutants to streams. However, few studies have actually done this, either via measured data or modeling, and such work is particularly needed in complex urbanizing catchments that drain a variety of land cover types, i.e., mixed land cover catchments that include urbanizing areas, which are not addressed in most LID research.

The extent to which LID practices effectively mediate downstream water quantity and quality needs to be assessed for sustainable catchment management. Furthermore, additional related research questions remain unanswered. For example, what is the best spatial configuration of GI practices in a catchment? What are the cumulative impacts of localized GI practices on downstream hydrology (e.g., peak flows, baseflow) and pollutant fluxes in both predominately urban/suburban and mixed land cover catchments? What is the extent to which these effects perpetuate at nested catchment scales? What factors (e.g., land cover; geology; soils; climate; anthropogenic inputs, such as leakage from water supply or waste disposal systems; or alterations to the stream network) contribute to variations in this scaling response?

To begin answering questions about scaling LID practices to catchments, the focus of our non-technical overview is to: (1) synthesize key findings from recent literature reviews on the local-scale effects of LID on water quantity, water quality, and groundwater storage processes; (2) explore the concept of scaling local-scale studies to assess LID at the scale of catchments (e.g., 0.1 km² to 1000 km²); (3) discuss recently published research at the vanguard of catchment-scale water quantity and quality analysis of LID practices; and (4) present catchment modeling as a primary tool for scaling LID practices, including the key challenges and considerations for making these future advances.

STATE OF THE SCIENCE: SYNTHESIS OF LOCAL-SCALE STUDIES

Within the past decade, multiple papers have been published synthesizing the effects of LID practices at
local scales, focusing on different LID practices and their effectiveness for a variety of endpoints (e.g., improving water quality, increasing soil infiltration capacity). We recognize that such literature reviews may not represent the full compendium of existing studies and a complete range of water quality constituents or pollutants of concern, water quality processes, or LID practices. However, the goal of this brief ‘state of the science’ discussion is to focus on emergent key concepts from previous reviews, which may target specific water quality or hydrological impacts (or LID practices). These emergent concepts provide a foundation to discuss scaling up local-scale LID studies to catchments. We divide the discussion into findings extracted from (1) laboratory and field study reviews and (2) modeling reviews.

**Reviews of Laboratory and Local-Scale Field Studies: Key Findings**

Highlights from recent literature reviews about how LID practices affect local-scale water quantity and quality can be synthesized into three central concepts: (1) the efficiency of different LID practices varies widely across sites; (2) bioretention systems, green roofs, and permeable pavements (Figure 1; Table 1) are promising approaches for reductions in peak flow and runoff volume but exhibit varied potential for the attenuation of pollutant delivery to a stream or other surface water and (3) the efficacy of total nitrogen retention is difficult to quantify and depends on the specific LID practice that is implemented.

It is important to tailor LID to fit site-specific needs. The heterogeneous response to different LID practices is dependent on the site-specific physical and chemical conditions of the landscape. For example, the variability in stream baseflow responses to urbanization and alternative stormwater control practices (i.e., LID activities) is associated with physiographical conditions (e.g., soil, climate, topography), human-mediated factors (such as leakage from water supply and stormwater pipes, infiltration of shallow groundwater into stormwater networks, and irrigation), the spatial distribution of impervious surfaces across the landscape, and uncertainties in assessment and measurement methodologies. However, by accounting for these factors in LID implementation, LID approaches offer effective methods for stormwater management—as standalone approaches or combined with traditional stormwater management approaches.

Bioretention systems hold considerable promise for meeting the goals of reducing peak flows, yet exhibit variable responses in their capacity to mediate water quality. Bioretention systems (also called bioretention cells) are small areas (<0.02 km²) that receive runoff from upgradient impervious areas and are made of materials to increase soil infiltration and decrease rapid runoff. While robust in their ability to attenuate the transport of precipitation, runoff, and snowmelt to streams and other water bodies, bioretention systems exhibit limited capacity to retain nitrate-nitrogen and phosphorus. However, they can be efficient sinks for the metals, solids, pathogens, and petroleum hydrocarbons transported via stormwater flows. Furthermore, bioretention approaches can affect aquatic ecology and ecosystem services by buffering thermal energy increases that can lead to cold water fishery declines and increasing biodiversity compared to the typical lawn and garden beds implemented in urban areas.

Green roofs and permeable pavements exhibit considerable potential for minimizing rapid runoff and peak flows, although they may be less effective for solute and particulate matter retention. Green roofs, rooftops covered with vegetation that have the capacity to enhance infiltration and evapotranspiration processes, retain between 20 and 100% of rainfall inputs and typically exhibit diminishing returns as the rainfall amounts increase. The percentage of rainfall retention by green roofs varies based on the thickness of the roof’s soil substrate and its water storage capacity, other characteristics of the green roof (e.g., age, vegetation cover and type, slope), and the size and distribution of rainfall events. The retention capacity of green roofs for nutrients and metals also varies, and accumulation of both where green roofs are implemented could pose risks to water quality during high rainfall-runoff periods. Permeable pavements, porous material that represents an alternative to conventional pavements and allows for slow water infiltration into soils, can reduce average runoff volumes by 50–93%, total suspended solids (TSS) and nutrients between 0 and 94%, and metals by 20–99%, and has also proven effective at reducing transport of motor oils via a variety of microbial activities to downstream waters.

Removal of total nitrogen, a particular concern in urbanizing systems due to its prevalence in stormwater from point and nonpoint sources, using LID practices has been measured across multiple studies; however, it is one of the most difficult LID impacts to evaluate. Furthermore, results estimating the efficiency of total nitrogen (TN) removal by bioretention and other approaches (permeable pavements, green roofs) compared across multiple studies are
Reviews of Local-Scale Modeling Studies: Key Findings

Models provide a means for simulating the effects of LID practices at multiple spatial scales. A review published in 2007 of 10 existing stormwater models that simulate the local-scale effects of LID practices suggests that each of the reviewed models handles runoff generation and stormflow routing similarly by using conventional hydrological methods. However, the models vary in their capacity to quantify groundwater; incorporate specific LID practices; and apply different spatial and temporal resolutions of the model domain, input data, and processes. Furthermore, models used for LID practices typically do not have modules for specific contaminants. However, they can estimate responses of sediments, nutrients, metals, pathogens, and other contaminants by simulating generalized contaminant process modules, modeling a constituent or particulate-bound compound as another contaminant with similar behavior, or associating a particular contaminant with sediment transport processes or a different constituent (e.g., dissolved organic carbon) to which it typically binds.

A more recent synthesis in 2014 of 20 simulation modeling tools that incorporate LID practices for stormwater management identifies the Stormwater Management Model (SWMM) as one of the most accurate, yet one of the most complex, existing models for modeling stormwater runoff (quality and quantity) and the performance of LID practices. As part of the review, the authors call for numerous areas of research, such as development of model-driven decision support systems, integration of GIS and remote sensing into catchment-scale LID modeling, coupling of hydrological and atmospheric modeling for catchment-scale LID practices, and improvements to LID model optimization and uncertainty approaches. Furthermore, while many models are being updated to consider different types of LID practices, progress is needed with regard to modeling capacity to handle baseflow components of the run-off, surface–subsurface interactions, a wide range of contaminant fate and transport, links to ecological responses and calibration methods, and catchment-scale predictions.

CURRENT CHALLENGE: SCALING LOCAL LID TO CATCHMENT RESPONSES

What Do We Mean By ‘Scaling’?

As new studies emerge following the most recent literature reviews on the local-scale efficacy of LID approaches, questions remain about how to scale these practices to catchments. To answer these questions, an initial question needs to be asked: What do we mean by ‘scaling’ in the sense of LID practices? We define the baseline spatial scale of a study as the domain, and the inherent spatial heterogeneity, of the original measured or modeled data (e.g., plot, sub-catchment, catchment of size ‘x’; Figure 2). Here, ‘scaling’ is therefore considered to move beyond these original measured or modeled domains to answer research or management questions at broader spatial scales (e.g., multiscale catchments). Therefore, we discuss scaling as quantifying variations in the cumulative effects of LID practices on downstream waters, focusing largely on moving from plots to multiple nested catchment scales. Moving toward broader spatial scales may also require a change in the spatial resolution of the domain of interest as well, aggregating from heterogeneous parameters (e.g., soil hydraulic conductivity) and processes (e.g., nutrient uptake) to increasingly coarser-scale resolutions that necessarily require a level of spatial homogenization, and potentially the magnitude, of these characteristics (Figure 3). While not fully addressed here, scaling can also be considered in the temporal sense, using models to project the effects of LID practices beyond the measured data and with a focus on future variations in precipitation and temperature.

Scaling is a concept that has deep roots in ecology and catchment and hillslope hydrology literature. It is from this literature that we can consider how to most effectively quantify the effects of LID practices at the scale of catchments. Most scaling challenges have focused on aggregating complex and spatially heterogeneous processes at fine spatial scales.
to broader ecosystem or catchment scales (also
termed ‘upscaling’). However, sometimes, the inverse
is true, i.e., the challenge is moving from conceptual
understandings of system processes to more sophisti-
cated mathematical descriptions. Some of these scal-
ing challenges have begun to be addressed. For
example, Cadenasso et al.32 championed a concep-
tual framework to downscale generalities about bio-
complexity in ecological systems to
finer levels of
understanding about spatial heterogeneities, organi-
zational connectivity, and system history. Dent
et al.33 used a conceptual hierarchical approach,
moving from particle scales to stream segments, to
link physical aquatic exchange processes and nutrient
dynamics across multiple spatial scales.

In catchment hydrology, conceptual models for
scaling have promoted quantifying dominant pro-
cesses and similarity measures in a system based on
extensive system-specific knowledge of processes at a
fine spatial scale.34–36 Scaling to a broader spatial
domain may therefore involve either applying equa-
tions or modified parameters (or both) to synthesize
the heterogeneous information at a finer spatial scale
to a coarser spatial scale.37 For example, early work
by Wood et al.30 proposed the concept of representa-
tive elementary areas (REAs), areas with characteris-
tic lengths above which the variance in hydrological
responses (e.g., streamflow) and properties relating to
hydrological responses (e.g., soil hydraulic proper-
ties) diminish with increasing scale. REAs can there-
fore be considered a minimum scale within which the
statistical distribution of physical properties, such as
saturated hydraulic conductivity, represents the full
area of study.38 Refsgaard and others updated the
REA concept by replacing minimum areas with a
minimum scale (i.e., the representative elementary
scale, or RES) at which a model has predictive
capability—meaning the spatial extent, or spatial
domain, at which an acceptable level of uncertainty
in the model output is reached (Figure 4).39,40 To
scale beyond the REA’s or RES’ various upscaling
approaches for multiple parameters (e.g., soil thick-
ness), different methods can be used (see Models as
Critical Scaling Tools for Future Research). While
challenges remain in conceptualizing, refining, and
implementing these ideas, science continues to move
toward providing foundations for scaling upon
which the LID research and management community
can build.

The Emergence of Catchment-Scale LID
Studies

Scaling LID practices to catchments is an emerging
science. Research scientists and managers operate
under the hypothesis that local-scale LID practices

![Figure 3](https://example.com/figure3.png)

**Figure 3** The effect of the scale of a measurement or modeling unit on the magnitude of a flow path. The spatial resolution of the measurement or modeling domain may coarsen when scaling up, as demonstrated here by upscaling the representative magnitude of a single flow path of water. The flow path’s magnitude may decrease if the grain/pixel/scale of the observations increases (from left to right). This is because the representation of fine-scale connectivity along the flow path is minimized when upscaling, which thereby dampens the flow path signal. (Reprinted with permission from Ref.25 Copyright 2011 Elsevier)

![Figure 4](https://example.com/figure4.png)

**Figure 4** Demonstration of the representative elementary scale (RES) concept. The example shows a preidentified acceptable level of uncertainty for modeled or estimated streamflow (y-axis) that is matched to the spatial extent of a model domain (the spatial scale of the model). The RES is the minimum spatial scale at which an acceptable level of uncertainty in modeled or estimated output is reached. (After Refsgaard et al.39)
will affect cumulative catchment-scale flow regimes and water quality and improve the ecological integrity of streams. However, current knowledge on the efficacy of LID practices at catchment scales is relatively uncertain and remains a fertile area of research. This is beginning to change as catchment-scale LID studies have gained momentum in the past several years. However, questions remain regarding the type, extent, or number of LID practices needed to return a catchment to its predevelopment flow regimes—and the state of the science is youthful enough that cogent evidence to answer these questions is limited.

Results from the burgeoning area of catchment-scale LID studies indicate that potential exists to regulate a catchment’s baseflow, peak flow, and water quality conditions using LID—but to varying extents. For example, Yang et al. compared measured hydrological and water quality data between two suburbanized catchments (55 km² and 89.4 km²) near Houston, Texas, US; one catchment had LID integrated into the community design, including infiltration-based drainage basins, preservation of high soil infiltration areas for open spaces, bioswales, and porous pavements, and the other catchment was a control with traditional stormwater management practices. The LID design resulted in runoff volumes that were lower compared to non-LID management and demonstrated LID’s capacity to improve the catchment’s water quality, specifically by decreasing catchment export of nitrate, ammonia, and total phosphorus. Pennino and others used measured hydrological and water quality data in multiple catchments (0.5–34.3 km²) in the mid-Atlantic coastal plain of the US and corroborated that stormwater LID—including rain gardens, detention ponds, bioswales, and green roofs—lowers the magnitude, frequency, and variability of stormwater runoff and decreases nitrate and TN export compared to catchments with limited LID implementations. In fact, when controlling for catchment size and percent impervious cover, catchments with higher percentages of LID implementation were found to have less flashy hydrological responses to storm events. In a separate study, Bhaskar et al. measured the hydrological effects of 73 LID implementations (including bioretention, dry wells, and dry swales) that promoted infiltration directly downgradient of impervious surfaces during the urbanization of a 1.1 km² catchment. The authors found that the LID attenuated the seasonality of baseflow and resulted in gradual stormflow recessions. However, the LID practices also increased total streamflow volumes, possibly resulting from the removal of the evapotranspiration capacity of the catchment in favor of increased water infiltration.

Recent studies also provide evidence that the placement of LID practices, as well as the type of LID and type and extent of urban development within the catchment, impacts cumulative catchment-scale hydrological effects. Distributed stormwater best management practices, or BMPs (i.e., those dispersed throughout a watershed), can (1) increase baseflow and the precipitation threshold required in a catchment for a rainfall-runoff response and (2) decrease runoff volumes from an extreme (1000-year) precipitation event compared to centralized stormwater BMPs (i.e., those directly adjacent to the source of runoff). For example, Avellaneda et al. modeled the effects of retrofitting a small 0.12 km² residential catchment with 16 street-side bioretention cells, 7 rain gardens, and 37 rain gardens and used SWMM to simulate water balances. The study results suggested that retrofitting with LID increased evaporation (1.4%) and infiltration (7.6%) and reduced surface runoff (9.0%) and discharges with return periods of 0.5, 1, 2, and 5 years, by an average of 29%. Moreover, two recent studies in the Midwestern US demonstrated runoff reduction using modeling scenarios that retrofit two urbanized catchments (40 and 70 km²) with rain barrel/cistern and porous pavements and the effects of various implementations of LID practices (porous pavement, rain barrels, and rain gardens; 87.6 km² catchment). Results from these studies suggested reduced average annual catchment runoff and flood events, as well as pollutant loads. Furthermore, the percent reduction in catchment runoff increased linearly, from 25 to 100% implementation levels of LID across the watershed, based on locations that met criteria for potential LID placement. Finally, a study by Gagran et al. used the Model of Urban Stormwater Improvement Conceptualization (MUSIC) in a 1.92 km² urbanizing watershed in Southeastern US and found that a mandatory load reductions of TSS (by 85%) and TP (by 70%) would require the diversion of 70% of the contributing areas to existing urban stormwater control measures to retrofitted bioretention basins.

Distributed BMPs, or LID practices, can functionally mimic a hydrological landscape of preurbanized conditions. However, the configuration of their implementation with respect to directly connected impervious areas (DCIAs) is important. For example, Fry and Maxwell used a physically based hydrological model and found that distributing LID approaches in ‘spatially sensitive areas’—such as along preferential flow paths or street sides—
improves the efficiency of the LID, particularly for minimizing rapid runoff responses to intense storm events. Shuster and Rhea\textsuperscript{54} measured stream discharge 3 years before and after retrofitting a small suburban catchment (1.8 km\textsuperscript{2}) with rain gardens and rain barrels and observed small yet statistically significant decreases in runoff volumes. However, hydrological storage and transport responses in this catchment may have been greater if large portions of impervious area in the catchment were not connected to stormwater drains.\textsuperscript{55} Furthermore, results from before and after LID implementation measurements by Jarden et al. indicated that including street runoff in stormwater LID retrofits (here, street-connected rain barrel, rain gardens, and bioretention cells) of previously built areas could substantially reduce stormwater runoff volumes.\textsuperscript{56} However, the study concluded that even minimal differences in LID design can have disproportionately large impacts on this overall benefit. In fact, reductions in stormwater catchment-scale runoff with LID practices may be most advantageous if placed near the catchment outlet.\textsuperscript{57}

Models as Critical Scaling Tools for Future Research
Models that integrate and assimilate novel measured data will play a central role in projecting how LID practices scale from plots or very small drainage areas to catchments. As novel and ‘big’ data, i.e., large compilations and time series of spatial (e.g., remote sensing, satellite, GIS) and other measured data (e.g., from sensors and tracer experiments), become increasingly available, the integration of these data with models for scaling LID practices will be a key research direction. The evolution of big data can, for example, provide models with information for scaling the cumulative catchment impacts of LID practices and can improve hypotheses testing and trend predictions. However, this advancement is also leading to a rethinking of model development and refinement in catchment hydrology and biogeochemistry because the new, widely available data may not directly match the types and structure of data inputs, parameters, and processes needed for existing models.

As scientists and water resources managers begin integrating models with novel data, the underlying key question remains: How can we use models to understand the effects of LID practices on multi-scale catchments—and in catchments with mixed land cover? Mixed land cover catchments, i.e., ones in which urban or suburban land cover is just one of multiple components, present a challenge for explicitly modeling the effects of LID implementation. This is particularly true because the cumulative interacting effects of water storage, transport, and biogeochemical processes occurring within other land cover and use types can render management that is explicitly targeted to limit the negative outcomes from urbanization ineffective. Furthermore, existing models that explicitly integrate LID practices focus solely on urban systems. For example, several modeling tools, such as SWMM,\textsuperscript{58} the Green Infrastructure Flexible Model (GIFMod),\textsuperscript{59} the Long-Term Hydrologic Impact Assessment-Low Impact Development (LTHIA-LID) model,\textsuperscript{60,61} MUSIC,\textsuperscript{62,63} the National Stormwater Calculator,\textsuperscript{58} and RECARGA\textsuperscript{64} to name a few, quantify the local, sewershed, or small catchment effects of LID practices within urban or suburban landscapes. To address this urban-only challenge, research is advancing toward recently developed LID modules or model parameter representations within hydro-ecological models, such as the Regional Hydro-Ecological Simulation System (RHESSys)\textsuperscript{65,66} and Visualizing Ecosystem Land Management Assessments (VELMA)\textsuperscript{67,68} (Robert McKane, personal communication, US EPA, 2017), to simulate the cumulative effects of LID in urban areas along with other land cover types at the catchment scale.

Given the challenges of the application of models to upscale from plot to multiple catchment scales, several key considerations are required, including (1) the type of model that will be used, (2) the spatial representation of parameters and processes in the model, (3) the domain of the measurement and modeling units, (4) scaling fine-scale variability in parameters and processes to coarser spatial scales, (5) the placement of LID practices in the catchment, and (6) model uncertainty. Furthermore, most existing models that can simulate LID practices focus primarily on local or small catchment domains. Therefore, innovative approaches are needed, such as integrating output from models with LID modules as input to catchment-scale models that handle multiple land cover types (e.g., a nested modeling approach)\textsuperscript{69} or coding an interaction between models so that a fine-scale LID model can communicate via forward or bilateral feedbacks with catchment-scale models.

Process-based models will continue to be refined as the primary type of model used to quantify the dynamic spatial and temporal responses of catchments to LID practices. Process-based models simulate catchment-scale hydrological and biogeochemical processes, with outputs that include streamflow and water quality concentrations and loadings to streams.
or other water bodies. In contrast, empirical models rely on observations to develop conceptual or statistical relationships between predictor and response variables. While process-based models afford a certain level of reality regarding the dynamic nature of catchment processes, balancing model fidelity, complexity, and resources (labor, money, computational time) in selecting a model is important. Model fidelity can be characterized as the degree to which a model faithfully represents the processes and attributes of the modeled system (e.g., a catchment), and model complexity is the number of parameters, variables, or fluxes considered in the model and the degree to which the physical processes of the system are characterized. There is an important compromise between fidelity and resources: as one increases, so does the other.

For models to be effective at upscaling LID practices, consideration must be given to how variations in parameters and processes are represented spatially across the landscape. In some systems, these variations may be limited, e.g., the same physics could be used to represent processes at each spatial scale. Often, however, fitted model parameters and processes can vary widely across spatial scales. A particular challenge for LID is how the implementation is discretized (i.e., subdivided and represented as spatial elements), both on the ground and within a model—such as separating DCIAs from the total impervious area and incorporating buffers between runoff generating areas and DCIAs. These effects could be explicitly represented or parameters within a model could be adjusted to indirectly reflect different LID configurations.

Process-based models that represent the effects of LID practices may range from spatially explicit, in which parameters and processes vary across the catchment based on the spatial resolution of the model, to spatially lumped, whereby all parameters and processes are considered similar at the catchment scale. The spatial representation of LID practices may also be informed by both the spatial resolution of measurements (e.g., individual soil moisture retention measurements compared to those of US Soil Survey Geographic Database (SSURGO) spatial data) and the management questions. For example, management questions related to the amount (e.g., a percentage of the catchment) of LID required to reduce peak flow volumes may be best served by using a spatially lumped process-based model. However, if the goal is to find the lowest cost-to-benefit ratio by optimizing the placement and distribution of LID in a catchment for a targeted management outcome (e.g., a return to predevelopment baseflow regime), a spatially explicit process-based model may be required.

A key consideration for scaling LID practices from local measurements to catchments is the domain of the LID implementation (e.g., plot-scale) and that of which the model is scaling to (e.g., multiple nested catchments). Furthermore, what is the effect of the scale of measurement or modeling unit on the accuracy of the upscaling? For example, as the scale of the measurement or modeling unit coarsens (plot to suburban neighborhood), the magnitude of the process, such as a flow path to the stream, may appear more attenuated (Figure 3).

Regardless of the domain of the initial measurement or modeling unit, the challenge is selecting how to most accurately parameterize the aggregate effects of subgrid heterogeneity (the variability within a model grid cell or measurement unit) to grid-averaged or model simulation unit-averaged values. This has begun to be addressed for catchment-scale models. We can also learn from recent advances in the land surface model community. For example, multiple model parameterizations at different scales may be favored in place of aggregation, particularly when parameters do not vary linearly as they are upcaled. Properties may be scaled up using numerical methods or aggregation may be based on an explicit upscaling approach via the use of scaling operators, e.g., the arithmetic, harmonic, or geometric means of parameters at a finer spatial resolution. These operators can assist in scaling parameters to a fine spatial scale (such as heterogeneous elevation or soil characteristics) to a coarser spatial scale in order to discretize a model to best characterize dominant catchment hydrological processes. Catchment models may also use empirical relationships, such as Horton’s scaling laws that scale small streams to river networks, to upscale the variability in measured data to coarser spatial scales.

A final primary consideration for upscaling LID practices via models is the research or management target germane to the LID implementation, which thereby affects the placement of LID practices in the catchment. For example, LID practices are often implemented to restore flow regimes to their predevelopment conditions to the possible extent, aiming toward environmental flows that support the biotic integrity of the stream. While we currently lack studies that translate model hydrological outputs to metrics related to ecological and biological outcomes, research is beginning to reveal that a focus on the appropriate placement of LID practices can be one of the most important factors in their success. For example, riparian zone processes could potentially
mask the signal of water transported from the hillslope to the stream, \(^{79}\) i.e., a path through which water emanating from LID areas in the catchment may travel. Therefore, LID implementation may be most needed where an active riparian zone is absent. This underscores the need to first consider the research or management target (e.g., minimizing peak flows for the biotic integrity of the stream) and then spatially optimize the implementation of LID practices across the catchment to meet that objective. \(^{41}\) Novel catchment modeling approaches are evolving to do just that, including the use of multibjective evolutionary algorithms that integrate with simulation models to optimize the distribution of BMPs for particular management goals. \(^{80,81}\)

**Uncertainty in Upscaling**

Water and land resource managers are continually challenged by a need for uncertainty estimates that can be translated into informed decision making. \(^{82}\) This is particularly true when implementation of LID targets a specific management goal, such as minimizing peak streamflow conditions. Uncertainties in the model inputs (e.g., initial and boundary conditions, assumptions and global parameters, or constants used in model equations, as well as measurement errors and the inherent uncertainty or randomness of the system) and the model structure (e.g., the model equations) can propagate through the LID upscaling process to catchments, resulting in uncertainty in the model outputs. This uncertainty therefore needs to be quantified and communicated to the target audience (e.g., managers and decision makers).

Many tools exist for quantifying model uncertainties, although most fall within approximation and sampling methods. \(^{83}\) Approximation methods propagate one or more statistical moments (e.g., mean, variance) of input data to quantify and characterize model output uncertainty. Sampling methods propagate the rigorous sampling of input data distributions to characterize model output distributions. Regardless of the selected methods, scaling heterogeneous data to coarser resolutions or spatial extents may involve an analysis of the uncertainty associated with this upscaling process. For example, Crow et al. \(^{84}\) tested methods of upscaling field-scale moisture measurements using modeling approaches. They conducted parameter uncertainty analyses associated with upscaled model parameters (e.g., surface albedo, saturated soil hydraulic conductivity, pore size distribution) by varying these parameters by factors of 0.80 and 1.20 to compare the normalized root mean squared error of model simulations. Their work showed that the upscaling strategy was most robust when merging field-scale observations and modeling together rather than using observations or modeling in isolation.

Communicating uncertainties in model output has decidedly moved toward quantifying and representing them as probability distributions. \(^{82}\) However, this can often be challenging, particularly when multiple uncertainties need to be considered. Probabilistic models, those that incorporate uncertainty at all stages of the modeling process (e.g., Mäntyniemi et al. \(^{85}\)), can handle most uncertainties well. This becomes more difficult with the use of deterministic catchment-scale models, i.e., those that do not integrate system randomness and produce the same output provided the same model inputs or initial conditions. Recent work suggests that the use of multiple models, i.e., ensemble modeling, that provides uncertainty boundaries on simulation outputs \(^{86}\) and approaches that increase model complexity or resolution stepwise to estimate uncertainties in deterministic models are highly applicable advances in this area. \(^{87,88}\)

**CONCLUSION**

Quantifying how LID practices mediate downstream water quality and quantity has become a critical science and management need. Based on previous literature reviews, it is clear that LID practices provide promising cost-effective measures for increasing a catchment’s capacity for infiltrating, storing, and releasing water in transit from impervious surfaces to pervious areas as baseflow and evapotranspiration. LID can also assist in meeting local-scale (i.e., plots/parcels, <0.1 km\(^2\) drainage areas) hydrological targets, such as reducing peak flow volumes and returning baseflow to predevelopment conditions. However, research results across multiple studies are mixed with regard to how different LID practices contribute to these responses and the local-scale effects of LID on water quality.

Scientific advances on how to upscale and evaluate local LID to catchments are emerging, providing both land managers and scientists novel insights. A common thread across these studies is that the location and spatial distribution of LID throughout the landscape contributes to the catchment-scale effectiveness of LID practices. This is particularly true when considering the location of LID with respect to that of impervious surfaces directly connected to stormwater discharges (DCIAs) and the type and extent of urban development in the catchment.

While research will continue to evolve, we argue that process-based models—in combination
with novel measurements and ‘big data’—will be primary tools for projecting how the local-scale effects of LID extend to multiscale catchments, particularly in catchments with additional land cover types (e.g., forest, agriculture). Future questions that need to be answered relate to the cumulative impacts of LID practices on downstream hydrology and water quality and the extent to which these effects perpetuate at nested catchment scales, what catchment factors (e.g., land cover, soils, anthropogenic activities) contribute to the variations in this response, and what the optimal spatial configurations for LID practices should be to ensure the targeted catchment-scale management outcome. To make these advances in quantifying the catchment-scale effects of LID practices using models, we recommend the following considerations: (1) the type of model needed for the specific management or research questions, (2) how parameters and processes in the model are spatially represented, (3) the domain of the measurement and modeling units, (4) ‘best’ approaches to upscale heterogeneity in parameters and processes, (5) the placement (location) and spatial configurations of LID practices in the catchment, and (6) best practices for handling model uncertainty given the targeted research or management goals.

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