

**Refining Measurements of Effective Impervious Area in
Urban Watersheds to Support Targeted Green
Infrastructure Retrofits**

**A Dissertation Presented for the
Doctor of Philosophy
Degree**

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DEDICATION

To the kind and generous people in my life that supported me through this work,
I thank you greatly. You know who you are and how much you mean to me.

To the natural world and beauty that gave me all the inspiration for this pursuit,
I am here for you.

To the rains that fall, the puddles that collect, the trickles that grow, the creeks that quietly meander,
the rivers that roar, the lakes that reflect, and the oceans that smell so sweet and make me feel small,
you are the guiding force that my life has organized around and I take delight every day in your ways.

To urban pathways, engineered by those past and present, that seek to corral the rain and channel it
away, through, under, alongside, and amongst us all, I hope we can find your highest form and build
within you resilience by softening your edges and shading you green.

And to the creeks I grew up with, the ones I have found and loved, those I have waded, walked along,
sat beside, and stared upon seeking answers in this work, this one is for you.

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ABSTRACT

Urban streams worldwide are degraded due to the intensity of development and activity in our most populated watersheds. These streams that flow amongst our most thriving cities have been recognized as valuable assets to restore for the natural and cultural values they provide. In order to undo the factors that have led to their decline, we must understand these drivers better so that we can create the most affordable and sustainable solutions possible. Impervious surfaces are widespread in urban areas and their role on shifting urban hydrology has been well-studied. While the total impervious area (TIA) can be quantified readily, the subset of the TIA that is more closely connected hydrologically to the stream network, the effective impervious area (EIA) is not as easy to quantify nor locate. This is due to complex urban drainage patterns, ambiguous runoff pathways, connective underground infrastructure that may not be easily inventoried, and influences on hydrology that are spatially and temporally variable. Recent advances in geospatial assessment capabilities and high-resolution data availability have shown promise in updating and improving the measurement of EIA. This is important because many studies have shown that it is the EIA that is a greater determinant of urban stream health as measured by a variety of different metrics. Additionally, restoration efforts to disconnect the EIA using distributed at-source stormwater control measures (SCM) have become popular in many cities. Therefore, the determination of EIA in quantity and location across a watershed can greatly assist these types of watershed management approaches that are attempting to build in green infrastructure (GI) within our cities to achieve a balance between effective stormwater management and natural hydrologic functioning. The sum of this work represents the effort to provide rapid assessment capabilities for urban watershed managers that can target efforts in GI placement so that the impacts of EIA can be diminished for the benefit of urban streams everywhere.

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INTRODUCTION

“Now the storm is over, the sky is clear, the last rolling thunder-wave is spent on the peaks, and where are the raindrops now – what has become of all the shining throng? In winged vapors rising some are already hastening back to the sky, some have gone into the plants, creeping through invisible doors into the round rooms of cells, some are locked in crystals of ice, some in rock crystals, some in porous moraines to keep their small springs flowing, some have gone journeying on in the rivers to join the larger raindrop of the ocean.” – John Muir, My First Summer in the Sierra

“We abuse land because we regard it as a commodity belonging to us. When we see land as a community to which we belong, we may begin to use it with love and respect.” – Aldo Leopold, A Sand County Almanac

Urbanization and human activity have a degrading impact on the hydrology, water quality, and ecology of waterways worldwide. The consistent suite of changes that rivers and streams undergo in response to development and intense activities in urbanized areas has been referred to as the “urban stream syndrome” (Walsh et al. 2005b). The symptoms of this syndrome include altered hydrologic regime and diminished water quality that influences urban geomorphology and ecologic potential. Degraded conditions in these natural resources are detrimental to society, especially considering worldwide urban populations are growing (Cohen 2003). Rivers and streams are important sources of ecosystem services that are not limited to that of the natural resources that they provide alone (Assessment 2005). These water bodies also offer difficult to measure services related to aesthetic qualities that provide cultural identity, recreational opportunities, and public health benefits as well as contributing to increased property value when they are in healthy conditions (Bin et al. 2016, Netusil et al. 2014). These ecosystem services are becoming more important in cities considering urban population trends.

Efforts to protect these ecosystem services in developing areas as well as to restore those in already urbanized watersheds have focused on altering not only how we develop land with strategies such as low impact development (LID) or water sensitive urban design (WSUD), but also the hydrologic infrastructure we use in cities for flood protection and stormwater management (Roy et al. 2008). Urban stormwater management typically operates under a “collect and convey” paradigm in which “grey” infrastructure moves urban runoff from storm events quickly to receiving water bodies by way of piped or impervious conveyance. This is often necessary due to the increased runoff in urban areas resulting from impervious surfaces. Recognition of the hydrologic effects of imperviousness and

stormwater “sewerage” by piping on receiving waterways predates the Clean Water Act of the United States (Leopold 1968). Increased regulations and public interest worldwide have motivated efforts to restore urban rivers and streams, and these have mostly focused on undoing the effects of hydromodification and infrastructure-related hydrologic shift. This is being accomplished with a combination of physical restoration in-stream and distributed restoration throughout urban watersheds with the incorporation of “green” infrastructure (Bernhardt and Palmer 2007).

Green infrastructure (GI) is the utilization of natural areas or engineered applications of stormwater control measures (SCM) that mimic natural hydrologic functions (Tzoulas et al. 2007). These practices attempt to reinstate more natural hydrologic functioning to an urban watershed by strategically employing infiltration of urban stormwater so that resulting runoff to urban streams better matches the delayed response that may have existed in pre-development conditions. The proliferation of impervious surfaces and stormwater pipes in urban watersheds results in increased surface runoff that moves quickly to receiving streams, often carrying increased pollutants related to human activity from surface washoff. Strategies to incorporate GI in cities alongside existing stormwater infrastructure to diminish surface runoff effects on urban streams has become increasingly popular today, but the practice needs more research in how effective it can be in addressing stream conditions when employed throughout an urban watershed (Roy et al. 2008). This approach reflects the opening quotes presented here as we shift towards stormwater management strategies that incorporate natural hydrologic functioning and pathways back into urban areas with intensely developed lands that strikes a balance between the natural and developed in attempts to meet both human and ecological hydrologic needs.

Applications of GI are more easily accomplished in new development using LID or WSUD strategies, but they have been increasingly adopted in already urbanized areas with stormwater retrofits (Ladson et al. 2006). These urban retrofits are typically expensive due to the high value and opportunity costs of land in the urban setting, and they have been typically employed to address localized flooding issues or opportunistically where public land is available (Bernhardt and Palmer 2007, Roy et al. 2008).

Watershed-wide efforts to incorporate GI into stormwater management have been undertaken but increased guidance as to how these distributed practices can be most effectively placed within the urban watershed is needed. The goal of this research is to address this need by utilizing hydrologic and geospatial analysis to better inform distributed restoration efforts so that limited funding and resources may be utilized for optimal improvement in urban stream conditions. The following overall research questions will be investigated throughout this document.

OVERALL RESEARCH QUESTION

Can green infrastructure practices be sited throughout urban watersheds using spatially-explicit metrics of impervious surface connectivity to effectively disconnect these impervious surfaces and diminish the effect they have on urban hydrologic regime shift? Can measures of impervious surface connectivity related to surface runoff be used to produce multi-objective management guidance for both urban runoff and water quality?

BACKGROUND LITERATURE REVIEW

Stream restoration initiatives, innovative SCMs, and GI practices have emerged to improve the quality of urban streams and protect those in developing areas. These efforts are largely due to the proliferation of impervious surfaces in urban watersheds and the associated hydrologic consequences. The negative relationship between the total impervious area (TIA) in a watershed and stream health has been strongly established for a number of different hydrologic, geomorphologic, chemical, and ecologic parameters as discussed by such studies as Paul and Meyer (2001), Brabec et al. (2002), Shuster et al. (2005), Walsh et al. (2005b), and Jacobson (2011). TIA is a popular measure of the degree of development in a watershed. Because it is related to land cover, it tends to grow with the intensity of development, and it is fairly simple to measure using geospatial analysis. When expressed as a percentage of the watershed area it can be easily compared between watersheds and is often utilized in hydrology models as a lumped parameter.

Initial investigations of the relationship between TIA and stream health displayed a consistent negative trend which was best described by the Impervious Cover Model (ICM) of Schueler (1994). Watersheds in diverse climates and geophysical settings exhibited declines in a variety of stream quality parameters with increasing imperviousness. The TIA of a watershed became useful as a comparative metric of the degree of urbanization as well as stream health through the ICM. Subsequently, land planners began to adopt it as a tool to guide more environmentally friendly development that sought to protect surrounding water resources (Arnold and Gibbons 1996). The existence of a threshold value of TIA in developing watersheds (before which stream health declines occurred) was noted in several studies (Arnold and Gibbons 1996, Booth and Jackson 1997, Brun and Band 2000, King et al. 2011, Klein 1979), but results were inconsistent and the sensitivity to TIA differed by stream health parameter. The noted variability in stream health among watersheds of identical TIA led to a revision of the ICM that

incorporated this range in conditions (Schueler et al. 2009). Thus, while the strength in the relationship between TIA and stream conditions is strong, it does not entirely capture the variability in the relationship between watershed land cover and urban stream degradation.

Flood mitigation in urban areas has been traditionally accomplished through artificial drainage networks that collect runoff derived from impervious surfaces and convey it rapidly along hard infrastructure towards receiving streams. This rapid conveyance by connected infrastructure increases the impacts of impervious surfaces and land-use associated pollutants on in-stream measures of runoff, geomorphology, water quality, and ecological function (Brabec et al. 2002). Thus, there is a large body of research that has identified the degree of connection of these impervious surfaces as a more important factor than their magnitude alone. Focus has been placed on impervious areas that exhibit connectivity to the stream network (known as Directly Connected Impervious Areas, DCIA, or Effective Impervious Areas, EIA) because they are most closely related to the physical drivers of change in urban hydrology (Walsh et al. 2005a). It has been noted that drainage connection and DCIA/EIA have a higher degree of influence on urban hydrology than TIA alone for quite some time (Hammer 1972, Leopold 1968, Miller 1978). However, widespread use of DCIA/EIA as a watershed characteristic has been hampered by the difficulty of accurate measurement which requires extensive monitoring or fine-scale knowledge of urban drainage networks and runoff flowpaths.

Research in urban hydrology has more recently focused on DCIA/EIA to better explain the variability in stream health noted for watersheds with very similar TIA. The subset of TIA that is directly connected to the stream network has alternatively been referred to as EIA, DCIA, sewerage, and percent connectance with each of these terms having been used with slight distinctions in the literature depending on the method of measurement used. This discrepancy is most obvious in a few studies that distinguish EIA (measured through regression analysis of rainfall-runoff data) as a further subset of DCIA (measured by surface cover mapping of drain-connected impervious areas) (Fig. 1) (Boyd et al. 1993, 1994, Chiew and McMahon 1999). Storm-specific, spatially-variable conditions may impact connectivity as some impervious surfaces will be connected for some storms and not others (Alley and Veenhuis 1983), while some pervious areas may behave as impervious due to soil compaction or antecedent soil moisture conditions (Booth and Jackson 1997). Walsh et al. (2009) noted that definitions of EIA or DCIA are not binary but represent a continuum of connectivity that is storm-specific, related to antecedent moisture and rainfall characteristics. Abstraction of incidental rainfall can also vary spatially as in the case of clogged pipes due to seasonal leaf litter (Chiew and McMahon 1999). It is the opinion of the author that

the term Effective Impervious Area best describes the subset of TIA that is most closely connected to the stream network while maintaining the idea that it is a dynamic measurement subject to variable natural and anthropomorphic conditions both spatially and temporally as connectivity is established or diminished. The term EIA will be used exclusively for the remainder of this review.

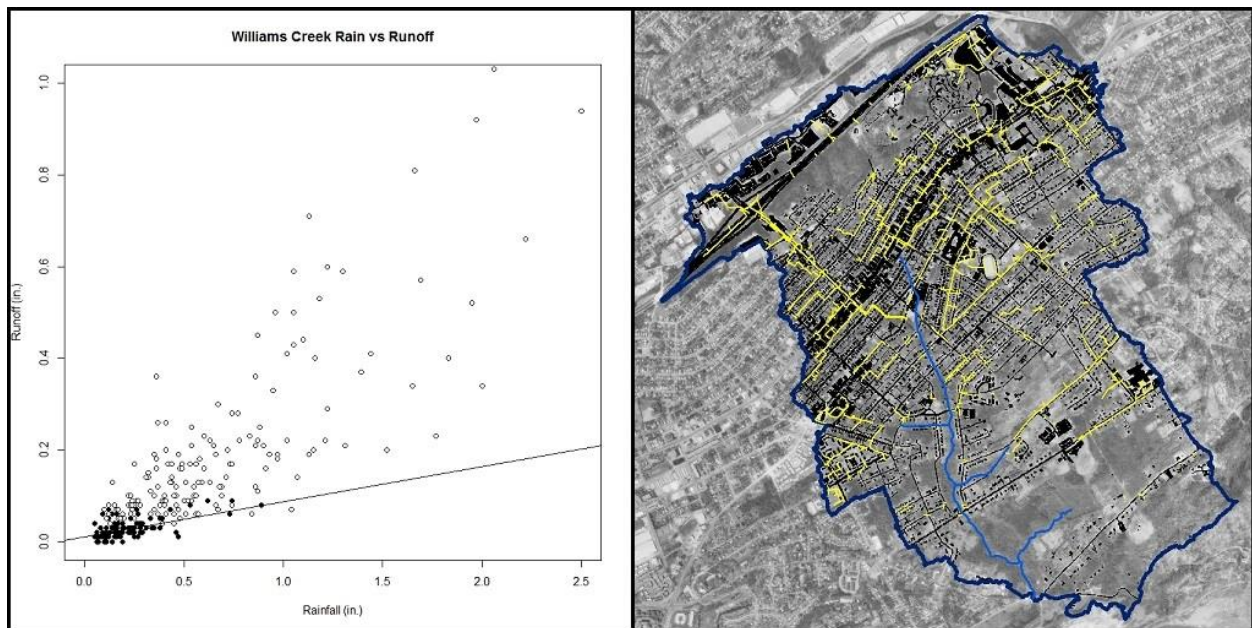


Figure 1 - Rainfall-runoff analysis offers insight into runoff dynamics in urban watersheds that can be related to the distribution of impervious surfaces (black) and connectivity along drainage pipes (yellow) in relation to the stream network (blue).

The adoption of EIA as the most important metric of basin urbanization for inferring stream conditions has been well supported in the literature. In a review of urban impervious impacts on water quality, Brabec et al. (2002) concluded that the distinction between TIA and EIA needs to be made because of their differential contributions to the urban hydrologic regime responsible for impacting stream health and water quality. Lee and Heaney (2003) surmised that because EIA produces a greater portion of runoff and is hydrologically active for smaller and more frequent storms than other surface covers, it

warrants accurate characterization despite being difficult to measure. In a study of urban density impacts on stream water quality, Hatt et al. (2004) proposed that the degree of drainage connection likely explains the variability in water quality between streams of similar TIA. The strength of refining impervious measurements to EIA in hydrology studies was discussed by Roy and Shuster (2009) as the movement of the science from ecological indicators of impairment to the identification of impacting mechanisms (and their location) in watersheds informing changes in management for better restoration of resources.

Evidence supporting the adoption of EIA over TIA

The incorporation of EIA into models relating basin characteristics to in-stream measures has offered improved explanatory power over the use of TIA in many studies covering various stream health and water quality indicators. A review of studies that specifically demonstrate this improvement (Table 1) provides an understanding of methodologies that are being utilized to identify the strength of this relationship. These have been grouped based upon the class of stream quality parameters measured in the study to highlight the breadth of processes that EIA impacts in urban stream systems.

Hydrologic Regime and Geomorphology

In a study of the impacts of EIA on runoff production, Lee and Heaney (2003) developed runoff models for a basin with 44% EIA and showed that these areas accounted for a disproportionate 72% of the runoff volume over long term modeled data. This study was performed at the development scale and impervious surface coverage was established using GIS while EIA was determined through on-site visual investigation of connecting infrastructure. Miller et al. (2014) studied two differently developed catchments, one highly urbanized and the other much lighter development, and found that EIA was a stronger determinant for the runoff response than TIA, independent of development type or density. Runoff models showed that the degree of connection in impervious surfaces was the greatest determining factor in changes in runoff patterns as land was developed. Geomorphic stream characteristics were better predicted in basins when using EIA over TIA as measured by Vietz et al. (2014). Bank instability, channel incision, and sediment characteristics at stream cross-sections downstream of development displayed a negative relationship with upstream EIA and large changes in geomorphic characteristic were detected at low levels of change in this parameter (< 2-3 %) in developing basins.

Table 1 - Summary of studies specifically illustrating the improvement in the use of EIA over TIA in predicting in-stream measures of concern.

Study	Stream Quality Parameters	EIA Measurement Method	Indication of Improvement over TIA
Lee and Heaney (2003)	Runoff volume, peak flows	Digital map data and connection ground-truthing	EIA was 44% and produced disproportionate 72% of runoff; variation in accuracy of EIA resulted in modeled peak flow differences of up to 265%
Miller et al. (2014)	Runoff volume, peak flows	Digital map data and extrapolation based on land cover and drainage data	Modeled runoff changes were far greater when drainage connection occurred (increased EIA) than just the addition of TIA alone
Vietz et al. (2014)	Geomorphic cross-section parameters (bank instability, width/depth ratio, bedload sediment depth, frequency of bars/benches, and large woody debris)	Digital map data, drainage infrastructure data, and connection verification	EIA was a better predictor of all parameters than TIA in linear regressions; large changes of parameters were detected for very low levels of EIA
Taylor et al. (2004)	Benthic algal biomass	Digital map data, drainage infrastructure data, and connection verification	Several measures of urban density jointly explained a large portion of the variance in algae levels and drainage connection (EIA) independently accounted for a significant portion of this (while TIA did not)
Walsh et al. (2005a)	14 water chemistry and ecological indicators	Digital map data, drainage infrastructure data, and connection verification	Linear regressions showed that EIA was a better predictor of indicator variables than TIA except for dissolved organic carbon (DOC); all showed strong degradation with increasing EIA down to a maximum level
Shields and Tague (2015)	Vegetative water use and net primary production (NPP)	Digital map data and connection by local drainage towards roadways	Model results incorporating EIA displayed a significant difference from those using solely TIA and indicated the ability for disconnected impervious surfaces to alter water fluxes and NPP enough in local pervious areas to offset the changes induced by increased TIA
Hatt et al. (2004)	10 chemical water quality indicators	Digital map data, drainage infrastructure data, and connection verification	Loadings of all variables were correlated with both TIA and EIA; concentrations of 4 variables showed independent correlation specifically to EIA while others were not significantly correlated to any urban density measures or to source-specific variables (septic density)

Biologic Assemblage and Ecologic Health

A large number of studies have revealed improvements in the prediction of stream biotic health by using EIA instead of or in addition to TIA. Taylor et al. (2004) showed that drainage connection was a stronger explanatory variable for in-stream algae measurements than TIA or other measures of urbanization, indicating the role that stormwater delivery by connected impervious surfaces plays in eutrophication. Walsh et al. (2005a) showed that a variety of ecological indicators decreased with increasing EIA up to a threshold of no further degradation and that nearly all were better predicted than when using TIA. In both studies, impervious areas were identified using GIS and EIA was determined by the presence of stormwater infrastructure with data provided by municipal management agencies. Vegetation characteristics and associated water cycling have also been shown to be influenced by EIA, as Shields and Tague (2015) showed that the spatial pattern of runoff impacts surrounding vegetation through changes in water fluxes. EIA was assumed in this study to be any impervious area touching a stream or roadway due to the high degree of drainage connection along roadways in the area of study. The use of EIA offered much greater explanation of the variability in plant production than did TIA, which was attributed to differences in soil water availability in areas adjacent to EIA.

Water Quality

In the aforementioned study by Hatt et al. (2004), drainage connection was shown to explain the variability in several water quality measures on basins with similar TIA. The stronger relationship between EIA and several water quality indicators was observed likely due to the defined transport pathways associated with EIA. These surfaces transmit pollutants with no attenuation directly to the stream. Baseflow concentrations were also well related to EIA, and it was posited that this might indicate transport along EIA in the absence of rainfall due to anthropogenic water inputs to the drainage system.

Methods of measurement of EIA

Measuring and identifying EIA in urban watersheds is often difficult because knowledge of urban drainage infrastructure is often unknown and fine-scale drainage patterns often must be resolved through time-intensive ground-truthing. Because of this, a number of earlier studies used various methods to approximate EIA by proxy. Hammer (1972) assumed impervious areas were connected in the presence of curbing that was associated with sidewalks. Alley and Veenhuis (1983) developed an empirical relationship for EIA as a function of TIA and different land cover classes for Denver that have sometimes been adapted elsewhere according to local development patterns. Booth and Jackson

(1997) used a similar approach by defining EIA as a percentage of each land cover class based on local observations. Road density was used as a surrogate for EIA by Konrad and Booth (2002) because it was well correlated to hydrologic metrics and because it was observed that a large proportion of transportation-related impervious surfaces were connected in study basins. The need for more accurate characterization of watershed EIA led to more rigorous approaches involving fine-scale investigation of drainage connections as well as using rainfall-runoff dynamics to estimate the EIA from observed hydrology.

As discussed above, Boyd et al. (1993) estimated EIA as a subset of the mapped connected impervious area through regression analysis of basin rainfall-runoff data within each watershed. This methodology uses the slope of a linear regression performed on the rainfall vs. runoff data for smaller storm events (typically less than 6mm) as an estimate of EIA. This assumes that these areas transmit 100% of coincident rainfall to streams as runoff (minus a slight initial abstraction) and that 100% of runoff for these smaller storms derives from these areas, as other land covers would presumably retain these events. This method is valuable in displaying the effect of differences between basin EIA and runoff dynamics, but it does not carry the spatial dimension needed in distributed restoration approaches. Advances in mapping software and digital data resolution improved the ability to measure EIA remotely, but field investigations were still often used to assess the accuracy of such measures. Drainage connections and impervious surface subtypes were investigated by Roy and Shuster (2009) who used extensive field surveying of public and private lands to verify remotely sensed impervious surface measures. Though field assessments revealed an additional 10% of TIA that was previously unaccounted for, it was nearly all disconnected private sector surfaces. It was concluded that municipal surface cover data sources represent hydrologically relevant impervious surfaces well because EIA is mostly composed of publicly held infrastructure and transportation related surfaces. Lee and Heaney (2003) measured EIA on a watershed by 5 different methods of varying complexity requiring increasing effort. These ranged from simple map interpretation to automated geospatial identification with additional ground-truthing. Findings indicated that EIA decreased with increasing measurement complexity as the true EIA was approached. Modeled runoff estimates using these different measures of EIA varied by over 250% indicating the importance of accurate assessment of EIA in refining urban runoff models.

Automated methods for the spatial identification of EIA have been proposed but they have been hampered by the need to objectively classify connected infrastructure (Kunapo et al. 2009), the difficulty in resolving areas of pervious interception along impervious pathways (Walsh et al. 2002), and spatial

data resolution and uncertainty (Han and Burian 2009). Recent improvements in remote-sensing, spatial data accuracy, and urban data availability have the potential to produce better methods for EIA measurement and mapping but these have thus far not been established. Some of this difficulty lies in the dynamic nature of EIA. Impervious connectivity may change considering the spatial variability of rainfall, temporally variable conditions impacting runoff production and the ability of pervious areas to disconnect it, as well as infrastructure that may not always convey runoff conservatively to the stream network. Automated measurement of EIA may be difficult in ungaged watersheds without the ability to compare identified areas to runoff trends. This topic of research presents many opportunities for improvement that this dissertation hopes to address.

Gaps in Knowledge and Opportunities in Accounting for Variability in Urban Runoff Processes

There is still a large opportunity for research on the effects of the spatial distribution and connectivity of impervious surfaces, how form and patterns in the urban environment translate to stream degradation, and how these qualities can be reliably and rapidly measured or modeled for effective management. Opportunities for future research have been identified from the literature, mostly centering on a lack of consistent definitions and methods, the challenges of relating spatial data to in-stream measures taken at discrete locations, data resolution and accuracy, and accounting for all relevant runoff components. Better models will result through further investigation into measuring the spatial variability in urban runoff processes, how model inputs vary in space and effect results, and how the dominant variables in urban stream degradation can be managed to impart positive change in urban stream conditions.

Considerations in relating watershed-scale measures to in-stream measurements

In a review of remote-sensing techniques for measuring impervious surfaces, Slonecker et al. (2001) noted that definitions of the classes of impervious surfaces (TIA vs. EIA vs. DCIA, etc.) may differ slightly between studies making comparison between studies and validation of results difficult. They also suggest that some error in remote-sensing of impervious surfaces is to be expected due to anomalies in the chain from data collection to interpretation. Data accuracy can be addressed by accounting for uncertainty in the analysis, but a consistent definition of EIA is also warranted. As more sophisticated geospatial analysis techniques are applied to the measurement of EIA and hydrologic connectivity, care must be taken not to violate the assumptions of spatial statistics in drawing conclusions. As noted by King et al. (2005), linking land cover to in-stream measures may be problematic as it can violate assumptions of independence because developed and undeveloped proportions of watersheds are usually highly correlated. Also, spatial autocorrelation can exist due to certain land uses and

infrastructure that is commonly sited alongside landscape features that define drainage pathways to utilize topography and the stream network for rapid runoff conveyance. Resolving these issues may be best approached through multidisciplinary work to couple hydrologic concepts with sound geospatial statistics. Matching landscape effects to in-stream conditions can also be hampered by utilizing data that do not match the scale of the process measured (Boyd et al. 1994), lack accuracy (Nowak and Greenfield 2010), or do not capture the spatial variability of data inputs or processes (Aronica and Cannarozzo 2000).

Spatial data resolution and urban runoff assessment

The ability for GIS to organize various data types together over large areas is valuable for urban hydrologists in accounting for the high spatial variability of factors influencing runoff production. When Djokic and Maidment (1991) presented an early framework for using digital terrain data to represent urban hydrology in GIS, they noted that the difficulty lies in incorporating both smooth landscape drainage patterns with the sharper drainage features of the urban hydrologic environment and in coupling surface drainage with subterranean piped networks. Because of the fine-scale drainage processes at play in urban watersheds, Hunsaker and Levine (1995) advised that to target source areas for runoff and NPS pollution management, high resolution distributed models are necessary. These acknowledgements were echoed by Kunapo et al. (2009) who highlighted the need for accurate mapping of drainage infrastructure and derivation of runoff flowpaths from high-resolution elevation data for modeling and measuring the capabilities of an urban watershed to employ GI in stormwater management.

Higher surface cover data resolution has been shown to improve results in hydrologic modeling and relating watershed conditions to various measures of urban stream health. Grove et al. (1998) measured the Curve Number (CN) for an urbanizing watershed in a distributed manner by localized grid cells and found better runoff prediction than using lumped composite CNs due to better discretization of the urban area. Tormos et al. (2014) investigated the relationship between watershed and riparian scale vegetation and an in-stream biotic index using medium resolution land cover data (100 m cells) and high-resolution photo-interpreted land cover data (0.5 m cells). The high-resolution land cover data were able to accurately model riparian vegetation conditions and exhibited the strongest relationship with in-stream biology for a 20 m buffer. This higher resolution data was also able to discern riparian effects from those at the watershed scale which is important for targeted restoration. Verbeiren et al. (2013) used a grid-based fully distributed model to assess urban runoff production, finding that

incorporating fine-scale “sub-pixel” representations of impervious surfaces (derived from photo interpretation) modeled peak flows better than with medium resolution land cover maps. The high resolution impervious surface data was incorporated into a fully distributed runoff model and allowed the identification of areas with greater runoff generation. Though these results are promising, increasing the data and modeling resolution does not always contribute to better understanding because there is the potential for more variability in the data itself, clouding the benefits of the fine-scale data. Weng (2012) examined the techniques used to estimate impervious surfaces in remote-sensing and noted that the appropriate technique for measurement may differ depending on the data utilized, the spatial and temporal scale of processes investigated, and the scale of features to be extracted. Use of highly distributed models should be adapted to incorporate appropriate sensitivity and uncertainty analysis so that results are well represented. This is especially true for urban watersheds where high spatial variability is typical.

Variability in urban runoff model inputs and parameters

The most basic input to runoff models is rainfall, yet the spatial variability of this critical variable is rarely considered. With the goal of fine-tuning runoff estimates from impervious surfaces that are themselves spatially distributed, the spatial distribution of rain falling onto these surfaces should also be well defined. As noted by Fletcher et al. (2013), the fine temporal scale (1 to 10 min) and spatial scale of urban rainfall-runoff processes necessitates better knowledge of rainfall patterns and measurement for modeling. Quirmbach and Schultz (2002) advised the use of more spatially explicit radar rainfall data in urban settings if the gage location is outside the catchment or if gage density is insufficient. Rain falling in urban watersheds transmits rapidly to streams by way of EIA, but some impervious surface abstraction of rainfall does occur. Runoff models often assume that impervious surfaces offer near-zero infiltrative capacity, but depending on several climate, surface condition, and topographical factors, there can be a measurable abstraction of rainfall by impervious surfaces before runoff is initiated. Hollis and Ovenden (1988) noticed this abstraction as a threshold before runoff was produced for many smaller storms. This was also shown by Ramier et al. (2011) in a long-term monitoring study of road surfaces where observed losses were larger than typically accounted for, likely due to evaporation and crack-infiltration. Fletcher et al. (2013) summarized a wide body of urban hydrology research and noted that impervious surfaces are associated with a slight amount of infiltration (soaking) and initial abstraction depending on slope and subject to rainfall amount, intensity, and duration. There is potential to assess the sensitivity of runoff models to this impervious surface abstraction in relation to

climate and spatial variables to determine the magnitude of this effect, especially in regards to smaller less-intense storms.

Similar to impervious surface abstraction, reductions in infiltrative capacity for urban pervious areas are often unaccounted for. Development activities and frequent traversal by very heavy equipment have been shown to compact soils greatly and diminish infiltration rates to near impervious levels (Price et al. 2010). The actual infiltration by urban pervious areas is difficult to model due to high spatial variability as noted by Robert Pitt et al. (2002) who advised the use of average infiltration rates and Monte Carlo analysis to account for this error. Several studies have measured the effects of compaction on the infiltration rate of different soil types and the effects of this diminished capacity on the accuracy of runoff models. Gregory et al. (2006) noted that inaccuracies in modeled runoff when soil compaction is not considered might result in site-planned GI features, installed to offset the effects of development on local hydrology, being overwhelmed by the extra runoff unaccounted for from development-related compacted soils. Soil compaction is highly variable across urban watersheds, having the potential for large localized effects on runoff generation. Because of this, further research is needed to address urban soil compaction to better understand its dynamic nature (subject to human activity) and how it can be best estimated and incorporated into urban runoff models. This is an important topic in urban watershed management because runoff production on highly compacted pervious surfaces approaches that of impervious surfaces. Also, more GI practices are utilizing undeveloped areas for their infiltrative potential. Thus, care needs to be taken to ensure that handling of upstream runoff by these installations adequately protects downstream areas.

Addressing the Need for Reliable Spatial Methods to Measure Impervious Connectivity

As Fletcher et al. (2013) noted, one of the most important gaps in scientific literature is the reliable measurement of EIA, how its spatial distribution is accounted for, and determining how efficient and spatially optimized SCMs can be installed to shift urban hydrology back to more natural regimes. While much research has identified the connectivity of impervious surfaces as the greatest determinant of urban stream conditions (across a range of indicators), new methods are still needed to move beyond lumped metrics to develop more spatially-informed accounting for the distribution and connectivity of impervious surfaces. Advances in geospatial analysis software and techniques, the wide availability of high-resolution urban drainage data, and greater computing capability to handle larger datasets point to the utilization of highly distributed modeling techniques to address this problem. These models must be capable of resolving the fine-details and spatial variability of urban environments to identify where

runoff and water pollutants are produced. To achieve this, these approaches should draw on methods developed in geostatistics, landscape ecology, and urban hydrology to better address the complexity of urban flowpaths over impervious or pervious surfaces and along pipes or stream networks. Building on the strength of research that has established the link between EIA and in-stream conditions, these methods could provide rapid assessment of connectivity for urban watersheds. This information can be utilized by urban planners to guide scientifically informed placement of SCMs throughout a city. This network of SCMs will better impart more natural flow characteristics to urban streams than traditional, opportunistic approaches, as they will target the portions of the watershed most responsible for causing stream degradation. Flexibility should be built into these models to allow for multiple objectives that address not only the increased runoff from EIA but also water quality concerns. Fortunately, distributed modeling with GIS can provide this type of adaptable functionality as programmed routines can be both modified to include updated datasets and used to rapidly assess multiple future scenarios. Next generation urban watershed management must be guided by methodologies that account for the spatially variable hydrologic processes within an urban watershed, use new methodologies to account for the distribution and connectivity of impervious surfaces, and be predicated on well-informed disconnection of paved surfaces and flow routes. Such approaches will lead the way to healthier urban stream systems and promote more sustainable cities in an ever-urbanizing world.

DISSERTATION OUTLINE & OBJECTIVES

The overall research question will be addressed in four parts by addressing the following research questions with final conclusions to summarize the findings.

1. Can a spatial modeling framework be developed to utilize observed runoff trends to identify the most probable impervious areas to comprise the EIA subset with high-resolution urban datasets?
2. How much benefit could be expected for GI installations utilizing spatial EIA identification over less spatially informed methods of GI implementation throughout an urban watershed?
3. How do spatial EIA results vary related to model inputs used to represent runoff attenuation and how effectively do these spatial models predict variability in surface runoff for observed storm events?

4. Do accurate EIA measurements help explain variability in inter-event and intra-event pollutant differences and dynamics for several different common constituents in urban streams?

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CHAPTER 1

Establishing a GIS Framework for the Spatial Identification of Effective Impervious Areas in Gaged Basins: A Review and Case Study

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This article was developed and written entirely by the student with editing assistance from his advisor, the co-author on the paper. It represents original work by the student that was developed through funding by his advisor, who played a crucial supporting role, offering guidance, critique, and grounding to see it accomplished and contribute to his overall research program.

ABSTRACT

Effective impervious area (EIA) is defined as the subset of the total impervious area (TIA) more often hydrologically connected to stream networks via stormwater infrastructure. Its importance in runoff modeling and watershed health has been well established in the literature, making it a governing characteristic of urban watersheds. However, there is a critical need to move beyond quantification of EIA at the watershed outlet toward explicitly identifying locations of connectivity. This paper reviews existing methods to quantify and identify EIA and proposes a new model framework which builds on these methodologies to offer an automated and objective way to spatially identify the most probable impervious areas comprising EIA. Impervious runoff is modeled on a volumetric basis with connectivity measured by accounting for attenuation across different surface types that can be calibrated to match observed direct runoff trends. A simplified model representation is presented for three watersheds in Knoxville, TN, USA. The results illustrate the influence of pervious attenuation in urban watersheds, showing a threefold difference in EIA is possible within a watershed based on this variable. However, patterns of EIA and watershed sensitivity to pervious attenuation are variable among watersheds, highlighting how watershed specific characteristics influence runoff and should be accounted for in management plans. The model results capture the spatial variation in impervious connectivity between watersheds and offer insight into the potential for disconnection using targeted infiltrative enhancements such as green infrastructure. Further research is needed to inform the pervious attenuation variable and allow it to change based on site-scale characteristics such as land cover, soil type and compaction, rooftop connections to stormwater networks, and antecedent moisture conditions. Such explicit quantification of pervious attenuation will allow application of this method to ungauged watersheds. This work is the first step toward spatially identifying impervious connectivity in

watersheds using this spatial modeling framework, providing the potential for more scientifically informed watershed management strategies through targeted green infrastructure installation.

Keywords: effective impervious area; distributed stormwater management; GIS for urban hydrology; impervious runoff; green infrastructure

INTRODUCTION

The importance of clean water and healthy streams in cities has been shown to create value well beyond that of the resources alone through wide-reaching ecosystem services (Board 2005). Stream restoration initiatives, innovative stormwater control measures (SCMs), Water Sensitive Urban Designs (WSUDs), and green infrastructure (GI) practices have emerged to improve the hydrologic function and water quality of urban streams, while still allowing adequate runoff drainage. These efforts are largely necessary due to the proliferation of impervious surfaces in urban watersheds and the associated hydrologic consequences (Barbosa et al. 2012).

Impervious surfaces have been shown to alter runoff processes and shift hydrology toward an urban regime that contributes to degraded stream conditions worldwide (Booth and Jackson 1997, Leopold 1968, Paul and Meyer 2001, Walsh et al. 2005b). Traditional urban drainage infrastructure typically consists of stormwater pipe networks that collect the surplus of runoff from impervious surfaces and move it rapidly towards receiving streams for the sake of flood mitigation. This rapid conveyance by connected infrastructure networks increases the impacts of these impervious surfaces on measures of stream quality (Alley and Veenhuis 1983, Brabec et al. 2002, Lee and Heaney 2003, Shuster et al. 2005). Thus, there is a large body of research that has identified the subset of these impervious surfaces connected to streams by piped drainage networks as more important than the total impervious area (TIA), because they are most closely related to the physical drivers of change in urban hydrology (Walsh et al. 2005a). This subset has been referred to as the effective impervious area (EIA) in the literature and will be referenced as such herein. Despite this understanding of the closer relationship between EIA and various measures of stream quality than that of the TIA (Fletcher et al. 2014), there is still a knowledge gap in how to both accurately measure the quantity of these surfaces and physically locate them for targeted disconnection. Better guidance in this area would help managers position limited resources more strategically throughout the watershed (i.e. to where they are needed most) to address in-stream hydrology issues that have been linked to EIA.

The importance of accurate determination of EIA

As mentioned above, it has been demonstrated in a number of studies that variability in a range of measures of stream quality between different watersheds is more closely explained by differences in EIA than by TIA (Fletcher et al. 2014). Lee and Heaney (2003) surmised that because EIA produces a greater proportion of storm-event runoff and is hydrologically active for smaller and more frequent storms than other surface covers, it warrants accurate characterization despite being difficult to measure. The importance of refining impervious measurements from TIA to EIA in hydrology studies was stated by Roy and Shuster (2009) as the movement of the science from using surrogate ecological indicators of impairment (i.e., TIA) to the identification of actual impacting mechanisms (i.e., EIA). To sustainably restore urban stream quality, these impacting mechanisms must be undone.

Impervious surfaces have been hydraulically disconnected in cities worldwide using distributed GI and SCMs to reduce runoff volumes, diminish runoff frequency, slow runoff response time, and decrease pollutant transport (Fletcher et al. 2013). This has mostly been approached with opportunistic, empirical placement strategies. An accurate characterization and spatial identification of EIA is critical to optimize these management activities seeking to further disconnect impervious areas. One of the greatest difficulties in accurately identifying EIA for urban watersheds is unraveling the spatial complexity of the mosaic of urban surface cover as it relates to runoff generation and the drainage pathways this runoff takes towards a stream or receiving water. These drainage pathways are influenced by elevation, infrastructure (location, type, condition), surface cover types, and temporally-changing soil moisture conditions among other variables related to human activity in the watershed. This complexity is difficult to fully account for, but it is warranted as distributed at-source restoration activities in urban watersheds using GI are becoming the norm in urban stormwater management. The ability to determine not only the quantity of EIA but its location in an urban watershed will provide a more accurate prescription of distributed GI for urban watersheds that will optimize resources by focusing efforts where they are most needed.

Existing Methods for EIA Quantification/Identification

The earliest measurements of EIA were time-intensive and involved physical map assessment of surface cover, drainage network, and topographic data (Miller 1978) often combined with extensive field-verification for areas of ambiguous drainage patterns (Alley and Veenhuis 1983). Early EIA estimates were most widely used to refine urban hydrology models due to the sensitivity of modeled runoff to parameters associated with impervious cover. A study by Lee and Heaney (2003) demonstrated the

wide variability in runoff modeled using EIA measurements deriving from methods of varying degrees of technical rigor (up to 256 %). These methods ranged in complexity from simply applying literature values, to the application of GIS analysis and the addition of field-verification for points of runoff connectivity by pipe, downspout, or other form. Field surveys have often been employed to verify data obtained from mapping or early GIS analysis to reduce uncertainty in EIA estimates, but this is a time-consuming effort (Alley and Veenhuis 1983, Lee and Heaney 2003, Roy and Shuster 2009). Several additional studies have employed more automated analysis methodologies to produce unbiased estimates of EIA with each differing by the data used and the estimation methodology. These will be briefly reviewed to both utilize and make advancements to methodology in literature.

EIA Quantity Estimation with Trends in Rainfall-Runoff Data

The quantity of EIA in a catchment is typically estimated by analysis of trends in storm event rainfall-runoff depth data where available. It was first noted by Miller (1978) that the map-identified EIA percentage was closely related to the slope of the line for rainfall-runoff pairs for rain events up to about 38 mm in a plot of rainfall versus runoff for observed storms in an urban watershed. The slope of this line approximates the portion of rainfall that is consistently translated to the stream as runoff so it is intuitive that this would be related to the quantity of EIA which is known to directly transmit runoff to the stream for all storm events. Boyd et al. (1993) further codified this concept on several watersheds in Australia and elsewhere. In their methodology, the EIA is approximated by the slope of the linear regression of the rainfall-runoff data for smaller storms (typically < 40 mm) with the intercept term representing an initial abstraction value under which no amount of runoff is ever generated. This concept assumes that the highly connected EIA will contribute nearly 100% of incidental rainfall (minus the afore-mentioned initial abstraction) as direct runoff for every storm. Thus, any storm event greater than the initial abstraction value will produce at least as much runoff as would derive from the EIA, with any excess being attributed to either more loosely connected impervious areas (portions of TIA not considered EIA) or from pervious areas of the watershed. This procedure has recently been updated to provide a more unbiased statistical method that screens storm events between groupings of EIA or non-EIA depending on the regression residuals to improve results (Ebrahimian et al. 2016b). The determination of EIA using these methodologies provides a good approximation of the quantity of connected imperviousness in the catchment but lacks the valuable spatial information of the more time-intensive methods employing rigorous map analysis. Despite this, it represents the best means to

couple observed hydrology (processed via the regression method) to spatial identification of EIA (such as those proposed herein) for verification.

Distance-Weighted Landscape Metrics

In efforts to measure connections between the effects that different land cover has on stream quality based on its spatial distribution, Van Sickle and Johnson (2008) utilized a parametric distance-weighted model to assess how different land covers exhibit influence on in-stream measures of biological integrity based on flowpath distances. In this model, it was assumed that a given location's influence on stream conditions decreases with flowpath distance from the stream, and this decline was modeled using different functions of distance (exponential decay, inverse distance, and threshold distance). Walsh and Kunapo (2009) expanded on this method to better capture the complexity between the sources of stream quality issues (impervious surfaces, point sources such as septic tanks) and the spatial distribution of these sources along different types of urban runoff flowpaths. Distance-weighting was viewed in this study as analogous to an attenuation rate for a stressor moving along its flowpath and declining in influence towards the stream. Attenuation rates were varied for overland and in-stream pathways as well as along stormwater pipe networks, over which it was assumed there was no attenuation. Most relevant to this review was the distance-weighted metric of impervious surfaces, referred to as attenuated imperviousness (AI) by the authors (Walsh and Kunapo 2009). AI considers impervious surfaces as stressors to in-stream measures, with distance-weighting that represents a continuum of connectivity for any given impervious surface defined by spatial configuration and runoff pathway types. The study measured macroinvertebrate assemblages and found that the AI metric with overland attenuation and stormwater pipe flowpath representation was the most plausible model explaining variation in biologic indices. These results were further supported by Burns et al. (2015) when they found that AI was a better predictor of biologic indices than TIA and an array of other models containing various hydrologic metrics. While AI is not equivalent to EIA, it does represent a surrogate measure of impervious surface connectivity that provides both measurement along a continuum and spatial location which can be used to identify areas of greater connectivity within the watershed for more targeted management.

EIA from Geospatial Analysis

A method for automated identification of EIA using geospatial analysis was most recently proposed by Han and Burian (2009) to classify impervious surfaces as connected (EIA) or not (non-EIA). This method identifies the EIA by stepping through the flowpath that runoff travels using accepted flow direction

methodology in ArcGIS (Jenson and Domingue 1988). If the flowpath crosses a drainage inlet before a pervious surface, it is classified as connected and accounted for in the EIA. Any impervious surface draining to a pervious area is classified as disconnected. Results of the automated identification of EIA by Han and Burian (2009) were lower than estimates obtained from land cover maps and field-verification. The authors preceded the automated classification of EIA with image classification to identify surface cover and provide an accurate measure of TIA. EIA estimates were likely affected by the results of this process as noted by the authors (Han and Burian 2009), especially in areas with dense canopy cover and underlying impervious surfaces that were often misclassified as pervious. The process used to classify imagery produced surface cover data with a resolution of 4-m, which was also noted as a factor in EIA estimate error, especially in urban areas with heterogeneous surface cover that is not well captured at this resolution.

A few considerations need to be made when considering this automated GIS approach. The first arises from the resolution of data used (4-m) (Han and Burian 2009). Stormwater inlet structures are typically much smaller than a 4-m square, yet any flow directed to the 4-m square classified as a stormwater inlet would be connected. This is problematic considering urban microtopography and the representation of infrastructure that is not well captured with the resolution of the data. Also, impervious surfaces were considered completely disconnected (non-EIA) if the modeled runoff pathway (as determined from elevation data) crossed one raster cell of pervious surface cover. This binary classification of connectivity becomes problematic as data resolution increases, especially when you consider how close a stormwater pipe outfall might be to the stream. An outfall located 3 m from the stream could appear adjacent to the stream using 4-m resolution data and therefore connected. This would not be so if the data resolution were 1-m, which is now available in many cities. Considering fine-scale measurement of connectivity is important, especially if one is to incorporate SCMs into the measurement of EIA as these might be located at the end-of-pipe and capable of appreciable runoff disconnection.

Synthesizing existing methods to spatially identify EIA

Established methodologies for quantifying EIA in urban catchments are sufficient for modeling endeavors, but the increased use of distributed stormwater restoration efforts that seek to disconnect impervious areas and decrease EIA need better spatial guidance than these methods provide. Fine-scale urban drainage information is becoming more widely available due to advances in geospatial analysis and watershed assessment performed in GIS. Urban infrastructure inventories have increased in resolution as well as accuracy, and thorough high-resolution datasets are now available in most cities.

This data better matches the scale of complexity in urban runoff generation and movement, and thus presents the potential for more accurate measurement of EIA in both amount and location. It stands to reason that recent advances in urban datasets and geospatial analysis could be used to adapt traditional geospatial methodologies to reproduce the time-consuming physical map delineation and field verification practices of the past to more quickly and accurately identify EIA in urban watersheds today.

The three EIA measurement methodologies described above can be synthesized and adapted using high-resolution data to provide a framework that seeks to identify the impervious areas most likely to be EIA through surface cover and flowpath analysis. Specifically:

- Methods similar to those utilized by Han and Burian (2009) can identify pathway connectivity, employing elevation based flow direction data to identify points of surficial discontinuity that differentiate EIA from TIA.
- The relationship between impervious surface distance, configuration within the drainage and stream networks, and attenuation that diminishes the influence of an impervious surface on stream conditions as measured by Walsh and Kunapo (2009) can be adapted to account for the physical components of runoff connectivity in urban watersheds.
- The flowpath framework and runoff attenuation model can then be calibrated to match the EIA percentage identified by rainfall-runoff analysis (Boyd et al. 1993, Ebrahimian et al. 2016b) to spatially identify the most closely connected impervious areas (that are equivalent in area to the EIA determined from the runoff data).

The intersection of these three methods should represent the concept of impervious runoff connectivity well by accounting for urban form, spatial distribution, pathway routing, and physical processes.

Objectives

To optimize distributed stormwater management efforts within the complexity of urban drainage systems, the measurement and identification of EIA must be adapted to produce results that are spatially explicit. This paper proposes a framework for such a methodology using commonly available urban data types combined with geospatial analysis. Results are presented for three watersheds in Knoxville, TN, United States. Discussion of opportunities for future work will highlight ways that this framework can be adapted to consider even greater levels of detail for the further refinement of EIA identification.

METHODS

Model Framework and Assumptions

The model framework proposed herein measures the connectivity of impervious surfaces on a volumetric basis related to impervious runoff production and attenuation of a given runoff volume over different pathways as it moves toward the stream. The model does not purport to account for the timing of flow, instead focusing on how much runoff is produced by impervious surfaces and contributes to the direct runoff portion of the storm event hydrograph. This connected portion of runoff forms the basis for identifying those impervious areas comprising the EIA. A schematic of the model is provided in Figure 2 and the basic methodology as well as the assumptions that the model makes to identify EIA are discussed below.

In the model, surface cover is broken into four classes: impervious, drain pipe, stream, and pervious. The classification of all impervious surfaces as the same has been used in this introduction of the spatial model framework for simplicity. The connection of impervious surfaces to pipe networks is assumed to be represented well by the pipe data. While this assumption may not hold true in all cases (especially building rooftops), the focus of the paper is on methodology and not the absolute integrity of the data. Data uncertainty and rooftop connection to pipe networks can be further studied within the modeling framework given sufficient pipe data accuracy and downspout connectivity representation. The Digital Elevation Model (DEM) is reconditioned to the drain pipe network to enforce flow along these subterranean features. Additional geospatial tools are subsequently used to develop both a filled DEM that ensures flow is routed towards the watershed outlet, and the flow direction raster to determine the direction of runoff for any given point. Surface cover and flow direction rasters are converted to NumPy arrays (Walt et al. 2011) to identify points of surficial transition along runoff flowpaths (i.e. changes in land cover along the flow path) as these are the points in the watershed that define connectivity. These points are identified in Figure 1 as directional arrows pointing away from the impervious surface or drain pipes indicating transition to pervious surfaces or the stream itself. They will be referred to as Impervious waterShed Points (ISPs).

The ISPs can be used in conjunction with the flow direction data to delineate local micro-watersheds along the impervious surfaces that represent contiguous areas draining to a common ISP. These are delineated in the schematic (Fig. 2) and it is assumed in the model that all points within any given micro-watershed are identically connected with no attenuation of runoff across them. The runoff volume

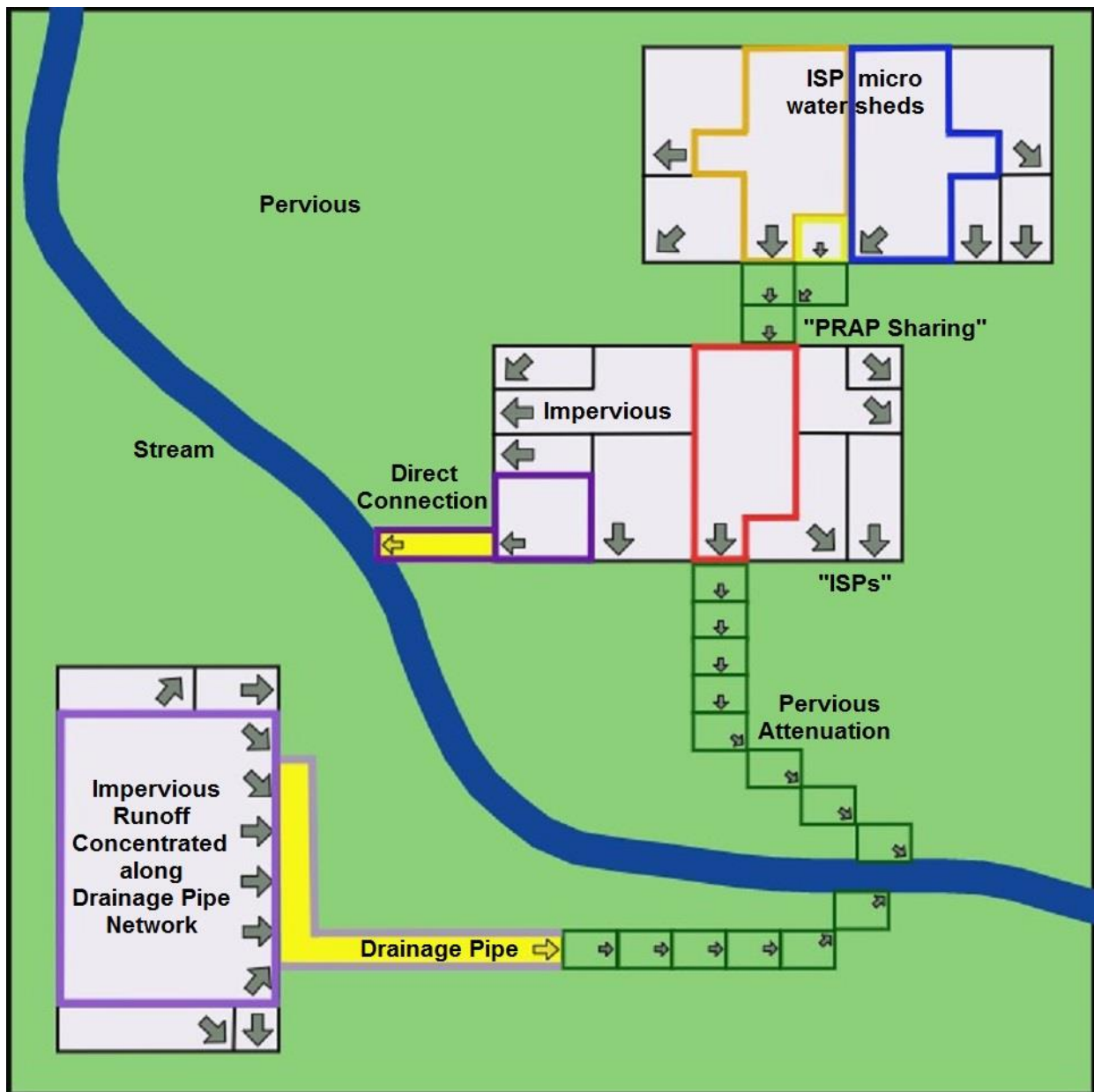


Figure 2 - Model framework schematic depicting surface cover representation, impervious micro-watershed delineation, and runoff attenuation across pervious surfaces in relation to the elevation-derived flow direction data.

associated with any given ISP is then calculated for the storm depth of interest using the area of the micro-watershed. Runoff attenuation is defined in the model as a volumetric decrement of runoff as it moves across a pervious surface, akin to a transmission loss. It can be thought of as any resistance to runoff connectivity that surface runoff encounters in moving from the impervious surface towards the stream as a transmission loss, be it through infiltration, detention, or otherwise. Given sufficient runoff attenuation along the runoff flowpath, disconnection will occur. While there are many physical landscape variables that could influence this attenuation negatively or positively, the simplest form of the model will be presented in this study as a baseline that can be further investigated in future studies. Runoff attenuation in this case will be defined as a single homogenous parameter across all pervious surfaces representing an average or uniform transmission loss and will be referred to as the pervious runoff attenuation parameter (PRAP). This is an obvious simplification in the analysis necessary for this initial study, as pervious attenuation should vary spatially throughout the watershed. Future studies will aim to inform PRAP through soil and watershed characteristics, thus increasing the applicability of the method to ungauged watershed.

This simple form of the runoff connectivity model (which assumes identical runoff attenuation potential for all pervious surfaces) is utilized except when a given pervious location is coincidental to runoff sourced from multiple ISPs. This case is noted in the schematic as “PRAP Sharing”, and in this case, the value of the PRAP is evenly shared between all coincidental runoff paths. This handling distinguishes the model from solely distance-based measures as it attempts to account for variability in attenuation across pervious surfaces given runoff generated upstream. Runoff from each ISP is then routed along the flowpath toward the stream until it is either fully attenuated or an unattenuated portion reaches the stream. Runoff routing from ISPs proceeds by greatest distance from the stream so that runoff sourced from further away is attenuated first along shared pathways. The unattenuated portion of runoff reaching the stream (0 if fully attenuated along pervious portions of the flowpath) is then divided by the runoff produced at the ISP providing a ratio that will be referred to as the impervious runoff connectivity (IRC). The IRC thus ranges from 0 to 1 and represents a continuum of connectivity that measures the portion of runoff produced that is directly connected to streamflow for a given storm event by way of surficial flowpaths.

Adapted from Ebrahimian et al. (2016b), estimation of EIA from rainfall-runoff data assumes that for smaller storms, runoff can be assumed to be sourced entirely from impervious surfaces and determined from the equation:

$$Q_t = (P - I_a) * f_{EIA} \quad (1)$$

where Q_t = total runoff depth, P = rainfall depth, I_a = impervious initial abstraction, and f_{EIA} = fraction of watershed area considered EIA. While the IRC does not measure connectivity as binary, it does measure the portion of runoff for any given impervious surface that is connected to streamflow by surficial pathways. Thus, the following equation:

$$Q_t = (P - I_a) * \frac{\sum_{ISP} IRC * A_{ISP}}{A_{watershed}} \quad (2)$$

where the IRC is multiplied by the area associated with the ISP, summed for all ISPs and divided by the watershed area will yield a measure equivalent to f_{EIA} for this model of impervious connectivity. If f_{EIA} and I_a are determined from regression analysis, they can be utilized within this model framework. Specifically, rainfall can be decremented by the regression determined I_a value before ISP runoff volumes are calculated and the value for the PRAP can then be calibrated so that the resulting summed IRC matches the graphically determined f_{EIA} . While regression estimates of I_a may be influenced by uncertainties in the observed data (Ebrahimian et al. 2016a), they are used here to illustrate differences between watersheds and the effect that they have on model results will be studied further in future work.

Model Scripting and Workflow

The model framework has been automated using watershed data preprocessing and Python scripting as outlined in Figure 3. The pre-processing steps described above involve defining surface cover by the four classes and converting this data to raster layers that match the resolution of the elevation data used. The DEM is reconditioned using the streams and drain pipes with the ArcHydro toolbox, and subsequent processing produces the flow direction raster that is used to assess runoff flowpaths. The IRC is calculated using a six-step process of Python scripts, the first two of which can be run once per watershed with the remaining four necessary for calibration. Because the scripts use numpy arrays, analysis is restricted to a certain watershed area depending on the raster resolution as numpy arrays are limited in dimension. Computing power also necessitated the use of multiple scripts as these large

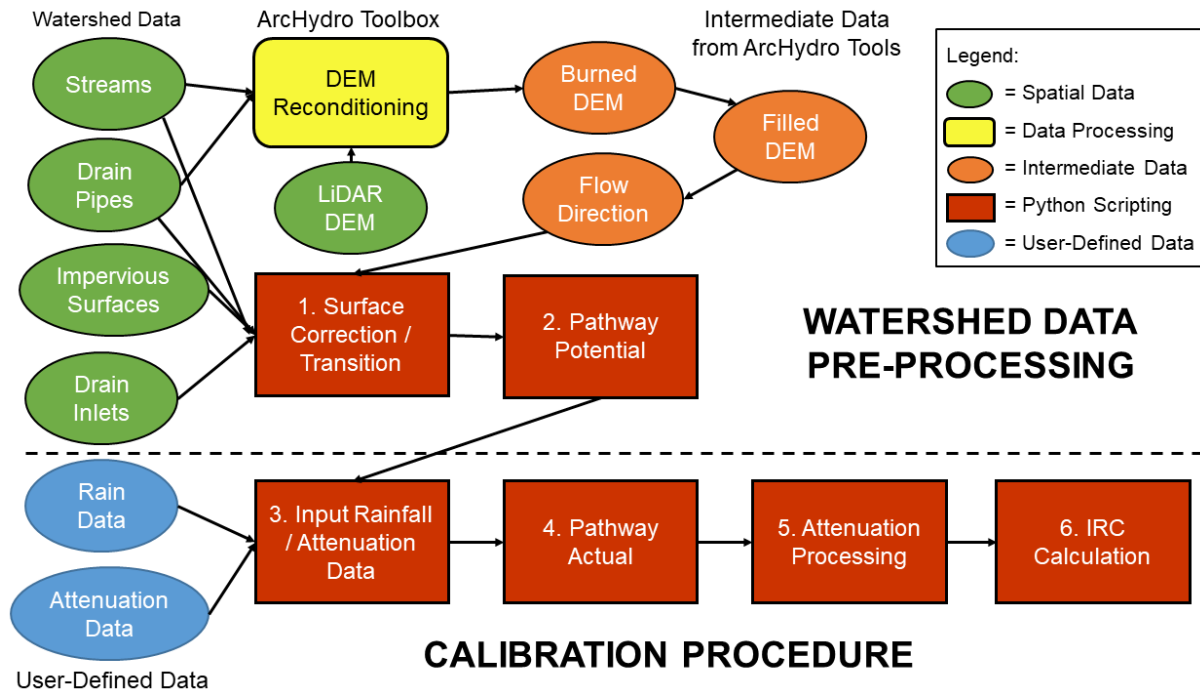


Figure 3 - Model processing workflow utilizing data pre-processing and a succession of six Python scripts.

arrays often fully utilized computer memory allocation. These restrictions warrant a maximum watershed area of approximately 5 km² for processing depending on the shape of the watershed, and larger watersheds must be split into subbasins. The overall analysis is accomplished by the following six subscripts:

1. **Surface Correction / Transition** – This process assesses the surface cover data in conjunction with the flow direction raster, applying small corrections to locations along the stream and drain pipe networks to ensure that once flow enters them it stays within them until the outlet. It also identifies the ISPs for further steps of the analysis.
2. **Pathway Potential** – This process iterates through each ISP, tracing its runoff pathway to identify points of coincidental runoff flow and to determine how many ISP flowpaths potentially share any given pervious surface location.

3. Input Rainfall / Attenuation Data – In this script, rasters representing rainfall and the PRAP are input for incorporation into the model. This step is reiterated for each calibration step, altering the PRAP value accordingly.
4. Pathway Actual – With ISP runoff values determined from rainfall data, this step involves routing the runoff volume along its pathway and updating attenuation values to properly account for pathway sharing of runoff from ISPs.
5. Attenuation Processing – The full processing of ISP runoff along its flowpath occurs here with proper PRAP accounting established in the previous step. The amount of unattenuated runoff is determined and assigned to the ISPs for final calculations.
6. IRC Calculation – This last step calculates the IRC for all ISP locations and summarizes it across the watershed for comparison to the graphically determined EIA.

Study Sites and Spatial Data

Impervious connectivity analysis was performed for three urban watersheds in Knoxville, TN (Fig. 4). Fourth, Second, and Williams Creeks vary in watershed area, drainage network shape, and overall development patterns in relation to the stream network (Table 2). These watersheds represent a range of development intensity and scale that can be used to validate the model across varying conditions contributing to variability in storm event runoff. Spatial data for this study was obtained from Knoxville Geographic Information Systems (KGIS), a municipal clearinghouse for spatial data supporting various agencies in the City of Knoxville. LiDAR data with a 1-m resolution was used to create the DEM for analysis. The most recently updated impervious surface cover data of various classes (roads, parking, sidewalks, supporting, etc.) was provided from digital imagery processing by KGIS in vector format as development patterns in relation to the stream network (Table 2). These watersheds represent a range of development intensity and scale that can be used to validate the model across varying conditions contributing to variability in storm event runoff. Spatial data for this study was obtained from Knoxville Geographic Information Systems (KGIS), a municipal clearinghouse for spatial data supporting various agencies in the City of Knoxville. LiDAR data with a 1-m resolution was used to create the DEM for analysis. The most recently updated impervious surface cover data of various classes (roads, parking, sidewalks, supporting, etc.) was provided from digital imagery processing by KGIS in vector format as were the stream and drain pipe networks with inlet and outlet points. Data was assessed for accuracy

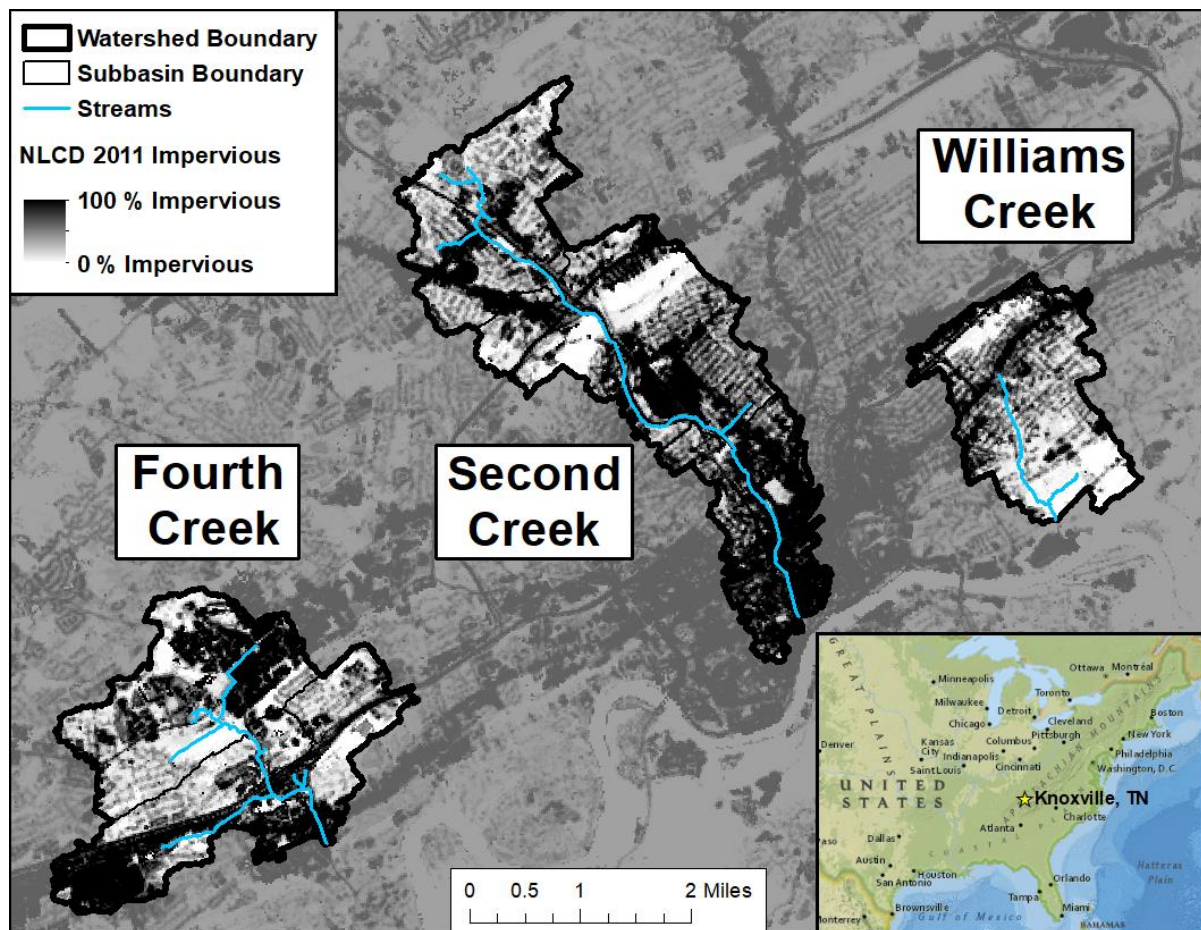


Figure 4 - Map of study sites located in Knoxville TN, USA with National Land Cover Dataset 2011 impervious surface data to illustrate differences between watersheds development patterns and stream networks.

Table 2 - Summary of watershed characteristics and observed data used in the study.

Characteristic	Second Creek	Fourth Creek	Williams Creek
Watershed Area (ha)	1,847	1,382	671
TIA (%)	36.09	35.23	26.94
Years Observed	2014 - 2016	2004 - 2014	2007 - 2014
# Storm Events	36	156	90

by visual comparison to satellite imagery with minor corrections applied to ensure the continuity of the stream network related to ephemeral drainages.

Vector impervious cover data was converted to raster format to match the resolution of the elevation data and ensure proper processing. The DEM was reconditioned to account for the drain pipe network and enforce flow along existing infrastructure by artificially decreasing DEM values where storm pipes are located by an elevation of 2 m based on guidance from Gironás et al. (2009). Watershed boundaries were then delineated using the reconditioned DEM to provide more accurate watershed areas. Where necessary, watersheds were divided into subbasins at appropriate points along the stream to enable connectivity processing as mentioned above in regards to scripting size limits. Second and Fourth Creeks contain three subbasins each with Williams Creek assessed as one. Because runoff connectivity is assessed from the source to the stream only, splitting the watershed into subbasins does not necessitate any further accounting as once runoff reaches the stream it is assumed to be connected to the downstream outlet by way of conservative streamflow.

Rainfall-Runoff Data Development and EIA Quantity Estimation

Historical records of rainfall and streamflow were obtained for Fourth Creek and Williams Creek from the City of Knoxville's Stormwater Engineering while data for Second Creek was monitored by the authors. All rainfall was measured using tipping bucket rain gages paired with streamflow monitoring at the basin outlet. Single gage readings were used for each watershed for reasons that will be expanded upon later related to the non-uniform spatial distribution of EIA. Streamflow was measured on Fourth and Williams Creeks using acoustic Doppler velocity meters in culverts of known cross-sectional area. The same was done on Second Creek, but monitoring switched to a laser level gage paired with stage-discharge curves when flashy flows proved detrimental to monitoring equipment. Storm data was collected for the time periods indicated in Table 2 with some gaps where data records for rainfall or streamflow were incomplete.

Storm events were defined as rainfall of greater than 1.27 mm separated by at least six hours preceding and following during which no more than 0.254 mm of rain fell in a given hour. Events were extracted from the record using scripting and these events were further screened to include only events up to 25.4 mm of rainfall that fell in a close distribution. This was done to reduce any bias that the temporal distribution of rainfall might have on runoff movement to the outlet and subsequent baseflow separation process, during which uncertainty increases with more complex hydrographs. Baseflow

separation was performed using the constant k-method of Blume et al. (2007) that assess the receding limb of the storm event hydrograph and defines the endpoint of direct runoff as the inflection point when the recession constant of streamflow approaches a constant value. This method is based on linear reservoir theory that assumes that direct runoff and baseflow discharge at different rates, and once streamflow has returned to a constant recession rate, it is sourced from only the baseflow reservoir. A linear interpolation from the initial outflow just before the hydrograph rise to this identified inflection point separates the streamflow between the direct runoff portion above and the baseflow portion below. Direct runoff volumes were then calculated for each storm event and converted to depths by dividing the volume by the watershed area. This provided a matching runoff depth for each storm event rainfall observation. The number of rainfall-runoff pairs is summarized in Table 2. These values were used to determine an estimate for EIA for each watershed using successive ordinary least-squares regression analysis following the guidance of Boyd et al. (1993) and Ebrahimian et al. (2016b). Final regression parameters were used to estimate f_{EIA} and I_a , and these were then employed in the spatial model to match the IRC values during model calibration.

IRC Model calibration

The spatial model was calibrated by varying the PRAP value until the resultant IRC metric was within 0.01 of the previously determined EIA portion of the watershed. This was performed by applying the smallest event size analyzed for the rainfall-runoff data (1.27 mm). The approach was chosen based on the assumption that event runoff is most likely sourced solely from EIA for the smallest storm sizes. Though regression analysis was carried out for storms ranging up to 25.4 mm in size to obtain the EIA through the trend in runoff across these sizes, the volumetric nature of the model insists that the IRC increases with rainfall when the PRAP is held constant. Through calibration of the IRC to the smallest storm size, the model identifies the most likely areas of runoff production across storm sizes while reducing the uncertainty surrounding model assumptions for larger events that have a higher likelihood of being sourced from other areas, impervious or otherwise. Further, initial abstraction values from graphical analysis were applied to the rainfall amount before runoff volumes were calculated.

RESULTS AND DISCUSSION

EIA Estimation by Regression

Trends in the observed rainfall-runoff pairs for storm events and EIA regression lines for the three watersheds are shown in Figure 5a-c. The final regression equations are shown with each graph with the EIA and I_a values summarized in Table 3 as well. Storm events are classified as either EIA-sourced (dots) or non-EIA (x's) based on the successive regression analysis. Figure 5d provides a visualization for the proportion of each watershed's TIA that was measured as EIA from this analysis that can be used as a comparison. While Second and Fourth Creeks differed in TIA by only 0.86%, they differ in EIA by 2.2%, indicating a higher degree of connectivity on Second Creek. Williams Creek had substantially lower TIA than the other two but higher EIA with the highest impervious connectivity of the three watersheds.

This is clear when you consider the degree of connectance (Table 3) which is 0.35, 0.29, and 0.51 for Second, Fourth, and Williams Creek watersheds respectively. Differences in impervious connectivity for these watersheds are related to how impervious surfaces are configured along the drainage pipe network and in relation to the stream itself as well. The EIA parameters determined through this analysis provide a means to connect the spatial elements of runoff distribution and pathway configuration to the observed hydrology as measured by the rainfall-runoff trends. That is, these data from the regression analysis can now be paired with the new proposed methodology.

IRC Calibration and Results

Results of the IRC analysis for each watershed are displayed in Figure 6. The IRC value is depicted on a scale ranging from a high value of 1.0 (dark) to low values nearing 0.0 (light). Highly connected areas are frequently the impervious areas most adjacent to the streams themselves, but there are also substantial areas of connectivity in each watershed located further from the stream. These further areas are connected along drain pipes and are considered just as connected as the impervious areas directly adjacent to the stream. Visually, this figure provides a map for locating the impervious areas most likely to comprise EIA. Because the IRC is measured along a continuum, the impervious areas with the highest connectivity (IRC = 1.0) are the best candidates for disconnection followed by areas of lesser connectivity. In this way, managers can use this information to prioritize limited funds or restoration timelines to place GI or SCMs in locations where they are most needed, whether near the stream or further away along drain pipe networks.

Further information about the impervious connectivity of these watersheds and the potential for disconnection can be determined by examining the calibration data from the proposed model framework. Figure 7 shows the values of the PRAP from calibration plotted against the resultant IRC. Horizontal lines indicate the TIA, EIA, and the directly connected impervious area (DCIA). In many studies, the DCIA is defined as impervious surfaces that drain directly to the stream while crossing no areas of pervious surface along the way. DCIA values were calculated for these watersheds following this strict definition of connectivity assuming that these areas exist only where impervious surfaces or pipes drain directly to the stream with zero interception of pervious cells along the flowpath. This value, below 1% of the watershed area for all three watersheds, represents a portion of the TIA that is connected regardless of changes in the PRAP and is the lower threshold for the IRC metric. Values are much lower than typical studies due to the strict definition and use of high-resolution data. Conversely, the TIA value naturally represents an upper threshold for the IRC metric that would be realized given a PRAP value of 0.0, as all runoff volumes from impervious surfaces would move to the stream unattenuated. The EIA line represents the calibration target, and final PRAP values resulting in an IRC equal to the graphical EIA are summarized in Table 3. The range in these values is of interest, and possibly reflects differences in the quality of pervious surfaces in regard to runoff attenuation potential in these watersheds. However, the homogeneous nature of the PRAP in the simple form of the model pipes drain directly to the stream with zero interception of pervious cells along the flowpath. This value, below 1% of the watershed area for all three watersheds, represents a portion of the TIA that is connected regardless of changes in the PRAP and is the lower threshold for the IRC metric. Values are much lower than typical studies due to the strict definition and use of high-resolution data. Conversely, the TIA value naturally represents an upper threshold for the IRC metric that would be realized given a PRAP value of 0.0, as all runoff volumes from impervious surfaces would move to the stream unattenuated. The EIA line represents the calibration target, and final PRAP values resulting in an IRC equal to the graphical EIA are summarized in Table 3. The range in these values is of interest, and possibly reflects differences in the quality of pervious surfaces in regard to runoff attenuation potential in these watersheds. However, the homogeneous nature of the PRAP in the simple form of the model framework utilized herein does not likely capture the spatial distribution of landscape factors affecting runoff potential. This is a source of error that will be discussed further below.

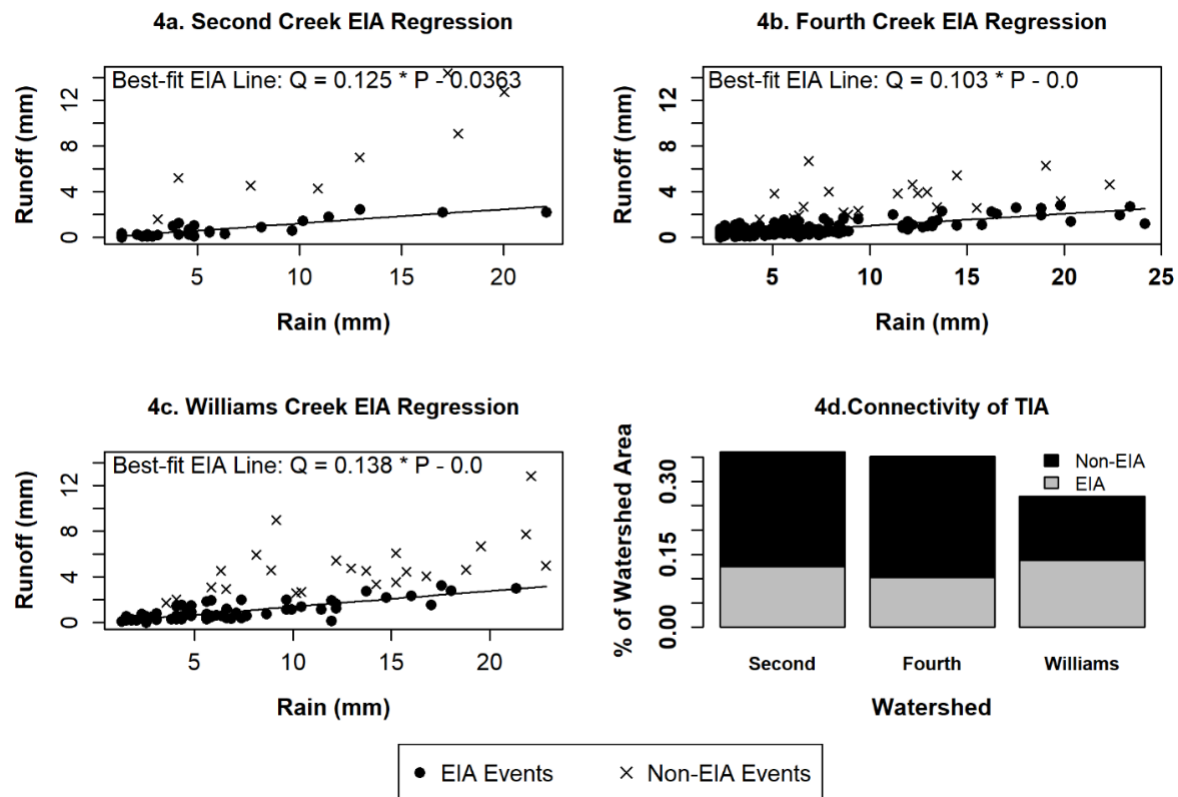


Figure 5 - Graphical EIA regression results for observed rainfall/runoff data and comparison of EIA portions of TIA determined for each watershed. Smaller events (0 – 10 mm) with runoff from non-EIA events are believed to be related to wet antecedent conditions.

Table 3 - Summary of results from graphical EIA determination and IRC model calibration.

	Second Creek	Fourth Creek	Williams Creek
EIA % (from regression)	12.5	10.3	13.8
I_a , mm (from regression)	0.29	0.00	0.00
Adjusted R^2 (from regression)	0.74	0.82	0.85
Connectance (EIA/TIA)	0.35	0.29	0.51
Calibrated PRAP	0.245	0.862	0.0243

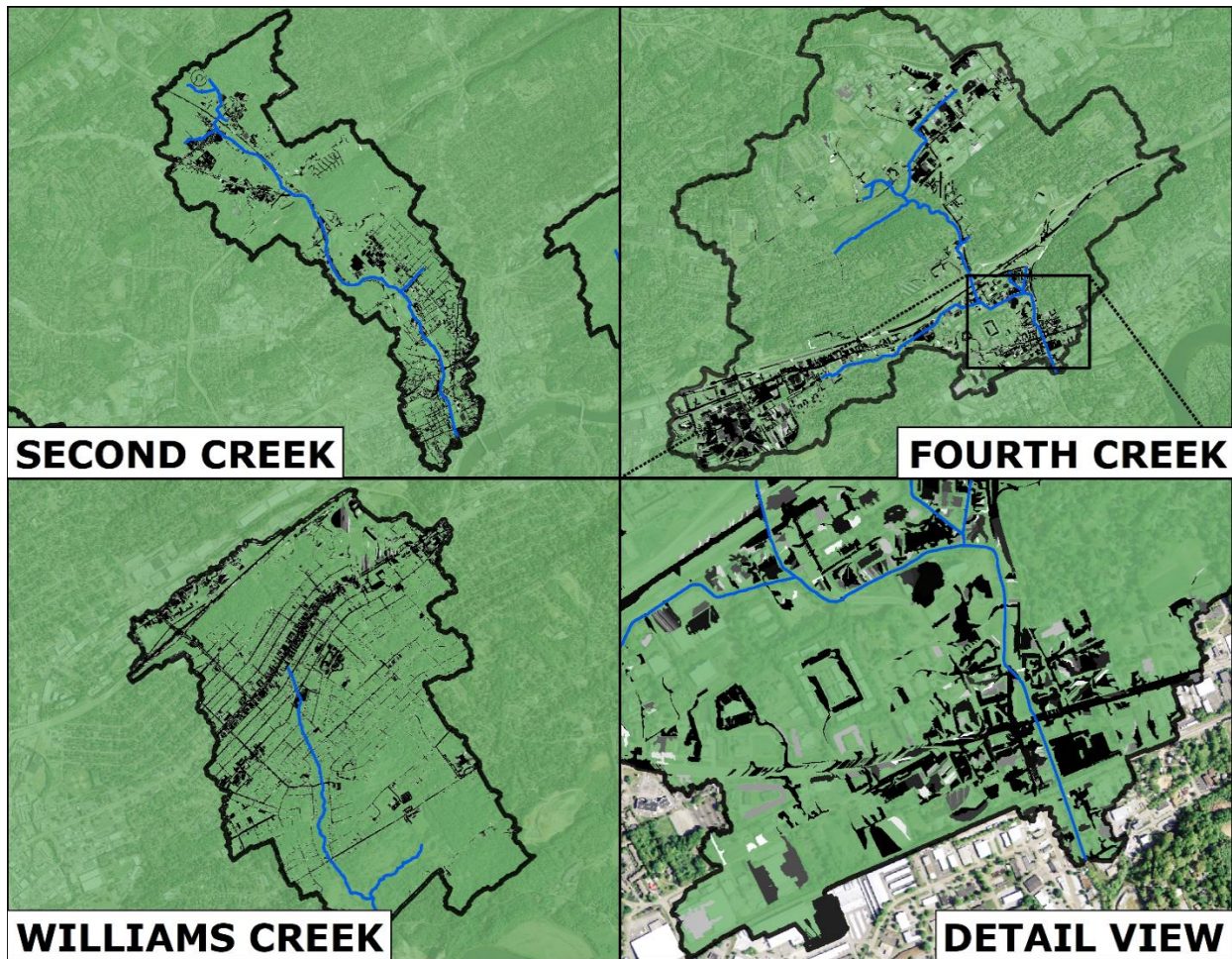


Figure 6 - Calibrated IRC for each watershed with inset detailed view of lower portion of Fourth Creek. IRC values vary from 1.0 to 0.0 along a spectrum from black to white. Green areas indicate pervious areas or impervious areas that are non-EIA.

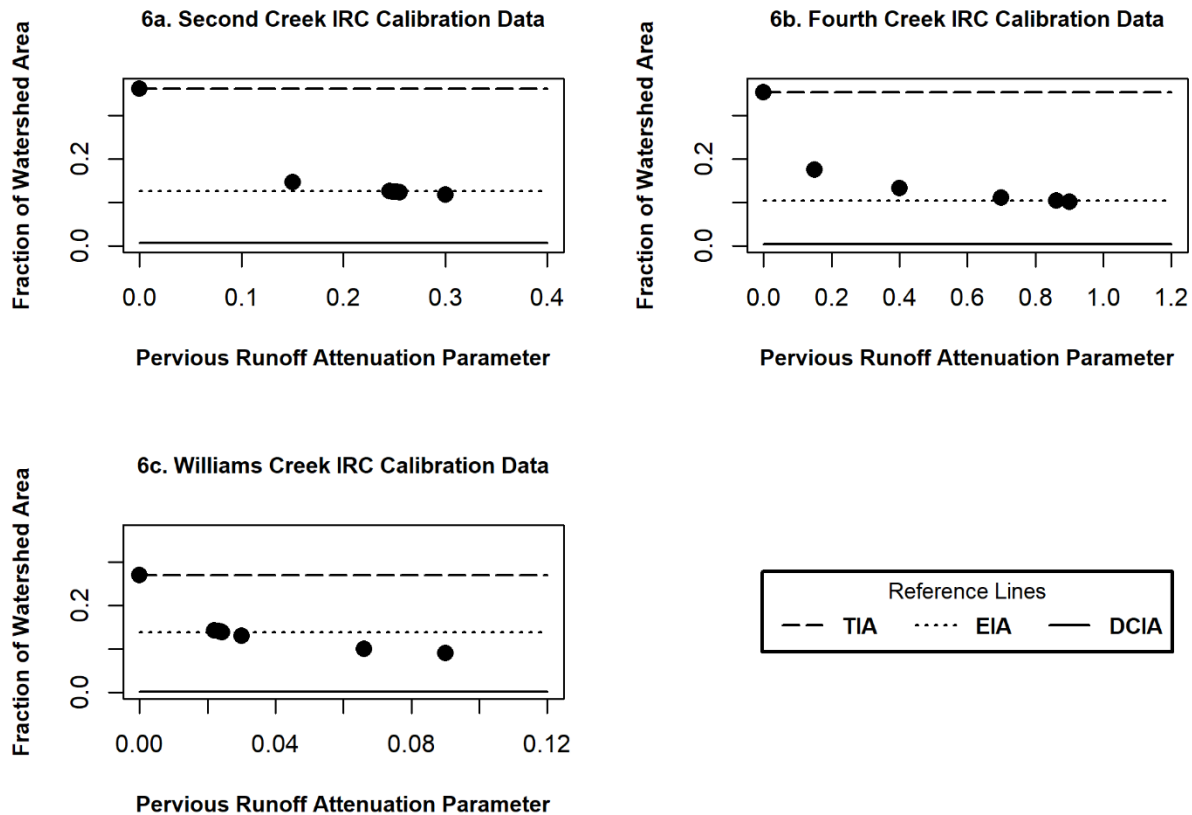


Figure 7 - Calibration data for the IRC model. Curves formed by calibration points reveal model sensitivity to the PRAP value in the vicinity of the EIA value that reflect differences in spatial data related to model representations.

Of greatest interest in examining the calibration data is the shape of the curves formed by these points that reflects differences in sensitivity on each watershed to the parameter itself. On all three watersheds, these points appear to form logarithmic recession curves that model the decline in the IRC metric as the PRAP increases. In terms of the spatial model, the shape of these curves is defined by the configuration of impervious surfaces, the runoff they produce, their proximity to the drainage pipe network, and their separation from the stream network by pervious surfaces. The intersection of the calibration data curves in the proximity of the EIA line reflects the sensitivity of the spatial identification of the EIA as the IRC metric in relation to the PRAP value.

On both Second and Fourth Creek (7a and 7b, respectively), the curve of calibration points appears to flatten considerably near the EIA line indicating lower sensitivity to changes in the PRAP value for the IRC near the EIA value. To illustrate what this means in terms of the spatial model, consider a scenario where EIA is hypothesized to vary with antecedent moisture conditions and this is accounted for by varying the PRAP. A higher PRAP could be used for drier antecedent conditions indicating greater runoff attenuation. This would result in a decrease in IRC measured by the model for dry conditions, with runoff from typically connected areas now being disconnected by the increased attenuation. The opposite would be true for wet antecedent conditions using a lower PRAP, with a higher IRC being measured as runoff from areas typically disconnected during average conditions would then connect to the stream. Because the IRC for Second and Fourth Creeks is less sensitive to changes in the PRAP near the EIA value, it could be concluded that antecedent moisture conditions are less influential on impervious connectivity for these watersheds, or that there is finite green space storage available regardless of antecedent moisture. Essentially, this information reflects the spatial distribution of impervious areas for these watersheds in terms of connective runoff pathways and indicates that areas identified as EIA are tightly connected while additional candidate impervious areas are substantially disconnected. This provides a higher degree of certainty that these areas are in fact EIA.

In the case of Williams Creek (Figure 7c), the curve formed by calibration points near the EIA line is steeper, indicating a higher sensitivity to the PRAP value. The calibration curve flattens farther to the right and below the area where the IRC meets the graphical EIA value. This indicates that some areas defined as EIA using the IRC metric for Williams Creek are not as tightly connected to the stream network as those found in the other watersheds. A slight increase in the PRAP would result in substantial changes in the IRC as these less tightly connected areas would disconnect under slightly higher runoff attenuation. If one considers this topic in terms of distributed restoration, impervious areas in Williams Creek have a higher potential for disconnection by slight modifications in connectivity than those in the other watersheds based on the shape of these curves. At-source applications of GI and SCMs would represent localized increases in runoff attenuation in the model, and while the PRAP is a watershed-wide metric, the spatial model provides guidance as to exactly where this increased attenuation would be most effectively applied. It should be noted that it is possible the calibration curve could also be related to uncertainty in the rainfall-runoff data forming the basis for the EIA and calibrated values. However, it is also possibly related to simplifications in the model that deserve further testing within the context of the model.

Issues and Opportunities

It is difficult to fully verify the exact source for runoff from any given storm event, but this model framework demonstrates a step toward identifying the most probable sources of impervious runoff that make up the EIA in a watershed. The above analysis indicates both positive outcomes from the simplified model framework and some important areas where it could be improved with further study. These areas focus on adding increased spatial information regarding the model input of rainfall and heterogeneous representation of influential runoff attenuation properties that can be captured within the modeling framework. The strength of the model lies in the ability to incorporate these additional factors influencing runoff connectivity into the model with high spatial resolution that should increase the certainty of spatial EIA identification. Further description of these elements is provided below.

One of the greatest assumptions of this model is that the best available geospatial data effectively represents hydrologic and hydraulic conditions on the watersheds studied to enable the spatial identification of EIA. Uncertainties in this data will influence final results directly, so data quality and resolution is very important in the use of this methodology. Stormwater pipe inventories are often incomplete or mischaracterized due to the difficulty in measuring underground assets. The accuracy of EIA results using this method are dependent on the quality of this stormwater pipe information, so data quality should be considered first and foremost in the applicability of the results. Secondly, elevation data resolution is important to consider as the methodology relies on DEM-based flowpaths. Urban flowpaths can be greatly influenced by curbing or infrastructure with abrupt changes in elevation that should be effectively accounted for in the data so as to reflect the physical hydrology. The data resolution of 1 m used in this study seemed adequate based on flowpath assessment, but results would likely be improved with greater elevation data resolution that better captures the fine-scale variables impacting urban hydrologic pathways.

In the simplest form of the model used in this study, runoff attenuation is limited to a homogenous value over only pervious surfaces, thus representing “average” attenuation across the entire watershed. Considering other factors influencing runoff attenuation and their spatial distribution is likely to produce a more accurate identification of EIA. Some factors that warrant investigation are the effect of different vegetative cover, soil types, and the conditions of these two that may influence the magnitude of transmission losses. One assumption of the model is that no runoff is attenuated across impervious surfaces or drain pipes. While a portion of rainfall is abstracted from impervious surfaces initially (based on EIA regression coefficients), this value may not truly reflect the physical process as it was determined

from EIA estimation methodology using regression of observed runoff data (Ebrahimian et al. 2016a). Additionally, drainage pipes are well-known to leak into the aquifer, and this represents a loss of impervious runoff to baseflow that could be better quantified with appropriate attenuation values. These could be varied based on the age of infrastructure, pipe materials, or known failure values.

Secondly, in most geospatial analysis of hydrology, a filled DEM is used to produce flow direction data used in the establishment of runoff pathways. This filled DEM modifies the values of the reconditioned DEM to ensure that all flow within a watershed boundary moves toward the outlet with no internal sinks. This enforcement of flow along the surface of the filled DEM alters the reality of watershed hydrology wherein internal depression storage areas do not exist. At these locations, runoff infiltrates into the groundwater aquifer and moves to the stream via subsurface flow at a much slower time step than that of surface runoff. The volume of these depressions may be slight, but for small storm sizes it could represent substantial disconnection of runoff. Depression storage volumes can be difficult to accurately characterize, but with increasing resolution of elevation data, estimates should improve. In considering such attenuation by infiltration, proximity to the stream network may also have an influence due to shallow groundwater flow. Runoff estimates for this study were taken from streamflow observations as opposed to end-of-pipe measurements (where groundwater inputs are likely minimal). Because of this, the runoff measured likely includes a shallow subsurface component not directly related to surface runoff. Separating the two is very difficult, but the shallow subsurface component could be very closely related to infiltration occurring near the stream network that moves towards the outlet at a faster rate than baseflow. These runoff dynamics have the potential to be accounted for by varying the PRAP value based on proximity to the stream network (subject to local groundwater conditions).

Last, rainfall observations for this study were taken from single gage locations for each watershed located near the outfall of each watershed. Most studies employ a network of rain gages when available, using areal-weighting to account for spatial variability and statistical analysis of spatial variations in rainfall data has been used to strengthen graphical estimates of EIA as well (Ebrahimian et al. 2016a). This was not done for this study though for the reason that any spatial assumptions about the distribution of rainfall across the watershed must also be coupled with information regarding the spatial distribution of EIA. This is due to the use of Eq. 1 under the assumption that all runoff derives from EIA for smaller storms. If a Thiessen polygon method is used to derive a storm-event rainfall measurement and then this data is used to estimate EIA, it assumes that the EIA is uniformly distributed among Thiessen polygons. While the work presented in this paper aimed to estimate the characteristic

EIA for each watershed, deviation from this EIA for any single storm event could be investigated more thoroughly with fine-scale rainfall data since runoff volume produced is the basis for measurement and this is highly dependent on incidental rainfall. The incorporation of more spatially dense rainfall observations will strengthen future applications of the IRC model and may offer a better means for verification of parameterization and calibration results. A reflexive approach may be best, wherein the EIA is estimated from observed data, the spatial model is calibrated, and then the EIA estimates can be refined using more accurate rainfall data at the appropriate spatial distribution matching that of the EIA.

CONCLUSIONS

The model framework presented above represents an automated and objective methodology that can be used to spatially locate the impervious areas in an urban watershed that are most likely to comprise EIA in gaged basins. The measurement of IRC on a volumetric basis provides the spatial identification of EIA that can be used to prioritize distributed restoration strategies among the most highly connected areas of the urban watershed as well as to guide design efforts in selecting appropriate practices and sizing them. The use of runoff volumes as the basis for establishing impervious connectivity allows for GI and SCMs that are installed to be incorporated into the model framework by raising runoff attenuation parameters appropriately at the location of installation in proportion to the amount of infiltration provided by the control. In this way, EIA and impervious connectivity measures can be updated as restoration takes place. Paired with monitoring, changes in connectivity can then be more closely tied to associated changes in stream hydrology that could provide greater information on how distributed practices function collectively as well as to guide future management actions.

The correct identification of EIA using this model is subject to uncertainty related to both the observed runoff data as well as the quality of spatial data and the ability to accurately incorporate the dominant properties influencing the connectivity of impervious-derived runoff to the stream as direct runoff. In this study, resistance to runoff connectivity was modeled simply as a homogenous runoff attenuation parameter. The ability for additional physical properties that influence runoff connectivity to be incorporated into the model remains to be studied. A strength of this model framework is that runoff attenuation values can be varied per differences in spatial data already incorporated within the model itself. Future work in this area will further strengthen model results and improve the accuracy of automated identification of EIA. Efforts to inform pervious attenuation with physical, spatially-variable

properties of the watershed, such as soil types and compaction, could also potentially lead to methods for ungaged basins.

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CHAPTER 2
**Using Spatially-Identified Effective Impervious Area to Target Green
Infrastructure Retrofits: A Modeling Study in Knoxville, TN**

This article was developed and written entirely by the student with editing assistance from his advisor, the co-author on the paper. It represents original work by the student that was developed through funding by his advisor, who played a crucial supporting role, offering guidance, critique, and grounding to see it accomplished and contribute to his overall research program.

ABSTRACT

There is a need for enhanced guidance in siting distributed green infrastructure (GI) practices, especially in densely developed urban watersheds where retrofits come at a high cost. To maximize the hydrologic benefit of Stormwater Control Measures (SCM) on urban streams, the disconnection of Effective Impervious Areas (EIA) has been identified as a strategic management approach that is expected to have the greatest impact. This is based on the body of evidence that has demonstrated the relationship between impervious surface connectivity (associated with greater EIA) and overall urban stream health. Methods to better distinguish EIA from overall imperviousness have recently been developed that offer explicit spatial identification of EIA that can be utilized in more effective placement of SCMs throughout watersheds. The overall effect of full disconnection of spatially-identified EIA on watershed hydrology is uncertain because this type of full disconnection is rarely brought to full-scale implementation. In this study, spatial EIA identification is used to parametrize an urban runoff model using the United States Environmental Protection Agency's Storm Water Management Model (SWMM). The calibrated model is used to assess runoff reductions resulting from SCMs distributed through the watershed via different placement strategies, both spatially-informed and not. Full treatment of the spatially-identified EIA using bioretention cells was compared to two scenarios treating the same amount of impervious surfaces, but with random placement either among all impervious areas or placement focused in areas of higher imperviousness. Model results indicate that substantially higher runoff reduction could be realized by targeting EIA, with a median runoff reduction of nearly 30% more runoff than other treatment scenarios across all storm events ranging from 1.27 to 20.7 mm using this strategic siting. Further improvements in optimizing distributed GI/SCM placement are needed, and targeting of spatially-identified EIA appears to be a viable method for increasing the hydrologic improvements realized through watershed scale implementations.

INTRODUCTION

In an effort to protect and restore stream health and water quality in streams worldwide, urban watershed managers seek to reinstate more natural flow regimes in highly developed watersheds. Streamflow has been recognized as a “master variable” defining ecological potential in riverine systems (Poff et al. 1997), and the impacts of impervious surfaces on urban hydrology and a range of other symptoms of degradation have been well established (Brabec et al. 2002, Leopold 1968, Shuster et al. 2005, Walsh et al. 2005b). The value of healthy streams as both financial and cultural assets (Assessment 2005) has led urban managers to seek watershed management strategies that both maintain flood protection from stormwater but also undo the effects of intense development on local hydrology. Increasingly worldwide, this is accomplished with distributed stormwater control measures (SCMs) and green infrastructure (GI) retrofits. Specifically, these at-source, smaller-scale surface runoff treatment practices are being used in many urban watersheds to restore pre-development runoff frequencies and volumes (Bernhardt and Palmer 2007). By shifting hydrology back to more natural patterns and addressing water quality issues at their source, it is believed that urban stream systems will have a better chance of supporting thriving ecosystems without the need for ongoing active channel restoration projects; that is, restoration efforts will better match the scale of the degrading process (Walsh et al. 2005a).

Research on the effectiveness of distributed SCMs to produce this hydrologic shift at the watershed scale is limited, but several studies have begun to add to the knowledgebase. Modeling has shown that site runoff dynamics are sensitive to the location, type, and number of SCMs installed (Gilroy and McCuen 2009). For instance, comparisons of hydrologic response to rainfall for developed catchments with different stormwater management strategies (centralized vs. distributed) revealed that distributed SCMs can yield more natural runoff dynamics than centralized stormwater systems (Loperfido et al. 2014). A small number of monitoring studies have also been conducted to measure the efficacy of distributed SCM strategies at several different scales. Notably, though not exhaustively, these studies include investigation at the small residential scale (0.53 ha) (Page et al. 2015), larger development tracts (2-6 ha) (Bedan and Clausen 2009), and catchment-wide studies with Shepherd Creek in Cincinnati, USA (180 ha) (Roy et al. 2014, Shuster and Rhea 2013), and Little Stringybark Creek (450 ha) in Melbourne, Australia (Walsh et al. 2015). The results of these studies indicate improvements in stated hydrologic and water quality goals, though they are difficult to compare due to differences in study approaches, SCMs employed, the timeline of installation, and siting strategies. These are nonetheless valuable

studies, as the lack of adequate supporting evidence for distributed SCMs to effectively address watershed-wide goals remains an impediment to widespread use of this multi-benefit management strategy (Roy et al. 2008).

Another impediment to wider use of distributed SCM retrofits in existing urban areas is that these practices carry a higher cost related to land value in densely developed areas. Costs are further increased when you consider the opportunity costs of land used for stormwater management as opposed to other uses in the urban setting (Roy et al. 2008). Because of this, distributed SCMs have mostly been sited in an opportunistic, empirical manner where public land is available or where redevelopment occurs. The high costs for urban retrofit projects warrants strategic siting of these SCMs so that they impart the greatest good to stream hydrology, especially considering limited water resource budgets and increased urbanization (Barbosa et al. 2012).

Research has shown that the effective impervious area (EIA), a subset of the total impervious area (TIA), has a much greater effect on stream hydrology than TIA due to hydraulic connectivity via rapid surface drainage and efficient stormwater infrastructure (Brabec et al. 2002, Shuster et al. 2005). This watershed characteristic may be leveraged to optimize the hydrologic benefits of SCM installations. However, quantifying and identifying EIA is more difficult than TIA because it can be subject to ambiguous urban drainage patterns and variable conditions that influence runoff production (Alley and Veenhuis 1983, Boyd et al. 1993, Brabec et al. 2002, Chiew and McMahon 1999, Ebrahimian et al. 2016a, Han and Burian 2009). Streams exhibit declining conditions as TIA increases, but these declines have been shown to be even more tightly coupled to increases in connectivity (ie, a higher percentage of TIA that is EIA) (Hatt et al. 2004, Lee and Heaney 2003, Leopold 1968, Walsh et al. 2005a).

Although disconnection of EIA by implementation of SCMs can theoretically maximize the effectiveness of watershed restoration efforts, rapid and reliable identification of these areas is often time-consuming (Roy and Shuster 2009). Recently developed methodology by Epps and Hathaway (2017, in press) provides spatially explicit identification of EIA that is informed by geospatial data and observed runoff trends. The results of this method account for spatial differences in runoff pathways to identify areas most likely to be EIA in a GIS framework that can be used to prioritize stormwater management projects for runoff reduction. However, it is difficult to assess the accuracy of the results of this new methodology or determine what the hydrologic effects might be given implementation of GI retrofits (as full disconnection of the EIA with SCMs would take several years). Modeling can provide an initial

means to assess the potential for this type of watershed-wide SCM deployment, assess how targeting spatially-identified EIA for disconnection compares to other less spatially guided strategies, and determine what level of watershed-wide changes in storm-event response should be expected given watershed-wide implementation.

One of the most widely-used urban runoff models is the United States Environmental Protection Agency's (EPA) Stormwater Management Model (SWMM) (Rossman 2004). Like most urban runoff models, SWMM is very sensitive to impervious parameter inputs. The need for accurate representation of impervious characteristics in urban runoff models has been noted specifically related to EIA (Alley and Veenhuis 1983, Lee and Heaney 2003). A recent review of research applying SWMM to urban hydrologic investigations and the modeling of management paradigms for planning and decision-making (Niazi et al. 2017) has identified several gaps and opportunities for future studies to strengthen the use of this model. This review points to the gap in knowledge in accounting for hydrologic continuity and GI spatial orientation as one of the most important foci for future research due to the importance of assessing different GI configurations to support current urban watershed management approaches. Incorporating spatially-identified EIA information into a SWMM model to inform strategic GI retrofits forms the basis of the study presented here. Results can be used to guide to better approaches in assessing distributed restoration initiatives and potential performance related to locational siting and configuration. This information will be pursued in this study using SWMM to model First Creek, a large urban watershed in Knoxville, TN. This will help determine what level of runoff reduction may be possible by installing SCMs strategically to disconnect EIA and to what degree this may be necessary to meet certain hydrologic goals.

Objectives

The goal of this study is to utilize the spatial identification of EIA areas to assess the runoff reduction that might be realized given targeted GI applications to disconnect EIA areas. Results will be compared to other scenarios of similar treatment level that use other criteria for site selection not related to EIA location to help quantify the potential advantage of using this spatial EIA information at the watershed scale.

METHODS

Study Site and Data

The focus of this study is the First Creek watershed in Knoxville, TN, United States (Fig. 8). First Creek is a large mixed-development watershed (5,320 ha) with an upland tributary that runs through rural areas with sparse residential development and some agricultural lands and a main stem that flows through a densely developed urban corridor following a main arterial road with flood-protection channelization. Watershed statistics have been summarized in Figure 8. EIA quantity estimates were developed from rainfall-runoff data using rainfall and streamflow records from the City of Knoxville Stormwater Engineering department. Rainfall data was obtained from three locations near the First Creek watershed and storm event depths were calculated based on a Thiessen polygon weighted-average. Storm events between 1.27 mm and 25.4 mm with at least 6 hours of separation from any additional rainfall were isolated from the data record. Storm events were screened to focus on events where all rainfall fell mostly in close temporal succession to focus on simpler single-peaked hydrographs. Because First Creek has two distinct areas of very different development patterns, there was evidence of multiple peaks in some hydrographs, but this response was consistent for larger storm events and these events were included.

Direct runoff depths for these storm events were estimated by hydrograph separation using the constant- k method of Blume et al. (2007). This method assumes that baseflow discharges from a linear reservoir with exponential decline such that the point on the receding limb of the hydrograph when the recession coefficient (k) becomes nearly constant represents the end of direct runoff and the streamflow's return to solely baseflow sources (Fig. 9). The recession coefficient was calculated for all points on the receding limb of the storm-event hydrographs via the equation from Blume et al. (2007):

$$k = -\frac{dQ}{dt} * Q(t) \quad (1)$$

Flow data were assessed visually using a 24-hour moving average to visually select the point in the receding limb of the hydrograph at which k stabilized to a near constant value. This point in the hydrograph was then connected by straight-line to the point just before hydrograph rise to complete hydrograph separation (Fig. 9). The volume of water above this line was then summed and converted to a depth through division by the watershed area so that rainfall-runoff trends could be used to quantify EIA. The quantity of EIA in the First Creek watershed was estimated in the same manner used in Epps and Hathaway (2017, in press), employing regression analysis of rainfall-runoff data using the methods

of Boyd et al. (1993) and Ebrahimian et al. (2015) as a guide. This EIA quantity was used as a target for calibration of spatial EIA models presented in Epps and Hathaway (2017, in press). This spatial EIA data both: (1) forms the impervious connectivity input for a SWMM model (as opposed to using impervious connectivity as a calibration parameter), and (2) is the focal point of various SCM siting methodologies that are compared herein to evaluate how volumetric runoff reduction varies based on restoration approach. Spatial differences in connectivity (EIA / TIA) for the First Creek watershed are shown in Figure 1, summarized at the subcatchment level used in the SWMM model.

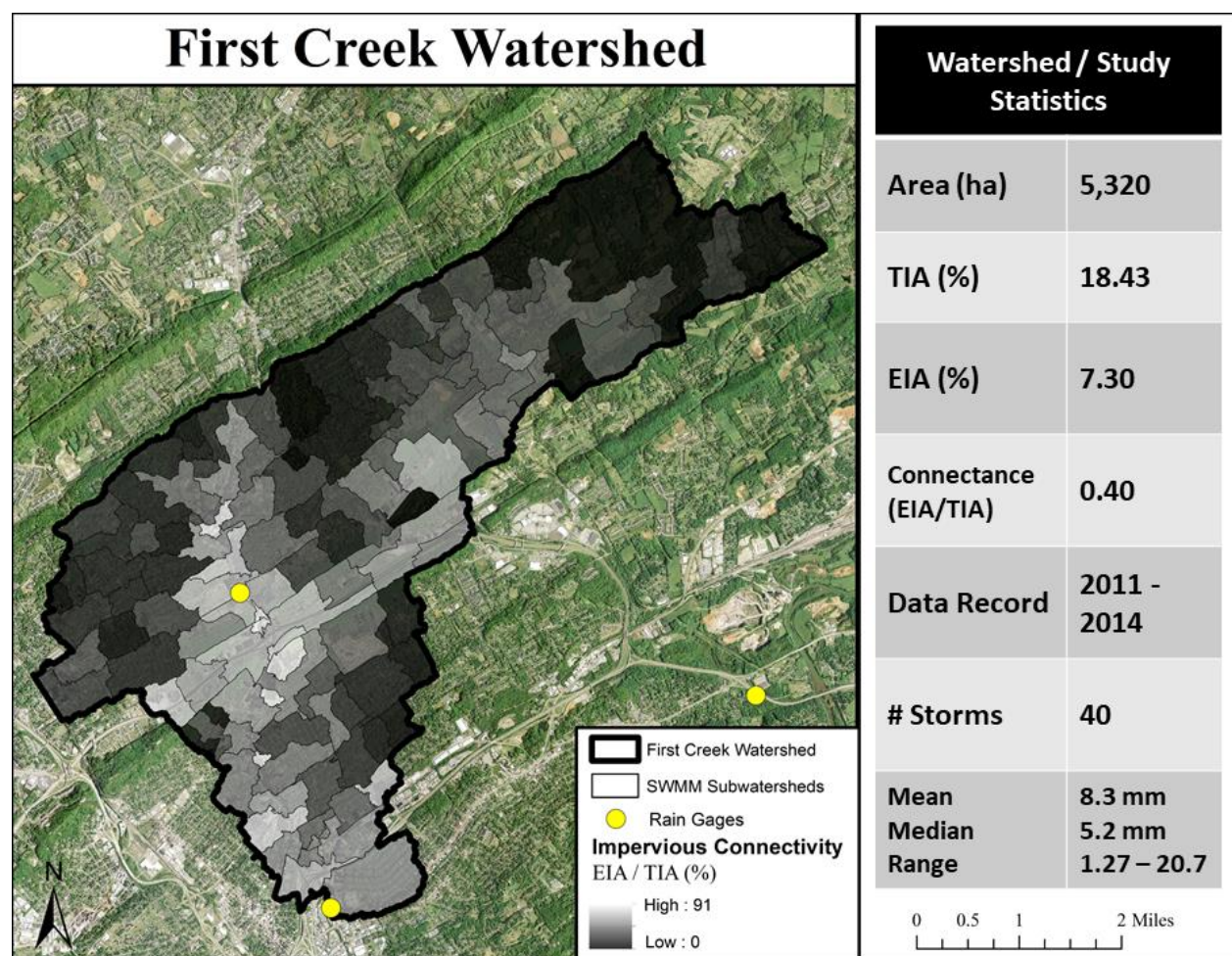


Figure 8 - Map of study watershed, First Creek in Knoxville TN, U.S.A. with summarized characteristics related to imperviousness and rainfall-runoff analysis used to estimate EIA. EIA spatial locations determined per Epps and Hathaway (in press).

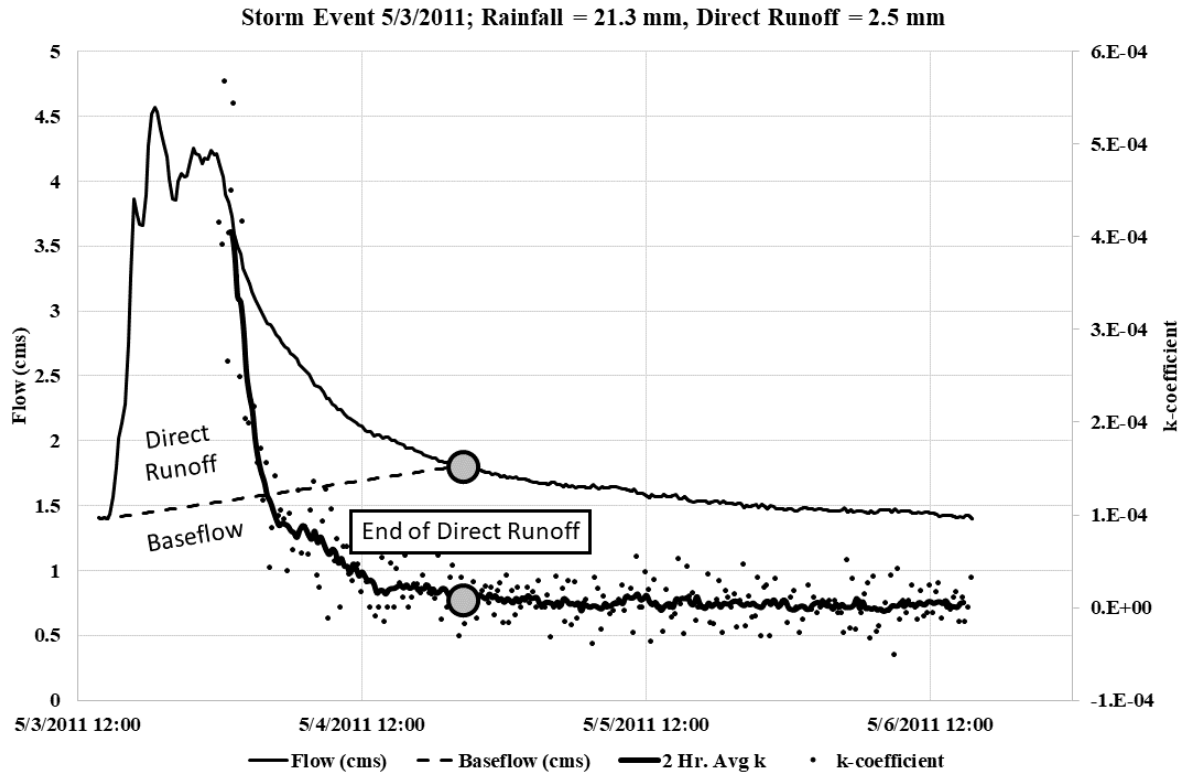


Figure 9 - Demonstration of hydrograph separation used to develop rainfall-runoff pairs for the estimation of EIA.

a depth through division by the watershed area so that rainfall-runoff trends could be used to quantify EIA. The quantity of EIA in the First Creek watershed was estimated in the same manner used in Epps and Hathaway (2017, in press), employing regression analysis of rainfall-runoff data using the methods of Boyd et al. (1993) and Ebrahimian et al. (2015) as a guide. This EIA quantity was used as a target for calibration of spatial EIA models presented in Epps and Hathaway (2017, in press). This spatial EIA data both: (1) forms the impervious connectivity input for a SWMM model (as opposed to using impervious connectivity as a calibration parameter), and (2) is the focal point of various SCM siting methodologies that are compared herein to evaluate how volumetric runoff reduction varies based on restoration approach. Spatial differences in connectivity (EIA / TIA) for the First Creek watershed are shown in Figure 1, summarized at the subcatchment level used in the SWMM model.

Surface Runoff Model

A previously developed SWMM model for First Creek was provided by the City of Knoxville Stormwater Engineering for this study. This model had been developed for flooding analysis and did not include a groundwater component. Because the goal of the study was to assess the representation of impervious connectivity and the disconnection of EIA using GI retrofits as they pertain to surface runoff, the development of a groundwater component was deemed unnecessary. The existing SWMM model disaggregated the First Creek watershed into 125 subcatchments based on infrastructure location and grouping of homogeneous surface cover and topography units. All surveyed channel information, stormwater infrastructure, hydraulic parameterization, and internal storage portions of the model were preserved for this study. Subcatchments were also preserved and the impervious areas for each was altered where necessary to ensure model inputs were consistent with data generated by the spatial EIA models.

SWMM Model Setup and Parameterization

Aside from subcatchment geospatial data mentioned above, the SWMM model parameters were adapted based on guidance from SWMM documentation (Rossman and Huber 2016). The Green-Ampt method was used to represent infiltration in the model and runoff routing was modeled using the kinematic wave approximation. Rainfall observations from three tipping bucket gages (Fig. 8) were used in the model, being assigned to subcatchments based on where they were located per a Thiessen polygon representation of the three gages.

Model parameters were developed from literature values and based on the assumptions of the spatial EIA model. Infiltration parameters for the Green-Ampt model were taken from literature based on subcatchment soil properties obtained from the National Resources Conservation Service's SSURGO soil survey database (SSURGO 2017). The distribution of each subcatchments soils among different Hydrologic Soil Groups (HSG) was used to produce weighted values for the literature-based Green-Ampt parameters. Impervious routing parameters were parsed between TIA and EIA according to the amount of EIA identified in each subcatchment from the previously described spatial models. For each subcatchment, the EIA was routed directly to the outlet while the balance of TIA was routed to pervious areas representing the disconnected portion of impervious surfaces. The original SWMM model obtained from the City of Knoxville had routed impervious and pervious areas directly to the outlet, utilizing model calibration of other surface runoff parameters to achieve adequate model fitting. The

inclusion of the spatially-identified EIA routing represents an improvement over this representation that reflects surface connectivity data.

Model Calibration and Assessment

Surface runoff was modeled over the period from March 2011 to June 2014 during which continuous records for streamflow and three rain gages existed. A total of 40 storm events were selected from this data record per the selection criteria described above and the additional criteria discussed below. The events had a range of rainfall from 1.27 mm to 20.7 mm with an average storm size of 8.3 mm. While more than 40 valid storm-events were identified during the period of record, only storms that had been identified to derive from predominantly EIA in regression analysis were used. Some larger rain events produce runoff that is likely sourced from non-EIA impervious areas as well as pervious areas, and these are associated with a greater degree of shallow groundwater influence that is not well captured by the SWMM model. Results for storm-event runoff from the SWMM model were summed over the equivalent time period that direct runoff occurred in the observed storm events, and these values were converted to an equivalent storm-event depth. Model fit for storm-event runoff depths was assessed using the Nash-Sutcliffe efficiency index (NSE) (Nash and Sutcliffe 1970) and the Kling-Gupta efficiency (KGE) (Gupta et al. 2009).

Simple manual calibration was performed to improve the base SWMM model fit by varying the starred parameters in Table 4 between their high, mean, and low values identified in the literature to determine model sensitivity and provide the best model of surface runoff. This calibration was simple in that the parameters for all 125 subcatchments were assigned the same value class (low, median, high) for the parameter of interest for each calibration iteration. Final model parameters are noted in bold (Table 4). Calibration was assessed for the storm events during 2011 – 2012 (23 events) and verified by the remaining events during 2013 – 2014 (17 events).

Green Infrastructure Scenarios

To study differences in runoff reduction that may be realized given alternative approaches to SCM application, the calibrated SWMM base model was used to assess runoff reduction under different siting strategies for GI in the First Creek watershed. Since EIA was estimated as 7.3% of the watershed, this forms the targeted amount of area to be treated by GI in all scenarios to facilitate disconnection. Three scenarios of GI siting were compared.

- The first scenario (“EIA”) applied SCMs only to the spatially-identified EIA areas (treating 7.3% of the watershed). This represents the targeted GI scenario where spatial models of EIA are used to identify locations for SCM application to disconnect EIA runoff from the stream network.
- The second scenario (“Random”) distributed SCMs randomly by first using a random number generator to apportion the 7.3% treatment level amongst the subcatchments, and then using a second random number generator to divide that apportioned percentage for a given subcatchment between EIA and non-EIA areas (subject to availability of each of these impervious types). In this scenario, it is assumed that the equivalent area of impervious surfaces (7.3%) are treated for disconnection, but that the placement of SCMs among the TIA is not guided by any spatial information (ie, random).
- The third scenario (“TIA-weighted”) was the guided by subcatchment imperviousness wherein the 7.3% treatment level was apportioned amongst subcatchments using a weighted average of the TIA in each subcatchment to the overall watershed TIA. This TIA-weighted impervious percentage was then divided between EIA and non-EIA areas in each subcatchment based on a random number generator. This scenario represents an intermediate guidance strategy in which the treatment amount in each subcatchment is proportional to the TIA distribution over the watershed, but that there is no further spatial differentiation between EIA and non-EIA areas receiving treatment. This scenario was chosen as an intermediate level of spatial guidance since distributed SCMs are typically placed more often in the most highly impervious areas of a watershed.

This process was iterated for each alternative siting strategy (Random and TIA-weighted) with different randomization to produce 30 different applications of SCM for each to be compared to the EIA-focused siting strategy. Each of these scenarios was then modeled in SWMM by placing SCMs appropriately within the model to identify differences in runoff reduction between each model. Average runoff reductions over the 30 model iterations were then used to compare to the EIA scenario.

Green Infrastructure Modeling

To apply the appropriate GI treatment in each scenario, a generic bioretention cell was modeled to treat EIA and non-EIA impervious areas in each subcatchment. Parameterization of these bioretention cells is summarized in Table 5. Bioretention cells were sized vertically per guidance from municipal stormwater management manuals (Table 5). For each GI scenario, the impervious surface area identified for treatment (EIA and non-EIA separately) was used to calculate the runoff volume for a storm event of

Table 4 - Summary of pertinent SWMM model parameters. Bolded values represent final parameters values for the calibrated model. Starred parameters indicate those that were varied during simple manual calibration.

Parameter	Description	Initial Value	Range Lo	Range Hi	Guidance/Source
Subcatchment Parameters					
Nimp*	Manning's n for Impervious	0.015 (avg. Impervious)	0.01	.018	Yen (2001)
Nperv*	Manning's n for Pervious	0.05 (avg. grass)	0.038	0.12	Yen (2001)
Simp (mm)	Depress. Storage for Impervious	0.3	---	---	Ebrahimian et al. (2016a)
Sperv* (mm)	Depress. Storage for Pervious	6.4	2.5	10.2	ASCE (1992)
%Zero	Portion of IMP w. no Simp	0	---	---	Accounted for in EIA Spatial Model
%Routed	Portion of IMP routed to PERV/Outlet	EIA %	---	---	EIA % within each Subcatchment
Infiltration Parameters					
Suction (mm)	Suction head at wetting front	$\psi_s = 0.127 * K_{sat}^{-0.328}$			Brakensiek et al. (1981)
Ksat* (mm/hr)	Sat. hydraul. conductivity	Avg. value from soil composition	Low value from soil composition	High value from soil composition	Musgrave (1955); based on soil HSG comp.
IMD*	Max moisture deficit avail.	Based on K _{sat} /soil classification	Low value from table range	High value from table range	Rawls et al. (1983)

25.4 mm. The required surface area of bioretention cells to treat this amount of runoff was then calculated based on the storage available in the bioretention cell to accommodate this volume. SWMM summarized in Table 5. Bioretention cells were sized vertically per guidance from municipal stormwater management manuals (Table 5). For each GI scenario, the impervious surface area identified for treatment (EIA and non-EIA separately) was used to calculate the runoff volume for a storm event of 25.4 mm. The required surface area of bioretention cells to treat this amount of runoff was then calculated based on the storage available in the bioretention cell to accommodate this volume. SWMM allows a given GI unit to receive runoff from a subset of the subcatchment impervious areas. Thus, two bioretention cells were defined and sized for each subcatchment, based on the EIA and non-EIA impervious areas to be treated in each scenario, and the appropriate percentage of the impervious area was routed to each accordingly. SWMM also allows underdrain flow and excess water from the GI component to be routed back to pervious areas or directly to the outlet. This option was utilized to maintain the model representation of surface routing, with the bioretention cell treating non-EIA routed to pervious areas and that treating EIA routed to the outlet. Storm event runoff depths were calculated from model outputs and the percent runoff reduction was calculated by comparison to surface runoff depths for the base model with no GI application. The average percent reduction of runoff for the 40 storm events was calculated for the 30 iterations in each alternative scenario to compare to the EIA-focused runoff reductions. Pairwise comparison of storm event runoff reduction between the three siting strategies was then used to assess whether there were statistical differences. This was done for all storm events as well as by 3 groupings of storm event size (< 6 mm, 6 – 12 mm, and 12+ mm) to aid in discussion of differences in runoff reduction by storm size.

RESULTS AND DISCUSSION

SWMM Model Results

The base model performed well in matching storm-event runoff depth given simple manual calibration. Model performance results over the entire period and the calibration and verification periods are summarized in Table 6, and modeled runoff depth versus the observed runoff depth has been plotted in Figure 10. The model typically performs well, but shows some underprediction of larger storm events, an expected outcome given the lack of a groundwater component within the model.

Table 5 - Summary of bioretention cell parameterization and source of information for application of SCMs in different siting scenarios.

BIORETENTION CELL BMP (Type = BC)			
Parameter	Description	Value Used	Rationale
Surface Layer Parameters			
<i>StorHt</i>	Max depth water can pond (in)	6.0	TNPSWMDG Manual
Soil Layer Parameters			
<i>Thick</i>	Thickness of soil layer (in)	24.0	TNPSWMDG Manual
<i>Por</i>	Soil porosity (pore space/total volume)	0.44	MN SWM (loamy sand)
<i>FC</i>	Soil field capacity (volume pore water/ total volume when fully-drained)	0.09	MN SWM (loamy sand)
<i>WP</i>	Soil wilting point (vol. pore water/ total volume for well-dried soil)	0.04	MN SWM (loamy sand)
<i>Ksat</i>	Saturated hydraulic conductivity (in/hr)	0.5	TNPSWMDG Manual (MIN)
<i>Kcoeff</i>	Slope of curve of log(conductivity) vs soil moisture content (dimensionless)	50	0.48(%Sand) + 0.85(%Clay); SWMM Manual
<i>Suct</i>	Soil capillary suction (in)	4.06	Brakensiek et al. (1981)
Storage Layer Properties			
<i>Height</i>	Thickness of storage layer (in)	12.0	TNPSWMDG Manual
<i>Vratio</i>	Void ratio (porosity = $vr/(1+vr)$)	0.4	TNPSWMDG Manual
<i>Seepage</i>	Rate of drainage into native soil (in/hr)	Ksat	Model parameter for subcatchment
<i>Vclog</i>	Clogging parameter	0	Clogging ignored
Drain System Properties			
<i>Coeff</i>	Determines rate of flow through drain as a function of hydraulic head (C)	0.6	Nashville Metro SWM Manual
<i>Expon</i>	Determines rate of flow through drain as a function of hydraulic head (n)	0.5	Nashville Metro SWM Manual
<i>Offset</i>	Ht. of drain above bottom of storage layer (in)	12.0	TNPSWMDG Manual

Table 6 - Summary of SWMM base model performance for prediction of storm event runoff depth.

Model Period	Nash-Sutcliffe Efficiency	Kling-Gupta Efficiency
Overall (2011 – 2014)	0.77	0.88
2011/2012 (23 events)	0.79	0.72
2013/2014 (17 events)	0.74	0.73

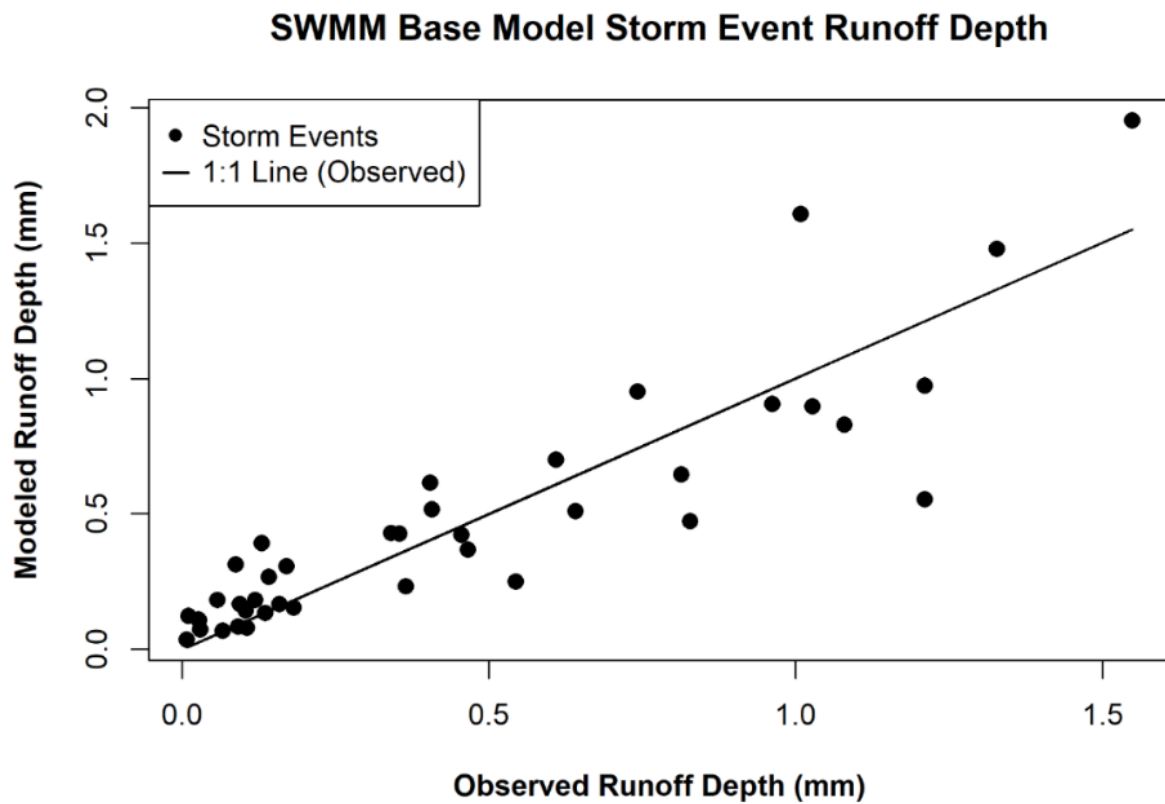


Figure 10 - Observed runoff versus predicted runoff depth for the final SWMM runoff model for First Creek.

Hydrograph separation distinguishes total runoff between a baseflow component and direct runoff, the latter which may contain some portion of interflow, or shallow subsurface return flow not related entirely to surface runoff dynamics (Beven 1989). This portion is not easily discernible through graphical analysis and may over-estimate true surface runoff for any given event. Manual parameter adjustment for this SWMM model used mean literature values as a starting point and adjusted parameters to minimum and maximum literature values for these across all subcatchments to identify the greatest sensitivities in the model for surface runoff to arrive at the final calibrated base model. Parameters that were adjusted in this process away from the mean value were all related to soils and pervious area runoff, and the calibrated values were all on the low end of the literature ranges. It is possible that this reflects the condition of urban soils which typically have poorer infiltration and thus contribute to greater surface runoff. However, this may also be due to the aforementioned overestimate of surface runoff in the streamflow data due to the inclusion of interflow which is not included in the SWMM model. Overall, these results demonstrate that the model is well-suited to serve as a basis for comparing runoff reduction between SCM placement scenarios.

Spatial EIA Distribution among Subcatchments

The inclusion of spatially-explicit estimates of EIA that are informed by physical geography and hydrologic trends (Epps and Hathaway 2017, in press) in this SWMM model produced acceptable model results with only simple manual calibration. EIA has been identified as one of the most sensitive parameters in SWMM models, and its accurate representation in the model can allow more efficient and accurate calibration for other important urban runoff parameters in the model (Mancipe-Munoz et al. 2014). Comparing the spatially-derived results of EIA from this study to those from literature regression estimates offers a demonstration of how different EIA values can be given the method of estimation which can greatly impact surface runoff modeling results. A plot of the EIA versus TIA for the SWMM model subcatchments derived from spatial analysis (Fig. 11) demonstrates a very different relationship for the First Creek watershed than predicted by literature regression equations sometimes used for EIA estimation (Alley and Veenhuis 1983, Roy and Shuster 2009, Wenger et al. 2008). This plot indicates that EIA would be mostly overpredicted by regression equations for the First Creek watershed, especially for intermediate values of TIA.

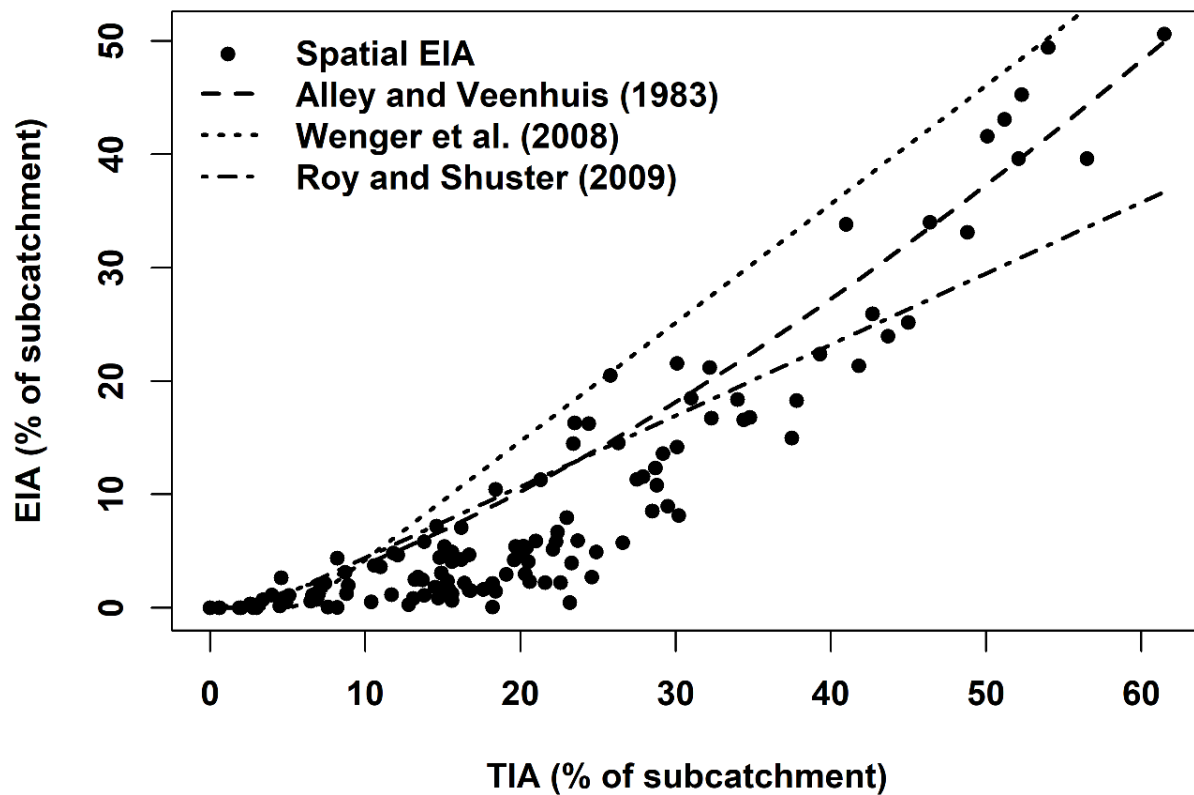


Figure 11 - The spatial distribution of EIA among SWMM model subcatchments as a function of TI are not well represented by literature regression equations.

The use of these regression equations to predict EIA in catchments other than where they were developed has been demonstrated to poorly reflect actual EIA measurements (Roy and Shuster 2009) and this is further demonstrated here. While this is not the focus of this paper, it demonstrates that the method utilized to estimate EIA can vary greatly, and because runoff modeling results are sensitive to this parameter, it makes sense to use the most site-specific information available. Spatial EIA estimates used in this study were developed based on surface runoff trends and not solely spatial data. Because of this, they reflect not only catchment hydrology but also the spatial distribution of the EIA parameter which can easily be incorporated into SWMM model subcatchment discretization for more accurate runoff production and routing information. Estimations of EIA using regression equations or through model calibration may corroborate subcatchment runoff through other parameter values and thus provide a less accurate representation of impervious surface connectivity and urban runoff processes.

Runoff Reduction for GI Placement Scenarios

Average percent runoff reductions achieved via different GI placement scenarios are summarized overall and by storm size groupings in Table 7 and with boxplots to demonstrate the range of values (Fig. 12). The results of pairwise comparison for each grouping by the Wilcoxon signed-rank test are presented in Table 8. This non-parametric test of pairwise comparisons was used due to non-normality in the runoff reduction data. Results indicate that focusing GI applications in locations identified as EIA can result in significantly greater runoff reduction, especially for smaller storms up to 12 mm. Over all storm events, GI placement focused on EIA resulted in nearly 30% greater runoff reductions (Table 8) than those for less spatially guided strategies with an overall mean runoff reduction of 37.3% (Table 7). Differences in runoff reduction of storms by different size groupings offer information on modeled runoff dynamics and the performance of GI treatment that can inform future model parameterization and utilization of this information for application of distributed SCMs in terms of runoff reduction potential and management strategies.

Table 7 - Summary of average percent runoff reductions for different treatment scenarios for all storms and by size groupings.

Percent Runoff Reduction	EIA Treatment		Random Treatment		TIA-weighted Treatment	
	Mean	Median	Mean	Median	Mean	Median
All Storms	37.3	39.8	8.1	6.6	7.9	6.0
< 6 mm	49.2	49.4	5.5	4.9	5.5	4.9
6 – 12 mm	32.2	34.6	10.7	12.1	10.4	11.9
12+ mm	16.9	17.8	10.8	11.9	10.5	11.9

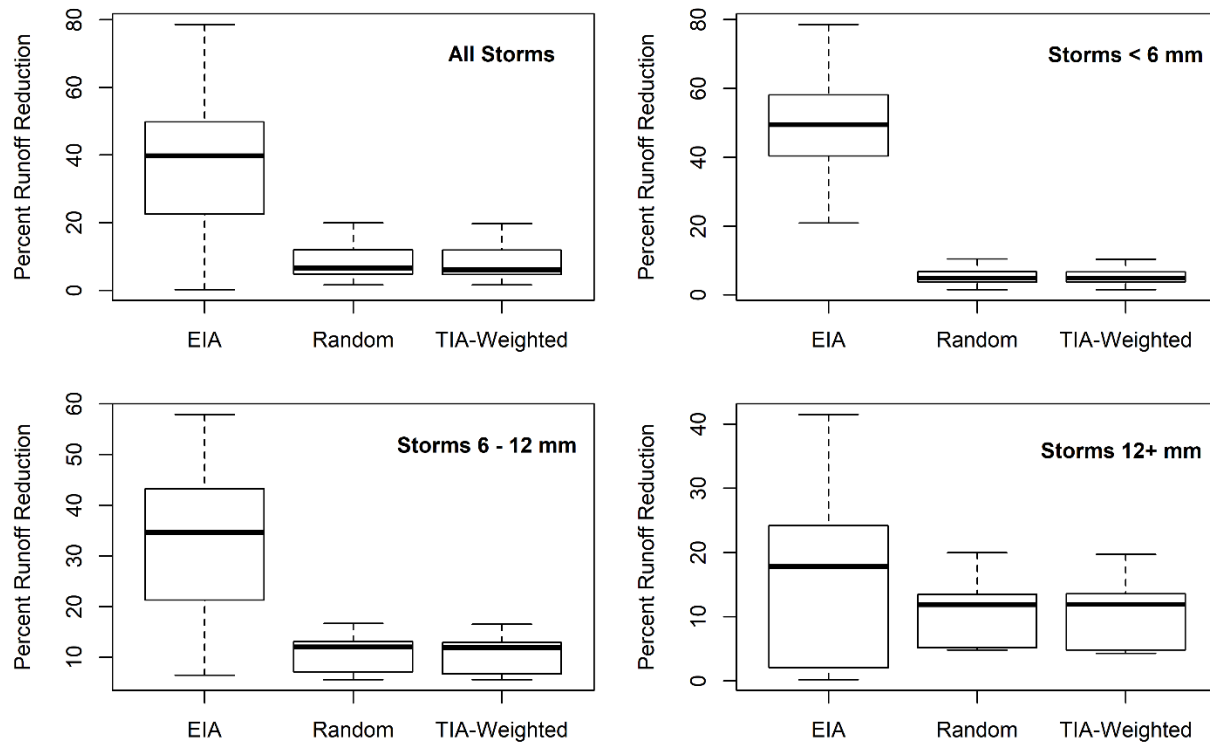


Figure 12 - Boxplots of runoff reduction over all storms and for different storm size groupings between different SCM siting strategies.

For smaller events less than 6 mm, runoff reduction is highest when SCMs are placed according to spatially-identified EIA with a mean runoff reduction of 49.2%. Runoff from connected impervious surfaces is well-handled by the modeled bioretention cells and precipitation is sufficiently small that pervious areas do not likely produce substantial runoff, if any. This is important to note when you consider that the higher frequency of runoff from smaller storm events is one of the indicators of urban hydrologic regime shift. Substantially greater runoff reduction for small storm events using EIA-focused placement may have a large impact on decreasing runoff frequency overall. While runoff would not be eliminated entirely, the amount would be negligible considering the size of the events.

For intermediate events greater than 6 mm but less than 12 mm, runoff reduction using EIA-focused siting was still greater than other scenarios with an average runoff reduction of 32.2% over these storm events. EIA-focused siting of SCMs resulted in runoff reductions that were more than 20% greater than

those for other siting strategies based on the pseudo-median values from the Wilcoxon signed-rank test. Runoff reductions for these intermediate storm events was still substantially greater for the EIA treatment scenario, though not great as for the smallest storms. Events in this size range are typically frequent, especially in more humid climates like the southeastern United States. Full treatment of all EIA with distributed SCMs could thus reduce runoff by greater than 30% annually for storms less than 12 mm in size. While the magnitude of this reduction overall would be dependent on local precipitation statistics, it could represent a substantial amount of annual runoff reduction if a larger percentage of storm events for a given urban watershed were in this range.

When rainfall exceeded 12 mm, there was not a statistically significant difference in storm event runoff reduction between siting strategies at the $\alpha = 0.05$ confidence level though they do appear to be greater for storm events overall using EIA-focused siting based on mean and median percent reduction statistics (Table 8). There was greater variability in runoff reductions for EIA treatment scenarios for these larger storm events than for the other storm size groupings, and this is also evident in the Random and TIA-weighted treatment scenarios. One possible explanation for this could be the influence of antecedent moisture conditions and pervious areas on runoff production for larger storm events in the SWMM model. When rainfall exceeds infiltrative capacity, pervious areas begin to produce runoff, and this is more likely to occur for larger storm events. Infiltrative capacity for pervious areas ranges based on soil moisture conditions and thus varies by storm event depending on recent rainfall. Runoff from impervious areas routed onto pervious areas as in the case of non-EIA portions of the watershed would additionally influence soil saturation and further increase runoff from pervious areas for larger events. For the EIA treatment, all runoff from non-EIA is routed to pervious areas without treatment. For larger storms, and especially those falling when soil saturation is higher due to recent rainfall, all runoff from these non-EIA areas is routed to pervious areas in the SWMM model, which may produce runoff for these events. This effect would be lessened in the random and TIA-weighted scenarios which treat a portion of non-EIA runoff and thus would contribute less to pervious saturation. For larger storms, surface runoff thus becomes the sum of interactions between pervious conditions and surface runoff routing from different portions of the TIA that are subject to a range in antecedent moisture conditions. Treatment location may become secondary to simply the level of treatment for maximum runoff reductions as pervious influences impact surface runoff more for these larger events.

Table 8 - Summary of Wilcoxon signed-rank tests for runoff reduction between SCM siting strategy overall and for storm size groupings.

Storm Events	Comparison	Statistical	Pseudo-	95 % Confidence Interval	
		Difference (p-value)	Median Difference	Lower Bound	Upper Bound
All Storms	EIA to Random	< 0.001	29.31	22.09	36.43
	EIA to TIA-weighted	< 0.001	29.48	22.24	36.48
	Random to TIA-weighted	< 0.001	0.18	0.06	0.21
Storms < 6 mm	EIA to Random	< 0.001	43.81	36.42	50.41
	EIA to TIA-weighted	< 0.001	43.85	36.48	50.51
	Random to TIA-weighted	0.30	No statistical difference at $\alpha = 0.05$		
Storms 6–12 mm	EIA to Random	0.003	22.56	10.18	32.84
	EIA to TIA-weighted	0.002	22.82	10.75	33.08
	Random to TIA-weighted	0.002	0.27	0.14	0.54
Storms 12+ mm	EIA to Random	0.074	No statistical difference at $\alpha = 0.05$		
	EIA to TIA-weighted	0.055	No statistical difference at $\alpha = 0.05$		
	Random to TIA-weighted	0.020	0.28	0.04	0.55

Table 9 - Summary of revised EIA estimates from linear regression of rainfall versus modeled runoff.

EIA Regression Results	EIA-Focused	Random	TIA-weighted
EIA	5.90%	6.37%	6.40%
R ²	0.77	0.85	0.85
% reduction of EIA	19.2%	12.7%	12.3%

Because EIA quantity was estimated from rainfall-runoff trends, it is possible to assess how these different SCM siting strategies might affect this parameter through modeled runoff reductions. Revised estimates for EIA were obtained from linear regression of the rainfall versus modeled runoff for each of the SCM scenarios and these have been summarized in Table 9. The original estimate of EIA for First Creek was 7.3%. Runoff reduced by the modeled distributed SCMs resulted in a reduction of 1.4% in EIA for the EIA-focused siting strategy as assessed by runoff trends. Other siting strategies resulted in less reduction of EIA though it was still substantial, especially considering the disparity in runoff reduction for smaller storm events between the different siting strategies. EIA estimates by runoff trend regression are more influenced by larger storm events for which differences in runoff reductions were not as great based on model results, thus the closer results in overall EIA reduction between scenarios than runoff results indicated.

Modeling Considerations and Further Opportunities

While these results indicate that utilizing spatial EIA information for SCM placement can result in greater runoff reduction, some considerations should be made regarding model representation that will point to areas for further study. This modeling exercise utilized a single idealized SCM for EIA and non-EIA areas to represent runoff reduction potential given watershed wide application. However, the impacts of surface routing and treatment and pervious areas in the context of EIA and non-EIA portions of the watershed's impervious surfaces, were apparent considering performance by different storm sizes. This suggests interactive effects in surface runoff processes as modeled that may be at play in urban hydrology, however it could also be a function of the idealized modeling structure. Realistic application of SCMs in this watershed would likely necessitate the disaggregation of the idealized SCM into smaller

units that were further distributed within each subcatchment, i.e., modeling at a finer scale for both the SCMs and their contributing watersheds. To holistically model this interactivity at the watershed scale, investigation of the relationship between groundwater conditions and surface runoff may also be warranted. Additionally, bioretention may not always be the most applicable or feasible type of GI for all areas. Detention-based SCMs may be more effective than infiltrative practices given certain site conditions and objectives, and vice versa.

Another consideration is the feasibility for GI retrofits in areas identified as EIA. Placement of GI where EIA has been identified may not always be feasible due to site constraints not identified by the spatial model. This could be related to poor infiltration rates, difficult topography, or adequate space. For the First Creek watershed, 3.1% of the watershed was identified as EIA in the public domain, less than half of the total EIA. Targeting these areas first for any GI retrofit efforts in the watershed would be a good strategy to begin implementation of distributed restoration efforts based on these modeling results. This would represent the intersection of opportunistic GI applications with spatially-informed siting that would provide watershed managers with the best hydrologic benefit for the watershed using readily available spaces for distributed restoration. Spatial EIA models could then be revised given the added GI to reassess connectivity and further identify areas where runoff reductions would be greatest given the disconnection of those where GI has been established.

CONCLUSIONS

There is a need to prioritize areas for GI retrofits in urban watersheds that enable cities to place limited resources in areas where they will have the greatest impact on urban streams. Watershed assessment using high-resolution geospatial data can provide robust information concerning priority areas for distributed watershed restoration when coupled with hydrologic information. Modeling that incorporates the best information from both of these sources can be used to assess management options and refine approaches in order to optimize results for urban watershed improvement. The results of this study indicate that spatial EIA information can be applied to a SWMM model to adequately predict surface runoff using literature-based parameters with simple manual calibration. The calibrated model was used to investigate three GI placement scenarios. The strategy specifically targeting EIA within the watershed showed significant differences in runoff reduction compared to more random SCM placement strategies which treated both EIA and less-connected portions of TIA. The EIA

based strategy was estimated to average a nearly 30% improvement in runoff reduction over the other two methods. These results highlight the importance of focusing GI applications to areas identified as EIA to optimize urban hydrologic benefits and point to how this methodology can help watershed managers prioritize restoration efforts. Further investigation with higher-resolution runoff modeling should lead to management recommendations that fully account for the spatial variability of urban runoff production, but this initial study demonstrates that the utilization of spatially-identified EIA data can be used as a basis for GI siting that should provide substantially greater runoff reductions to help lessen the impacts of impervious surfaces and runoff connectivity on urban stream hydrology.

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CHAPTER 3
Investigating Differences in Effective Impervious Areas Identified
Using Spatially Variable Runoff Attenuation and Radar Rainfall
Estimates

This article was developed and written entirely by the student with editing assistance from his advisor, the co-author on the paper. It represents original work by the student that was developed through funding by his advisor, who played a crucial supporting role, offering guidance, critique, and grounding to see it accomplished and contribute to his overall research program.

ABSTRACT

The application of distributed stormwater control measures (SCM) in urban watersheds is occurring worldwide as a means to disconnect effective impervious areas (EIA) and promote more natural drainage methods for runoff. Identification of EIA can be difficult due to complex urban runoff pathways and ambiguous surface connectivity. However, recently updated geospatial models provide a way to rapidly identify the impervious areas most likely to comprise EIA at the watershed scale through surface cover and runoff pathway analysis coupled with hydrologic analysis of observed runoff trends. Variability in runoff production and connectivity across the landscape can shift how much of the EIA is active for any given storm event, and it was hypothesized that this might be better accounted for in spatial assessments of the EIA by using more accurate representations of variables influencing urban runoff. Three spatial models for identifying EIA that vary based on how runoff attenuation (RA) is accounted for have been calibrated for three urban watersheds in Knoxville, TN. Assessment of model results utilizing spatially-distributed rainfall estimates as they pertain to natural variability in observed runoff was conducted to determine if geospatial models would be able to explain differences in active EIA between storm events. The results of this study indicate that spatial models capture the distribution of EIA well but that variability in active EIA for any given storm-event is more related to antecedent conditions than spatial differences in RA. Discussion of sources of uncertainty in these models and an investigation of how areas identified as EIA by each model differ helps to inform future applications of these models, how they may be improved, and important areas for further study toward optimizing SCM placement at the watershed scale.

INTRODUCTION

Distributed installations of green infrastructure (GI) are occurring worldwide, yet questions remain as to the effectiveness of this stormwater management paradigm to meet the needs of dense urban populations (Roy et al. 2008). The ability of these efforts to disconnect effective impervious areas (EIA) and manage urban surface runoff has been studied primarily at the local scale, but more study is still

needed to understand how GI type stormwater control measures (SCMs) function together at the watershed scale and what spatial density of these practices is needed to effect change (Wenger et al. 2009). Urban population growth, increased stormwater regulations, and the recognition of the ecosystem services that healthy streams provide make this an important problem as cities worldwide attempt to rebuild pre-development hydrologic function into the world's urban waterways (Gill et al. 2007).

Research on urban hydrologic impacts has focused on impervious surfaces and how they are connected to the stream network via stormwater piping. Such infrastructure shifts the hydrologic regime, thereby increasing surface runoff and hydraulic efficiency. The quantity of EIA in a watershed has been shown to be a greater determinant for various measures of stream quality and condition than the total impervious area (TIA) in multiple studies (Brabec et al. 2002). Estimation of EIA quantity can be challenging, necessitating either time-consuming and data-intensive map analysis (Lee and Heaney 2003), determination from observed streamflow and rainfall records (Boyd et al. 1994), or through model calibration due to the high sensitivity of urban runoff models to this parameter (Alley and Veenhuis 1983). Automated methods have also been employed, using geospatial analysis to determine not only the quantity of EIA but also its location in the watershed, but these rely heavily on accurate surface cover and stormwater infrastructure connectivity data (Han and Burian 2009). Recent improvements in urban spatial data resolution, availability, and accuracy have led to refinement in these methods utilizing increased computing power and geospatial analysis methodologies (Epps and Hathaway 2017, in press). Epps and Hathaway (in press) developed a geospatial framework that incorporates observed rainfall-runoff trends with spatial model calibration as a means to better assess urban impervious connectivity, identify the most influential variables, and begin to understand how SCM placement can be optimized to improve hydrologic function.

A Spatial Modeling Framework for the Identification of EIA

Epps and Hathaway (2017, in press) presented a modeling framework that utilizes high-resolution urban elevation and surface cover data along with stormwater infrastructure inventories to spatially identify impervious areas most likely to comprise EIA. The model incorporates runoff volumes deriving from impervious surfaces (subject to an initial abstraction) and elevation-determined hydrologic pathways to assess the connectivity of any given impervious surface. Resistance to connectivity is represented with the pervious runoff attenuation parameter (PRAP), akin to a transmission loss for each unit of pervious surface that runoff crosses as it moves toward the stream network. The PRAP represents any barrier to

runoff transmittal such as infiltration or depression storage, but does not distinguish between potential loss factors. Runoff movement along impervious surfaces, stormwater pipes, and the stream itself are assumed to be conservative with no attenuation taking place.

The quantity of EIA is first estimated in this methodology based on trends in observed rainfall-runoff data (Boyd et al. 1993, Ebrahimian et al. 2016b). Spatial models are then calibrated to match the estimated EIA quantity for a given watershed to provide spatially-explicit identification of the EIA. Because EIA estimates are based on stream observations, there is natural variability in runoff production for any given storm event that may indicate runoff greater than or less than the amount that would be expected from EIA alone. This is potentially related to storm-dependent watershed conditions affecting runoff production, but also the spatial distribution of rainfall and how it coincides with impervious surface locations. Because EIA can vary from storm to storm, models that estimate these areas should account for factors affecting this variability. The methods of Epps and Hathaway (2017, in press) have attempted to measure EIA at the watershed scale to provide spatial information that can assist watershed-wide applications of distributed GI. It is therefore important to assess whether these EIA estimates, both in quantity and location, are accurate.

Variability in the spatial distribution of rainfall for any given storm event is also related to observed runoff variability. EIA quantity estimates from rainfall-runoff trends have been typically conducted using the most spatially dense rainfall gage data available. While some screening of rainfall events to eliminate those with greater spatial variability has occurred in these approaches (Ebrahimian et al. 2016a), some uncertainty may still exist depending on watershed size and rainfall gage density. Improving the resolution of rainfall observations to better reflect the scale of variability in urban runoff processes has been identified as an important focus in urban hydrology modeling (Fletcher et al. 2013). Utilization of highly distributed radar-based rainfall observations is not yet widespread due to errors in the data and the difficulty of uncertainty measurement, but these types of data offer valuable input to high-resolution urban hydrology modeling. In terms of the spatial EIA models evaluated herein, higher resolution rainfall data could account for variability in runoff observations and help refine EIA estimates.

Initial studies using the calibrated EIA spatial model featured a homogenous PRAP across all pervious areas of several urban watersheds in Knoxville, TN (Epps and Hathaway 2017, in press). This spatial EIA model is robust in its conduciveness to vary the PRAP in a highly distributed manner given geospatial data that is representative of physical watershed characteristics influencing runoff connectivity or

attenuation. The focus of this study will be to examine different representations of runoff attenuation (RA) akin to the homogenous PRAP to determine the most plausible model of spatial EIA identification as determined by their ability to explain variability about the EIA trend line, and to identify further factors that may warrant inclusion in spatial models of connectivity.

Objectives

Alternative spatial EIA models to the homogenous PRAP representation of RA (Epps and Hathaway 2017, in press) will incorporate remotely-sensed data to better account for spatial variations in runoff connectivity. These two alternative models will include the effects of (1) soil/surface cover and (2) topography on runoff connectivity. Differences in spatially located EIA between the models will be compared for each watershed as well as between watersheds to highlight watershed characteristics that may influence EIA differences. Spatially-variable NEXRAD (NOAA Next Generation Weather Radar data) rainfall estimates, calibrated to local gage data, will then be utilized to assess the degree to which variability in observed runoff may be explained by spatial rainfall variability, spatial EIA models, or other factors that may not be well-represented in the spatial models.

METHODS

Site Description and EIA Estimates

This study, building on the work of Epps and Hathaway (2017, in press), was conducted on the Second Creek, Third Creek, and Williams Creek watersheds in Knoxville, TN, United States (Fig. 13). Watershed characteristics are summarized in Table 10, including estimates of EIA quantity from regression analysis of rainfall-runoff data (additionally displayed in Fig. 14). Greater detail about EIA quantity estimation can be found in Epps and Hathaway (2017, in press), and this methodology was based on the work of Boyd et al. (1993) and Ebrahimian et al. (2016b). This method utilizes observed rainfall and runoff records to estimate the EIA quantity based on trends in runoff production. In particular, for smaller storm events, these methodologies assume runoff is derived nearly entirely from EIA. For this study, rainfall data was taken from a network of gages operated by both the City of Knoxville Stormwater Engineering Department as well as the University of Tennessee at Knoxville. Locations for these gages are displayed in Figure 13, and storm event rainfall depths were distributed for each watershed based on Thiessen polygons, using an area-weighted average of gage observations to obtain storm-event depths. The development of storm-specific runoff depths from streamflow records was performed

using hydrograph separation to measure only the direct runoff portions of flow. Direct runoff is generally understood to include both surface runoff and shallow subsurface interflow components that are difficult to reliably differentiate (Beven 1989, Kulandaiswamy and Seetharaman 1969). EIA impacts on runoff are predominantly related to surface runoff, but it is possible that they may also influence the magnitude of interflow where impervious-related surface runoff is separated from the stream network by only moderate distances of pervious space. The effects of impervious surface disconnection (by infiltration) on more delayed components of streamflow remains a topic for further research. As it

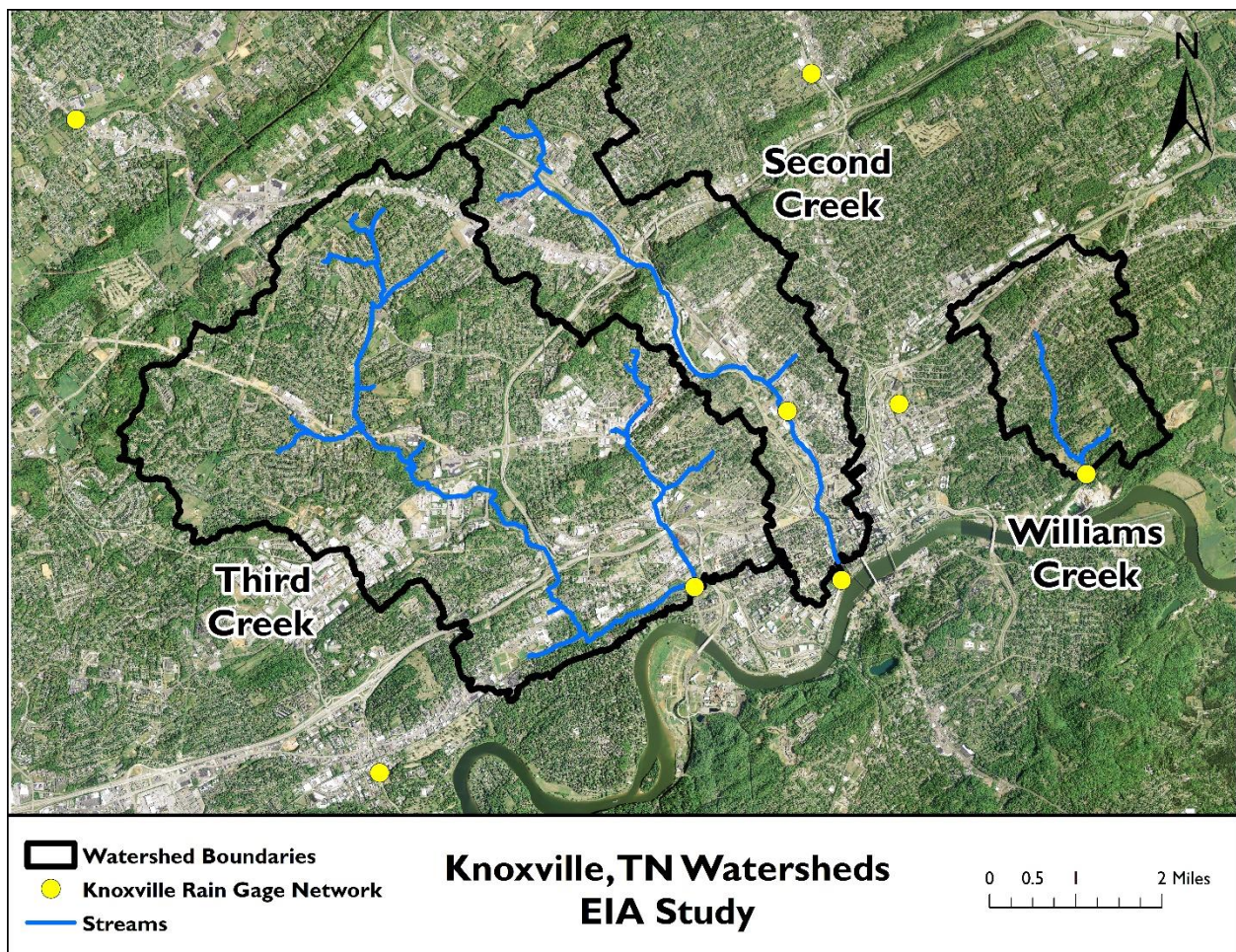


Figure 13 - Study watersheds in Knoxville TN, United States with rain gage network.

relates to this study, which specifically focuses on surface runoff, observed runoff depths from hydrograph separation are likely overpredicted for larger storm events since an interflow component may be larger and more related to additional runoff from pervious areas. This will be accounted for in the analysis of model results and discussion.

Spatial EIA Model Parameterization

To refine spatial models of EIA identification using the framework of Epps and Hathaway (2017, in press) and determine if spatial models can better capture variability in observed runoff about the EIA trend line, different representations of RA were employed for comparison and assessed using NEXRAD radar rainfall observations. Three spatial EIA models were developed for each watershed using: (1) a homogenous pervious runoff attenuation parameter (PRAP), (2) a Curve Number based attenuation parameter (CNAP), and (3) a topographical based attenuation parameter (TOPAP). Descriptions of each of these approaches are described further below. Spatial models were parameterized and calibrated to match the estimated EIA quantity for an artificial, uniformly distributed storm event of 5.0 mm with an initial abstraction of 0.3 mm in line with the median abstraction value found by Ebrahimian et al. (2016a). This event size was chosen as it represents a small storm that is likely to produce runoff from only EIA areas but not large enough that substantial pervious runoff should be expected.

EIA Model Attenuation Parameterization

The homogenous PRAP model from Epps and Hathaway (2017, in press) was used to assess the simplest form of the spatial model, whereby all pervious areas are assumed to attenuate runoff identically according to the calibrated parameter value. More spatially variable representations of RA (CNAP and TOPAP) were employed to investigate whether greater spatial disaggregation of RA would explain the variability in observed runoff as it relates to EIA. These two methods utilize geospatial data to account for the effects of spatially-varying soil type/surface cover (CNAP) and topography (TOPAP) on EIA identification.

Land cover variation in surface runoff attenuation (CNAP)

The CNAP spatial model was developed using guidance from Curve Number (CN) methodology, specifically United States Department of Agriculture Technical Release 55 (TR-55) (Cronshey 1986) to account for greater spatial variation in RA related to soil type and surface cover. Because the CN method assigns empirical values to all areas of the watershed based on surface cover and soil properties

Table 10 - Watershed and impervious characteristics for study watersheds.

Characteristic	Second Creek	Third Creek	Williams Creek
Watershed Area (ha)	1,847	4,357	671
TIA (%)	36.09	25.21	26.94
EIA (%)	14.9	6.31	12.4
(R ² for regression of EIA events)	(0.839)	(0.767)	(0.934)
Connectance (EIA/TIA)	0.41	0.25	0.46

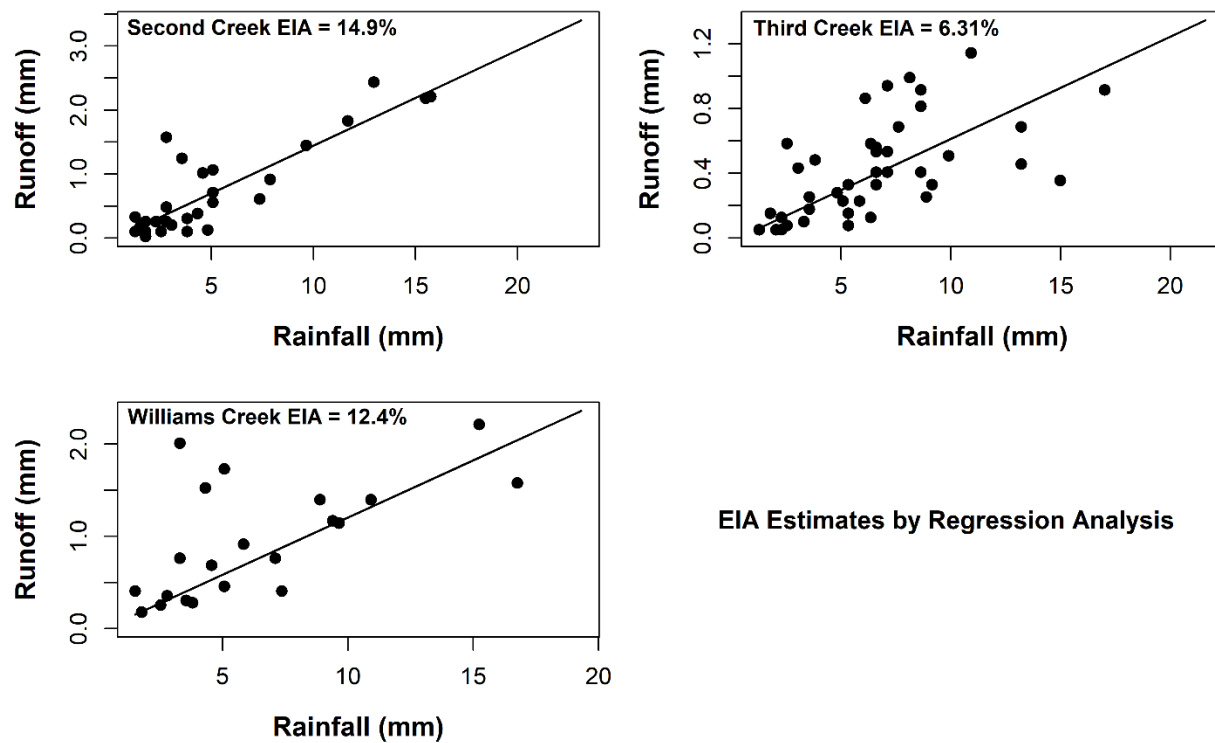


Figure 14 - EIA quantity estimates are derived from regression analysis of rainfall-runoff data.

that are used to estimate surface runoff, the development of CNs for study watersheds based on available data provides a way to vary the PRAP according to localized RA potential. CNs were assigned based on the intersection of surface cover type and the hydrologic soil group (HSG) from soil surveys. Spatial soils data and HSG were obtained from the National Resources Conservation Service's SSURGO database (SSURGO 2017). Impervious areas identified from municipal data were assigned the highest CN (98), and pervious areas were assigned CNs in conjunction with TR-55 and the United States Geologic Service's National Land Cover Dataset (NLCD) for 2011. CN values in these pervious areas were varied by matching NLCD classifications with those in TR-55 and using the median condition for surface cover type (where appropriate) for different vegetation classes. Final CNs were then assigned based on surface class and HSG using TR-55 values. CN values vary along the theoretical range of 0 – 100 with higher values indicating greater runoff production (and likely less RA), though actual values in TR-55 vary from 30 – 98. Watershed CN values were normalized to a unit scale based on the equation

$$(100 - \text{CN}) / 100 \quad (1)$$

This normalization ensures that differences in attenuation parameters preserve the relative differences of the CN scale while indicating that areas with lower CN would have a greater disconnecting effect (higher RA) on surface runoff than those with higher CN (lower RA).

Topographical variation in runoff attenuation (TOPAP)

The effect of topography on runoff processes and connectivity has been studied on the landscape level using indices to measure the likelihood of runoff production and connectivity (Beven and Wood 1983, Lane et al. 2009, Quinn et al. 1995). Surface runoff movement has been shown to increase with local slope and where soil saturation is most likely (e.g. topographic wetness index). In assessing runoff flowpaths using geospatial assessment at the watershed scale, digital elevation models (DEM) are often modified using filling techniques to enforce that runoff moves towards the watershed outlet without entering small-scale sinks and surface depressions in the landscape (Olivera and Maidment 1999). Full assessment of surface sinks in the landscape is time-consuming, and it can be difficult to fully discern between actual sinks and uncertainties in elevation data (Kenny et al. 2008). However, in terms of surface runoff flowpaths across depressions in the landscape, these features can have a large effect on runoff connectivity. Such influences are typically ignored using DEM modification in favor of rapid watershed hydrologic flowpath analysis.

To account for these topographical effects on runoff connectivity, runoff flowpaths were assessed using the original unmodified DEM (Fig. 15).

For each location in the landscape, the runoff flow direction and unmodified DEM were used to assess the localized percent slope for runoff moving to the next downstream location. Negative values represent runoff moving downhill while positive values represent runoff that would have had to move uphill given the original unmodified DEM. As indicated above, typically this is overcome by DEM-modification fill processing, ensuring that all runoff always moves downhill or laterally. By using an unmodified DEM, locations exist where runoff would actually have to overcome the positive slope of the depression elevation to flow beyond this location. For this study, the range in slopes was assigned an upper boundary of 50% in the positive or negative direction (i.e. ± 0.50) with any value above this being assigned this maximum value on either end of the scale. These values were then increased by 0.5 across all values to normalize the TOPAP scale to a range of [0,1] as represented by the equation

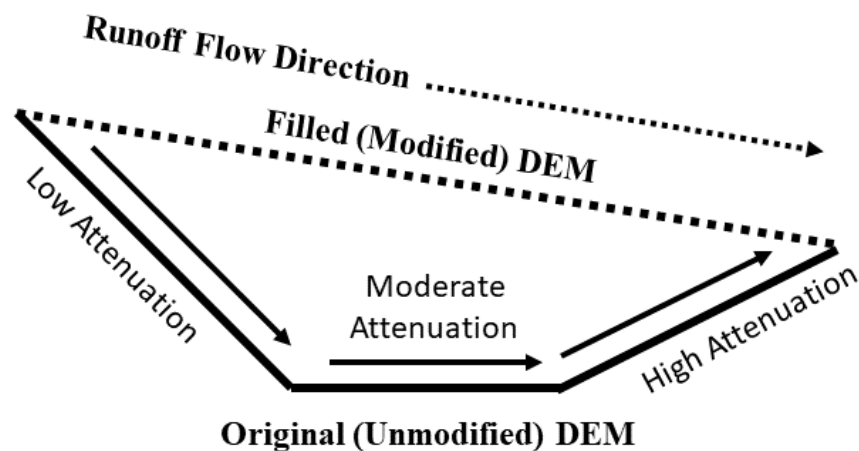


Figure 15 - Schematic representing the TOPAP representation of attenuation associated with landscape depressions.

$$TOPAP_i = 0.5 + \begin{cases} \max(S_i, -0.5), & S_i < 0 \\ \min(S_i, 0.5), & S_i \geq 0 \end{cases} \text{ where } S_i = \frac{\Delta Elevation_{ij}}{\Delta Distance_{ij}}$$

TOPAP values of 0 represent locations where runoff would move downhill with a slope greater than or equal to 50% and no attenuation would then take place. Increasing TOPAP values indicate increasing attenuation as the slope varies from 50% downhill to 0 and upwards to greater than or equal to 50% where attenuation would be greatest.

Calibration of CNAP and TOPAP Models

Each spatial variable of interest (CN or topography) was assessed over the watersheds using remotely sensed data and measures were then normalized to a nominal unit scale that was the same for all watersheds as described above. This ensures that the base scale of variation in RA for either the CNAP or TOPAP is consistent between watersheds and not influenced by watershed-specific minimum or maximum values in CN or slope. Each watershed has a different range and distribution of CNAP and TOPAP values that will reflect the degree to which these factors influence runoff connectivity, which accounts for path-dependent differences in RA. The unit scale is then modified in model calibration to account for watershed-specific variation using a single parameter value that is multiplied by the unit scale values for every location. The spatially-varying unit scale values are thus transformed through multiplication by the single calibrated value to account for spatial heterogeneity in RA along runoff pathways. The calibrated parameter is adjusted until the EIA area identified matches the quantity estimate from regression. The final calibrated value for each watershed reflects the degree that the spatial variation in RA for the given property of interest (soil/surface cover or topography) varies according to the unit scale for that property in relation to impervious surface cover distribution.

Spatial Rainfall Representation

To explore how differences in the spatial models of EIA account for variability in observed runoff related to EIA quantity and location, NEXRAD storm event rainfall was applied to each model. Observed gage rainfall and direct runoff from hydrograph separation are used to estimate the EIA quantity per Boyd et al. (1993) and Ebrahimian et al. (2016b), but the variance between observed runoff points and the EIA regression line may be explained by a variety of factors (as noted above), including the spatial variability of rainfall. Storm event rainfall observations were spatially distributed using gage readings and conditional merging (Sinclair and Pegram 2005) with NEXRAD rainfall measurements (DOC/NOAA/NWS/ROC 2017). This methodology utilizes spatial interpolation of the observed rainfall amount at each gage location, applies the same interpolation to the NEXRAD readings at these gage

locations, and then applies the difference between these two interpolated rainfall fields to the original NEXRAD data to correct the data to observed gage observations while maintaining the spatial variability of the radar data. This provides a spatially-variable rainfall field for each storm event.

To produce spatially-varying rainfall estimates to coincide with observed storm events, the start and end times for the observed runoff events were determined, and the NEXRAD Level III storm total rainfall products were obtained from the NOAA database. This data represents a running 24-hour total for rainfall, summed since the onset of any precipitation, at an average spatial resolution of 250 m.

NEXRAD storm total rasters for these endpoints were subtracted to provide a storm event total over the watershed. Data interpolation was performed using inverse-distance weighing of the observed rainfall at each gage location (Fig. 16).

While there are more spatially unbiased methods available for rainfall data interpolation (Haberlandt 2007, Jewell and Gaussiat 2015), these require greater spatial detail and analysis of the distribution of the rainfall for each individual storm event that was not available or feasible for this study. Rainfall data and relevant statistics are summarized in Table 11. Spatial rainfall data for each storm event was then applied to each spatial model of EIA to determine the resulting runoff depth that would be expected given full runoff connectivity from all EIA. Runoff was measured by subtracting the initial abstraction (0.3 mm) from the rainfall field then multiplying the effective rainfall to the spatial EIA raster, summing the results to obtain a runoff volume for EIA areas, and dividing this by the watershed area to obtain an overall runoff depth for each event. Variation in the spatial model for EIA as well as rainfall for any given event resulted in variable runoff prediction that differed from observed values. This was then assessed against variation in observed runoff about the EIA regression line to determine which spatial model of EIA best explained variability in the observed runoff data.

Summary of Data Development Methodology:

1. EIA quantity estimates obtained from regression analysis of observed rainfall and runoff data
2. Spatially variable CNAP and TOPAP values calculated for each location in watershed and simplified to the unit scale ([0,1])
3. Spatial models calibrated to EIA (as determined by step 1) using three representations of RA (PRAP, CNAP, and TOPAP) using uniformly distributed storm event of 5.0 mm with an initial abstraction of 0.3 mm. Calibration / scaling parameter determined for each watershed and each spatial model
4. Spatially-varying observed rainfall estimates developed from NEXRAD radar products

5. Expected runoff from EIA determined for each spatial EIA model using spatial rainfall estimates for comparison to variability in observed runoff
6. Runoff estimates for each spatial model compared to assess their ability to explain variability about the EIA regression line.

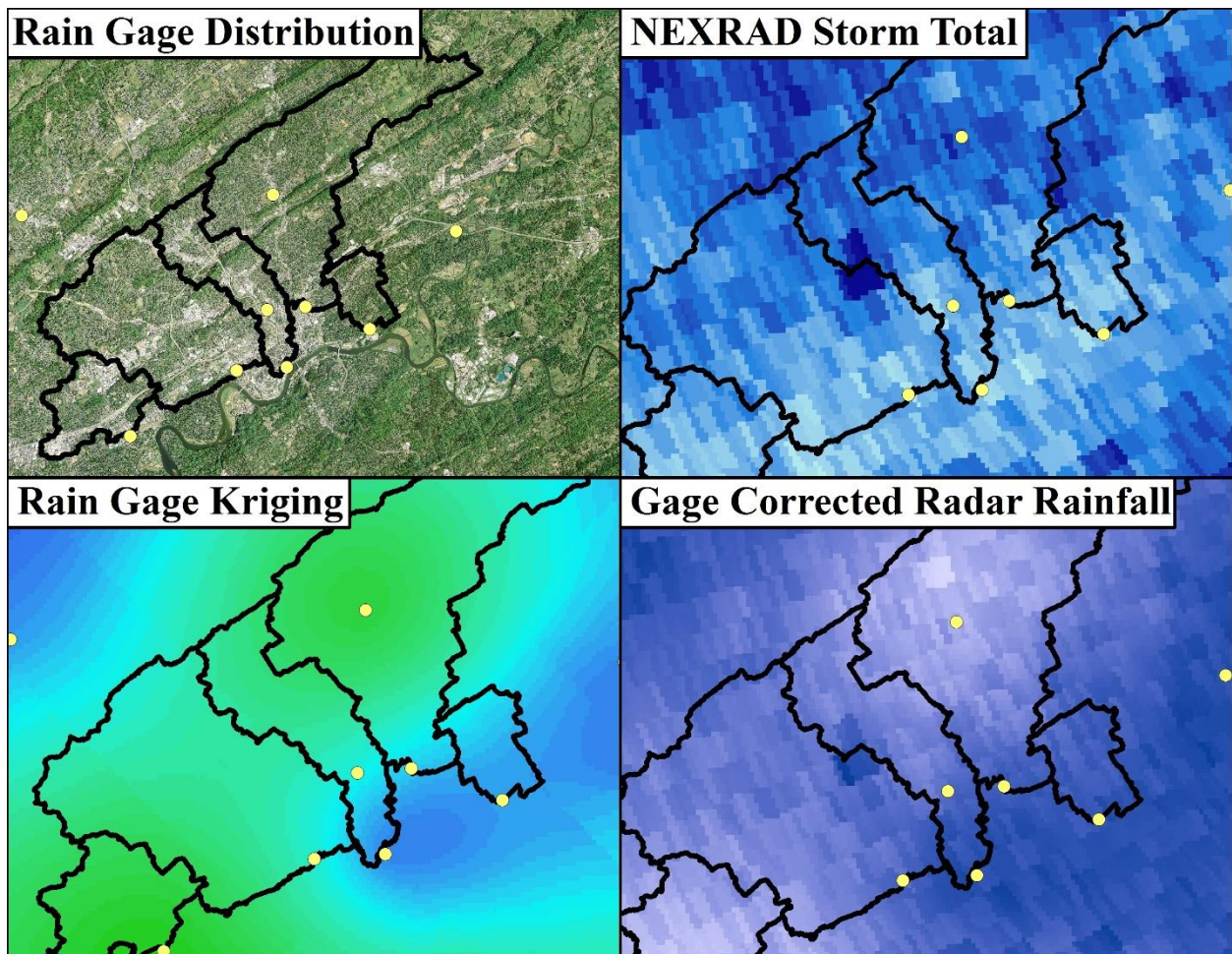


Figure 16 - Pictograph illustrating the conditional merging process to produce the gage-corrected radar rainfall field for Knoxville watersheds. Additional watersheds depicted will be studied in future work.

Table 11 - Storm event rainfall statistics for the three watersheds. Statistics for the difference between Thiessen polygon weighted rainfall and NEXRAD conditionally merged rainfall are based on the absolute value of the difference.

Statistic	Second Creek	Third Creek	Williams Creek
# of storm events	28	43	32
Time period of data	October 2014 – March 2016	January 2013 – October 2014	May 2010 – October 2014
Median Thiessen rainfall depth (mm)	4.8	6.6	9.1
Range of Thiessen rainfall depths (mm)	1.5 to 16.51	1.3 to 21.6	1.5 to 19.3
Median NEXRAD rainfall depth (mm)	4.2	6.1	9.9
Range of NEXRAD rainfall depth (mm)	0.5 to 18.5	1.8 to 30.7	1.5 to 24.1
Median difference between Thiessen and NEXRAD rainfall (mm)	0.8	1.0	1.4
Range of difference between Thiessen and NEXRAD rainfall (mm)	0.0 to 4.1	0.0 to 10.4	0.0 to 13.2

RESULTS AND DISCUSSION

Calibrated model comparison

The calibrated parameter values have been summarized in Table 12, where they are shown to differ between the spatial models and across the watersheds. The PRAP value is very similar between the Second and Third Creek watersheds and considerably higher than that for Williams Creek. Because the PRAP is homogenous over all pervious areas, this indicates that EIA areas in Second and Third Creek are separated from the stream by a shorter distance across pervious areas than in the Williams Creek watershed. Differences in the PRAP value between watersheds reflect the average of different spatial dimensions that influence runoff connectivity that can sometimes be visually. These differences could be related to the proximity of impervious surfaces to the stream network, as runoff is most likely to

connect to the stream network if it is sourced locally. But it could also reflect the concentration of large amounts of runoff along connecting infrastructure that is less influenced by pervious pathways due to a greater magnitude of runoff volume overwhelming any RA before connecting to the stream. The relative trends of the PRAP are mirrored in the CNAP and TOPAP values when comparing watersheds, thus it seems plausible that the PRAP captures this spatial dimension well and it is reflected to a certain degree in the CNAP and TOPAP values as well.

Table 12 - Summary of calibrated model parameters for the study watersheds.

Model	Second Creek	Third Creek	Williams Creek
PRAP	0.330	0.327	0.131
CNAP	1.316	0.961	0.399
TOPAP	0.704	0.700	0.276

The calibrated parameter values for CNAP and TOPAP reflect the degree that spatially variable approaches to describing RA influence runoff connectivity on each watershed. The single parameter value for these spatial models is multiplied by the unit scale values calculated for each location. The unit scale was utilized to provide a range of variation for RA that is then expanded or contracted based on the final calibrated parameter value to reflect watershed-specific variation while preserving relative differences in RA. For example, suppose the calibrated parameter value equals 1.0. This indicates that for the given RA model, differences in impervious runoff connectivity are perfectly reflected by the unit scale, with a RA value of 0.5 representing the attenuation of twice as much runoff as an RA value of 0.25. Were the final calibrated parameter value equal to 3.0, runoff attenuation would be higher for these unit scale values (1.5 and 0.75 respectively) but they would still reflect the relative difference of the unit scale with twice as much RA by comparison.

Parameter values greater than 1.0 indicate that variations in RA as modeled exceed that of the unit scale and thus have a greater influence on runoff connectivity than the unit scale values alone. This occurred for only one model, the CNAP for Second Creek, and it indicates that for this watershed, the combined effect of soil type and surface cover (and the spatial variation of these characteristics) influences runoff attenuation to a higher degree than the CN scale captures. The CNAP value for Third Creek is near unity, indicating that the CN scale is nearly adequate to represent spatial variation in RA using CN parameterization. The calibrated TOPAP values for Second and Third Creek were very similar, indicating that topographic variation in runoff attenuation has a similar effect on runoff connectivity in these watersheds. However, the values in TOPAP varied across the three watersheds in relative magnitude to that of the PRAP values. This is indicative of an interactive effect between the variation in TOPAP parameters and the spatial dimensions captured by the PRAP. Values of TOPAP may also be more homogenous than those of CNAP (thus being more similar to PRAP) or less influential on spatial differences in EIA. Overall, CNAP was found to be the most sensitive among watersheds as evidenced by the larger variation of the calibrated CNAP parameters between watersheds.

Modeled EIA results were compared spatially at each location to determine the degree of dissimilarity between each model by measuring the percentage of EIA areas that were not co-located between each spatial model (Table 13). Results indicate that the PRAP and TOPAP models are very similar for all three watersheds. This may signify that topographical differences in the watersheds do not have a large effect on the identification of EIA as mentioned above. It could also indicate that variation in topographical differences influencing runoff connectivity was not well captured by the unit scale used in this study, and may warrant further study. The CNAP models identified EIA areas that were less similar than the PRAP and TOPAP models, and the degree of this difference varied by watershed. Larger variation in areas identified as EIA between spatial models signifies greater uncertainty in EIA predictions between them. Differences in predicted EIA could be due to differences in sensitivity to RA representation between watersheds. Less variation indicates less ambiguously defined EIA areas that may not vary as much from storm to storm given other factors influencing runoff connectivity. This variation was lowest for Williams Creek, and it is possible that this reflects the higher connectance (EIA/TIA ratio; 0.46) for this watershed that would create more consistent runoff from impervious surfaces along connecting infrastructure. Conversely, the dissimilarity in spatial EIA models was highest where connectance was lowest (0.25).

Table 13 - Degree of dissimilarity between spatial EIA models.

Model Comparison	Second Creek	Third Creek	Williams Creek
PRAP to CNAP	16.34%	21.89%	6.50%
PRAP to TOPAP	1.54%	1.85%	1.10%
CNAP to TOPAP	16.43%	22.65%	6.70%

EIA runoff assessed by spatial rainfall variation

As discussed previously, the estimation of EIA quantity for each watershed was conducted using linear regression of observed runoff data points plotted against observed rainfall (i.e. Boyd et al. (1993) and Ebrahimian et al. (2016b)). Each rainfall-runoff pair has some variance from the EIA regression line (Fig. 14). It was hypothesized that the spatial rainfall data might explain a portion of the variance from the EIA regressions, since the analyses were conducted using Thiessen polygon weighted gage rainfall which accounts for only a portion of the spatial variability of a given storm event. By providing more spatially explicit rainfall data to overlay on the distributed EIA, a better estimate of runoff production from EIA may be derived.

The EIA regression technique (i.e. Boyd et al. (1993) and Ebrahimian et al. (2016b)) separates storm events into those with runoff deriving solely from EIA and those with runoff from both less-connected impervious portions of the TIA and pervious areas. Thus, this analysis aims to determine if some of the variance from the EIA regression line can be accounted for with more spatially informed rainfall and also how this variability may be reflected in different representations of RA. Spatial EIA models are not intended to predict runoff, but it was also hypothesized that different representations of RA might better reflect variability in observed runoff in conjunction with spatial rainfall estimates. To assess this, variance in the observed runoff from the EIA regression lines were plotted against spatial model variance. Discussion of these trends and how they apply to the spatial models and variability in observed runoff as related to EIA follows.

The different quadrants in Figure 17 offer some explanation to how well these models explain variability in runoff in relation to EIA quantity estimates and spatial models. With the variance of the EIA

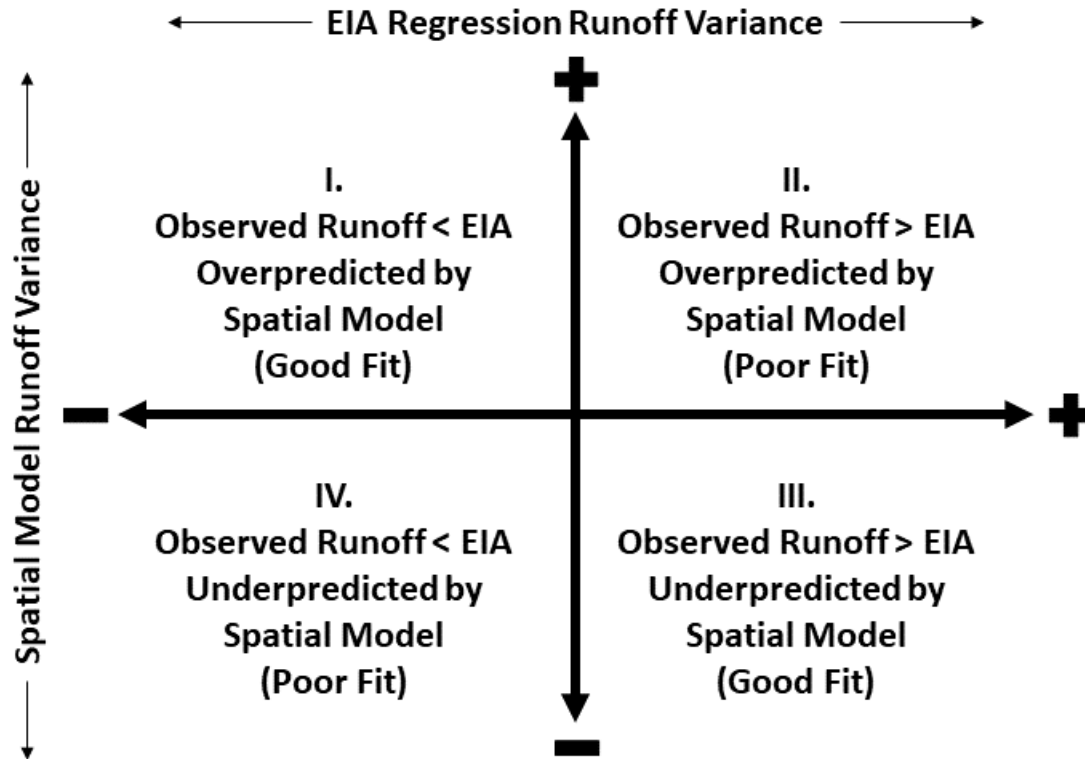


Figure 17 - Schematic representing variance analysis related to variance in observed runoff from EIA regression analysis and the application of spatial rainfall to spatial EIA models.

regression on the x-axis, data falling in quadrants II and III represent points located above the EIA regression line (Fig. 14). Positive variance indicates that runoff for these storm events was sourced from a larger area than just the EIA. This could be the case given wet antecedent moisture conditions that contribute to limited RA, resulting in greater runoff production and connectivity. Data falling in quadrants I and IV represent storm events for which the observed runoff was less than would be expected from EIA. Variance from the EIA regression line for these events could be due to dry antecedent conditions or any other physical mechanism inhibiting runoff connectivity.

Variance in spatial EIA model variance is plotted on the y-axis. For each storm event, all EIA areas were considered a source of runoff, and the amount that was measured was commensurate to the spatial rainfall field minus an initial abstraction. This assumed that all EIA areas were connective for all storms, so model results of runoff do not account for runoff from additional areas nor storm-dependent

disconnection of EIA areas due to antecedent conditions or otherwise. This is important in interpreting the data in Figure 18. For storms with greater observed runoff than would be expected from the EIA estimate, spatial model results that fit the observed runoff trend well would lie in quadrant III (Fig. 17) as opposed to quadrant II. Spatial models should under predict runoff for these events since they do not account for any more sources of runoff than EIA. Overprediction indicates a poor model fit that is either related to rainfall-runoff data uncertainty or misidentified EIA areas. For storm events with less observed runoff than would be expected given full connection of EIA, model results that fit the observed runoff trend well would lie in quadrant I (Fig. 17) as opposed to quadrant IV for similar reasons. Runoff estimates from spatial models for these events should overpredict runoff (positive variance) because they are measured over all EIA areas which may not have produced runoff for that particular event. The degree that the data aligns within these quadrants should indicate how well the spatial EIA model and rainfall data reflect the variability in observed runoff related to EIA source areas. These trends will now be discussed in terms of the results for the three watersheds (Fig. 18).

Modeled results for the three watersheds (Fig. 18) indicate varying degrees of model fit related to variability in observed runoff. There is a strong linear trend in the data for both the Second and Third Creeks. This trend shows data points largely in quadrants I and III, indicating that model results tend to be in line with what is expected given the discussion above. For these watersheds overall, storm events with positive EIA regression variance are underpredicted by the model and those with negative EIA regression variance are overpredicted. This indicates that the variance in observed runoff from EIA regressions is in line with that from the spatial models. Differences between models in these watersheds are slight though they do indicate a better fit for the PRAP and TOPAP models (Table 14) which are very similar on these watersheds as indicated before, with the TOPAP model fitting slightly better on Third Creek.

Investigation of the linear regressions in Figure 18 offers some insight into model performance and how it differs between these two watersheds. The intercept values are both positive with larger values for Third Creek than Second. In terms of the variance, the intercept equates to a general bias of the spatial model to overpredict runoff. This could be related to spatial rainfall estimates and how they were measured or processed. It could also be related to the initial abstraction value used in this study, which was the median value observed in a study of many urban watershed by Ebrahimian et al. (2016a). The positive bias could warrant a higher value to be used for the initial abstraction for these watersheds.

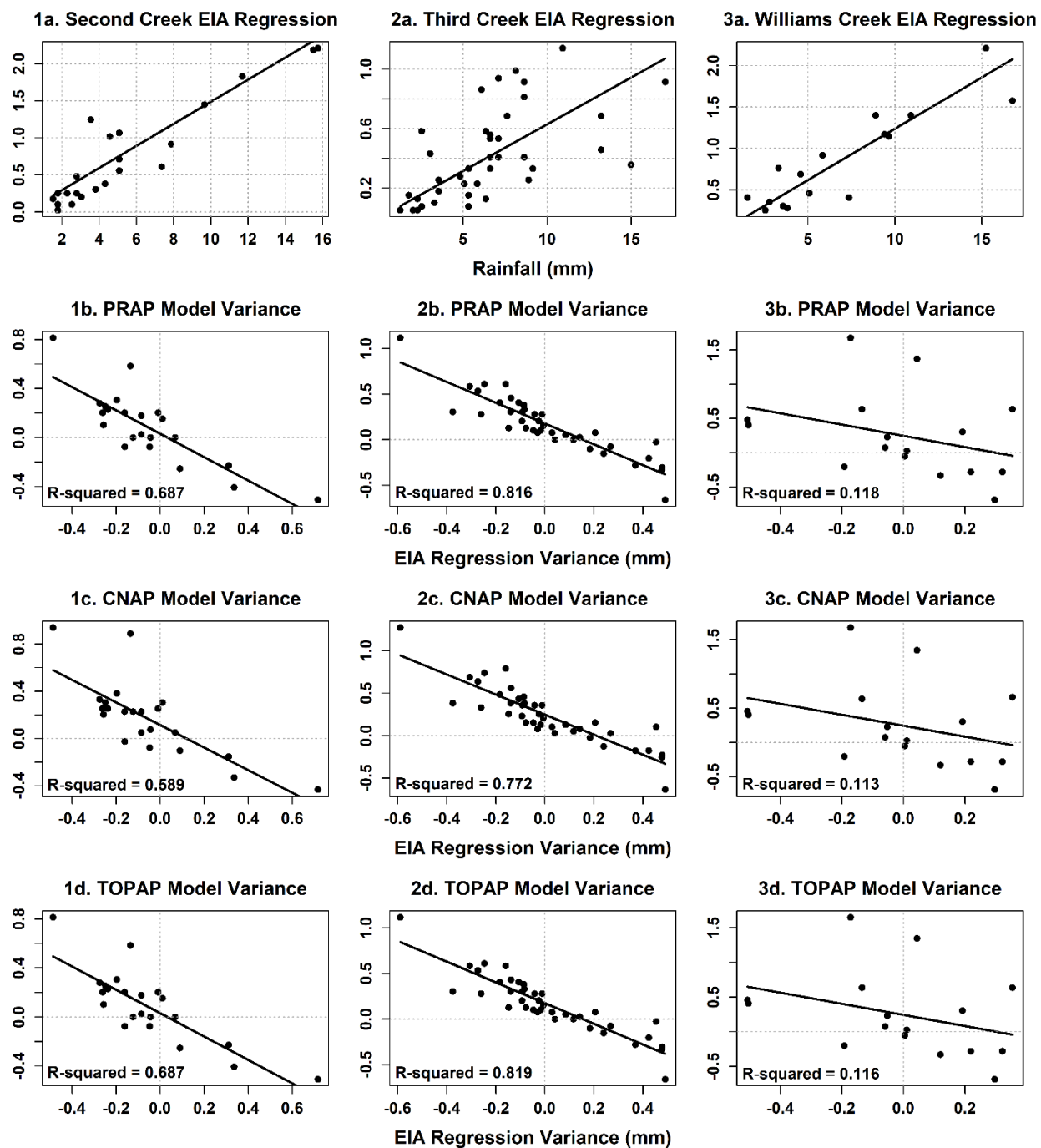


Figure 18 - EIA regression results (line a) and variance plots for the PRAP (line b), CNAP (line c), and TOPAP spatial models (line d).

Table 14 - Linear regression results for analysis of the variance for storm events between the EIA regression and spatial model predictions of runoff from EIA.

Watershed	Regression Parameter	PRAP	CNAP	TOPAP
Second Creek	Slope	-0.954	-0.955	-0.954
	Intercept	0.072	0.156	0.072
	R2	0.687	0.589	0.687
	p-value	< 0.001	< 0.001	< 0.001
Third Creek	Slope	-1.139	-1.179	-1.136
	Intercept	0.199	0.269	0.197
	R2	0.816	0.772	0.819
	p-value	< 0.001	< 0.001	< 0.001
Williams Creek (full)	Slope	-0.822	-0.801	-0.806
	Intercept	0.277	0.275	0.272
	R2	0.118	0.113	0.116
	p-value	0.193	0.203	0.197
Williams Creek (w/o outliers)	Slope	-0.637	-0.615	-0.624
	Intercept	0.094	0.094	0.093
	R2	0.193	0.179	0.187
	p-value	0.116	0.132	0.123

The slope values for the Second and Third Creek watershed variance regression also differ slightly. Values for Second Creek are closer to -1.0 than those for Third Creek. In terms of the variance data, this indicates that model results differ by a greater degree than the observed for Third Creek than for Second Creek. Spatial model variance for Second Creek is in line with EIA regression variance meaning that the spatial models tend to over predict runoff with nearly the same magnitude as it is underpredicted by the EIA regression. This is slightly less so for Third Creek where spatial model variance tends to be slightly greater in magnitude than EIA regression variance. This could indicate error in the spatial model but may also be related to uncertainty in the original estimates of EIA due to the fact that the variance data is very highly correlated. Uncertainty in original EIA estimates could be related to hydrograph separation methodology or a negative bias in observed rainfall.

Because variance results for the spatial model are dependent on the accuracy of rainfall data, how this might be reflected in the results is of high importance. The degree that the spatial model and rainfall data explain the EIA regression variance together is related to the slope of the linear regression through the variance points. As the slope gets closer to 0, the model and rainfall likely explain more of the variance from the EIA regression. If you consider the idealized situation where the spatial model accounts perfectly for natural variation in runoff connectivity and spatial rainfall is fully accurate, the resultant variance plots would be a nearly straight line along the x-axis. All variability in the observed runoff would be explained with the spatial model. While results for Second and Third Creek models appear to be well-organized in terms of the quadrants, slope values for the regression lines for both are closer to -1.0 than 0. Though it is difficult to disseminate the two, this indicates that spatial rainfall estimates and spatial EIA models are in line with observed data but that they do not capture storm-specific variations in runoff-producing portions of impervious areas.

Results for Williams Creek are not well organized among the quadrants previously discussed. Linear regression results for the variance data do not indicate a high correlation overall and results are not statistically significant. Visual inspection indicated may be some sort of the trend in the data if outliers are omitted. For a two storm events on this watershed, the spatial model variance was greater than 1.0 mm, and for both of these storms the spatial rainfall data was more than double that of the observed gages while all other storm events were reasonably similar. Omission of these events does not result in statistically significant regression parameters either (Table 14) due to scatter in the data, but visual inspection of the results seems to indicate that for some storms, the spatial model variance is closer to 0 than that of the EIA regression variance. While this may indicate that spatial rainfall data improves

model results for EIA deriving from impervious areas for some storm events, overall uncertainty is much greater than for the other watersheds. Scatter may indicate storm-specific sources of uncertainty in the data that are not explained by the model.

A possible source for error could be the initial estimates of EIA quantity that were made using Thiessen polygon weighted rainfall data. EIA might better be estimated using radar rainfall observations on this watershed due to higher spatial variability of rainfall or poorly calibrated rain gages. This was investigated by revising the EIA regression estimate using the average radar rainfall values for storm events and subsequently recalibrating the PRAP model utilizing the updated EIA estimate. The revised estimate for EIA was only 10.8% of the watershed area ($R^2 = 0.793$), 1.6% less than the original estimate of 12.4% using Thiessen-derived rainfall values. Regression results are shown in Figure 19a. The PRAP model was recalibrated to match this revised EIA estimate with a parameter value of 0.196, an increase over the original calibrated value (0.131) reflecting greater runoff attenuation necessary to reduce the identified EIA. Spatial rainfall data was applied to the PRAP model to revise runoff estimates and the variance plot is shown in Figure 19b indicating substantial improvement in the model fit. The revised linear regression had a slope of -1.145, an intercept of 0.01 with an R^2 value of 0.916 ($p < 0.001$). This iterative improvement in the spatial model illustrates how initial model results, dependent on accurate EIA estimates from regression, can be refined through uncertainty analysis to provide a robust estimation of the spatial distribution of EIA within a watershed.

CONCLUSIONS

The analysis presented herein demonstrates that results from spatial models identifying EIA throughout a watershed seem plausible given trends in observed rainfall-runoff patterns and the application of spatial rainfall data. Models employing a higher degree of spatial variation in RA did not account for variation in observed runoff from the overall estimated EIA trend. While this may indicate that the homogenous PRAP parameter is sufficient to capture runoff connectivity and identify EIA, the other models could be improved by greater sensitivity analysis and temporal variation related to storm-specific conditions. The CNAP parameter could be adapted to account for more of the variance in storm event deviation from EIA runoff production as it relates to antecedent moisture conditions, as these have been studied in other applications of CN methodology. While spatial rainfall estimates did not

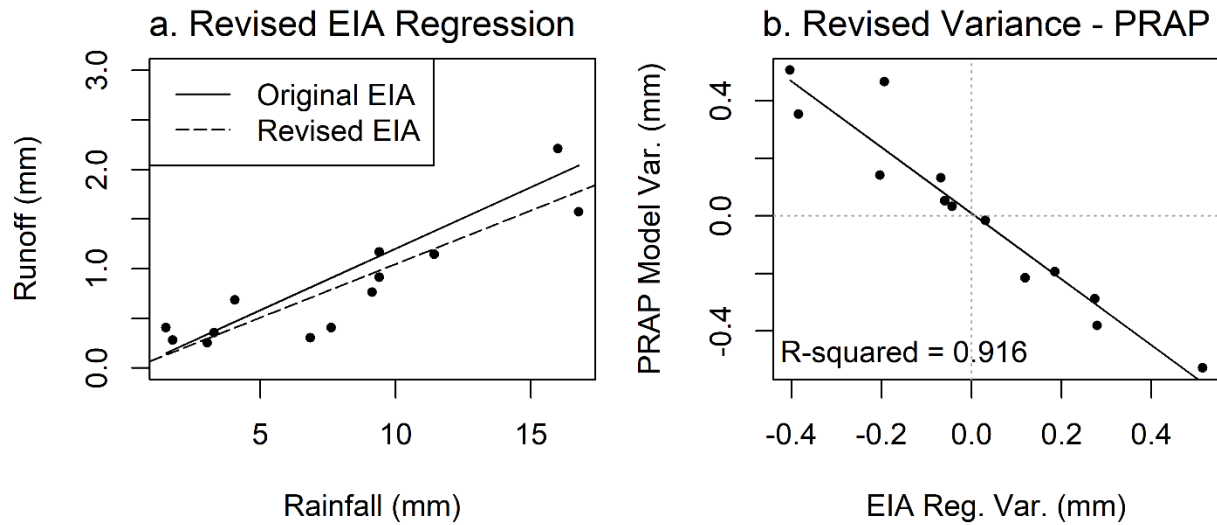


Figure 19 - Revised EIA Regression and variance results for the recalibrated PRAP model for Williams Creek.

seem to reduce the variance in the EIA regression for storm events appreciably, they did help refine EIA estimates for Williams Creek, resulting in a much better spatial model fit. This study helps to validate the spatial EIA models to some degree but it would be benefited by further investigation of other sources of uncertainty in impervious runoff production and storm-specific connectivity in urban watersheds. This approach has the potential to provide rapid and repeatable EIA assessments that can better guide distributed at-source restoration efforts as well as better indicate urban runoff issues. This is especially important for watersheds like the ones presented herein, which are not as fully connected as denser urban areas and larger cities with less green space. It is in these moderately urban, mixed residential watersheds where impervious connectivity is most ambiguous and variable that guidance is most needed to guide distributed SCM investments so that they will have the greatest impact on overall runoff management for the betterment of the urban streams that drain them.

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CHAPTER 4
**Assessment of Inter-Event Water Quality Variability and Pollutant
Dynamics in the Context of Effective Impervious Area**

ABSTRACT

Water quality modeling has been studied extensively to better manage urban runoff impacts on stream health and effectively address stormwater permitting requirements. Recent studies have indicated that previous modelling approaches using build up and washoff models or regression equations are inadequate because they fail to capture important dimensions in urban runoff and pollutant transport processes. The effective impervious area (EIA) has been identified as one of the greatest determinants of urban stream health in many studies due to connection of these areas via stormwater infrastructure. Thus, accurate measured of EIA should offer additional explanatory power in assessing the variability in urban water quality. Recently refined estimates of EIA were used to assess water quality variability between storms and within storms to provide insight to pollutant dynamics and identify the role of EIA in these trends. Variability between storm events for *E. coli*, TSS, copper, and zinc was assessed over multiple storm events on three urban watersheds in Knoxville, TN. Inter-event variability supported findings from other studies but indicated differences between storm events associated with runoff expected to be confined to the EIA, and those with runoff generated by less closely connected impervious areas and pervious sources. Qualitative investigation of pollutant dynamics using hysteresis loops indicated complex patterns that differed by pollutants as well as by the most probable runoff source for the event. Transport trends were well-organized for some events, but reflected harder to explain variability for others. Antecedent moisture conditions (AMC) are believed to play a role in this, as wet conditions (higher soil moisture) promote runoff connection from areas outside of the EIA. Pollutant delivery along these more disconnected pathways is not well-predicted by typical water quality modeling. These results demonstrate the utility in including both the EIA and AMC in urban water quality modeling moving forward as well as the need for further research in variably-sourced runoff effects on water quality loading in urban systems.

INTRODUCTION

Water quality in urban streams has been the focus of a great amount of research as part of an effort to protect public health, ensure the integrity of local resources, and contribute to improved ecological conditions. In more densely developed areas, water quality typically declines due to more concentrated populations and the intensity of local activity in the watershed (Walsh et al. 2005b). Construction activities, soil disturbance, vehicle traffic, fertilizer application, chemical leaching, sewer systems, and any other number of sources for pollutants exist in highly developed urban watersheds (Duncan 1995). Most studies have focused on the influence of rainfall and runoff processes in water quality, but the delivery of pollutants to the stream is also path-dependent. Runoff pathways for the movement of pollutants from the land to the receiving water body are complex. However, there is growing evidence that urban water quality is not adequately predicted by just rainfall-runoff variables. Some measure of urban form that captures the complexity of these pathways may be necessary to fully explain the variability in observed water quality (Liu et al. 2013).

The proliferation of impervious surfaces in urban watersheds provides extensive surface area for the buildup of pollutants that are then flushed towards stream networks when rainfall occurs (Brabec et al.

2002). Falling rain and subsequent runoff provide the energy for the entrainment of these pollutants which then flow along hydraulically-efficient urban stormwater infrastructure to the stream. The connectivity of impervious surfaces and stormwater pipes has been shown to be the greatest predictor of several measures of stream health related to water quality (Burns et al. 2015, Fletcher et al. 2013, Hatt et al. 2004, Taylor et al. 2004). The impervious areas that are most-connected to the stream network via piped infrastructure and other pathways are referred to as the Effective Impervious Area (EIA). For even small storm events, rainfall on these areas produces runoff that moves to the stream. This runoff typically transmits a variety of pollutants that can vary based on local land use, land cover, and variable source material depending on nearby activity in the watershed. This variability is difficult to capture in water quality models and it has been one of the greatest sources of continued research efforts in urban watershed management (Fletcher et al. 2013).

Urban water quality models have attempted to provide greater information about pollutant dynamics in stream systems to allow proper management activities that will effectively diminish their delivery to receiving waters. These models typically capture source buildup/washoff processes or they use regression to relate pollutant concentrations to more easily measured variables such as flowrate or precipitation intensity (Fletcher et al. 2013). While some water quality constituents are well predicted by these models, there is often a greater amount of variability in observed pollutant dynamics than these models identify (Anne-Sophie et al. 2015, Hathaway et al. 2010, McCarthy et al. 2012). One factor for this variability is the large spatial variation in the buildup of pollutants in urban watersheds related to source material and activity. Washoff processes are also spatially-variable, as rainfall is not uniformly distributed and runoff pathways are complex. Stormwater infrastructure can itself be a source of water quality issues as well through resuspension (Anne-Sophie et al. 2015). Discerning the most likely sources and pathways for pollutants is of great interest to enhance watershed management efforts. Because the EIA has been shown to have the greatest impact on stream conditions, and because it can be a surrogate variable for connectivity in urban watersheds, it likely will have an influence over pollutant dynamics in urban stormwater.

The quantity of EIA in a watershed can be estimated from overall trends in runoff for smaller storms (up to approximately 20 mm), typically being defined as the areas of TIA that translate all rainfall (minus an initial abstraction) into runoff across these event sizes (Boyd et al. 1993, Ebrahimian et al. 2016). Regression analysis of rainfall versus runoff captures the overall trend in runoff production and assumes the percentage of the watershed area that is EIA is equivalent to the slope value of the regression line through these smaller storms producing runoff from EIA only. Individual events may exhibit some variance from this amount of EIA runoff (i.e., distance from the regression line) due to measurement uncertainty but also spatially variable rainfall and conditions that influence runoff connectivity that are not always discernable (Chapter 3). Some of this variability may be related to antecedent moisture conditions when rain occurs as this will influence runoff connectivity over pervious surfaces as well as contributions from pervious areas to runoff (Booth and Jackson 1997, Walsh et al. 2005a). Thus, for any given storm event, the amount of runoff variance from the overall EIA trend indicates potential source areas for that runoff. For events falling below the EIA regression line, it is likely that the bulk of the runoff is from EIA alone. For events above the EIA trend, it is likely that this excess is sourced from less-

connected portions of TIA or pervious areas as well. This is important when you consider water quality modeling, as different source areas for runoff and the pathway it takes to the stream will influence pollutant loading for any given event (Liu et al. 2013). To refine water quality models and account for more inter-event variability, it may be necessary to account for the variable surficial composition from which measurements of water quality downstream are likely sourced to produce better predictive models.

Intra-event pollutant dynamics for any given storm can also be an indication of different sources and pathways for runoff and water quality constituents. This has been studied using regression models that equate pollutant concentrations to precipitation and flowrate, but these methods can be difficult due to varying time of concentrations for different areas of the watershed and spatial variations in rainfall (Dotto et al. 2010, McCarthy et al. 2012). A qualitative approach can be useful to approximate this by examining pollutant hysteretic loops. For most events, pollutant loads do not always correlate with flowrate due to washoff and delivery processes that exhaust local sources of water quality constituents (Williams 1989a). Thus, for identical flowrates on the ascending and receding limbs of the hydrograph, pollutant concentrations may be very different. The shape and directionality (clockwise vs. counter-clockwise) of the hysteretic loop when plotting pollutant concentration by flowrate offers insight into pollutant delivery dynamics within a given storm-event. This shape has been studied related to antecedent moisture conditions and storm-event characteristics for sediments (Seeger et al. 2004, Soler et al. 2008) but not extensively for other pollutants.

Recently updated spatial models for EIA identification have demonstrated the ability for refinement of EIA estimates using high-resolution surface cover data and rainfall observations (Chapter 3). These EIA estimates can be used to assess inter-event variability in pollutant loading as well as intra-event dynamics that may offer some indication of factors affecting variability observed, delivery mechanisms for a range of storm-event conditions, and most probable sources of pollutants (EIA or more loosely connected areas of runoff production). Refined EIA estimates have been developed for three urban watersheds in Knoxville, TN, using several years of rainfall and runoff observations and spatial models. Water quality monitoring over a number of storm events on each has been conducted to assess the variability in pollutant loading between events for these watersheds as well as intra-event dynamics that can lead to a greater understanding of how pollutant delivery to the stream outlet is impacted by different urban forms. These dynamics will be studied herein for *E. coli*, total suspended sediments (TSS), as well as copper and zinc, two common metals of concern in the urban stormwater matrix (Makepeace et al. 1995).

Objectives

To refine water quality modeling for urban watersheds, a greater understanding of inter-event differential loading as well as intra-event dynamics is needed. Because EIA has been identified as a leading determinant of stream conditions, pollutant variability will be assessed in the context of refined estimates of EIA for three urban watersheds in Knoxville, TN. The goals of this study are to

1. Assess inter-event variability for *E. coli*, TSS, copper, and zinc related to runoff observations, the estimated portion of EIA producing runoff, and other storm-event characteristics
2. Assess intra-event dynamics for these pollutants of concern with qualitative assessment of hysteretic loops and storm-event conditions that may be most influential to pollutant delivery as it pertains to the most probable source area

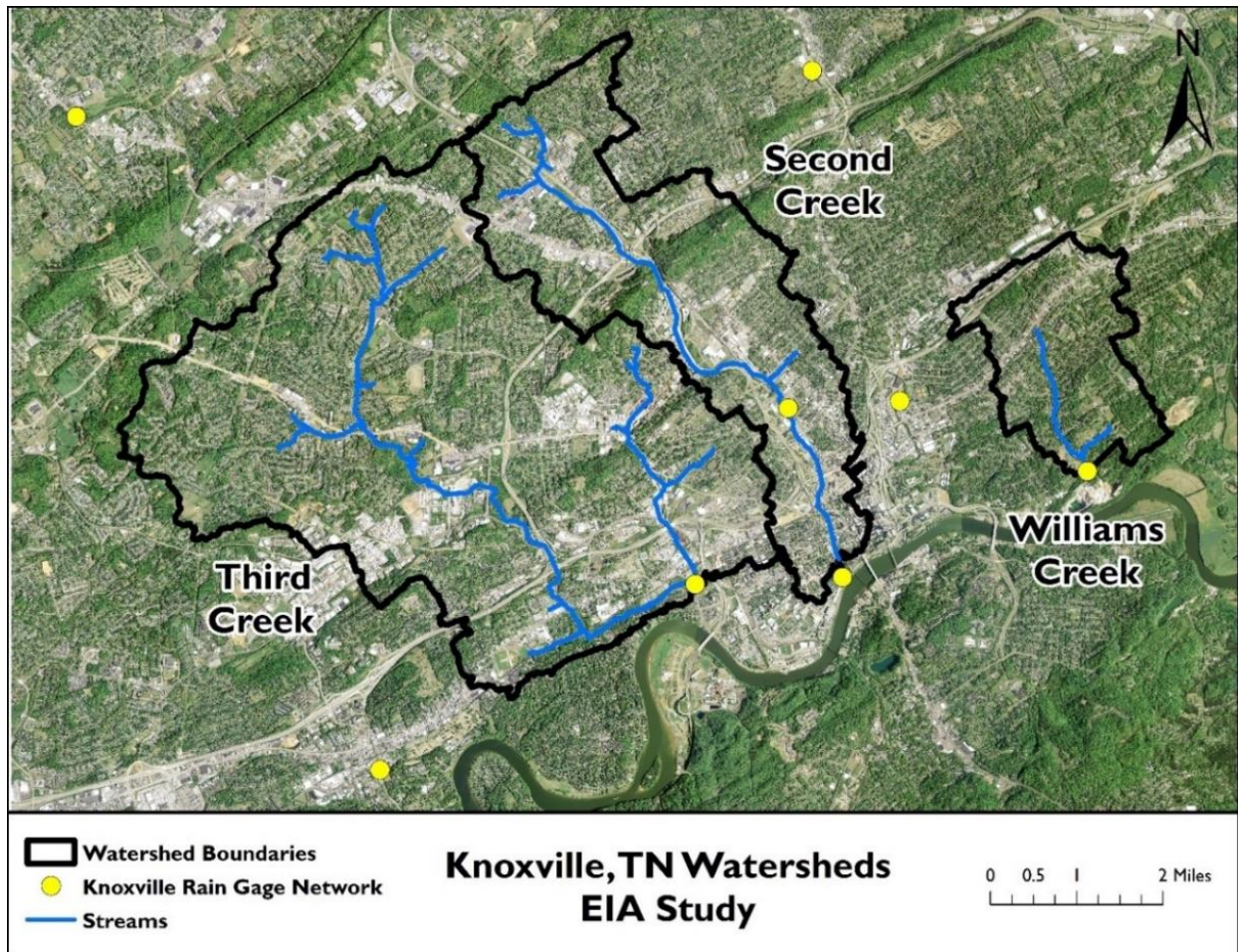


Figure 20 - Map of study watersheds in Knoxville, TN with rain gage network.

Table 15 - Summary of watershed characteristics.

Characteristic	Second Creek	Third Creek	Williams Creek
Watershed Area (ha)	1,847	4,357	671
TIA (%)	36.09	25.21	26.94
EIA (%)	14.9	6.31	10.8
(R ² for regression of EIA events)	(0.839)	(0.767)	(0.793)
Period of Record (EIA Estimation)	2014 - 2016	2012 - 2014	2010 - 2014

METHODS

Study Sites

This study focuses on stream monitoring and water quality observations made for Second Creek, Third Creek, and Williams Creek in Knoxville, TN (Fig. 20). These three urban streams range in size, imperviousness, and patterns of development that will help highlight differences in water quality related to these variables. They are summarized in Table 15. EIA quantity estimation for these watersheds was accomplished with regression analysis of rainfall-runoff pairs (Boyd et al. 1993, Ebrahimian et al. 2016), and this was further refined using spatial models for the most accurate estimation (Chapter 3). More details of the methodology involved in the development of these EIA estimates can be found in Epps and Hathaway (2017, in press).

Data Collection

Monitoring data for this study came from various sources. Streamflow for Third Creek and Williams Creek as well as rainfall data at several gage locations were obtained from the City of Knoxville Stormwater Engineering Department which uses this data in support of their National Pollutant Discharge Elimination System (NPDES) permit. Streamflow for Second Creek as well as two rain gages in the watershed were operated by the University of Tennessee at Knoxville. Data from a rain gage operated by the United States Geological Survey (USGS) was also used for Third Creek (Beaver Creek gage number 03535200).

Rainfall and Streamflow Data

All rainfall measurements were collected with tipping-bucket rain gages at several locations near Knoxville at 5-minute increments. Storm-event rainfall was calculated using Thiessen polygon weighting. Rainfall records were not continuous for all gage locations, so the densest network with available data for each storm event was used to calculate the area-weighted precipitation depth. Streamflow data was measured continuously at Third Creek and Williams Creek using area-velocity meters and bubbler level meters in box culvert locations. Measurements at Second Creek were obtained using a Doppler-based area-velocity meter but later changed to a bridge-mounted laser-level sensor when flashy stream responses proved difficult to monitor in the streambed. Level measurements were converted to flowrates based on the stage-discharge relationship established for the site using the area-velocity meter.

Water Quality Data

Multiple discrete water quality samples were taken during storm-events at each watershed using automatic samplers paired with flow measurement equipment. Monitoring occurred during the period of 2014 – 2015 for Second Creek and over 2015 – 2016 for Third Creek and Williams Creek. For each targeted storm event, the sampler trigger was set in relation to antecedent streamflow levels to begin sampling when a rise of approximately 50 mm occurred, though this was variable depending on the amount of forecasted rainfall. Sampling was conducted using flow-pacing which was adjusted according to antecedent streamflow conditions as well as forecasted rain. Monitoring objectives were to sample streamflow over the duration of the event hydrograph with at least 5 discrete samples capturing intra-event dynamics. Relevant data for the sampled events is shown in Table 16.

Storm-event samples were analyzed for a range of water quality indicators of which *E. coli*, TSS, copper, and zinc will be discussed in this paper. *E. coli* was measured using the Colilert method (IDEXX, Westbrook, ME) with a dilution of 1:100 for sampled aliquots providing measurable values in the range of 100 – 240,000 MPN (Most Probable Number) per 100 mL. TSS was measured using vacuum filtering with glass fiber filter according to EPA Standard 160.2 (EPA 1999). Metals in each sample were tested using inductively coupled plasma mass spectrometry (ICP). All lab protocol was operated under the guidance of accepted water quality testing standard procedures (Association et al. 1915, Kopp and McKEE 1979). Further details of these measurement protocols can be found in Christian et al. (in review).

Storm Event Metrics and Statistical Analysis

To assess inter-event variability for the storm-events, a variety of statistics of each water quality constituent included here were calculated across all events (Table 17). Additionally, storm-event characteristics were also summarized to determine the most influential climate and antecedent moisture variables on inter-event variability (Table 18). Runoff depths (RD) were calculated for each water quality event using the hydrograph separation method used to develop EIA quantity estimates (Blume et al. 2007). Further details of this process can be found in Chapter 3. The RD was divided by the storm-event rainfall (P) to calculate the runoff coefficient (ROC). This was multiplied by the

watershed area (WA) to estimate the storm-event active area (AA) which was used to calculate the Event Flux (EF) (Bi et al. 2015). The AA is an indicator of how much of the watershed is producing runoff for a given event that is analogous to EIA estimates from regression analysis. The AA term does not intend to directly represent the amount of area that is producing runoff, as a different percentage of rainfall may be translated as runoff for different areas. It merely serves as a comparative to the EIA for any given event to provide an indication of how much runoff may differ from that which would be expected to be produced by the EIA. Thus, it serves as a storm-event indicator of runoff production that can be compared to the EIA to assess the likelihood that runoff for a given event was confined to EIA portions of the watershed or whether it may be sourced from less connected impervious or pervious areas. Because EIA has been reported as a percentage of the watershed area already, dividing the ROC by the EIA percentage provides the Active Area to EIA ratio (AERAT) that will be used to assess inter-event water quality related to most probable source areas.

The AERAT captures the variance of an individual storm-event about the EIA regression line with values greater than 1.0 falling above this line and values less than 1.0 falling below it. Calculation of these metrics is summarized by the following equations where the subscript i indicates storm-event specific calculations:

- (1) $ROC_i = DRD_i / P_i$
- (2) $AA_i = ROC_i * WA$
- (3) $AERAT_i = ROC_i / EIA$

To determine if there was a difference in the five water quality metrics (Table 3) for storms deriving from only the EIA (AERAT value ≤ 1.0) and those from areas greater than the EIA (AERAT values > 1.0), the Mann-Whitney U-test was used. This non-parametric test was utilized due to low sample sizes ($n=13$ for storms with AERAT ≤ 1.0 , $n=12$ for storms with AERAT > 1.0) and non-normality. Additionally, the relationship between each of the water quality metrics and storm event characteristics (Table 3) was assessed using the Spearman's rank correlation coefficient. Correlations were calculated for the storm events overall as well as separately for events with an AERAT value above or below 1.0 to assess the relationship between storm characteristics and water quality observations. Discussion of these results focuses on assessing whether different storm characteristics might be more influential on water quality observations for different event runoff source (AERAT), water quality metric, or water quality constituent.

Qualitative Assessment of Intra-event variability

Differences in pollutant dynamics for each event were assessed qualitatively by classification of hysteresis loops according to Williams (1989b). Classification focuses on differences in the ratio of concentration to flowrate (C/Q) at different points of the hydrograph when the sample is taken, be it on the rising or falling limb. Plots of flowrate at the time of sampling versus discrete concentration observations for each event and water quality constituent were assessed according to the directional shapes that have been observed in previous studies (summarized in Table 19). Characteristic events were chosen based on these classifications, water quality sampling distribution over the hydrograph,

Table 16 - Summary of storm-event data from water quality monitoring.

Watershed	Date	Rainfall Depth (mm)	# of samples	Pollutants Analyzed	Direct Runoff (mm)	AERAT
Second Creek	9/11/14	14.32	8	EC,TSS,CU,ZN	2.21	1.04
Second Creek	10/6/14	20.45	12	EC,TSS,CU,ZN	3.38	1.11
Second Creek	10/14/14 A	31.27	13	EC,TSS,CU,ZN	3.68	0.79
Second Creek	10/14/14 B	12.69	6	EC,TSS	1.96	1.04
Second Creek	10/29/14	14.93	14	EC,TSS,CU,ZN	2	0.90
Second Creek	11/6/14	4.64	5	EC,TSS,CU,ZN	0.46	0.67
Second Creek	1/12/15	45.1	19	EC,TSS	7.39	1.10
Second Creek	6/26/15	13.19	6	EC,TSS,CU,ZN	1.18	0.60
Second Creek	6/30/15	7.79	6	EC,TSS,CU,ZN	0.61	0.53
Second Creek	7/14/15	37.67	11	EC,TSS,CU,ZN	6.26	1.12
Third Creek	6/30/15	5.5	5	EC,TSS,CU,ZN	0.37	1.07
Third Creek	7/14/15	37.19	11	EC,TSS,CU,ZN	1.86	0.79
Third Creek	8/8/15	20.65	10	EC,TSS,CU,ZN	0.64	0.49
Third Creek	11/2/15	10.9	10	EC,TSS,CU,ZN	0.94	1.37
Third Creek	11/18/15	30.01	10	EC,TSS,CU,ZN	3.13	1.66
Third Creek	1/26/16	17.02	9	EC,TSS,CU,ZN	2.82	2.63
Third Creek	3/24/16 A	9.14	6	EC,TSS,CU,ZN	0.42	0.73
Third Creek	3/24/16 B	7.11	6	EC,TSS,CU,ZN	0.35	0.78
Williams Creek	6/26/15	17.78	8	EC,TSS,CU,ZN	1.79	0.93
Williams Creek	6/30/15	31.5	7	EC,TSS,CU,ZN	1.92	0.56
Williams Creek	7/14/15	36.07	10	EC,TSS,CU,ZN	2.29	0.59
Williams Creek	11/2/15	16.27	5	EC,TSS,CU	2.47	1.41
Williams Creek	7/26/16	12.95	14	EC,TSS	4.24	3.03

Table 16. Continued.

Watershed	Date	Rainfall Depth (mm)	# of samples	Pollutants Analyzed	Direct Runoff (mm)	AERAT
Williams Creek	7/28/16	13.21	14	EC,TSS	3.05	2.14
Williams Creek	8/16/16	9.91	6	EC,TSS	0.71	0.66

Table 17 - Summary of storm-event metrics used to assess inter-event variability.

Metric	Equation	Description
Event Mean Concentration (EMC)	$\frac{\sum G_i * V_i}{\sum V_i}$	Mean concentration as mass distributed over entire storm event volume
Event Peak Concentration (EPC)	$\max(C)$	Maximum individual sample concentration taken over storm event
Event Peak-to-Min Ratio (ERAT)	$\max(C)/\min(C)$	Ratio of maximum to minimum for all individual samples taken over storm event
Event Flux (EF)	$(EMC * DRD)/AA$, where DRD is direct runoff depth and AA is the active area (Eq. 2 below)	Effective load of pollutant delivered per unit area producing runoff
Time to Peak Ratio (TPR)	$\frac{\text{Time to EPC}}{\text{Time to max(flowrate)}}$	Comparative between the timing of peak observed pollutant concentration and peak flowrate of the storm event hydrograph

Table 18 - Summary of storm characteristics, both event-based and antecedent, used to assess water quality observations

Storm Characteristic	
Rainfall Depth (mm)	P
Storm Duration (min)	D
Average Rainfall Intensity (mm/hr)	I
Maximum 5 min. Rainfall Intensity (mm/5min)	I _{max}
Antecedent Moisture Characteristics	
Antecedent Flowrate	Q ₀
Antecedent Rainfall (1,3,5,7 days)	P _{1,3,5,7}

Table 19 - Hysteresis loop classifications and descriptions adapted from Williams (1989).

Hysteresis Classification	Description
Linear	Concentration well correlated to flowrate on rising and falling limbs
Clockwise	Concentration on rising limb greater than falling limb (source exhaustion)
Counter-clockwise	Concentration on rising limb less than falling limb (delivery lag)
Figure-eight	Combined clockwise and counter-clockwise effects
Indeterminate	Complex dynamics with no discernible pattern

storm characteristics, and AERAT values in order to highlight a range of pollutant dynamics that were observed.

RESULTS AND DISCUSSION

Intra-Event Variability

Boxplots of water quality metrics for each constituent (*E. coli*, TSS, copper, and zinc) are shown in Fig. 2, grouped by events with AERAT less than or greater than 1.0 to demonstrate differences in observed water quality between events related to EIA (Fig. 2). Visual inspection of the plots indicates that pollutant variability tends to be greater for storm-events with AERAT values less than 1.0. Based on observed runoff for these events, it would be expected that this runoff is sourced predominantly from the EIA. Variability may be higher for these events due to spatial variability in source material across the EIA or along stormwater infrastructure. It could also be that pollutant delivery for these events is more sensitive to storm-event characteristics. For storm-events with an AERAT greater than 1.0, the boxplots for water quality observations tend to indicate less variable responses for different water quality constituents. Observations were also typically slightly lower across the metrics for these events except for the event with the largest AERAT value (3.03; Williams Creek 7/26/16) which exhibited a very high loading for *E. coli* and TSS. The lower variability and magnitude for water quality metrics for events with runoff sourced from areas in excess of EIA may indicate that these additional areas do not carry pollutant loads as great as from EIA or that they are attenuated along the less connected runoff pathways. It could also be that with higher runoff, there are dilution or mixing effects that contribute to lower concentrations overall. Water quality observations between the two AERAT groups are statistically different based on the Mann-Whitney U-Test for all water quality metrics and constituents at an $\alpha = 0.05$ significance level except for the EMC and EPC for *E. coli* (p-values = 0.98 and 0.27 respectively). These results indicate that for the most part, the water quality response differs based on whether the AERAT value is less than or greater than 1.0.

Analysis of correlation coefficients between storm characteristics, antecedent moisture conditions, and water quality metrics offer further explanation of variables affecting this variability. Spearman's rank correlation coefficients have been summarized in Table 20 for all events and Table 21 for events with an AERAT value less than 1.0. Correlation coefficients for events with an AERAT value greater than 1.0 have not been summarized in a table for brevity as there were only six significant correlations measured ($\alpha = 0.05$). These will be discussed along with other significant relationships for different metrics to highlight some of the determining factors in the observed water quality variability.

Variability by water quality constituent

It is useful to discuss the most influential variables by water quality constituent since each of these demonstrate slightly different relationships to storm characteristics as well as overall trend in terms of the AERAT.

E. coli

Overall trends for *E. coli* in relation to AERAT were fairly consistent outside of the very large runoff producing event at Williams Creek. For this event, all metrics except for the TPR exhibited very high values compared to other events with AERAT values greater than 1.0. The TPR was low (0.74), indicating that the peak concentration occurred before the peak flowrate. Correlation analysis did not indicate that TPS was well-related to any of the storm-event variables, so it is difficult to discern an explanation for this lower value. The EMC for *E. coli* was most closely related to antecedent precipitation across all storms and for smaller AERAT values wherein greater rainfall in the days prior to an event either flush existing *E. coli* from the system or inhibit their growth. The EMC was also related to rainfall intensity (I), especially for larger AERAT values, though this relationship may be skewed by the outlier event. Trends on peak concentration (EPC) was very similar to EMC (for *E. coli* as well as for other water quality constituents) in terms variables with the strongest correlation. The ERAT metric was not significantly related to any storm characteristics measured. The value of this metric is influenced by the pollutant source available since peak concentrations are limited by pollutant presence. This has been shown to have seasonal and additional climactic determinants for *E. coli* that were not measured here (McCarthy et al. 2012). Event flux (EF) had a positive relationship with rainfall (P) amount and intensity and a negative relationship with antecedent moisture measures. This relationship was even stronger for storms with runoff only from EIA. This may indicate that there is an appreciable flushing effect for *E. coli* given dry antecedent conditions and appreciable rain producing runoff from EIA. This is potentially related to bacteria accumulation along stormwater infrastructure that is mobilized along connected runoff pathways.

TSS

Variability between storm events for TSS observations also followed the trend of high variability for lower AERAT values and a more consistent response for greater AERAT values. The strongest relationships between TSS metrics were rainfall-related (positive correlation) as well as antecedent rainfall (negative correlation). This supports previous research that has shown TSS to be more closely related to buildup and washoff from surfaces via rainfall characteristics. The negative correlation with antecedent rainfall, strongest for that falling one day previous, indicates diminished source material from previous runoff events. Correlations were stronger for events deriving from only EIA compared to all storm events. This demonstrates the effects of impervious surface connectivity on pollutant movement to the stream. Runoff pathways that provide little attenuation of water quality across them should be expected to translate pollutants freely. Thus, rainfall characteristics explain a large amount of variability in pollutant differences between storms deriving from EIA because the processes of washoff and transport describe the movement of the pollutant to the stream well. The relationship between rainfall and ERAT and EF were both significant for larger AERAT values as well ($r = 0.66$ and 0.70 respectively). This indicates that for storms where runoff may come from additional areas of the watershed, bulk rainfall influences TSS loading in the stream. This could be related to erosive forces or transport of sediment from pervious areas. It should also be noted that for larger AERAT values, the TPR was very close to 1.0 for most events. This indicates that peak concentrations are well-correlated with peak flowrates which may be more related to in-stream processes than sediment sources coming from

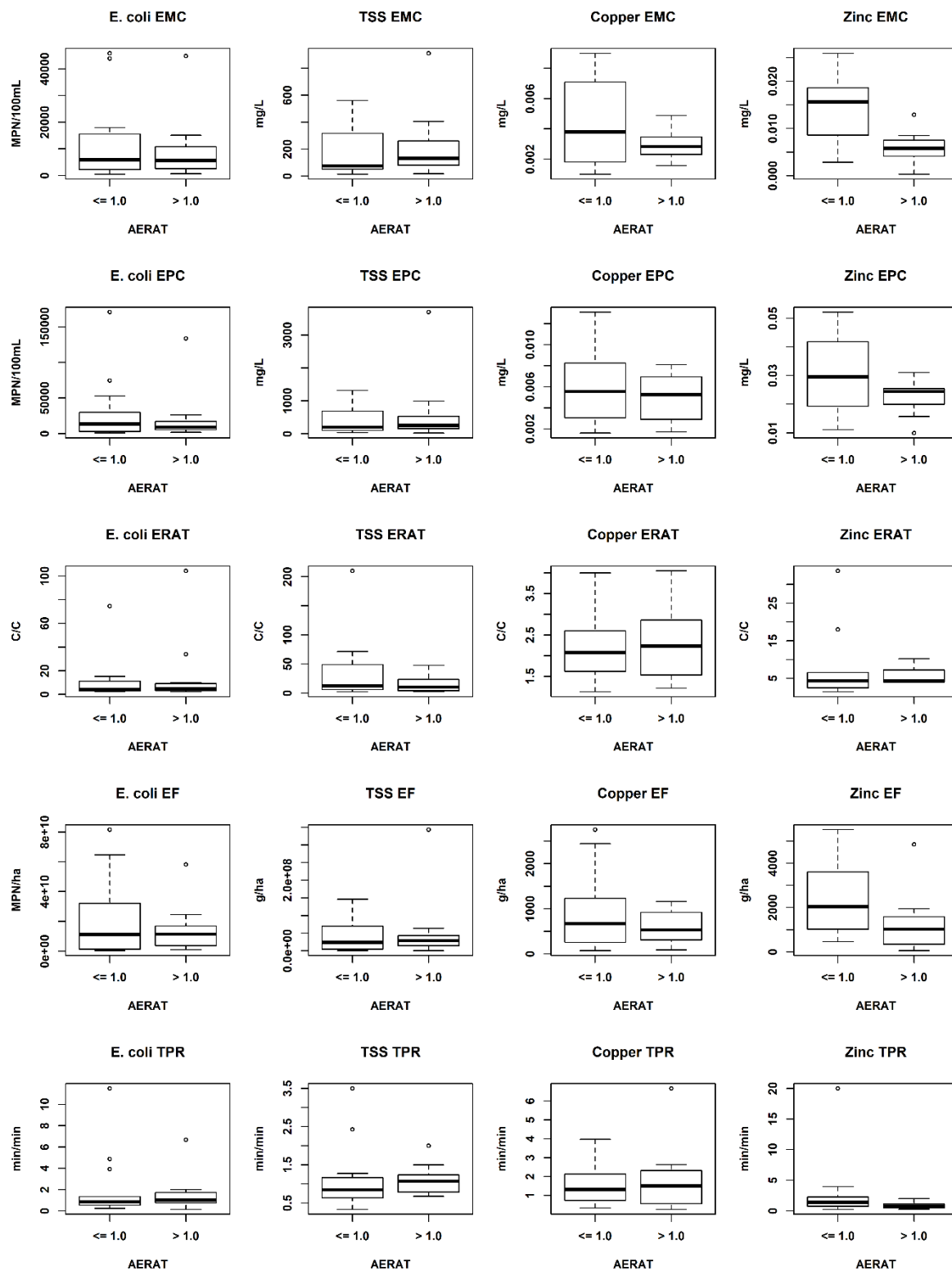


Figure 21 - Plots of water quality metrics against AERAT for the four water quality constituents.

Table 20 - Summary of Spearman's rank correlation coefficients over all storm events. Only events significant at the $\alpha = 0.05$ were included.

	All Storms	P	D	I	I _{max}	Q ₀	P ₁	P ₃	P ₅	P ₇	AERAT
E. coli	EMC				0.43		-0.52	-0.45			
	EPC				0.43	-0.46	-0.56	-0.47			
	ERAT										
	EF	0.46		0.44	0.51	-0.43	-0.54				
	TPR										
TSS	EMC	0.46		0.53	0.54						
	EPC	0.50		0.44	0.51		-0.45	-0.42			
	ERAT	0.44					-0.48	-0.47			
	EF	0.71		0.49	0.54		-0.42				
	TPR					0.53	0.42				
Copper	EMC			0.45							
	EPC			0.48							
	ERAT										
	EF	0.76		0.46	0.56						
	TPR				0.44						
Zinc	EMC										
	EPC						-0.52	-0.51	-0.46		
	ERAT										
	EF	0.61		0.52	0.53						
	TPR										-0.55

land surfaces. This is an important distinction to make when upland management options are explored, and has been the topic of a great deal of recent research.

Metals – Copper and Zinc

Variability between events for metals was mostly related to rainfall characteristics (rainfall and intensity), again exhibiting a stronger relationship to these variables for smaller AERAT values. Copper loading as measured by the EF was very strongly related to rainfall depth for smaller AERAT as well as larger ($r = 0.83$). Copper and zinc demonstrated a significant relationship to AERAT when AERAT was less than one for the TPR metric. This relationship was also significant for zinc across all events, and the only other metric with a significant relationship to AERAT was for TSS TPR for larger AERAT values. This relationship indicates that within storm events, pollutant supply is most likely exhausted before or near the peak flowrate with lower concentrations occurring at all points on the falling limb of the hydrograph than the rising limb. This will be discussed more in terms of pollutant dynamics below, but it is worth noting here. Runoff in the beginning of an event is likely derived from the most connected impervious surfaces first with contributions from other areas coming later in the hydrograph. Strategic

management of runoff from EIA areas by disconnection may have a large impact on in-stream levels of these pollutants that seem to derive from these most connected surfaces.

Table 21 - Summary of Spearman's rank correlation coefficients for storms with an AERAT value less than or equal to 1.0. Only coefficients significant at $\alpha = 0.05$ level were included.

AERAT ≤ 1.0		P	D	I	I _{max}	Q ₀	P ₁	P ₃	P ₅	P ₇	AERAT
E. coli	EMC						-0.75	-0.59			
	EPC					-0.63	-0.65				
	ERAT										
	EF	0.65			0.60		-0.65				
	TPR										
TSS	EMC	0.56		0.59	0.68		-0.68				
	EPC	0.61			0.64		-0.80				
	ERAT										
	EF	0.75		0.57	0.73		-0.66				
	TPR										
Copper	EMC			0.67							
	EPC			0.64							
	ERAT										
	EF	0.72		0.66	0.71						
	TPR										-0.64
Zinc	EMC										
	EPC							-0.59			
	ERAT										
	EF										
	TPR										-0.55

Intra-Event Pollutant Dynamics

Hysteresis can be useful to assess pollutant dynamics as they relate to storm event characteristics and most probable source related to runoff production and pathways. Variability in discrete sample timing as well as the temporal distribution can make observed data difficult to discern in terms of the classifications discussed by Williams (1989b). This is due to differences in time of concentration from different areas of the watershed that influence transport of pollutants to the point of observation as well as the lack of continuous water quality data. Despite this, evidence from the water quality events presented herein does indicate some of these different classifications types that differ by storm event

characteristics. Discussion of these serves to illuminate some of these processes as they relate to EIA. Hysteresis loops for four events with different characteristics will highlight some of the variability in pollutant dynamics observed in this dataset.

Figure 22 depicts the pollutant dynamics for Second Creek for the storm event on 9/11/14. Rainfall for this event measured 14.3 mm and antecedent rainfall was average compared to other storms. The AERAT value for this event was 1.04 indicating that runoff would be likely to derive from an area just slightly larger than the EIA. Hysteresis loops for all four water quality constituents demonstrate a figure-eight trend. Concentrations are higher on the rising limb of the hydrograph than the falling limb for the most part, but peak concentrations for all constituents fell after the peak flow in a similar pattern. Initial near-stream sources exit the system early and the delayed peak in pollutant loads indicates a source that is transported to the stream via runoff with a higher time of concentration. This could be also due to the temporal distribution of rainfall. TSS observations increased towards the peak of runoff while bacteria was relatively constant and the metals decreased until the delayed peak in concentration. Metals may be more associated with impervious surface transport pathways, with this supply quickly exiting with the most highly connected runoff. TSS and *E. coli* dynamics are likely to be sourced from surficial pathways but also the natural stream system itself, so there is a greater amount of source load near the stream. This is difficult to discern without more sophisticated tracing. Nevertheless, the figure-eight trend in the hysteresis loops indicates that the peak concentrations for all pollutants was likely co-located and is likely to be sourced in a more disconnected area of the watershed.

Figure 23 shows the event dynamics for the storm on 6/30/15 on Third Creek. This smaller event (5.5 mm) occurred just after considerable rainfall had previously occurred, with 56.5 mm of rain during the three days previous. This contributed to higher direct runoff and an AERAT value of 1.07. This is similar in magnitude to the previous storm discussed despite considerably less rainfall. It would be expected that runoff is sourced from all EIA areas, but it is possible that this may not be the case given substantial antecedent moisture. Hysteresis loops indicate a similar counter-clockwise trend for TSS and the metals with the opposite for *E. coli* (clockwise). For the counter-clockwise pattern, pollutant concentrations are low during the rising limb of the hydrograph then higher during the falling limb. Though the hydrograph peak was not fully captured by discrete samples taken for this storm, this trend is still evident regardless of what concentration may have been present at the peak. This dynamic is likely explained by two reasons. One is that recent rainfall may have exhausted the pollutant supply on the EIA so concentrations remain low for the more connected runoff portions of the hydrograph. Second is that antecedent moisture conditions were high and probably contributed to connection of runoff pathways with greater time of concentration as seen before in the figure-eight pattern. For *E. coli*, the initial concentrations were higher than for the rest of the storm though there is also evidence of end-flushing that has been noted in other bacteria studies (Hathaway and Hunt 2010). This pattern may be more related to antecedent movement of bacteria towards the stream and subsequent transport once this event occurred rather than EIA as a source itself.

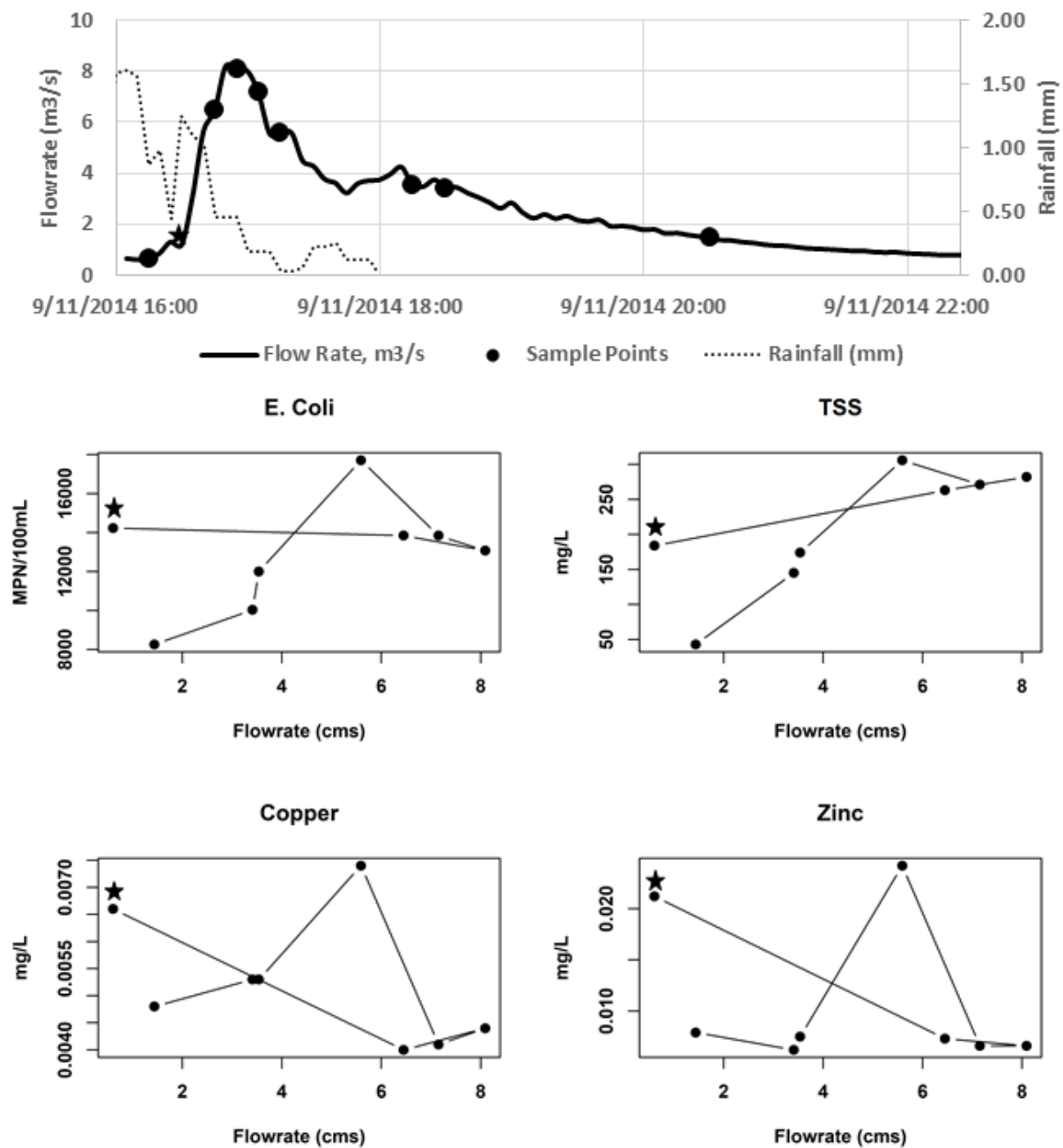


Figure 22 - Hydrograph and hysteresis loops for the storm-event on Second Creek on 9/11/14. Stars indicate the first sample observed.

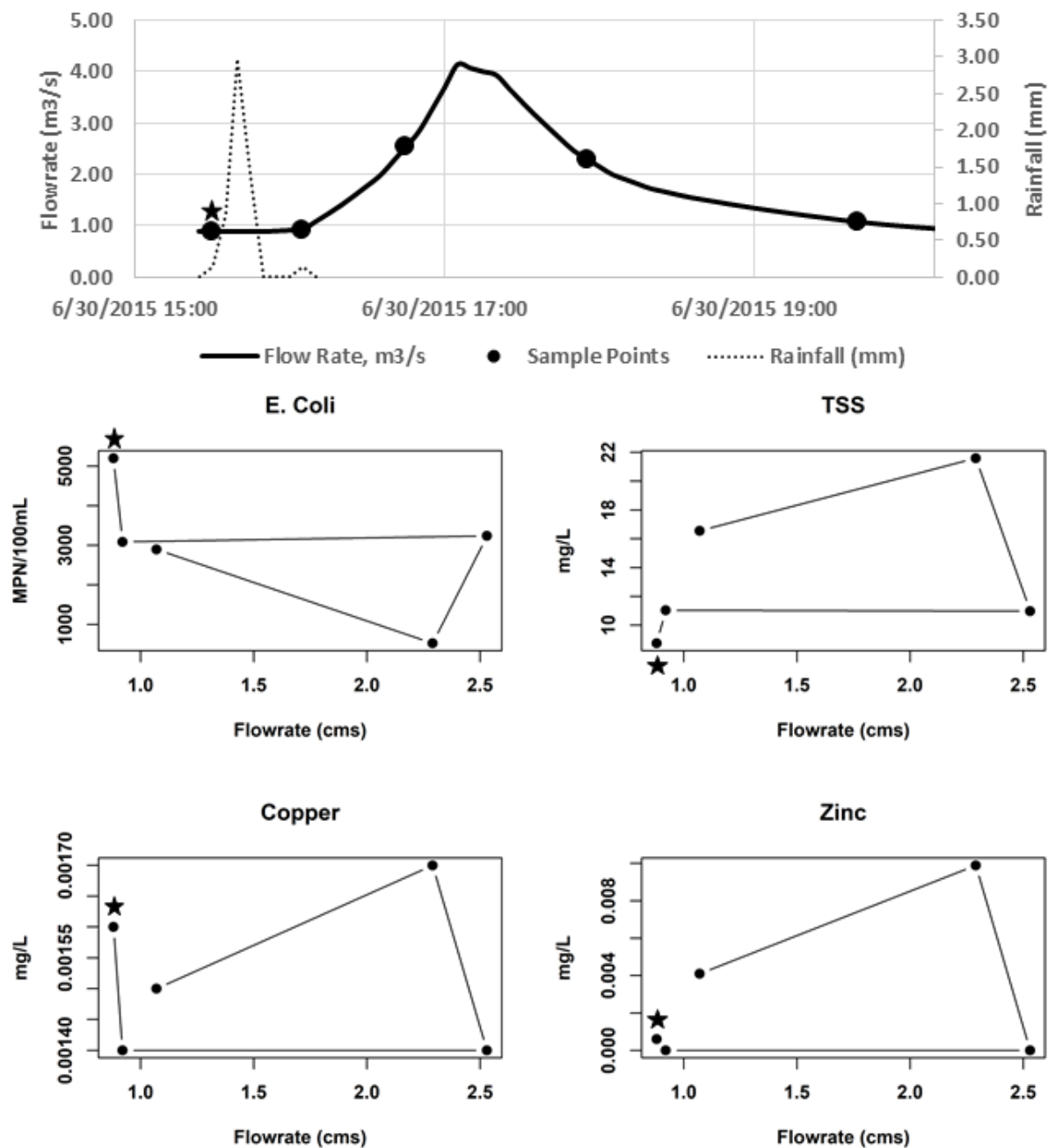


Figure 23 - Storm hydrograph and hysteresis loops for the Third Creek storm event on 6/30/15.

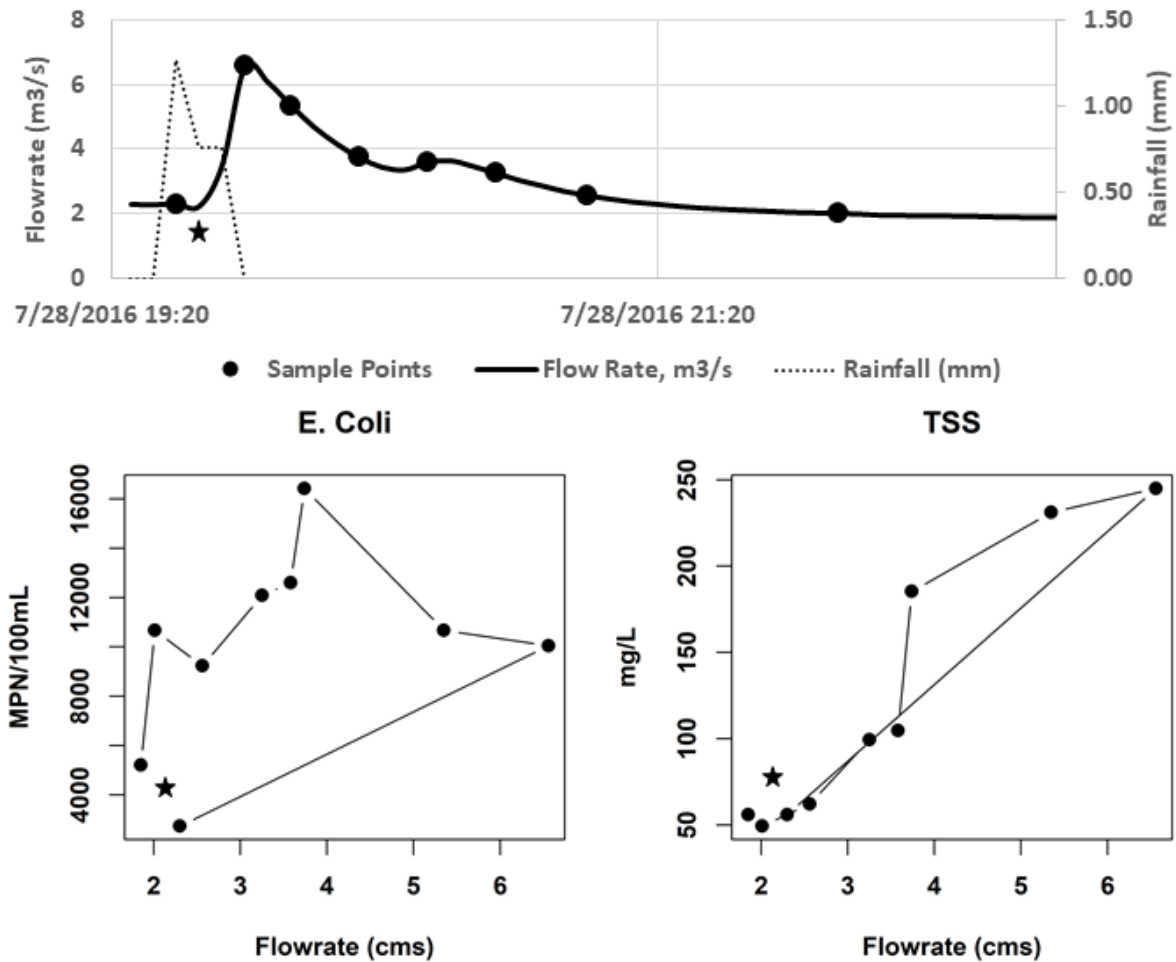


Figure 24 - Storm hydrograph and hysteresis loops for the Williams Creek storm event on 7/28/16.

Figure 24 depicts storm event observations for Williams Creek on 7/28/16. Rainfall for this event was 13.2 mm and antecedent conditions were moist with 19.8 mm of rain falling in the 3 days before. This event had a high AERAT value of 2.14 indicating substantial runoff from areas in excess of the EIA. This event was bi-modal and only the second peak has been displayed here as runoff had already receded substantially after the first peak (associated with just over half of the rainfall for the full event). This is important considering the pollutant dynamics. Only *E. coli* and TSS were measured for this event and both displayed a counter-clockwise trend with some variation. Peak concentration of *E. coli* occurred well after the hydrograph peak while these were coincidental for TSS. Concentrations were proportional to flowrate for TSS for most of the hydrograph, with some positive deviation occurring during the falling limb. Again, this indicates a source from less connected areas of the watershed that is well supported by the high AERAT for this event. This is more pronounced for *E. coli* with much larger concentrations

occurring during the falling limb of the hydrograph than near the beginning of the event. Sources for fecal bacteria are often related to sewer systems that may be septic in older developments, and these can become point sources for bacteria during wet conditions. It is possible that this is the case for this event given that substantial runoff in excess of the EIA may come from pervious areas where these systems are located.

Figure 25 depicts the compound event that began on Third Creek on 3/24/16 (A and B, Table 16). This was split into separate events for previous analysis but has been depicted here together to illustrate pollutant dynamics for closely spaced rainfall events. Both storms were similar in magnitude with the first peak associated with rainfall of 9.1 mm and 7.1 mm for the second. Antecedent moisture was low for these events with 4.0 mm falling in the 3 days previous. AERAT values for these events were similar (0.73 for the first peak and 0.78 for the second). Greater runoff was produced during the second portion of rainfall despite the lower rainfall amount. This is due to the wet conditions produced by the first rainfall portion. Hysteresis loops highlight both predictable exhaustion of supply by the first rainfall event as well as the complexity that is difficult to discern. For both TSS and copper, the compound event resulted in a clockwise trend for both portions of the event. Concentrations were higher for the first event than the second and these were higher on the rising limb of the hydrograph than the falling limb for each event individually. Because the event featured runoff primarily from EIA based on the low AERAT values, pollutant loading would be closely connected and associated with rapid transport once rainfall occurred. There is no delayed source of pollutant for these events from less connected areas, and this dynamic repeats itself during the second event, though with a pollutant supply diminished by the first event. While this dynamic is clear for TSS and copper, it is much more complex for *E. coli* and zinc. While there appears to be some organization along the expected trend, *E. coli* exhibits end-flushing again and zinc displays an intermediate peak concentration during the second event that was nearly as high as those for the first. This peak for zinc was observed on the receding limbs of both hydrographs and may indicate a consistent source as these events were similar in temporal runoff response. This storm highlights how trends in pollutant dynamics do occur but there is still additional variability that is difficult to fully explain. In the case of *E. coli*, for example, aging sanitary sewer infrastructure likely influences these dynamics.

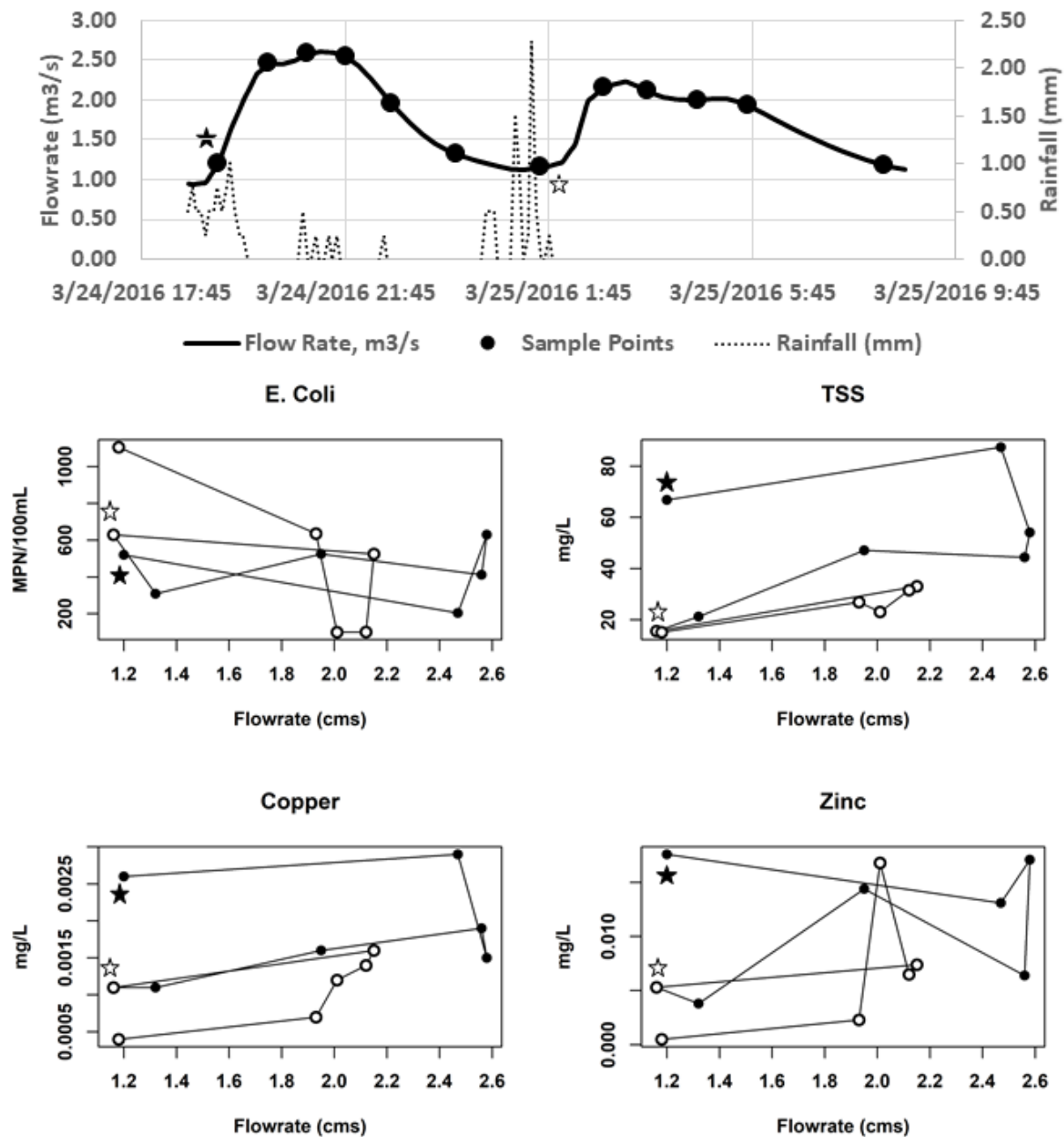


Figure 25 - Storm hydrograph and hysteresis loops for the compound event on Third Creek on 3/24/16. Filled dots represent samples from the first hydrograph peak and open dots, the second.

CONCLUSIONS

The results of this study support previous work identifying some of the dominant influences on water quality for urban streams. While these are largely related to rainfall characteristics, they also indicate that urban form plays a substantial role in the variability of water quality for any given storm event. Water quality observations for the four constituents in this study were different for nearly all metrics depending on whether runoff was expected to be sourced from EIA or less or from additional areas not necessarily considered EIA. This was highlighted by assessment of the variability between storm-event pollutant loading and variations in intra-event pollutant dynamics. Water quality models that only account for buildup and washoff of surfaces or utilize regression equations relating pollutant load to runoff rates / rainfall intensity fail to capture this variability. Some of the variability between storm events can be explained by the EIA depending on how much runoff is produced for a storm event and whether runoff is sourced from the EIA or additional areas. The stronger relationship between water quality metrics and rainfall characteristics for events with an AERAT value less than 1.0 demonstrates that these models do describe some elements of the physical processes of pollutant movement well since loading from EIA is more conservative along connected infrastructure.

However, these models do not capture other variability in urban pollutant loading well, be it from less connected sources or within the stream system itself. Antecedent moisture conditions should be considered in urban runoff models, as these appear to influence overall source areas for pollutants through enhanced runoff connectivity. Focusing management strategies to disconnect the EIA with green infrastructure practices should decrease some of the variability in pollutant loading that was shown for runoff from only EIA areas. Despite this, green infrastructure practices designed to manage runoff for smaller storms (when runoff is likely only from the EIA) may in turn become a source of further variability in pollutant dynamics during larger storm events.

Overall, water quality dynamics are complex and require detailed study and adequate accounting to allow optimal infrastructure design that will help to diminish their effects on urban stream health. Considering the influence of connectivity in these models appears to be one valid addition that can be made to water quality models. Despite this understanding, water quality modeling in urban watersheds remains a complex challenge necessitating continued research.

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FINAL CONCLUSIONS

The preceding body of work entails a comprehensive assessment of the ability for spatial models to identify the areas in a watershed that are most likely to comprise the effective impervious area. Chapters of this work detail methodology that can be used to identify these areas in a spatially explicit manner to better target distributed applications of green infrastructure. This work highlights both the effects that comprehensive targeting of EIA can have on urban hydrology related to the storm-event runoff response as well as the water quality implications that targeting these areas may have in terms of variability in urban water quality that has been observed. In summing the implications of these results, it is useful to look to the specific research questions that were posed at the onset of research. These conclusions serve to summarize how well the objectives of this work have been addressed and opportunities for future study to further refine the results. The following is a summary specific to these questions that serves as an evaluation of the effectiveness of this work to produce meaningful changes in urban watershed management, specific topics that were not effectively covered, and sources for future research that will further strengthen the understanding of urban runoff dynamics and how they can best be managed moving forward.

Chapter 1 - Establishing a GIS Framework for the Spatial Identification of Effective Impervious Areas in Gaged Basins: A Review and Case Study

Can a spatial modeling framework be developed to utilize observed runoff trends to identify the most probable impervious areas to comprise the EIA subset with high-resolution urban datasets?

The answer to this question is resoundingly affirmative. The results of this chapter demonstrated that EIA quantity estimates deriving from observed patterns in runoff production on several urban watersheds can be translated into spatially explicit estimates of the distribution of EIA among previously identified TIA locations. This geospatial analysis utilized high-resolution urban datasets and runoff pathway analysis to identify the impervious areas most hydrologically connected to the urban streams. This was accomplished using very basic rules defining connectivity based on a homogenous representation of runoff attenuation across pervious surfaces as well as the assumption that runoff is conservative across impervious surfaces and along stormwater pipes. One of the weaknesses of the results of this study is that they are difficult to verify. While they are based in sound assumptions, these may not always be correct given site-specific variation in runoff connectivity. Verification of spatial models was addressed further in Chapter 3. Specific to the results presented in this chapter, areas for

future work will be the refinement of the methodology in terms of computing power necessary to conduct it. While the methodology presented seems viable given the larger areas that it is capable of assessing, one of the strengths of the methodology detailed is that it is repeatable/updateable. This was discussed in terms of refining connectivity measurements related to ongoing implementation of green infrastructure within a given watershed to assess these changes as they relate to realized shifts in stream conditions to fine-tune modeling results. This is possible, but the methodology as it was presented in this chapter is computationally demanding. Some of the assumptions and specific algorithms used to produce final results might be assessed using sensitive analysis compared to more simple representations that might offer similar results with more rapidly implementable analysis. While this work represents a finished product of sorts, continued refinement of these methodologies will continue well beyond its acceptance.

Chapter 2 - Using Spatially-Identified Effective Impervious Area to Target Green Infrastructure Retrofits: A Modeling Study in Knoxville, TN

How much benefit could be expected for GI installations utilizing spatial EIA identification over less spatially informed methods of GI implementation throughout an urban watershed?

The results of the study in this chapter highlight the effectiveness of spatial models identifying EIA as a target for distributed application of stormwater control measures. Scenarios using this spatial information for targeted disconnection were clearly better than other less-spatially informed scenarios in diminishing storm-event runoff volumes. While there may be some bias in these results since the runoff models were defined based upon the location of EIA, model performance with simple manual calibration that used literature-defined ranges for parameter values indicates that the models employed were representative of urban runoff dynamics. Idealized modeling studies such as this serve as a basis to define bounds for potential performance that may be realized given the inherent variability in actual performance of green infrastructure as well as complex urban runoff dynamics. The main takeaway from this study may be that targeting EIA with distributed management is likely to greatly reduce runoff for smaller storm events. For larger events, the location of infiltrative stormwater control measures that were modeled in this study may not be as important as just the magnitude of impervious surfaces that is effectively treated. Depending on specific management goals, this may be more or less relevant. In terms of protecting stream systems from the increased frequency of runoff from event small events that has been observed related to EIA, targeted management may be very effective. However, comprehensive management of runoff for larger events may be best addressed by treating runoff from

as much of a watershed's impervious areas as possible. Future opportunities for study related to this chapter would be to refine runoff models to adequately capture BMP implementation at the most relevant scale of disaggregation. The role of pervious areas on runoff production for larger events was influential on the results of this study, but this may be related to the scale of modeling based on subcatchment size and the idealized nature of the SWMM model. Interactive effects between surface runoff, soil moisture, and subsequent downstream runoff production from pervious areas might not have been well captured in this study. Single idealized BMPs were modeled at the downstream locations of impervious areas. Given actual implementation, the coverage of these BMPs would be more distributed specific to impervious drainage points and topography, and how these might interact and influence downstream conditions is a relevant topic that should be addressed given full implementation of targeted SCMs in the context of EIA.

Chapter 3 - Investigating Differences in Effective Impervious Areas Identified Using Spatially Variable Runoff Attenuation and Radar Rainfall Estimates

How do spatial EIA results vary related to model inputs used to represent runoff attenuation and how effectively do these spatial models predict variability in surface runoff for observed storm events?

The answer to this research question is simple but nuanced. Different spatial models employed in this chapter using variations on runoff attenuation identified different impervious areas as EIA, but this variance differed by watershed as well as runoff attenuation representation. Results indicated that the homogenous PRAP model, the most simplistic representation of runoff attenuation first proposed in Chapter 1 establishing the modeling framework, captures spatial dimensions of impervious runoff connectivity on each watershed. Alternative representations of runoff attenuation (CNAP and TOPAP) that are more spatially variable than the PRAP model did not predict variability in surface runoff any better than the base PRAP model, though they did identify different areas as EIA. Despite this, the use of high-resolution rainfall from radar products (NEXRAD) indicated that runoff predicted by spatial models has very similar variance trends related to observed runoff as the regression methodology used to estimate EIA quantities. Where this was not true for Williams Creek, iterative recalibration of spatial models using spatial rainfall observations was used to refine EIA quantity estimates for this watershed that gave greater confidence in final spatial models. Representations of spatially variable runoff attenuation did not explain variability in the amount of EIA producing runoff that was expected given the variance of observed runoff from the regression trendline, and this remains a topic for further study. Spatial models utilized in this chapter offered a simplistic measurement of runoff connectivity that best

measures the overall trend in runoff production related to EIA but does not account for antecedent conditions that may impact storm-specific variability in runoff production. Further work to refine the results of this methodology will focus on sensitivity analysis related to the scale of spatial variation of runoff attenuation as well as how these temporally-variable conditions might better be incorporated into these models. This will provide a more complete capture of EIA across realistic conditions in these watersheds that more fully integrates the dominant factors influencing variation in impervious area connectivity. In this way, spatial identification of EIA will be able to account for variable antecedent conditions that influence connectivity that can be used for a more robust management approach to target not only the most frequently connected areas but also those that may only connect given certain storm-specific characteristics but still have a substantial impact on urban stream hydrology.

Chapter 4 - Assessment of Inter-Event Water Quality Variability and Pollutant Dynamics in the Context of Effective Impervious Areas

Do accurate EIA measurements help explain variability in inter-event and intra-event pollutant differences and dynamics for several different common constituents in urban streams?

Results from this chapter demonstrated that trends in variability observed in water quality between storm events differ depending on runoff production that was related to EIA. For storm events with runoff production less than would be expected from the full EIA, pollutant loading across water quality constituents was more highly variable but better explained by rainfall and antecedent moisture characteristics that support the use of well-established water quality models. However, storm events that exhibited runoff production likely to derive from areas in excess of the EIA were less variable between events but exhibited inter-event pollutant dynamics that may be more difficult to account for with established models. These results demonstrate the need for further study of variable source areas in water quality modeling that are mostly related to an interactive effect between antecedent moisture conditions and storm-event characteristics that increase the complexity in the movement of source material to the stream. Further study into these dynamics that would strengthen the role of EIA on inter-event variability in pollutant dynamics should focus on source-tracking as well as a more robust study of the time of concentration along runoff pathways that would help further elucidate runoff pathway dynamics.

Overall Research Objective

Can green infrastructure practices be sited throughout urban watersheds using spatially-explicit metrics of impervious surface connectivity to effectively disconnect these impervious surfaces and diminish the effect they have on urban hydrologic regime shift? Can measures of impervious surface connectivity related to surface runoff be used to produce multi-objective management guidance for both urban runoff and water quality?

The overall conclusions of this research indicate that the work presented herein can in fact be applied in a realistic way to urban watersheds to target spatially explicit measurement of EIA to produce meaningful change in urban hydrology and water quality. Improvements in the model representations of runoff attenuation are likely necessary as indicated by the variability in influences influencing urban runoff for any given storm event. As more and more distributed green infrastructure is employed in urban watersheds, the resultant effects on hydrology will increase in complexity. With each SCM that is installed, local hydrologic conditions are changed that may propagate downstream or influence runoff production and water quality transport differently. One of the greatest barriers to more widespread application of these practices is that their effectiveness across a broad scale is difficult to demonstrate. While modeling studies offer some evidence and explanation, the inherent variability in performance that has been realized by actually implemented practices remains to be demonstrated. Final verification of the work presented herein will likely come from the application of this methodology to watersheds with intentionally sited SCMs in relation to the spatial guidance that this methodology provides. Despite this, the summation of this work indicates the potential for such approaches and will be valuable to urban watershed managers to establish spatially explicit targets for distributed stormwater management goals that are likely to diminish the effects of urban form and activity on stream health.

VITA

Thom Epps grew up in the suburbs of Baltimore, MD where he explored creeks from an early age. He left home to get his Bachelor's of Science degree from Georgia Tech in Industrial and Systems Engineering. While that field did not end up suiting him, the basis in systems optimization analysis has guided his approach to environmental and hydrologic problems ever since. He went back to school to restructure his career focus, earning a Master's of Science in Biosystems Engineering from Clemson University. While there he produced a thesis on runoff production in streams in the lower coastal plain that has helped set realistic stormwater management goals to protect sensitive downstream ecosystems in an area with rapid development. Thom spent a few years in Portland, Oregon pursuing further graduate studies and understanding of the way that cities influence stream systems, how people interact with them, and how the sum of these interactions must be accommodated in stormwater management pursuits. He moved back east to Knoxville, TN to conduct his PhD research on impervious connectivity and the urban stream response. Thom now resides in San Diego, CA where he helps design large-scale regional BMPs that are the link between grey and green infrastructure that is necessary in the highly impervious watersheds of Southern California.