Evaluating Trends Using Total Impervious Cover as a Metric for Degree of Urbanization

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Abstract

Impervious cover (IC) is a common metric for assessing the degree of urbanization in watersheds. However, there are different methods for determining IC, and use of IC correlation with urban watershed response to hydrologic and geochemical inputs can be strongly influenced by the end members (IC below 10% and above 40%). The resolution of the imagery (e.g., 1 m versus 30 m) used to measure IC can influence the estimate of IC, with differences up to 15% observed between these two resolutions for 21 watersheds along the east coast of the United States. The differences are greatest in the middle range between 10 - 40% IC. When using IC for correlation with urban watershed responses such as discharge flashiness or median solute concentrations, fits with R^2 between 0.4 and 0.78 were obtained when including end members of IC from 0 to 50%. However, when trying to distinguish behavior between urban watersheds that fall in the middle ranges of IC, these same parameters do not correlate well with IC. Correlations fail significance tests, can switch direction, and fall below an R^2 of 0.1 without the end members of very low or very high IC. Because of improved accuracy, the finest resolution is preferred when available, and mixing IC estimation methods should be avoided. Furthermore, using regressions that include end members may not contribute to differentiating how IC in the 10-40% range impacts hydrologic and geochemical responses in urban watersheds. Understanding this middle range of IC is important for comparing urban and suburban watersheds or planning watershed development to minimize impacts.

Keywords: Urban hydrology, impervious cover, road salt, flashiness

1. INTRODUCTION

1.1 Impervious cover as a metric in urban watershed

Hydrologic and geochemical responses in urban watersheds are complex because the land use varies on a fine scale. The increase in impervious cover (IC) leads to faster overland runoff to streams and even slight changes in topography can reroute water and dissolved constituents. The complex distribution of impervious surfaces and engineered subsurface structures that capture or release water create fast flow paths to further accelerate runoff. Both surface and subsurface features are difficult to characterize in urban watersheds (Broadhead et al., 2013; McGrane, 2016; Oswald et al., 2023). Comparison of responses from watersheds within a city or among different cities can identify key processes that impact the hydrology of urban watersheds. However, a metric is needed to compare urban watersheds.

Total IC is a commonly used metric to compare urban watersheds and identify the intensity of urbanization. IC increases as cities densify, and IC as low as 10% can increase stormwater response (rate and peak) in streams (Schueler et al., 2009), degradation of habitats (Wenger et al., 2008, 2-4%), and alteration of channel morphology (Walsh et al., 2005). IC has been used to compare urban watersheds using metrics such as temperature (Somers et al., 2013), specific conductivity and variation in specific conductivity (Moore et al., 2020), chloride (Blaszczak et al., 2019), water yield (Li et al, 2020), flooding (Blum et al., 2020) and flashiness (McPhillips et al., 2019; Hurley et al., 2024). IC has also been used in training machine learning models to predict stormwater quality (Guzman et al., 2022).

However, the threshold for IC response is hard to define and the distribution of IC within a watershed may impact response (Jacobson, 2011). Several studies have suggested accounting for connected IC can better predict response (Sutherland, 2000; Roy and Shuster, 2009; O'Driscoll et al., 2010; Ebrahimian et al., 2016), but this requires understanding IC patterns at a fine scale (Rahimi and Ebrahimian, 2024) along with subsurface drainage. Using % IC also neglects the potential role of compacted low vegetation surfaces (such as lawns) in contributing to urban runoff. Compaction is common in urban soils particularly in the top few cm, which can inhibit infiltration (Pitt et al., 2008; Yang and Zhang, 2011; Yang and Zhang, 2015; Shuster et al., 2021). Given the demands to compile data for these alternate measures of IC, most studies use total IC when comparing watersheds rather than detailed metrics like effective or directly connected IC.

In this paper, we evaluate how using total IC as a metric influences interpretation of hydrologic and geochemical impacts in urban watersheds. Specifically, we are not trying to understand how the watersheds are impacted by IC, but how the metric is used. First, we compare coarse and fine spatial resolutions commonly used to measure total IC to quantify how they differ. Then we evaluate whether watershed characteristics are correlated with 10-40% IC when the lower IC values and higher IC values are not included in the correlation. An important distinction here is that correlating watershed response to end members at low IC (<10%) and high IC (>40%) would not lead to a surprising prediction – these end members are expected to differ. The question is how do watershed responses vary in the middle range between 10-40% IC. This range is typical of many urban and suburban areas, and important for considering effects of development and stormwater control measures.

1.2 Types of land cover data sets in the United States

One of the most widely used land cover data sets in the United States (US) is the National Land Cover Database (NLCD) which provides national-scale land cover and impervious cover at 30-m resolution. The NLCD was developed by a consortium of government agencies to map land cover at 30-m resolution over time across the US (Dewitz, 2021; USGS, 2024a). The database makes use of cloud-free Landsat imagery, with an emphasis on providing an annual time series of land cover from 1985-2023.

In contrast, more detailed land cover provides data at a 1-m resolution, but these data are often confined to a single city, watershed, or state. The University of Vermont Spatial Analysis Lab (VT-SAL) database uses a combination of imagery, planimetric data (e.g., house and road footprints), and LiDAR (light detection and ranging for fine resolution topography) to estimate IC both with and without tree canopy cover at 1-m resolution (O'Neil-Dunne et al., 2014a,b). This resolution provides readily downloadable rasters at 900 times more resolution than the 30-m NLCD but is currently only available for the Chesapeake Bay and Delaware River watersheds plus selected cities across the United States. VT-SAL coverage of several northeast states is in progress. Yang et al. (2018) report differences between IC at a fine resolution and the NLCD of 3 to 29%, while Wickham et al. (2018) report a mean fine-to-coarse difference of 1.5 % in mostly non-urban watersheds of the Chesapeake Bay but ranging up to 15% for urban watersheds.

For cities without high resolution land cover, coverages similar to the VT-SAL estimates can be approximated with tools in Geographic Information System (GIS) software and high-resolution imagery, but the process is time intensive (as described in methods below). An example of high-resolution imagery to supplement with GIS classifications tools is the National Agricultural Imagery Program (NAIP) which is collected on a statewide basis in alternate years, although national infrared-on coverage did not begin until around 2018 (USDA, 2024). Another product, the NOAA Coastal Change Analysis Program (CCAP) is developing a high-resolution data set, but depending on the state may not estimate impervious cover under canopy and is currently limited to coastal zones in the US (Office for Coastal Management, 2024). Rahimi and Ebrahimian (2024) found an average increase of 22% in IC when accounting for shaded IC in several Minnesota urban watersheds. The shading can be accounted for by comparing the IC data with planimetric maps to break out rasters that should be labeled IC under canopy. However, using planimetric maps for correction still would not likely capture canopy over parking lots. Thus, gaps in fine resolution mapping remain.

2. METHODOLOGY

We compared total IC at 1-m resolution (VT-SAL and calculated) with 30-m resolution (NCLD) for 17 urban watersheds and 4 non-urban watersheds that drain to U.S. Geological Survey (USGS) gages along the east coast of the US from Georgia to New York (Figure 1). We used the 2011 NLCD data set (USGS, 2014) because it was readily available and split the difference between the time range used for watershed characteristics (2000-2022). The VT-SAL uses multiple years for imagery and LiDAR, all within the range of the study period. The 1-m resolution data that were calculated for this project are based on more recent (late 2010's) imagery from NAIP. However, because the selected watersheds are not developing at a rapid rate, slight changes over time are not expected to greatly influence estimates of total IC. Nonetheless, such differences would occur in any data set comparing urban watersheds across different regions. Our study includes a local region with data from the same time period for investigation under more uniform conditions (as described below). For the rest of this paper, we refer to total IC simply as IC.

The data set was divided into 12 northern and 9 southern watersheds based on road salt application and observed conductivity data (Moore et al., 2020). Northern Virginia and higher latitudes are included in the 12 northern watersheds; North Carolina and lower latitudes are designated as the 9 southern watersheds. Watersheds were selected for the availability of longterm discharge data, extensive geochemical data, along with fine resolution land cover mapping. The watersheds vary in size from 0.3 km^2 to 172 km^2 (Table S1). The non-urban watersheds span the range of watershed sizes. The two smallest watersheds are non-urban, with the largest non-urban watershed reaching 42 km^2. For the northern watersheds, 20-year median chloride (Cl) concentrations were calculated based on baseflow samples collected at gages by the USGS (USGS, 2024b) and the Baltimore Ecosystem Study (Groffman et al., 2023). Two northern watersheds from the National Science Foundation Urban Critical Zone Network were included with just 3 years of chloride data at USGS gages. Variations in data set collection are not expected to be critical to the purpose of comparing correlation methods (rather than detailed comparison of watersheds). To illustrate the robustness of median Cl concentrations as a metric, Moore et al (2020) compared correlations of grab sample measurements and continuous conductivity data with % IC and found similar median values. Mean daily discharge data using the same 20-year period was used to calculate streamflow flashiness measured by the ratio of the 90th percentile discharge divided by the average discharge (Q_{90}/Q_{ave}). The daily flow metric we selected was somewhat linear when using the full range of data and daily data were available for all sites, so it provided an illustrative case. It is important to note that we were not trying to understand flashiness, but rather to evaluate different ranges of IC. Nested watersheds (stations within a selected watershed) were not included.

We identified non-urban watersheds as having less than 10% fine resolution IC, which is a commonly used threshold for urbanization (Walsh et al., 2005; Schueler et al., 2009). The non-urban watersheds ranged from 0 to 5% at the fine resolution. We further classified watersheds as highly urbanized when IC exceeded 40%. There was a gap in the IC above 40% with the

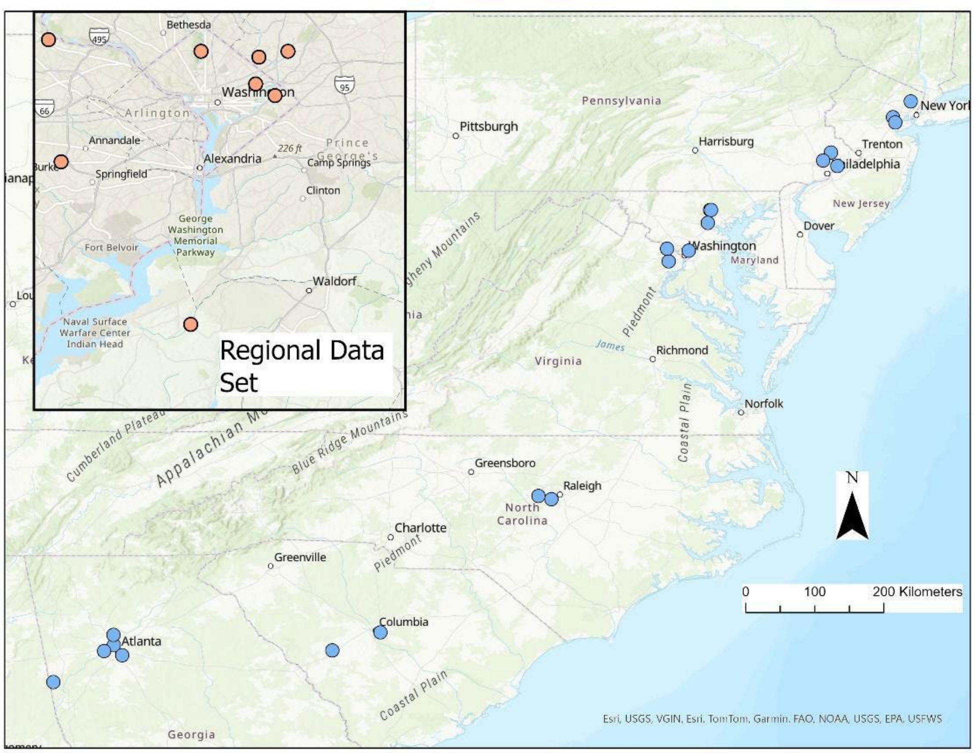

Figure 1: Location of 21 east coast USGS gages associated with each watershed for comparing fine and coarse resolution % IC and regressions on urban watershed characteristics. The gap between northern Virginia and North Carolina delimits the break between northern and southern watersheds. Inset shows regional D.C. area data set for Cl comparison.

highest two points at 47 and 54%. We define 10 to 40% as the mid-range of urbanization when considering regression with urbanization parameters. Because the fine resolution IC tends to increase the percent IC, these watersheds in this midrange of urbanization fall between 2 and 30% at the coarse resolution. Otherwise, the watersheds classified as non-urban and highly urban would be inconsistent between fine- and coarse-resolution IC.

An additional data set from a smaller region around the Washington, D.C. area (D.C., Maryland, and Virginia) was also examined to evaluate correlations with median Cl at a more local scale. This local data includes 3 watersheds in the larger east coast data set combined with 5 watersheds in the D.C. area (Moore et al. 2020) that include Cl data. The data from these watersheds were all from USGS gages, providing a data set with consistent sampling methodology and time period. VSTAL imagery was available for fine resolution IC.

For the southern watersheds outside the Chesapeake Bay and Delaware Watersheds, we estimated high-resolution IC using GIS and NAIP imagery. Planimetric maps were overlaid on clustered NAIP infrared-on aerial photography. Rasters for roads and structures were automatically labeled as IC. Then, the spectral clusters in the aerial photography were used to delineate parking lots, sidewalks and other impervious cover not mapped in planimetric data. These mapped impervious surfaces were checked for accuracy by comparison with aerial photography. Furthermore, to match the land cover for IC under canopy provided in the VT-SAL database, manual projection of roadways and parking lots was used to identify IC under canopy since leaf-off photographs were not available in the NAIP imagery.

3. RESULTS

3.1 Differences in Impervious Cover for 1-m and 30-m Resolution

IC based on fine-resolution data was typically higher than coarse resolution IC with deviations of -2 to 15% fine minus coarse resolution IC (Figure 2a). Only one watershed had lower % IC for the fine resolution (Intrenchment Creek near Atlanta, GA). The overall absolute value mean deviation was 7%, but the largest deviation was in the middle range between 10-40% fine resolution IC. The deviations were not well correlated to basin size (R^2 = 0.19, p = 0.05) (Figure 2a, Figure S1). However, basins less than 7 km^2 in size had deviations less than 5%, and the non-urban basins also had less than 5% deviation in IC. The most urbanized watershed at 53% showed only a 0.1% deviation.

Furthermore, the rank order of watersheds from least to most urban differed between the fine and coarse IC metrics (Figure 2b). At the low end of IC, in the non-urban watersheds, the rank order was the same for both fine and coarse. At the high end, the watersheds with the highest IC also had the same order, but these were smaller watersheds (7 and 14 km^2). In the middle range, a watershed that ranked 9th on the fine resolution IC ranked 1th3 on the coarse resolution IC, and one that ranked 20th on the fine resolution IC ranked 15th on the coarse resolution IC. In other words, fine and coarse resolution IC provided *different* ordinal metrics. The distribution of the two data sets is not statistically different, but the correlation between the data sets shows heteroskedasticity because the middle range of IC shows more variation than the full data set with the end members included. Furthermore, the distribution varies in that the fine resolution data set has 6 watersheds between 30-40% IC whereas the coarse data set has only one site.

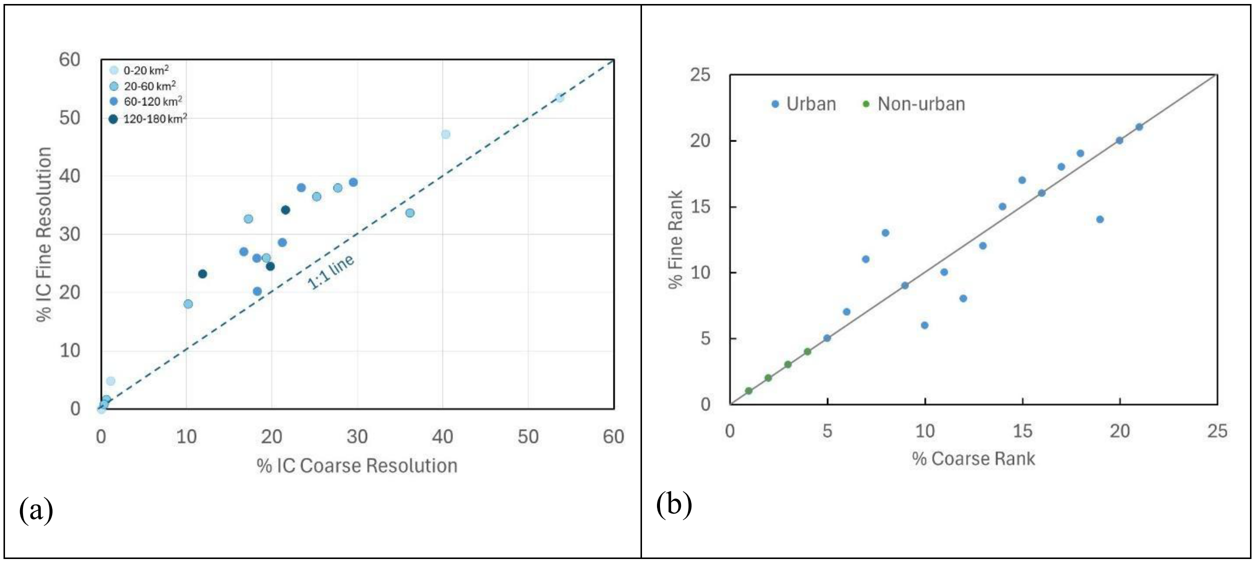

Figure 2 Comparison of fine and coarse resolution % IC. Differences are greater in the middle range. (a) Fine resolution has up to 15% higher IC, and averages 8% higher for urban watersheds. Symbol color indicating watershed size. (b) Ranked IC shows that the order of % IC is not presented correctly by the coarse scale in the middle range. Symbol color indicates urban and non-urban watersheds.

In addition to mapped IC, including semi-pervious areas (low vegetation that is mowed and compacted) increases the percentage of land cover in urban watersheds contributing to low infiltration and high runoff volume (rapid runoff). For example, including low vegetation areas as semi- or impervious cover increased the percentage of watershed likely to produce rapid runoff from 36 to 60% in the Pennypack Creek (Figure 3). Low vegetation is not typically considered in urban land cover classification, but it can increase connectivity of impervious surfaces. This land cover can be difficult to break out in the coarse resolution NLCD maps because some low vegetation, particularly in residential areas, is difficult to identify at 30-m resolution (Wickham et al., 2013).

3.2 Regression Analysis: Uncertainty in the Middle Range of IC

When using IC for linear regression or correlation analysis of site characteristics it is important to consider the influence of end members from both non-urban watersheds and highly urban watersheds. Linear regression is often used as an initial assessment for the influence of IC on watershed parameters even when the response may be influenced by other factors or be non-linear. We examined the influence of the end members by comparing linear regressions of flashiness and median Cl concentration over the full range of IC and in the middle range of IC (10 to 40% fine resolution). Additional results for 10 to 40% for coarse resolution are presented primarily in supporting information (Table S2).

Discharge flashiness (Q_{90}/Q_{ave}) is expected to increase with % IC. Linear regressions for discharge flashiness demonstrated R^2 of 0.49 ($P<0.001$) for fine resolution IC from 0 to 50% (that is, including end member IC) (Figure 4). As expected, as IC increased, streamflow flashiness increased. However, when trying to distinguish behavior between urban watersheds that fall in the middle ranges of IC between 10-40%, there was no significant correlation with IC (Figure 4). In the middle range, neither resolution of IC followed the trend predicted by the data set with a full range of IC from 0 to 50% (Table S2).

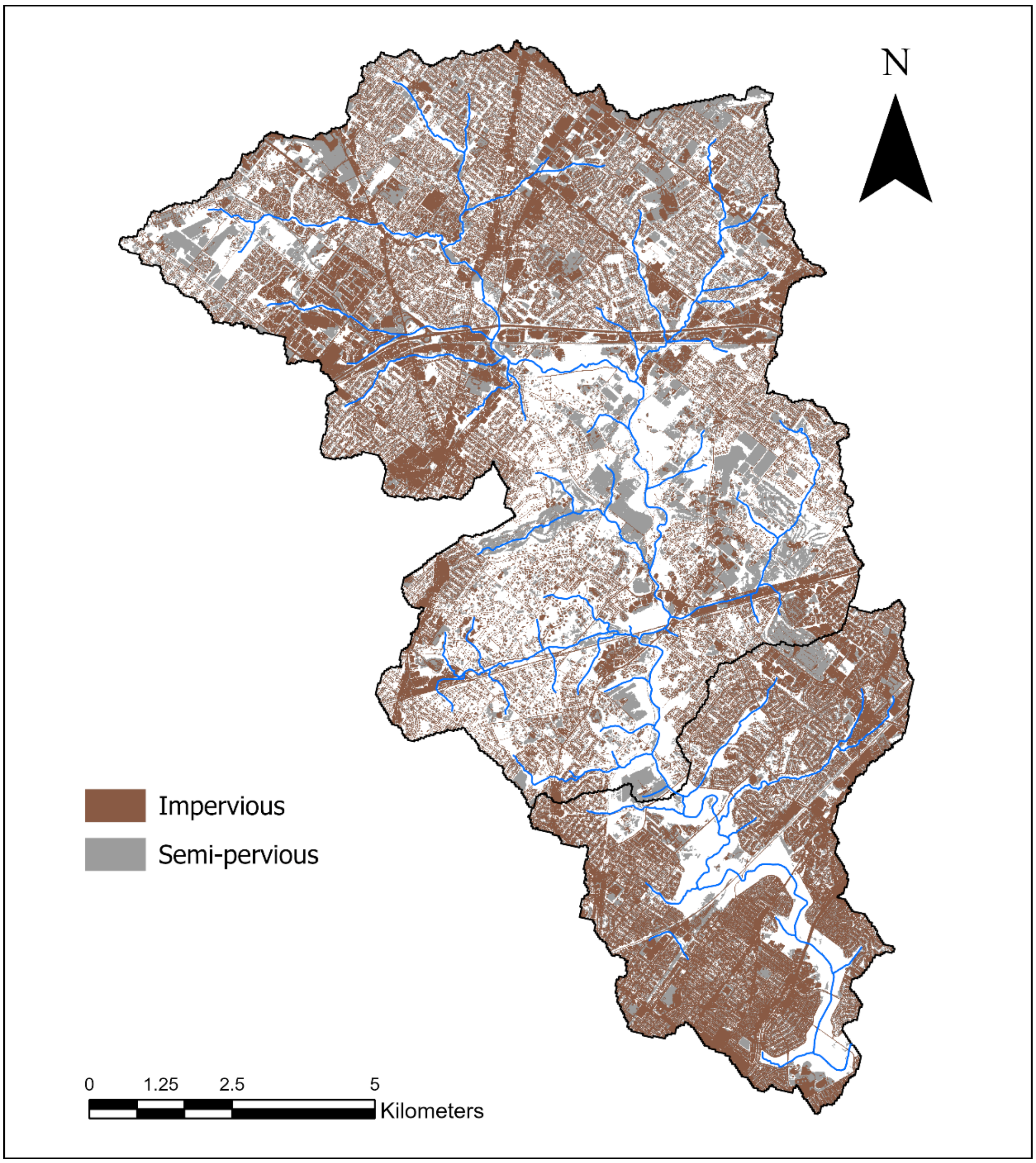

Figure 3 Impervious and semi-pervious land cover in the Pennypack Creek Watershed in the Philadelphia area based on VT-SAL database. Semi-pervious land cover is typically low vegetation or compacted mowed area which can increase overland runoff and connectivity.

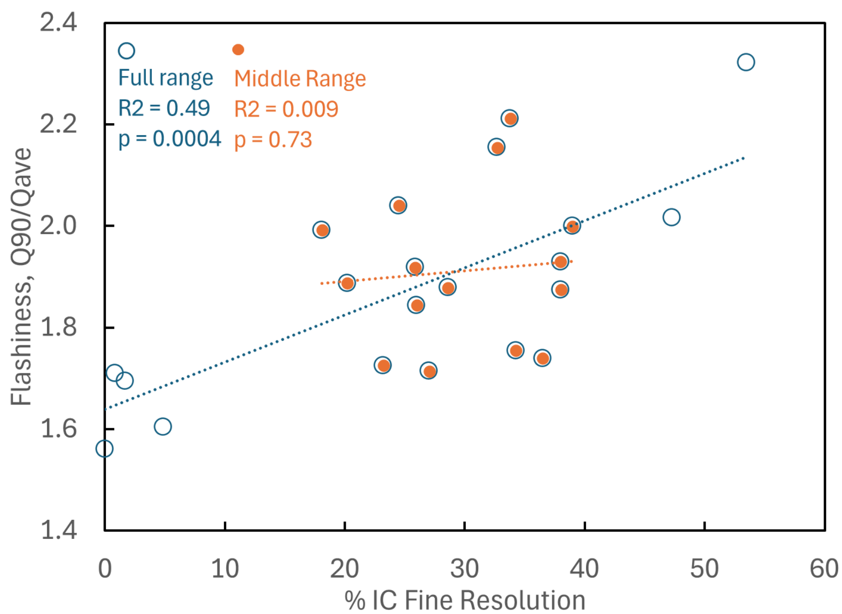

Figure 4 Discharge ratio (Q_{90}/Q_{ave}) as a measure of flashiness showed different regressions for the full range of % IC (fine resolution) and the middle range (10-40% IC).

Chloride (Cl) is another parameter that is expected to increase with % IC in regions where de-icing salt is used. Linear regressions between % IC and median Cl were only examined for the northern watersheds (Table S1). As expected, when the full range of IC was included, the linear regression between % IC and Cl had an R^2 of 0.6 ($p < 0.001$) for fine resolution % IC (Figure 5). However, the data were not correlated in the 10 to 40% range. Interestingly, the coarse resolution showed a weak correlation ($R^2 = 0.5$, $p<0.02$) between 10 and 40% but only when including the point at the upper end that was over 40% in the fine resolution. When this point is excluded, which is indicated by the higher % IC with more accurate resolution, the data are no longer correlated (Table S2). This example illustrates how data could be misinterpreted by predicting a relationship based on underestimation of % IC when using coarse resolution data.

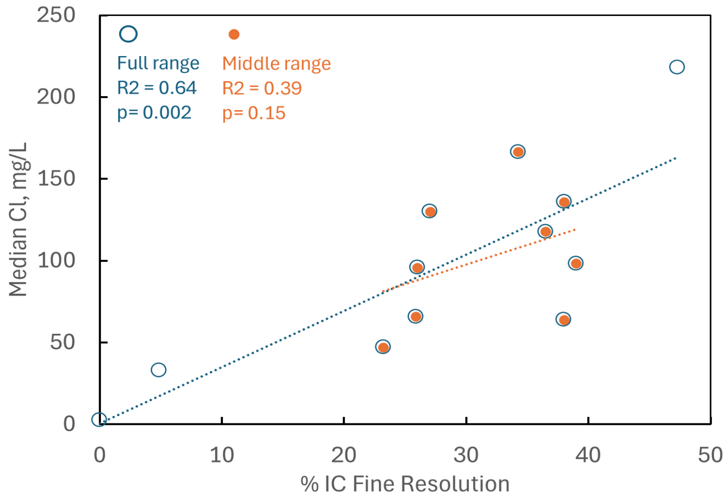

Figure 5 Median Cl concentration for northern watersheds showed different regressions for the full range of % IC (fine resolution) and the middle range (10-40% IC).

Watersheds in the D.C. area with Cl data were examined separately to evaluate trends in a local area and also showed a correlation when including the end member point at 62% IC (Figure 6). A regional data set (Figure 1) can reduce variability due to climate or other factors. The positive correlation in the entire local data set increased with R^2 of 0.78 ($p < 0.003$) compared to an R^2 of 0.63 for the larger fine resolution data set. In the middle range (without the end member data point), the Cl no longer correlates with % IC (Figure 6). It is noteworthy that the middle range data set has only one point less than the full range, and the correlation for the full range was essentially dependent on this one extreme value.

When trying to compare urban watersheds, it could be argued that the higher values of % IC would produce an obvious contrast with non-urban watersheds. In other words, it is not surprising that watersheds with less than 10% IC would differ from watersheds with over 40 or 50% IC. Given the lack of fits in the 10-40% range, using linear regressions that include end members may not contribute to differentiating how IC in the middle range impacts hydrologic and geochemical behavior in urban watersheds. These examples show that there is high uncertainty in regression in the middle range of % IC.

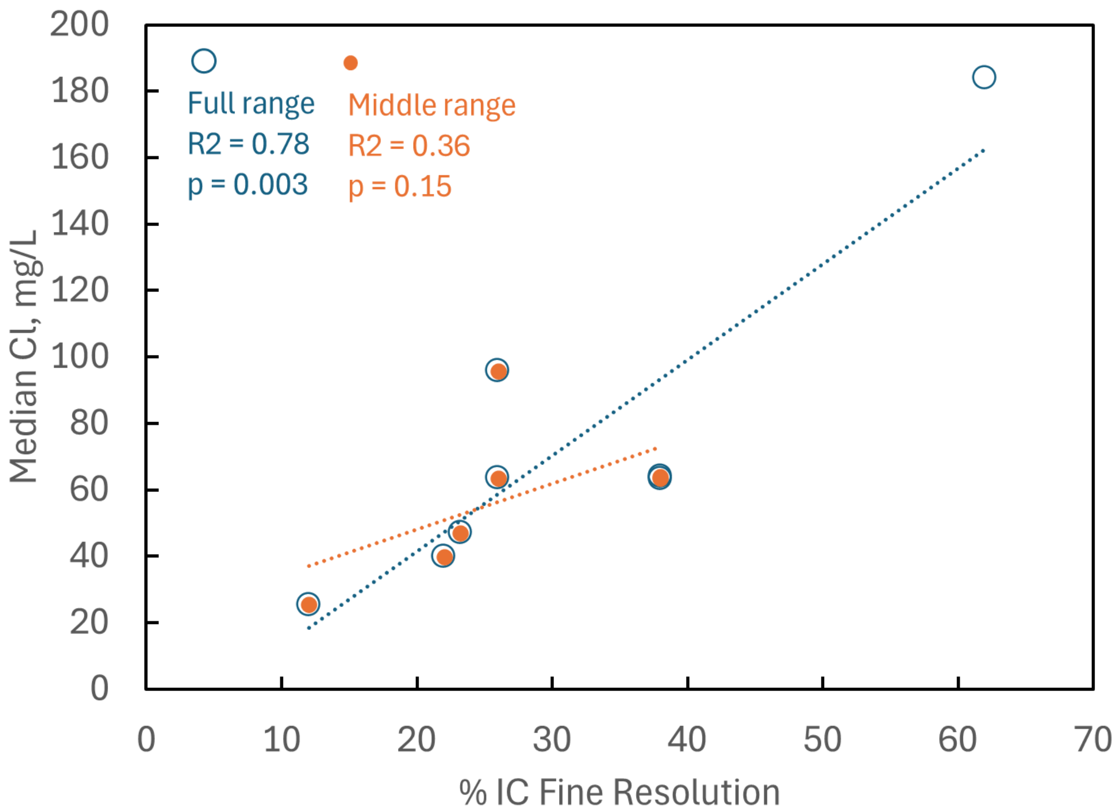

Figure 6 Cl concentration for the regional data set showed different regressions for the full range of % IC (fine resolution) and the middle range (10-40% IC).

4. DISCUSSION

Coarse and fine resolution IC can substantially differ in the values of % IC that they report. In our study of 21 east coast US watersheds, we found differences up to 15% IC. A previous comparison of fine and coarse resolution IC by Wickham et al. (2018) over the entire Chesapeake Bay watershed (262,000 km^2) found only 1.5% mean absolute difference. However, only 1.5% of their watersheds had IC greater than 25%. They observed deviations up to 13% in urban centers, similar to our study. Another study by Smith et al. (2010) compared fine and coarse IC in urban watersheds of Baltimore County, MD. Smith et al. (2010) found that the pavement fine and coarse resolution IC values were closer to each other than the total IC values. They reported differences between fine and coarse resolution IC similar to values in our study (up to 18%) for total IC, and they cautioned about using coarse resolution metrics to understand fine resolution heterogeneity. Both studies identified an offset where fine resolution data identified larger % IC, but the correlation included both high and low IC values. Including watersheds at the low and high end of % IC can mask large differences between individual watersheds. In other words, caveats are needed when using coarse resolution data sets in urban watersheds, and coarse resolution IC values cannot be used to estimate fine resolution IC with a predictable offset.

Although % IC seems like an obvious metric for describing urbanization, using readily available coarse resolution % IC data could lead to misinterpretation, particularly if the resolution is too coarse to define IC adequately. For example, the National Resource Conservation Service uses coarse resolution NLCD data to identify sites for urban soil sampling (Hernandez et al, 2017) which could potentially result in a distribution of samples that misses the actual IC variation, particularly in the middle ranges of IC. Rahimi and Ebrahimian (2024) found that metrics for connected IC could not be obtained accurately with coarse NLCD data. NLCD data are commonly used for studies of how urbanization changes over time because these are often the only data available for historic comparisons (e.g., Bhaskar et al., 2020; Blum et al., 2020). However, if errors in % IC are not the same over time, then the evolution will not be correctly identified. Including uncertainties as error bars could be considered when presenting such data.

Moreover, trying to understand hydrologic processes in urban watersheds is problematic when the source of % IC data is not reported or the data resolution is not included in the description. Consistency in sources of data does not equate with correct ranking from high to low IC when comparing fine and coarse resolution IC. Watersheds were observed to rank 4-5 positions lower on coarse resolution than fine resolution and vice versa. Differences in ranking can change the interpretation of the data when a watershed is assumed to be more urban (as measured by % IC) but is not. Further uncertainty occurs when some data sets include IC covered with canopy while some do not, or when low vegetation surfaces cannot be accurately identified.

The weakness of using % IC to evaluate associations with hydrologic and geochemical responses is manifested by the higher uncertainties in the middle range of 10 to 40% IC. Our study found that linear regressions between % IC and discharge flashiness and median Cl were not correlated in the middle range, in contrast to regression over the full range of IC (0 to 50%). These results indicate using regressions that include end members may not contribute to differentiating how IC in the middle range impacts hydrologic and geochemical fluxes in urban watersheds.

Many studies of urban watersheds look at the middle range of % IC, and the lack of correlation suggests that there are missing factors that describe water flow in urban watersheds. Others have recognized that additional factors need to be considered when using IC as a metric (e.g., Schueler et al., 2009) because correlations to IC do not lead to strong predictions (e.g., $R^2 < 0.6$). Comparing data over a smaller region or similar climatic zones (Moore et al., 2020; Blaszczak et al., 2019; Gannon et al., 2022; Hurley et al. 2024) can improve correlations. Examples of additional factors include road density and watershed slope (Hopkins et al., 2015); soil infiltration and its influence on connectivity (Voter and Loheide, 2018; Sytsma et al., 2020; Kirker and Toran, 2023a), previous land use (Li et al., 2020), and subsurface infrastructure such as storm pipes (Ledford et al., 2020). Modeling can be used to assess additional urban runoff metrics and help focus field characterization efforts (Sytsma et al., 2022; Zhang and Parolari, 2022; Kirker and Toran, 2023b; Mayou et al., 2024).

Given the issues with using % IC as an urban metric, improved data descriptions and data evaluation are needed for design of stormwater control measures and other urban planning. When reporting urban metrics, particularly IC, it is important to state what resolution is applied, whether IC under canopy is included as a land cover, and whether semi-pervious surfaces are considered. Without an understanding of how % IC is obtained, it is difficult to interpret the values. Coarse resolution land cover and land cover analysis that omits IC under canopy tend to underestimate % IC, particularly in vegetated regions such as the east coast US. Furthermore, including end members in the metrics applied when comparing watersheds in the middle range of % IC could create a bias based on non-urban and highly urban watersheds. Although fine scale characterization of urban watersheds is challenging, it is critical to advancing our understanding of the impacts that urbanization has on watershed processes.

5. CONCLUSIONS

Our study of 17 urban and 4 non-urban watersheds on the east coast confirmed previous reports that showed fine resolution tends to have greater % IC than coarse resolution measurements. Our study pointed out that including non-urban and highly urban watersheds in comparisons of fine and coarse resolution % IC can mask differences in the middle range. We did not find a uniform offset that could estimate the fine resolution from coarse resolution data. Furthermore, the rank order of % IC changed for fine and coarse resolution data, which could change interpretation of comparison data sets when using % IC as a metric.

An additional issue with using % IC as a metric to describe urban watersheds is that parameters that correlate linearly over the full range of % IC (including non-urban and highly urban watersheds) do not correlate in the middle range between 10 to 40% IC. Both median chloride concentrations and discharge ratio did not correlate linearly with % IC in the middle range, even when examining a regional subset of watersheds over a smaller area. This range in % IC is typical of many urban and suburban areas, and important for considering effects of development and stormwater control measures. These results indicate using regressions for % IC that include end members influences interpretation of results and may not contribute to differentiating how IC in the middle range impacts hydrologic and geochemical fluxes in urban watersheds. The lack of linear correlation with % IC in the middle range points to other important processes that contribute to quantifying urban watershed behavior.

ACKNOWLEDGEMENTS

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DATA AVAILABILITY

Data used to create the graphs are available in Table S1.The data were derived mostly from the SGS Water Data for the Nation: National Water Information System Database. U.S. Geological Survey. https://doi. org/10. 5066/ F7P55KJN.

REFERENCES

Bhaskar, A. S., Hopkins, K. G., Smith, B. K., Stephens, T. A., & Miller, A. J. (2020). Hydrologic signals and surprises in US streamflow records during urbanization. *Water Resources Research*, *56*(9), e2019WR027039.

Blaszczak, J. R., Delesantro, J. M., Zhong, Y., Urban, D. L., & Bernhardt, E. S. (2019). Watershed urban development controls on urban streamwater chemistry variability. *Biogeochemistry*, *144*, 61-84.

Blum, A. G., Ferraro, P. J., Archfield, S. A., & Ryberg, K. R. (2020). Causal effect of impervious cover on annual flood magnitude for the United States. *Geophysical Research Letters*, *47*(5).

Broadhead, A. T., Horn, R., & Lerner, D. N. (2013). Captured streams and springs in combined sewers: a review of the evidence, consequences and opportunities. *Water Research*, *47*(13), 4752-4766.

Dewitz, J. (2021). *National Land Cover Database (NLCD) 2019 Land Cover Science Product (ver. 2.0, June 2021)*: U.S. Geological Survey data release, https://doi.org/10.5066/P9KZCM54.

Ebrahimian, A., Wilson, B. N., & Gulliver, J. S. (2016). Improved methods to estimate the effective impervious area in urban catchments using rainfall-runoff data. Journal of Hydrology, 536, 10 https://doi.org/10.1016/j.jhydrol.2016.02.023

Gannon, J. P., Kelleher, C., & Zimmer, M. (2022). Controls on watershed flashiness across the continental US. *Journal of Hydrology*, *609*, 127713.

Groffman, P. M., Rosi, E., & Martel, L.D. (2023). Baltimore Ecosystem Study: Stream chemistry for core sites in Gwynns Falls version 602. Environmental Data Initiative. https://doi.org/10.6073/pasta/34959288c24b476548115b4c97a537e9

Guzman, C. B., Wang, R., Muellerklein, O., Smith, M., & Eger, C. G. (2022). Comparing stormwater quality and watershed typologies across the United States: A machine learning approach. *Water Research*, *216*, 118283.

Hernandez, L., Levin, M., Calus, J., Galbraith, J., Muñiz, E., Ryan, K., Riddle, R., Shaw, R.K., Dobos, R., Peaslee, S. and Southard, S., 2017. Urban soil mapping through the United States national cooperative soil survey. In *Urban soils* (pp. 15-60). CRC Press.

Hopkins, K. G., Morse, N. B., Bain, D. J., Bettez, N. D., Grimm, N. B., Morse, J. L., ... & Suchy, A. K. (2015). Assessment of regional variation in streamflow responses to urbanization and the persistence of physiography. *Environmental science & technology*, *49*(5), 2724-2732.

Hurley, R., Brandes, D., & Kelleher, C. (2024). Drivers and Buffers of Stream Flashiness in the Mid-Atlantic United States. *Hydrological Processes*, *38*(10), e15302.

Jacobson, C. R. (2011). Identification and quantification of the hydrological impacts of imperviousness in urban catchments: A review. Journal of environmental management, 92(6), 1438-1448. https://doi.org/10.1016/j.jenvman.2011.01.018

Kirker, A. N., & Toran, L. (2023a). Dual isotopes of nitrate reveal varying flow paths to stormwater retention basins. *Catena*, *220*, 106681.

Kirker, A. N., & Toran, L. (2023b). When impervious cover doesn't predict urban runoff: Lessons from distributed overland flow modeling. *Journal of Hydrology*, *621*, 129539.

Ledford, S. H., Zimmer, M., & Payan, D. (2020). Anthropogenic and biophysical controls on low flow hydrology in the Southeastern United States. *Water Resources Research*, *56*(9), e2020WR027098.

Li, C., Sun, G., Caldwell, P. V., Cohen, E., Fang, Y., Zhang, Y., Oudin, L., Sanchez, G.M. & Meentemeyer, R. K. (2020). Impacts of urbanization on watershed water balances across the conterminous United States. *Water Resources Research*, *56*(7), e2019WR026574.

Mayou, L. A., Alamdari, N., Ahmadisharaf, E., & Kamali, M. (2024). Impacts of future climate and land use/land cover change on urban runoff using fine-scale hydrologic modeling. *Journal of Environmental Management*, *362*, 121284.

McGrane, S. J. (2016). Impacts of urbanisation on hydrological and water quality dynamics, and urban water management: a review. *Hydrological Sciences Journal*, *61*(13), 2295-2311.

McPhillips, L. E., Earl, S. R., Hale, R. L., & Grimm, N. B. (2019). Urbanization in arid central Arizona watersheds results in decreased stream flashiness. *Water Resources Research*, *55*(11), 9436-9453.

Moore, J., Fanelli, R. M., & Sekellick, A. J. (2020). High-frequency data reveal deicing salts drive elevated specific conductance and chloride along with pervasive and frequent exceedances of the US Environmental Protection Agency aquatic life criteria for chloride in urban streams. *Environmental science & technology*, *54*(2), 778-789. https://doi.org/10.1021/acs.est.9b04316

O'Driscoll, M., Clinton, S., Jefferson, A., Manda, A., & McMillan, S. (2010). Urbanization effects on watershed hydrology and in-stream processes in the southern United States. *Water*, *2*(3), 605-648.

O'Neil-Dunne, J., MacFaden, S., Royar, A., Reis, M., Dubayah, R., and Swatantran, A. (2014a). An object-based approach to statewide land cover mapping. ASPRS Annual Conference, Louisville, KY, Mar 23-28.

O'Neil-Dunne, J., MacFaden, S., & Royar, A. (2014b). A versatile, production-oriented approach to high-resolution tree-canopy mapping in urban and suburban landscapes using GEOBIA and data fusion. *Remote sensing*, *6*(12), 12837-12865.

Office for Coastal Management. (2024). Coastal Change Analysis Program (C-CAP) High Resolution Land Cover and Change Data. NOAA National Centers for Environmental Information, https://www.fisheries.noaa.gov/inport/item/48232.

Oswald, C.J., Kelleher, C., Ledford, S.H., Hopkins, K.G., Sytsma, A., Tetzlaff, D., Toran, L. and Voter, C. (2023). Integrating urban water fluxes and moving beyond impervious surface cover: A review. *Journal of Hydrology*, *618*, 129188.

Pitt, R., Chen, S. E., Clark, S. E., Swenson, J., & Ong, C. K. (2008). Compaction's impacts on urban storm-water infiltration. *Journal of Irrigation and Drainage Engineering*, *134*(5), 652-658.

Rahimi, A. Y., & Ebrahimian, A. (2024). Urban impervious cover characterization for rainfall-runoff analysis: Impacts of data availability and resolution. *Journal of Hydrology*, *641*, 131807.

Roy, A. H., & Shuster, W. D. (2009). Assessing impervious surface connectivity and applications for watershed management 1. *JAWRA Journal of the American Water Resources Association*, *45*(1), 198-209.

Schueler, T. R., Fraley-McNeal, L., & Cappiella, K. (2009). Is impervious cover still important? Review of recent research. *Journal of Hydrologic Engineering*, *14*(4), 309-315.

Shuster, W. D., Schifman, L., Kelleher, C., Golden, H. E., Bhaskar, A. S., Parolari, A. J., Stewart, R.R., & Herrmann, D. L. (2021). K in an urban world: New contexts for hydraulic conductivity. *JAWRA Journal of the American Water Resources Association*, *57*(3), 493-504.

Smith, M. L., Zhou, W., Cadenasso, M., Grove, M., & Band, L. E. (2010). Evaluation of the national land cover database for hydrologic applications in urban and suburban Baltimore, Maryland 1. *JAWRA Journal of the American Water Resources Association*, *46*(2), 429-442.

Somers, K. A., Bernhardt, E. S., Grace, J. B., Hassett, B. A., Sudduth, E. B., Wang, S., & Urban, D. L. (2013). Streams in the urban heat island: spatial and temporal variability in temperature. *Freshwater Science*, *32*(1), 309-326.

Sutherland, R. C. (2000). Methods for Estimating the Effective Impervious Area of Urban Watersheds, The Practice of Watershed Protection Article 32. From Technical Note #58 from Watershed Protection Techniques 2(1):282-284. Ellicott City, MD, Center for Watershed Protection. 2: 193-195. https://yourcleanwater.org/wp-content/uploads/2021/10/CWP-Sutherland-DCIA-Paper.pdf. Accessed Mar 19, 2025.

Sytsma, A., Bell, C., Eisenstein, W., Hogue, T., & Kondolf, G. M. (2020). A geospatial approach for estimating hydrological connectivity of impervious surfaces. *Journal of Hydrology*, *591*, 125545.

Sytsma, A., Crompton, O., Panos, C., Thompson, S., & Mathias Kondolf, G. (2022). Quantifying the uncertainty created by non-transferable model calibrations across climate and land cover scenarios: A case study with SWMM. *Water Resources Research*, *58*(2), e2021WR031603.

USGS (2014). U.S. Geological Survey, 2014, National Land Cover Database (NLCD) 2011 Land Cover Conterminous United States: U.S. Geological Survey data release, https://doi.org/10.5066/P97S2IID.

USDA (2024) U.S. Department of Agriculture NAIP GeoHUB. https://naip-usdaonline.hub.arcgis.com

USGS (2024a). Annual NLCD Collection 1 Science Products: U.S. Geological Survey data release, https://doi.org/10.5066/P94UXNTS.

USGS (2024b). USGS Water Data for the Nation: National Water Information System Database. U.S. Geological Survey. https://doi.org/10.5066/F7P55KJN (accessed November 2023-January 2024).

Voter, C. B., & Loheide, S. P. (2018). Urban residential surface and subsurface hydrology: Synergistic effects of low-impact features at the parcel scale. *Water Resources Research*, *54*(10), 8216-8233.

Walsh, C. J., Roy, A. H., Feminella, J. W., Cottingham, P. D., Groffman, P. M., & Morgan, R. P. (2005). The urban stream syndrome: current knowledge and the search for a cure. *Journal of the North American Benthological Society*, *24*(3), 706-723.

Wenger, S. et al., 2008. Stream fish occurrence in response to impervious cover, historic land use, and hydrogeomorphic factors. Can. J. Fish Aquatic Sci. 65 1250-1264

Wickham, J., Herold, N., Stehman, S. V., Homer, C. G., Xian, G., & Claggett, P. (2018). Accuracy assessment of NLCD 2011 impervious cover data for the Chesapeake Bay region, USA. *ISPRS journal of photogrammetry and remote sensing*, *146*, 151-160.

Wickham, J. D., Stehman, S. V., Gass, L., Dewitz, J., Fry, J. A., & Wade, T. G. (2013). Accuracy assessment of NLCD 2006 land cover and impervious surface. *Remote Sensing of Environment*, *130*, 294-304.

Yang, L., Jin, S., Danielson, P., Homer, C., Gass, L., Bender, S. M., Case, A., Costello, C., Dewitz, J., Fry, J., Funk, M., Granneman, B., Liknes, G.C., Rigge, M., & Xian, G. (2018). A new generation of the United States National Land Cover Database: Requirements, research priorities, design, and implementation strategies. *ISPRS journal of photogrammetry and remote sensing*, *146*, 108-123.

Yang, J. L., & Zhang, G. L. (2015). Formation, characteristics and eco-environmental implications of urban soils–A review. *Soil science and plant nutrition*, *61*(sup1), 30-46.

Yang, J. L., & Zhang, G. L. (2011). Water infiltration in urban soils and its effects on the quantity and quality of runoff. *Journal of soils and sediments*, *11*, 751-761.

Zhang, K., & Parolari, A. J. (2022). Impact of stormwater infiltration on rainfall-derived inflow and infiltration: A physically based surface–subsurface urban hydrologic model. *Journal of Hydrology*, *610*, 127938.

SUPPORTING INFORMATION

Additional figure showing regression between % difference (fine minus coarse resolution IC) and watershed area and two data tables. Tables show watershed characteristics and regression statistics.