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Research Paper

Watershed features and stream water quality: Gaining insight through path analysis in a Midwest urban landscape, U.S.A.

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HIGHLIGHTS

- Stream water conductivity, total nitrogen and phosphorus concentration were studied.
- Path analyses integrated social and biophysical variables' effect on water quality.
- Road density, percent crop land, and education level had greatest total effects.
- Quantifying relationships among variables can inform actions to protect urban streams.

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ABSTRACT

Urban stream condition is often degraded by human activities in the surrounding watershed. Given the complexity of urban areas, relationships among variables that cause stream degradation can be difficult to isolate. We examined factors affecting stream condition by evaluating social, terrestrial, stream hydrology and water quality variables from 20 urban stream watersheds in central Iowa, U.S.A. We used path analysis to examine and quantify social and ecological factors related to variation in stream conditions. Path models supported hypotheses that stream water quality was influenced by variables in each category. Specifically, one path model indicated that increased stream water conductivity was linked to high road density, which itself was associated with high human population density. A second path model revealed nitrogen concentration in stream water was positively related to watershed area covered by cropland, and that cropland increased as human population density declined. A third path model indicated phosphorus concentration in stream water declined as percent of watershed residents with college education increased, although the mechanism underlying this relationship was unclear and could have been an artifact of lower soil-derived nutrient input from watersheds dominated by paved surfaces. To improve environmental conditions in urban streams, land use planning strategies should include limiting or reducing road density near streams, installing treatment trains for surface water runoff associated with roads, and establishing vegetated buffer zones to reduce inputs of road salt and other pollutants. Additionally, education/outreach should be conducted with residents to increase understanding of how their own behaviors influence stream water quality.

1. Introduction

In 2011, more than half of the world's population (52.1%) resided in urban areas. In the United States (U.S.A.), the proportion of urban dwellers was much greater at 82.4% (United Nations, 2011). The growth of the urban population in the U.S.A. is increasing at a faster rate (12.1% between 2000 and 2010) than the global population growth rate (9.7% during the same period; U.S. Census Bureau, 2012). Further, the rate of expansion of urban land cover is disproportionately greater than human population growth alone. For

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example, in four Iowa (U.S.A.) cities, population growth rates from 3% to 11% between 1990 and 2000 drove urban land cover expansions of 26% to 80% (Bowman, Thompson, Tyndall, & Anderson, 2012; see also Liu, 2005; Seto, Guneralp, & Hutyra, 2012). Changes associated with expansion of urban land cover types (e.g., hard surfaces associated with roads and buildings) are profound, cumulative, and rarely, if ever, reversed (McGranahan & Satterwaite, 2003; Seto, Fragkias, Guneralp, & Reilly, 2011; Wu & Thompson, 2013). Thus, understanding the relationships among humans, their activities, and natural systems in urban landscapes is increasingly important.

1.1. Urban landscapes and watersheds

Urban landscapes are complex systems with many potential linkages between human and natural elements (Grimm et al., 2008; Liu et al., 2007). Addition of infrastructure, such as roads, buildings, and storm sewers often causes damage to natural landscapes that is difficult to repair or mitigate. For example, declines in the size and quality of natural areas embedded in urban and peri-urban landscapes have strong negative effects on biodiversity (e.g., McKinney, 2002, 2008). Human activities within urban systems, such as pet ownership (and pet waste management), motor vehicle use, and application of lawn fertilizer, also can lead to high concentrations of pollutants (Fissore et al., 2011).

Conditions in urban streams reflect changes in the upland landscape, including changes in hydrology and water quality (Arnold & Gibbons, 1996; Carvalho et al., 2010; DiDonato et al., 2009; Hatt, Fletcher, Walsh, & Taylor, 2004; Nagy, Lockaby, Kalin, & Anderson, 2012; Olivera & DeFee, 2007; Sun, Chen, Chen, & Ji, 2013; Walsh et al., 2005; Wu, Thompson, Kolka, Franz, & Stewart, 2013). For example, increases in total discharge, peak discharge, and flashiness have been reported in urban streams as impervious land cover increases within a watershed (Nelson et al., 2009; Schoonover, Lockaby, & Helms, 2006; Wu et al., 2013). Elevated concentrations of nutrients, metals and sediments have also been reported in urban streams (Deemer et al., 2012; Grayson, Finlayson, Gippel, & Hart, 1996; Hatt et al., 2004). Phosphorus and nitrogen from fertilizer applied to lawns, sediment and salts from roads, and increased runoff from roofs delivered to streams rapidly via storm sewers have been identified as potential contributors to stream degradation in urban areas (Adachi & Tainosho, 2005; Fissore et al., 2011; Negishi, Negochi, Sidle, Ziegler, & Nik, 2007; Ragab, Bromley, Rosier, Cooper, & Gash, 2003). Given changes in urban stream hydrology and habitat and water quality, biological communities are also likely to be affected in urban streams (Walsh et al., 2005).

1.2. Use of path analysis to integrate social and environmental variables affecting urban streams

Complex social and ecological interactions in urban systems make it difficult to identify mechanisms that drive variation in urban stream characteristics (Cadenasso, Pickett, & Schwartz, 2007). Path analysis, an extension of multiple linear regression, is a helpful tool for gaining insight into strengths and mechanisms of cause–effect relationships within interaction webs (Bollen, 1989; Cohen, Cohen, West, & Aiken, 2003; Grace, 2006). Path analysis operates by simultaneously evaluating multiple hypotheses of causal relationships, and generating quantitative estimates of direct, indirect, and total effects of independent variables on dependent variables. This technique has been applied, for example, to examine relationships among land cover, storm characteristics, stream hydrology, and water quality variables in Phoenix, Arizona, U.S.A. (Lewis & Grimm, 2007). In that study, path models indicated that abundance of impervious surface was an especially important contributor to nitrogen export from streams located within the watershed. Thus, this approach has promise for furthering our understanding of complex relationships in urban systems, and we propose that it could be especially useful for more strongly integrated assessments of social and environmental system variables as factors that directly and indirectly influence urban stream water quality.

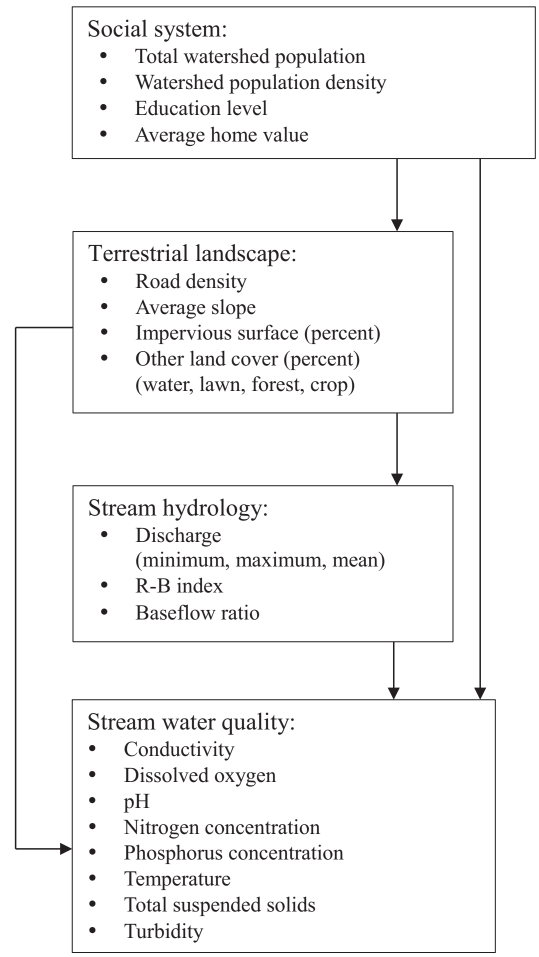

Fig. 1. Hypotheses of direct and indirect relationships among four categories of variables: social system, terrestrial landscape, stream hydrology, and stream water quality. Arrows represent hypothesized relationships among variables measured in this study.

1.3. Research objective and hypotheses

Our research objective was to gain insight into relationships among social system, terrestrial landscape, stream hydrology, and stream water quality attributes within urban headwater basins. We measured multiple variables within each of these four attribute categories for 20 urban watersheds in five central Iowa (U.S.A.) cities. We used path analysis to explore hypotheses of relationships within each watershed (Wright, 1934). Path analysis was conducted based on an overall conceptual model of mechanisms by which humans were predicted to directly and indirectly influence the terrestrial landscape, instream hydrology, and water quality (Fig. 1). The structure of our overall conceptual model was based on results from previous investigations of relationships among social systems, terrestrial landscape characteristics, and stream characteristics (e.g., Arnold & Gibbons, 1996; Quinn, 2013; Rose & Peters, 2001; Walsh et al., 2005; Wenger et al., 2009).

Specifically, we expected to find evidence from our investigation that humans (social system) both directly and indirectly influence stream water quality. For example, humans may directly and negatively affect water quality by additions of fertilizer and pesticides used for yard maintenance, or by leakage of oil and other pollutants from motor vehicles (e.g., Akhtar, Oki, Adachi, Murata, & Khan, 2007; Roberts, Prince, Jantz, & Goetz, 2009; Sun et al., 2013). Additionally, humans can indirectly affect stream water quality through their impacts on the terrestrial landscape and stream hydrology. For example, as watershed population density increases, road density and the percent of watershed area covered by impervious surface would be expected to increase (Quinn, 2013; Wu & Thompson, 2013). This, in turn, could lead to changes in stream hydrology such as increased variation in discharge (Nagy et al., 2012; Wu et al., 2013). Such effects on hydrology would be indicated by elevated stream values for R-B index (flashiness), increased variation in minimum and maximum water flow, and change in baseflow ratio (Nagy et al., 2012; Wu et al., 2013). Further, these hydrological changes in discharge can influence stream water quality because stream flashiness contributes to instream erosion, greater total suspended solids, and higher turbidity in stream water (Booth, Hartley, & Jackson, 2002).

Changes in the terrestrial landscape can also affect stream water quality through other mechanisms. For example, streamwater conductivity, an indicator of inputs of road salt and other contaminants, is likely to increase as a function of increasing road density and percent impervious surface (Perera, Gharabaghi, & Howard, 2013). Streamwater temperature also would likely be relatively high in watersheds with high impervious surface cover due to elevated temperature of contributed runoff (e.g., Frazer, 2005). In both urban and cropland-dominated agricultural landscapes, nutrients (nitrogen, phosphorus), total suspended solids, and turbidity may increase in stream water, whereas dissolved oxygen would likely decline (Herringshaw, Stewart, Thompson, & Anderson, 2011). Based on similar putative relationships reported in earlier research, we were interested in assessing the effects of additional variables (such as influence of education level of residents on stream water quality) as well as the relative strength of direct and indirect effects of other system variables on stream water quality parameters.

2. Methods

2.1. Study area

The study area consisted of four headwater stream watersheds in each of five cities located in Polk County, Iowa, U.S.A., including Altoona, Ankeny, Des Moines, Johnston, and Pleasant Hill ($n = 20$ study watersheds; Fig. 2). The watersheds were located within the Upper Midwest climatic region, with average annual precipitation of 838 mm (NCDC, 2012), of which 75% occurred between April and September. The mean elevation of these watersheds was 284 m above sea level. Four of these cities (Altoona, Ankeny, Johnston, and Pleasant Hill) experienced rapid population increases (between 40.6% and 99.8%) from 2000 to 2010 (SDCI, 2010). The City of Des Moines grew at a rate of 2.4% during the same time period (SDCI, 2010).

2.1.1. Watershed delineation

To delineate watershed boundaries, we generated digital elevation models (DEMs) at one-meter resolution from Light Detection and Ranging data (Iowa LiDAR Mapping Project, GeoTREE, 2011) using ArcHydro Version 2.0 (Environmental Systems Research Institute, ESRI, Redlands, CA, U.S.A.) associated with ArcMap Version 10.0 (ESRI, Redlands, CA, U.S.A.). Watershed areas ranged from 0.5 km^2 to 20.5 km^2. The 20 watersheds were chosen to represent different degrees of urban development, with percent impervious surface area that ranged from 4% to 44% of total watershed area. Other major land cover types included open space (mostly lawns), crop land, and small areas of forest.

2.1.2. Attributes and variables

Multiple variables were measured for each of four attributes within each watershed: social system, terrestrial landscape, stream hydrology, and stream water quality (Fig. 1). Social system variables included total watershed population, watershed population density, education level, and average home value. Terrestrial landscape variables included road density, average slope, and percent of total watershed area covered by impervious surface and other land cover types (water, lawn, forest, cropland). Stream hydrology variables included discharge (minimum, maximum, and mean), stream flashiness (R-B index), and baseflow ratio. Water quality variables included conductivity, dissolved oxygen, pH, nutrient concentrations (total nitrogen and phosphorus), temperature, total suspended solids and turbidity.

2.2. Social system variables

We used census data and local records to characterize social system variables included in our overall conceptual model (Fig. 1). Census block-group population and education data were extracted from 2010 census data (U.S. Census Bureau, 2012). These data were matched to watershed boundaries in ArcMap (ESRI, Redlands, CA, U.S.A.) and used to calculate an area-weighted total population and number of residents with specific education levels (e.g., the assumption was made that the portion of the census block within watershed boundaries was representative of the whole census block). Population density was determined by dividing estimated watershed population by watershed area. Percent of watershed residents having a high school- or college degree was determined by dividing numbers from each group (categorized by the highest degree attained) by estimated watershed population. Average home value was obtained from Polk County Assessor records (Polk County Assessor, 2013).

2.3. Terrestrial landscape variables

Terrestrial landscape variables were used to quantify land cover characteristics. Road surface and slope data were downloaded from the Natural Resources Geographic Information Systems Library (NRGIS, 2013). Road density and average slope were determined for areas within watershed boundaries using ArcMap. Impervious surface data were obtained from the City of Des Moines GIS department (A. Whipple, personal communication, June 17, 2010). Additional land cover data (percent of watershed covered by water, lawn, forest, and crop land) were extracted from the 2006 National Land Cover Dataset (NLCD; Fry et al., 2011).

2.4. Stream hydrology variables

For each of the 20 streams, flow rate was measured twice monthly using a FLO-MATE 2000 Water Current and Flowmeter™ (Hach Company, Loveland, CO, U.S.A.) at permanently marked channel cross-sections between April and October 2011 (resulting in 9–15 measurements per stream depending on amount of flow). Stream channel area was determined by measuring flow rate and stream depth in evenly distributed cells (varying from one to seven depending on stream width) and multiplying by cell width (Rantz, 1982). The maximum distance between adjacent measuring points was 0.5 m. Stream discharge was then determined using the cross-section method of Rantz (1982).

One HOBO U20 water level data logger (Onset Computer Corporation Inc., Pocasset, MA, U.S.A.) was installed in each of the 20 streams at the sampling location to record stream stage at 5-min

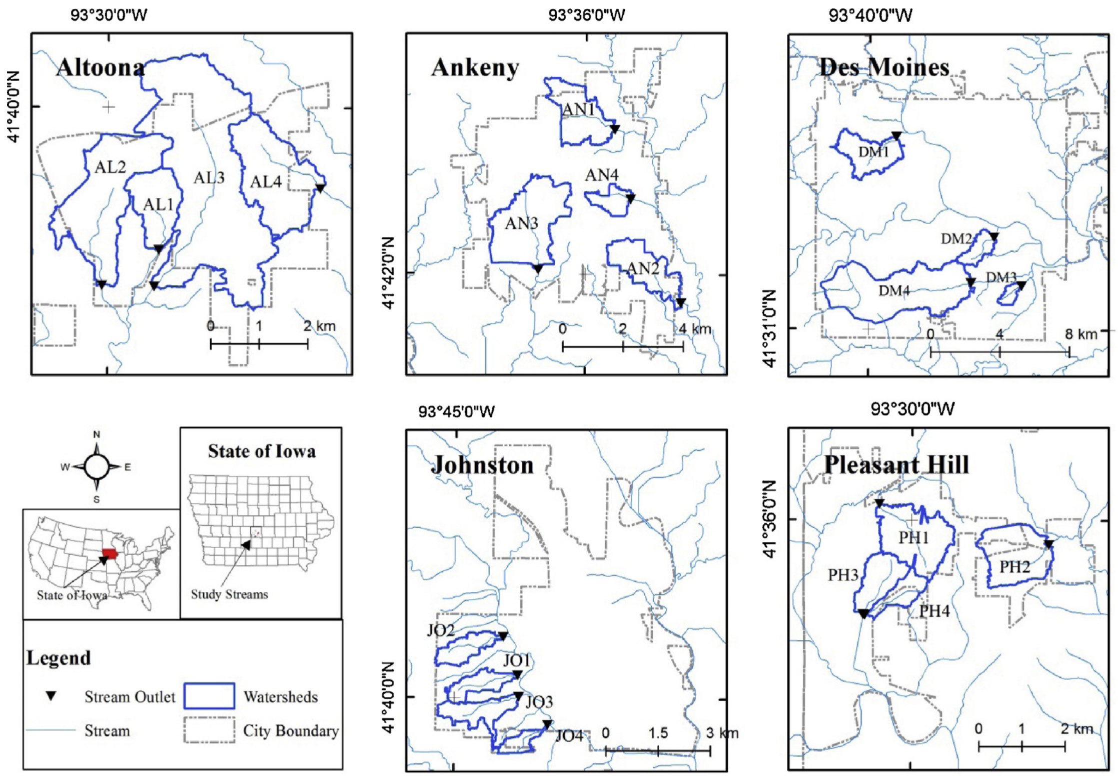

Fig. 2. Location of Iowa in the United States, and Polk County within Iowa (inset). The 20 headwater stream watersheds included in this study were distributed across five cities in Polk County.

intervals. These measurements were used in conjunction with flow rate data to create a stage-discharge rating curve, which was then used to transform stream stage data to discharge. Richards-Baker Flashiness Index (R-B index; Baker, Richards, Loftus, & Kramer, 2004) and baseflow ratio (Dingman, 2008) were calculated based on estimated discharge. The R-B Index measures oscillations in discharge relative to total discharge, also referred to as "flashiness"; a greater value of the R-B index indicates more pronounced differences between high and low flows. Baseflow ratio measures the relationship of baseflow quantity to precipitation quantity, which we calculated over the study period. A digital filter (Eckhardt, 2005) was applied using the Web-based Hydrograph Analysis Tool (WHAT; Lim et al., 2005) to separate baseflow from total flow. To allow for incorporation in path analysis, mean values of each hydrologic variable for each stream were used in subsequent analyses because they were most representative of all values for each variable.

2.5. Stream water quality variables

Water quality variables were measured each time flow rate measurements were made (9–15 sample events per stream, April to October 2011). Conductivity, dissolved oxygen, pH, and temperature were determined on-site using a portable Hach HQ40d^{TM} meter (Hach Company, Loveland, CO, U.S.A.) and turbidity was measured on-site using an Oakton Model T-100^{TM} turbidimeter (Oakton Instruments, Vernon Hills, IL, U.S.A.). Water samples for determination of total phosphorus, and total suspended solids were collected in 1000-ml acid-prewashed bottles. Samples for determination of total nitrogen were collected in acidified 50-ml bottles. All samples were transported in a cooler and analyzed in the Riparian Management Systems Laboratory in the Department of Natural Resource Ecology and Management, Iowa State University, Ames, Iowa. Unfiltered water samples were analyzed to determine concentrations of total nitrogen and total phosphorus using the total Kjeldahl nitrogen technique and colorimetric ascorbic acid technique, respectively (U.S. EPA methods 351.2 and 365.3; U.S. EPA, 1978, 1993). Total suspended solids were determined using filtration (Eaton, Clesceri, Rice, Greenberg, & Franson, 2005). Again, to facilitate incorporation in path models the mean of each variable for each stream was calculated for use in subsequent analyses.

2.6. Data analysis

Descriptive statistics (mean, minimum, maximum, and standard deviation, Table 1) were calculated for each variable included in the conceptual path model (Fig. 1). Prior to statistical analysis, data were transformed using $\ln(x+1)$ or arcsine-square root to obtain greater linearity and normality, and reduced heteroscedasticity (Cohen et al., 2003).

We used path analysis to test hypotheses that were illustrated in the previously-described overall conceptual path model of relationships between the social system, terrestrial landscape, and stream hydrology and water quality (Fig. 1). Stream water quality variables were outcome (dependent) variables in this model. The theoretical basis for the conceptual model were the results from previous analyses of urban stream systems as previously described (e.g., Arnold & Gibbons, 1996; Quinn, 2013; Rose & Peters, 2001; Walsh et al., 2005; Wenger et al., 2009).

Prior to path analysis, correlation analyses were conducted within each attribute category and results were used to reduce the number of variables selected for path analyses. Variables used in path analysis were then selected using two criteria: (1) within each of the four attribute categories, only one variable was selected from among groups of highly correlated variables; and (2) among each of the four categories, variables with greater likelihood of strong relationships with other variables (based on earlier studies) were given selection priority (please see Section 3 for a description of

Table 1
Descriptive statistics (mean, minimum, maximum, and standard deviation) for measured variables in 20 urban headwater stream watersheds in central Iowa.

	Mean	Minimum	Maximum	Standard deviation
Social system variables				
Population (number of persons)	3082	47	17,136	4718
Population density (persons km^{-2})	890	41	2318	653
High school education (%)	26.2	12.8	42.5	9.9
College education (%)	25.8	8.8	39.2	9.2
Average home value (US Dollars)	138,870	83,011	234,230	36,533
Terrestrial landscape system variables				
Road density (km km^{-2})	7.0	1.7	12.9	2.8
Average slope (%)	6.7	4.4	10.9	2.0
Impervious surface (%)	25.4	4.2	44.3	10.0
Water (%)	0.1	0	1.5	0.3
Lawn (%)	20.7	8.2	37.1	8.3
Forest (%)	5.6	0	25.7	8.7
Crop land (%)	13.5	0	70.4	18.1
Stream hydrology variables				
Minimum discharge ($m^3 s^{-1} km^{-2}$)	0	0	0.005	0.001
Maximum discharge ($m^3 s^{-1} km^{-2}$)	2.587	0.339	9.167	2.726
Mean discharge ($m^3 s^{-1} km^{-2}$)	0.023	0.002	0.072	0.018
R-B index	0.057	0.017	0.118	0.031
Baseflow ratio	0.87	0.77	0.96	0.06
Stream water quality variables				
Conductivity ($\mu S\ cm^{-1}$)	764.8	615.9	1128.5	119.6
Dissolved Oxygen ($mg\ L^{-1}$)	8.9	7.8	10.7	0.7
pH	8.2	7.9	8.5	0.1
Temperature (°C)	18.8	16.1	22.1	1.5
Total nitrogen ($mg\ L^{-1}$)	2.5	0.9	6.7	1.6
Total phosphorus ($\mu g\ L^{-1}$)	150.1	88.6	275.1	44.0
Total suspended solids ($mg\ L^{-1}$)	33.5	17.5	105.2	19.5
Turbidity (NTU)	13.9	3.6	51.2	11.2

selected variables). We used SPSS Version 19.0 (IBM Corp., Armonk, NY, U.S.A.) to conduct all calculations and analyses.

Exploratory path analysis was conducted on a number of path models ($n = 23$) to evaluate relationships between different combinations of attribute variables, and to select a small set of models that collectively described likely relationships between the social system, terrestrial landscape, and stream features. In path analysis, standardized regression coefficients (i.e., path coefficients) were obtained by simultaneously regressing a dependent variable on each independent variable directly linked to it by an arrow in the path model. The resulting path coefficients were then used to estimate direct, indirect, and total effects of an independent variable on a dependent variable (Bollen, 1989; Cohen et al., 2003). The estimated direct effect of an independent variable on a dependent variable was equivalent to the associated path coefficient. An indirect effect of an independent variable was estimated by multiplying coefficients in each path from the independent variable through all intervening variables to the dependent variable, then summing values for all indirect paths (Garson, 2008). The estimated total effect of an independent variable on a dependent variable was equal to the sum of direct and indirect effects. We tested for spurious relationships by monitoring changes in path coefficients when another variable was added to a model. We selected only those models in which coefficients remained stable during this process. The path analyses were conducted using AMOS Version 17.0 (AMOS Development Corp., Crawfordville, FL, U.S.A.), a software package designed for structural equation modeling (SEM) and path analysis (Byrne, 2010). We report statistical significance at $p \le 0.05$.

Multiple statistics were used to evaluate the performance of different path models, including the Chi-square (χ^2) test, with associated degree of freedom and probability values, the comparative fit index (CFI), and root mean square error approximation (RMSEA). We used this approach because no single goodness-of-fit statistic is universally accepted (Byrne, 2010). The χ^2 test measures the discrepancy between the observed covariance matrix and the implied covariance matrix. A greater *p*-value associated with the χ^2 test indicates a better fit of the hypothetical model to the data (Bollen, 1989). The CFI is a goodness-of-fit statistic for studies with a small sample size (Bentler, 1990). The model is considered a good fit when the CFI value (ranging from 0 to 1) is greater than 0.9 (Bentler, 1992). The RMSEA also measures how well the hypothetical model fits the observed data; an RMSEA value less than 0.05 indicates a good fit (Browne & Cudeck, 1992).

3. Results

3.1. Variable description

There was a strong gradient in social system, terrestrial landscape, stream hydrology, and water quality variables across the 20 sites (Table 1). For example, human population density ranged from 41 to 2318 persons km^{-2}, and 8.8% to 39.2% of the population had attained at least a college degree. For terrestrial landscape variables, road density ranged from 1.7 to 12.9 km km^{-2} and impervious surface area ranged from 4.2% to 44.3% of total watershed area. In addition to impervious surface, lawn (from 8.2% to 37.1%) and crop land (from 0% to 70.4%) were also important land cover types. For stream hydrology variables, mean discharge ranged from 0.002 to 0.072 $m^3 s^{-1} km^{-2}$, and R-B index ranged from 0.017 to 0.118. Baseflow ratio was more consistent among watersheds, with a mean of 0.87 and a range of 0.77–0.96. For water quality variables, conductivity ranged from 615.9 to 1128.5 $\mu S\ cm^{-1}$, dissolved oxygen from 7.8 to 10.7 $mg\ L^{-1}$, pH from 7.9 to 8.5, and temperature from 16.1 °C to 22.1 °C. Total nitrogen concentrations ranged from 0.9 to 6.7 $mg\ L^{-1}$, total phosphorus from 88.6 to 275.1 $\mu g\ L^{-1}$, total suspended solids from 17.5 to 105.2 $\mu g\ L^{-1}$, and turbidity ranged from 3.6 to 51.2 NTU.

Table 2
Pearson correlation coefficients (r) among variables within the social system category.

	Average home value	Population	Population density	High school education (%)	College education (%)
Average home value	–				
Population	−0.39	–			
Population density	−0.05	0.78*	–		
High school education (%)	−0.55*	0.22	0.02	–	
College education (%)	0.64*	−0.28	−0.02	−0.94*	–

* Indicates statistical significance at 0.05 level.

3.2. Correlation analyses for variable selection

Among social system variables, four significant correlations were found: average home value was positively related to percent of watershed residents with a college education ($p = 0.003$) and negatively related to percent of residents with a high school education but without a college degree ($p = 0.012$; Table 2). Total population was positively related to population density ($p < 0.001$), and the two education attainment variables were negatively related to each other ($p < 0.001$). To avoid choosing variables that were closely related to each other, only population density and college education were selected for inclusion and were used in separate path models.

For terrestrial landscape variables, eight significant correlations were detected: road density was positively related to percent impervious surface ($p = 0.017$) and negatively related to crop land cover ($p = 0.008$); average slope was positively related to percent forest ($p < 0.001$) and negatively associated with percent crop land ($p = 0.044$); percent impervious surface was positively related to percent lawn ($p = 0.041$) and negatively related to percent crop land ($p < 0.001$); and percent of lawn was positively related to percent of water surface ($p = 0.048$) and negatively related to percent crop land ($p = 0.032$; Table 3). Of these variables, road density, crop land, and impervious surface were selected for subsequent use in individual path models.

For stream hydrology variables, four significant correlations were found: maximum discharge was positively related to mean discharge ($p = 0.009$) and R-B index ($p = 0.012$), and negatively related to baseflow ratio ($p = 0.004$; Table 4). R-B index was negatively related to baseflow ratio ($p < 0.001$). Baseflow ratio, mean discharge, and R-B index were selected for subsequent use in separate path models.

Among water quality variables, 12 significant correlations were detected; those used for variable reduction included: negative relationships between dissolved oxygen with total phosphorus and with total suspended solids ($p < 0.038$); a negative relationship between temperature and total nitrogen ($p < 0.001$); positive relationships between total phosphorus with total suspended solids and turbidity ($p < 0.001$); and a positive relationship between total suspended solids and turbidity ($p < 0.001$; Table 5). Conductivity, total nitrogen, and total phosphorus concentrations were chosen as the outcome variables to investigate three independently generated path models.

3.3. Development of path analysis models

The path models generated collectively describe relationships among social system, terrestrial landscape, and stream variables based on the preliminary analyses indicating they were important determinants and indicators of stream condition. One path model is reported for each of the three selected water quality outcome variables, including stream water conductivity, and total nitrogen and total phosphorus concentrations. We developed the path models using single variables from within each previously described attribute category, and related to outcome variables to quantify direct and indirect effects on stream water quality.

For the first model we tested the hypotheses that population density would lead to increased stream water conductivity through a direct effect on road density, and that road density would have both direct and indirect (via baseflow ratio) effects on conductivity. In this model all direct, indirect and total effects were statistically significant (Table 6, Fig. 3). Our results support the prediction that increases in human population density would lead to increased road density, which itself negatively affected baseflow ratio. Conductivity increased with road density and declined with increasing baseflow ratio. Indirect effects of population density and road density on stream water conductivity were also significant (Table 6).

In the second model (Table 7, Fig. 4), we tested the hypotheses that increasing human population density would increase stream water nitrogen concentrations through a direct mechanism (e.g., addition of fertilizer N), and that increasing crop land cover and mean discharge would also lead to increased nitrogen levels. However, in this model only the direct positive effect from percent of crop land was statistically significant (Table 7, Fig. 4).

For the third model, we expected that greater proportions of residents with college education would lead to decreased levels of phosphorus in stream water, and that greater percent impervious surface and flashiness would lead to increased phosphorus concentrations. Direct, indirect and total effects of proportions of residents with college education on phosphorus concentrations were all negative and significant. Percent impervious surface area had a negative and significant total effect on total phosphorus. Flashiness (indicated by R-B index) had little effect on total phosphorus concentrations in stream water (Table 8, Fig. 5).

3.4. Statistical evaluation of path models

All three path models were characterized by acceptable values for goodness-of-fit statistics. The p-values for χ^2-tests ranged from 0.782 (model with conductivity as outcome variable) to 0.749 (model with total nitrogen as outcome variable) and 0.429 (model with total phosphorus as outcome variable). All three models had CFI = 0.999 and RMSEA = 0.001, indicating that they fit the observed data well (Bentler, 1990; Bollen, 1989; Browne & Cudeck, 1992).

4. Discussion

Path analysis allowed us to integrate effects of the social system, terrestrial landscape, and stream hydrology on water quality outcome variables, and generated insight into direct and indirect mechanisms of human impacts on streams, and the relative importance of factors affecting urban streams. Path analysis supported the hypotheses that for our study sites, social system variables (human population density, educational attainment) had direct effects on terrestrial landscape variables (road density, percent impervious surface) which in turn had direct and indirect effects on stream hydrology and water quality (conductivity, concentrations of total nitrogen and phosphorus). Although we present models that include a limited number of the variables we studied, our

Table 3
Pearson correlation coefficients (r) among variables within the terrestrial landscape category.

	Road density	Average slope	Impervious surface (%)	Water (%)	Lawn (%)	Forest (%)	Crop land (%)
Road density	–						
Average slope	0.22	–					
Impervious surface (%)	0.53*	−0.12	–				
Water (%)	0.00	−0.20	0.33	–			
Lawn (%)	0.31	0.02	0.46*	0.45*	–		
Forest (%)	−0.11	0.84*	−0.36	−0.26	−0.04	–	
Crop land (%)	−0.57*	−0.46*	−0.70*	−0.33	−0.48*	−0.25	–

* Indicates statistical significance at 0.05 level.

Table 4
Pearson correlation coefficients (r) among variables within the stream hydrology category.

	Minimum discharge	Maximum discharge	Mean discharge	R-B index	Baseflow ratio
Minimum discharge	–				
Maximum discharge	−0.17	–			
Mean discharge	0.01	0.57*	–		
R-B index	−0.23	0.55*	0.11	–	
Baseflow ratio	0.35	−0.62*	−0.05	−0.89*	–

* Indicates statistical significance at 0.05 level.

Table 5
Pearson correlation coefficients (r) among variables within the stream water quality category.

	Conduct-ivity	Dissolved Oxygen	pH	Temp.	Total nitrogen	Total phosphorus	Total susp. solids	Turbidity
Conductivity	–							
Dissolved oxygen	0.18	–						
pH	0.13	0.24	–					
Temperature	−0.29	−0.34	0.29	–				
Total nitrogen	0	0.07	−0.39	−0.70*	–			
Total phosphorus	0	−0.59*	−0.37	0.05	0.18	–		
Total susp. solids	−0.08	−0.47*	−0.38	−0.24	0.31	0.79*	–	
Turbidity	−0.34	−0.44	−0.43	−0.01	0.10	0.75*	0.89*	–

* Indicates statistical significance at 0.05 level.

Table 6
Direct (DE), indirect (IE), and total effects (TE) of population density, road density, and baseflow ratio on dependent variables in path analysis for stream water conductivity.

Dependent variable	Population density effect			Road density effect			Baseflow ratio effect		
	DE	IE	TE	DE	IE	TE	DE	IE	TE
Road density	0.81[a]		0.81[a]						
p-Value	0.041		0.041						
Baseflow ratio		−0.36[a]	−0.36[a]	−0.45[a]		−0.45[a]			
p-Value		0.019	0.019	0.017		0.017			
Conductivity		0.45[a]	0.45[a]	0.40[a]	0.16[a]	0.56[a]	−0.36[a]		−0.36[a]
p-Value		0.025	0.025	0.035	0.017	0.023	0.024		0.024

[a] Statistically significant effects ($p \leq 0.05$).

preliminary analyses indicated that those variables were often closely correlated with others from the same category, and that the effects of those variables on the outcomes were themselves stable when we tested alternative variables in other categories.

4.1. Path model: conductivity as outcome variable

Human population density, road density, and baseflow ratio were all important causes of variation in stream water conductivity. Specifically, human population density had a strong positive direct effect on road density, which corroborates other evidence for this linkage (e.g., Owens et al., 2010; Quinn, 2013). In turn, results support the hypothesis that road density had a strong positive direct effect on stream water conductivity. We suspect that road salt input is one of the more important contributors to elevated conductivity (Perera et al., 2013) in these streams. For example, approximately 181,440 metric tons of rock salt is used annually in Iowa for highway deicing operations (Iowa Department of Transportation, 2013). Other pollutants contributing to conductivity may include sediment and heavy metals that could be delivered to urban streams via pipes, surface runoff or groundwater discharge (Adachi & Tainosho, 2005; Earon, Olafsson, & Renman, 2012; Herngren, Goonetilleke, & Ayoko, 2006; Perera et al., 2013).

Because roads limit infiltration, producing more surface discharge and less groundwater recharge, greater road densities also usually lead to lower baseflow ratios (e.g., Arnold & Gibbons, 1996; Wu et al., 2013). Our results imply that baseflow ratio declined as road density within the watershed increased, which in turn led to increased conductivity. However, the total effect of road density on conductivity was stronger than the total effect of baseflow on conductivity. Thus, for this set of watersheds, roads were the most important contributor to high stream water conductivity. To mitigate conductivity levels in urban streams, civic officials should consider actions that minimize additional road surface area in proximity to streams, provide “treatment trains” to filter salts and other pollutants from road runoff, and consider alternatives to the application of road salt (Earon et al., 2012; Nixon, Kochumman, Qiu, Qui, & Xiong, 2007).

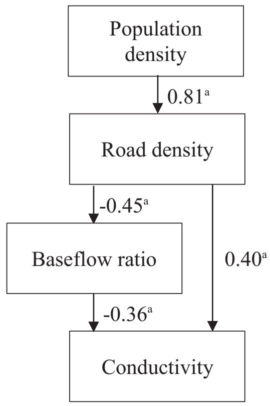

Fig. 3. Path model of direct and indirect effects of social (population density), landscape (road density), and stream hydrology (baseflow ratio) variables on stream water conductivity. Each value associated with an arrow is a path coefficient (standardized regression coefficient) and is equivalent to the direct effect of the independent variable on the dependent variable. The symbol “a” denotes a statistically significant effect at $p \le 0.05$.

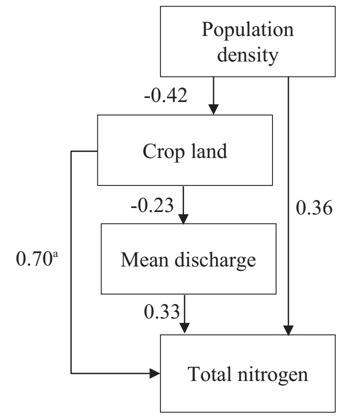

Fig. 4. Path model of direct and indirect effects of social (population density), landscape (percent of crop land), and hydrology (mean discharge) variables on total nitrogen concentration. Each value associated with an arrow is a path coefficient (standardized regression coefficient) and is equivalent to the direct effect of the independent variable on the dependent variable. The symbol “a” denotes a statistically significant effect at $p \le 0.05$.

4.2. Path model: total nitrogen as outcome variable

In the path model describing potential causes of variation in total nitrogen, human population density, percent of crop land, and mean stream discharge were included as causal variables. Among these variables, percent crop land had the strongest direct and total effect on stream total nitrogen concentration. The negative relationship between population density and percent crop land was expected since crop land is located in low population density areas (e.g., at the periphery of the city). The model identified crop land as a more important contributor to stream water nitrogen concentration even when compared to population density, which we had hypothesized might have a strong positive direct effect via application of lawn fertilizers. However, intermixing of urban land and crop land is typical for cities in the Midwest Cornbelt region, and this analysis provides evidence that streams in this landscape may receive greater amounts of pollutants from agricultural than from urban sources (Carpenter et al., 1998; Dinnes et al., 2002; Hatfield et al., 1999; Herringshaw et al., 2011). Attention to the potential negative effects of elevated nitrogen levels are important and several strategies, as among them vegetated buffer strips (e.g., Osborne & Kovacic, 1993; Schultz, Isenhart, Simpkins, & Colletti, 2004) or nitrogen bioreactors (e.g., Christianson et al., 2012; Shih, Robertson, Schiff, & Rudolph, 2011) could be adapted for these settings.

4.3. Path model: total phosphorus as outcome variable

Unlike the other two models, preliminary analysis suggested that percent of watershed residents with college education was more important than population density in determining stream water phosphorus concentration. Percent impervious surface also appeared to influence total phosphorus. In the path analysis, college education had a negative direct effect on total phosphorus, and a positive direct effect on percent impervious surface. Although the effect of socioeconomic factors such as education on stream water phosphorus levels is likely to be complex (Fissore et al., 2011), we

Table 7
Direct (DE), indirect (IE), and total effects (TE) of population density, percent of land cover in crop land, and mean discharge on dependent variables in path analysis for stream water nitrogen concentration.

Dependent variable	Population density effect			Crop land (%) effect			Mean discharge effect		
	DE	IE	TE	DE	IE	TE	DE	IE	TE
Crop land (%)	−0.42		−0.42						
p-Value	0.084		0.084						
Mean discharge		0.10	0.10	−0.23		−0.23			
p-Value		0.243	0.243	0.429		0.429			
Total nitrogen	0.36	−0.27	0.10	0.70[a]	−0.07	0.63	0.33		0.33
p-Value	0.056	0.065	0.809	0.051	0.238	0.072	0.161		0.161

[a] Statistically significant effect ($p \le 0.05$).

Table 8
Direct (DE), indirect (IE), and total effects (TE) of college education, percent of impervious surface, and R-B index (flashiness) on dependent variables in path analysis for stream water phosphorus concentration.

Dependent variable	College education effect			Impervious surface effect			R-B index effect		
	DE	IE	TE	DE	IE	TE	DE	IE	TE
Impervious surface (%)	0.33[a]		0.33[a]						
p-Value	0.028		0.028						
R-B index		0.08	0.08	0.24		0.24			
p-Value		0.185	0.185	0.305		0.305			
Total phosphorus	−0.44[a]	−0.10[a]	−0.54[a]	−0.26	−0.03	−0.29[a]	−0.11		−0.11
p-Value	0.026	0.026	0.053	0.069	0.463	0.025	0.700		0.700

[a] Statistically significant effects ($p \le 0.05$).

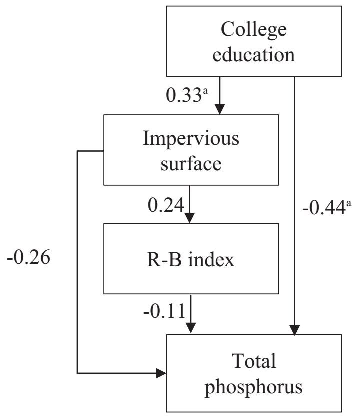

Fig. 5. Path model of direct and indirect effects of social (percent of college education), landscape (percent of impervious surface), and hydrology (R-B index) variables on total phosphorus concentration. Each value associated with an arrow is a path coefficient (standardized regression coefficient) and is equivalent to the direct effect of the independent variable on the dependent variable. The symbol "a" denotes a statistically significant effect at $p \leq 0.05$.

speculate that highly educated residents are more aware of the environmental problems associated with lawn fertilizers and pet waste containing phosphorus, and that they may be more likely to use phosphorus-free labeled products and to dispose of pet wastes properly (Fissore et al., 2011; Lehman, Bell, Doubek, & McDonald, 2011). This effect also suggests that community education delivered across a wider spectrum of socioeconomic status could be very important in future phosphorus mitigation programs. With respect to the positive relationship between education level and impervious surface, we hypothesize that more well-educated residents live in areas with wider roads and larger homes. This is contrary to results of at least one prior study, in which percent of college graduates was negatively related to percent impervious surface (Li & Weng, 2007, for Indianapolis, IN, U.S.A.), perhaps indicating that the relationship between these variables might vary by specific location.

Prior studies of the relationship between impervious surface abundance and total phosphorus in streams have not generated consistent results. For example, Nagy et al. (2012) reported increased levels of total phosphorus when percent impervious surface increased among study watersheds, but others (e.g., Roberts et al., 2009) have reported the opposite pattern. In our analysis, percent impervious surface had a direct negative effect on total phosphorus concentration. Because impervious surfaces act as a part of the stormwater conveyance system (via hard-surfaced road gutters and drains), runoff accumulates less sediment as it moves, possibly limiting one potential source of phosphorus contributions to these streams (Carvalho et al., 2010).

5. Conclusions

Urban landscapes are complex systems for which identification of linkages and mechanisms driving change in natural systems can prove difficult. We conducted this study examining urban headwater streams using path analysis to quantify direct, indirect and total effects among social system, terrestrial landscape, and stream hydrology variables on water quality outcomes including conductivity, total nitrogen, and total phosphorus concentrations. This approach allowed us to examine both social and biophysical factors in small, well-characterized landscape units in an effort to identify important factors and the relative magnitude of their effects.

Stream water conductivity increased across a gradient of increasing human population density and road density, and decreasing baseflow ratio. Stream water total nitrogen concentration was most strongly and positively affected by crop land cover in the watershed. Stream water total phosphorus concentration declined as percent of residents with college-level education and watershed percent impervious surface increased. In terms of total effects, road density, percent of crop land, and percent of residents with college education were the most important variables affecting stream water conductivity, total nitrogen and total phosphorus, respectively. Goodness-of-fit statistics indicated that models describing these relationships are relatively robust. However, because of our relatively small sample size ($n = 20$ streams), the total number of variables that could be included in each of the three path models was limited (Byrne, 2010). We carefully selected these variables based on preliminary analyses, previous studies, and our knowledge of the study area to quantify the major cause and effect relationships in these models. The models presented here reflect the strongest causal relationships we detected as determined by path coefficients.

Differences among the variables linked to specific water quality outcomes indicate that mitigation strategies should be focused on different actions for these response variables. For example, actions to limit road salt and other road-related pollutant delivery to streams will be important to decrease stream water conductivity. For total nitrogen concentration, crop land was a primary driver for the set of streams we studied. This phenomenon may be common in areas where municipalities are embedded in agricultural landscapes similar to those in the Midwest, particularly where considerable crop land exists within urban political boundaries. To address elevated nitrogen levels in stream water, strategies such as vegetated buffer strips or incorporation of nitrogen-reducing bioreactors may be applied. Total phosphorus levels in our study streams were negatively related to overall education level of watershed residents, and associated increases in impervious surface, suggesting that more broad-spectrum community education about causes and consequences of elevated stream phosphorus levels should be carried out. Overall, these findings indicate that selecting single mitigation strategies that address multiple stressors or adoption of approaches that include multiple mitigation strategies may be necessary for improvement of urban stream water quality.

Finally, we present here a small set of path analysis models and the results should be interpreted with some caution. For practical reasons, our overall study design consisted of a limited number of variables that were measured over a relatively short time-frame. Further, although path analysis allows exploration of linkages among variables, it does not establish causation nor does it allow complete falsification of hypotheses not supported by the results (Bollen, 1989; Grace, 2006). However, path analysis did enable us to identify likely pathways by which social system, terrestrial landscape and stream hydrology influence stream water quality in urban landscapes. These findings should provide insights for the design of future investigations aimed at advancing our understanding of urban streams.

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