Do Water Body Classifications Predict Water Quality?

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Abstract

Many states classify waterbodies according to groups of designated uses, which suggests that classifications may be correlated with water quality. The primary assessments of water quality in the United States (the Biennial Integrated Water Quality Report) do not consider classification, so the relationship between classification and water quality is untested. Additionally, water quality has been shown to be influenced by watershed land use; however, land use is not typically part of waterbody classification systems. To determine the relationships between water body classification, water quality, watershed land cover, and forest fragmentation, we analyzed existing water quality data for the State of Connecticut from the United States Geological Survey and the Connecticut Department of Energy and Environmental Protection and land cover data from the National Land Cover Dataset. Connecticut uses a unique classification system that includes separation of drinking water sources (Class AA) and waterbodies receiving waste water discharges (Class B). Using a comparison of multiple means, we found that Class B waters had higher levels of nitrogen, solids, chloride, sodium, dissolved copper, total iron, and dissolved manganese than Class AA waters. Watersheds upstream of Class B segments had less forest cover, more development and more impervious cover than watersheds upstream of Class AA segments. Class A sites had some similarities in water quality and land cover with Class AA sites and some with Class B sites. The subset of Class B waterbodies with “Class AA-like” water quality also had “Class AA-like” land cover. Based on this and a multiple linear regression analysis, we found that water quality is more closely related to watershed land cover and forest

fragmentation than to water body classification. We recommend that watershed land cover likely is a better proxy for water quality than waterbody classification.

Keywords:

Water Quality, Waterbody Classification, Land Cover, Forest Fragmentation, Water Policy, Designated Use

1. Introduction and Background

The United States (US) Federal Water Pollution Control Act of 1972 (Clean Water Act) (*Clean Water Act of 1972*, 2002, sec. 303) requires that states identify the designated use(s) for each water body and develop applicable water quality standards for each designated use. Common designated uses include drinking water supply, recreation, fishing, and navigation (e.g. CT Department of Energy and Environmental Protection, 2013; Revisor of Statutes, State of Minnesota, 2008; State of Maine, 2015; Texas Commission on Environmental Quality, 2014; Washington State Department of Ecology, 2012). This system serves as a relatively simple regulatory tool for assessing water quality in a binary fashion. Waterbodies are identified as “supporting” or “not supporting” each designated use and categorized by the number of supported uses and the need for management intervention (US EPA, 2005).

Some states group designated uses into classifications (sets of designated uses) (e.g. CT Department of Energy and Environmental Protection, 2014a; Department of Environmental Protection, State of Florida, 2016). In these systems, each distinct combination of designated uses is a different class and each water body is assigned to one class. Other states use class synonymously with designated use (Environmental Protection Division, State of Georgia, 2015; Revisor of Statutes, State of Minnesota, 2008); in this type of system a waterbody is assigned to one or more classes. For the purposes of this paper, we use classes to refer to sets of designated uses. Classification systems based on designated uses (with associated water quality standards) could lead one to conclude that water quality metrics are correlated with classification; however, this may not be the case as the classes are assigned based on desired use and not measured water quality (for a notable exception see State of Maine, 2015). Water quality standards establish the minimum quality necessary for a given use and as such do not reflect the range in quality that may exist above or below that standard among waterbodies designated for that use.

The primary means of evaluating the quality of water in the US is the Biennial Integrated Water Quality Report (IWQR), which is required by the US Environmental Protection Agency (EPA) of every state and includes an assessment of the waters of the state and an update on the condition of previously impaired waters (*Clean Water Act of 1972*, 2002, sec. 305(b)). The IWQR is an important management tool, but it does not directly address water quality differences across classes. For example, the 2014 Connecticut IWQR (CT Department of Energy and Environmental Protection, 2014b) indicates that 78% of assessed rivers meet the water quality standards for aquatic life (Stevens Jr and Olsen, 2004) but it does not address how chloride levels (part of the aquatic life standard) vary across waters of different classes (CT Department of Energy and Environmental Protection, 2014b).

All three freshwater classes of surface water in the Connecticut system (Class AA, Class A, and Class B) have aquatic life, fish consumption, and recreation as designated uses. The primary differences between classes are allowable discharges and use (or proposed use) as a drinking water source (Table 1). Approximately 24% of the stream kilometers are Class AA, 64% are Class A, and 12% are Class B (Figure 1a and Table S 1). Though a small percentage of stream kilometers, the Class B rivers include many major rivers in the state (State of Connecticut, Department of Environmental Protection, 2011).

Table 1 - Connecticut inland freshwater classifications (CT Department of Energy and Environmental Protection, 2014a)

Classification	Designated Uses	Discharges
AA	existing or proposed drinking water supply, fish and wildlife habitat, recreational use (may be restricted), agricultural and industrial supply	discharges from public or private drinking water treatment systems, dredging and dewatering, emergency and clean water discharges
A	potential drinking water supply; fish and wildlife habitat; recreational use; agricultural and industrial supply and other legitimate uses including navigation	same as allowed in AA
B	recreational use, fish and wildlife habitat; agricultural and industrial supply and other legitimate uses including navigation	same as allowed in A and cooling waters, discharges from industrial and municipal wastewater treatment facilities (providing Best Available Treatment and Best Management Practices are applied), and other discharges subject to the provisions of section 22a-430 CGS

The origins of Connecticut's classification system are in the topography and settlement patterns of the state, which led to the establishment of most cities in the coastal regions or along major rivers. This arrangement allowed Connecticut cities to discharge effluent downstream, towards coastal waters, and to use unpolluted, upland watersheds for water supply. The historic division between wastewater and drinking water supply and the goal of

high quality water was codified into the Connecticut classification system after the Connecticut Pollution Control Act of 1967 (Appendix A in (Focht, 1969)).

FIGURE 1 (2 column width)

The complete separation of drinking water supply and wastewater discharge is unique (see for instance, Department of Environmental Protection, Commonwealth of Massachusetts, 2010; Office of Water Resources, Department of Environmental Management, State of Rhode Island and Providence Plantations, 2010) and makes Connecticut an ideal context for analyzing water quality differences across water body classes. The intention is that the separation of drinking water and wastewater discharge protects drinking water sources, resulting in higher quality water in those waterbodies. If the water quality in Class B waterbodies is indistinguishable from the water quality in Class AA waterbodies, this could suggest the need for a review of the policies that apply to water uses in Class B waterbodies. Here, we test the hypothesis that Class AA waters have higher water quality than Class B waters in Connecticut.

We expect high variation within classes and some overlap between classes. Designated use-based classification systems do not directly account for the effects of watershed land cover and associated non-point source pollution on water quality. However, many studies have found strong linkages between watershed land cover and water quality, in particular that increased amounts of agriculture, development, and impervious cover are associated with increased levels of nutrients and solids in downstream waters (Ahearn et al., 2005; Arnold and Gibbons, 1996; Ballantine and Davies-Colley, 2014; Bellucci, 2007; Mehaffey et al., 2005; Sliva and Dudley Williams, 2001; Tong and Chen, 2002; Walsh et al., 2005). Therefore, we hypothesize that variation in water quality within classes and overlap in water quality between classes may be strongly related to watershed land cover.

Our overarching objective was to quantify patterns in water quality between and within different water body classes for streams and rivers in Connecticut using existing data from the United States Geological Survey (USGS) and the Connecticut Department of Energy and Environmental Protection (CT DEEP). Specifically, we asked four questions: 1) How does water quality vary within and among classes?; 2) To what extent does water quality overlap between classes?; 3) Does watershed land cover predict overlap between classes?; and 4) What are the potential policy implications of these patterns?

2. Methods

2.1. Data Acquisition and Scope

We used water quality data from the CT DEEP Water Quality Database (CT Department of Energy and Environmental Protection, 2014c) and the USGS National Water Information System (United States Geological Survey, n.d.) for non-tidal, surface water sampling stations in streams and rivers in Connecticut during non-storm periods between October 29, 1996 and November 14, 2011. For each sampling location, we performed a spatial join in ArcGIS 10.2.2 (ESRI, 2014) using a Surface Water Body Classification layer (State of Connecticut, Department of Environmental Protection, 2011) and the NHDplus (US EPA and USGS, 2012) to determine the water body classification and stream order, respectively. We manually checked a subset of the sites to confirm the class and order (see Supplemental Information for details).

The sampling covered 609 stream segments (Figure 1b). Of these, 570 (79 Class AA, 328 Class A, and 163 Class B; 8% of the stream segments in the state; Table S 1) represent NHDPlus flowline segments in New England (US EPA and USGS, 2012). An additional 9 segments (1 Class A.A, 5 Class A, and 3 Class B) were created by splitting NHDPlus segments due to mid-segment class changes (e.g. if the upstream portion of an NHDPlus segment is Class A and the downstream portion Class B, we considered those separate segments). The remaining 30 (4 Class AA, 24 Class A, and 2 Class B) are segments from the CT DEEP waterbody classification (State of Connecticut, Department of Environmental Protection, 2011) that are not mapped in the NHDPlus. The sampled NHDPlus segments are well distributed across the 10 HUC8 areas in the state, encompassing 4-12% of the segments in most areas (Table S 1). Class AA segments were least frequently sampled (2-7% of segments in most areas), and Class B segments were the most (13-19% in most areas).

For the land cover analysis, we used accumulated land cover within the upstream drainage area (i.e., watershed land cover). The data is originally from the 2001 National Land Cover Dataset (NLCD; 30m resolution) (Homer et al., 2007) and is available in aggregated form as part of the NHDPlus (US EPA and USGS, 2012). We assumed the 2001 NLCD is representative of the study period (1996-2011) and did not account for land use changes during that time. We created a forest fragmentation raster (30m resolution) using Morphological Spatial Pattern Analysis (MSPA) (Soille and Vogt, 2009) and the forest land cover classes from the 2001 NLCD. The resulting forest fragmentation raster categorized each forest pixel according to the following forest fragmentation features:

core (all adjacent cells are forested), edge (forest cells at the perimeter of core forest, adjacent to both forest and non-forested cells), and fragments (all other forested cells, primarily strips of forest extending from blocks of core forest or small clusters of forest) (Soille and Vogt, 2009). We used the Catchment Allocation and Accumulation Tool (CA3TV2) that is available with NHDplus (US EPA and USGS, 2012) to calculate the percent of upstream land with each forest fragmentation feature for each stream reach.

2.2. Water Quality Parameter Selection

We selected the most frequently measured parameters, which we defined as those with 3000 or more samples from 100 or more segments. This list included nine dissolved metals, so for the sake of comparison we added the corresponding total metals for eight of them, which met the selection criteria for total sites but were below the sample criteria (1068 – 1377 instead of 3000+ samples). We did not add Total Manganese because the number of sites (34) and number of samples (329) was well below the selection criteria. The final list contained 38 parameters (Table 2).

Table 2 Parameters selected for analysis

Parameter	Number of Segments	Number of Samples	Mean Number of Samples per Segment
Nutrients			
Ammonia	522	6067	12 ± 32
Dissolved Oxygen	266	5975	22 ± 43
Nitrate plus Nitrite ^a	490	5809	12 ± 32
Organic Nitrogen ^a	469	5062	11 ± 27
Orthophosphate	493	5430	11 ± 30
Total Nitrogen ^a	492	5605	11 ± 30
Ions			
Calcium	111	3623	33 ± 48
Chloride ^a	533	5847	11 ± 28
Fluoride	130	3088	24 ± 37
Magnesium	111	3622	33 ± 48
Sodium ^a	191	3918	21 ± 39
Specific Conductance ^a	267	6317	24 ± 44
Metals, Total (Dissolved)			
Aluminum	185 (205)	1080 (4255)	6 ± 12 (21 ± 39)
Cadmium	193 (212)	1375 (4406)	7 ± 16 (21 ± 39)
Chromium	146 (176)	1098 (4000)	8 ± 17 (23 ± 41)
Copper ^a (Dissolved Copper)	192(225)	1375 (4282)	7 ± 16 (19 ± 38)

Iron ^a (Total Iron)	170 (224)	1242 (4579)	7 ± 16 (20 ± 38)
Lead	191 (211)	1377 (4411)	7 ± 16 (21 ± 39)
Manganese ^a	NA (164)	NA (3867)	NA (24 ± 43)
Nickel	149 (179)	1068 (4047)	7 ± 16 (23 ± 41)
Zinc	193 (233)	1277 (4425)	7 ± 13 (19 ± 37)
Other Parameters			
Alkalinity ^a	535	5800	11 ± 29
Dissolved Solids ^a	181	3944	22 ± 41
Drainage Area	583	8499	15 ± 34
Escherichia coli	238	3044	13 ± 16
pH	503	5266	10 ± 27
Stream Order	609	8606	14 ± 34
Total Solids ^a	478	5028	11 ± 27
Turbidity	529	4081	8 ± 17
Water Temperature	268	6039	23 ± 43

^aIndicates parameters used in the AA-like and B-like analyses

2.3. Data Analysis

To prevent bias from differing detection limits (i.e., a sample with a higher detection limit suggesting a higher concentration), detection limits were standardized for each parameter by analyzing the range of reported detection limits. The median detection limit for each parameter was chosen as the standardized limit and values that were reported “at or below” detection limits below the standardized detection limit were increased to the median. All values that were reported “at or below” a detection limit higher than our standardized detection limit were deleted.

Because multiple sample locations sometimes occurred within the same stream segment and there was a range in sampling frequency, samples were aggregated by stream segment for all analyses and the median value was used. We did not include seasonal patterns or annual trends in this study due to limitations in the number of samples collected across different seasons and years at most sites. We determined statistically significant differences between classes for water quality parameters and watershed land cover using the method of analysis of multiple means described by Herberich et al. (2010), which does not require normality, equal variances or equal sample sizes. We performed the statistical analysis using R 3.1.2 (R Core Team, 2014).

To quantify the overlap in water quality among water bodies of different classes, we developed an AA-like Index and a B-like Index that identify waters that consistently have “Class AA-like” (or “Class B-like”) water quality. For the 12 parameters (those indicated with an ^a in Table 2) for which we found a difference between Class AA and Class B waters ($p \leq 0.10$), we counted the number of parameters for which the median value for a segment was below the third quantile for Class AA segments (for the AA-like Index), or above the first quantile for Class B segments (for the B-like Index). We normalized the two sets of counts using the total number of parameters (out of the 12) that had been measured in a given segment to determine the AA-like Index and the B-like Index. To determine if AA-like water quality in Class B waterbodies was correlated with AA-like land cover, we created three subsets of Class B with AA-like Index values of 0-25%, 50-75% and 75-100%. We only included segments in the subsets for which 6 or more of the 12 different parameters had been measured.

We used multiple linear regression (MLR) to analyze the relative strength of watershed land cover, water body classification, and stream order in predicting AA-like water quality. For land cover variables, we considered percent developed, percent forested, percent impervious, and the percent of forested land that was core forest. We used a logit transformation (Warton and Hui, 2011) of the land cover variables to improve normality, standardized the data by subtracting the mean and dividing by the standard deviation, and then used principle component analysis (Mardia et al., 1979; `prcomp` function in R Core Team, 2014) with the highly correlated variables ($|r| = 0.68$ to 0.95) to avoid violating the multicollinearity assumptions of multiple regression. We extracted all four principal components (with variable loadings ≥ 0.45) and used them as the land cover inputs for the MLR analysis.

To select the best MLR model, we performed an exhaustive search of models using the `regsubsets` algorithm from the `leaps` package in R (Thomas Lumley using Fortran code by Alan Miller, 2009), which considers every parameter and every model level. Candidate models included 8 potential parameters – four land cover metrics derived from our PCA analysis, stream order, and three water body class metrics: Class AA, Class A, and Class B (i.e., whether or not the water body is Class AA, Class A, or Class B, respectively). We used the Akaike information criterion (AIC) (Akaike, 1974) to compare candidate models. All data analyses were completed using R 3.1.2 (R Core Team, 2014).

3. Results

3.1. Water Quality

Class B segments (industrial and municipal wastewater discharges allowable) had higher levels of total nitrogen, nitrate plus nitrite, and organic nitrogen than Class AA or Class A waters (Figure 2a-c). Although the median level of orthophosphate was similar for all three classes (0.055 mg L^{-1}), the upper range was much greater for Class B waters, resulting in significantly higher orthophosphate for Class B waters (Figure 2d). Ammonia and dissolved oxygen levels were not significantly different between classes (Figure 2e & f). Thirteen segments (6 of 26 Class A and 7 of 98 Class B) had one or more dissolved oxygen measurements below the Surface Water Criteria (5 mg L^{-1}) (CT Department of Energy and Environmental Protection, 2013) and one of the Class A segments was consistently (median value of the segment) below the limit (Figure 2f).

FIGURE 2 (2 column width)

We also found significantly higher levels of sodium, chloride, and specific conductance in Class B compared to Class AA and A waters (Figure 3a-c). Although the median level of fluoride was similar in all three classes (0.1 mg L^{-1}), the upper range is much greater among Class B waters, resulting in statistically higher fluoride for Class B waters (Figure 3d). Calcium and magnesium were not significantly different between Class AA & Class B waters, but Class B concentrations were higher than Class A (Figure 3e & f). The acute and chronic aquatic life criteria for chloride are $860,000 \text{ mg L}^{-1}$ and $230,000 \text{ mg L}^{-1}$ (CT Department of Energy and Environmental Protection, 2013), respectively, and they were not exceeded in any of the analyzed segments.

FIGURE 3 (2 column width)

Class B waters had higher levels of dissolved copper, total iron, and dissolved manganese than Class A or AA (Figure 4a-c). Although the median values of total copper, total lead, dissolved nickel, total zinc and dissolved zinc were similar in all classes, the range of concentrations is greater among Class B waters, resulting in significantly different series (Figure 4d-h). We saw no differences in concentrations of dissolved iron levels (Figure 4i). We found no significant difference in the total or dissolved concentrations of the remaining metals due to low levels in most samples (the third quantile for each class was the detection limit; Figure S 1). For five metals (aluminum, cadmium, lead, copper, and zinc) the median dissolved concentration in some segments was at or above the limit set by the CT Aquatic Life Criteria (CT Department of Energy and Environmental Protection, 2013). A

total of 3 (out of 19) Class A segments exceeded the chronic aluminum criterion ($87 \mu\text{g L}^{-1}$), 3 segments (1 of 111 Class A and 2 of 85 Class B) exceeded the acute cadmium criterion ($1 \mu\text{g L}^{-1}$), 8 segments (2 of 19 Class AA and 6 of 84 Class B) exceeded the chronic lead criterion ($1.2 \mu\text{g L}^{-1}$), 13 segments (5 of 115 Class A and 8 of 85 Class B) exceeded the acute copper criterion ($14.3 \mu\text{g L}^{-1}$), 34 segments (13 of 115 Class A and 21 of 85 Class B) exceeded the chronic copper criterion ($4.8 \mu\text{g L}^{-1}$), and 6 segments (2 of 119 Class A, and 4 of 86 Class B) exceeded the zinc criterion (65 mg L^{-1}) (Figure 4a,g; Figure S 1).

FIGURE 4 (2 column width)

Compared to Class AA waters, Class B waters had higher pH, water temperatures, alkalinity, solids (total and dissolved), stream order, and drainage area (Figure 5a-g). Turbidity and *Escherichia coli* were not significantly different among classes (Figure 5h&i). Class A waters were warmer than Class AA, but were indistinguishable in terms of alkalinity, solids (total and dissolved), stream order, pH, and drainage area (Figure 5a-g). A total of 52 (out of 151) Class B segments had one or more pH measurements above the Surface Water Criteria for Class B (6.5 – 8.0) (CT Department of Energy and Environmental Protection, 2013) and 26 (out of 151) Class B segments had one or more pH readings below the Surface Water Criteria (Figure 5a). A total of 175 segments (28 of 33 Class AA, 68 of 116 Class A, and 79 of 89 Class B) had one or more samples that exceeded the single sample maximum *Escherichia coli* criterion for swimming (235 / 100 ml) (CT Department of Energy and Environmental Protection, 2013) and 112 segments (18 of 33 Class AA, 40 of 116 Class A, and 54 of 89 Class B) had median *Escherichia coli* levels above the allowable geometric mean (126/100 ml) (Figure 5i).

FIGURE 5 (2 column width)

3.2. Land Cover

The watersheds of Class AA segments were more forested (70% vs 61%) and less developed (8.3% vs 16.6%) than the watersheds of Class B segments (Figure 6, columns 1-3). As with many water quality parameters, the values for Class A fall between those of Class AA and Class B. There is no difference in the amount of wetlands, cultivated land, herbaceous vegetation, shrubland or barren land between Class AA and Class B (Figure S 2-Figure S 6). Class A watersheds are indistinguishable from Class AA, but have more shrubland than Class B (1.13% vs. 0.98%). Class B watersheds have more open water than Class AA or Class A (1.96% vs 0.62% or 0.47%, respectively) (Figure S 7). Class B watersheds also have a greater percentage of impervious cover than Class AA (4.2% vs 1.1%; Figure 6, columns 1-3). We found no differences in the forest spatial structure between Class AA,

Class A, and Class B (Figure 7, columns 1-3). Despite differing amounts of forest, the percent of forested land classified as core, edge, or fragment is not significantly different among the classes.

FIGURE 6 (2 column width)

FIGURE 7 (2 column width)

3.3. Overlap among classes

The median AA-like Index of Class B waters was 50% and the median B-like Index of Class AA waters was 33% (Figure 8a & b), indicating that a greater percentage of Class B waterbodies have AA-like water quality than the reverse. We found a wide range in the percent (0-100%) of measured parameters that are below the third quartile of Class AA (Figure 8A), and the same range of measured parameters above the first quartile of Class B (Figure 8B). For both indices, the base class (Class AA for AA-like and Class B for B-like) had the greatest percentage of overlap, Class A had the second, and the other (Class B for AA-like, Class AA for B-like) had the least. The most common parameters for Class B segments to overlap with Class AA are nitrate plus nitrite, alkalinity, organic nitrogen, specific conductance, and total iron. The most common parameter for Class AA waters to overlap with Class B is dissolved solids.

FIGURE 8 (1.5 column width)

When we examined the land cover and forest fragmentation patterns for the three Class B subsets based on the AA-like Index (0-25% AA-like, 50-75% AA-like and 75-100% AA-like), we found that forest area, developed area, and impervious cover were related to the AA-like Index (Figure 6, columns 4-6). The Class B watersheds with the least AA-like water (0-25% AA-like) had the least forest cover, most developed area, and most impervious cover of all the groups (Figure 6). The Class B watersheds with more AA-like water (50-75% AA-like and 75-100% AA-like) have land cover and impervious cover patterns like Class AA watersheds. The AA-like Index was also related to forest fragmentation patterns in Class B watersheds (Figure 7, columns 4-6). The Class B watersheds with 0-25% AA-like Index had less core forest than Class AA, A or B (58% of forested area vs 68%, 67% or 67%, respectively), the subset with 50-75% AA-like Index was in the middle (71%) with no significant difference between it and Class AA, and the subset with 75-100% had more (76%). This trend remains when combined with the total amount of forest to compare core forest as a percent of total watershed area (Figure S 8).

3.4. Predictors of water quality

Dimensional reduction of the watershed land cover variables (percent developed, percent forest, percent impervious, and percent of forested land that is core forest) resulted in four composite land cover variables (LC1-LC4; Table 3). The first component accounts for the majority (86%) of the watershed land cover variation and represents a continuum from watersheds with high levels of development and impervious cover to watersheds with large amounts of intact forest. The second component highlights unique watersheds with high levels of impervious cover and unfragmented forests or low levels of impervious cover and high levels of forest fragmentation (as might be found with exurban development). The third component addresses forest fragmentation, ranging from large areas of forest that are fragmented to small areas of unfragmented forest. The fourth component incorporates the variation in impervious cover within developed areas, ranging from watersheds with large areas of development that are not impervious to watersheds with smaller, highly impervious developed areas.

Table 3 – Principle component analysis results for all streams. LC1-LC4 indicate the four composite land cover variables and the numbers indicate the loading to each component of the transformed, standardized land cover data. Loadings with magnitude < 0.45 were dropped and are indicated by dashes.

Land Cover	LC1	LC2	LC3	LC4
Developed	0.52	-	-	0.73
Forest	-0.50	-	0.83	-
Impervious	0.50	-0.56	-	-0.66
Core Forest	-0.48	-0.72	-0.48	-
Cumulative Proportion of Variation	0.86	0.95	0.99	1.00

The best fit MLR model explained 45% of variation in the AA-like index (i.e., how similar water quality is to Class AA streams, Table 4). The best model included negative regression coefficients for class B and stream order (Table 5, AA-like Index=68.53-7.90*Class B-2.24*Stream Order-10.54*LC1), suggesting that AA-like index was lower for Class B and larger streams. The best fit model also included a positive regression coefficient for the composite land cover variable (LC1, see Table 3), suggesting that AA-like index was lower in watersheds with higher levels of development and impervious cover. The land cover variable LC1 was included in best fit models at all parameter levels, and alone explained 42% of the variation in AA-like index (Table 4).

Because Class B was a significant predictor in the best fit model and we were particularly interested in identifying Class B waters that have AA-like water quality, we also completed dimensional reduction and MLR selection using only Class B waterbodies. The land cover components of the Class B waterbodies (LC1_B – LC4_B) were very similar to those of the full dataset (Table S 5). For Class B waters, the best fit MLR model explained 48%

of variation in the AA-like index (Table 7). Similar to the best fit model for all water bodies, the best fit model for Class B waters included a negative coefficient for stream order and a positive coefficient for the first land cover component (LC1_B) (Table 7, AA-like Index=49.06-12.30*LC_B1 +9.27*LC_B3). The best fit model also included a negative coefficient for the third land cover component (LC3_B), suggesting that forest fragmentation is important for water quality in Class B waters. Also similar to the best fit model for all stream classes, the best fit model for Class B streams included LC1_B for all parameter levels (Table 6). LC1_B alone explained 48% of variation in AA-like index for class B waters, suggesting that AA-like index for Class B waters is strongly driven by the level of development in the watershed (Table 6).

Table 4 Candidate multiple regression models for AA-like index for all streams using LC1-LC4 (see Table 3), class, and stream order for each possible number of model coefficients (K) including the intercept. Reported statistics include adjusted r^2 ($Adj\ r^2$), Mallows' C_p , the residual sum of squares (RSS), Akaike information criterion (AIC), and the difference between the candidate and best model's AIC (Δ AIC). Candidate model with lowest AIC is in bold, and coefficients are reported in Table 5.

Model Variables	K	Adj r^2	Cp	RSS	AIC	Δ AIC
LC1	2	0.42	42.00	477873	5429	41
Class B, LC1	3	0.44	6.95	458112	5394	6
Class B, Stream Order, LC1	4	0.45	0.68	453705	5388	0
Class B, Stream Order, LC1, LC2	5	0.45	2.31	453505	5390	2
Class B, Stream Order, LC1, LC2, LC3	6	0.45	4.18	453435	5392	3
Class B, Stream Order, LC1, LC2, LC3, LC4	7	0.45	6.04	453359	5394	5
Class AA, Class B, Stream Order, LC1, LC2, LC3, LC4	8	0.45	8.00	453340	5392	3

Table 5 Multiple linear regression coefficient estimates and standard error for all waterbodies model with the lowest AIC (Table 4) for AA-like Index

Variables	Coefficient	Standard Error	p
Intercept	68.53	1.94	≤ 0.01
Class B	-7.90	1.87	≤ 0.01
Stream Order	-2.24	0.78	≤ 0.01
LC1	-10.54	0.43	≤ 0.01
p	≤ 0.01		

Table 6 Candidate multiple regression models for AA-like index for Class B streams using LC_B 1-4 (see Table S 5), class, and stream order for each possible number of model coefficients (K) including the intercept. Reported statistics include adjusted r^2 ($Adj\ r^2$), Mallows' C_p , the residual sum of squares (RSS), Akaike information criterion (AIC), and the difference between the candidate and best model's AIC (Δ AIC). Candidate model with lowest AIC is in bold, and coefficients are reported in Table 7.

Model Variables	K	Adj r^2	Cp	RSS	AIC	Δ AIC
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LC_B 1	2	0.48	15.18	117859	1771	11
LC_B 1, LC_B 3	3	0.50	4.24	112879	1760	0
Stream Order, LC_B 1, LC_B 3	4	0.50	3.75	111919	1760	0
Stream Order, LC_B 1, LC_B 3, LC_B 4	5	0.50	4.15	111301	1760	0
Stream Order, LC_B 1, LC_B 2, LC_B 3, LC_B 4	6	0.50	6.00	111245	1762	2

Table 7 Multiple linear regression coefficient estimates and standard error for Class B model with the lowest AIC (Table 6) for AA-like Index

Variables	Coefficient	Standard Error	p
Intercept	49.06	1.14	≤0.01
LC_B 1	-12.30	0.80	≤0.01
LC_B 3	9.27	2.58	≤0.01
p	≤0.01		

4. Discussion

Although we found significant differences in water quality among Class AA, A, and B river segments (Figure 2 - Figure 5), there was high variation within classes and some Class B segments consistently have water quality that is more similar to Class AA than Class B (Figure 8). Our results highlight the wide range of variation within classes not directly addressed by current state classification systems based on designated uses. Water quality variation in Class B segments is strongly linked to watershed land cover. In general, Class B segments with less watershed development and more core forests have water quality similar to Class AA waters. These patterns have implications for both policy and management.

As expected, water quality parameters were significantly different ($p \leq 0.05$) between Class AA and Class B waters, particularly for chloride, sodium, dissolved copper, dissolved manganese, total iron, total nitrogen, nitrate plus nitrite, organic nitrogen, solids (total and dissolved), and water temperature. Compared to Class AA water bodies, Class B segments were warmer, and higher order, with higher levels of contaminants and larger drainage areas. It is worth noting, however, that even in the Class B segments, the median values seldom exceed established aquatic life criteria, except sodium, copper, pH, and *Escherichia coli* (CT Department of Energy and Environmental Protection, 2013). We considered only a small fraction of the currently regulated contaminants (US EPA, 2014) and none of the candidate or emerging contaminants such as pharmaceuticals (Monteiro and Boxall, 2010; Petrie et al.,

2015). A more thorough assessment of trace contaminants would be needed to further assess the health implications of the water quality differences.

We also found significant differences between watershed land cover of Class AA and Class B segments. In our analysis, watersheds of Class B segments were more developed, less forested, and with more impervious cover. These differences were more pronounced upstream of the Class B segments with the least AA-like water. The 0-25% AA-like subset is a “Super-B” subset – highly developed and highly impervious, with small amounts of forest that are highly fragmented. These land cover differences between classes are likely the combined result of source water protection efforts, regulations limiting development in drinking water watersheds (Ainsworth and Jehn, 2005; *Connecticut General Statutes § 8-3i*, n.d., *Connecticut General Statutes § 25-43*, n.d., *Safe Drinking Water Act*, 2002), and the fact that wastewater treatment plants (and their associated receiving waters, which are Class B) tend to be located in areas of greater development (e.g. rural areas tend to have septic systems and cities tend to have sewers).

Although median water quality levels did differ between Class AA and Class B segments, water quality appears to be more closely correlated with watershed land cover than with waterbody classification. Best fit MLR models for all stream segments and Class B stream segments included a composite land cover metric that was closely related to the percent of developed and impervious watershed land cover. In fact the land cover metric alone explained over 40% of the variation in AA-like index values for all stream segments and Class B stream segments. The connection between watershed land cover and water quality is not new and has been the focus of many previous studies. For example, Tong and Chen (2002) found percent forest to correlate with lower nitrogen, phosphorus, coliforms, and conductivity; and Mehaffey et al. (2005) found percent developed and agricultural land to correlate with higher in-stream nitrogen, phosphorus, and coliforms. Brabec et al. (2002) review the extensive literature linking increased impervious cover with decreased water quality. In Connecticut, Bellucci et al. (2013) found impervious cover to be one important predictor of water quality. Sliva and Dudley Williams (2001) found that urban development increased in-stream pollutant loads and that forest cover mitigated water quality impairment. Our work suggests that well established relationships between land cover and water quality may provide useful information that can be integrated into water body classification systems.

We also found that forest fragmentation patterns may play an important role in determining water quality, and that intact forest may in some way compensate for the water quality effects of wastewater discharge. The

watershed land cover of the subset of Class B segments with the highest AA-like Index has significantly more core forest than the land upstream of Class AA and Class B segments (which are indistinguishable from one another). Also, the percentage of the watershed that is core forest is part of the composite land cover variable that is important in our best fit model for Class B stream segments. This is consistent with work by Riva-Murray et al. (2010), who found forest fragmentation was correlated with lower stream biotic indicators. Core forest in headwaters regions may deliver fewer pollutants to the river network than fragmented forests. Alternately, core forest may provide a cleansing function (Clinton and Vose, 2006), though Harding et al. (2006) did not find this to be the case in agricultural areas. This pattern may also be driven by small wastewater treatment systems in largely undeveloped regions. Future research is needed to determine the causal relationship between water quality and the amount of core forest.

Although the current classification system does result in water quality differences between the classes, we caution against using designated use classes to infer water quality, recommending the use of land cover instead when a water quality proxy is needed. Surface waterbody classifications based on designated uses can be used as a simple regulatory tool (e.g. indicating the type and location of allowed discharges), to create a baseline goal for water quality (sufficient to support the designated uses), and to identify impaired waterbodies (CT Department of Energy and Environmental Protection, 2014b). The causal link, however, between classifications and water quality seems to be relatively minor and limited to regulating discharges. We recommend that the current system in Connecticut be amended to provide increased watershed protection for Class B waters that have AA-like water (Table S 4). These watersheds currently have more forest, particularly unfragmented forest, and less development than other Class B waters and minimizing development in these areas could ensure they continue to have AA-like water into the future, when they may be needed to meet other uses.

5. Conclusion

We found that water quality in Connecticut streams and rivers is related to water body classification, with Class B waters tending to have higher contaminant levels than Class AA waters, however water quality is more closely associated with watershed land cover. Some Class B water bodies consistently have water quality similar to Class AA waters, and their watersheds tend to have land cover that is also similar to Class AA watersheds. Our results suggest that the relationships between water quality and land cover could potentially improve water body

classification systems, and we recommend enhanced protections for these Class B watersheds to maintain their AA-like water quality for potential future drinking water supply.

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Figure Captions

Figure 1 Connecticut freshwater surface water quality classifications (State of Connecticut, Department of Environmental Protection, 2011). a) All classified segments; b) Stream segments used in analysis. Legend and scale bar in panel b apply to both panels. See Table 1 for definition of classes.

Figure 2 Nutrient concentrations and dissolved oxygen across surface waterbody classes for streams and rivers: a) Total Nitrogen; b) Nitrate plus Nitrite; c) Organic Nitrogen; d) Orthophosphate; e) Ammonia; and f) Dissolved Oxygen (*gray line* median, box upper and lower bound = 25% and 75%, whiskers = 1.5 times the interquartile range). The value above the whiskers is the median value and series with different letters above the whiskers are statistically different at the p value given in the top left. The dark black lines on the Total Nitrogen graph (a) indicate the boundaries between mesotrophic and eutrophic (0.6 mg-N L^{-1}) and between eutrophic and highly eutrophic (1 mg-N L^{-1}) (CT Department of Energy and Environmental Protection, 2013). Gray areas of the Dissolved Oxygen graph indicate areas below the Surface Water Criteria (CT Department of Energy and Environmental Protection, 2013). Y-axis type (logarithmic or linear) in each graph was selected to best display the full range of data.

Figure 3 Ion concentrations across surface waterbody classes: a) Chloride; b) Sodium; c) Specific Conductance; d) Fluoride; e) Calcium; and f) Magnesium (*gray line* median, box upper and lower bound = 25% and 75%, whiskers = 1.5 times the interquartile range). The value above the whiskers is the median value and series with different letters above the whiskers are statistically different at the p value given in the top left. Gray areas on the Sodium graph indicate areas above the Surface Water Criteria for Class AA (CT Department of Energy and Environmental Protection, 2013). Y-axis type (logarithmic or linear) in each graph was selected to best display the full range of data.

Figure 4 Metal concentrations across surface waterbody classes: a) Copper, Dissolved; b) Iron, Total; c) Manganese, Dissolved; d) Copper, Total; e) Lead, Total; f) Nickel, Dissolved; g) Zinc, Dissolved; h) Zinc, Total; and i) Iron, Dissolved (*gray line* median, box upper and lower bound = 25% and 75%, whiskers = 1.5 times the interquartile range). The value above the whiskers is the median value and series with different letters above the whiskers are statistically different at the p value given in the top left. Gray areas, if present, indicate areas above the Acute Aquatic Life Criteria and horizontal gray lines, if present, indicate areas above the Chronic Aquatic Life Criteria (CT Department of Energy and Environmental Protection, 2013). Y-axis type (logarithmic or linear) in each graph was selected to best display the full range of data.

Figure 5 Other parameters across surface waterbody classes: a) pH; b) Water Temperature; c) Alkalinity; d) Total Solids; e) Dissolved Solids; f) Stream Order; g) Drainage Area; h) Turbidity; and i) *Escherichia coli* (*gray line* median, box upper and lower bound = 25% and 75%, whiskers = 1.5 times the interquartile range). The value above the whiskers is the median value and series with different letters above the whiskers are statistically different at the p value given in the top left. Gray areas of the pH graph indicate areas above and below the Surface Water Criteria for Class B. On the *Escherichia coli* graph, gray areas indicate areas above the single sample maximum for swimming designated waters, and horizontal gray lines indicate areas above the geometric mean maximum for recreational use (CT Department of Energy and Environmental Protection, 2013). Y-axis type (logarithmic or linear) in each graph was selected to best display the full range of data.

Figure 6 Land cover patterns in Class AA, A and B. Groupings along the x-axis indicate waterbody classification (AA, A, or B) or subsets of Class B (<25% AA-like, 50-75% AA-like, 75-100% AA-like). Values below the x-axis indicate the number of segments in each group. Orange boxes indicate percent of the upstream watershed with developed land cover, white boxes indicate the percentage of forested land cover, and the purple boxes indicate impervious cover (*gray line* median, box upper and lower bound = 25% and 75%, whiskers = 1.5 times the interquartile range). The value above the whiskers is the median value and series of the same land cover with different letters above the whiskers are statistically different at $p \leq 0.05$.

Figure 7 Forest spatial patterns in Class AA, A and B. Groupings along the x-axis indicate waterbody classification (AA, A, or B) or subsets of Class B (<25% AA-like, 50-75% AA-like, 75-100% AA-like). Values below the x-axis indicate the number of segments in each group. Orange boxes indicate percent of the forested area in the upstream watershed classified as core forest, white boxes indicate the percentage of forested land cover classified as fragments, and the purple

boxes indicate the percentage of forested area classified as edge (*gray line* median, box upper and lower bound = 25% and 75%, whiskers = 1.5 times the interquartile range). The value above the whiskers is the median value and series of the same forest type with different letters above the whiskers are statistically different at $p \leq 0.05$.

Figure 8 AA-like Index (a) and B-like Index (b) of waterbodies by class (*gray line* median, box upper and lower bound = 25% and 75%, whiskers = 1.5 times the interquartile range). The value above the whiskers is the median value.

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

Figure 7

Figure 8