RUNNING HEAD: Measuring downstream influence of headwater disturbance

Use of spatially explicit physicochemical data to measure downstream impacts of headwater stream disturbance

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Abstract

Regulatory agencies need methods to quantify the influence of headwater streams on downstream water quality as a result of litigation surrounding jurisdictional criteria and the influence of mountaintop removal coal mining activities. We collected comprehensive, spatially-referenced physicochemical data (pH, dissolved oxygen, temperature, and specific conductance) from the partially mined Buckhorn Creek, KY watershed in summer 2005 (n = 239 sites) and spring 2006 (n = 494 sites). We found conductivity was >10X higher in mined streams than in forested streams. Semivariograms, which quantify the degree of spatial dependence in chemistry values, indicated summer temperatures in both mined and unmined portions of the watershed had similar lag distances (ca. 5 km). Data for other parameters and seasons however, violated model assumptions because of strong confluence effects in headwaters. We therefore developed a post-hoc predictive model for water physicochemistry downstream of confluences using watershed areas as weighting factors. This weighted-average model accurately predicted downstream conductivity (mean absolute error [MAE] = 55.34 $\mu S\ cm^{-1}$), pH (MAE = 0.16 units), and temperature (MAE = 0.41°C) for confluences in Buckhorn Creek and two additional watersheds with headwater disturbance in WV and OH. Use of semivariograms or predictive confluence models can help regulatory agents identify downstream influence of headwater streams and presence of a "significant nexus" with downstream waters.

Keywords: conductivity, geostatistics, mining, ph, temperature, valley fill

1. Introduction

Headwater streams, both individually and cumulatively, are important components of stream networks that can ultimately influence health of downstream aquatic ecosystems [*Gomi et al*., 2002; *Meyer and Wallace*, 2001; *Naiman et al*., 1987; *Vannote et al*., 1980; *Wipfli and Gregovich*, 2002; and see featured collection in *Journal of American Water Resources Association*, 2007, Vol. *43(1)*]. State and Federal regulations however, have traditionally afforded less protection to headwater streams than to larger downstream waters because of their abundance on the landscape and more variable hydrologic periods. Small headwaters are also not usual direct sources of drinking water, commerce, or recreation. Permits for filling (Clean Water Act [CWA] §401 & §404) or discharging to (CWA § 402) intermittent, and particularly ephemeral, headwater streams are sometimes not required or, if so, critical reviews by regulatory agencies and any mitigation requirements have typically been less than for downstream waters [e.g., *Department of Defense*, 2007]. Such inadequate protection of headwater streams and the failure to properly mitigate their loss has been criticized in a recent federal court decision [*Ohio Valley Environmental Coalition v. United States Army Corps of Engineers, et al.*, *No. 03, 05-0784*, 2007].

Language of the CWA, which often references "navigable waters" or "waters of the United States", also does not clearly indicate the extent of CWA jurisdiction and has created confusion among regulatory agencies and the public. This has resulted in a number of Federal court cases that have specifically challenged whether the CWA applies to headwater streams and isolated wetlands [see special issues of *Wetlands* 2003, Vol. *23(3)*; *Wetlands* 2007, Vol. *43(1)*; and *Natural Resources and Environment* 2007, Vol.

22(1)]. A 2001 Supreme Court decision first questioned whether some headwater streams and isolated wetlands could be considered jurisdictional under the Clean Water Act [*Solid Waste Agency of Northern Cook County (SWANCC) v. U.S. Army Corps of Engineers, 531 U.S. 159*, 2001]. A subsequent joint decision then required that non-navigable waters must be "relatively permanent" or "possess a significant nexus" to navigable waters to be considered jurisdictional [*John A. Rapanos et al. v. United States,* U.S., *No. 04-1034*, 2005; and *June Carabell et al. v. United States Army Corps of Engineers and the United States Environmental Protection Agency*, U.S., *No. 04-1384*, 2005].

As a result of these decisions, regulatory agencies are faced with the challenge of accurately measuring hydrologic permanence of headwater streams and their degree of influence on the quality of downstream, navigable waters [*Leibowitz et al*., 2008]. Some state and federal agencies have developed tools for both measuring permanence and for ecological assessment in headwater streams [*Fritz et al*., 2006; *NCDWQ*, 2005; *OEPA*, 2002]. However, directly quantifying the influence of headwater streams on downstream resources is difficult given the large spatial scale and the mosaic of disturbance that often exists among headwater tributaries within branched stream networks. Determining the presence of a "significant nexus" may therefore require stream ecologists to move beyond the habitat or reach spatial scales that are typically the focus of stream studies. Spatially explicit studies that incorporate measures from throughout stream networks may be a useful strategy for quantifying the downstream influence of headwater streams and to help identify presence of a "significant nexus".

In the central Appalachians, headwater streams are often buried under fill material as a result of coal mining activities. The largest fills result from mountaintop removal mining (MTM) where overburden is placed in adjacent stream valleys, creating valley fills (VF). During a single ten year span (1992-2002), it was estimated that more that 1,200 miles of headwater streams were impacted by MTM/VF activities [*USEPA*, 2003]. Though sediment ponds constructed downstream of fills facilitate deposition of fine particles, the total dissolved solids (TDS) can remain high downstream because there are currently no feasible methods for their removal. Elevated ion concentrations are produced from groundwater leaching the valley fill materials. Stream conductivity at filled sites can be 100X greater than for unmined streams in the region [*Bryant et al*., 2003] (i.e., from ca. 50 $\mu S\ cm^{-1}$ to 5,000 $\mu S\ cm^{-1}$) and evidence suggests that conductivity can remain high for decades after fill construction [*Merricks et al*., 2007].

Ionic constituents resulting from valley fills are conserved and therefore potentially impact water quality far downstream. Potential cumulative effects of multiple valley fills within a watershed must also be taken into consideration as required by the National Environmental Policy Act (NEPA) and other federal permitting programs (e.g., CWA Section 404[b][1] 40 CFR §230, Nationwide Permit Program 33 CFR §330). However, as with measuring the downstream influence of impaired headwater streams, methods for measuring cumulative downstream effects are also lacking. Measurements of cumulative effects are complicated by the large temporal and spatial scales involved and the potential interaction of multiple stressors [*Reid*, 1998].

The study objective was to develop or refine methods that better quantify the influence of headwater streams and cumulative effects of headwater disturbance on downstream water quality. Our efforts focused on, but were not limited to, MTM/VF and associated specific conductance (surrogate for TDS) in streams of the central Appalachians. We took multiple approaches that included geostatistical analysis of extensive field-collected physiochemical data and development of predictive models for water chemistry downstream of confluences.

2. Methods

2.1 Study Areas

The Buckhorn Creek (BC) watershed (drainage area 118 km^2) is in the Dissected Central Appalachian Plateau ecoregion [Level IV (69d); *Woods et al*., 2002] of eastern Kentucky, U.S.A., and lies at the juncture of Breathitt, Knott, and Perry Counties (Figure 1). The ecoregion is unglaciated, consisting of steep ridges and narrow valleys and is underlain with Pennsylvanian sandstone, shale, siltstone, and coal (*Woods et al*., 2002). Robinson Forest (RF) (drainage area 60 km^2) lies within the BC watershed and is a research forest operated by the University of Kentucky. The two major subwatersheds included in RF are drained by Clemons Fork and Coles Fork, both of which are tributaries to the BC mainstem. Much of the remainder of the Buckhorn watershed has been heavily mined for coal, and includes some gas drilling, low density housing, and pasture (Figure 1). Coal mining in the watershed includes presence of multiple MTM/VF operations [*Wunsch et al*., 1999].

The BC watershed was sampled during summer 2005 (Sept. 12-14) and spring 2006 (May 1-4) to cover base and average stream flow conditions, respectively. Multi-probe (Hydrolab®) measurements (pH, dissolved oxygen [mg/l], temperature [°C], and conductivity [$\mu S\ cm^{-1}$]) and latitude/longitude were recorded at stream sites every 100-

500 m in both seasons (summer: n = 239; spring: n = 494). Data were collected from origin of surface flow in multiple mined and reference headwater streams downstream to the confluences with the mainstem Buckhorn Creek and along the Buckhorn mainstem to the confluence with the receiving stream, Troublesome Creek. Special attention was given to stream confluences during data collection to measure any tributary effects on receiving streams. Multi-probe measures were collected ca. 100 m above the confluence on each tributary and ca. 100 m above and below the tributary confluence on the receiving stream. Multi-probes were calibrated daily and duplicate measures were collected within 10 m for every 25 sampling locations.

2.2 Geospatial Analysis

Unlike conventional statistical tests that typically require observations to be independent and normally distributed (e.g., ANOVA, *t*-test, X^2), geostatistics refers to a set of statistical tools that are specifically used to model the degree of spatial dependence among values. Geostatistics are therefore particularly valuable for describing spatial patterns within complex stream networks where site values are often spatially correlated. Modeling spatial dependence can provide ecologically meaningful information about many aspects of stream network dynamics and have been successfully used to describe spatial patterns in stream physiochemistry parameters [*Dent and Grimm*, 1999; *Gardner et al*., 2003] as well as cutthroat trout distribution [*Ganio et al*., 2005].

Geospatial methods use some measure of statistical distance to model the degree of spatial dependence between sites within the spatial domain. Following recent development of GIS tools, stream researchers have made increasing use of hydrologic, or in-stream, distance measures when exploring spatial patterns in stream networks [e.g., *Gardner et al*., 2003; *Peterson et al*., 2007*; Ver Hoef et al*., 2006]. Hydrologic distance is the shortest distance between points within the stream channel network and it may be further divided into either symmetric or asymmetric by incorporating a directional component. Symmetric stream distance is simply the distance between any two points along the stream network, regardless of flow direction, so that all sites within the network can be connected. For asymmetric stream distance, two sites within the stream network can only form a distance pair if one site is either contributing to or receiving flow from the other. Asymmetric distance is thus limited to either the upstream or downstream direction [*Peterson et al*., 2007]. Since our primary objective was aimed at longitudinal changes in water chemistry, we used unweighted, asymmetric (downstream) stream distance when calculating spatial dependence.

A semivariogram is a geostatistical tool that quantifies the change of spatial dependence with increasing distance among observations, or how site pairs covary with separation distance. Data points that are closer together are expected to be more similar than those that are farther apart. All observations from the stream network are binned by distance and semivariance is calculated as half the average, squared difference between pairs of points located a given distance apart:

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2$$

where $\hat{\gamma}(h)$ is the estimated variogram value for distance h; $z(x)$ is the value of a variable at location x_i; $z(x_i+h)$ is the value of the same variable some distance away; and $N(h)$ is the number of pairs of observations separated by h. Semivariograms plot $\hat{\gamma}(h)$ as a function of distance h [*Liebhold et al*., 1993; *Rossi et al*., 1992] and are typically interpreted by fitting theoretical models [e.g., *Dent and Grimm*, 1999; *Peterson et al*., 2007; *Schlesinger et al*., 1996]. The nugget refers to the semivariance value at lag distance zero and is usually >0 because of fine scale sampling variability (or variability at distances smaller than the minimum sampling distance) or measurement error. Error increases with increasing lag distance on the x-axis because the number of observations used for semivariance calculation declines. For the spherical semivariogram model, the point where semivariance levels off is referred to as the *sill* and the lag distance where the sill occurs is the *range*. The range indicates the average distance over which values are spatially correlated, or average "patch size" [*Dent and Grimm*, 1999]. At least 30 pairs of points should be included for each separation distance when plotting semivariograms [*Cressie*, 1993]. Also implicit in semivariogram models is the assumption of stationarity, which states that spatial dependence must be the product only of distance between two points in the spatial domain and not their specific locations within the domain [*Cressie*, 1993].

The National Hydrologic Database (NHD) underestimated total stream coverage for BC, resulting in many observations that were not associated with mapped stream channels. A new stream network was therefore generated for the watershed using the ArcHydro 9 toolset for ArcGIS 9.1. The stream network was constructed using a 30 m Digital Elevation Model (DEM) available from the Seamless Data Distribution System of the USGS. Flow direction and flow accumulation grids were then created from the DEM. The new stream network was then generated using a minimum threshold of 35 cells flowing into the destination cell for initiation of a stream channel. Observations were snapped to the new ArcHydro stream network and distances between observations were calculated with the Fast Network Shortest Path extension for ArcView 3.2. Distance pairs that were not flow connected were manually removed. Multi-probe values were then merged with the distance dataset. Empirical semivariograms were estimated with a function developed for R statistical software [*R Development Core Team*, 2009] using the Cressie-Hawkins robust estimator. Spherical semivariogram models were then fitted with the variofit function in geoR [*Ribeiro and Diggle*, 2001] using weighted least squares and Cressie's weights.

2.3 Predictive Model Development

Initial analysis of empirical semivariograms revealed the stationarity assumption was often violated for measured parameters because of strong tributary influences, primarily in the headwaters. As a result of these model violations in the semivariogram approach, a post hoc deterministic model was developed using only a weighting factor and chemistry data from three locations at each stream confluence. Watershed area was used as the weighting factor for tributary influence, both because of the known correlation between watershed area and stream discharge [e.g., *Knighton*, 1998] and the relative ease of drainage area measurement. Such a deterministic model may be used to predict water chemistry values below confluences within the watershed, regardless of location or degree of spatial dependency. The weighted average model simply incorporates watershed area and parameter values from two confluent tributaries:

$$y_{ij} = d_i * x_i / (d_i + d_j) + d_j * x_j / (d_i + d_j)$$

where: y = downstream water chemistry value, i and j = contributing tributaries, x_i = water chemistry measurement on tributary i, d_i = drainage area of tributary i, x_j = water chemistry measurement on tributary j, d_j = drainage area of tributary j.

Model performance was first evaluated by the average difference between observed (*O*) and predicted (*P*) values using the root mean square error (RMSE):

$$\text{RMSE} = \left[N^{-1} \sum_{i=1}^{N} \left(P_i - O_i \right)^2 \right]^{0.5}$$

Additionally, mean absolute error (MAE) was calculated because it is less sensitive to extreme values than RMSE [*Willmott*, 1982] and provides a more intuitive measure of model error:

$$\text{MAE} = N^{-1} \sum_{i=1}^{N} \left| P_i - O_i \right|$$

Both of these difference measures are preferred over use of the correlation coefficient (r) or coefficient of determination (R^2) because such measures of significance are not consistently related to accuracy of model prediction [*Willmott*, 1982]. Furthermore, confluence site locations were not random and thus violate assumptions of conventional tests for significance.

The deterministic model was first developed with data collected at confluences within the BC watershed in both spring (n = 78 cofluences) and summer (n = 22 confluences). The model was then tested with additional confluence data collected from watersheds in two other states using the same sampling methods, but only at confluence locations. Confluences from an urbanizing watershed (Little Miami River) in Clermont Co., OH were sampled in Sept. 2006 (n = 37 confluences) (Fig. 2). Clermont County lies in the Pre-Wisconsinan Drift Plains of the Eastern Corn Belt Plains ecoregion [Level IV (55d), *Woods et al*., 1998] and is underlain by pre-Wisconsinan glacial till and thin loess. An additional watershed with multiple valley fills was also sampled in southern WV (Twentymile Creek watershed, Nicholas Co., WV [n = 14 confluences]) in May 2007

(Figure 2). The Twentymile Creek watershed lies within the same Central Appalachian Plateau ecoregion as the BC watershed, but differs by having a trellised drainage basin rather than the dendritic pattern found in BC.

3. Results

3.1 Water Chemistry

There were strong hydrologic differences between the two sampling seasons in the BC watershed. Summer discharge of the BC mainstem, measured near its confluence with Troublesome Creek, dropped to < 20% of spring discharge, from 0.95 $m^3 s^{-1}$ in spring to only 0.18 $m^3 s^{-1}$ in summer. Less than half (48%) the number of locations were sampled during the summer dry period (n = 239 locations) than in spring (n = 494 locations) due to this contraction of the stream network.

Water chemistry results often revealed distinct patterns, both seasonally and longitudinally, and indicated differences between RF and the remainder of the BC watershed (Table 1, Figures 3-5). Since our sampling design was aimed at testing for spatial dependency and the sites do not constitute a random sample, comparisons of water chemistry values between seasons and between mined and unmined portions of the watershed are for descriptive purposes only. The most obvious differences were apparent for stream conductivity in both spring and summer (Table 1, Figure 3). In both seasons, conductivity values within the RF averaged ca. 100 $\mu S\ cm^{-1}$, whereas outside of RF, values averaged >1000 $\mu S\ cm^{-1}$ and >2500 $\mu S\ cm^{-1}$ in spring and summer, respectively. Within RF, three small tributaries draining to Clemons Fork (CF) from the north (Millseat Branch, Rich Hollow, and Maple Hollow) had springtime conductivities ranging from 200-800 $\mu S\ cm^{-1}$, whereas other CF tributaries typically ranged from 40-70 µS cm^{-1}. In the upper and lower portions of the BC watershed, as in RF, small headwater tributaries that were forested generally had conductivity values <100 µS cm^{-1} and were typically dry in summer. Spring conductivities in the entire BC watershed (excluding RF) ranged from 32-3190 µS cm^{-1}, whereas during the summer dry period, values ranged from 93-11810 µS cm^{-1} (Table 1). In summer, three measurements in one upper BC tributary, Eli Fork, were >11,000 µS cm^{-1}, but the majority of measures (82%) were between 2000-3000 µS cm^{-1}.

Differences between RF and the rest of the BC watershed (upper and lower BC) were less apparent for other parameters. Stream temperatures generally displayed the expected longitudinal and seasonal trends, with warmer temperatures in summer and cooler temperatures in headwaters (Table 1, Figure 4). Average stream temperatures were slightly cooler in RF than in the surrounding watershed for both seasons. Outside of RF, headwater temperatures were also often higher than both the RF headwaters and locations much farther downstream. Dissolved oxygen and pH measures generally followed a spatial pattern similar to temperature. Values for pH were circumneutral (6.5-7.5) and were consistent between seasons. Average pH values were ca. 0.5 units lower in RF than in the surrounding portion of the BC watershed in both seasons (Table 1, Figure 5). Dissolved oxygen (D.O.) was the most variable parameter, as expected, and was influenced by stream temperature, canopy cover, and hour of collection. Dissolved oxygen concentrations were therefore not mapped or modeled as other parameters. Median D.O. values were nearly identical for RF and the other BC tributaries in spring (ca. 9.5 mg/l), but RF values were slightly lower than BC in summer (5.5 mg/l and 8.0 mg/l, respectively) (Table 1).

3.2 Geospatial Analysis

Summer temperatures in the upper BC watershed fit the spherical semivariogram model (Figure 6). Sites within RF were placed in 100 m bins, whereas sites from the rest of the BC watershed were placed in 200 m bins to ensure a minimum of 30 distance pairs in each bin. The nugget, sill, and range for RF were 0.59, 1.40, and 5152.78, respectively (Figure 6a). Corresponding nugget, sill, and range values for upper BC were 0, 3.74, and 5250.00 (Figure 6b). The sill of the Buckhorn semivariogram was thus 2.7X greater the sill for CF, indicating greater temperature variation in the mined portion of the watershed. No nugget was fit to the mined model, suggesting that all spatial dependency was captured by the model. Despite these differences in variation and nugget effect, the range for both CF and BC was ca. 5200 m, indicating that temperature is spatially dependent over this stream length.

Violations of the stationarity assumption prevented fitting conductivity, pH, and spring temperature data to semivariogram models because of strong confluence effects that often occurred between adjacent sampling locations. For example, covariance between two points 300 meters apart with an intervening tributary was not the same as covariance for two points 300 meters apart without an intervening tributary. Conductivity in the headwaters of BC showed higher semivariance at shorter lag distances resulting from high variability in headwater tributary values (e.g., < 100 µS cm^{-1} to >3,000 µS cm^{-1}). Thus, spatial dependence between points was conditional on their locations within the stream network. Non-stationarity even occurred in RF because of the tributary influences associated with the few streams that had locally elevated conductivity. The confluence effect was most evident in the abrupt changes in conductivity along the BC mainstem, where major forested tributaries lowered conductivity and mined tributaries increased it in both spring (Figure 7a) and summer (Figure 7b). The magnitude of change in BC conductivity was directly related to the discharge and conductivity of the contributing stream.

3.3 Predictive Modeling

Despite the large difference in stream discharge between seasons, the confluence model showed a strong ability to predict downstream conductivity, pH, and temperature in the BC watershed in both spring and summer (Table 2). Model error for conductivity was greater than for pH and temperature in both seasons, largely because of the much greater range of observed values within the watershed (Table 2). Model error for conductivity showed a general increase with increasing conductivity. RMSE and MAE were therefore greater during the summer low flow period and in the mined portion of the watershed than during higher flows and for unmined areas. Model average error in summer was 158.18 $\mu S\ cm^{-1}$, whereas error dropped to 34.56 $\mu S\ cm^{-1}$ in spring. Error associated with the predicted pH values was stable between seasons, averaging 0.18 units in both spring and summer. Predicted temperature values however, had higher error in summer (MAE = 0.68) than in spring (MAE = 0.43) (Table 2), but average model error for the year was only ca. 0.5° C.

Confluence data from the additional watersheds in WV and OH followed similar trends, indicating the model predictions for conductivity, temperature, and pH were robust across different landuse types and geologic regions (Table 3). Conductivity values were generally lower in the urbanizing Little Miami River, OH (LMR) watershed than in the Twentymile Creek, WV (TMC) watershed where extensive coal mining has taken place (Table 3). Model error for conductivity was again higher in each of these watersheds than for other chemistry variables. Futhermore, model error for TMC confluences was more than 4 times higher than that of the LMR. Average model error (MAE) was 98.20 µS cm^{-1} and 21.79 µS cm^{-1} for the TMC and LMR confluences, respectively (Table 3). Temperature regimes were similar between the two watersheds and MAE was ca. 0.25° C for each. There was a greater range of pH values in TMC than LMR, and MAE was correspondingly higher for TMC (0.19 pH units) than for LMR (0.11 pH units) confluences (Table 3).

Given the strong predictive performance across seasons and geographic locations, data from all confluences in the BC, LMR, and TMC watersheds were thus combined and model errors were recalculated. The resulting full model MAE was 55.34 µS cm^{-1} for conductivity (RMSE = 103.03)(Figure 7a), 0.16 pH units (RMSE = 0.29) (Figure 7b), and 0.41°C for temperature (RMSE = 0.66) (Figure 7c). The conductivity model predictions had greater error when observed values were >1,500 µS cm^{-1} so error terms were also calculated for confluences above and below this threshold value. When including only confluences where observed values were <1,500 µS cm^{-1} (n = 114 confluences), MAE and RMSE decreased to only 19.58 µS cm^{-1} and 39.57, respectively. However, when observed confluence values were >1,500 µS cm^{-1} (n = 37 confluences), MAE and RMSE increased to 165.54 µS cm^{-1} and 253.32, respectively.

4. Discussion

4.1 Water Chemistry

Conductivity measures downstream of fills in both BC and TMC were typically >1,000 µS cm^{-1}, which is consistent with other coal mining studies from the eastern

United States [*Fulk et al.*, 2003; *Hartman et al*., 2005; *Howard et al*., 2001; *Kennedy et al.*, 2003; *Kennedy et al.*, 2004; *Merricks et al*., 2007; *Pond*, 2004; *Pond et al*., 2008]. Furthermore, these values were from 10-25X greater than forested streams in RF and >2X levels associated with the loss of sensitive Ephemeroptera taxa [*Howard et al*., 2000; *Pond*, 2004; *Pond et al*., 2008]. Elevated conductivity in BC is primarily attributed to conservative ions such as sulfate, calcium, manganese, magnesium, and iron. As these ions are transported downstream there is little biological uptake or physical adsorption, so they tend to accumulate in the downstream direction where multiple fills are located in the same watersheds. At the headwaters of the BC watershed, Eli Fork conductivity was nearly ¼ that of seawater during summer sampling (>11,000 $\mu S\ cm^{-1}$). The unusually high conductivity we measured on Eli Fork in summer had however, returned to ca. 100 $\mu S\ cm^{-1}$ the following spring. The frequency of such transient events and the associated potential acute toxicity effects in small streams of the Appalachian region remain poorly understood.

As in previous mining studies [*Howard et al*., 2001], filled headwater streams in BC also had slightly higher pH and temperature when compared to nearby forested streams. Increased temperatures were likely caused by the numerous ponds located downstream of fills and by a general reduction in canopy cover compared to RF. Elevated pH possibly resulted from increased buffering capacity of fill materials. Mining companies also frequently add chemicals to the sediment ponds downstream of fills to regulate pH and facilitate deposition of potentially harmful metals [*Skousen et al*., 1998].

4.2 Geospatial Analysis

Semivariograms provide a relatively simple tool for quantifying the degree of spatial dependence for water physicochemical values within stream networks [e.g., *Dent and Grimm*, 1999; *Ganio et al*., 2005], from small headwaters to large downstream rivers. Our semivariograms for summer temperature in RF and upper BC watersheds both had a similar range of ca. 5 km, indicating temperature measures are significantly related to each other over this stream length. This 5 km distance thus represents a quantifiable linkage in temperature from headwaters to downstream (or between any two points <5 km apart within these watersheds). Temperatures were slightly higher in the upper BC watershed, likely due to effects multiple ponds below valley fills and less canopy cover than in RF. The absence of strong confluence effects for summer temperature may have been due to the low flows and greater influence of ambient air temperature along the continuum.

The semivariogram approach, however, failed for the spring season and other water quality parameters because of high semivariance at shorter lag distances that resulted from the strong differences in water chemistry, especially conductivity, between some small mined and forested tributaries. *Likens and Buso* [2006] found similar tributary effects downstream of human disturbances on the lower Hubbard Brook mainstem. Other researchers have also noted potential non-stationarity when applying geostatistics to data from stream networks [e.g., *Ganio et al*., 2005] and have discussed alternative distance measures and weighting factors that may better address the issue [e.g., *Gardner et al*., 2003; *Peterson et al*., 2006; *Peterson et al.*, 2007; *Ver Hoef et al*., 2006].

4.3 Predictive Modeling

As a result of non-stationarity and confluence effects, we developed a post-hoc deterministic model that used only a single weighting factor, watershed area, along with water chemistry values from only stream confluences. Errors associated with model predictions were small relative to observed range of values in the BC watershed. Furthermore, the model showed strong predictive ability for watersheds in two adjacent states. The TMC and BC watersheds are located within the same ecoregion and have been subject to similar disturbances from mountaintop removal mining and valley filling and gas well drilling. The glaciated LMR watershed in southern OH, however, has very different geologic and topographic features compared to the Central Appalachian BC and TMC watersheds and has been subject to heavy suburban development. Yet the model again showed strong predictive ability for conductivity, pH, and temperature in this watershed, indicating model predictions are robust across varying geographic areas and disturbance types. Though the confluence measurements used in the model were collected in the near vicinity (~ 100 m) of tributary junctions, the downstream predictive ability is not diminished because mainstem conductivity changed little between tributary junctions in the BC watershed (see Figures 3 and 7). Some watersheds however, may have greater groundwater influx that would contribute to model error.

Conductivity had the largest error of the three parameters modeled, due largely to the extensive range of observed values at tributary junctions. There was no apparent trend in direction of conductivity error, either high or low, among predicted values. Error tended to be greater for mined confluences where conductivity measures were >1,000 μS cm^{-1}, or >10X higher than that of adjacent forested tributaries. For the mined tributaries, error in the discharge to watershed area relationship may also have contributed to error in predicted conductivity values. Stream discharge is highly correlated with watershed area [e.g., *Gordon et al*., 1995], however during mountaintop removal mining the landscape and topography are so drastically altered that contributing areas often change and are difficult to delineate. Watershed areas used in our model were based on pre-mine topographic coverages because the disturbance was relatively recent (<10 years old) and updated maps were unavailable. The hydrologic effects of the fills themselves and associated sediment ponds may also have contributed to model errors. Hydrologic studies by the U.S. Geological Survey have shown that valley-filled streams have higher flows when compared to unmined streams in West Virginia [*Messinger and Paybins*, 2003; *Wiley et al*., 2001]. The greater discharge from filled streams has been attributed to reduced evapotranspiration due to loss of vegetation and soils during mining [*Messinger and Paybins*, 2003]. These findings were supported by our observations during the summer dry period in BC, when many forested tributaries were dry, or nearly so, yet valley filled streams of similar size often continued to flow. Given the difficulty in delineating source areas and potential fill effects on hydrology, use of an alternative weighting factor, such as mean annual discharge, would likely reduce model error. These small streams are rarely gauged however, so reliable discharge data are typically unavailable.

4.4 Applications

The value of our deterministic model is in its simplicity and potential ease of use for regulatory agents. The model requires no special software or programming skills, yet can be easily used to estimate potential downstream impacts of disturbance from a proposed permit action. For example, regulators of CWA §401 & 404 (i.e., “dredge and fill" activities) could use the model to evaluate valley fill permit applications based on the potential increase in conductivity and potential degradation of aquatic life downstream of proposed permit locations. This would only require a conservative estimate of the conductivity increase associated with a proposed valley fill, information that could be easily gathered from similar existing fills in the watershed or ecoregion or use of existing data sources. In this manner, the effects of elevated TDS (i.e., conductivity) from a single valley fill at the head of a watershed, or cumulative effects of multiple fills within a watershed, could be conservatively estimated several kilometers downstream without need for extensive data collection or modeling efforts. Conductivity measures are easily collected *in situ* with affordable sondes or multi-probes and data from the streams where impacts are proposed and the surrounding watersheds could potentially be required along with CWA §401/404 permit applications.

As an example of how the predictive model could be used by regulators, we modeled downstream effects on stream conductivity if valley fills were proposed for the undisturbed Clemons Fork watershed within RF (Figure 9). For simplicity, we assumed placement of a valley fill would increase conductivity to 2,000 $\mu S\ cm^{-1}$ (the approximate annual mean of actual filled streams in the greater BC watershed) immediately downstream of hypothetical fills. Observed springtime baseflow conductivity values were used elsewhere for "non-filled" tributary streams. We modeled placement of 1-4 fills separately to evaluate potential cumulative effects. Results indicated that, with placement of a single fill, conductivity of the immediate receiving streams were elevated to >500 $\mu S\ cm^{-1}$, but the majority of the CF watershed remained safely below this threshold (Figure 9a). Placement of a second fill, however, elevated conductivity such that the majority of the CF mainstem was near or above 500 μS cm^{-1}. With addition of a 3^{rd} and 4^{th} fill, conductivity of the entire CF mainstem increased to >700 μS cm^{-1} and actually increased conductivity of the larger receiving stream, BC, as well (Figure 9c and 9d).

Given the documented accumulation of ions downstream and resulting adverse biological effects, valley filled headwater streams may have a detrimental cumulative downstream effect that outweighs their individual size and relative discharge regime. The conservative nature of the dissolved ions downstream of fills and absence of appropriate and viable treatment technologies suggests that the only way to mitigate for elevated conductivity may be dilution from undisturbed forested tributaries. The importance of dilution was evident in our hypothetical CF example, where placement of a single fill had relatively small effects compared to those of multiple fills. The effect of dilution, and the absence thereof, is also evidenced by the difference in conductivity of the Buckhorn mainstem between seasons. During the spring wet period, forested tributaries effectively reduced mainstem conductivity such that BC conductivity near the mouth was 838 μS cm^{-1}, whereas in summer when most forested headwater streams were dry, conductivity at the BC mouth was ca. 2510 μS cm^{-1}.

Regulatory agencies may therefore need to implement a watershed based management strategy that would preserve forested streams within mined watersheds to provide appropriate dilution and prevent downstream degradation of aquatic ecosystems. Such a holistic approach to CWA §401 and §404 permitting is one option for mitigating potential cumulative effects of increased ion loads downstream of valley fills. Our deterministic model is one tool that could be used to estimate dilution provided from forested watersheds to reach a targeted conductivity range that is protective of aquatic life. Elevated TDS that result from valley fillings is however, only one potential adverse impact and should be considered in concert with other environmental, human health, and socioeconomic factors.

5. Conclusion

In the future, the deterministic model will continue to be tested across other geographic areas and disturbance types. Furthermore, additional water chemistry parameters such as nitrate, ammonia, or orthophosphate may be used for testing model predictions at stream confluences. However, model error may be greater for these nutrients because they are more bioreactive than the more conserved physiochemical parameters used here. *Dent and Grimm* [1999] however, successfully modeled spatial dependence of nutrient concentrations in a desert stream over a 3 km lag distance using semivariograms. *Strager et al.* [2009] also used a spatially explicit, GIS-based watershed model to evaluate downstream effects of acid mine drainage in West Virginia. This demonstrates that no single geostatistical or modeling approach may accurately characterize downstream influence for all variables or stressors at all spatial scales within stream networks. Use of such methods, however, requires that investigators expand beyond the stream reach spatial scales commonly used in lotic research. Choice of the best modeling approach can also provide unique insight into underlying spatial scale variation and ecological processes operating in the watershed. Others have studied spatial variation in streamwater chemistry [e.g., *Dent and Grimm* 1999; *Likens and Buso*, 2006] and have noted the need for understanding ecological patterns at these larger spatial scales when assessing anthropogenic impacts [*Likens and Buso*, 2006]. Though "significant nexus" was not clearly defined in *Rapanos and Carabell v. United States* [2006], if use of quantitative tools such as those presented here demonstrate spatial dependence or substantial influence on downstream water quality, this would likely constitute a "nexus" and therefore meet the intended criterion.

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Table 1. Summary statistics for water chemistry parameters from the Buckhorn Creek, KY watershed in a) spring (May 2006, n = 494) and b) summer (Sept. 2005, n = 239). RF = Robinson Forest (unmined), BC = remainder of Buckhorn watershed (partially mined).

a)	**RF (n = 245)**				**BC (n = 249)**			
Parameter	*Min.*	*Max.*	*Median*	*Range*	*Min.*	*Max.*	*Median*	*Range*
Conductivity (μS cm^{-1})	34	782	50	748	32	3190	871	3158
Temperature (°C)	11.37	18.56	14.33	7.19	12.04	25.74	16.69	13.7
pH (su)	5.13	7.96	6.46	2.83	3.25	8.71	7.28	5.46
D.O. (mg/l)	5.79	11.27	9.52	5.48	5.05	14.11	9.65	9.06

b)	**RF (n = 110)**				**BC (n = 129)**			
Parameter	*Min.*	*Max.*	*Median*	*Range*	*Min.*	*Max.*	*Median*	*Range*
Conductivity (μS cm^{-1})	20	212	86	192	93	11810	2330	11717
Temperature (°C)	14.53	25.02	18.44	10.49	15.70	25.55	19.66	9.85
pH (su)	5.78	8.15	6.72	2.37	5.05	8.34	7.35	3.29
D.O. (mg/l)	7.35	13.40	5.50	11.40	3.00	11.71	8.00	8.71

Table 2. Root mean square error (RMSE) and mean absolute error (MAE) for predictive model results from the Buckhorn Creek, KY watershed, combined data from spring (May 2006) and summer (Sept. 2005).

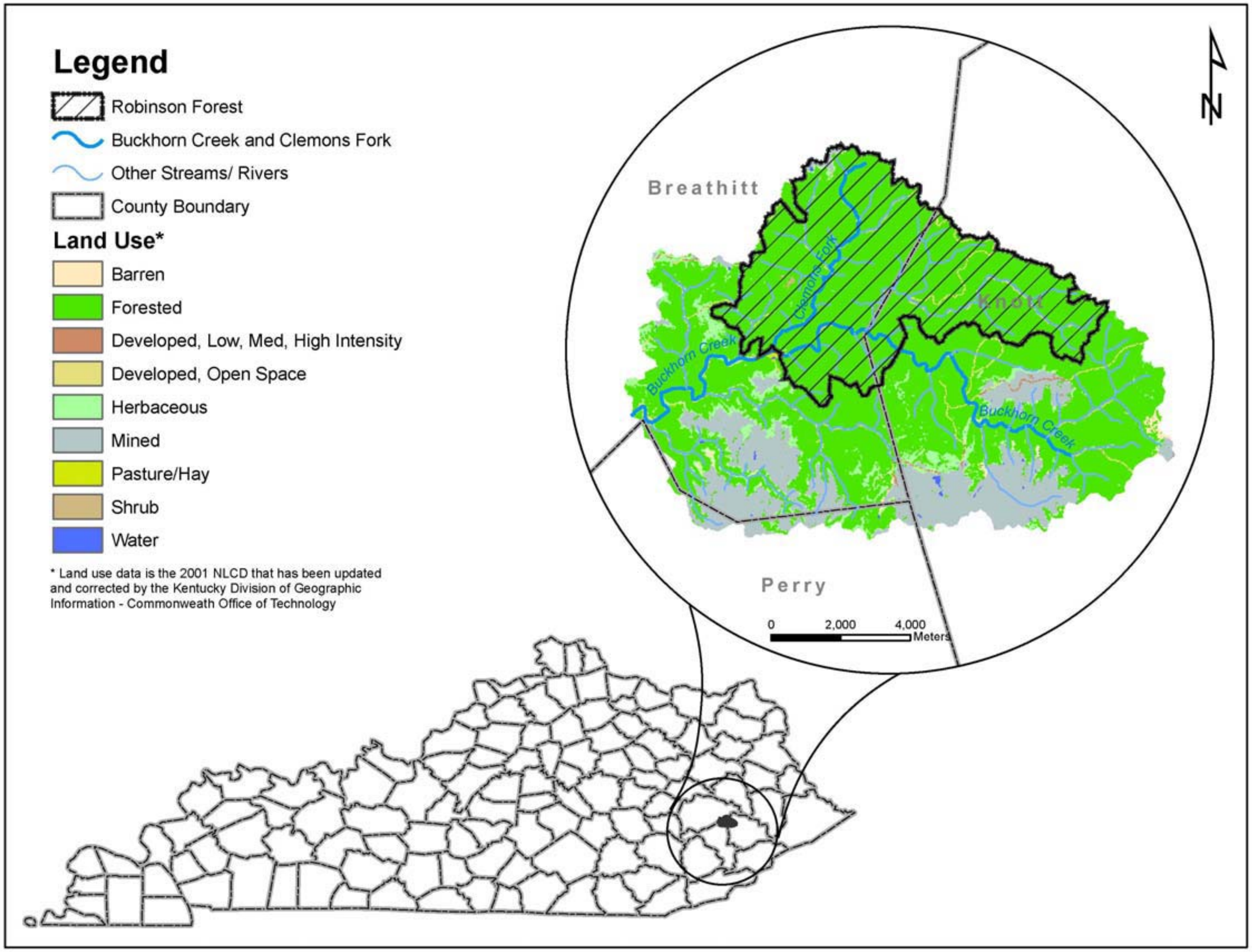
	Summer		**Spring**	
Parameter	***RMSE***	***MAE***	***RMSE***	***MAE***
Conductivity ($\mu S\ cm^{-1}$)	267.05	158.18	74.62	34.56
pH	0.28	0.18	0.33	0.18
Temperature (°C)	1.03	0.68	0.63	0.43

Table 3. Summary water chemistry for observed values and predictive model error (RMSE = root mean square error & MAE = mean absolute error) for Little Miami River (LMR)(Clermont Co., OH; Sept. 2006, n = 118 sites) and Twentymile Creek (TMC)(Nicholas Co, WV; May 2007, n = 51 sites).

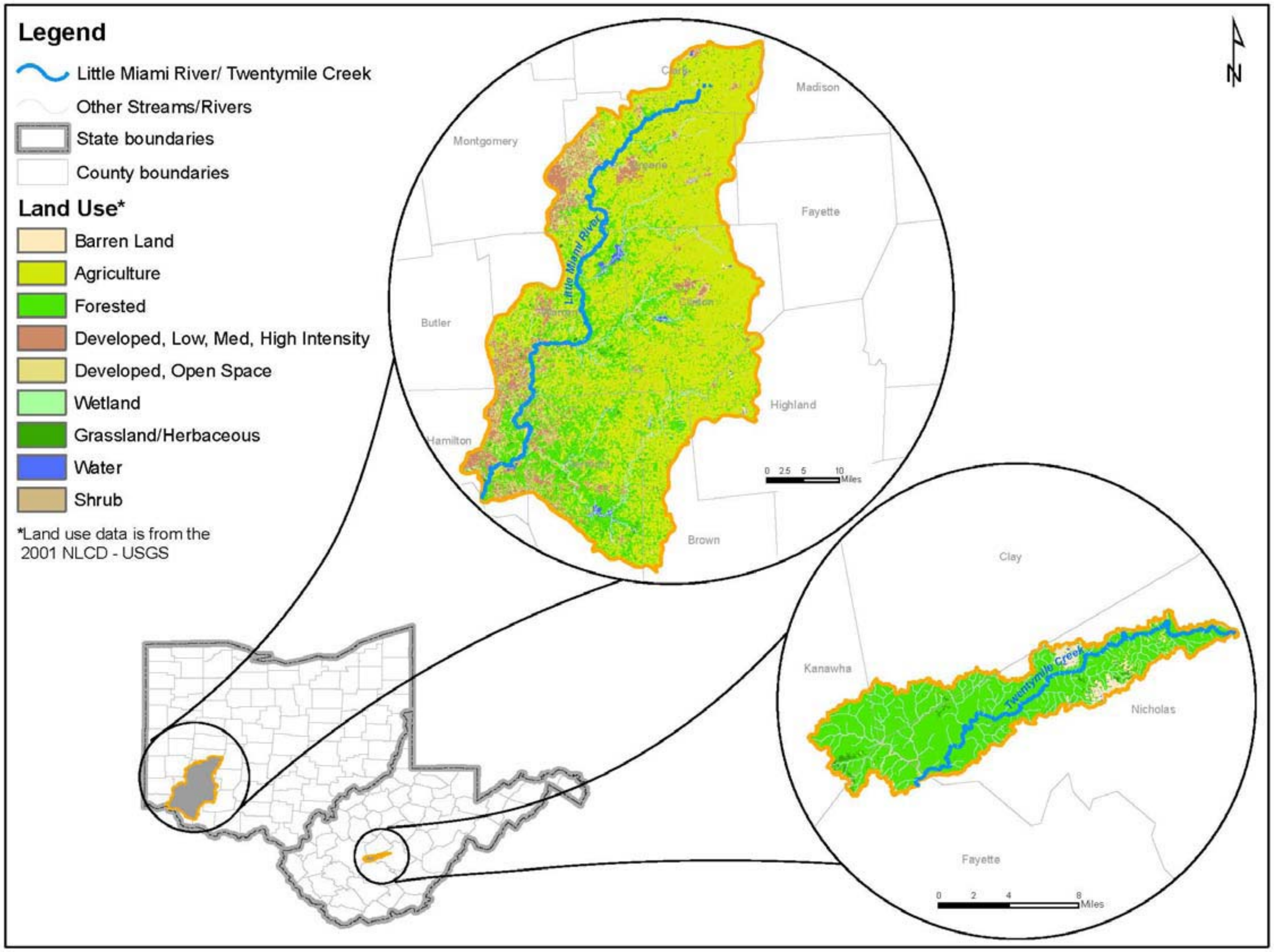
	LMR			**TMC**		
	Cond. (µS cm^{-1})	Temp. (°C)	pH	Cond. (µS cm^{-1})	Temp. (°C)	pH
Min.	86	18.18	6.98	37	13.34	4.91
Max.	667	23.54	8.81	3970	21.35	8.5
Median	312	20.14	7.71	1483	18.05	7.73
Range	581	5.36	1.83	3933	8.01	3.59
RMSE	37.67	0.45	0.17	188.46	0.42	0.29
MAE	21.79	0.27	0.11	98.20	0.25	0.19

LIST OF FIGURES

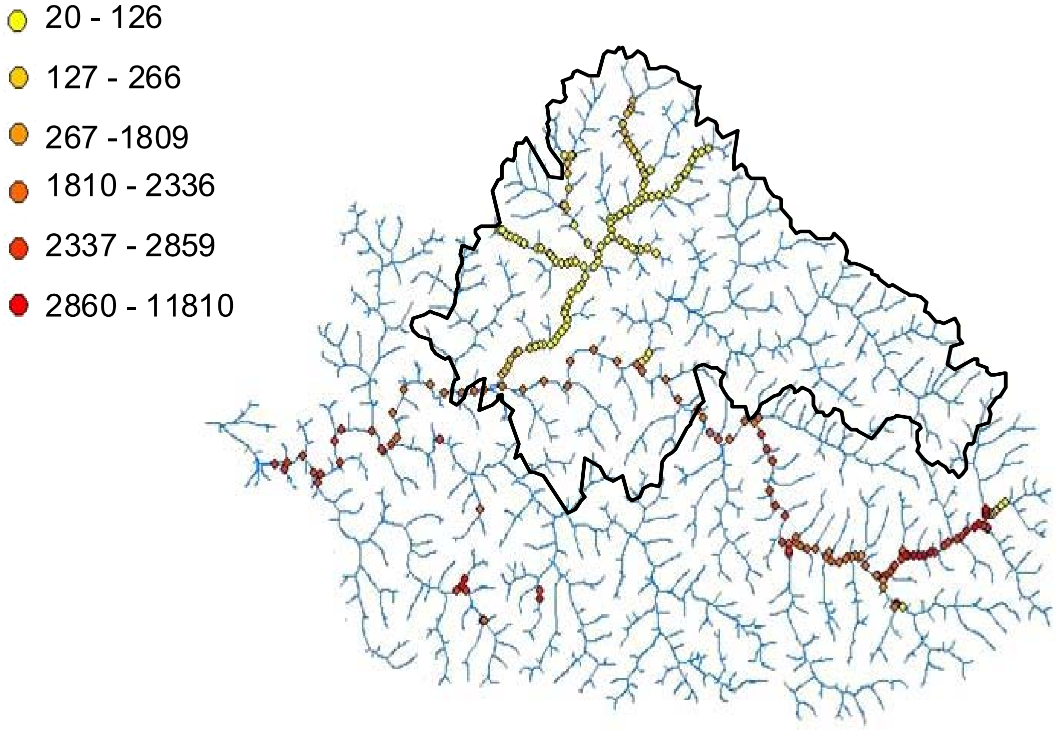
Figure 9. Predicted conductivity values ($\mu S\ cm^{-1}$) downstream of confluences in the forested Clemons Fork Watershed, Robinson Forest, KY, with hypothetical valley filling of one (a), two (b), three (c), and four (d) headwater stream tributaries.


Legend
Robinson Forest
Buckhorn Creek and Clemons Fork
Other Streams/ Rivers
County Boundary
Land Use*
Barren
Forested
Developed, Low, Med, High Intensity
Developed, Open Space
Herbaceous
Mined
Pasture/Hay
Shrub
Water
* Land use data is the 2001 NLCD that has been updated and corrected by the Kentucky Division of Geographic Information - Commonweath Office of Technology
Breathitt
Knott
Perry
Clemons Fork
Buckhorn Creek
Buckhorn Creek
0
2,000
4,000
Meters
N

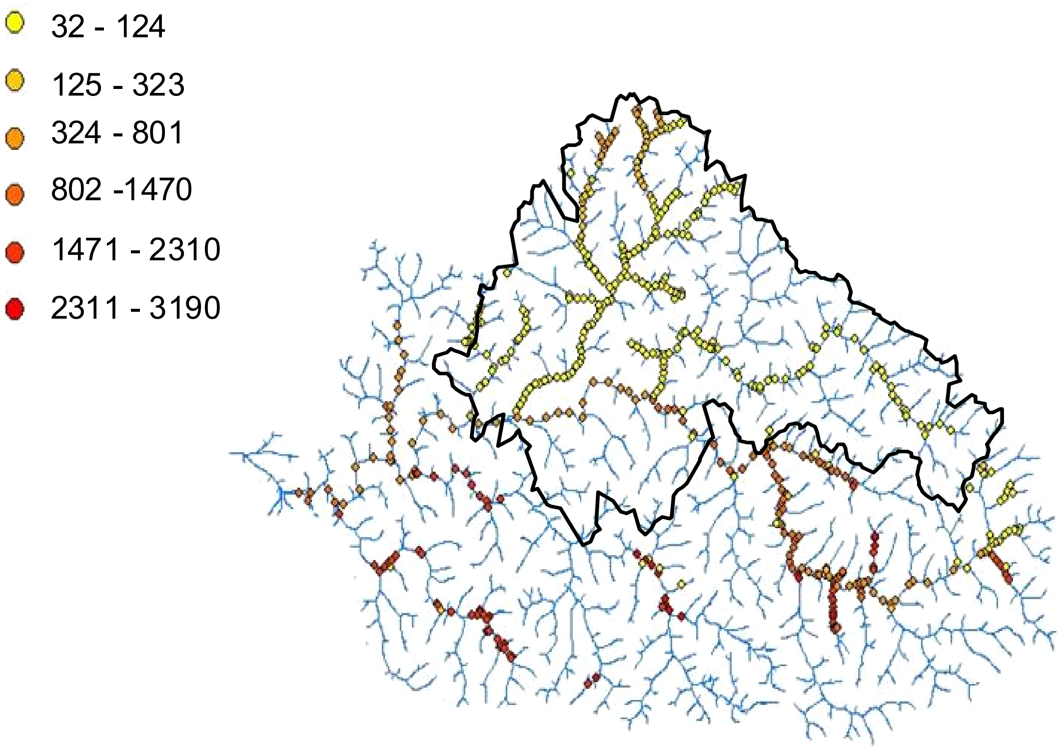
744


Legend
Little Miami River/ Twentymile Creek
Other Streams/Rivers
State boundaries
County boundaries
Land Use*
Barren Land
Agriculture
Forested
Developed, Low, Med, High Intensity
Developed, Open Space
Wetland
Grassland/Herbaceous
Water
Shrub
*Land use data is from the
2001 NLCD - USGS
N
Montgomery
Madison
Fayette
Butler
Highland
Hamilton
Brown
Little Miami River
0 2.5 5 10 Miles
Clay
Kanawha
Nicholas
Fayette
Twentymile Creek
0 2 4 8 Miles

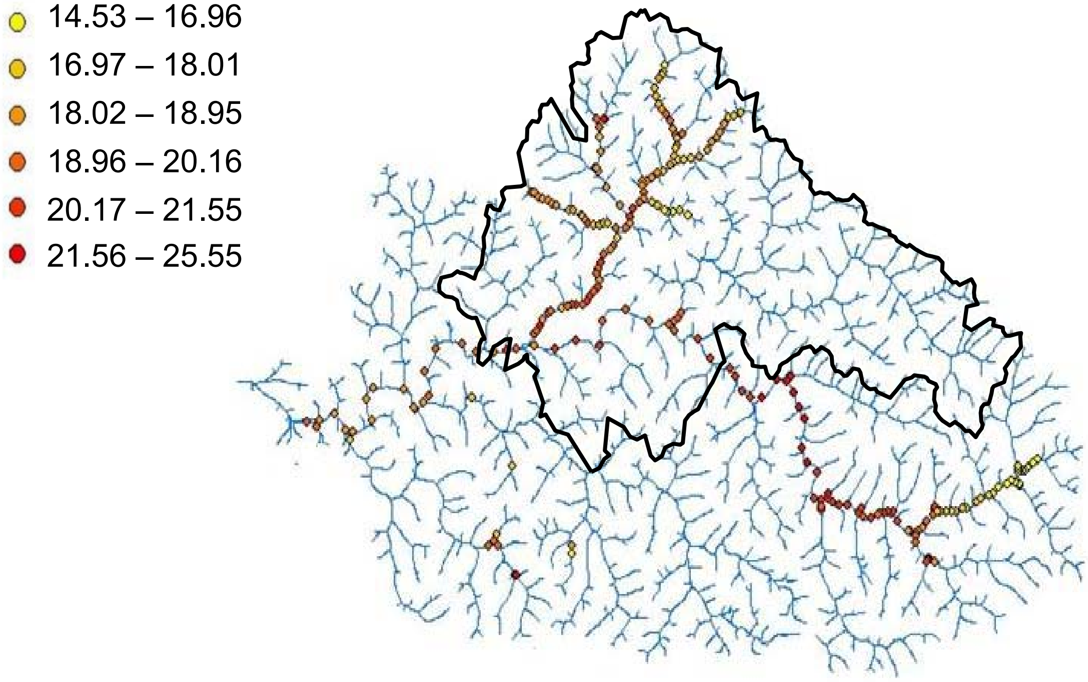
A)


20 - 126
127 - 266
267 -1809
1810 - 2336
2337 - 2859
2860 - 11810

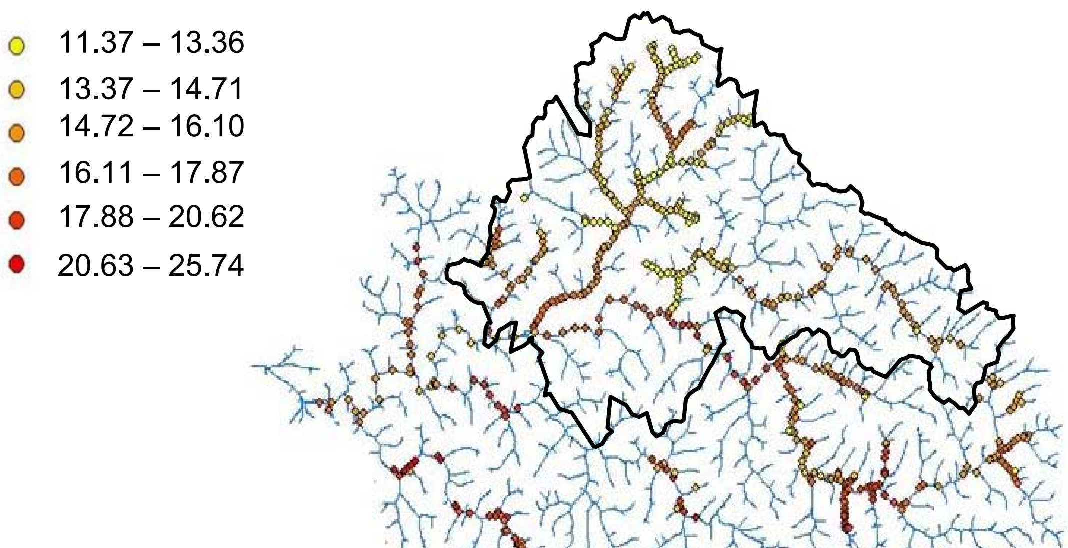
B)


32 - 124
125 - 323
324 - 801
802 -1470
1471 - 2310
2311 - 3190

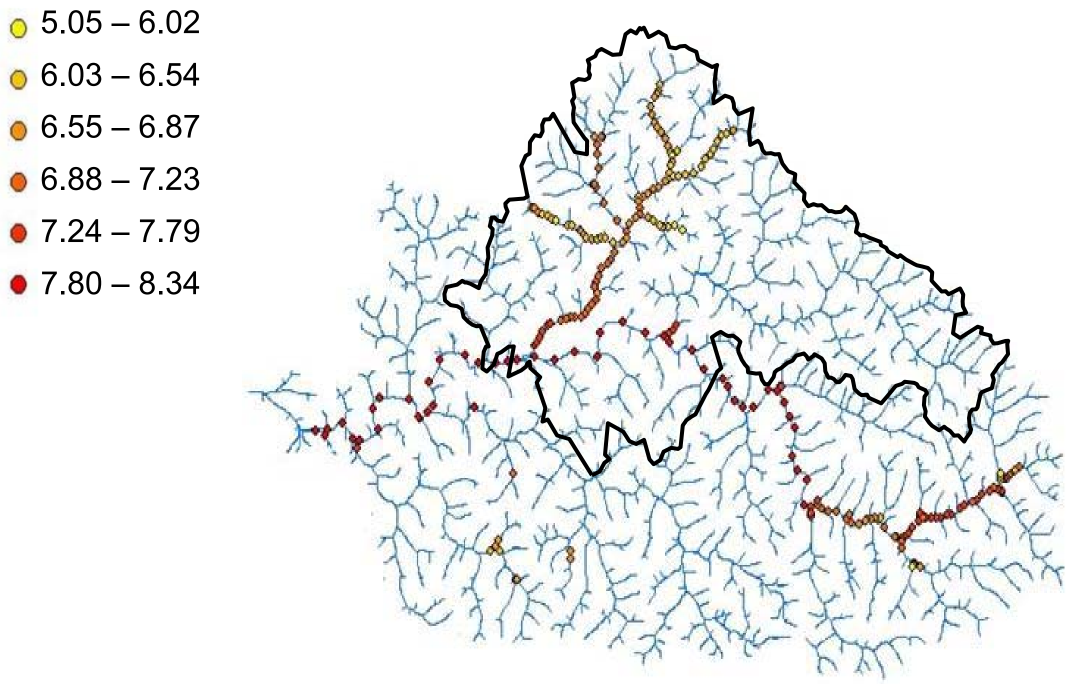
A)


14.53 – 16.96
16.97 – 18.01
18.02 – 18.95
18.96 – 20.16
20.17 – 21.55
21.56 – 25.55

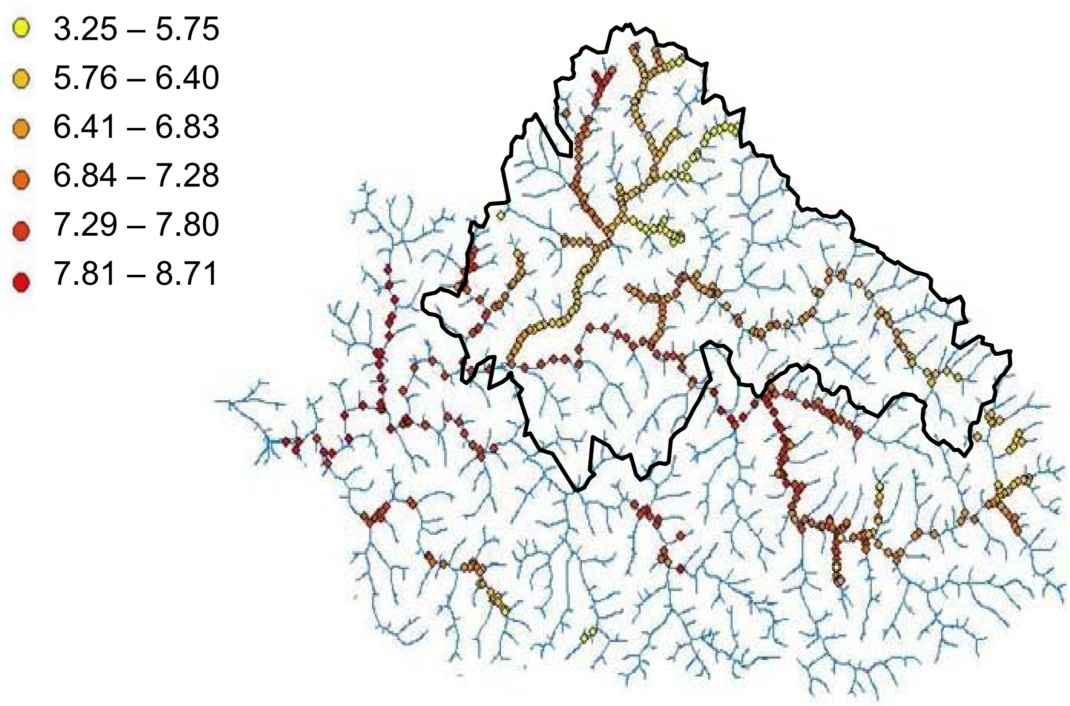
B)

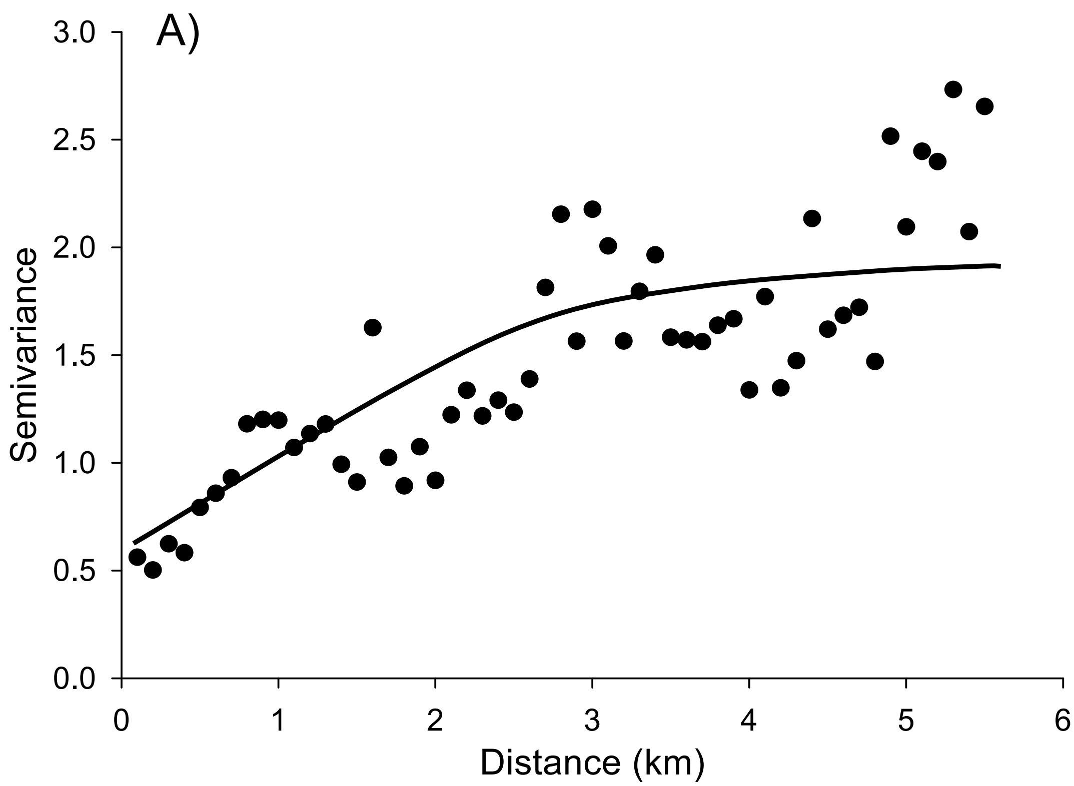

11.37 – 13.36
13.37 – 14.71
14.72 – 16.10
16.11 – 17.87
17.88 – 20.62
20.63 – 25.74

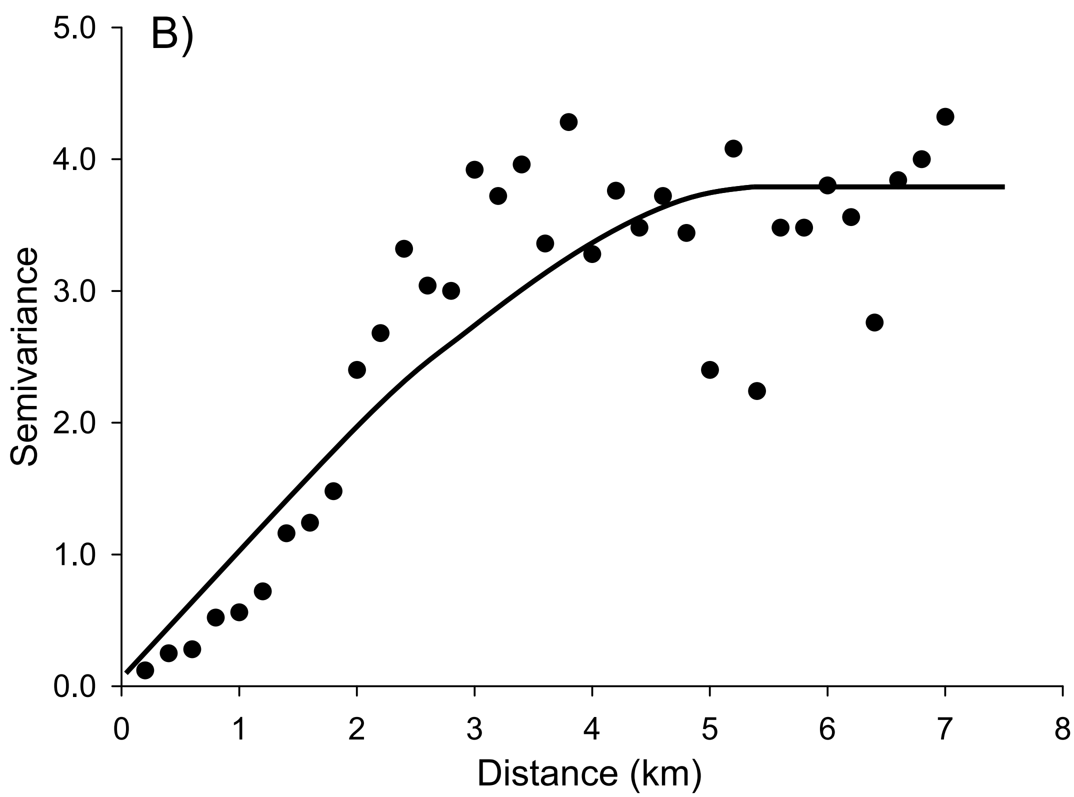
A)

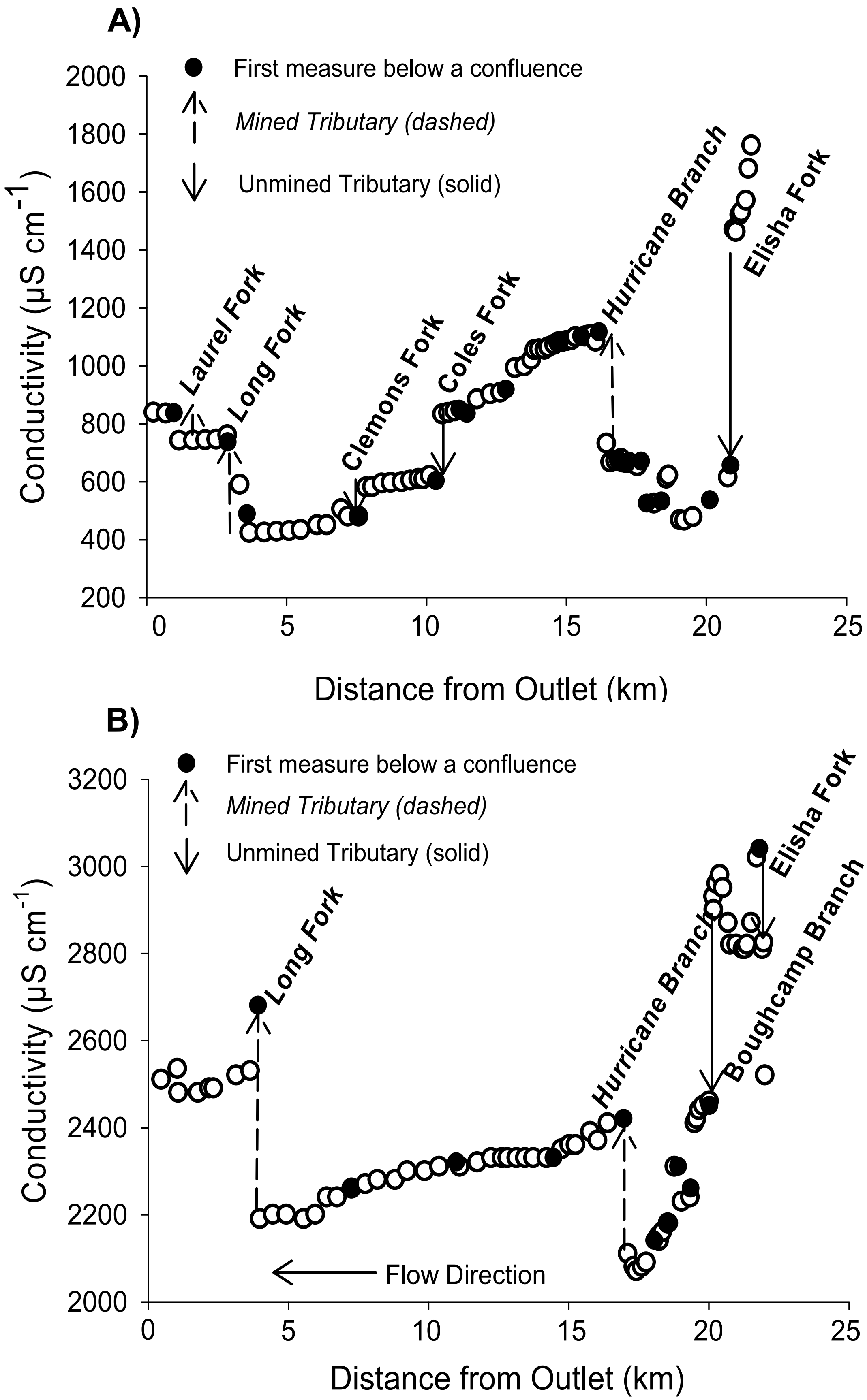

5.05 – 6.02
6.03 – 6.54
6.55 – 6.87
6.88 – 7.23
7.24 – 7.79
7.80 – 8.34

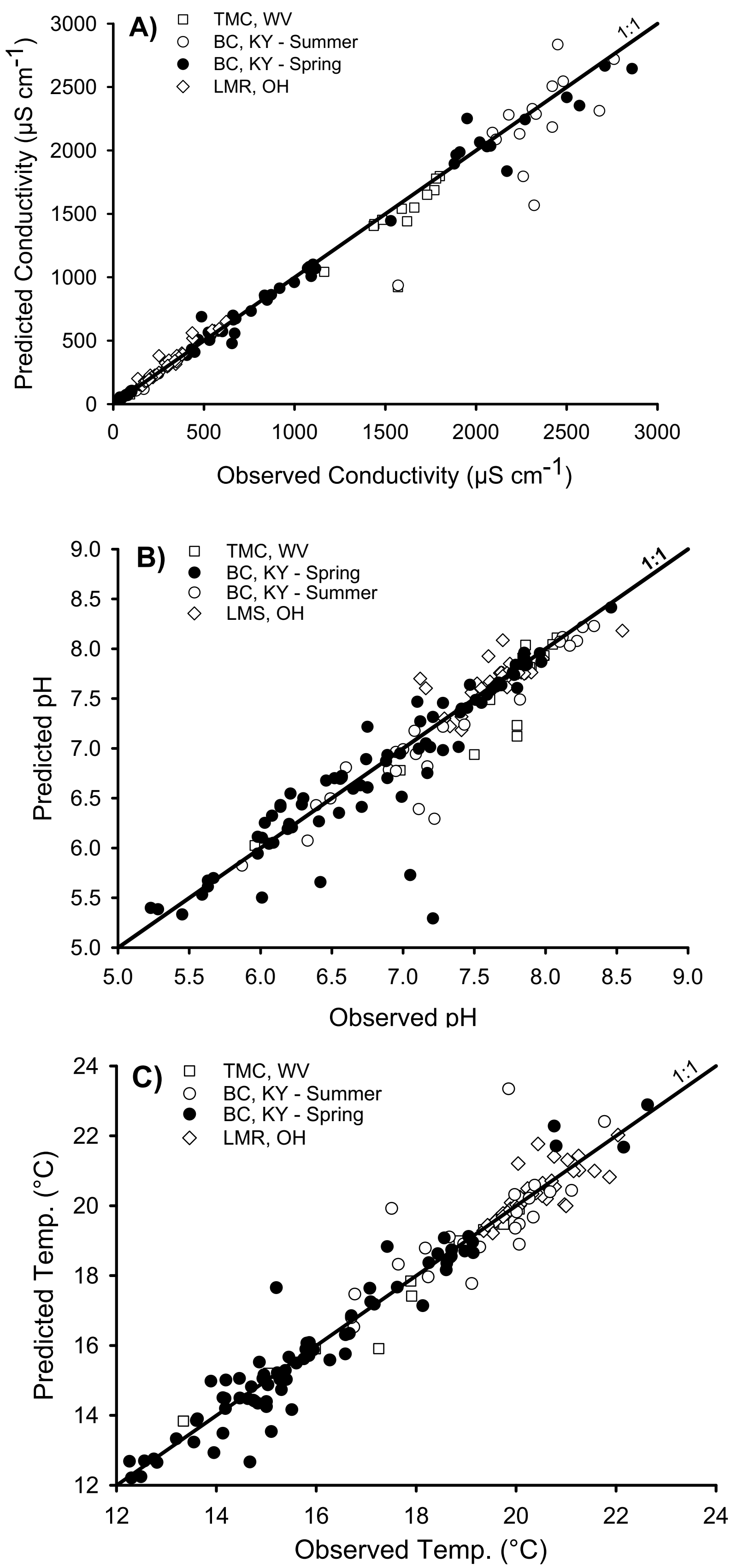
B)

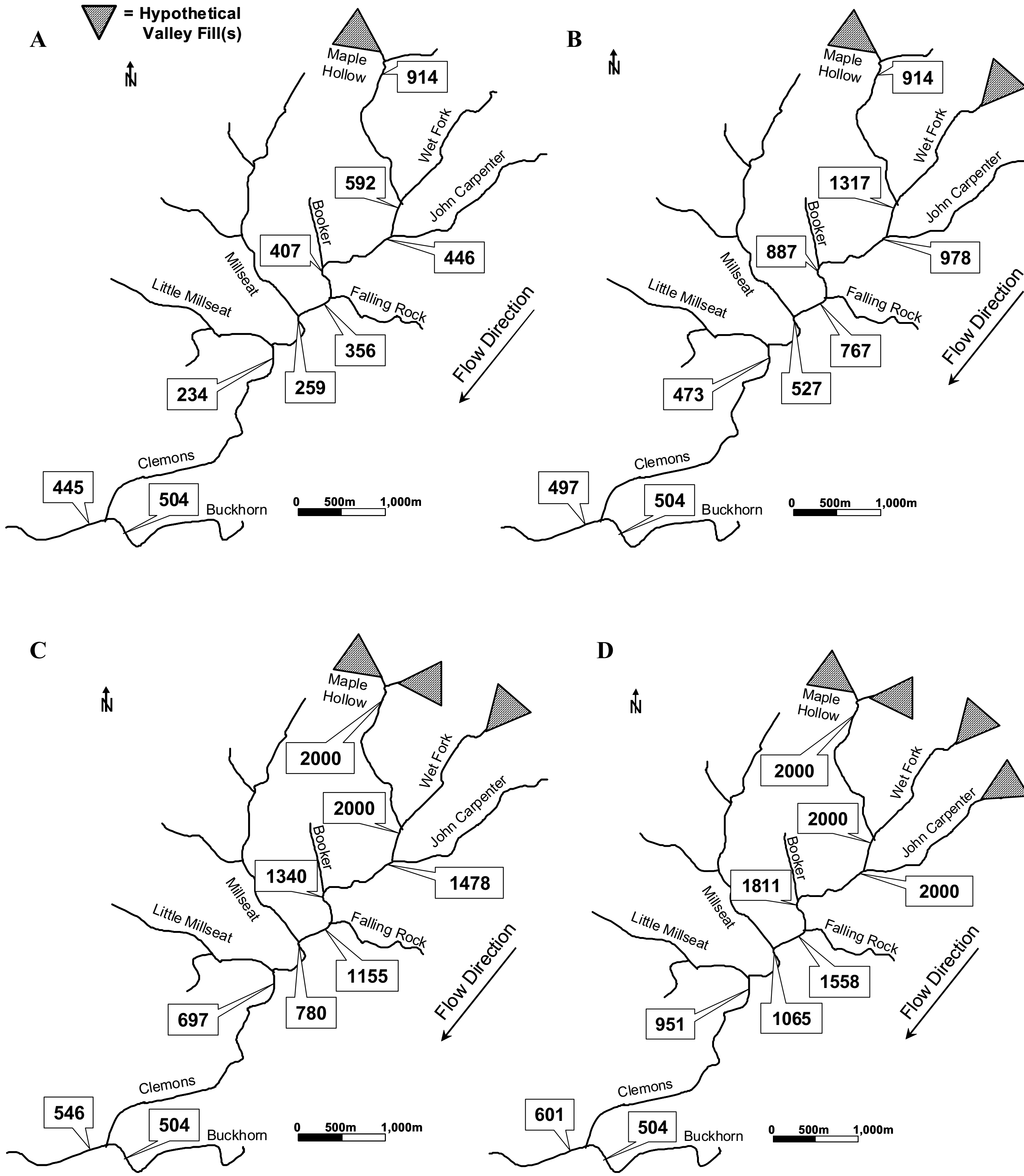

3.25 – 5.75
5.76 – 6.40
6.41 – 6.83
6.84 – 7.28
7.29 – 7.80
7.81 – 8.71


A)
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Semivariance
0
1
2
3
4
5
6
Distance (km)


B)
5.0
4.0
3.0
2.0
1.0
0.0
Semivariance
0
1
2
3
4
5
6
7
8
Distance (km)


A)
First measure below a confluence
Mined Tributary (dashed)
Unmined Tributary (solid)
Laurel Fork
Long Fork
Clemons Fork
Coles Fork
Hurricane Branch
Elisha Fork
Conductivity (µS cm-1)
2000
1800
1600
1400
1200
1000
800
600
400
200
0
5
10
15
20
25
Distance from Outlet (km)
B)
First measure below a confluence
Mined Tributary (dashed)
Unmined Tributary (solid)
Long Fork
Hurricane Branch
Elisha Fork
Boughcamp Branch
Flow Direction
Conductivity (µS cm-1)
3200
3000
2800
2600
2400
2200
2000
0
5
10
15
20
25
Distance from Outlet (km)


A)
TMC, WV
BC, KY - Summer
BC, KY - Spring
LMR, OH
1:1
Predicted Conductivity (µS cm-1)
Observed Conductivity (µS cm-1)
B)
TMC, WV
BC, KY - Spring
BC, KY - Summer
LMS, OH
1:1
Predicted pH
Observed pH
C)
TMC, WV
BC, KY - Summer
BC, KY - Spring
LMR, OH
1:1
Predicted Temp. (°C)
Observed Temp. (°C)


= Hypothetical Valley Fill(s)
A
Maple Hollow
914
Wet Fork
592
John Carpenter
Booker
407
446
Millseat
Little Millseat
Falling Rock
356
234
259
Flow Direction
Clemons
445
504
Buckhorn
0 500m 1,000m
B
Maple Hollow
914
Wet Fork
1317
John Carpenter
Booker
887
978
Millseat
Little Millseat
Falling Rock
767
473
527
Flow Direction
Clemons
497
504
Buckhorn
0 500m 1,000m
C
Maple Hollow
2000
Wet Fork
2000
John Carpenter
Booker
1340
1478
Millseat
Little Millseat
Falling Rock
1155
697
780
Flow Direction
Clemons
546
504
Buckhorn
0 500m 1,000m
D
Maple Hollow
2000
Wet Fork
2000
John Carpenter
Booker
1811
2000
Millseat
Little Millseat
Falling Rock
1558
951
1065
Flow Direction
Clemons
601
504
Buckhorn
0 500m 1,000m