JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION
Vol. 49, No. 2
AMERICAN WATER RESOURCES ASSOCIATION
April 2013

ASSESSING LINKAGES IN STREAM HABITAT, GEOMORPHIC CONDITION, AND BIOLOGICAL INTEGRITY USING A GENERALIZED REGRESSION NEURAL NETWORK[1]

Bree R. Mathon, Donna M. Rizzo, Michael Kline, Gretchen Alexander, Steve Fiske, Richard Langdon, and Lori Stevens[2]

ABSTRACT: Watershed managers often use physical geomorphic and habitat assessments in making decisions about the biological integrity of a stream, and to reduce the cost and time for identifying stream stressors and developing mitigation strategies. Such analysis is difficult since the complex linkages between reach-scale geomorphic and habitat conditions, and biological integrity are not fully understood. We evaluate the effectiveness of a generalized regression neural network (GRNN) to predict biological integrity using physical (i.e., geomorphic and habitat) stream-reach assessment data. The method is first tested using geomorphic assessments to predict habitat condition for 1,292 stream reaches from the Vermont Agency of Natural Resources. The GRNN methodology outperforms linear regression (69% *vs*. 40% classified correctly) and improves slightly (70% correct) with additional data on channel evolution. Analysis of a subset of the reaches where physical assessments are used to predict biological integrity shows no significant linear correlation, however the GRNN predicted 48% of the fish health data and 23% of macroinvertebrate health. Although the GRNN is superior to linear regression, these results show linking physical and biological health remains challenging. Reasons for lack of agreement, including spatial and temporal scale differences, are discussed. We show the GRNN to be a data-driven tool that can assist watershed managers with large quantities of complex, nonlinear data.

(KEY TERMS: geomorphology; watershed management; artificial neural networks; generalized regression; computational methods; stream habitat.)

Mathon, Bree R., Donna M. Rizzo, Michael Kline, Gretchen Alexander, Steve Fiske, Richard Langdon, and Lori Stevens, 2013. Assessing Linkages in Stream Habitat, Geomorphic Condition, and Biological Integrity Using a Generalized Regression Neural Network. *Journal of the American Water Resources Association* (JAWRA) 49(2):415-430. DOI: 10.1111/jawr.12030

INTRODUCTION

According to a U.S. Environmental Protection Agency (USEPA) (2006) study, nearly half (42%) of the nation's stream lengths are in poor biological condition. Reach-scale geomorphic and physical habitat assessment data are increasingly used to identify streams with a high environmental risk and fluvial hazard (Kline and Cahoon, 2010). These reach-scale metrics, in combination with fish and macroinvertebrate biodiversity and abundance indices, are essential for a

[1]Paper No. JAWRA-12-0191-P of the *Journal of the American Water Resources Association* (JAWRA). Received August 20, 2012; accepted November 5, 2012. **Discussions are open until six months from print publication.**

[2]Respectively, Graduate Student (Mathon) and Associate Professor (Rizzo), School of Engineering, University of Vermont, 33 Colchester Avenue, Burlington, Vermont 05405; State Rivers Program Manager (Kline), River Scientist (Alexander), Aquatic Biologist (Fiske, Langdon), Vermont Agency of Natural Resources, Waterbury, Vermont 05671; and Professor (Stevens), Department of Biology, University of Vermont, Burlington, Vermont 05405 (E-Mail/ Mathon: bree.mathon@gmail.com).

proactive adaptive watershed management approach and for prioritizing mitigation strategies to help reverse the impacts of human activities. Such efforts require environmental managers to assess various forms of information — quantitative, qualitative, and subjective, collected at a variety of spatial (e.g., reach and sub-reach) and temporal scales. Since physical stream processes form the habitat, habitat assessments address the physical parameters needed to understand the relationship between fluvial processes and aquatic communities (Schiff *et al.*, 2008). However, while physical geomorphic characteristics and conditions suggest strong linkages to ecosystem integrity (Lammert and Allan, 1999; Roy *et al.*, 2003; Brierley and Fryirs, 2005; Chessman *et al.*, 2006), the nonlinear relationships between physical geomorphic condition, aquatic habitat, and biological integrity are complex and poorly understood (Sweeney *et al.*, 2004; Lepori *et al.*, 2005; Chessman *et al.*, 2006). From a management viewpoint, these geomorphic and habitat assessments, taken together, may be used to identify potential physical habitat problem areas and the steps necessary for mitigation (Kline, 2007) to improve or maintain the biological integrity of the reach.

Habitat is linked to geomorphology and fluvial processes (channel hydraulics, sediment transport) of a stream reach, which are ultimately controlled by watershed hydrology and erosional processes (Buffington and Goode, 2010). Matching these physical conditions to the biology present in the stream has proven to be challenging. Some of these challenges result from the fact that biological assessments have been developed with different monitoring objectives (e.g., evaluating the impact of polluting discharges) than fluvial geomorphic and habitat assessments (i.e., looking at departures in physical processes). Another challenge is that the temporal and spatial scale at which the physical habitat and geomorphic conditions are measured may not match the scale of the water quality data and/or detailed biological indices (i.e., indices of fish and macroinvertebrate community integrity).

Our overall goal is to introduce a methodology that helps mine large nonlinear datasets to improve integrated assessments. The USEPA's Healthy Watershed concept views watersheds as integrated systems that can be understood through the dynamics of a variety of spatially and temporally collected data (EPA, 2012). The USEPA as well as the State of Vermont advocate for developing GIS-based "frameworks for assessing and reporting on ecological condition." In this work, we use a least-squares generalized regression neural network (GRNN) (Specht, 1991) to examine nonlinear linkages between the physical habitat, geomorphic condition, and the biological integrity to assist watershed managers in making informed decisions about where to focus their limited resources. We believe data-driven approaches (such as the GRNN) are ideal for integrated assessments of dynamic systems.

The GRNN, in particular, is powerful because it is a least-squares regression methodology familiar to scientists and engineers for approximating complex, nonlinear relationships. However, unlike traditional regression, the best-fit polynomial (e.g., linear, quadratic, cubic) does not need to be known prior to data analysis. In addition, the data-driven nature of the algorithm enables continual updates and large quantities of data to be reanalyzed as understanding/condition of fluvial geomorphology evolves. The GRNN algorithm can learn directly from the data without human intervention (i.e., it is a statistical model driven by data, not a physics-based model), enabling a more adaptive management approach.

BACKGROUND

Over the past two centuries, human impact (e.g., deforestation, channel straightening, urbanization) has greatly altered Vermont streams from their original physical condition (Vermont River Management Program, 2009). The Vermont Agency of Natural Resources (VTANR) River Management Program has developed and adopted protocols for physical stream geomorphic (Kline *et al.*, 2007) and habitat assessments (Schiff *et al.*, 2008) throughout the state to document and better understand how these impacts affect stream conditions over time. There has been much controversy in adopting any one particular stream classification system. See, for example, discussions on the applicability of the Rosgen (1994; 1996) classification system for restoration projects (Juracek and Fitzpatrick, 2003; Smith and Prestegaard, 2005; Simon *et al.*, 2007; Roper *et al.*, 2008). The VTANR developed protocols to classify stream stability (Rapid Geomorphic Assessment — RGA) using a combination of stream classification systems by Rosgen (1994), Montgomery and Buffington (1997), Schumm (1977), Schumm *et al.* (1984), and Simon and Hupp (1986). These protocols were nationally recognized by the USEPA-COE sponsored study of the physical stream assessment methodologies for use in the Clean Water Act section 404 Program. The study found that the VTANR approach deserved the highest overall score of the 44 protocols examined nationwide. An important contribution of the VTANR stream classification system is the inclusion of stream sensitivity, defined as the likelihood of a stream responding, through lateral and/or vertical adjustment, to a watershed or local disturbance, caused by natural events or human activity. The sensitivity is a function of: (1) geomorphic condition and (2) the stream's inherent vulnerability to adjustment. Inherent vulnerability is the susceptibility of a reach to lateral and vertical adjustment as determined by the reach's inherent characteristics and boundary conditions including its geologic, vegetation, and valley dimension parameters. Therefore, a channel could be in dynamic equilibrium, however it may still be highly sensitive to adjustment due to its high inherent vulnerability (Besaw *et al.*, 2009b).

Stream physical habitat health (i.e., the ability of the stream's physical features to support aquatic life) protocols (Rapid Habitat Assessment — RHA), originally a modified version of the USEPA's Rapid Bioassessment Protocols, have been used in Vermont since 2002. Kline and Cahoon (2010) note that data from geomorphic and habitat assessments spanning a six-year period indicate that due to widespread incision, most streams lack access to floodplains during floods with 1- to 10-year recurrence. This has resulted in a tremendous increase in stream power and channel adjustment and erosion. These induced changes likely have altered the abundance and diversity of the natural biota (Allan, 2004).

Separate from the River Management Program's habitat assessments, the VTANR Biomonitoring and Aquatic Studies Section (BASS) assesses the health of biological communities in streams. The biological assessments are based on the Biological Condition Gradient (BCG) concept (Davies and Jackson, 2006) that describes how biological community structure and function respond to increased levels of stress. In Vermont, BASS developed a biological assessment methodology and biocriteria using empirical data involving multiple metrics that measure the fish and macroinvertebrate community level of departure from "reference" or least disturbed watersheds, resulting in an assessment rating along the BCG. These assessments then relate measured biological integrity to narrative language in the Vermont Water Quality Standards, to inform VTANR water quality planning and management activities (VTDEC, 2004).

Several studies demonstrate a relationship between stream geomorphic condition, physical habitat, and biological integrity (Sullivan *et al.*, 2004, 2006; Chessman *et al.*, 2006; Sullivan and Watzin, 2008). However, the complex linkages are not well understood, easily studied, or particularly strong, and include many factors such as variation in fish, macroinvertebrate, and bird species present, metrics used, and/or spatial and temporal measurement scales (Chessman *et al.*, 2006; Clark *et al.*, 2008).

Generalized Regression Neural Network

Artificial neural network (ANN) algorithms, in general, are used in pattern classification, pattern completion, function approximation, prediction, optimization, and system control applications among others (Wasserman, 1993). Although the most commonly used ANNs are either the feed-forward back-propagation network or the radial basis function neural network (Govindaraju and Ramachandra, 2000; Abdalla, 2010), we use the GRNN to explore linkages between geomorphic conditions, physical habitat, and biological integrity for reasons stated in the Introduction.

The GRNN has extensive applications in the water resources and hydrological fields. Several studies found the GRNN outperformed the feed-forward back-propagation network when forecasting intermittent (Cigizoglu, 2005a), monthly (Cigizoglu, 2005b; Kisi, 2008), or daily (Firat, 2008) streamflow and outperformed radial basis function and multiple linear regression when predicting rainfall runoff (Cigizoglu and Alp, 2004). Turan and Yurdusev (2009) predicted streamflow from measured upstream flow records, while Besaw *et al.* (2009a) used a recurrent GRNN to predict flow in ungauged streams. The GRNN has also been used to estimate daily mean sea level heights (Sertel *et al.*, 2008); to predict water quality as a function of rainfall, surface discharge, and nutrient concentration (Kim and Kim, 2007); and to model river sediment transport (Cigizoglu and Alp, 2006; Kisi *et al.*, 2008; Cobaner *et al.*, 2009; Wang *et al.*, 2009). To the best of our knowledge, this is the first application of the GRNN to explore the nonlinear relationships between the physical (geomorphic and habitat) conditions of a stream and its biological integrity.

STREAM ASSESSMENT DATA

The VTANR developed a three-phase system to perform stream geomorphic assessments. Each successive phase is more detailed and improves knowledge about the condition of the reach. The first phase, a remote sensing phase, uses data obtained from topographic maps, aerial photos, previous studies, and from very limited field studies. Phase 1 assessment is considered provisional, enabling large watersheds (100-150 square miles) to be assessed in a few months. Using Phase 1 assessments, ~35% or 8,279 of Vermont's ~23,000 stream miles have been assessed as of September 2009 (Kline and Cahoon, 2010).

Phase 2, or the rapid field assessment phase, includes the RGA and habitat assessment (RHA), where field data are collected by experts at the stream reach or sub-reach scale. A one-mile reach requires one to two days to assess; and to date, 6% or 1,371 stream miles (~2,500 stream reaches) have been assessed at the Phase 2 level (Kline and Cahoon, 2010). The geomorphic condition, physical habitat condition, adjustment processes, reach sensitivity, and channel evolution stage are determined from quantitative and qualitative field evaluation of erosion and depositional processes, changes in geometry, and riparian land use/land cover. Phase 2 assessments identify "at risk" reaches and allow reaches to be flagged for protection, restoration, or further Phase 3 assessment.

Phase 3, the survey-level field assessment phase, requires detailed field measurements at the sub-reach scale that allow for stream types; and adjustment processes to be further documented and confirmed. Quantitative measurements of channel dimension, pattern, profile, and sediments are measured during this level of assessment. Phase 3 assessments require three to four days on average to survey a sub-reach of two meander wavelengths; and approximately 60 Phase 3 studies have been conducted.

Data used in this study were obtained from Vermont Department of Environmental Conservation (DEC) and are available at https://anrnode.anr.state.vt.us/SGA/default.aspx. All Phase 2 assessments, quality assured by the River Management Program as of August 2009, that had RGA, RHA, and channel evolution stage data were selected resulting in 1,292 reaches (Figure 1).

Vermont Rapid Geomorphic Assessments

The assessed stream reach condition is based on its perceived departure from reference condition. Reference condition for each reach is inferred based on watershed zone, confinement, and valley slope from Phase 1, as well as entrenchment, width/depth ratio, sinuosity, channel slope, substrate d50, and bed form collected during the Phase 2 assessment (Kline *et al.*, 2007). Quantification of the adjustment processes involves an expert assigning a score between 0 (*poor*) and 20 (*reference*) for each of the four adjustment processes (degradation, aggradation, widening, and planform change) resulting in a summed total RGA score ranging from 0 to 80 (i.e., overall geomorphic condition of a particular stream reach); the latter is then classified by experts into one of four categories — *poor*, *fair*, *good*, or *reference* (Table 1).

Vermont Physical Habitat Assessments

Stream habitat assessments record physical features believed to be key in determining aquatic habitat and hence the biota that inhabit it. These data complement existing biological data and may indicate biotic health stressors in the reach where the biological data alone cannot explain the cause (Schiff *et al.*, 2008).

Vermont's RHAs are slightly modified versions of the USEPA's Rapid Bioassessment Protocols (Barbour *et al.*, 1999). The RHAs comprise 10 parameters that explore physical properties of the channel bed, bank, and riparian vegetation (Table 1). Each parameter is scored between 0 (*poor*) and 20 (*excellent*) by an expert and then summed to obtain a total score (no greater than 200) categorizing the reach as *poor*, *fair*, *good*, or *reference*. The histogram of RHA scores (Figure 1) for the 1,292 reaches used is normally distributed (Shapiro–Wilkes test, $W = 0.9976$, $p < 0.0579$), with the majority of the reach scores falling into *fair* or *good* habitat condition.

Biological Community Integrity

The biological integrity of Vermont streams and rivers is determined by VTANR protocols (VTDEC, 2004). Metric assessments of fish and macroinvertebrate assemblages are used to classify streams based on their departure from the reference condition, which varies with stream type. To define reference biological condition or integrity in the current biomonitoring protocol, VTANR biologists selected sites with macroinvertebrate and fish data from watersheds that appeared minimally impacted by human activity. These data were then used to determine biological stream type and associated numeric biological criteria for characterizing community integrity. The numeric criteria define the narrative criteria in the Vermont Water Quality Standards.

Both fish and macroinvertebrate community criteria quantify the five water management classes of the Vermont Water Quality Standards, Class A1: (Excellent) minimal impacts from human activity, Class B1: (Very Good) minor changes from reference, and Classes B2, B3, and A2: (Good) moderate change from reference condition. Classes A and B denote classifications from the Vermont Water Quality Standards and the numbers represent management types within those classes. Biological assessments of Fair and Poor do not meet any class standards. Metric values falling on the threshold are hyphenated (e.g., Excellent-Very Good, Very Good-Good, Good-Fair, and Fair-Poor).

VTDEC (2004) identified four categories of macroinvertebrate communities: Small High Gradient Streams, Medium High Gradient Streams, Warm Water Moderate Gradient Streams and Rivers, and Low Gradient Slow Winders (Table 2). Few sites fall

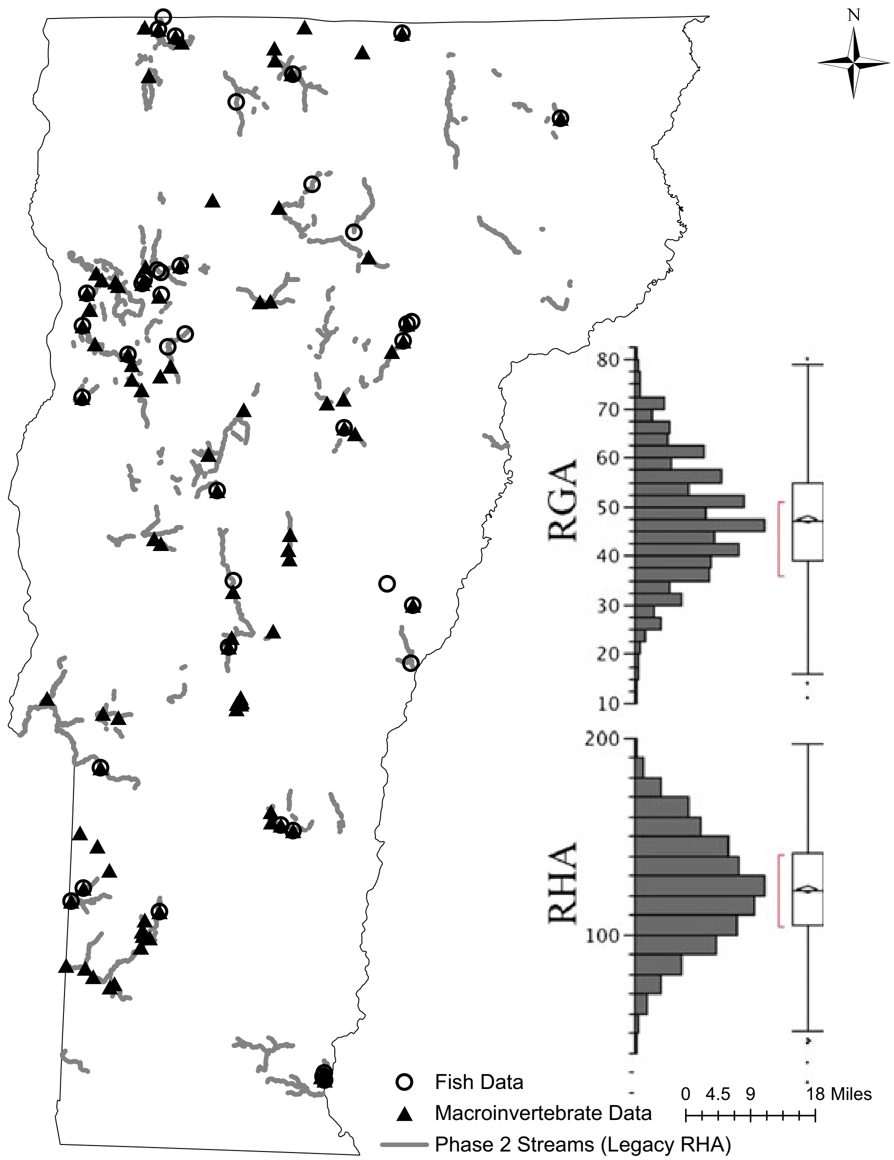


FIGURE 1. Map of the State of Vermont Showing the Phase 2 Locations Used in This Study. Also indicated are the 46 and 133 locations of the fish and macroinvertebrate datasets, respectively. Note: Only 1,006 of the 1,292 Phase 2 reaches used in this study are included; the others were not part of the GIS database at the time this map was created. Histograms of Rapid Geomorphic and Rapid Habitat Assessment (RGA and RHA) scores for the 1,292 reaches used in this study are also included.

into the latter category; as a result, biocriteria have not yet been developed for Low Gradient Slow Winders. Currently, eight metrics are used to assess reaches for macroinvertebrate health. These eight metrics were selected (from over 30 metrics) because in combination they: (1) describe the structural and functional integrity of a macroinverterbrate community; (2) demonstrate the least natural variability within the reference data set; and (3) respond in a relatively predictable manner to a variety of physical and chemical environmental stressors. Fish community health (Table 3) uses two Vermont-calibrated Indices of Biotic Integrity (IBI) (VTDEC, 2004). The mixed-water IBI is applied to streams containing five or more native fish species and is comprised of nine metric scores that sum to values ranging from 9 to 45 corresponding to categories ranging from Poor to Excellent (Table 3). The second index, the coldwater IBI, applies to smaller coldwater streams that contain two to four native species and has six metrics with a range of 9 to 45 (Table 3). Biological and geomorphic data were not collected at the same physical coordinates and not necessarily in the same year. Variation in physical location was accommodated by including all biological survey data located within 200 m of the 1,292 Phase 2 assessment locations resulting in 46 reaches for fish data and

TABLE 1. Parameters That Comprise the Vermont Rapid Geomorphic Assessments (RGAs) and Rapid Habitat Assessments (RHAs).

Parameters (20 Points Each)		Condition (Based on Total Assessment Score) Poor	Fair	Good	Reference
RGA	1. Degradation 2. Aggradation 3. Widening 4. Planform change	0-27	28-51	52-67	68-80
RHA	1. Epifaunal substrate/ available cover 2. Embeddedness or pool substrate 3. Velocity/depth patterns or pool variability 4. Sediment deposition 5. Channel flow status 6. Channel alteration 7. Frequency of riffles/steps or channel sinuosity 8. Bank stability (score each bank) 9. Bank vegetative protection (score each bank) 10. Riparian vegetative zone width (score each side of channel)	0-68	69-128	129-168	169-200

133 for macroinvertebrate data. To retain sufficient sample sizes, no data were excluded due to differences in the time of the biological and geomorphic assessments. If biological assessments were performed over multiple years at the same reach location, the assessment that best matched (i.e., closest to in time) the seven-year time frame of the RGA and RHA was selected.

METHODOLOGY

Generalized Regression Neural Network

The GRNN introduced by Donald Specht (1991) is a parallel, one-pass network that performs least-squares regression. To perform traditional nonlinear regression, one assumes a particular form of the best-fit polynomial. This is often done poorly (e.g., one assumes a linear form for a nonlinear problem) resulting in a poor fit between the observed data and the assumed model and the resulting predictions. Donald Specht took this as a challenge when designing the GRNN and as a result, developed an algorithm that does not require *a priori* knowledge for the regression function. Instead, it bases predictions on the probability density function (pdf) of the response variable associated with the training data described below (e.g., in this study the response variable is the continuous RHA score or biological integrity values depending on the desired algorithm output). The algorithm keeps track of the pdf and assigns weights to generate an appropriate regression curve. The data-driven nature of the algorithm is an important feature; the GRNN algorithm can learn directly from the data without human intervention, enabling a more adaptive management approach. With traditional statistics, one (presumably an expert) selects input variables along with some model (e.g., linear regression) believed to be a good predictor of some predefined dependent variables. The selection of "appropriate" input variables is often challenging. Once "appropriate" variables have been identified, an expert analyzes the output to determine the best model. If the dataset changes (or is added to over time), the analysis (expert's selection of variables to produce a "good" model and "best" model selection) would begin all over.

Figure 2 shows the structure of the GRNN algorithm as applied, for example, to the prediction of the RHA scores. Many of the most popular ANN algorithms in commercial software (e.g., the feed-forward back-propagation network) require training to optimize the number of hidden nodes and weight updates before application. These algorithms can take a large number of iterations to converge to the desired solution. As a result, these networks can be difficult to use by people unfamiliar with its theory (or worse, may easily over-fit data unbeknownst to the user). One advantage of the GRNN is that it is a one-pass algorithm; that is, it does not require training. The weights are pre-set to values of the observed data (in

TABLE 2. Threshold Values for Macroinvertebrate Assemblages in Vermont Wadeable Streams.

Class Criteria Metric[1]	Small High Gradient Streams			Medium High Gradient Streams			Warm Water Moderate Gradient Streams and Rivers		
	Excellent A1	Very Good B1	Good A2, B2,B3	Excellent A1	Very Good B1	Good A2, B2,B3	Excellent A1	Very Good B1	Good A2, B2,B3
Richness	>35	>31	>27	>43	>39	>30	>40	>35	>30
Ephemeroptera, Plecoptera, Trichoptera – EPT index	>21	>19	>16	>24	>22	>18	>21	>19	>16
Percent model affinity of orders – PMA-O	>65	>55	>45	>65	>55	>45	>65	>55	>45
Hilsenhoff biotic index – BI	<3.00	<3.50	<4.50	<3.50	<4.00	<5.00	<4.25	<4.75	<5.40
% Oligochaeta	<2	<5	<12	<2	<5	<12	<2	<5	<12
EPT/EPT+ Chironomidae	>0.65	>0.55	>0.40	>0.65	>0.55	>0.40	>0.65	>0.55	>0.40
Pinkham-Pearson coefficient of similarity – functional groups – PPCS-FG	>0.50	>0.45	>0.40	>0.50	>0.45	>0.40	>0.50	>0.45	>0.40
Density	>500	>400	>300	>500	>400	>300	>500	>400	>300

Note: Adapted from VTDEC (2004).
[1]Metric details can be found at http://www.vtwaterquality.org/bass/docs/bs_wadeablestream1a.pdf.

our case the collected reach scale RGA parameters and the corresponding reach-scale RHA score). In addition, the algorithm is nonparametric (i.e., some of the underlying assumptions necessary for traditional, parametric statistics (e.g., continuous real-valued data, normally distributed, etc.) may be relaxed.

The network consists of four nodal layers. The Input Layer simply passes the n user-defined input variables, $X^p = \{x^p_{i=1}, x^p_{i=2}, \ldots, x^p_{i=n}\}$ (equivalent to the independent variables associated with traditional regression techniques) to the weights of the second network layer, where p is the current input pattern. The weights, w_{ij}, connect the Input Layer to the Pattern Unit Layer (e.g., w_{12} connects input node $x_{i=1}$ with pattern unit node $I_{j=2}$, Figure 2). The weights, w_{ij}, are set to measured values (i.e., expert-assessed scores for degradation, aggradation, widening, planform change, or channel evolution stage) for which there are corresponding stream-reach output (expert-assessed RHA score). These weights do not update as in other artificial neural network algorithms. Similarly, the training output (the corresponding expert-assessed RHA scores) are assigned to the pattern weights, $w_{jA} = y_j$, associated with node A of the Summation Unit Layer. The Pattern Unit Layer has one node, I_j, for each of the k training patterns and calculates a distance metric (e.g., for this study the Euclidean distance) between all sets of training weights and the current input pattern p (Equation 1):

$$I_j = \sqrt{\sum_{i=1}^{n} (w_{ij} - x_i^p)^2} \tag{1}$$

where $j = 1, 2, \cdots, k$.

Here x_i^p refers to the i^{th} input variable associated with the input pattern p and w_{ij} are the training weight associated with the i^{th} input variable of the j^{th} training pattern. The resulting, Euclidean distance, I_j is passed through an exponential activation function (Equation 2):

$$f(I_j) = \exp\left(\frac{-I_j}{2\sigma^2}\right), \tag{2}$$

where σ is a smoothing parameter used to optimize the GRNN output and is the only parameter that needs tuning in the GRNN algorithm. As σ approaches 0, the predicted network output, $\hat{y}$, tend to over-fit the training data. When σ is too large, $\hat{y}$ is smoothed and assumes the value of the sample mean. Trial and error is required to prevent over-fitting. An optimal value of σ can be found easily when the density estimate is being used in Equation (3). A general rule for optimizing σ for a given number of observations is to start with σ close to 1.0, calculate a mean squared error between the GRNN predictions and the

TABLE 3. Fish Mixed Water Index of Biotic Integrity (a) and Cold Water Index of Biotic Integrity (b) Metrics and Scoring Thresholds for Associated Water Quality Classes and Water Management Types.

(a)

For Streams Naturally Supporting More Than Four Native Fish Species		Scoring Criteria 5	3	1
1. Total number of native fish species		Follows maximum species richness lines		
2. Number and identity of native, intolerant species (A nonnative trout may be substituted for brook trout when absent)	Site >400 ft.	>1	1	0
	Site <400 ft.	>0	–	0
3. Number and identity of native benthic insectivores	Site <400 ft. with site drainage <25 km^2	>0	–	0
	All other sites	>1	1	0
4. Proportion of individuals as white suckers and creek chubs		<11%	11-30%	>30%
5. Proportion of individuals as generalist feeders	Site >500 ft.	<20%	20-45%	>45%
	Site <500 ft.	<30%	30-60%	>60%
6. Proportion of individuals as water column and benthic insectivores (score a "1" if blacknose dace is >60% of total assemblage)	Site >500 ft.	>65%	30-65%	<30%
	Site <500 ft.	>55%	20-55%	<20%
7. Proportion of individuals as top carnivores (Nonnative trouts included)	Cold water assemblage	>15%	5-15%	<5%
	Warm water with site drainage >25 km^2	>10%	3-10%	<3%
	Warm water with site drainage <25 km^2	≥ 0	–	–
8. Proportion of individuals with deformities, fin erosion, lesions, or tumors		<1%	1-4%	>4%
9. Abundance in Sample (one pass — 100m^2) (Nonnative species included)	Site <500 ft.	>20	–	10-20
	Site >500 ft. and alk. >9 mg/l	>10		7-10
	Alk. <9 mg/l	>6		3-6

(b)

For Coldwater Streams Naturally Supporting Two to Four Native Fish Species	Scoring Criteria 7.5	4.5	1.5
1. Number of intolerant species (one exotic trout species may be substituted for brook trout)	2	1	0
2. Proportion of individuals as coldwater stenothermic species	> 75%	50-75%	< 50%
3. Proportion of individuals as generalist feeders	< 5%	5-9%	> 9%
4. Proportion of individuals as top carnivores	> 35%	25-35%	< 25%
5. Brook trout density (#s/100 m^2-1 pass)	>4.0	2.0-4.0	<2.0
6. Brook trout age class structure (young-of-the-year = yoy, adult =>100 mm)	yoy present and adults	yoy only, no adults	yoy absent

Note: Adapted from VTDEC (2004).

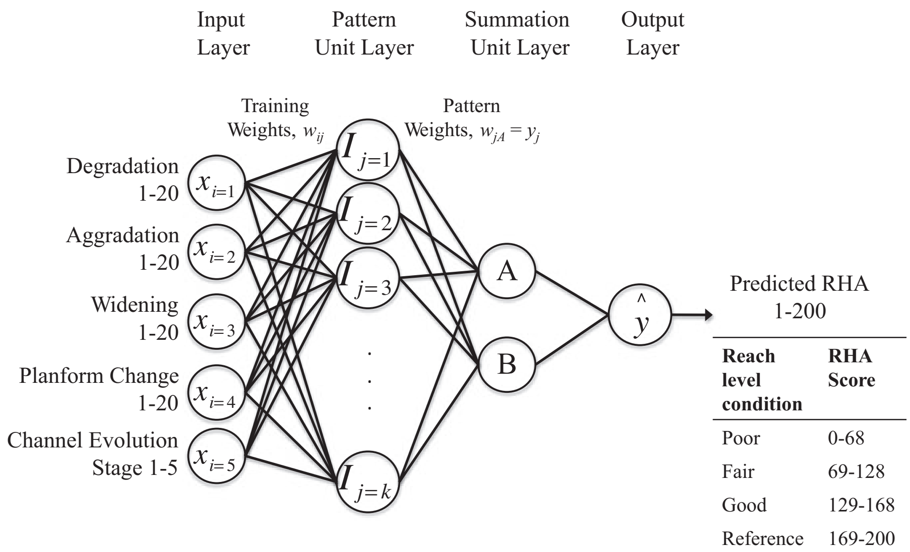


FIGURE 2. GRNN Structure Showing the Components of the RGA and Channel Evolution Stage as Inputs Used to Predict the Total RHA Score.

data held back for validation and testing, and gradually lower σ until the mean squared error is sufficiently low. Typically, the values range between 1.0 and 0.5. In the worst-case scenario, the algorithm would need to iterate over six sigma values (σ = 1.0, 0.9, 0.8, 0.7, 0.6, and 0.5), compare the associated RMSE values, and chose the lowest. On average, a σ value of 0.5 was used in this work.

The third layer, Summation Unit Layer, calculates the dot product of the output from the Pattern Units (Equation 2) and, for node A, the corresponding y_j pattern weights. The pattern weights associated with node B are set equal to 1 (i.e., node B calculates the dot product between the output from the Pattern Units and a vector of ones). The final output is the result of dividing nodes A and B (Equation 3):

$$\hat{y}(X) = \frac{\sum_j y_j \bullet f(I_j)}{\sum_j 1 \bullet f(I_j)} = \frac{A}{B}. \tag{3}$$

This term is derived from the conditional mean and a nonparametric estimate for the probability density from Parzen (1962). See Specht (1991) for details. The GRNN algorithm described in this paper was coded in MATLAB Version 7.10.0 Release 2010a.

RESULTS

The scatter plot (Figure 3) provides a means of looking at the raw RGA and RHA data (total summarized scores for the n = 1,292 individual stream reaches) to illustrate where RGA is high and RHA is low and visa versa. The plot should be viewed as a matrix to highlight areas where RGA and RHA lack a 1:1 correlation. The linear correlation between the 1,292 expert-assigned RGA and RHA scores (Figure 3) was statistically significant and accounted for less than half the variability (r^2 = 0.414, p < 0.05). Figure 4 is an attempt to visualize the subset of sites with RGA, RHA, and detailed biological data (fish or macroinvertebrates). This is a very simple visualiza-

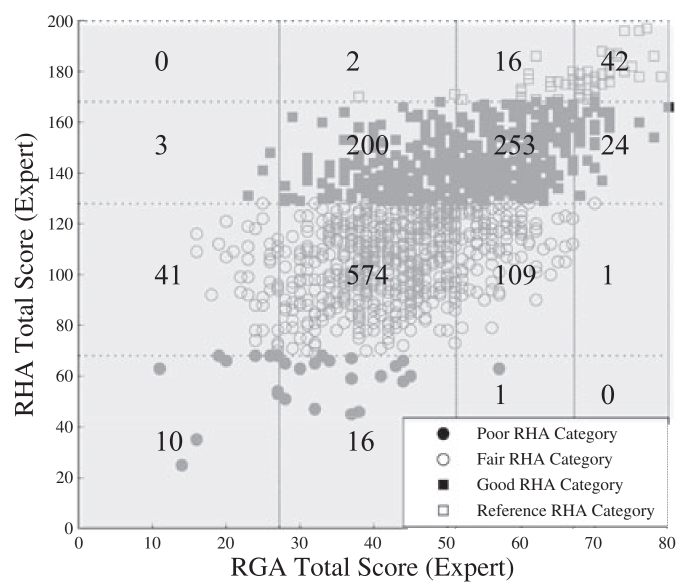


FIGURE 3. Correlation Between RGA and RHA Scores. The vertical lines mark divisions between categories of Poor (0-27), Fair (28-51), Good (52-67), and Reference (68-80) for RGA scores. The dashed horizontal lines show the category boundaries for RHA scores, Poor (0-68), Fair (69-128), Good (129-168), and Reference (169-200).

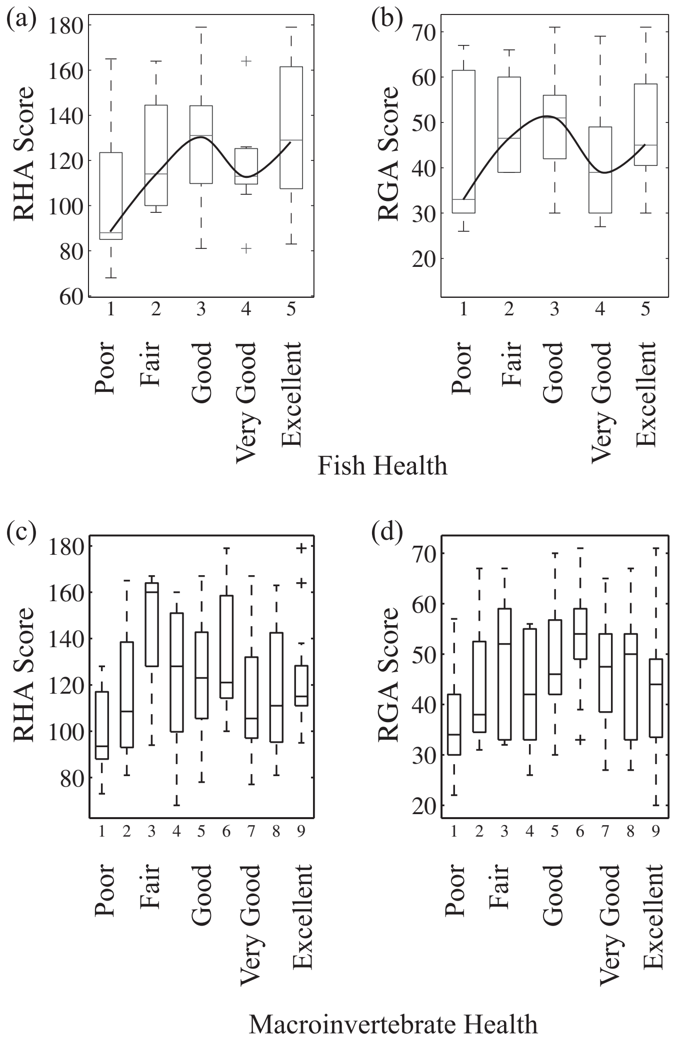


FIGURE 4. Plot Showing Biological Health *vs*. RHA and RGA. Results for fish at 46 Vermont stream reaches are shown in (a) and (b). Results for macroinvertebrates at 133 Vermont stream reaches are shown in (c) and (d). The boxplots extend from the 25th to the 75th percentile (or first to third quartile) and the line in the middle represents the median. The curves in (a) and (b) represent the best fit through the median.

tion (i.e., one where data may be plotted on a 2-D page). We show fish health as a function of RHA (Figure 4a) or RGA (Figure 4b) and macroinvertebrate health against RHA and RGA (Figures 4c and 4d, respectively). We have added cubic lines to Figure 4 to emphasize the high degree of nonlinear correlation between RGA and RHA for fish health. No significant linear correlation exists between the RHA and either fish or macroinvertebrate community assessments (r^2 = 0.053, $p > 0.05$ and r^2 = 0.0004, $p > 0.05$, respectively, Figures 4a and 4c). Further, no linear correlation was observed between RGA scores and fish and macroinvertebrate community assessments (r^2 = 0.0002, $p > 0.05$ and r^2 = 0.0026, $p > 0.05$, respectively, Figures 4b and 4d).

Our ultimate goal, from a science and management point of view, is to estimate biological integrity using rapid geomorphic and habitat assessment data. However, we began this study by building on work by Besaw *et al.* (2009b) and predict RHA using the RGA data, both with and without channel evolution, simply because we have sufficient, multiple data (i.e., n = 1,292 stream reaches) to show proof-of-concept. Next, we assess the utility of the reach-scale GRNN for predicting fish and macroinvertebrate community integrity using a smaller sample of reaches (n = 46 and n = 133, respectively). The GRNN results are summarized in Table 4. The number of data, the dependent variable (GRNN output), and the corresponding independent variables (GRNN inputs) for each test trial are provided. Trials are identified by the dependent variable. For each trial, 50% of reaches from each RHA category were selected randomly to construct the training set, except as noted below. The remaining 50% are used for validation/prediction. To assess "error," we report % match between the GRNN predictions (last column of Table 4). The GRNN predictions may also be represented by what is known as a confusion matrix (e.g., Figure 5b); explanation to follow in statistical classification.

Linkages Between Rapid Geomorphic Assessment and Rapid Habitat Assessment

The initial GRNN trials (Table 4) use RGA (RHA2) and channel evolution (RHA1) as the independent data to predict habitat assessment (RHA) scores. The GRNN percent match was almost twice as accurate (68.6%, Trial RHA2) as traditional linear regression. The results improved slightly when channel evolution data were included (69.9%, Trial RHA1). The latter is not unexpected given the attention to channel evolution stage by experts in constructing the overall reach-scale RGA metrics.

Figure 5a compares the predicted RHA against the expert-assigned RHA scores. Figure 5b displays the number of sites predicted to be in a particular RHA category (rows of matrix) against the site's expert-assigned category (matrix columns). The confusion matrix is a more comprehensive assessment of the GRNN predictions than reporting % match of Table 4 (i.e., the matrix diagonals). The GRNN correctly predicts 69.9% of the RHA categories (195 misclassified out of 647) compared to a 66.8% match (215 misclassified out of 647) using traditional multiple linear regression. Thirteen stream reaches categorized as *poor* by VTANR experts were categorized as *fair* by the GRNN and 1 reach was estimated as *good*. In addition, only 15 of the *reference* stream reaches were correctly classified; while 14 were predicted as *good* and 1 as *fair*.

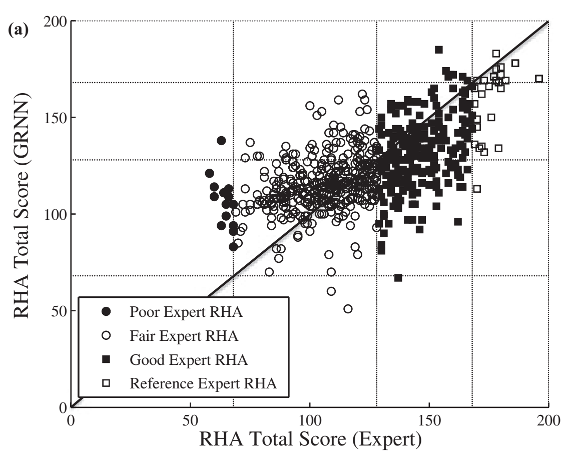
TABLE 4. Summary of GRNN Trials Highlighting Data Inputs, Output, and Their Percent Match.

Stream Reach Data	Trial ID	GRNN Inputs[1]	GRNN Output	Correctly Classified/Total	% Match
Original n = 1,292 reaches	RHA1	Deg., Agg., Wid., PC, channel evolution	Total RHA	452/647	69.9
	RHA2	Deg., Agg., Wid., PC	Total RHA	445/647	68.6
Fish subset of RHA data n = 46 reaches	RHA3	Deg., Agg., Wid., PC, channel evolution	Total RHA	22/23	95.7
	FISH1	Deg., Agg., Wid., PC, channel evolution, total RHA	Fish community health	12/25	48.0
	FISH2	Deg., Agg., Wid., PC, channel evolution (NO RHA)	Fish community health	10/25	40.0
Macroinvertebrate subset of RHA data n = 133 reaches	RHA4	Deg., Agg., Wid., PC, channel evolution	Total RHA	56/67	83.6
	MAC1	Deg., Agg., Wid., PC, channel evolution, total RHA	Macroinvertebrate community health	16/69	23.2
	MAC2	Deg., Agg., Wid., PC, channel evolution (NO RHA)	Macroinvertebrate community health	15/69	21.7

[1]Deg., degradation; Agg., aggradation; Wid., widening; PC, planform change.

Biological Integrity Correlations

For comparison purposes, the same GRNN used to predict RHA on the 1,292 reaches (Trial RHA1) was re-run on the subset of 46 and 133 reaches associated with fish and macroinvertebrate assessment data (i.e., raw data presented in Figure 4). The GRNN correctly classified RHA for 22 of the 23 reaches associated with detailed fish data (a 95.7% match, Table 4, Trial RHA3), and 56 out of 67 (or 83.6% match) on the subset of reaches with detailed macroinvertebrate assessments (Table 4, Trial RHA4).



		(b) Expert Assigned RHA Category (69.9% match)			
		poor	fair	good	reference
GRNN Predicted RHA Category	poor	0	2	1	0
	fair	13	303	98	1
	good	1	58	134	14
	reference	0	0	7	15

FIGURE 5. (a) Results of GRNN Predicted RHA Using Degradation, Aggradation, Widening, Planform Change, and Channel Evolution Stage as Inputs to the Algorithm (Trial RHA1, Table 4) Plotted Against the Expert Assigned Total RHA Score. (b) Frequency of predictions after output is categorized.

The more interesting trials, from an integrated management perspective, are those that predict fish and macroinvertebrate health directly. The accuracy of the GRNN predictions for biological health (using RGA and channel evolution stage as input data) is much lower (40% accuracy for fish and 21.7% for macroinvertebrates (Table 4: Trials FISH2 and MAC2)) than the GRNN predictions of RHA (95.7 and 83.6% match for Trials RHA3 and RHA4, respectively). The addition of the RHA score as an input variable showed only slight improvement (8% for fish and only 1.5% for macroinvertebrates) in predictions of biological health; with the accuracy higher for fish (48%, Trial FISH1) than that for macroinvertebrates (23.2%, Trial MAC1).

DISCUSSION

In our attempt to demonstrate the practicality of using a GRNN with large, complex data sets we see that the GRNN had difficulty predicting stream reaches in the extreme classes. For example, reaches categorized as *poor* (results of Trial RHA1, Figure 5b) by the expert were mostly predicted as *fair*. One possible explanation is that of the 14 *poor* RHA reaches, only 3 are associated with a *poor* RGA score; the remaining 9 reaches are associated with *fair* RGA scores. This limited number of *poor* reaches (three in total) creates challenges when using the GRNN to classify a reach as having "poor" habitat because some number of data need to be used for "training" the network; others should be used for testing/validation. We would expect the network's prediction performance for reaches with *poor* RHA to increase as the number of data points with *poor* RHA characteristics are entered into the VTANR database. Another possibility is that since the RHA is more subjective than the RGA, there is information (in the experts' neural networks) that is currently not being used in the GRNN. Also, the cutoffs for the habitat categorization were selected prior to data collection. Now that VTANR has a significantly large data set, the category boundaries could be optimized (i.e., natural breakpoints in the distribution of RHA data). Besaw *et al.* (2009b) showed that the current VTANR stream sensitivity classification may need to be adjusted based on analysis of RGA and stream inherent vulnerability.

Our ultimate research goal was to explore the GRNN's predictive capability in estimating biological integrity (rather than RHA from RGA). As a result, the GRNN trials that predict fish and macroinvertebrate health given RGA, channel evolution stage (Table 4, Trials FISH2 and MAC2), and RHA (Table 4, Trials FISH1 and MAC1) are more interesting from a management perspective. Using rapid assessments to predict biological integrity might be considered a first step in a process to focus limited resources because the geomorphic and habitat rapid assessment tools would have the potential to identify or flag reaches in more immediate need of detailed fish or macroinvertebrate field assessments to confirm or validate reaches suspected of having impaired habitat. It is interesting to note in the 2-D plots of raw data for fish health (Figures 4a and 4b) the strong nonlinear (cubic) correlation between RHA and RGA. The decline in fish health for RGA and RHA classified as "Very Good" or "Excellent" is not intuitive. We believe this to be a scaling issue. In addition, we hypothesize that the complete lack of RGA/RHA correlation with macroinvertebrate health (beyond RGA/RHA classifications "Fair"), although due in part to scaling issues, may be more telling of sample bias. An analyst might be able to select (*a priori*) a cubic model as the best choice for predicting fish health in this simplified test case. However, this becomes more challenging when an analyst must visualize/select the shape of the plane (for the case of two dependent variables), the volume (for three variables), or hyperspheres (for the four, five, and six variables of test trials in Table 4). We view the network's ability to best fit a polynomial (given a data set) as a key advantage over traditional generalized regression methods.

Another intriguing observation about the plots is there appears to be an increasing linear relationship between categories Poor through Good for fish and Poor through Fair for macroinvertebrates. There appears to be some threshold (beyond the classification Good or Fair) at which correlation to RGA and RHA break down (for both fish and macroinvertebrates, respectively). The lack of linear correlation is not entirely unexpected as the complexities between the physical geomorphic and habitat conditions, and biological integrity are not completely understood and are compounded by scale incompatibilities (we believe this is evidenced in the case for fish when we see lower RGA and RHA scores associated with Very Good and Excellent biological health categories), species present, and metrics used (Chessman *et al.*, 2006; Clark *et al.*, 2008). Also, in the case of macroinvertebrates, sampling bias can play a role in the lack of correlation, as experts tend to seek out locations where riffles occur (perhaps up or downstream from a bridge where the physical assessment may not support what is found biologically).

In an attempt to improve the prediction results of macroinvertebrate community health (trial MAC1), we tested a suggestion from VTANR personnel and weighed embeddedness more heavily (1-6 times) than the other variables. The only improvement in prediction occurred with a weighting of 4, when the GRNN predicted only one more reach correctly. We suspect that water quality information at the same locations could improve prediction rates since it obviously has an impact on habitat. A study is currently underway to include water quality data and 376 reaches that have both RGA and RHA data have been identified to also have water quality data within a 200 m buffer.

In addition, identifying relationships between physical and biological conditions is complicated by the fact that experts hired to perform the stream (RGA/RHA) assessments each come to the table with different backgrounds and a prior knowledge. The study presented by Besaw *et al.* (2009b) examined bias and variation across expert opinion using 19 and 20 reaches in two Vermont watersheds. This was a one-time study designed to explore the expected variance across expert opinions performing the same assessment on the same reaches at the same time. Limited resources prevent the same stream reaches from being assessed by multiple experts over the same time frame. Five experts independently examined the same stream reaches. Fifteen of the 19 reaches had classifications that were in agreement by + or – one category (out of 8 categories). One reach, in particular, varied significantly from the ANN prediction primarily because assessors with different geographic backgrounds viewed culverts differently (e.g., one weighted it as a potential problem, while others viewed it as a beneficial grade control). The VTANR now has a State QA officer to review all field assessment data for consistent interpretations; this is a process that has improved over time. Other information currently not available in assessments is the assessor's uncertainty associated with assigning a single real-valued score to the RGA or RHA parameters. Mathon (2011) created a fuzzy GRNN algorithm that enables expert uncertainty to be incorporated into site assessments. Ideally, an assessor might provide their "uncertainty" (a fuzzy number, hence the fuzzy GRNN) along with their current numerical RGA or RHA score. This would enable prediction of a range in reach condition value that could lead to a stream having a condition rating in more than one category (i.e., *fair*/*good*). In addition, the biological health assessments used in this study were collected at different times from the physical assessments (in some cases, several years). While it is important for these assessments to be conducted independently to prevent biased results, temporal gaps of several years can result in a change in physical or biological condition and consequently a reduced correlation between the two. Landscape history, as well as, Vermont's increasing population and growing infrastructure also adds to the complexity of extracting correlations between reach-scale physical and biological data that only exist at one snap shot in time. However, as more multi-date data are gathered over the years, these relationships and change in assessments will be easier to understand.

Interestingly, King and Baker (2010) show that community metrics may be insensitive to changes in individual taxa or groups of taxa as to why relationships between the physical environment and the biological integrity are difficult to define. Knowing which taxa respond to stressors in the environment will help in understanding the mechanisms driving habitat changes. While BASS (VTANR Biomonitoring and Aquatic Studies Section) use an IBI for assessing fish, they are, for the most part, generalists and relatively tolerant as a group; and the IBIs may be reflecting just that for fish in Vermont. The macroinvertebrate assessments do include EPT, but also include seven additional metrics believed to capture what is important/relevant to Vermont Water Quality Standards. The ability to more accurately predict fish communities may be because fish are more mobile and as habitats change, fish communities rapidly respond, whereas macroinvertebrates take longer to recolonize.

Clark *et al.* (2008) examined the lack of correlation between geomorphic assessments and biological assessments of six fish species showing sampling scale incompatibility may hinder the discovery of linkages between the physical and biological assessments. Geomorphic reach assessments are conducted with the intent of capturing the best representation of dominant physical processes within the reach as a whole. Biological assessments tend to be more specific to certain locations within a reach, especially when water quality is not a limiting factor. The fact that the GRNN was able to predict fish health better than macroinvertebrate health may reflect that the fish assessments are conducted on a scale more similar to that of habitat assessments (RHA) than are the macroinvertebrate assessments. However, macroinvertebrate populations may be distributed more on the basis of microhabitat than the reach-scale geomorphic conditions. A reach-scale geomorphic framework may include clusters of reaches with uncharacteristically poor habitat and vice versa (Thompson *et al.*, 2001).

The RHA data used in this study were collected through 2007. In 2008, the VTANR implemented new reach habitat assessment protocols. These new protocols were developed to allow for more specific assessment of the various stream types found in Vermont and more precise evaluation of the key ecological attributes and requirements for aquatic life. For example, while the legacy RHA categorized a stream as either low or high gradient, the new RHA allows the assessor to select from five stream habitat types: cascade, step-pool, plane bed, riffle-pool, or dune-ripple. The new RHA uses only eight parameters; however, like the legacy RHA, each component is scored between 0 and 20 and the total score is used to categorize the stream reach into four categories (i.e., *poor*, *fair*, *good*, or *reference*). We use the previous protocol (legacy) data in this work, because the data were readily available and provided a statistically large data set. The new RHA protocol data may help improve the understanding of linkages between the physical and biological conditions.

CONCLUSIONS

The idea that physical habitat condition influences the biological integrity of a stream seems obvious; however, quantifying this relationship with preexisting data is challenging. Although many studies have used physical stream characteristics as a surrogate for habitat (see Maddock, 1999 for a review), our results show that clear linkages are difficult to construct using the Vermont legacy habitat data (RHA). Despite these challenges, the GRNN methodology is significantly better at finding relationships between physical assessments and biological integrity than traditional linear regression. Recall that the GRNN was able to correctly predict fish health in 48% of streams and macroinvertebrate health in 23.2% of streams and essentially no relationship can be explained by linear regression. The algorithm is a generalized regression algorithm and as such will provide comparable predictions to traditional generalized regression; however, a key advantage of the GRNN is that one does not need to know the order of the best-fit polynomial *a priori*. This is particularly useful when the model predictions are multi-dimensional (i.e., one wishes to predict RHA, fish, and macroinvertebrate health simultaneously, or predict value(s) over some larger spatial extent) making it difficult to select or validate the best-fit model when output cannot be visualized/plotted in two or three dimensions. In addition, the GRNN is data-driven (i.e., derived directly from the measurement data). From a management point of view, this means that the model does not need to be altered/updated as new data are collected; and predictions will improve as more multi-date VTANR data become available.

Although filtering the n = 1,292 Vermont stream reaches with both RGA and RHA data for reaches with detailed fish and macroinvertebrate data reduced our sample sizes to n = 46 and 133, respectively, we believe the results to be interesting. We see an increasing linear trend when comparing fish health (categories Poor through Good) to RHA and RGA and a similar trend for macroinvertebrates (categories Poor through Fair). However, there appears to be some threshold (beyond the classification Good for fish) at which correlation to RGA and RHA breaks down. We believe this to be a scaling issue as RGA and RHA are predominantly reach-scale measurements. Reach-specific water quality data (perhaps more indicative of the watershed scale) have not yet been added to this analysis. The lack of correlation between macroinvertbrates and RGA or RHA (beyond the classification Fair) is most likely due to a combination of scaling and sampling bias since experts typically seek out microhabitats within a stream. For example, a riffle supporting a healthy macroinvertebrate community may be classified at the reach-scale with low RGA or RHA scores (e.g., upstream or downstream of bridges or culvert).

This study reaffirms that physical and geomorphological characteristics affecting biotic communities are complex. Habitat includes many physical, chemical, and biological components. In addition, the simple indices of physical habitat at the reach scale, such as geomorphic and habitat assessment scores, do not capture the scales of response of fish and macroinvertebrates; the spatial distribution of usable habitats, size, and their connectedness are also important. While habitat studies have been done at various scales (Statzner and Higler, 1986; Pringle *et al.*, 1988; Statzner *et al.*, 1988; Poff and Ward, 1990; Harper *et al.*, 1992; Palmer and Poff, 1997; Newson *et al.*, 1998; Padmore, 1998; Kemp *et al.*, 2000; Crowder and Diplas, 2000a,b; Clark *et al.*, 2008), few discuss the scale dependence of the measurements used and how they would extrapolate to an overall assessment of the reach or even watershed being studied. An important question to address may be what site-scale physical processes formed the habitat features (e.g., pools and riffles) sampled for fish and macroinvertebrates, and how are these related to the larger scale physical processes that characterize the fluvial geomorphic condition at the reach scale. Until such questions are explored, spatial scale differences will continue to cloud the linkages between the physical and biological integrity of streams. This body of work focuses primarily on building a data-driven tool to assist watershed managers with large quantities of complex, nonlinear data. We do not believe the real advantages of such an algorithm will be known until large sets of multi-scale, multi-date data become available.

ACKNOWLEDGMENTS

The authors acknowledge that this research was supported by VT EPSCoR Grant NSF EPS #0701410 and the National Science Foundation Grant DEB-0842152 (D. M. R., L. S.). We would also like to thank Alison Pechenick and Nikolaos Fytilis for their assistance with GIS and the creation of Figure 1.

LITERATURE CITED

Abdalla, O.A., 2010. A Comparison of Feed-Forward Back-Propagation and Radial Basis Artificial Neural Networks: A Monte Carlo Study, in Information Technology, 2010 International Symposium, Kuala Lumpur.

Allan, J.D., 2004. Landscapes and Riverscapes: The Influence of Land Use on Stream Ecosystems. Annual Review of Ecology, Evolution and Systematics 35:257-284.

Barbour, M.T., J. Gerritsen, B.D. Snyder, and J.B. Stribling, 1999. Rapid Bioassessment Protocols for Use in Streams and Wadeable Rivers: Periphyton, Benthic Macroinvertebrates and Fish, (Second Edition). EPA 841-B-99-002. U.S. Environmental Protection Agency, Office of Water, Washington, D.C.

Besaw, L.E., D.M. Rizzo, P.R. Bierman, and W. Hackett, 2009a. Advances in Ungauged Streamflow Prediction Using Artificial Neural Networks. Journal of Hydrology 386(1-4):27-37.

Besaw, L.E., D.M. Rizzo, M. Kline, K.L. Underwood, J.J. Doris, L.A. Morrissey, and K. Pelletier, 2009b. Stream Classification Using Hierarchical Artificial Neural Networks: A Fluvial Hazard Management Tool. Journal of Hydrology 373(1-2):34-43.

Brierley, G.J. and K.A. Fryirs, 2005. Geomorphology and River Management: Applications of the River Styles Framework. Blackwell Publishing, Malden, Massachusetts.

Buffington, J.M. and J. Goode, 2010. How Will Climate Change Affect Channel Morphology and Salmonid Habitat in Mountain Basins? presented at AGU Fall Meeting, San Francisco, California, December 2010, Abstract H41I-04.

Chessman, B.C., K.A. Fryirs, and G.J. Brierley, 2006. Linking Geomorphic Character, Behaviour and Condition to Fluvial Biodiversity: Implications for River Management. Aquatic Conservation: Marine and Freshwater Ecosystems 16:267-288.

Cigizoglu, H.K., 2005a. Application of Generalized Regression Neural Networks to Intermittent Flow Forecasting and Estimation. Journal of Hydrologic Engineering 10(4):336-341.

Cigizoglu, H.K., 2005b. Generalized Regression Neural Network in Monthly Flow Forecasting. Civil Engineering and Environmental Systems 22(2):71-84.

Cigizoglu, H.K. and M. Alp, 2004. Rainfall-Runoff Modelling Using Three Neural Network Methods. Lecture Notes in Artificial Intelligence 3070:166-171.

Cigizoglu, H.K. and M. Alp, 2006. Generalized Regression Neural Network in Modelling River Sediment Yield. Advances in Engineering Software 37(2):63-68.

Clark, J.S., D.M. Rizzo, M.C. Watzin, and W.C. Hession, 2008. Spatial Distribution and Geomorphic Condition of Fish Habitat in Streams: An Analysis Using Hydraulic Modeling and Geostatistics. River Research and Applications 24:885-899.

Cobaner, M., B. Unal, and O. Kisi, 2009. Suspended Sediment Concentration Estimation by an Adaptive Neuro-Fuzzy and Neural Network Approaches Using Hydro-Meteorological Data. Journal of Hydrology 367(1-2):52-61.

Crowder, D.W. and P. Diplas, 2000a. Evaluating Spatially Explicit Metrics of Stream Energy Gradients Using Hydrodynamic Model Simulations. Canadian Journal of Fisheries and Aquatic Sciences 57:1497-1507.

Crowder, D.W. and P. Diplas, 2000b. Using Two-Dimensional Hydrodynamic Models at Scales of Ecological Importance. Journal of Hydrology 230:172-191.

Davies, S.P. and S.K. Jackson, 2006. The Biological Condition Gradient: A Descriptive Model for Interpreting Change in Aquatic Ecosystems. Ecological Applications 16(4):1251-1266.

EPA, 2012. http://water.epa.gov/polwaste/nps/watershed/index.cfm, *accessed* June 2012.

Firat, M., 2008. Comparison of Artificial Intelligence Techniques for River Flow Forecasting. Hydrology and Earth System Sciences 12(1):123-139.

Govindaraju, R.S. and R.A. Ramachandra, 2000. Artificial Neural Networks in Hydrology. Kluwer Academic Publishers, Dordrecht, The Netherlands, ISBN 13: 978-0792362265.

Harper, D.M., C.D. Smith, and P.J. Barham, 1992. Habitats as the Building Blocks for River Conservation Assessment. *In*: River Conservation and Management, P.J. Boon, P. Calow, and G.E. Petts (Editors). John Wiley, Chichester, pp. 311-319.

Juracek, K.E. and Fitzpatrick F.A., 2003. Limitations and Implications of Stream Classification. Journal of the American Water Resources Association 39(3):659-670.

Kemp, J.L., D.M. Harper, and G.A. Crosa, 2000. The Habitat-Scale Ecohydraulics of Rivers. Ecological Engineering 16:17-29.

Kim, M.Y. and M.K. Kim, 2007. Dynamics of Surface Runoff and Its Influence on the Water Quality Using Competitive Algorithms in Artificial Neural Networks. Journal of Environmental Science and Health Part A-Toxic/Hazardous Substances & Environmental Engineering 42(8):1057-1064.

King, R.S. and M.E. Baker, 2010. Considerations for Analyzing Ecological Community Thresholds in Response to Anthropogenic Environmental Gradients. Journal of the North American Benthological Society 29(3):998-1008.

Kisi, O., 2008. River Flow Forecasting and Estimation Using Different Artificial Neural Network Techniques. Hydrology Research 39(1):27-40.

Kisi, O., I. Yuksel, and E. Dogan, 2008. Modelling Daily Suspended Sediment of Rivers in Turkey Using Several Data-Driven Techniques. Hydrological Sciences Journal-Journal Des Sciences Hydrologiques 53(6):1270-1285.

Kline, M., 2007. Draft Vermont Agency of Natural Resources River Corridor Planning Guide to Identify and Develop River Corridor Protection and Restoration Projects. Vermont River Management Program, Waterbury, Vermont.

Kline, M., C. Alexander, S. Pytlik, S. Jaquith, and S. Pomeroy, 2007. Vermont Stream Geomorphic Assessment Protocol Handbooks. Vermont Agency of Natural Resources, Waterbury, Vermont. http://www.vtwaterquality.org/rivers/htm.

Kline, M. and B. Cahoon, 2010. Protecting River Corridors in Vermont. Journal of the American Water Resources Association 46 (2):227-236.

Lammert, M. and J.D. Allan, 1999. Assessing Biotic Integrity of Streams: Effects of Scale in Measuring the Influence of Land Use/Cover and Habitat Structure on Fish and Macroinvertebrates. Environmental Management 23:257-270.

Lepori, F., D. Palm, E. Brannas, and B. Malmqvist, 2005. Does Restoration of Structural Heterogeneity in Streams Enhance Fish and Macroinvertebrate Diversity? Ecological Applications 15:2060-2071.

Maddock, I., 1999. The Importance of Physical Habitat Assessment for Evaluating River Health. Freshwater Biology 41:373-391.

Mathon, B.R., 2011. Assessing Uncertainty Associated with Groundwater and Watershed Problems Using Fuzzy Mathematics and Generalized Regression Neural Networks. Ph.D. Dissertation, University of Vermont, Burlington, Vermont.

Montgomery, D.R. and J.M. Buffington, 1997. Channel-Reach Morphology in Mountain Drainage Basins. Geological Society of America Bulletin 109(5):596-611.

Newson, M.D., M.J. Clark, D.A. Sear, and A. Brooks, 1998. The Geomorphological Basis for Classifying Rivers. Aquatic Conservation: Marine and Freshwater Ecosystems 8:415-430.

Padmore, C.L., 1998. The Role of Physical Biotopes in Determining the Conservation Status and Flow Requirements of British Rivers. Aquatic Ecosystem Health and Management 1:25-35.

Palmer, M.A. and N.L. Poff, 1997. The Influence of Environmental Heterogeneity on Patterns and Processes in Streams. Journal of the North American Benthological Society 16:169-173.

Parzen, E., 1962. On Estimation of a Probability Density Function and Mode. Annals of Mathematical Statistics 13:1065-1076.

Poff, N.L. and J.V. Ward, 1990. Physical Habitat Template of Lotic Systems — Recovery in the Context of Historical Pattern of Spatiotemporal Heterogeneity. Environmental Management 14:629-645.

Pringle, C.M., R.J. Naiman, G. Bretschko, J.R. Karr, M.W. Oswood, J.R. Webster, R.L. Welcomme, and M.J. Winterbourn, 1988. Patch Dynamics in Lotic Systems: The Stream as a Mosaic. Journal of North American Benthological Society 7:503-524.

Roper, B.B., J.M. Buffington, E. Archer, C. Moyer, and M. Ward, 2008. The Role of Observer Variation in Determining Rosgen Stream Types in Northeastern Oregon Mountain Streams. Journal of the American Water Resources Association 44(2):417-427.

Rosgen, D.L., 1994. A Classification of Natural Rivers. Catena 22:169-199.

Rosgen, D.L., 1996. Applied River Morphology. Wildland Hydrology Books, Pagosa Springs, Pagosa, Colorado, 325 pp., ISBN-13: 978-0965328906.

Roy, A.H., A.D. Rosemond, M.J. Paul, D.S. Leigh, and J.B. Wallace, 2003. Stream Macroinvertebrate Response to Catchment Urbanisation (Georgia, USA). Freshwater Biology 48:329-346.

Schiff, R., M. Kline, and J. Clark, 2008. The Reach Habitat Assessment Protocol. Prepared by Milone and MacBroom, Inc. for the Vermont Agency of Natural Resources, Waterbury, Vermont.

Schumm, S.A., 1977. The Fluvial System. Wiley-Interscience, New York, New York, 338 pp.

Schumm, S.A., M.D. Harvey, and C.C. Watson, 1984. Incised Channels: Morphology, Dynamics and Control. Water Resources Publications, Littleton, Colorado, 200 pp., ISBN-13: 978-0918334534.

Sertel, E., H.K. Cigizoglu, and D.U. Sanli, 2008. Estimating Daily Mean Sea Level Heights Using Artificial Neural Networks. Journal of Coastal Research 24(3):727-734.

Simon, A., M. Doyle, M. Kondolf, F.D. Shields, Jr., B. Rhoads, and M. McPhillips, 2007. Critical Evaluation of How the Rosgen Classification and Associated "Natural Channel Design" Methods Fail to Integrate and Quantify Fluvial Processes a Channel Response. Journal of the American Water Resources Association 43:1117-1131.

Simon, A. and C.R. Hupp, 1986. Channel Evolution in Modified Tennessee Channels. Proceedings, Fourth Federal Interagency Sedimentation Conference, Las Vegas 2(5):71-82.

Smith, S.M. and K.L. Prestegaard, 2005. Hydraulic Performance of a Morphology-Based Stream Channel Design. Water Resources Research 41:W11413, doi:10.1029/2004WR003926.

Specht, D.F., 1991. A General Regression Neural Network. IEEE Transactions on Neural Networks 2(6):568-576.

Statzner, B., J.A. Gore, and V.H. Resh, 1988. Hydraulic Stream Ecology: Observed Patterns and Potential Applications. Journal of the North American Benthological Society 7:307-360.

Statzner, B. and B. Higler, 1986. Stream Hydraulics as a Major Determinant of Benthic Invertebrate Zonation Patterns. Freshwater Biology 16:127-139.

Sullivan, S.M.P. and M.C. Watzin, 2008. Relating Stream Physical Habitat Condition and Concordance of Biotic Productivity Across Multiple Taxa. Canadian Journal of Fisheries and Aquatic Sciences 65:2667-2677.

Sullivan, S.M.P., M.C. Watzin, and W.C. Hession, 2004. Understanding Stream Geomorphic State in Relation to Ecological Integrity: Evidence Using Habitat Assessments and Macroinvertebrates. Environmental Management 34(5):669-683.

Sullivan, S.M.P., M.C. Watzin, and W.C. Hession, 2006. Influence of Stream Geomorphic Condition on Fish Communities in Vermont, U.S.A. Freshwater Biology 51:1811-1826.

Sweeney, B.W., T.L. Bott, J.K. Jackson, L.A. Kaplan, J.D. Newbold, L.J. Standley, W.C. Hession, and R.J. Horwitz, 2004. Riparian Deforestation and Stream Channel Narrowing: Loss of Stream Ecosystem and Its Services. Proceedings of the National Academy of Sciences of United States of America 101(39):14132-14137.

Thompson, J.R., M.P. Taylor, K.A. Fryirs, and G.J. Brierly, 2001. A Geomorphological Framework for River Characterization and Habitat Assessment. Aquatic Conservation: Marine and Freshwater Ecoystems 11:373-389.

Turan, M. and M. Yurdusev, 2009. River Flow Estimation from Upstream Flow Records by Artificial Intelligence Methods. Journal of Hydrology 369:71-77.

U.S. Environmental Protection Agency, 2006. Wadeable Streams Assessment a Collaborative Survey of the Nation's Streams. Office of Water and Office of Research and Development, EPA 841-B-06-002.

Vermont River Management Program, 2009. Data Management System (DMS), Corridor Plans, and ArcGIS Tool: Vermont Stream Geomorphic and Habitat Assessment Data, Map Serve, and River Corridor Plans and Delineation Tools. Vermont Agency of Natural Resources, Waterbury, Vermont. http://www.vtwaterquality.org/rivers/htm.

VTDEC, 2004. Wadeable Stream Biocriteria Development and Implementation Methods for Fish and Macroinvertebrate Assemblages in Vermont Wadeable Streams and Rivers. Vermont Department of Environmental Conservation, Waterbury, Vermont.

Wang, Y.M., T. Kerh, and S. Traore, 2009. Neural Networks Approaches for Modeling River Suspended Sediment Concentration Due to Tropical Storms. Global NEST Journal 11(4):457-466.

Wasserman, P.D., 1993. Advanced Methods in Neural Computing. Van Nostrand Reinhold, New York, New York, ISBN-13: 978-0442004613.