Journal of Hydrology 373 (2009) 34–43

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Stream classification using hierarchical artificial neural networks: A fluvial hazard management tool

Lance E. Besaw[a,1], Donna M. Rizzo[a,*], Michael Kline[b,4], Kristen L. Underwood[c,5], Jeffrey J. Doris[d,6], Leslie A. Morrissey[e,2], Keith Pelletier[e,3]

[a] Department of Civil and Environmental Engineering, University of Vermont, 213 Votey Building, 33 Colchester Ave., Burlington, VT 05405-0156, USA
[b] Department of Environmental Conservation, Vermont Agency of Natural Resources, 103 South Main St., Building 10 North, Waterbury, VT 05671-0408, USA
[c] South Mountain Research and Consulting, 2852 South 116 Rd., Bristol, VT 05443, USA
[d] Sanborn, Head and Associates Inc., 2 South Main St., Suite 2, Randolph, VT 05060, USA
[e] Rubenstein School of Natural Resources, University of Vermont, Aiken Center, 81 Carrigan Dr., Burlington, VT 05405-0156, USA

ARTICLE INFO

Article history:
Received 26 November 2008
Received in revised form 27 March 2009
Accepted 6 April 2009

This manuscript was handled by G. Syme, Editor-in-Chief

Keywords:
Stream classification
Artificial neural networks
Kohonen self-organizing maps
Counterpropagation
Channel instability
Geomorphology

SUMMARY

Watershed managers and planners have long sought decision-making tools for forecasting changes in stream-channels over large spatial and temporal scales. In this research, we apply non-parametric, clustering and classification artificial neural networks to assimilate large amounts of disparate data types for use in fluvial hazard management decision-making. Two types of artificial neural networks (a counterpropagation algorithm and a Kohonen self-organizing map) are used in hierarchy to predict reach-scale stream geomorphic condition, inherent vulnerability and sensitivity to adjustments using expert knowledge in combination with a variety of geomorphic assessment field data. Seven hundred and eighty-nine Vermont stream reaches (+7500 km) have been assessed by the Vermont Agency of Natural Resources' geomorphic assessment protocols, and are used in the development of this work. More than 85% of the reach-scale stream geomorphic condition and inherent vulnerability predictions match expert evaluations. The method's usefulness as a QA/QC tool is discussed. The Kohonen self-organizing map clusters the 789 reaches into groupings of stream sensitivity (or instability). By adjusting the weight of input variables, experts can fine-tune the classification system to better understand and document similarities/differences among expert opinions. The use of artificial neural networks allows for an adaptive watershed management approach, does not require the development of site-specific, physics-based, stream models (i.e., is data-driven), and provides a standardized approach for classifying river network sensitivity in various contexts.

Introduction

Stream adjustments in response to watershed stressors of varying types, magnitude, duration, and periodicity result in degraded surface water quality, loss of agricultural lands, damaged infrastructure, and mobilization of phosphorus and other sediment-related pollutants. Modeling such complex instability is difficult because of process lag times, threshold relationships, and cumulative effects operating over broad and variable spatial and temporal scales (Jacobson et al., 2001). Community stakeholders and ecosystem managers are, thus, faced with the challenge of integrating data from disparate sources regarding the geomorphic condition and instability of their waterways. Assimilation of climatologic, geologic, and anthropogenic data is required over variable temporal and spatial scales to simulate the complex, nonlinear processes inherent in channel dynamics at the watershed or basin scale. Huge public investments in time and resources would be required to develop and apply traditional physics-based models. We examine here the use of artificial neural networks (ANNs) as an alternative to conventional hydrologic models to help stakeholders make stream management decisions. ANNs, used in this work to predict channel conditions (e.g., instability), offer many advantages, including the ability to accommodate both large amounts of spatial and temporal data, as well as multiple data types (i.e., remote sensing, quantitative field data, qualitative rankings, etc.). It also pro-

* Corresponding author. Tel.: +1 802 656 1495; fax: +1 802 656 8446.
E-mail addresses: lbesaw@cems.uvm.edu (L.E. Besaw), drizzo@cems.uvm.edu (D.M. Rizzo), mike.kline@state.vt.us (M. Kline), southmountain@gmavt.net (K.L. Underwood), jdoris@sanbornhead.com (J.J. Doris), lmorriss@uvm.edu (L.A. Morrissey), kpelleti@uvm.edu (K. Pelletier).
[1] Tel.: +1 802 656 1937; fax: +1 802 656 8446.
[2] Tel.: +1 802 656 2695.
[3] Tel.: +1 802 656 3153.
[4] Tel.: +1 802 241 3774; fax: +1 802 241 3287.
[5] Tel./fax: +1 802 453 3076.
[6] Tel.: +1 802 728 2000; fax: +1 802 728 9500.

0022-1694/$ - see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.jhydrol.2009.04.007

vides a standardized, expert-trained approach for classifying the sensitivity of river networks in various contexts (erosion hazard mitigation, habitat restoration and conservation).

Background

Watershed managers and planners have long sought decision-making tools for forecasting changes in stream-channels over large spatial and temporal scales. In an attempt to resolve and avoid conflicts between human stressors and natural fluvial processes, the Vermont Agency of Natural Resources (VTANR) has developed stream geomorphic assessment protocols (Kline et al., 2006a,b) that identify stream-reach susceptibility to lateral and vertical adjustment. VTANR combines components and theory from several nationally recognized stream geomorphic classification systems (e.g., Montgomery and Buffington, 1997; Rosgen, 1994; Rosgen and Silvey, 1996; Schumm, 1977) to capitalize on, or work around, what each system communicates or fails to communicate (Simon et al., 2007). In so doing, they combine components of the Rosgen stream classification system with Montgomery and Buffington (1997) to describe the role of both stream form and process when defining channel susceptibility. Components of the Schumm (1984) and Simon and Hupp (1986) channel evolution models, in turn, help capture the temporal and spatial sequence of vertical and lateral channel adjustments in response to natural or human stressors. Watershed stressor-response models (i.e., Schumm, 1977) hypothesize that a stressor of given type, magnitude, and duration will cause a river system to move out of a state of dynamic equilibrium by exceeding vertical and lateral threshold(s) for adjustment (Bull, 1979; Harvey and Watson, 1986). The channel will then adjust its slope, width/depth relationships, roughness factors, and velocity, in interdependent ways, to regain equilibrium (Leopold, 1994). Even when the stressor duration is relatively brief (hours to months), channel adjustments can play out over several years to decades, or longer (Schumm, 1977). In the VTANR approach, sensitivity ratings are assigned to streams in the context that some streams, due to their setting and location within the watershed, are more likely to be in an episodic, rapid, and/or measurable state of adjustment.

In summary, the VTANR stream classification system uses a set of broad descriptors and ratios that, together, characterize: (1) stream–floodplain relationships, (2) drivers and quantity of sediment transport, (3) channel boundary resistance, and (4) hydrologic runoff characteristics. In addition to increasing knowledge of the physical processes and features shaping a watershed, the VTANR protocols examine the risk of stream adjustment when deciding how to best protect, manage, and restore watershed resources, while balancing the needs for economic development.

Stream sensitivity

VTANR stream sensitivity is defined as the likelihood of a stream responding, through lateral and/or vertical adjustment, to a watershed or local disturbance, caused by natural events and/or human activity. This sensitivity is a function of (1) the stream's inherent susceptibility to adjustment (hereafter referred to as stream inherent vulnerability) and (2) its geomorphic condition. The classification maintains the distinction between channel *inherent vulnerability* and its *sensitivity*, i.e., its fluvial erosion hazard rating. Inherent vulnerability is the susceptibility of a reach to lateral and vertical adjustment as determined by the inherent characteristics and boundary conditions of the reach including its geologic, vegetation, and valley dimension parameters. Thus, a channel may be absent of stressors and in dynamic equilibrium, but may still be highly sensitive to adjustment due to its high inherent vulnerability.

G*eomorphic condition* is correlated to observations of stream adjustment, i.e., degree of departure from dynamic equilibrium. A stream's sensitivity may be heightened when human activities/stressors alter the characteristics that influence a stream's natural adjustment rate; these characteristics include boundary conditions, sediment and flow regimes, and the degree of confinement within the valley. Streams with low geomorphic condition scores are currently in adjustment (e.g., degradation or aggradation) and may become acutely sensitive. For example, a stream that is actively incising is at greater risk of further adjustment, given additional stressors, than a similar stream with no evidence of incision.

The majority of watersheds have experienced multiple stressors (of varying types, magnitude, duration, and periodicity) at multiple locations (of varying extent), especially over recent centuries of human habitation. These effects overlap in time and space and manifest themselves in specific channel morphology at specific watershed locations. ANNs are highly parallel, nonparametric, statistical methods that are ideally suited to model these dynamic and multiple-stressor, multiple-response river network systems without the constraints typically associated with traditional parametric statistical techniques (e.g., normal distributions and continuous variables).

Hierarchical artificial neural networks for examining stream sensitivity

In this research, two types of ANN algorithms are used in hierarchy to assimilate large amounts of multiple data types to predict stream channel conditions for use in fluvial hazard management decision-making. This hierarchy consists of supervised counterpropagation ANNs that predict geomorphic processes scores (Fig. 1a–d), geomorphic condition scores (Fig. 1e), and inherent vulnerability categories (Fig. 1f), and an unsupervised Kohonen self-organizing map ANN that *clusters* sensitivity to adjustments (Fig. 1g). A variety of reach- and watershed-scale field geomorphic assessment data and expert knowledge are used as inputs. The model is hierarchical in that output from each ANN module provides hydrologic information that is used as inputs to other ANN modules, and may be analyzed individually by experts to address objectives other than stream sensitivity. This ANN hierarchy: (1) provides a standardized, expert-trained approach for classifying the sensitivity of river networks in various contexts; (2) documents the weights experts place on various parameters when classifying stream geomorphic condition, inherent vulnerability, and overall sensitivity at the reach-scale; and (3) is data-driven, and therefore does not require the development of site-specific, physics-based stream models, or expert system if–then–else rules. The ANN system architecture is sufficiently flexible to allow for its continual update and refinement in light of new and expanded understandings of fluvial geomorphology. However, as a data-driven method, ANN predictions are only as good as the information provided to them, stressing the need for accurate and reliable expert assessments. Their use has potential to save time and resources, while enabling a truly adaptive management approach.

ANN training algorithms fall into one of two categories: supervised and unsupervised learning. Both are used in this work. Supervised algorithms (i.e., counterpropagation) are used to map non-linear relationships between input predictor variables and known output responses, and make up the majority of ANNs in use today. These ANNs iteratively adjust their behavior (internal weights) to better match the known response, similar to a teacher providing feedback to students on their performance. The most popular supervised algorithms include the feed-forward back-propagation network (Rumelhart and McClelland, 1988) and the radial basis function neural network (Bashkirov et al., 1964). The selection of the information-passing structure, number of layers

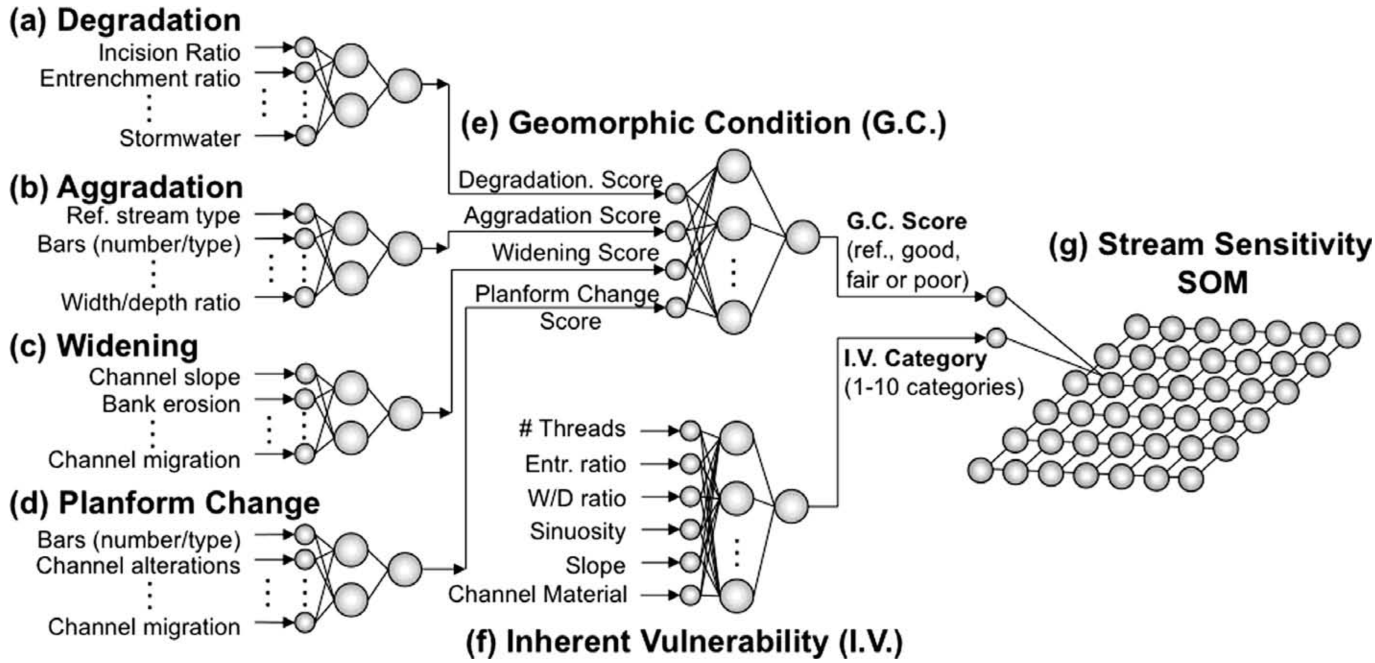

Fig. 1. System of hierarchical ANNs used to predict stream geomorphic condition and inherent vulnerability as well as categorize stream sensitivity to adjustment processes. ANN predictions channel (a) degradation, (b) aggradation, (c) widening and (d) plan-form change scores are used as inputs to the (f) geomorphic condition ANN. Outputs from the (e) geomorphic condition and (f) inherent vulnerability ANNs are used as inputs to the (g) stream sensitivity SOM. These outputs are used by the SOM ANN to cluster stream sensitivity.

and nodes, nodal activation functions, and internal weight-adjustment algorithms create numerous types of ANNs. For a concise introduction to ANNs, see Wasserman (1989) or Negnevitsky (2005). Govindaraju (2000) provides a good review of supervised ANNs used in a variety of water resource engineering applications.

In contrast, unsupervised ANNs (i.e., Kohonen self-organizing map) autonomously analyze inherent dataset properties using input data only. They are used primarily to extract relationships when the response (or output) classification is unknown. Although unsupervised (Hebb, 1949) and competitive training (Grossberg, 1972; Malsburg, 1973) algorithms had been previously developed, it was not until Kohonen (1989) merged these concepts into the self-organizing map (SOM) that unsupervised algorithms became useful to practitioners.

In this work, we use supervised counterpropagation ANNs to predict stream geomorphic condition (Fig. 1e) and inherent vulnerability (Fig. 1f) in tandem with an unsupervised SOM to cluster and visualize stream sensitivity relationships (Fig. 1g).

Counterpropagation ANNs

The supervised counterpropagation algorithm has found uses in a wide range of applications, including the classification of soil samples (Fidencio et al., 2001), the assessment of ecological status and prediction of ecosystem water quality (Park et al., 2003b), modeling of nonlinear pH-processes (Nie et al., 1996), prediction of spatial and temporal rainfall variation (Hsu et al., 1995; Hsu et al., 1999), and stream flow prediction (Chang and Chen, 2001). Rizzo and Dougherty (1994a,b) and Besaw and Rizzo (2007) modified the counterpropagation network to accommodate large amounts of spatially auto-correlated data for subsurface characterization applications and conditional simulation. Underwood and Rizzo (2003) and Doris et al. (2004) used this modified counterpropagation network to classify stream geomorphic condition.

Fig. 1a–d provides schematic counterpropagation ANNs for each of the four geomorphic processes (aggradation, degradation, widening, and plan-form change) that combine to predict the reach-scale geomorphic condition (Fig. 1e). Inputs to these four ANNs consist of reach-scale channel observations and characteristics (e.g., incision ratio, entrenchment ratio, channel slope and bed material, etc.). The outputs are geomorphic scores on a scale from 0 to 20 as developed by the VTANR (0–5 for poor, 6–10 for fair, 11–15 for good and 16–20 for reference). The geomorphic condition ANN (Fig. 1e) outputs geomorphic condition rating (0–1) to reflect reference, good, fair and poor conditions.

Counterpropagation is also used to predict the stream's inherent vulnerability (Fig. 1f) using six input variables (number of channel threads, entrenchment ratio, width/depth ratio, sinuosity, channel slope and bed material). Outputs from the geomorphic condition and inherent vulnerability ANNs are then used as inputs to the stream sensitivity SOM.

The self-organizing map (SOM)

The SOM approximates input data probability density functions, and is typically used to cluster data vectors into similar categories when a priori categories do not exist (Kohonen, 2001). Using a topology-preserving projection, SOMs may be used to convert non-linear, high-dimensional data to some user-defined lower-dimension. This nonparametric, clustering algorithm is also capable of incorporating large amounts of discrete and continuous data types (Kohonen, 1990), while avoiding many assumptions (e.g., normal distributed data) required by traditional statistical techniques.

To our knowledge, the SOM has not been used for stream classification purposes. It has, however, been used in numerous stream ecological studies to classify macroinvertebrate communities (Chon et al., 1996; Gevrey et al., 2004; Lek et al., 2005; Park et al., 2003a) and assess impacts of environmental disturbances on those communities (Park et al., 2004). SOMs have also been used for clustering and forecasting flood events (Chang et al., 2007) and modeling rainfall–runoff processes (Lin and Wu, 2007; Moradkhani et al., 2004).

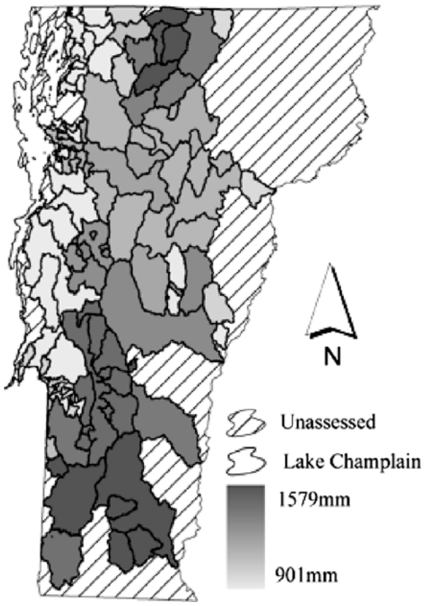

Fig. 2. Vermont watersheds assessed with VTANR protocols and average annual precipitation in mm (shading) within those watersheds; precipitation data courtesy of Prism-Group (2008).

Data and methodology

VTANR statewide assessment data

Historic and current land-use patterns throughout Vermont greatly impact stream and watershed characteristics. To date, the VTANR protocols have been applied to 789 stream reaches with a cumulative length that exceeds 7500 km, covering more than 18,500 km^2 of the Vermont landscape (Fig. 2). This study data was downloaded in May of 2007 from the VTANR website http://anrnode.anr.state.vt.us/ssl/sga/security/frmLogin.cfm.

As expected for a geographically diverse landscape, Vermont stream processes are broadly characterized by areas of sediment production, transport and storage. Streams varied in slope from 0% to 19.5%, with greater than 95% having a slope less than 5%. The average reach (or sub-reach) length was just over 1.5 km but varied from less than 0.15 km to almost 16 km. Drainage areas varied from 0.25 km^2 to more than 2700 km^2 with an average of 90 km^2. The assessed watersheds had a log-normally distributed average annual precipitation (Prism-Group, 2008) ranging from 900 mm (minimum) to 1600 mm (maximum) with an 1100 mm mean (Fig. 2). The majority of the study reaches had dominant parent geologic material consisting of either river or glacial sediments (Table 1). The dominant land cover type was forest (89%), while urban (7%) and agriculture (2%) made up the remainder. Urban land use varied from less than 1% to more than 95% across the basins. More than 90% of the reaches used in this study had channel headwaters less than 350 m above sea level. The majority of the reaches have been impacted by humans, including 58% with bank armoring, 65% straightening and 12% with a history of dredging. Due to these, and other human-induced stressors, only 4% of the assessed reaches had a reference geomorphic condition, while 33%, 57% and 6% were in a state of good, fair and poor, respectively. The following VTANR assessment protocols were designed to be equally applicable to reaches of all geomorphic conditions.

Table 1
Dominant geologic parent material of analyzed stream reaches.

Description	Erodibility	N^a
Alluvial river sediments	High	276
Glacial river deposits	High	139
Glacial lake deposits	Moderate–high	97
Glacial sea	Moderate–high	0
Till/glacial sediments	Moderate–high	153
Colluvium	Variable	0
Bedrock	Low	0
Miscellaneous/organic deposits	Variable	36

[a] Does not add up to 789 due to missing field data.

VTANR stream geomorphic assessment protocols

With limited resources in a state as rural as Vermont, the data collection protocols are not as quantitatively rigorous as those published in traditional geomorphic stream assessments (e.g., Montgomery and MacDonald, 2002). However, from a policy management and public interest perspective, stream indicator parameters should be: (1) scientifically based, (2) limited in number, (3) quantitative, (4) easily measured by non-specialists, (5) able to quantify stream power, resistance and work and (6) applicable to channels of various type and size (Graf, 2001). With these goals in mind, various divisions within VTANR (e.g., Department of Environmental Conservation, River Management Program, Department of Fish and Wildlife, Fisheries Division, and Vermont Geological Survey) collaborated to develop Vermont's stream geomorphic assessment protocols.[7] A short summary follows; for more details visit http://www.anr.state.vt.us/dec/waterq/rivers.htm.

The VTANR stream geomorphic assessment protocols consist of three phases of data collection and assimilation. Phase 1, the remote sensing phase, involves analyzing data on soils, geology, topography, and land use and land cover from existing topographic maps, aerial photography and existing field studies. Geomorphic reaches and provisional reference stream types are established based on valley landforms and geology. Estimates of channel condition, adjustment process, and reach sensitivity are based on evaluations of land use and channel floodplain modifications. While these estimates are provisional, the Phase 1 analyses allow large watersheds (250–400 km^2) to be assessed within a few months time.

Phase 2, the rapid field assessment phase, involves the collection of field measurements and observations at the reach or sub-reach scale. Stream types are established based on channel and floodplain cross-sections and stream substrate measurements. Stream geomorphic and physical habitat condition, adjustment processes, reach sensitivity, and channel evolution stage are assessed by evaluating basin geologic and topographic setting, field erosion and depositional processes, changes in channel and floodplain geometry, and riparian land use/land cover.

Phase 3, the survey-level field assessment phase, involves the collection of detailed field measurements (e.g., surveying) at the sub-reach or site scale and may take three to four days to survey a stream length of two meander wavelengths. Existing stream types and adjustment processes are further detailed and confirmed using quantitative measurements of channel dimension, pattern, profile, and sediment types and loads.

[7] 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.

The supervised counterpropagation ANN

The supervised counterpropagation algorithm (Hecht-Nielsen, 1987) was used to predict reach-scale geomorphic condition and inherent vulnerability (Fig. 1e and f, respectively). This relatively simple, yet powerful algorithm leverages the SOM's competitive learning (discussed below) with known output responses (a priori categories) to create statistical mappings between predictor and response vectors. The execution of the counterpropagation algorithm is defined by two phases: a training phase and a prediction phase.

The counterpropagation architecture consists of three nodal layers: input, hidden and output (Fig. 1a–f). All nodes in adjacent layers are connected via weights (or connection strengths). During training, the weights are iteratively adjusted to map the set of input predictor vectors, $\boldsymbol{x}$, to the set of associated response vectors, $\boldsymbol{y}$, defined by some non-linear function $\boldsymbol{y} = \varphi(\boldsymbol{x})$, represented by the training data. A given input vector, $\boldsymbol{x}$, consisting of n variables $(x_1, x_2, \ldots, x_n)$, is passed to the hidden layer and a similarity metric between the input vector and each node's weight vector, is computed. The hidden node with the weight vector most similar to the input vector is identified as the *winning* node and this node's weights are adjusted to be more similar to the input vector. Likewise, the winning node's output weights are adjusted to be more similar to the corresponding response vector, $\boldsymbol{y}$. This process is repeated for all input–output pairs until the network has learned the input–output relationship defined by $\boldsymbol{y} = \varphi(\boldsymbol{x})$ to some user defined convergence criterion (in this work, a root-mean-square error less than 10^{-6}). After convergence, the network weights are fixed and the ANN may be used for prediction. During the prediction phase, input vectors that were not used to train the ANN are presented to the network for estimation.

Unlike traditional feed-forward backpropagation learning algorithms, the counterpropagation algorithm cannot be over-trained and requires very little time for convergence. The counterpropagation algorithm, used here to predict geomorphic condition and inherent vulnerability, behaves as an expert system and is considerably more efficient than if–then–else rules from an adaptive management standpoint. The algorithm was written in MatLab V. 7.4.0.287 (R2007a). For more details refer to (Hecht-Nielsen, 1987). Pseudo-code is provided in Rizzo and Dougherty (1994a).

Geomorphic condition ANN

The geomorphic condition ANN (Fig. 1e) was trained, tested and validated using geomorphic data sets from two watersheds in Northwestern Vermont. Lewis Creek and Middlebury River were selected because of the similarities in their cumulative watershed area (210 km^2 and 163 km^2, respectively) and land cover type (forest: 70% and 87%, agriculture: 24% and 12% and impervious: 6% and 1%, respectively). In addition, both basins are western-facing slopes of the Green Mountains that span the eastern Champlain Valley and drain ultimately to Lake Champlain.

The ANN was trained on 20 contiguous reaches in Lewis Creek and then used to predict reach-scale geomorphic condition on 19 contiguous reaches along the Middlebury River. Five geomorphology experts classified geomorphic condition for the 39 reaches using field data collected at the site-level (e.g., field-inspection of geomorphic features, channel slopes, soil types, cross-sections, and pebble counts). The data was aggregated to the reach level to determine a dominant and subdominant channel adjustment for each reach, choosing from among four processes: degradation, aggradation, widening and plan-form change. The experts' geometrically-averaged process scores were used as inputs to the ANN. The corresponding output data were the expert derived (averaged) geomorphic condition ratings. The experts' output ratings were grouped into quadrants of unequal real-value ranges and coded on a scale of 1–4 (Table 2). The ranges are skewed such that Good and Excellent (Reference) condition scores are more difficult to achieve. Outputs were geometrically averaged and errors were quantified using fuzzy set membership functions (Doris, 2006; Zadeh, 1965). Error bars, reflecting the variance in expert opinion (minimum and maximum geomorphic condition scores) were computed by averaging the fuzzy set membership functions.

Table 2
Reach-level condition ANN input parameters: degradation, aggradation, widening, and plan-form change.

Reach-level condition	Input code	Geomorphic condition scores
Poor	1	0–0.34
Fair	2	0.35–0.64
Good	3	0.65–0.84
Reference	4	0.85–1.0

Inherent vulnerability ANN

Input data for testing and validating the inherent vulnerability ANN (Fig. 1f) was compiled by VTANR for all 789 reaches using available topographic, orthophotography, soils, geologic, and land use/land cover GIS data layers (Phase 1 protocols). These were then verified during the Phase 2 field surveys. Training data included the Rosgen stream classification indicators, Fig. 1f, modified to incorporate basin characteristics and boundary condition data (e.g., valley confinement, valley and channel slope, sediment regime characterization, boundary conditions, surficial geologic features, and degree of channel entrenchment). Input variables were continuous real numbers with the exception of the channel bed material and number of channel threads (coded as integers).

The ANN was trained on the data structure generated by the if–then–else rules of the modified Rosgen–Montgomery and Buffington classification system. Stream reaches were classified into one of ten inherent vulnerability categories that best represent VTANR's fluvial hazard mapping needs. Ten categories were used, compared with the 94 categories of the Rosgen classification system. Once trained, the ANN was used to predict the inherent vulnerability of 789 expert evaluated stream reaches.

The unsupervised self-organizing map

A two-dimensional SOM (Figs. 1 and 3g) was used to cluster the 789 stream reaches into groups of stream sensitivity. Training input vectors, $\boldsymbol{x}$, consisting of n variables $(x_1, x_2, \ldots, x_n)$ are passed sequentially to the SOM nodes. In this work, we used the experts'

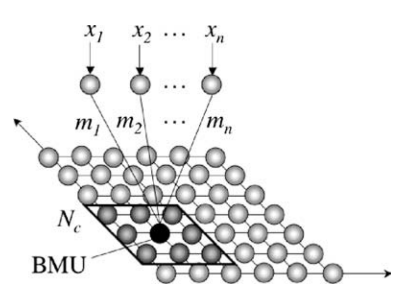

Fig. 3. Generic SOM with a 2-D nodal lattice. Input vectors comprised of n variables $(x_1, x_2, \ldots, x_n)$ are presented to each node (grey circles) in the network. A best matching unit (BMU – node shown in black) is defined as the node whose weights are most similar to the input vector. The SOM is trained by iteratively updating n weights $(m_1, m_2, \ldots, m_n)$ associated with each node within the neighborhood (N_c) of the BMU.

VTANR Phase 2 protocols of inherent vulnerability and geomorphic condition (e.g., $n = 2$), rather than generating scores with the counterpropagation ANN. A 30×30 *square* 2-D lattice topology was selected for the SOM with each lattice node having eight neighbors (N_c in Fig. 3). A hexagonal (rather than square) topology is typically used in SOMs when conditional bias exists between the input variables (Kohonen, 2001); however, prior statistical analysis verified unbiased data in this application. Each 2-D lattice node (Fig. 3) has a vector, $\boldsymbol{m}$, of n weights $(m_1, m_2, \ldots, m_n)$ associated with it. The weights are initially set to random values near the centroid of the input space. Therefore, weight vectors and input vectors are defined in the same dimensional space ($\boldsymbol{R}^n$).

SOM training is an iterative process. For each lattice node, a distance metric is computed between its associated weight vector, $\boldsymbol{m}$, and a given input vector, $\boldsymbol{x}$. The node whose weight vector is most similar to the input vector is called the best matching unit (BMU). Several training stages with various sized SOM lattices were performed to minimize the quantization and topographic error metrics. Quantization error reflects the average distance between training vectors and their BMUs; while the topographic error is the percentage of input patterns for which the first and second best matching units are not adjacent on the SOM map. The 30×30 node lattice minimized the quantization and topographic errors (9.4×10^{-4} and 0.084), respectively.

During training, the weights associated with the BMU, and the nodes in some neighborhood (N_c) of the BMU, are iteratively adjusted to be more similar to the input vectors. The neighborhood size, N_c, was initially set to 15 nodes and linearly decreased to one over the duration of training. The magnitude of adjustment is a function of the training coefficient, α, which was decreased linearly during training from 0.9 to 0 (e.g., larger α produces larger adjustment). The reduction of N_c and α over the training duration ensures that a global data structure is established in the early phases of training and more local refinement is established in the latter stages. The passage of all training input vectors to the SOM defines a single training iteration. A total of 1000 iterations were run with the 30×30 SOM to cluster the stream sensitivity data. Details of the SOM algorithm can be found in (Kohonen, 1990, 2001). Although several commercial SOM packages exist, the SOM used in this work was written in MatLab V. 7.4.0.287 (R2007a).

Once training was complete, the number of SOM clusters or groups were identified using the unified-distance matrix (U-matrix) formulated by Ultsch and Siemon (1990). The U-matrix technique involves computing the average distance between each SOM node and its eight neighbors (Fig. 3) and plotting the values associated with nodes in grey-scale. Groups of nodes with similar weight vectors (smaller average distances) are plotted in lighter shades of grey while those dissimilar weights vectors are plotted as darker shades.

After training, the SOM was used in several ways. Firstly, the input training patterns were identified/labeled and superimposed onto the U-matrix (results not shown) by mapping each label to its BMU. This allowed us to visualize which training vectors were most similar to each other (i.e., belong to similar clusters). Secondly, the individual scalar components associated with the vectors were mapped separately onto 2-D lattices, resulting in $n = 2$ "component planes". Mapping the input properties alongside of and in the same space as the clusters allowed experts to further explore and/or validate the resulting stream sensitivity clusters.

Evaluation criteria

Numerous mathematical measures are available to describe agreement of model predictions with available observations (Krause et al., 2005). Two metrics, the coefficient of determination and the coefficient of efficiency, were used to compare the predictive capabilities of the ANN models with expert opinions.

The coefficient of determination, r^2, is the square of the sample correlation coefficient calculated as:

$$r^2\left(\frac{\sum_{i=1}^{n}(O_i-\overline{O})(P_i-\overline{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\overline{O})^2}\sqrt{\sum_{i=1}^{n}(P_i-\overline{P})^2}}\right)^2,$$

where O represents measured observations (expert opinion in our case), P represents predictions, and n is the total number of observations. The coefficient describes the percentage of observed variance explained by the model and ranges from 0 to 1. A value of 0 implies no correlation, while a value of 1 implies that the model can explain all of the observed variance.

The coefficient of efficiency, E, compares the predictive abilities of the model with respect to the observed mean. It is calculated as:

$$E = 1 - \frac{\sum_{i=1}^{n}(O_i-P_i)^2}{\sum_{i=1}^{n}(O_i-\overline{O})^2},$$

where again, O represents measured observations, P represents the model predictions and n is the total number of observations (Nash and Sutcliffe, 1970). E ranges from 1 (perfect fit) to $-\infty$, where values less than zero indicate that the observation mean would be a better predictor than the model.

Results and discussion

We chose to structure individual ANNs in a hierarchy, rather than creating a single ANN because it allowed us to (1) leverage the most appropriate computational tools for the specific problems at hand (e.g., classification ANNs for geomorphic condition and inherent vulnerability, and clustering ANN for grouping reaches into stream sensitivity), and (2) provide decision makers with intermediate pieces of information needed for informed watershed-management decisions. The individual ANNs are capable of accommodating quantitative and qualitative data (e.g., continuous and categorical) more efficiently than traditional methods (e.g., site specific physics-based models, parametric statistical methods), allowing them to fill in gaps of qualitative stream assessment. The data-driven nature of these algorithms also eliminates the need for constructing traditional if–then–else rules associated with expert systems.

Stream geomorphic condition ANN

A proof-of-concept comparison between the ANN predicted geomorphic condition (classified into four categories: 1-poor, 2-fair, 3-good and 4-reference) and the experts' averaged classifications (with error bars) is provided in Fig. 4. The ANN predictions matched the experts for 15 of the 19 reaches (coefficient of determination $r^2 = 0.86$, coefficient of efficiency $E = 0.85$). Only one (out of 19) geomorphic condition predictions differ significantly from the experts' classification (reach 13, Fig. 4). And in this reach, the classification varied widely among experts from different geographic locations. (Further inspection identified reach 13 as having a culvert, viewed by some experts as a grade control and by others as a potential problem). These 39 reaches (20 for training and 19 for prediction) represent only a small subset of streams types within Vermont, rather than covering the entire spectra. Additional training data, with a broader range of training patterns is needed to predict geomorphic condition for all reaches within the entire state of Vermont.

The variability in the experts' classifications (error bars in Fig. 4) reflects differences in the experts' weighting of the four adjust-

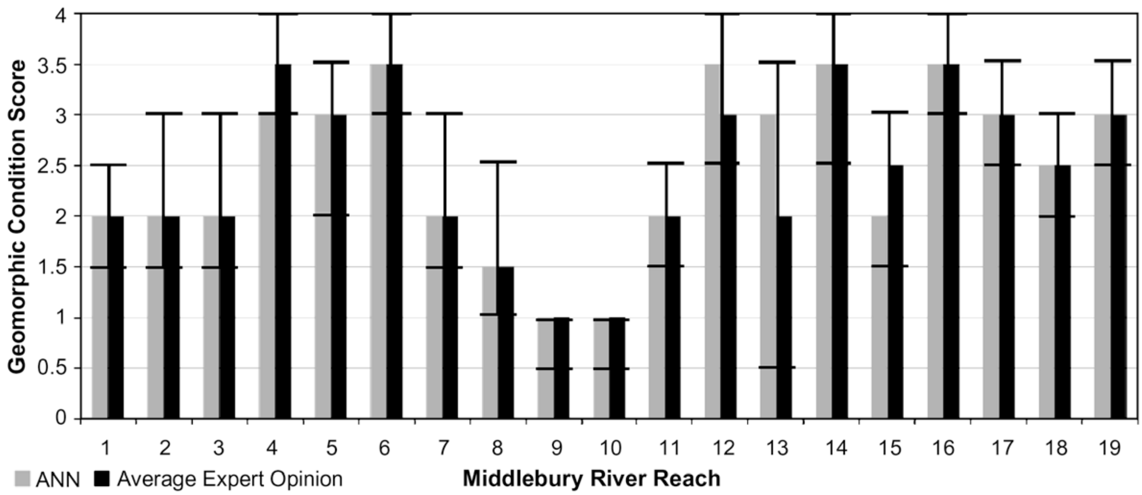

Fig. 4. Reach classifications of geomorphic condition determined by experts and geomorphic condition ANN (error bars indicate average expert minimum and maximum scores).

ment processes and the subjective nature of assigning overall reach-scale geomorphic condition scores. No quantitative approach was taken by any of the experts to average the four adjustment process scores. Additional reasons why the experts weighted these processes differently may include differences in training, experience, exposure to rivers in various geographic settings, and preconceived notions about conceptual models applicable to the watershed in question. For example, experts supportive of Schumm's channel evolution model might weigh incision more heavily than widening, aggradation, or plan-form change.

Stream inherent vulnerability ANN

The counterpropagation ANN (Fig. 1f) successfully predicted stream inherent vulnerability. The predictions matched the experts' classifications in 86.4% of the 789 assessed reaches with a coefficient of determination $r^2 = 0.50$ and coefficient of efficiency $E = 0.44$.

Reasons for misclassification of the remaining 13.6% (or 107) reaches were attributed to (1) data entry errors, i.e., errors incurred in transcribing field notes to the computer (54 of the 107 misclas-

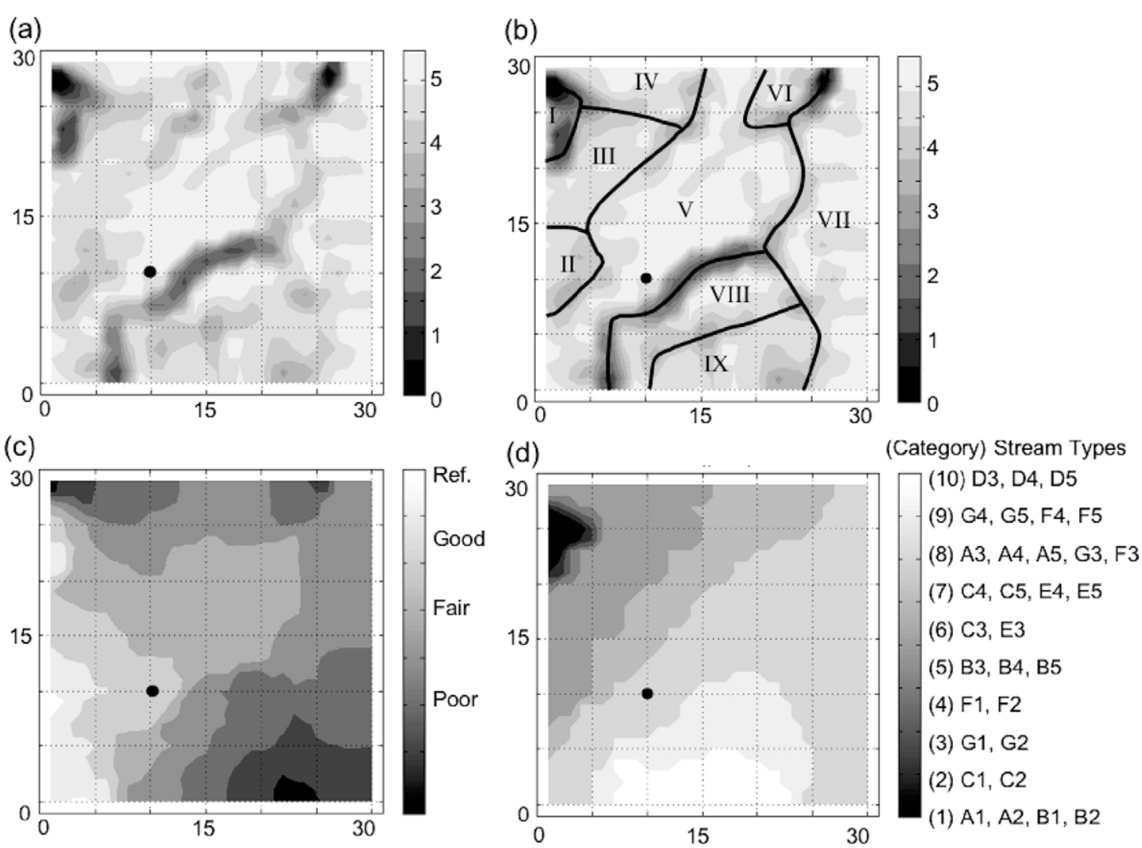

Fig. 5. Stream sensitivity U-matrix (a) without and (b) with nine delineated clusters using SOM inputs of stream (c) geomorphic condition and (d) inherent vulnerability component planes.

Table 3
SOM clusters of stream sensitivities for 789 reaches.

SOM cluster	Existing VTANR ratings of stream sensitivity					
	Very low	Low	Medium	High	Very high	Extreme
I	**8**	0	0	1	0	0
II	0	2	**20**	2	1	0
III	0	0	**29**	**32**	3	0
IV	0	1	2	**35**	8	0
V	0	2	36	**192**	**70**	1
VI	0	0	0	**4**	**4**	0
VII	1	0	1	13	**203**	1
VIII	0	0	1	5	**22**	**19**
IX	0	0	0	5	21	**45**

Table 4
New stream sensitivity labels for the nine SOM clusters.

Group	Sensitivity category
I	Very low–low
II	Medium
III	Medium–high
IV	High
V	High–very high
VI	High–very high
VII	Very high
VIII	Very high–extreme
IX	Extreme

sifications), (2) idiosyncratic differences between experts (9 out of 107 misclassifications), or (3) inherent ambiguity in the Rosgen stream classification system (41 out of 107 misclassified reaches). For example, a stream with an entrenchment ratio of 1.4, width/depth ratio greater than 12, and a sinuosity greater than 1.2 may be classified as either type F or B in the Rosgen classification system. Similarly, differences between experts in their decision-making logic and use of field observations not yet identified in the existing dataset were found to be important. These causes of misclassification provide opportunity for experts to further define their field observations and document their classification reasoning.

The counterpropagation ANN operates as an easy-to-modify expert system. Traditional expert systems are implemented using extensive if–then–else rules. These rules can be cumbersome and difficult to update (i.e., modifications due to recent progress and understanding in watershed/channel systems). The data-driven nature of the counterpropagation algorithm enables it to be readily modified simply by changing input–output training data files without modifying or constructing new if–then–else rules.

The process of defining stream type (inherent vulnerability) and dominant adjustment process (geomorphic condition) on the basis of Phase 1 and Phase 2 geomorphic assessments does involve inherent uncertainty. Field data are collected by a variety of protocol practitioners, e.g., consultants, Regional Planning Commissions, non-profit groups; some experts repeatedly visit stream reaches, while others rely on observations from a single point in time. Because ANNs are data driven, their predictions are only as good as the information provided to them. For example, the current ANN, trained to map VTANR geomorphic condition, is not immediately applicable to different geographic regions (e.g., North Western US). New data would need to be gathered and used to train the ANNs. The real value of using ANNs in stream classification applications may be in their role to systematically articulate and document how experts weigh various factors in their own decision-making.

Stream sensitivity SOM

Geomorphic condition (deduced by stream experts) and stream inherent vulnerability (deduced by the counterpropagation ANN) were used as equally weighted inputs to the SOM ANN to cluster streams into groups of sensitivity. The grey shading (Fig. 5a and b) represents the U-matrix associated with the 30×30 SOM lattice and delineates the clusters of sensitivity. In the grey-scale plot, white plateaus represent nodes with similar features forming clusters or subgroups, whereas dark "ravines" separate or delineate groups. A total of nine stream sensitivity clusters (outlined for better visualization in Fig. 5b) have been identified by the 30×30 SOM.

Fig. 5c and d plots the components of the trained SOM weight vectors in 2-D space (on a 30×30 lattice). Each panel represents the SOM weight associated with stream geomorphic condition and inherent vulnerability, respectively. The grey scale in panel (c) reflects the geomorphic condition score from 1 (reference) to 0 (poor). The 10 categories of inherent vulnerability, ranging from 1 (stream types A1, A2, B1 and B2) to 10 (D3, D4 and D5), are provided in the legend of panel (d) based on a modified Rosgen–Montgomery and Buffington system developed by the VTANR (see Background). To illustrate the interpretation of the SOM U-matrix and the component planes, a point is plotted at SOM node (10, 10) in all four panels of Fig. 5. The particular stream reach associated with this point has a geomorphic condition rating of good (panel c) and an inherent vulnerability associated with cate-

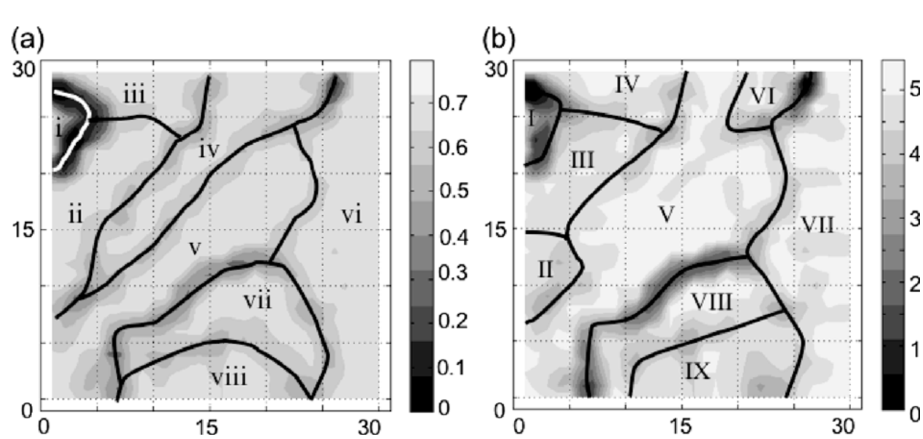

Fig. 6. SOM stream sensitivity U-matrices and corresponding clusters with (a) inherent vulnerability weighted 5-fold more heavily than geomorphic condition and (b) inputs weighted equally.

gory eight (modified Rosgen stream types A3, A4, A5, G3 or F3) (panel d). This particular stream reach has been clustered with similar reaches by the SOM into group V.

Since the SOM is an unsupervised ANN (with no predetermined output or classifications), it is common to subsequently ask experts to identify similar attributes or properties within clusters and provide names/labels for the clusters. In this work, we were in a unique situation, since experts at the VTANR (using their biological neural nets) had previously assigned stream sensitivity ratings to each of the 789 reaches without the aid of statistical clustering tools. The protocols had already distinguished a total of six stream sensitivity ratings: very low, low, medium, high, very high and extreme. For comparison purposes, we list the nine newly-derived SOM clusters with the six existing VTANR stream sensitivity classifications (Table 3) and provide new labels for the nine SOM-generated sensitivity ratings (Table 4). In Table 3, the sensitivity ratings that dominate a particular group have been highlighted in bold and are used to generate the new labels in Table 4. The point plotted in Fig. 5 falls into sensitivity cluster V and has a SOM sensitivity rating of High–very high. As with the reach-scale geomorphic condition scores, there is some natural variability of stream sensitivity within each group (e.g., group VII contains 203 out of 219 reaches with very high sensitivity ratings, 1 extreme, 13 high, 1 medium and 1 very low sensitivity ratings).

Given these results, we may use the SOM either to increase the number of classes in VTANR's current classification system or extract additional information from the experts to create an algorithm that would classify the data into the existing VTANR sensitivity classes. The results in Table 3 suggest that increasing the number of stream sensitivity classes could be achieved by simply stretching the scale over which the sensitivity ratings are currently ranked. What is most significant about the two groupings is how well they correlate despite being derived from different methodologies.

The SOM framework also provides for a truly adaptive management tool by allowing the experts to weight the relative contribution or importance of the inputs (if known), and customize the groupings based on these expert weightings. Fig. 6 shows the effect of weighting the stream's inherent vulnerability input 5-fold more heavily than the geomorphic condition. The resulting U-matrix is grouped into eight clusters and denoted with lower case Roman numerals: i, ii, . . . , viii. For comparison purposes, the U-matrix using equally weighted inputs (Fig. 5b) is repeated in Fig. 6b. The result of this weighting is a stream sensitivity clustering system that closely maps to the stream's inherent vulnerability. Including additional predictor variables or selecting a different threshold for the U-matrix would result in slightly different groupings.

Conclusions

This study demonstrates the usefulness of two artificial neural network algorithms used in tandem to assist decision makers in classifying stream sensitivity to adjustment for watershed management purposes. A series of supervised counterpropagation algorithms trained with expert knowledge, offers great potential for QA/QC of existing expert-derived stream assessments. In this study, the predicted reach-scale stream geomorphic condition and inherent vulnerability were used, in turn, as inputs to the unsupervised SOM algorithm to cluster 789 reaches into a stream sensitivity classification system. The methodology allows for the adjustment or weighting of the input variables. This provides flexibility and allows experts to fine-tune the SOM results and better document the similarities and differences among expert opinions. A related advantage of these ANNs is the creation of a consistent, repeatable process for classifying susceptibility to channel adjustment. It is important to note that the VTANR stream sensitivity groupings, in use today, evolved with the development of the protocols (from 2001 to 2007). And in fact, three different sets of if–then–else rules were developed over this period. Since the ANNs are data-driven, these algorithms circumvent the re-coding of if–then–else rules typically associated with traditional expert classification systems. While stream classification is arguably a subjective process, utilizing many qualitative values and rankings, the use of classification ANNs ensures that the process will be consistent from watershed to watershed and observer to observer.

The value in training and testing the hierarchical ANNs to classify reach-level stream sensitivity is multi-fold. The process: (1) elicits valuable information about the relative significance of governing factors in the overall determination of stream sensitivity; (2) helps articulate and document how different experts weigh various parameters in the classification of inherent vulnerability, geomorphic condition, and sensitivity; (3) provides a standardized, expert-trained approach for classifying sensitivity of river networks in various contexts (erosion hazard mitigation, habitat restoration and conservation) that saves time and resources; and (4) is sufficiently flexible and simple to modify, enabling a truly adaptive management approach. In addition, the method of developing and training supervised ANNs would be the same across geographic regions; providing the potential for geographic independence. However, each geographic region, given unique climatologic (e.g., droughts or extreme flood events) and geologic settings, would likely vary somewhat in their input parameters.

Acknowledgements

This research was supported in part by a grant from the U.S. Geological Survey and from the Vermont Agency of Natural Resources and is a contribution from the Water Resources and Lake Studies Center. The findings, conclusions, recommendations and opinions stated in this report are those of the authors and do not represent the views of the U.S. Geological Survey, the State of Vermont, or the Vermont Water Resources Research Center. Special thanks to Barry Cahoon, Christina Cianfrani, Evan Fitzgerald, W. Cully Hession and Maeve McBride.

References

Bashkirov, O.K., Braverman, E.M., Muchnik, I.B., 1964. Potential function algorithms for pattern recognition learning machines. Automatic Remote Control 25, 629–631.

Besaw, L.E., Rizzo, D.M., 2007. Stochastic simulation and spatial estimation with multiple data types using artificial neural networks. Water Resources Research 43, W11409. doi:10.1029/2006WR005509.

Bull, W.B., 1979. Threshold of critical power in streams. Geological Society of America Bulletin 90, 453–464.

Chang, F.J., Chen, Y.-C., 2001. A counterpropagation fuzzy-neural network modeling approach to real time stream flow prediction. Journal of Hydrology 245, 153–164.

Chang, F.-J., Chang, L.C., Wang, Y.-S., 2007. Enforced self-organizing map neural networks for river flood forecasting. Hydrological Processes 21 (6), 741–749.

Chon, T.-S., Park, Y.S., Moon, K.H., Cha, E.Y., 1996. Patternizing communities by using an artificial neural network. Ecological Modelling 90, 69–78.

Doris, J.J., 2006. Master's Thesis: Application of Counterpropagation Networks to Problems in Civil and Environmental Engineering. University of Vermont, Burlington, VT. 139 pp.

Doris, J.J., Rizzo, D.M., Underwood, K.L., 2004. A watershed classification system using hierarchical artificial neural networks for diagnosing watershed impairment at multiple scales, ASCE, World Water and Environment Resources Congress. ASCE, Salt Lake City, UT.

Fidencio, P.H., Ruisanchez, I., Poppi, R.J., 2001. Application of artificial neural networks to the classification of soils from Sao Paulo state using near-infrared spectroscopy. Analyst 126 (12), 2194–2200.

Gevrey, M. et al., 2004. Water quality assessment using diatom assemblages and advanced modelling techniques. Freshwater Biology 49, 208–220.

Govindaraju, R.S., 2000. Artificial neural networks in hydrology I: preliminary concepts. Journal of Hydrologic Engineering 5 (2), 115–123.

Graf, W.L., 2001. Damage control: restoring the physical integrity of America's Rivers. Annals of the Association of American Geographers 91 (1), 1–27.

Grossberg, S., 1972. A neural theory of punishment and avoidance: II. Quantitative theory. Mathematical Biosciences 15, 253–285.
Harvey, M.D., Watson, C.C., 1986. Fluvial processes and morphological thresholds in incised channel restoration. American Water Resources Association, Water Resources Bulletin 22 (3), 359–368.
Hebb, D.O., 1949. The Organization of Behavior. Wiley, New York, NY.
Hecht-Nielsen, R., 1987. Counterpropagation networks. Applied Optics 26 (23), 4979–4984.
Hsu, K., Gupta, H.V., Sorooshian, S., 1995. Artificial neural network modeling of the rainfall–runoff process. Water Resources Research 31 (10), 2517–2530.
Hsu, K.-l., Gupta, H.V., Gao, X., Sorooshian, S., 1999. Estimation of physical variables from multichannel remotely sensed imagery using a neural network: application to rainfall estimation. Water Resources Research 35 (5), 1605–1618.
Jacobson, R.B., Femmer, S.R., McKenny, R.A., 2001. Land-use changes and the physical habitat of streams—a review with emphasis on studies within the US Geolgical Survey Federal-State Cooperative Program, USGS Circular 1175.
Kline, M. et al., 2006a. Vermont Stream Geomorphic Assessment Phase 2 Handbook, Rapid Stream Assessment. Vermont Agency of Natural Resources, Waterbury, VT.
Kline, M. et al., 2006b. Vermont Stream Geomorphic Assessment Phase 1 Handbook, Watershed Assessment. Vermont Agency of Natural Resources, Waterbury, VT.
Kohonen, T., 1989. Self-Organization and Associative Memory. Springer Verlag, New York.
Kohonen, T., 1990. The self-organizing map. Proceedings of the IEEE 78 (9), 1461–1480.
Kohonen, T., 2001. Self-Organizing Map. Springer, Berlin, Germany.
Krause, P., Boyle, D.P., Base, F., 2005. Comparison of different efficiency criteria for hydrological model assessment. Advances in Geosciences 5, 89–97.
Lek, S., Scardi, M., Verdonschot, P.F.M., Descy, J.-P., Park, Y.-S. (Eds.), 2005. Modeling Community Structure in Freshwater Ecosystems. Springer, Berlin, Germany.
Leopold, L., 1994. A View of the River. Harvard University Press, Cambridge, MA.
Lin, G.F., Wu, M.-C., 2007. A SOM-based approach to estimating design hyetographs of ungauged sites. Journal of Hydrology 339 (3–4), 216–226.
Malsburg, C.V.d., 1973. Self-organizing of orientation sensitive cells in striate cortex. Kybernetik 14, 85–100.
Montgomery, D.R., Buffington, J.M., 1997. Channel-reach morphology in mountain drainage basins. Geological Society of America Bulletin 109 (5), 596–611.
Montgomery, D.R., MacDonald, L.H., 2002. Diagnostic approach to stream channel assessment and monitoring. Journal of the American Water Resources Association 38 (1), 1–16.
Moradkhani, H., Hsu, K., Gupta, H.V., Sorooshian, S., 2004. Improved streamflow forecasting using self-organizing radial basis function artificial neural networks. Journal of Hydrology 1–4, 246–262.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models, Part I – a discussion of principles. Journal of Hydrology 10, 282–290.
Negnevitsky, M., 2005. Artificial Intelligence. A Guide to Intelligent Systems. Addison-Wesley, New York, NY. 415 pp.
Nie, J.H., Loh, A.P., Hang, C.C., 1996. Modeling pH neutralization processes using fuzzy-neural approaches. Fuzzy Sets and Systems 78 (1), 5–22.
Park, Y.-S., Cereghino, R., Compin, A., Lek, S., 2003a. Applications of artificial neural networks for patterning and predicting aquatic insect species richness in running waters. Ecological Modelling 160, 265–280.
Park, Y.-S., Verdonschot, P.F.M., Chon, T.-S., Lek, S., 2003b. Patterning and predicting aquatic macroinvertebrate diversities using artificial neural network. Water Research 37 (8), 1749–1758.
Park, Y.-S., Chon, T.-S., Kwak, I.-S., Lek, S., 2004. Hierarchical community classification and assessment of aquatic ecosystems using artificial neural networks. Science of the Total Environment 327, 105–122.
Prism-Group, 2008. Annual Precipitation Normals (1971–2000). Oregon State University.
Rizzo, D.M., Dougherty, D.E., 1994a. Characterization of aquifer properties using artificial neural networks: neural kriging. Water Resources Research 30 (2), 483–497.
Rizzo, D.M., Dougherty, D.E., 1994b. Design optimization for multiple management period groundwater remediation. Water Resources Research 32 (8), 2546–2561.
Rosgen, D., 1994. A Classification of natural rivers. Catena 22, 169–199.
Rosgen, D., Silvey, H.L., 1996. Applied River Morphology. Wildland Hydrology, Pagosa Springs, Colorado.
Rumelhart, D.E., McClelland, J.L., 1988. Parallel Distributed Processing. Massachusetts Institute of Technology Press, Cambridge, MA. 547 pp.
Schumm, S.A., 1977. The Fluvial System. Wiley-Interscience, New York, NY. 338 pp.
Schumm, S.A., 1984. Incised Channels: Morphology, Dynamics and Control. Water Resources Publications, Littleton, CO.
Simon, A., Hupp, C.R., 1986. Channel evolution in modified Tennessee streams. In: Proceedings, Fourth Federal Interagency Sedimentation Conference, Las Vegas, NV, pp. 71–82.
Simon, A. et al., 2007. Critical evaluation of how the Rosgen classification and associated "natural channel design" methods fail to integrate and quantify fluvial processes and channel response. Journal of the American Water Resources Association 43 (5), 1117–1131.
Ultsch, A., Siemon, H.P., 1990. Kohonen's self-organizing feature maps for exploratory data analysis. In: Proceedings of the International Neural Networks Conference. Kluwer Academic Press, Dordrecht, Netherlands, pp. 205–208.
Underwood, K., Rizzo, D.M., 2003. Modeling of Sediment Transport in Geomorphically Unstable Alluvial Channels Using ANNs, ASCE World Water and Environmental Resources Congress, PA.
Wasserman, P.D., 1989. Neural Computing: Theory and Practice. Van Nostrand Reinhold, New York, NY.
Zadeh, L.A., 1965. Fuzzy sets. Information and Control 8 (3), 338–353.