Adaptive Classification of Landscape Process and Function – an Integration of Geoinformatics and Self-Organizing Maps

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Abstract

The advanced geospatial information extraction and analysis capabilities of Geographic Information Systems (GISs) and Artificial Neural Networks (ANNs), particularly Self-Organizing Maps (SOMs), provide a topology-preserving means for reducing and understanding complex data relationships in the landscape. The Adaptive Landscape Classification Procedure (ALCP) is presented as an adaptive and evolutionary capability where varying types of data can be assimilated to address different management needs such as hydrologic response, erosion potential, habitat structure, feature identification, instrumentation placement, forecasting, and what-if scenarios. The ALCP uses neurocomputing-based pattern-recognition methods for providing insight to spatial and spatiotemporal phenomena. These methods establish relationships among high-dimensional datasets that can (1) resolve large volumes of data into a structured and meaningful form; (2) provide an approach for inferring landscape processes in areas that have limited data available but exhibit similar landscape characteristics; and (3) discover the value of individual variables or groups of variables that contribute to specific processes in the landscape. The ALCP is demonstrated through the classification of hydrologic patterns in mountain landscape watersheds where 81.7% of the basins were classified similarly as with other methods.

1 Introduction

Environmental management and research across a heterogeneous landscape provides challenges for consistent evaluation and understanding of natural and anthropogenically influenced processes and functions. A landscape can present a wide variety of heterogeneous forms ranging from specific hydrogeomorphic processes, such as streamflow, groundwater recharge, and rates of erosion, and different ecological phenomena, including biotic diversity, patch densities, and community dynamics. The magnitude of heterogeneity is variable and subject to the domain of study. Understanding process, function, and response in the landscape can be partly achieved by organizing collective variables in a landscape.

Spatial and temporal processes have an explicit cause-and-effect relationship on landscape patterns. Landscape patterns are not random, rather a structure underlies their variability. These patterns are influenced and developed by complex interrelations of spatially distributed abiotic and biotic factors, including topography, climate, macroclimate, hydrological function, chemical and physical weathering, fluvial processes, soils, ecosystem function, and anthropogenic effects (TURNER et al., 2003), which in turn may be used in their detection. Because of the many possible variables influencing landscape evolution, it is necessary to consider adaptability in producing discrete and homogeneous measures of the landscape; i.e., to provide a method that is adaptive to a wide range of landscapes, processes, functions, and variables. Fundamentally, a "landscape" is composed of a patchwork of possibly recognizable spatial units, that vary in extension and character depending on the variables used to identify a homogeneous area (BAILEY, 2004; TURNER, 1989). The notion of landscape classification and the determination of homogeneous areas are important research issues across many disciplines and the need to regionalize the landscape, or divide it into different domains, has produced a variety of classification methods and variables as different views were applied and consequent requirements met.

2 Classification

As stated by BATHGATE & DURAM (2003), "Although the landscape is a continuum, it can be classified into discrete categories … ." The fuzzy nature of natural-process and function boundaries and the multiple scales at which these boundaries are observed increases the complexity of landscape classification. In addition, it can be difficult to capture or recognize hidden and/or unknown process interactions. Clearly, the elements that are brought into a classification scheme can range from very basic to highly complex, depending on the purpose and question(s) being addressed. Regardless of the classification subject (e.g., landscape units, species distribution, or demographics), the objective of classification is to reduce complexity and facilitate the interpretation of the real world by grouping similar elements together to provide a convenient abstraction from the original observations. A classification process, regardless of the method, sorts and organizes the input data space into a feature space through logical ordering and grouping.

Common and accepted practices in landscape classification traditionally have involved direct observations and interpretations of landscape patterns that frequently were based upon biotic factors (BAILEY, 2004; BRYAN, 2006; LIOUBIMTSEVA & DEFOURNY, 1999). While some approaches were rather simple, abstracting the landscape for broad-area regionalization, other approaches managed the complexity of the natural environment with a hierarchical approach in which patterns at multiple scales are assumed to be controlling ecosystem functions (SNELDER & BIGGS, 2002). For example, broad elements of time and space, such as climate, will have the largest control over the landscape, having the power to affect water resources, soil composition, land cover, etc. The hierarchical approach ranges from broad macro-processes to micro-processes where each successive element has less control over the environmental condition than the preceding element (BAILEY, 2004; SNELDER & BIGGS, 2002).

Statistical techniques have been a common theme in the arena of landscape classification, particularly in the last two decades where they could be applied more easily within a digital geospatial context. The advantages of using various statistical methods helped to provide classifications with stronger bases and quantitative significance than manual interpretations, hierarchical classing, and aggregation and/or weighting techniques. From a statistical point of view, classification problems can be resolved into three classes (MICHIE et al., 1994): (1) classic statistical approaches such as linear discrimination and explicit probabilities; (2) machine learning, which uses logic-based automated processing that require large amounts of data to develop interpretable classes; and (3) Artificial Neural Networks

(ANNs), which incorporate both statistical and machine learning methods and, subsequently, provide the core of the adaptive classification procedure presented here.

3 Artificial Neural Networks

Artificial Neural Networks have been used in landscape classification analyses (BAÇÃO et al., 2004; BRYAN, 2006; EHSANI, 2007; HILBERT & OSTENDORF, 2001; HSIEH & JOURDAN, 2006; JOY & DEATH, 2004; LENZ & PETERS, 2006; PARK et al., 2001), but are not as commonly used as the statistical and machine learning methods discussed previously. Potential reasons for this may be the complexity of the process, the number of parameters that need to be tuned, the many different types of ANNs, and the mixed results that have been published. KECMAN (2001) refers to ANNs as "universal approximators of any multivariate function … of particular interest for modeling highly nonlinear, unknown, or known complex systems, plants, or processes." ANNs are considered semi-parametric classifiers because they use both parametric discriminate functions and non-parametric shape discriminators. While ANNs have their foundations in conventional statistical models, they differ in that (1) Gaussian, or normal, distributions of data are not required; (2) linear or nonlinear data are acceptable for inputs; (3) adaptive learning is an integral part of the model; and (4) there is a high degree of error tolerance, provided a reasonable signal-to-noise ratio exists in the data. ANN models make no assumptions about the input data and will adjust the weights of the internal network directly from the input data. As stated by PERUS & KRAJINC (1996), "the most important thing is that ANNs allow a different view of problems which cannot be solved by [exact] statistical methods due to their theoretical limitations."

A specific class of ANNs, unsupervised ANNs, has the ability to discover structure and natural distinctions within data for which no classes have been defined. Unsupervised neural networks work to extract knowledge by exploring redundancy in the dataset and measuring dissimilarity between multivariate objects, ultimately finding and grouping similar data patterns. These types of clustering scenarios are typically constructed with a matrix of standardized or normalized values where a distance measure (e.g., the Euclidean distance or the city-block/Manhattan distance) is applied to formulate the measure of dissimilarity. Unsupervised neural networks rely on varying network topologies and adjustment parameters such as initial neighbourhoods, decay functions, and step size to control the internal learning. The most commonly used unsupervised ANN is the Self-Organizing Map (SOM) (KOHONEN, 2001).

4 Self-Organizing Maps

The SOM projects and maps high-dimensional, complex, linear, or nonlinear data to iteratively organized clusters in a topology-preserving geometric structure for the creation of a low-dimensional discrete data space. The space can be used for a wide variety of purposes, including speech recognition, industrial process control, image analysis, data mining, DNA sequencing, data visualization, climate downscaling, demographics, and more (BAÇÃO et al., 2008; Bryan, 2006; CHON et al., 1996; KOHONEN, 1982; KOHONEN, 2001; HEWITSON, 2008; OPENSHAW & OPENSHAW, 1997; SCHMUKER et al., 2007). The SOM "… can be characterized as a two-dimensional, finite-element 'elastic surface' or network that is fitted to the distribution of the input samples” (KOHONEN, 2001). The added value of the SOM is its ability to discover hidden data patterns, structures, and relationships in multivariate datasets. It can also conceptualize and map data in one-dimensional (1-D), two-dimensional (2-D), or three-dimensional (3-D) output space using a variety of topological structures (e.g., linear, rectangular, toroidal, spherical, cubic).

The concepts of the SOM were originally proposed by WILLSHAW and VON DER MALSBURG (1976), but it was KOHONEN (1982) who developed the algorithms and actively fostered their growth and capability. Because the SOM classifies data in an unsupervised form, no training data are presented to the network; thus, no *a priori* knowledge about the data distributions or placement of data into discrete output space is incorporated. In addition, input data and neurons are applied to a combined input-hidden layer of weighted connections, differing from most ANN models where the hidden layers are separate entities (see Fig. 1). This structure is obtained by repeatedly presenting the input data signals to the network and adjusting the network weights to create “meaningful order, as if some feature coordinate system were defined over the network” (KOHONEN, 2001).

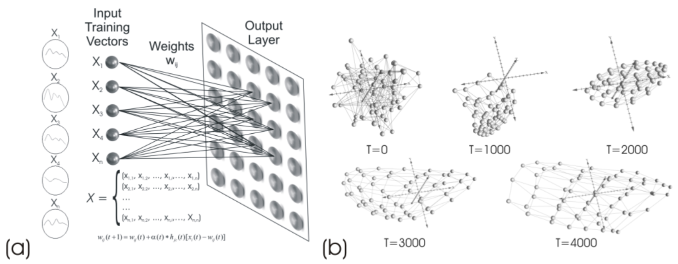

Fig. 1: (a) A representation of the single-layer SOM process as it presents data to the network, competes, and maps organized data clusters to a 1-D, 2-D, or 3-D topology. (b) The SOM process captured at multiple iterations reveals the competition, learning, and projection of neurons over the input data space.

5 The Adaptive Landscape Classification Procedure

Complexity and adaptability in the landscape are addressed by a recently developed procedure introduced here called the Adaptive Landscape Classification Procedure (ALCP) (COLEMAN, 2008). The ALCP uses available spatial and temporal information for a given landscape to establish data patterns and clusters where there are similarities in the data characteristics. The core of the ALCP provides the capability to process large volumes of complex data, discover relationships and patterns in the data, evaluate the sensitivity of variables, and reduce the data complexity to a more meaningful form by grouping common data patterns.

The ALCP can be used to propagate detailed information learned from a given spatial domain to other areas in the landscape without the same level of detailed information. This notion, among other things, allows for the intelligent and efficient pre-planning of research and monitoring studies to effectively capture the unique aspects in the landscape, and then apply the learned information to the “data gaps” or areas in between specific study sites. The procedure is well suited for use in adaptive environmental modeling, sustainability, and monitoring, as well as being a determinant for a wide range of topic areas (i.e., probable locations of groundwater recharge zones, ideal restoration and/or protection areas, field sampling and instrument location sites, land use assessment, what-if scenarios, etc.). The ALCP is specifically intended to be adaptive in the types of data that can be used and the problem sets for which it can be used for; this procedure is not just limited to addressing natural landscape-based questions, but conceivably, any type of landscape.

ALCP Components

The ALCP uses a hybrid mixture of geospatial processing and analysis, and tightly couples a GIS to a SOM processor. The ALCP uses a spatially enabled database for data input, storage, and queries; a spatial container process to prepare data into a domain; a SOM model to analyze and cluster input signals; and a GIS environment to provide visualization and analysis capabilities.

Input and Derived Data

The ALCP has the capability to incorporate a range of data types, thereby providing adaptability in the data inputs. The data elements that can be assimilated into the ALCP include (1) continuous raster-based data such as multi-spectral imagery or digital terrain models; (2) categorical data such as vegetation or land use; (3) discrete data such as census blocks, stream channels, or road networks; and (4) raster- or vector-based spatio-temporal data, such as climate, albedo, or *in situ* measurements. In addition to the flexible data inputs, a significant component of the ALCP is the extraction and derivation of primary and secondary topographic data. An evaluation of landscape terrain components is a fundamental element that has a direct effect on a variety of landscape processes, such as soil depth, soil moisture, surface and sub-surface hydrologic response, sediment transport, landslide probabilities, solar irradiance, slope stability, vegetation distribution, ecological response, and more (MOORE et al., 1991; WILSON & GALLANT, 2000). The ALCP functions by grouping spatially derived data patterns such as those found in Figure 2, which represents 67 normalized landscape metrics extracted from 65 drainage basins.

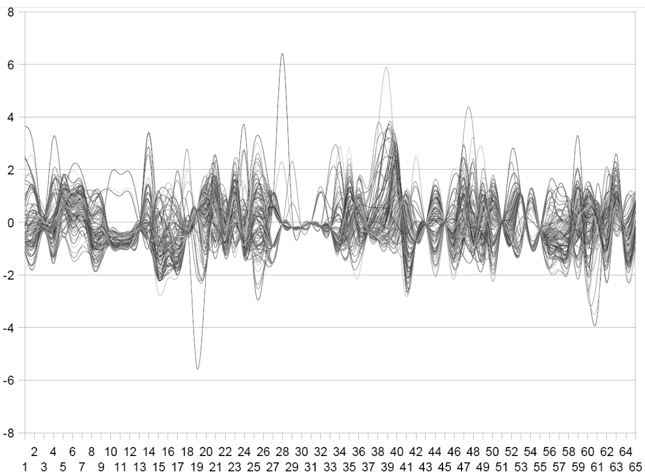

Fig. 2: Representation of landscape data patterns for 65 drainage basins (x-axis), each with 67 normalized landscape metrics (y-axis)

Spatial Container

Issues of spatial scale and resolution have been widely discussed in many disciplines over the past three decades. Many facets and complexities have been raised, but the basic concept, in essence, relates to the level of generalization that is applied to sufficiently interpret reality for a given need. This study did not attempt to solve complex scaling issues, but it did provide a path for bringing various data types and scales into a common entity so that they can be presented to the SOM model for pattern analysis. The open structure of the ALCP is intended to be used at multiple scales, from the individual pixel, to a small local watershed, to a continental or global scale.

The "spatial container" is a method by which multiple datasets of varying scales and data types can be gathered together under a specific domain defined by a polygon, point, or line, such that information about the data can be harvested and organized into a shared spatial database. Spatial containers can be used to represent any kind of spatial domain that is suitable for investigating the data and area of concern. For example, a spatial container can be defined by drainage boundaries, vegetation types, land use, or population density boundaries; random point samples; *in situ* observation points; or linear transects representing migratory routes or other meaningful linear entities. The only requirement for spatial containers is that enough data variability exists in the entire container set such that spatial patterns can become meaningful after the SOM model returns the results to the GIS.

The basic process for using spatial containers is to (1) use a single container to harvest and organize information from the required datasets; (2) store the data in a spatial database using a unique spatial container identifier; (3) repeat steps 1 and 2 for all containers; (4) present the results of all containers for input to the SOM model; (5) execute the SOM model; (6) process results back to the GIS by assigning classified values to spatial entities; and (7) view and analyze the classified spatial containers. A simplified representation of the ALCP system is shown in Figure 3.

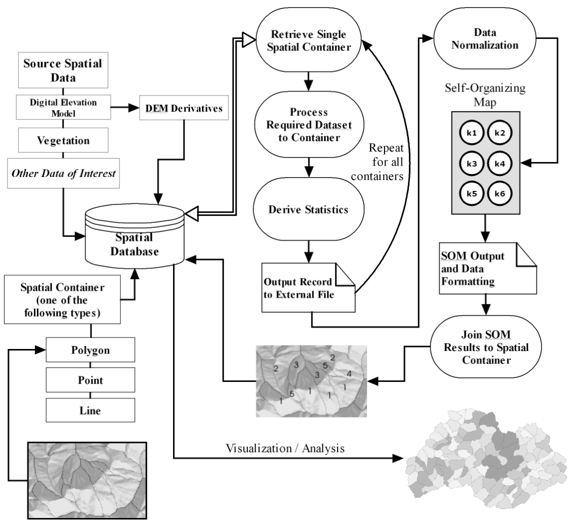

Fig. 3: A representation of the ALCP process steps including spatial containers, input data, statistical processing, SOM processing, and return of process results to the GIS

Self-Organizing Map

Providing the core strength of the ALCP, the SOM model contributes the strengths of neurocomputing, dimensionality reduction, competitive learning, and pattern-matching capabilities to learn and harvest data similarities. After experimentation and evaluation with numerous SOM implementations, SOMMER, an open-source software project from the Molecular Design Laboratory at Johann Wolfgang Goethe-University, was selected as the ALCP SOM model (SCHMUKER et al., 2007). This selection was based on usability, functionality, multiple topology selections, visualization capabilities, and feasibility for modifying the Java source code to meet the needs for GIS integration. The algorithm base for SOMMER stems from the DemoGNG work of LOOS & FRITZKE (1998).

Visualization and Analysis

The ALCP operates within a GIS environment, thus tools for visualization and data analysis of the SOM classified data are inherent. The visualization environment in a GIS provides a capability where the classified data can be viewed in a spatial environment along with other relevant datasets to help interpret and understand the results. Additionally, statistical analysis and numerous other geoprocessing tasks can be applied to the output ALCP data. It is important to keep in mind that the ALCP-classified data are unsupervised; thus the interpretation of the different classes is left to the analyst working with the data, and class definitions will vary depending on the intent of the classification and the data used to conduct the classification.

6 Example Application of the ALCP

Hydrologic processes, including the patterns and behaviours of precipitation, streamflow, and groundwater recharge, are important drivers in landscape characterization. For instance, sharp peaking streamflows may be an indicator of a landscape with steep terrain, low vegetation canopy, and less permeable soils such as clay-loams. In this example application of the ALCP, 10 spatially derived landscape variables were selected and extracted to classify hydrologic flow exceedence without the use of data from streamflow gages. The results of the ALCP classification are compared to results derived from multivariate regression equations used for estimating 20% flow exceedence (Q20) values (representing high flows that only occur 20% of the time) in ungaged basins (Hortness and Berenbrock, 2001).

The multivariate regression equations are based on relating data from approximately 200 stream gages with at least 10 years of record and four landscape metrics. HORTNESS & BERENBROCK (2001) indicate a higher confidence in the Q20 equations than in the lower flow equations (i.e., Q80); hence, the selection of the Q20 value used in this analysis. A regression equation is published for each month of the year; for example, the following is provided for April:

$$Q.20 = 1.26 \times 10^{-6} A^{0.978} E^{*-0.480} F^{*1.87} P^{2.10} \quad \text{(Eq. 1)}$$

where A is drainage area, E^* is the mean basin elevation, F^* is the percent of forested area, and P is the mean annual precipitation. Each of the required variables for the multivariate regression were calculated using a 10-m digital elevation model, 30-m Landsat classified land cover (MRLC, 2001), and an 800-m mean annual precipitation dataset for the United States (PRISM, 2006). A total of 160 ungaged basins ranging in size from 4–32 km^2, were extracted in the North Fork of the Clearwater River located in north-central Idaho, United States; the variation in basin size was intended to represent a diverse range in hydrologic properties. For each of the 160 drainage basins, the published regression equations were used to calculate a monthly Q20 value (Figure 4). Because the majority of the activity in the streamflow occurs between March and July, the snowmelt runoff season, the analysis was isolated to this time period. Results from the regression Q20 data were statistically grouped into eight classes and the mean flow for each class was derived. The grouped values were related back to the 160 GIS-based drainage basins (i.e., spatial containers), such that each of the analyzed basins was assigned to one of eight classes.

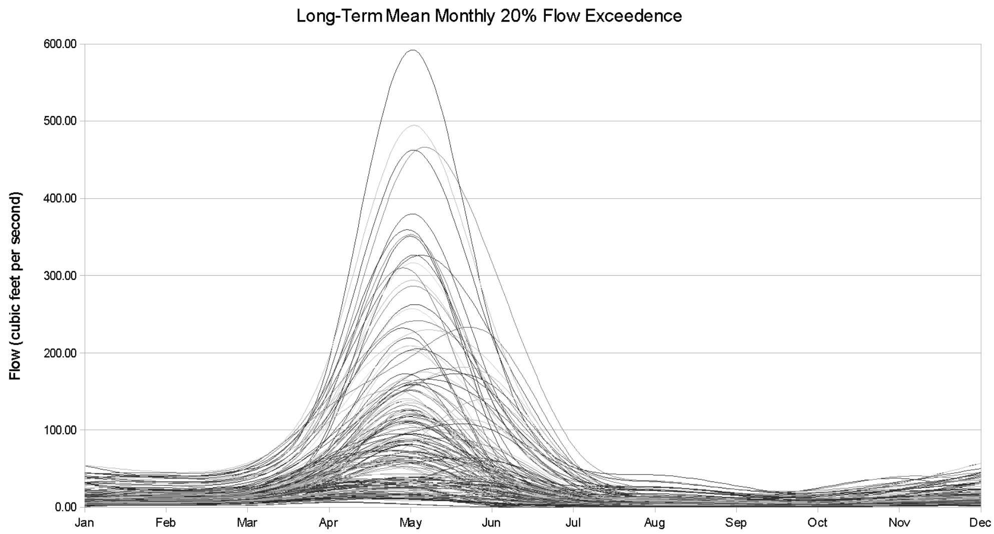

Fig. 4: Monthly values of 20% flow exceedence for all 160 test drainage basins. The snowmelt season, from March through July, was isolated for analysis.

The following 10 landscape metrics for each of the 160 test sub-basins were calculated and used in the ALCP: (1) basin area; (2) mean elevation; (3) maximum elevation; (4) minimum elevation; (5) elevation relief; (6) mean slope; (7) percent area slope > 30°; (8) percent area of north-facing slopes > 30°; (9) percent area forest cover; and (10) mean annual precipitation. These metrics were chosen after repeated data sensitivity analyses using a combination of different values. The source data behind the 10 landscape metrics come from a variety of spatial resolutions and their statistical properties within the spatial containers (i.e., the 160 drainage basins) are calculated through the ALCP. The final results were mapped back into the spatial database and a similarity comparison was made between the values calculated using the ALCP and those using multivariate regression. It was determined 81.7% of the basins were classified similarly, with an additional 11.8% of the basins falling within 1-class boundary. Results can be viewed in Figure 5.

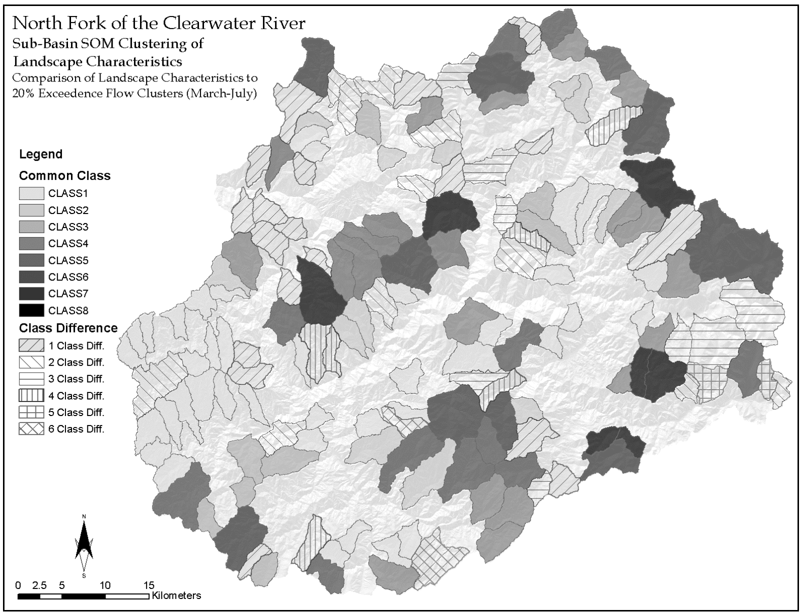

Fig. 5: Similarity index map showing likeness and difference between basins classified using multivariate regression and the ALCP

7 Conclusions

Determining hydrologic similarities, and related landscape similarities, was demonstrated using various spatial data attributes to predict Q20 flow exceedence values. These results were compared with established multivariate regression equations revealing promising results for inferring and propagating knowledge across the landscape. The ALCP has shown favourable results in several other demonstration applications, ranging from defining monitoring locations, instrumentation placement, multi-spectral imagery classification, temporal climatology classification over the landscape, and flood frequency classification (COLEMAN, 2008, COLEMAN & VAIL, 2007). It is clear that the diverse and adaptable capabilities of the ALCP allow for the intelligent use of available data for purposes of gaining a holistic perspective of many landscape aspects, understanding differences and similarities in the landscape by evaluating single or multiple elements, and relating known information to other areas within the study domain that exhibit similar qualities.

The coupling of geoinformatics and SOM technologies for reducing large amounts of diverse, complex, non-linear, and high-dimensional data into a simpler classified form provides a capability where resulting unsupervised classified data are available for query and exploration within a visual GIS environment and can further be used to infer and/or predict landscape processes by discovering spatial patterns in the data. The design and development of the ALCP was specifically intended handle diverse and complex data in a spatial environment. The procedure provides an alternative to traditionally used classification methods in GIS that typically rely upon linear, normally distributed data patterns.

References

BAÇÃO, F, LOBO, V. & PAINHO, M. (2004), Geo-self-organizing map (Geo-SOM) for building and exploring homogeneous regions, Geographic Information Science, Proc. Lecture Notes in Computer Science, pp. 22-37.

BAÇÃO, F., LOBO, V. & PAINHO, M. (2008), Applications of Different Self-Organizing Map Variants to Geographical Information Science Problems. In: AGARWAL & SKUPIN (Eds.), Self-Organising Maps – Applications in Geographic Information Science. West Sussex, Wiley.

BAILEY, R. G. (2004), Identifying ecoregion boundaries. Environmental Management, 34, (Suppl, 1), pp. 14-26.

BRYAN, B. A. (2006), Synergistic techniques for better understanding and classifying the environmental structure of landscapes. Environmental Management, 37 (1), pp. 126-140.

CHON, T. S., PARK, Y. S., MOON, K. H. & CHA, E. Y. (1996), Patternizing communities by using an artificial neural network. Ecological Modelling, 90 (1), pp. 69-78.

COLEMAN, A. M. (2008), An Adaptive Landscape Classification Procedure Using Geoinformatics and Artificial Neural Networks. MSc thesis. Vrije Universiteit, Amsterdam, The Netherlands, pp. 195.

COLEMAN, A. M. & VAIL, L. W. (2007), An Adaptive Multi-Scale Watershed Characterization Approach Utilizing Geoinformatics and Self-Organizing Maps. Proc. of the American Geophysical Union, Fall Meeting. American Geophysical Union, San Francisco, California, December 10-15, 2007.

EHSANI, A. H. (2007), Artificial Neural Networks: Application in Morphometric and Landscape Features Analysis. KTH, Royal Institute of Technology, Stockholm, pp. 53.

HEWITSON, B. C. (2008), Climate Analysis, Modelling, and Regional Downscaling Using Self-Organizing Maps. In AGARWAL & SKUPIN (Eds.), Self-Organising Maps – Applications in Geographic Information Science. West Sussex, Wiley.

HILBERT, D. W. & OSTENDORF, B. (2001), The utility of artificial neural networks for modelling the distribution of vegetation in past, present and future climates. Ecological Modelling, 146 (1-3), pp. 311-327.

HORTNESS, J. E. & BERENBROCK, C. (2001), Estimating Monthly and Annual Streamflow Statistics at Ungaged Sites in Idaho. Water-Resources Investigations Report 01-4093, United States Geological Survey, Boise, Idaho.

HSIEH, B. B. & JOURDAN, M. R. (2006), Watershed Similarity Analysis for Military Applications Using Supervised-Unsupervised Artificial Neural Networks. Proc. of the 25th Army Science Conference, Orlando, Florida.

JOY, M. K. & DEATH, R. G. (2004), Predictive modelling and spatial mapping of freshwater fish and decapod assemblages using GIS and neural networks. Freshwater Biology, 49 (8), pp. 1036-1052.

KECMAN, V. (2001), Learning and Soft Computing. Cambridge, Massachusetts, MIT Press, pp. 541.

KOHONEN, T. (1982), Self-organized formation of topologically correct feature maps. Biological Cybernetics, 43 (1), pp. 59-69.

KOHONEN, T. (2001), Self-Organizing Maps. Berlin, Germany, Springer, pp. 501.

LENZ, R. & PETERS, D. (2006), From data to decisions – Steps to an application-oriented landscape research. Ecological Indicators, 6 (1), pp. 250-263.

LIOUBIMTSEVA, E. & DEFOURNY, P. (1999), GIS-based landscape classification and mapping of European Russia. Landscape and Urban Planning, 44 (2-3), pp. 63-75.

LOOS, H. S. & FRITZKE, B. (1998), DemoGNG (Version 1.5). Institute for Neural Computation, Ruhr-Universität Bochum, Bochum, Germany.

MICHIE, D., SPIEGELHALTER, D. J. & TAYLOR C. C. (Eds.) (1994), Machine Learning, Neural and Statistical Classification. London, England, Ellis Horwood, pp. 289.

MOORE, I. D., GRAYSON, R. B. & LADSON, A. R. (1991), Digital Terrain Modeling: A Review of Hydrological, Geomorphological, and Biological Applications. Hydrological Processes, 5 (1), pp. 3-30.

MRLC (2001), 2001 National Land Cover Dataset, Multi-Resolution Land Characteristics Consortium. Accessed December 5, 2006 at http://www.mrlc.gov.

OPENSHAW, S. & OPENSHAW C. (1997), Artificial Intelligence in Geography. Chichester, Wiley.

PARK, Y. S., KWAK, I. S., CHON, T. S., KIM, J. K. & JORGENSEN, S. E. (2001), Implementation of artificial neural networks in patterning and prediction of exergy in response to temporal dynamics of benthic macroinvertebrate communities in streams. Ecological Modelling, 146 (1-3), pp. 143-157.

PERUS, I. & KRAJINC, A. (1996), AiNet: A Neural Network Application for 32-bit Windows Environment (Version 1.25), User's Manual. Celje, Solvenia. Accessed February 6, 2007 at http://www.winsite.com/bin/Info?500000014622 (undated webpage).

PRISM (2006), Parameter-elevation Regressions on Independent Slopes Model. Oregon State University, http://www.prism.oregonstate.edu.

SCHMUKER, M., SCHWARTE, F., BRÜCK, A., PROSCHAK, E., TANRIKULU, Y., GIVEHCHI, A., SCHEIFFELE, K. & SCHNEIDER, G. (2007), SOMMER: Self-Organizing Maps for Education and Research. Journal of Molecular Modeling, 13 (1), pp. 225-228.

SNELDER, T. H. & BIGGS, B. J. F. (2002), Multiscale River Environment Classification for Water Resources Management. Journal of the American Water Resources Association, 38 (5), pp. 1225-1239.

TURNER, M. G. (1989), Landscape ecology: the effect of pattern on process. Annual Review of Ecological Systems, 20, pp. 171-87.

TURNER, M. G., GARDNER, R. H. & O'NEILL, R. V. (2003), Landscape Ecology in Theory and Practice: Pattern and Process. New York, Springer, pp. 404.

WILLSHAW, D. J. & MALSBURG, C. VON DER (1976), How patterned neural connections can be set up by self-organization. Proc. of the Royal Society London, B194, pp. 431-445.

WILSON, J. P. & GALLANT, J. C. (Eds.) (2000), Terrain Analysis: Principles and Applications. Hoboken, New Jersey, Wiley, pp. 479.