Self-Organizing Map-based Applications in Remote Sensing

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1. Introduction

Remote sensing involves the collection of information about an object from a distance. Often remote-sensing instruments are mounted onboard an air- or space-borne platform and typically record electromagnetic energy in specific wavelength intervals, or bands. The electromagnetic energy recorded over a given area contains information about surfaces reflecting or emitting energy. This information can be used for a variety of applications; for example, remote-sensing image analysis can extract thematic information such as land-cover types (Jensen, 2005).

Artificial neural network (ANN) techniques have increasingly been employed in the analysis of remotely-sensed images. ANNs can be advantageous in digital image processing in that no assumption is made about the statistical properties of the images, and they are thus widely applicable to a variety of dataset types. In addition, ANNs learn adaptively through examples and have a high tolerance to noisy or incomplete data (Jensen, 2005). ANN model development can proceed via either supervised or unsupervised means, and if adequate training data are available, supervised training may be readily performed. However, obtaining reliable training data in remote-sensing applications is often problematic (Congalton and Green, 1999), as a remote sensor image typically covers a large area, and only a limited number of training locations can be sampled in the field due to cost, time, personnel requirements, and various other logistical constraints, including potential restrictions on access to the study area. Unsupervised image-processing methods—including unsupervised ANNs—can be of significant utility in such circumstances (Filippi et al., 2009). Unsupervised ANNs are used in situations where the correct outputs may not be known, or if it is desired that the network discover or categorize regularities or features in the training data on its own. There is no teacher signal (Hassoun, 1995).

The unsupervised Kohonen self-organizing map (SOM) is a two-layer network, with an input fan-out layer, and an output layer (known as the Kohonen or competitive layer), and the method is based upon competitive learning. The Kohonen layer is comprised of a physical net of neurons located at fixed positions (i.e., intersections in a grid of square meshes). Adjacent neurons are assumed to have a Euclidean distance of unity. The input

layer has the same dimensionality as the pattern (feature) vector. The primary goal of the SOM is to capture the topology and model the probability distribution of the input vectors around the unit circle or hypersphere. The weight vectors act as a model for the probability distribution function. In an adaptive and topologically-ordered manner, the SOM converts patterns of arbitrary dimensionality (the pattern space) into the responses of one- or two-dimensional virtual arrays of self-organizing neurons (feature space), which are essentially probability distribution maps. This feature-mapping component reduces the dimensionality. It is a topology-preserving map, as it preserves the neighborhood relations of the input pattern. Input and output neurons are fully connected via the synaptic weights (Kohonen, 1988; Lin and Lee, 1996; Haykin, 2009).

Self-organization involves adaptively modifying the synaptic weights as a result of input excitations while abiding by a learning rule until a useful configuration is produced. In the output layer, or lattice, output neurons become selectively tuned to the presented input patterns during a competitive-learning procedure. The topologically-ordered output space entails neurons close to one another representing similar input patterns. Learning is accomplished by first choosing an output neuron that most closely matches the presented input pattern, then determining a neighborhood of excited neurons around the winner, and finally, updating all of the excited neurons (Haykin, 2009). Learning decreases with intercellular distance; the nearest neighbors to the primary classifying cell learn the pattern very well, while more distant cells learn the pattern less well (Hassoun, 1995).

Supervised learning may also be incorporated through a related technique referred to as Learning Vector Quantization (LVQ). Similar to SOM, all output nodes compete and the winning node is selected according to its similarity with the presented input pattern. Unlike SOM though, only the winning neuron is updated, and thus, the resulting output feature space is not topologically ordered (Kohonen, 2001). If training data are available, often the SOM analysis is performed first, and then LVQ is applied to fine-tune the feature map.

This chapter provides a brief overview of the applications of SOM-based techniques and related self-organizing methods used in remote sensing, and it demonstrates the use of SOMs in remote sensing through a case study involving the classification of a Landsat Enhanced Thematic Mapper Plus (ETM+) surface reflectance image.

2. Overview of SOM-based and SOM-related Applications in Remote Sensing

The basic unsupervised SOM algorithm has been applied in various remote-sensing studies (Table 1). For example, it has been used for identifying characteristics ocean current patterns over semidiurnal, diurnal and sub-tidal time scales (Liu et al., 2006) and for identifying synoptic-scale wind patterns and sea surface temperature patterns (Richardson et al., 2003). In another oceanographic remote-sensing study, Marques and Chen (2003) proposed a Kohonen SOM-based approach for detecting the borders of eddies in the Mediterranean. These Mediterranean Water Eddies strongly affect Atlantic Ocean hydrodynamics and are important in the transport of particles, live organisms, and suspended material. The objective was to discover image pixels on cluster boundaries, rather than the clusters themselves. Compared with a conventional Canny gradient edge-detector, the SOM detected the more significant and continuous borders. The Canny algorithm did not detect all borders at high threshold values and generated excessive noise at low threshold values. The SOM was thus more robust to noise and ill-defined/amorphous borders (Marques and

Chen, 2003). SOMs have also been used in synoptic climatology to locate archetypal points describing the multi-dimensional distribution function of gridded sea level pressure data. In Hewitson and Crane (2002), the SOM nodes represented important regional-scale circulatory features. Boekaerts et al. (1995) used an unsupervised, one-dimensional SOM in an autoadaptive mono-spectral cloud identification scheme employing Meteosat imagery. In terrestrial remote sensing, atmospheric features often constitute a source of noise, and minimizing such effects are typically desirable. For instance, monitoring vegetation cover and bare agricultural soils during the intercrop season is important for soil and water quality-management purposes, particularly in agriculture-intensive areas. Latif et al. (2008) identified and monitored bare soil interannual spatial variation at the regional scale using low-resolution satellite time-series data; however, such images are often adversely affected by clouds and shadows. The SOM was used to predict spectral values of pixels contaminated by weather conditions (i.e., clouds and cloud shadows) for posterior bare-soil mapping (Latif et al., 2008). In other terrestrial applications, the SOM algorithm has also been applied to detecting and characterizing yardangs, which are streamlined, elongated, wind-abraded ridges (Ehsani and Quiel, 2008), as well as to land-cover classification in an agricultural region and mapping fire-damaged forests (Furrer et al., 1994). Additionally, Kohonen's SOM has been used for automatically generating texture-based visual thesauri of massive archives remote-sensor images (e.g., aerial photographs and Advanced Very-High Resolution Radiometer (AVHRR) images) (Ramsey et al., 1999).

Authors	Year	Application
Ehsani and Quiel	2008	Detecting and characterizing yardangs
Latif et al.	2008	Predicting spectral values of data contaminated by weather conditions
Liu et al.	2006	Identifying ocean current patterns over semidiurnal, diurnal and sub-tidal time scales
Marques and Chen	2003	Detecting Mediterranean Water Eddy borders
Richardson et al.	2003	Identifying synoptic-scale wind patterns and sea surface temperature patterns
Hewitson and Crane	2002	Synoptic climatology
Ramsey et al.	1999	Creating texture-based visual thesauri of image collections
Boekaerts et al.	1995	Cloud identification
Furrer et al.	1994	Mapping fire-damaged forests; agricultural/land-cover classification

Table 1. Basic SOM used in various example remote-sensing application domains

Applications of SOM variants in remote sensing have also been demonstrated (Table 2), and such SOM variants have been prompted by SOM limitations. For example, although the SOM has been a stable ANN model in high-dimensional data analysis, its utility is limited

by its static network architecture and its limited ability to represent hierarchical relations in the data (Hong et al., 2006). Thus, a growing hierarchical SOM (GHSOM) has been proposed that employs a hierarchical structure comprised of multiple layers, where each layer is composed of one or more SOMs. Based on the input data distributions, the size of the sub-layers dynamically adapts during network learning, and feature maps are added as needed. This layered architecture explicitly represents hierarchical relations between input data (Hong et al., 2006). The GHSOM is advantageous for processing large remote-sensor data sets and increasing image classification accuracy (Liu et al., 2006). GHSOM has been applied to the problem of cloud classification in satellite images (Hong et al., 2006) and the analysis of sea surface temperature patterns (Liu et al., 2006). Growing SOM (GSOM) changes its structure during the learning process by adding neurons to the output space, and it was successfully applied to the problem of unsupervised classification of a multispectral Landsat Thematic Mapper (TM) image (acquired over Colorado, USA, with multiple vegetation and soil classes) and a hyperspectral Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) scene (acquired over the Lunar Crater Volcanic Field (LCVF), Nevada, USA, which is dominated by mineralogic/geologic materials) (Vilmann et al., 2003). Another SOM variant involves magnification control through the use of an additional magnification control parameter, and the technique was applied to the same Landsat TM and AVIRIS scenes as GSOM (Vilmann et al., 2003). Another SOM variant, Multiple SOMs (MSOMs), fuse several small feature maps, each explicitly representing different cluster regions, thus better approximating each region, and thus better dealing with region borders (Wan and Fraser, 1999; Wan and Fraser, 2000). MSOMs vary in the type of SOM used and in the way the small feature maps are fused, which can be performed in accordance with unsupervised, supervised, or hybrid methods. MSOMs have been used for multisource data fusion and compound classification of a bitemporal, agricultural remote-sensor image data set (Wan and Fraser, 1999). In Wan and Fraser (2000), the applicability of MSOMs was demonstrated through land-cover classification of an AVIRIS image and a joint spatio-temporal classification of two Landsat TM images. A modified SOM based on the work of Hillermeier et al. (1994), which introduced self-organized lateral network connections, has also been used to perform land-cover classification, including mapping fire-damaged forests (Olbert et al., 1995; Schaale and Furrer, 1995).

Whereas the above studies demonstrate the applicability of SOM variants to remote-sensing image analysis, other studies specifically modify the basic/original SOM for achieving specialized tasks. For example, the Self-Organized Road Mapping (SORM) algorithm was developed for road extraction from high-resolution multispectral images where a pre-classified image is used as the input to a K-medians clustering algorithm, and the cluster locations are used as the input to a modified one-dimensional SOM (Doucette et al., 2008). Another SOM variant, the PicSOM, is used for the identification of specified anthropogenic structures such as buildings and for change detection using high-resolution images (Molinier et al., 2007). The technique involves the decomposition of images into subsets representing different structures and storing them in an image database. The stored image subsets are then used for SOM training, which subsequently allows for querying the image database for spatial structures of interest.

Supervised SOM is achieved by first coarse-tuning the feature map through unsupervised learning, and then fine-tuning the map using any supervised LVQ learning method (Kohonen, 1988). During LVQ training, the weights of the reference nodes are updated

Authors	Year	SOM Variant	Application
Doucette et al.	2008	SORM	Road extraction
Molinier et al.	2007	PicSOM	Detection of buildings; change detection
Hong et al.	2006	GHSOM	Cloud characterization
Liu et al.	2006	GHSOM	Sea surface temperature pattern analysis
Vilmann et al.	2003	GSOM Magnification control	Land-cover classification
Wan and Fraser	2000	MSOMs	Joint spatio-temporal agricultural classification
Wan and Fraser	1999	MSOMs	Multisource data fusion and joint spatio-temporal agricultural classification
Olbert et al.	1995	Population-coded, one-layer model of associative memory	Mapping fire-damaged forests
Schaale and Furrer	1995	Population-coded, one-layer model of associative memory	Mapping fire-damaged forests; land cover classification

Table 2. Example SOM variants applied to remote sensing

according to samples of specified classes. The originally-proposed LVQ1, LVQ2, and LVQ3 learning methods and their modifications have been applied to remote-sensing problems (Table 3). Fine-turning the classification of a Landsat TM image with LVQ performed better than a maximum likelihood classification (MLC) (Ji, 2000). Generalized relevance LVQ (GRLVQ) combines two important modifications of the Kohonen LVQs (Villmann et al., 2003). First, the cost function is minimized through stochastic gradient descent, and second, input weights are applied to obtain scaling of the input dimensions. In Villmann et al. (2003), GRLVQ was applied to Landsat TM and AVIRIS images for the purposes of land-cover/vegetation classification and geologic-mapping, respectively. The results were compared to the results obtained through GSOM and Magnification Control SOM (noted above), and it was demonstrated that GRLVQ produced the highest classification accuracy (Villmann et al., 2003). GRLVQ was further improved for use with high-dimensional hyperspectral images (Mendenhall and Merényi, 2008). GRLVQ Improved (GRLVQI) addresses the problem of poorly-utilized neurons by modifying the selection of winning neurons to encourage selection of infrequent winners. The technique was applied to a hyperspectral geologic AVIRIS image of the Lunar Crater Volcanic Field (LCVF) (noted above), and it was determined that higher classification accuracy can be obtained with GRLVQI relative to GRLVQ. The authors showed that relevance-selected features maintain or improve the performance of even basic classifiers (Mendenhall and Merényi, 2008).

Authors	Year	Technique	Application
Mendenhall and Merenyi	2008	GRLVQI	Land-cover classification
Vilmann et al.	2003	GRLVQ	Land-cover classification
Ji	2000	SOM/LVQ	Land-cover classification

Table 3. Supervised LVQ applications in remote sensing

The Kohonen self-organizing feature map, also referred to as the Kohonen clustering network (KCN) (Lin and Lee, 1996), exhibits some advantageous properties. For instance, weight vectors work to represent the natural tendency of a cluster of data points. It is unsupervised in that it requires no "teacher" during learning. KCN inherently reduces the dimensionality of the data by compressing and mapping it to the Kohonen layer, or mapping cortex. In addition, it always orients itself along the principal axes, but does not require the orthogonal and linear assumptions of standard principal component analysis (PCA). Thus, superior performance can be accrued when arbitrarily deformed distributions are present (Schaale and Furrer, 1995). And finally, KCN utilizes a parallel architecture, and it provides a graphical organization of topologically-preserved relationships. However, the KCN also entails several significant disadvantages: KCN is sequential, the termination strategy is artificial, and parameters such as the learning rate and the neighborhood size are selected heuristically, which does not ensure optimal performance. Convergence can be slow, and the network may not necessarily handle complexity accurately (Tsao et al., 1994).

Therefore, some attempts have been made in the ANN literature to address these disadvantages. For instance, Huntsberger and Ajjimarangsee (1990) first proposed a scheme that was essentially a partial integration of KCN and fuzzy c-means clustering (FCM), where the learning rates $\{\alpha_{ik}\}$ were replaced with fuzzy membership values $\{u_{ik,t}\}$ calculated with FCM. This approach was referred to as the Partial Fuzzy Kohonen Clustering Network (PFKCN). One extra layer, a membership layer, was added to the output layer, or *distance* layer, of the original KCN. The output u_{ik} represented the degree to which the input pattern x_k belonged to cluster I. During the learning process, however, in order to derive cluster centers that are the same as those of the FCM algorithm, it was necessary to feed these outputs back to update the cluster centers via a feedback path (Huntsberger and Ajjimarangsee, 1990). Note that m, the weighting exponent, still had to be chosen, and the approach lacked theoretical foundations and formal derivations (Bezdek and Pal, 1995). No properties pertaining to convergence were established; termination was forced. The fuzzy LVQ (FLVQ) algorithm (Bezdek and Pal, 1995) addresses these PFKCN shortcomings. Baraldi et al. (1998) gives a comparison of the properties of SOM and FLVQ algorithms.

Approaches based on the integration of ANN learning and fuzzy systems have been investigated in remote-sensing application domains (Table 4). Unsupervised fuzzy LVQ (FLVQ) combines FCM and unsupervised LVQ, and the technique has been applied to the task of coastal vegetation classification using hyperspectral AVIRIS surface reflectance image data (Filippi and Jensen, 2006). The effect of using continuum-removed AVIRIS image spectra as input to FLVQ for the same task was investigated in Filippi and Jensen (2007). Membership values are calculated for pixels according to a fuzzy c-partitioning of the

feature space, where, in a remote-sensing context, the feature vectors correspond to the set of input image bands (Filippi and Jensen, 2006). A modification of FLVQ incorporates Gaussian membership functions for calculating fuzzy membership grades for input pixels and consequently uses fuzzy membership grade and not Euclidean distance to estimate closeness of input pixels to output clusters (Qui and Jensen, 2004). Since Gaussian membership functions are used in fuzzifying Kohonen's LVQ2 algorithm, the Gaussian LVQ (GLVQ) employs supervised learning, though it can internally utilize unsupervised learning to generate natural clusters. Further modification of GLVQ uses training data to initialize the weights of the network and also ensures that only the winning neuron is updated (Qui, 2008). The improved GLVQ has been applied to Hyperion satellite image land-cover classification and achieved better classification accuracy compared to standard hyperspectral classification algorithms. Other FLVQ studies include Blonda et al. (1995) and Ceccarelli et al. (1995), where it was employed for Landsat image segmentation and SAR texture data classification; FLVQ was then known as the fuzzy Kohonen clustering network (FKCN). Baraldi et al. (1998) used FLVQ and SOM to classify 18 multitemporal Landsat TM bands into general land-cover categories. Benz (1999) proposed an adaptive system that integrated FLVQ with a supervised fuzzy distribution estimator to classify single- and multi-channel SAR data to identify flooded areas, water, and various land-cover classes.

FLVQ employs fuzziness in the learning rate and update strategies, but not typically in producing fuzzy outputs (Filippi and Jensen, 2006). Thus, remote-sensing studies utilizing FLVQ and related algorithms usually generate crisp, or hard, image classification results.

Authors	Year	Technique	Application
Qui	2008	GFLVQ Modified	Land-cover classification
Filippi and Jensen	2007	FLVQ	Coastal vegetation classification with continuum-removed spectra
Lee and Lathrop	2006	SOM-LVQ-GMM	Subpixel land cover
Filippi and Jensen	2006	FLVQ	Coastal vegetation classification
Qui and Jensen	2004	GFLVQ	Land-cover classification
Benz	1999	FLVQ integrated with supervised fuzzy distribution estimator	Flooded-area and land-cover classification
Baraldi et al.	1998	FLVQ and SOM	Land-cover classification
Ceccarelli et al.	1995	FKCN/FLVQ	Land-cover classification
Blonda et al.	1995	FKCN/FLVQ	Land-cover classification

Table 4. Fuzzy LVQ and related studies in remote sensing

Subpixel image analysis estimates the percentage of different land covers within a pixel. To estimate the percent cover of impervious surface, lawn, and woody tree cover in urban/suburban areas, Lee and Lathrop (2006) fine-tune a SOM with LVQ and then construct a Gaussian kernel density function for each SOM node. Using the Gaussian Mixture Model, the posterior probabilities of the land-cover classes were computed for each pixel. To apply the proposed approach to subpixel analysis, the authors equated the percent land-cover type composition with the posterior probability.

Other hybrid techniques have been used in remote sensing (Table 5). SOM, LVQ, fuzzy clustering, and parametric and non-parametric Bayesian approaches are used for deriving clusters, and selection of the best partitioning is accomplished through fuzzy multi-criteria decision-making (Guijarro and Pajares, 2009). The technique is applied to texture extraction from natural images. In Gonçalves et al. (2008), cluster analysis was performed on a set of SOM prototypes, rather than operating directly upon the original image patterns. Specifically, SOM was applied first; agglomerative hierarchical clustering with restricted connectivity was then applied to the SOM grid. Another hybrid approach uses wavelet fusion as a pre-processing step, and the results are used as input to SOM, which is then fine-tuned through LVQ (Bagan et al., 2008). Applying the technique for land classification of an ASTER image improved classification accuracy compared to using the original ASTER reflectance bands as input. A cascaded architecture of neural fuzzy neural networks with feature mapping (CNFM) involves feature extraction from multispectral images and inputting the features to an unsupervised SOM, which performs dimensionality reduction; the result is fed to a supervised neural fuzzy network which performs final clustering (Lin et al., 2000). Other attempts have also involved the Kohonen SOM being used for initial clustering as part of a modular network architecture, e.g., where supervised approaches have utilized a self-organizing component. Yoshida and Omatu (1994) used the SOM for initial clustering before the data was fed into a Multiple-Layer Feedforward Network (MLFN) trained with back-propagation (BP); in concert with geographical data, training areas were selected more precisely using the clustering results from the SOM. Blonda et al. (1996) used the Kohonen SOM as part of a modular neural classification system. A single-layer perceptron (SLP) (i.e., a multilayer perceptron (MLP) with no hidden neurons) was used as the supervised module. In another study, the weights at convergence of a Kohonen's self-organizing module have been used to initialize the weights between the input and hidden layers of a backpropagation ANN; this markedly increased the convergence rate, and thus decreased backpropagation network training time (Li and Si, 1992). Solaiman and Mouchot (1994) compared the MLC with the Kohonen SOM, LVQ2, MLP, and an unsupervised/supervised hybrid HLVQ network (consisting of an unsupervised SOM and a supervised LVQ2 network) in classifying an agricultural Landsat TM scene. In general, the hybrid method and the MLC produced the best results, but the SOM was comparable. These methods exceeded the classification accuracy of the MLP by about 10%. Ito and Omatu (1997) partitioned the training data to where a separate self-organizing competitive layer was assigned to each class. Once training was completed, a k-nearest neighbor approach was invoked such that k winner neurons were selected in order of minimum distance between the input vectors and the neuron weights. Although an artificial convergence criterion was used during self-organization, favorable results were still obtained. These modular systems have generally been successful when applied to multispectral remote-sensor images.

Authors	Year	Technique	Application
Guijarro and Pajares	2009	Fuzzy Multicriteria Decision Making Approach	Classifying textures in natural images
Gonçalves et al.	2008	SOM and agglomerative hierarchical clustering	Land-cover classification
Bagan et al.	2008	Wavelet Fusion and SOM/LVQ	Land-cover classification
Lin et al.	2000	CNFM	Land-cover classification
Ito and Omatu	1997	Self-organizing neural network and *k*-NN	Urban land-cover classification
Blonda et al.	1996	SOM and SLP	Land-cover classification
Solaiman and Mouchot	1994	Hybrid HLVQ (SOM and supervised LVQ2 network)	Agricultural classification
Yoshida and Omatu	1994	SOM and MLP	Land-cover classification
Li and Si	1992	Self-Organizing Backpropagation (SOBP)	Land-cover classification

Table 5. SOM hybrid studies in remote sensing

3. Unsupervised Classification of Landsat ETM+ Image Data Using SOM

An unsupervised snow-cover classification of a Landsat 7 ETM+ image demonstrates the application of SOM in remote sensing.

3.1 Data description

The Landsat ETM+ image used in the study was acquired on 27 March, 2002 and covers part of Wisconsin and Minnesota. The National Land Cover Database (NLCD) 2001 shows the predominant land covers as agricultural (cultivated crops, pasture/hay) and deciduous forest (Figure 1) (MRLC, 2009). The Mississippi River and several of its tributaries are notable spatial features in the scene. Snow cover is present in the northern half of the image and is easily distinguishable in cyan in a false-color composite of Landsat 7 ETM+ bands 5, 4 and 2 as R,G,B (Figure 2).

Landsat 7 ETM+ was launched in 1999 by National Aeronautics and Space Administration (NASA) and images the Earth once every 16 days in eight spectral bands (NASA, 2009). Bands 1-5 and band 7 have spatial resolution at nadir of 30 meters; band 6, which is a thermal infrared band, has a 60-meter resolution; and band 8, a panchromatic band, has 15-meter resolution. Bands 1-3 record electromagnetic energy in the visible portion of the spectrum, band 4 in the near-infrared, and bands 5 and 7 in the short-wave infrared. Bands 6 and 8 were not used in the study because of the difference in spatial resolution. The six bands used in the study (Table 7) were first scaled to radiance, then an atmospheric correction was applied using the MODTRAN4 radiation transfer code (Jensen, 2005), and the image was georegistered to an orthorectified Landsat ETM+ image.
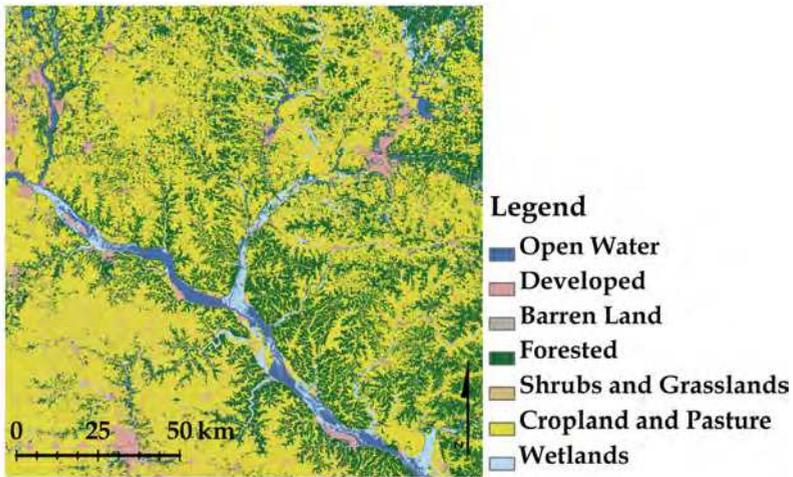
Fig. 1. Predominant land covers in the scene are cultivated crops, pasture/hay, and deciduous forests. The Mississippi River and some of its tributaries are major spatial features (Source: NLCD, 2001).
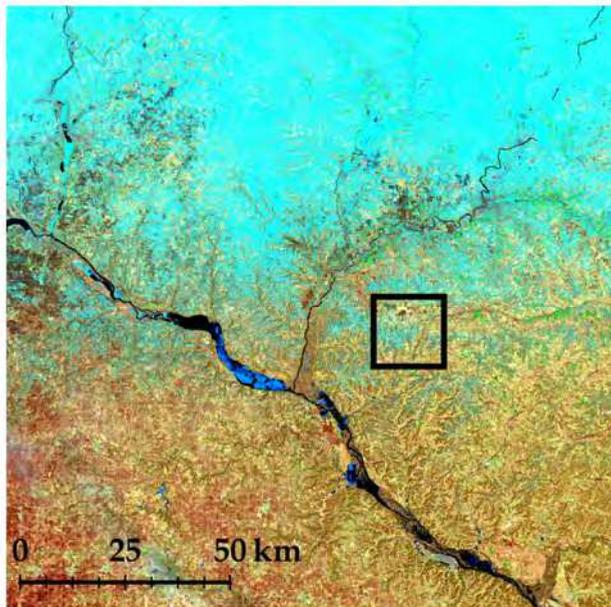

Fig. 2. A false-color composite image comprised of Landsat ETM+ bands 5, 4 and 2 as R,G,B shows snow cover as cyan colors in the northern half of the image. The square box represents the subset in Figure 4.

Input Data	Band pass (μm) / Equation
Landsat ETM+ Band 1	0.45 - 0.52
Landsat ETM+ Band 2	0.53 - 0.61
Landsat ETM+ Band 3	0.63 - 0.69
Landsat ETM+ Band 4	0.78 - 0.90
Landsat ETM+ Band 5	1.55 - 1.75
Landsat ETM+ Band 7	2.09 - 2.35
NDSI	$\dfrac{Band\ 4 - Band\ 6}{Band\ 4 + Band\ 6}$
NDVI	$\dfrac{Band\ 4 - Band\ 3}{Band\ 4 + Band\ 3}$

Table 7. Two input-combination permuations to SOM were assessed. The first one included six of the Landsat 7 ETM+ bands (bands 1-5 and band 7), and the second data set included two additional normalized difference index images, which have been demonstrated to be useful in mapping snow in forests (Klein et al., 1998).

3.2 Methodology

Image analysis was performed in the IDRISI 16 GIS/remote-sensing software package using the implemented SOM module, which is modeled after the method described in Kohonen (1990). The neural network was run with an initial neighborhood radius of 17.97; a minimum learning rate of 0.5; a maximum learning rate of 1; and a 12 × 12 lattice of output neurons. A k-means clustering was applied to the SOM results, and a maximum of 10 k-means classes/clusters was specified.

Two networks were developed with the same parameters, but with different input combinations. For the first input combination, inputs were the six Landsat ETM+ surface reflectance bands (Table 7). For the SOM with this input combination, the quantization error, which measures the average distance between each input and the neuron to which it is mapped, was 0.0775. For the second input combination, two additional normalized difference index bands were added (Table 7), lowering the quantization error to 0.0169. Reflectance bands 3 and 4 are used to calculate the Normalized Difference Vegetation Index (NDVI) which captures the inverse relationship between reflectance in the red and near-infrared portions of the electromagnetic spectrum associated with healthy green vegetation (Jensen, 2005). The index is useful in distinguishing vegetated areas that have higher NDVI values from non-vegetated or sparsely-vegetated areas with lower NVDI values. Normalized Difference Snow Index (NDSI) is calculated using bands 4 and 6, and, similarly to NDVI, it uses the inverse relationship between snow reflectance in the visible and near-infrared (Hall, 1995). Adding the two index images does not increase the information

content of the inputs, but it does increase the redundancy in the input data. Redundancy and structure in the input data is one of the principles of self-organization (Haykin, 2009), and therefore, the second input combination would be expected to produce better results.

The performance of SOM in detecting snow-covered pixels using the two input combinations was compared to the MODIS snow-mapping algorithm (SNOMAP) which has a long history of use in mapping snow and is the standard algorithm for producing global daily snow maps from MODIS (Hall, 1995; Hall et al., 2002). SNOMAP maps snow primarily using the NDSI, but a combination of NDSI and NDVI improves snow mapping in forests (Klein et al., 1998). Also, SNOMAP excludes water pixels from analysis (Hall, 1995). To facilitate the comparison of SOM results to SNOMAP, water is masked in the current study.

3.3 Results and discussion

The input combination including only reflectance bands returned 10 classes that were subsequently combined into snow-covered and snow-free areas. The resulting snow map has a 92% overall agreement with SNOMAP (Table 8). Commission errors, where SOM maps snow missed by SNOMAP, were 24.56%, whereas omission errors, pixels mapped as snow by SNOMAP but missed by SOM, is much lower (only 3.71%).

The second input combination which includes the additional index bands returned only three classes. Two of the classes are easily identified as snow and snow-free. The third class represented a combination of water and snow-covered pixels. Excluding water from the analysis, the remaining third class pixels were considered snow. (Figure 3). The overall agreement between the second SOM result and SNOMAP is 88% (Table 9). No omission errors occurred, meaning SOM did not miss any of the snow-covered areas mapped by SNOMAP. However, the commission errors were high, e.g., 35.38% for snow-covered, which is larger than the same error for the reflectance-only input combination.

Both input combinations resulted in a larger area mapped as snow compared to SNOMAP, with the input combination with additional index bands mapping the largest snow-covered area. SNOMAP mapped 4,499 km² as snow; SOM with the first input data combination mapped 5,703 km²; and SOM with the second input combination mapped 6,915 km² as snow.

The errors of commission between the input combination with additional index bands and SNOMAP were examined visually (Figure 4). The area mapped as snow by SOM appears to be snow-covered in the false color-composite of Landsat bands 5, 4 and 2, but failed to be mapped as snow by SNOMAP. So even though the second input combination has lower

Reflectance Bands Only	SNOMAP	
	Snow	*Snow-Free*
Snow	4,779,553 (21.075%)	1,556,011 (6.86%)
Snow-Free	184,057 (0.81%)	16,167,435 (71.26%)
Overall agreement: 92%		

Table 8. Confusion matrix between SNOMAP and SOM with reflectance bands only as input shows number of pixels that are in agreement or disagreement. Numbers in parenthesis indicate percentage of total count.

Reflectance and Index Bands	SNOMAP	
	Snow	*Snow-Free*
Snow	4,963,610 (21.88%)	2,718,029 (11.98%)
Snow-Free	0 (0%)	15,005,417 (66.14%)
Overall agreement: 88%		

Table 9. Confusion matrix between SNOMAP and SOM with both reflectance bands and index bands as input, indicating number of pixels and percent agreement and disagreement.
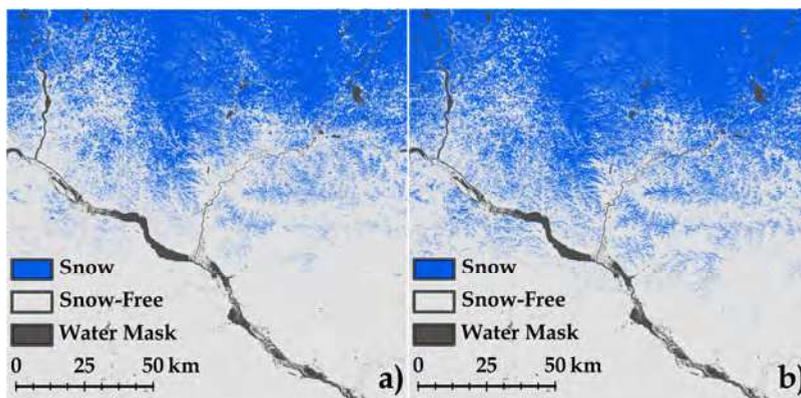

Fig. 3. Snow maps produced by SNOMAP (a) map lesser snow-cover extent compared to the snow maps produced by SOM with both reflectance bands (not illustrated) and index bands (b) as input.
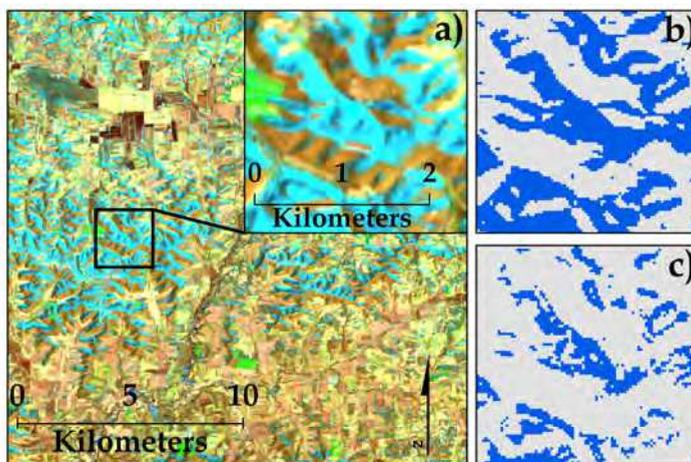
Fig. 4. Portion of false-color image composite examined (a). Comparing the results of SOM with both reflectance bands and index bands as input (b) and SNOMAP (c) shows that the larger snow-cover extent derived by SOM appears more correct.

overall accuracy as compared to SNOMAP than the first input combination, it appears to provide more accurate snow mapping. However, further validation of the SOM results requires the use of field observations or higher-resolution images. Note that the "errors" stated in study may not technically be considered as errors per se, as we treated the SNOMAP result as reference data, rather than obtaining ground reference data.

4. Conclusion

SOM-based and SOM-related techniques have been applied in remote sensing. Image-analysis tasks range from identifying synoptic-scale ocean or atmospheric characteristics to land-cover classification. The utility of the Kohonen SOM as an unsupervised classification technique was demonstrated here by generating a snow map based upon a Landsat 7 ETM+ image. SOM-mapping of snow compares favorably to the widely-used SNOMAP algorithm, which has a considerable heritage in mapping snow from satellite images. In the single test image, the SOM mapped snow that SNOMAP missed. Better results were achieved when the input bands were complimented by index bands, which increased the redundancy in the input.

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Self-Organizing Maps

Edited by George K Matsopoulos

The Self-Organizing Map (SOM) is a neural network algorithm, which uses a competitive learning technique to train itself in an unsupervised manner. SOMs are different from other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space and they have been used to create an ordered representation of multi-dimensional data which simplifies complexity and reveals meaningful relationships. Prof. T. Kohonen in the early 1980s first established the relevant theory and explored possible applications of SOMs. Since then, a number of theoretical and practical applications of SOMs have been reported including clustering, prediction, data representation, classification, visualization, etc. This book was prompted by the desire to bring together some of the more recent theoretical and practical developments on SOMs and to provide the background for future developments in promising directions. The book comprises of 25 Chapters which can be categorized into three broad areas: methodology, visualization and practical applications.

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