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A Review of Self-Organizing Map Applications in Meteorology and Oceanography

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1. Introduction

Coupled ocean-atmosphere science steadily advances with increasing information obtained from long-records of in situ observations, multiple-year archives of remotely sensed satellite images, and long time series of numerical model outputs. However, the percentage of data actually used tends to be low, in part because of a lack of efficient and effective analysis tools. For instance, it is estimated that less than 5% of all remotely sensed images are ever viewed by human eyes or actually used (Petrou, 2004). Also, accurately extracting key features and characteristic patterns of variability from a large data set is vital to correctly understanding the interested ocean and atmospheric processes (e.g., Liu & Weisberg, 2005). With the increasing quantity and type of data available in meteorological and oceanographic research there is a need for effective feature extraction methods.

The Self-Organizing Map (SOM), also known as Kohonen Map or Self-Organizing Feature Map, is an unsupervised neural network based on competitive learning (Kohonen, 1988, 2001; Vesanto & Alhoniemi, 2000). It projects high-dimensional input data onto a low dimensional (usually two-dimensional) space. Because it preserves the neighborhood relations of the input data, the SOM is a topology-preserving technique. The machine 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. This process iterates and fine tunes, and it is called self-organizing. The outcome weight vectors of the SOM nodes are reshaped back to have characteristic data patterns. This learning procedure leads to a topologically ordered mapping of the input data. Similar patterns are mapped onto neighboring regions on the map, while dissimilar patterns are located further apart. An illustration of the work flow of an SOM application is given in Fig. 1.

The SOM is widely used as a data mining and visualization method for complex data sets. Thousands of SOM applications were found among various disciplines according to an early survey (Kaski et al., 1998). The rapidly increasing trend of SOM applications was reported in Oja et al. (2002). Nowadays, the SOM is often used as a statistical tool for multivariate analysis, because it is both a projection method that maps high dimensional data to low-dimensional space, and a clustering and classification method that order similar data patterns onto neighboring SOM units. SOM applications are becoming increasingly useful in geosciences (e.g., Liu and Weisberg, 2005), because it has been demonstrated to be an

effective feature extraction technique that has many advantages over conventional data analysis method (e.g., Liu et al. 2006a). The present paper serves as a survey of the SOM applications in meteorology and oceanography community. Recent advance in applications of the SOM in analyzing a variety of data sets in meteorology and oceanography (in situ long time series, remotely sensed satellite and radar data, and numerical model output) are reviewed. The advantages and weaknesses of the SOM are discussed with respect to conventional data analysis methods as used in the community. Suggestions are also given on how to tune the SOM parameters for accurate mapping of meteorological and oceanographic features.
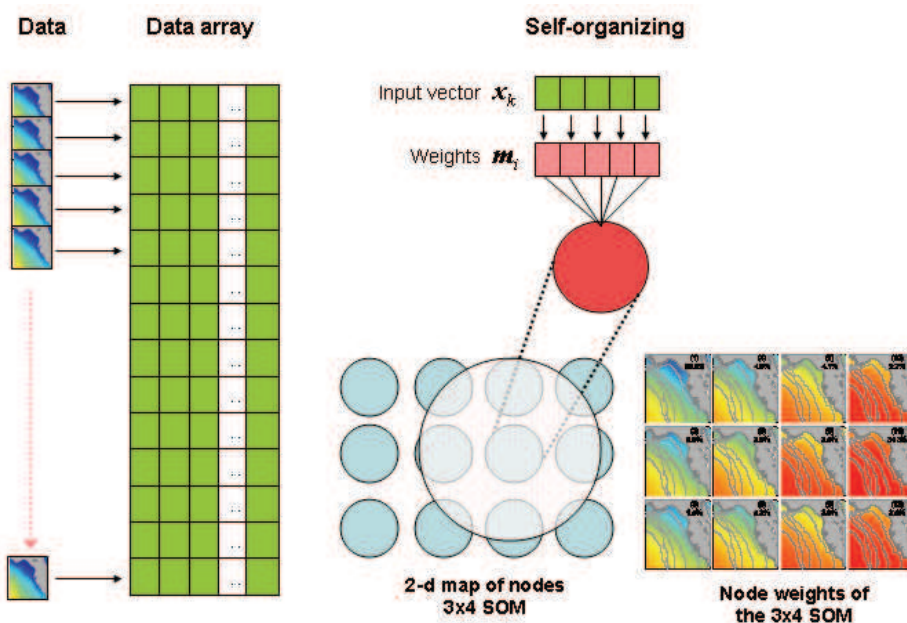

Fig. 1. Illustration of how an SOM works (adapted from Liu et al., 2006b). The data time series are rearranged in a 2D array such that the data at each time step are reshaped as a row vector. For each time step, the row vector is used to update the weight of the SOM via an unsupervised learning algorithm. This iterative process is called self-organizing. The outcome weight vectors of the SOM nodes are reshaped back into characteristic data patterns

2. Self-organizing map applications in meteorology

The SOM was introduced to meteorological and climatic sciences in late 1990s as a clustering and pattern recognition method (e.g., Hewitson & Crane, 1994, 2002; Cavazos, 1999, 2000; Malmgren & Winter, 1999; Ambroise et al., 2000). It is found to be a useful tool in meteorological applications of different spatial and temporal scales: synoptic climatology, extreme weather & rainfall pattern analysis, cloud classification, as well as climate change analysis (Table 1). Many types of meteorological data are analyzed using the SOM, for

example, observed and modeled sea level pressure, geopotential height at different pressure levels, air temperature, humidity, precipitation, evaporation, snow, sea ice, etc. Geographically, the SOM meteorological applications are found around the world: the Americas, Africa, Asia, Europe, Arctic and Antarctic (Table 1). The rest of this section is roughly organized by meteorological data type in SOM applications.

2.1 Sea level pressure and geopotential height data

The SOM is popular in synoptic climatology, especially in analyzing sea level pressure and geopotential height (Table 1). It is often used to summarize and describe the synoptic patterns of atmospheric circulation as indicated by sea level pressure and geopotential height at different levels, and to relate the characteristic circulation patterns with other meteorological variables. For example, Hewitson & Crane (2002) used SOM to describe synoptic atmospheric circulation changes with time as seen from sea level pressure and to relate the sea level pressure patterns with the precipitation time series. Cassano et al. (2006) used the SOM to produce a 55 yr synoptic climatology of daily sea level pressure patterns for the western Arctic, and to study circulation patterns associated with air temperature and high wind extremes. Schuenemann et al. (2009) applied the SOM to the 40-yr European Centre for Medium-Range Weather Forecasts Re-Analysis daily sea level pressure data to objectively identify synoptic sea level pressure patterns over the North Atlantic region. Schuenemann & Cassano (2010a, b) examined the changes of synoptic weather (sea level pressure) patterns from the 15 climate models, and related the SOM extracted circulation patterns with Greenland precipitation in the 20th and 21st centuries. Johnson & Feldstein (2010) presented an SOM analysis that illustrated coupled variability between the North Pacific sea level pressure field and outgoing longwave radiation in the tropical Indo-Pacific region so as to shed light on the relationship between the North Pacific continuum and tropical convection. Reusch et al. (2007) used the SOM to analyze the monthly mean sea level pressure for North Atlantic climate variability. A review of SOM classifications of atmospheric circulation patterns within synoptic climatology is provided in Huth et al. (2008), and an overview in remote sensing applications is seen in Filippi et al. (2010).

2.2 Air temperature, humidity, and wind data

Multiple variables can be simultaneously handled in the SOM algorithm. Thus, the SOM is often used to examine the patterns of co-variability among several meteorological variables. Cavazos (2000) used the SOM to explore the daily atmospheric variables (circulation and humidity) for climate anomalies of extreme precipitation events over the Balkan region. The SOM was used to discover meaningful intraseasonal evolution of North American monsoon from multiple daily atmospheric variables (850 hPa meridional winds, 700 hPa specific humidity, 500 hPa geopotential heights, and 850-500 hPa thickness), and to reveal interaction of the atmospheric variables during the monsoon evolution (Cavazos et al., 2002). The SOM was also used to classify the midtroposphere variables (700 hPa air temperature, geopotential height and specific humidity) for generalized atmospheric patterns, and to reconstruct the ice-core-based synoptic patterns of climate in Antarctic region (Reusch et al., 2005). SOM classification of the meteorological station data is seen in Raju & Kumar (2007), in which multiple variables (temperature, humidity, wind, sunshine hours and solar radiation, etc) are analyzed. Khedairia & Khadir (2008) also performed a classification analysis of meteorological data of Annaba region (North-East of Algeria) from

1995 to 1999 using the SOM and k-means clustering methods. Tambouratzis & Tambouratzis (2008) analyzed long-term (43 years) meteorological data from 128 weather stations in Greece.

Applications & data	Regions	References
Synoptic climatology or synoptic patterns of atmospheric circulation based on SOM analysis of sea level pressure, geopotential height at different pressure levels	Northeast America	Hewitson & Crane (2002), Crane & Hewitson (2003)
	Arctic and adjacent regions	Cassano et al. (2006, 2007, 2010), Higgins & Cassano (2009), Finnis et al. (2009a, b), Skific et al. (2009a, b)
	North Atlantic, Greenland	Reusch et al. (2007), Schuenemann et al. (2009), Schuenemann & Cassano (2010a, b)
	Europe, Middle East & Northern Africa	Michaelides et al. (2007)
	Northern hemisphere, North Pacific	Johnson et al. (2008, 2010), Johnson & Feldstein (2010).
	Australia	Hope et al. (2006), Verdon-Kidd & Kiem (2008), Alexander et al. (2010)
	Antarctic	Lynch et al. (2006), Uotila et a. (2007)
Extreme climate events, monsoon variability, synoptic variation based on various meteorological variables (air temperature, humidity, wind, etc.)	Balkan region	Cavazos (2000)
	Southeast Arizona	Cavazos et al. (2002)
	Europe	Luengo (2004)
	Antarctic	Reusch et al. (2005b)
	India	Raju & Kumar (2007)
	Northeast Algeria	Khedairia & Khadir (2008)
	Greece	Tambouratzis & Tambouratzis (2008)
	Taiwan Island	Chang et al. (2010), Lin & Wu (2010)
Evaporation, precipitation (rainfall, snow, sea ice), cloud classification based on in situ observations, model output, and satellite images	Eastern & central USA	Tian et al. (1999), Filippi et al. (2010)
	Atlantic	Ambroise et al. (2000)
	Europe	Walder & MacLaren (2000)
	Southwest USA	Hsu et al. (2002), Hong et al. (2004, 2005, 2006)
	South Africa	Tadross et al. (2005)
	China	Zhang et al. (2006)
	Japan	Nishiyama et al. (2007)
	Canada (Québec)	Pelletier et al. (2009)
	Taiwan Island	Lin & Chen (2006), Lin & Wu (2007, 2010), Hsu & Li (2010), Chang et al. (2010)
	Colorado River Basin	Fassnacht & Derry (2010)
	Puerto Rico	Malmgren & Winter (1999)
	Peru	Gutierrez et al. (2005)
	Antarctic	Reusch & Alley (2007)

Table 1. SOM applications in meteorology

2.3 Evaporation, precipitation and cloud data

Another category of SOM applications in meteorology include evaporation, precipitation (rainfall & snow) and cloud classification based on in situ observations, model output and satellite images. Many of these applications are also found in the field of hydrology. Malmgren & Winter (1999) used the SOM in climate zonation on the island of Puerto Rico in the Caribbean. They analyzed climate data, seasonal averages of precipitation, and maximum, mean, and minimum temperatures over the years 1960–1990, from 18 stations spread around the island, and identified four climate zones. Hsu et al. (2002) applied the SOM in a rainfall-runoff linear forecast model, called Self-Organizing Linear Output map (SOLO). Tadross et al. (2005) extracted characteristic rainfall patterns over South Africa and Zimbabwe from rainfall data products, and studied the rain-fed maize for the region. Gutierrez et al. (2005) applied the SOM to analyze atmospheric patterns over Peru and local precipitation observations at two nearby stations for the purpose of downscaling multi-model seasonal forecasts. Nishiyama et al. (2007) used the SOM to analyze a combined data set of precipitation and 850 hPa winds, and to identify the typical synoptic wind pattern that frequently causes heavy rainfall in Kyushu during the rainy season. Pelletier et al. (2009) applied the SOM in the characterization of 1-h rainfall temporal patterns in a Québec City case study. Lin & Chen (2006) and Lin & Wu (2007) used the SOM to analyze the rainfall data on Taiwan Island. Recently, Hsu & Li (2010) used the SOM and wavelet methods to explore spatio-temporal characteristics of the 22 years of precipitation data (1982–2003) for Taiwan Island. Chang et al. (2010) also proposed an SOM-based neural network to assess the variability of daily evaporation based on meteorological variables. Recently, the SOM was used to define regions of homogeneity in the Colorado River Basin using snow telemetry snow water equivalent data (Fassnacht & Derry, 2010). The SOM was also used to analyze a 24 year (1973-1996) sea ice data (monthly sea-ice edge positions) in Antartic (Reusch & Alley, 2007).

The SOM is often used as a feature extraction method in cloud classification of satellite imagery. In the pioneering work of the SOM-based cloud classification, Tian et al. (1999) showed the potential of such neural network system in extracting features from the multispectral Geostationary Operational Environmental Satellite (GOES)-8 satellite imagery. Ambroise et al. (2000) presented a probabilistic SOM-based method for segmenting multispectral satellite images, and applied this method in cloud classification of the Polarization and Directionality of the Earth's Reflectances (POLDER) data. Walder & MacLaren (2000) developed an SOM-based automatic cloud classificaton system and applied it to extract spectral and textural features from Advanced Very High Resolution Radiometer (AVHRR) images. Hong et al. (2004) presented a satellite-based rainfall estimation system, Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) cloud classification system, and used this SOM-based system to extract local and regional cloud features from infrared geostationary satellite imagery in estimating fine-scale rainfall distribution. Hong et al. (2005) developed a more accurate SOM-based neural network for cloud patch–based rainfall estimation, named as self-organizing nonlinear output (SONO) model. Hong et al. (2006) further introduced a satellite-based precipitation estimation system using watershed segmentation and growing hierarchical self-organizing map (GHSOM, Rauber et al. 2002), and found significant improvements of estimation accuracy in classifying the clouds into hierarchical sub-layers rather than a single layer.

3. Self-organizing map applications in oceanography

Early SOM applications in oceanography community were mainly limited to satellite and in situ biological/geochemical data analyses by remote sensing scientiests or biological/chemical oceanographers (e.g., Kropp & Klenke, 1997; Ainsworth, 1999; Ainsworth & Jones, 1999; Yacoub et al., 2001; Silulwane et al., 2001). Since the introducion and demonstration of the use of the SOM to the oceanography community by Richardson et al. (2003), SOM applications have been steadily increased in physical oceanography (e.g., Risien et al., 2004; Liu & Weisberg, 2005, 2007; Leloup et al., 2007, 2008; Iskandar et al., 2008), and other disciplinary of oceanography as well (e.g., Chazottes et al., 2006, 2007 ; Telszewski et al., 2009). The SOM is used in analyzing many kinds of oceanographic data, such as satellite ocean color, chlorophyll, sea surface temperature, sea surface height, in situ and modeled ocean currents, etc (Table 2). Geographically, SOM applications are seen in major world's oceans (Pacific, Atlantic, Indian Ocean, Antarctic, etc) and many coastal regions (e.g, Banguela upwelling region, West Florida Shelf, Washington-Oregon Shelf). The rest of this section is organized by oceanographic data type in SOM applications.

3.1 Satellite ocean color and chlorophyll

Satellite oceanography community needed effective feature extraction methods and used the SOM technique earlier because they have larger amount of data than other disciplinary of oceanography. Ainsworth (1999) and Ainsworth & Jones (1999) used the SOM to classify the Chlorophyll concentration data around the Pacific Ocean obtained from the Ocean Colour and Temperature Scanner on board of the Japanese Advanced Earth Observing Satellite (ADEOS), and demonstrated the use of the SOM in classifying ocean colors from multispectral satellite data. Yacoub et al. (2001) applied the SOM in satellite ocean color classifcation for the northwest African coast of the Atlantic Ocean. Niang et al. (2003) proposed an SOM-based automatic classification method to analyze ocean color reflectance measurements taken at the top of the atmosphere (TOA) by satellite-borne sensors, and identified aerosol types and cloud contaminated pixels from satellite ocean color reflectance spectra in the Cape Verde region of the Atlantic Ocean. Recently, Telszewski et al. (2009) applied the SOM to satellite chlorophyll-a concentration, reanalysis sea surface temperature, and mixed layer depth time series and estimated the partial pressure of carbon dioxide (pCO2) distribution in the North Atlantic.

3.2 In situ biological and geochemical data

Kropp & Klenke (1997) were among the earliest SOM users in oceanography. They applied the SOM to a data set of 170 sediment samples for biological and geochemical conditions of a tidal flat in the southern North Sea, and demonstrated the efficiency of the SOM technique in analyzing multivariate data sets of complex natural system (Kropp & Klenke, 1997). Silulwane et al. (2001) used the SOM to classify in situ vertical chlorophyll profiles from the Benguela upwelling system, and related the identified characteristic chlorophyll profiles to pertinent environmental variables, such as sea surface temperature, surface chlorophyll, mixed layer depth and euphotic depth. They pointed out that these relationships can be used semi-quantitatively to predict the subsurface chlorophyll field from known (water column depth) or easily measured variables from satellites, such as surface temperature or surface chlorophyll (Richardson et al., 2002). Lee et al. (2003) used the SOM to examine the plankton taxa in Antarctic area. Chazottes et al. (2006, 2007) applied the SOM to analyze the in situ absorption spectra of phytoplankton from ocean water, in conjunction with detailed

pigment concentrations. Solidoro et al. (2007) used the SOM to classify biogeochemical properties of 1292 water samples collected in a 3-year-long monitoring program in the northern Adriatic Sea, and identified a representative synthetic sample for each group. Bandelj et al. (2008) used the SOM to illustrate the spatial and temporal succession of multitrophic plankton assemblages in the Lagoon of Venice and relates them to biogeochemical properties. Astel et al. (2008) applied the SOM to evaluate the geochemical and environmental impact of 26th December 2004 tsunami disaster in Indian Ocean. Solidoro et al. (2009) applied the SOM to 9 biogeochemical parameters (temperature, salinity, dissolved oxygen, ammonia, nitrites, nitrates, phosphates, silicates, and chlorophyll a) of 7150 original water samples for water mass classification. Aymerich et al. (2009) presented an SOM-based technique for classifying fluorescence spectra, and found that if the data (emission spectra) were appropriately preprocessed, the SOM were able to properly identify between algal groups, such as diatoms and dinoflagellates, which could not be discriminated with previous methods.

3.3 Satellite sea surface temperature data

Remotely sensed sea surface temperature may be the most abundant type of satellite data in oceanography. It is an important variable in air-sea interaction, especially for heat budget. Along with the satellite chlorophyll data analysis, Ainsworth (1999) and Ainsworth & Jones (1999) used the SOM to classify the sea surface temperature around the Pacific Ocean obtained from the Ocean Colour and Temperature Scanner on board of ADEOS satellite. Richardson et al. (2003) gave an example SOM analysis of sea surface temperature in the southern Benguela region. Liu et al. (2006b) used a two-layer GHSOM to analyze the sea surface temperature on the West Florida Shelf in the eastern Gulf of Mexico, and summarized the seasonal evolution of the temperature patterns that were explained in terms of air-sea interactions on the shelf on seasonal time scale. Tozuka et al. (2008) investigated both satellite observed and coupled model outputs of sea surface temperature for tropical Indian Ocean climate variability using the SOM, and found that the SOM successfully captured the dipole sea surface temperature anomaly pattern associated with the Indian Ocean Dipole and basin-wide warming/cooling associated with El Ninō-Southern Oscillation (ENSO). Morioka et al. (2010) used the SOM to examine the climate variability in the southern Indian Ocean by classifying the sea surface temperature anomaly poles. Iskandar (2010) applied the SOM to study the seasonal and interannual variations of sea surface temperature patterns in Banda Sea. Leloup et al. (2007) used the SOM to analyze the climate indices of equatorial Pacific and found the SOM to be useful both for seasonal ENSO predictability and for the detection of decadal changes in ENSO behavior. Leloup et al. (2008) used the SOM to assess the spatial characteristics of the twentieth century ENSO sea surface temperature variability along the equatorial Pacific simulated by 23 climate models.

3.4 Satellite sea surface height data

Sea surface height from satellite altimetry is another important type of oceanographic data that is related to ocean circulation dynamics and ocean heat content in the upper layer. In open ocean regions, sea surface height is often used to calculate surface geostrophic currents and hence to approximate surface currents. Hardman-Mountford et al. (2003) used the SOM to identify characteristic patterns of satellite derived sea surface height (actually sea level gradient) data, and related to sardine recruitment in the Northern Benguela. Liu et al. (2008) applied the SOM to time series of altimetry (sea surface height anomaly) gridded data in the

South China Sea, extracted characteristic patterns of sea surface height variability, and calculated the associated surface geostrophic current anomalies. They found that the SOM successfully revealed the upper layer current variability in the South China Sea on seasonal and interannual time scales. Iskandar (2009) examined the satellite altimetry in the tropical Indian Ocean using the SOM, and found that the SOM was able to separate typical patterns associated with the ENSO and the Indian Ocean Dipole events.

3.5 Ocean current data from in situ observations and numerical models

Most of the SOM applications in physical oceanography were to extract characteristic circulation patterns from long time series of ocean current data. Liu & Weisberg (2005) and Liu et al. (2006a) used the SOM to extract the dominant patterns of ocean current variability from a mooed Acoustic Doppler Current Profiler (ADCP) array on the West Florida Shelf, and related the evolution of the characteristic coastal upwelling and downwelling current patterns with the local wind forcing. Liu & Weisberg (2007) examined velocity profiles from an across-shelf transect of ADCP moorings on the West Florida Shelf, and focused on the SOM extracted across-shelf structures of coastal upwelling/downwelling jet over the inner shelf. Cheng & Wilson (2006) also used the SOM to identify the characteristic vertical profiles of the currents in an estuary.

High frequency (HF) radar current data is an important type of data in coastal oceanography that has been developed quickly in recent years. The archived HF radar surface currents are usually hourly maps, i.e., the dimension of the data is high for multiple-year observations. Liu et al. (2007) applied the SOM to extract current pattern variability from a joint HF radar and ADCP dataset on the West Florida Shelf, and obtained dynamically distinctive spatial and temporal current structures on semidiurnal, diurnal and synoptic time scales. Mau et al. (2007) also used the SOM to characterize the Long Island Sound outflows from HF radar data.

Numerical ocean models also generate huge amount of "data" that need to be effectively analyzed. SOM has already found its application in describing numerical ocean model output. For example, Iskandar et al. (2008) applied the SOM to extract the characteristic vertical profiles of zonal currents in the equator of Indian Ocean from a numerical model output. Liu et al. (2009) used the SOM to summarize the synoptic variation of the Columbia River plume patterns (surface currents) from a numerical ocean circulation model. Recently, Jin et al. (2010) also used the SOM to examine modeled currents in Kerama Gap, and gained insights into the interaction of the Kuroshio in the East China Sea and the Ryukyu Current system east of the Ryukyu Islands. Additional opportunities abound for future use of SOM in analyzing numerical ocean model simulations.

3.6 Other oceanographic data

In addition to the above mentioned main data types, SOM applications were found in many other oceanographic data, such as wind stress, sea floor shape, tusnami and salinity. Richardson et al. (2003) and Risien et al. (2004) demostrated the use of SOM in characterizing coastal wind (wind stress) patterns and their variability. Chakraborty et al. (2003) implemented an SOM-based hybrid artificial neural network in sea-floor roughness classification of multibeam angular backscatter data in the central Indian Ocean basin. Liu et al. (2009) applied the SOM to analyze modeled surface salinity time series for characteristic patterns of Columbia River Plume, and associated these plume pattern evolution with local wind forcing and river flow temporal variation. Corchado et al. (2008)

and Mata et al. (2009) applied the SOM-based hybrid intelligent system to detect oil spill in the ocean. Borges et al. (2010) also applied the SOM in geographical classification of weathered crude oil samples. Some SOM applications in maritime environment (e.g., ship trajectory classification) were briefly reviewed in Lobo (2009). Recently, Ehsani & Quiel (2008) and Hentati et al. (2010) applied the SOM to geomorphology.

4. Advantages over other conventional methods

The empirical orthogonal function (EOF) or principal component analysis (PCA) method is often used to extract patterns of variability in meteorological and oceanographic data. Liu & Weisberg (2005, 2007) used both EOF and SOM to extract ocean current patterns from the same data set (a long time series of velocity from a moored ADCP array), and found that the SOM patterns were more accurate and intuitive than the leading mode EOF patterns. The asymmetric features (in current strength, coastal jet location and velocity vector veering with depth) between upwelling and downwelling current patterns extracted by the (nonlinear) SOM were not readily revealed by the (linear) EOF (Liu & Weisberg, 2005). Liu et al. (2006a) evaluated the feature extraction performance of the SOM by using artificial data representative of known patterns. The SOM was shown to extract the patterns of a linear progressive sine wave as the EOF did, even with noise added. However, in the experiment with multiple sets of more complex patterns, the SOM technique successfully chose all those patterns in contrast with the EOF method that failed to do that (Liu et al., 2006a). Reusch et al. (2005) also tested the SOM against the PCA method using synthetic datasets composed of positive and negative modes of four idealized North Atlantic sea level pressure fields, with and without noise components. They also found that the SOM was more robust than the PCA in extracting the predefined patterns of variability. Annas et al. (2007) and Astel et al. (2007) further confirmed the superior performance of the SOM over the PCA. These advantages, of course, must be tempered by the fact that PCA uses an empirical vector space that spans the data space, hence aspects of the data space may be quantitatively reconstructed from the vector space (Liu, 2006; Liu & Weisberg, 2005).

K-means is another popular artificial neural network widely used for clustering. After comparing the SOM and k-means methods, Bação et al. (2005) proposed the use of SOMs as possible substitutes for the k-means clustering algorithms. Lin & Chen (2006) tested the cluster accuracy of the SOM, the k-means method and Ward's method based on experimental data sets that the amount of cluster dispersion and the cluster membership are controlled and known. They found that the SOM determined the cluster membership more accurately than the K-means method and Ward's method. K-means somehow is a subset of SOM, meaning that SOM reduces to k-means for particular choice of parameters (e.g., Lobo, 2009), and therefore it is natural to assume that SOM is more flexible than k-means (Solidoro et al., 2007).

5. Self-organizing map parameter choices

Despite its wide applications as a tool for feature extraction and clustering, the Self-Organizing Map (SOM) remains a black box to most meteorologists and oceanographers. SOM new users may be perplexed by the choice of SOM parameters, because different parameter choices may result in different SOM patterns. This challenge may prevent some potential new users from pursuing further SOM applications. Liu et al. (2006a) evaluated the feature extraction performance of the SOM by using artificial time series data comprised of known patterns. Sensitivity studies were performed to ascertain the effects of the SOM

tunable parameters. A practical way to apply the SOM was proposed and demonstrated using several examples, including long time series of coastal ocean currents from the West Florida Shelf (Liu et al., 2006a).

Oceanographic data	Regions	References
Satellite ocean color, Chlorophyll	Pacific	Ainsworth (1999), Ainsworth & Jones (1999)
	Southeast Atlantic	Yacoub et al. (2001)
	Southwest Atlantic	Saraceno et al. (2006)
	North Atlantic	Niang et al. (2003), Telszewski et al. (2009)
In situ Chlorophyll, absorption spectra of phytoplankton, plankton taxa, ecological variables, microbiological and geochemical variables, pCO2	Southern North Sea	Kropp & Klenke (1997)
	Southeast Atlantic	Silulwane et al. (2001), Richardson et al. (2002)
	Europe	Barreto & Perez-Uribe (2007ab), Alvarez-Guerra et al. (2008), Aymerich et al. (2009), Skwarzec et al. (2009), Žibret & Šajn (2010)
	Lagoon of Venice	Bandelj et al. (2008)
	Northern Adriatic Sea	Solidoro et al. (2007, 2009)
	Antarctic	Lee et al. (2003)
	World oceans	Chazottes et al. (2006, 2007)
	Indian Ocean	Astel et al. (2008)
Satellite measured sea surface temperature, ENSO indices	Pacific	Ainsworth (1999), Ainsworth & Jones (1999)
	Tropical Pacific	Leloup et al. (2007, 2008)
	Southeast Atlantic	Richardson et al. (2003)
	West Florida Shelf	Liu et al. (2006b)
	North Atlantic	Telszewski et al. (2009)
	Indian Ocean	Tozuka et al. (2008), Morioka et al. (2010), Iskandar (2010)
Satellite measured sea surface height	Southeast Atlantic	Hardman-Mountford et al. (2003)
	South China Sea	Liu et al. (2008)
	Indian Ocean	Iskandar (2009)
Ocean currents from in situ observations and numerical models	West Florida Shelf	Liu & Weisberg (2005, 2007), Liu et al. (2006a, 2007)
	Columbia River plume	Liu et al. (2009)
	New York Harbor	Cheng & Wilson (2006)
	New York Bight	Mau et al. (2007)
	Indian Ocean	Iskandar et al. (2008)
	Kerama Gap	Jin et al. (2010)
Surface winds	Southeast Atlantic	Richardson et al. (2003), Risien et al. (2004)
Sea-floor roughness	South Atlantic	Chakraborty et al. (2003)
Salinity	Columbia River plume	Liu et al. (2009)
Oil spill	Galician coast, Europe	Corchado et al. (2008), Mata et al. (2009), Borges et al. (2010)
Maritime data	Europe	Lobo (2009)

Table 2. SOM applications in oceanography

6. Summary

In recent years, the SOM has gained its popularity in meteorology and oceanography community as a powerful pattern recognition and feature extraction method. The SOM analysis has been applied to a variety of data sets in meteorology and oceanography, such as in situ long time series, remotely sensed satellite and radar data, and numerical model output. With the steadily increasing quantity and type of data, the SOM users are expected to increase within the meteorology and oceanography community. Note that there are still many types of meteorological and oceanographic data not analyzed using the SOM, especially output from various numerical models. There are vast opportunities for meteorologists, oceanographers and climate scientists, especially modelers, to have fruitful applications of the SOM, a promising applied mathematical tool for feature extraction and pattern recognition from large and complex data sets.

The SOM has many advantages over conventional feature extraction methods in the community, such as the EOF, k-means methods. It is proposed as a complement to these established methods. One obstacle of SOM application, especially to new users, would be the choice of many tunable parameters, which may prevent potential users from pursuing further SOM applications. Suggestions were given in Liu et al. (2006a) on how to tune the SOM for accurate mapping of meteorological and oceanographic features.

7. Acknowledgements

8. References

Ainsworth, E. J. (1999), Visualization of ocean colour and temperature from multispectral imagery captured by the Japanese ADEOS satellite, *Journal of Visualization*, Vol. 2, 195–204, ISSN 1343-8875

Ainsworth, E. J. & Jones, I. S. F. (1999), Radiance spectra classification from the ocean color and temperature scanner on ADEOS, *IEEE Transaction on Geosciences Remote Sensing,* 37, 1645–1656, ISSN 0196-2892

Alexander, L. V.; Uotila, P., Nicholls, N. &, Lynch, A. (2010). A new daily pressure dataset for Australia and its application to the assessment of changes in synoptic patterns during the last century. *Journal of Climate,* Vol. 23, 1111-1126, ISSN 0894-8755

Alvarez-Guerra, M.; González-Piñuela, C., Andrés, A., Galán, B. & Viguri, J. R. (2008). Assessment of Self-Organizing Map artificial neural networks for the classification of sediment quality, *Environment International,* Vol. 34, No. 6, 782-790, ISSN 0160-4120

Ambroise, C.; Seze, G. Badran F. & Thiria S. (2000), Hierarchical clustering of self-organizing maps for cloud classification, *Neurocomputing,* Vol. 30, 47–52, ISSN 0925-2312

Annas, S.; Kanai T. & Koyama, S. (2007). Principal component analysis and self-organizing map for visualizing and classifying fire risks in forest regions, *Agricultural Information Research*, Vol. 16, No. 2, 44–51, *ISSN*, : 1881-5219

Astel, A.; Tsakouski, S., Barbieri, P. & Simeonov, V. (2007). Comparison of self-organizing maps classification approach with cluster and principal components analysis for large environmental data sets, *Water Research,* Vol. 41, 4566–4578, ISSN 0043-1354

Astel, A.; Boszke, L., Niedzielski, P. & Kozak, L. (2008). Application of the self-organizing mapping in exploration of the environmental impact of a tsunami disaster. *Journal of Environmental Science and Health, Part A: Toxic/Hazardous Substances and Environmental Engineering*, Vol. 43, No. 9, 1016–1026, ISSN 1532-4117

Awad, M. (2010). An unsupervised artificial neural network method for satellite image segmentation, *International Arab Journal of Information Technology,* Vol. 7, No. 2, 199 - 205, ISSN 1683-3198

Aymerich, I. F.; Piera, J., Soria-Frisch, A. & Cros L. (2009). A rapid technique for classifying phytoplankton fluorescence spectra based on self-organizing maps, *Applied Spectroscopy,* Vol. 63 No. 6, 716-726, ISSN 0003-7028

Bação, F.; Lobo, V. & Painho, M. (2005), Self-organizing maps as substitutes for k-means clustering, *Lecture Notes in Computer Science,* V. S. Sunderam, G. v. Albada, P. Sloot, and J. J. Dongarra (Eds.), Vol. 3516, PP. 476-483, ISSN 0302-9743, Berlin Heidelberg, Springer-Verlag

Bandelj, V.; Socal, G., Park, Y.-S., Lek, S., Coppola, J., Camatti, E., Capuzzo, E., Milani L. & Solidoro C. (2008). Analysis of multitrophic plankton assemblages in the Lagoon of Venice, *Marine Ecology Progress Series,* Vol. 368, 23–40, doi: 10.3354/meps07565, ISSN 1616-1599

Barreto, M. A. & Perez-Uribe, A. (2007a). Improving the correlation hunting in a large quantity of SOM component planes, Classification of Agro-ecological variables related with productivity in the sugar cane culture, J. Marques de Sa et al. (Eds.), ICANN 2007, Part II, *Lecture Notes in Computer Science,* Vol. 4669, pp. 379–388, ISSN 0302-9743, Springer-Verlag Berlin Heidelberg

Barreto, M. A. & Perez-Uribe, A. (2007b). Classification of similar productivity zones in the sugar cane culture using clustering of SOM component planes based on the SOM distance matrix, *Proceedings of the 6th International Workshop on Self-Organizing* Map (WSOM 2007), The Neuroinformatics Group, Bielefeld University, Germany, ISBN 978-3-000-022473-7

Borges, C.; Gómez-Carracedo, M.P., Andrade, J.M., Duarte, M.F., Biscaya, J.L. & Aires-de-Sousa, J. (2010). Geographical classification of weathered crude oil samples with unsupervised self-organizing maps and a consensus criterion, *Chemometrics and Intelligent Laboratory Systems,* Vol. 101, No. 1, 43-55, ISSN 0169-7439

Cassano, E. N.; Lynch, A. H., Cassano, J. J. & Koslow, M. R. (2006). Classification of synoptic patterns in the western Arctic associated with extreme events at Barrow, Alaska, USA, *Climate Research,* Vol. 30, 83-97, ISSN 1616-1572

Cassano, J. J.; Uotila, P., Lynch, A. H. & Cassano, E. N. (2007). Predicted changes in synoptic forcing of net precipitation in large Arctic river basins during the 21st century, *Journal of Geophysical Research*, Vol. 112, G04S49, doi:10.1029/2006JG000332, ISSN 0148-0227

Cassano, N.E. & Cassano, J. J. (2010). Synoptic forcing of precipitation in the Mackenzie and Yukon River basins, *International Journal of Climatology,* Vol. 30, 658–674, ISSN 0899-8418

Cavazos, T. (2000). Using self-organizing maps to investigate extreme climate events: An application to wintertime precipitation in the Balkans, *Journal of Climate,* Vol. 13, 1718–1732, ISSN 0894-8755

Cavazos, T.; Comrie, A. C. & Liverman, D. M. (2002). Intraseasonal variability associated with wet monsoons in southeast Arizona, *Journal of Climate,* Vol. 15, 2477–2490, ISSN 0894-8755

Chakraborty, B.; Kodagali, V. & Baracho, J. (2003). Sea-floor classification using multibeam echo-sounding angular backscatter data: a real-time approach employing hybrid neural network architecture, *IEEE Journal of Oceanic Engineering,* Vol. 28, NO. 1, 121–128, ISSN 0364-9059

Chang, F.-J.; Chang, L.-C. Kao, H.-S. & Wu, G.-R. (2010). Assessing the effort of meteorological variables for evaporation estimation by self-organizing map neural network, *Journal of Hydrology,* Vol. 384, No. 1-2, 118-129, ISSN 0022-1694

Chazottes, A.; Bricaud, A., Crépon, M. & Thiria, S. (2006). Statistical analysis of a database of absorption spectra of phytoplankton and pigment concentrations using self-organizing maps, *Applied Optics,* Vol. 45, No. 31, 8102-8115, ISSN 0003-6935

Chazottes, A.; Crépon, M., Bricaud, A., Ras, J. & Thiria, S. (2007). Statistical analysis of absorption spectra of phytoplankton and of pigment concentrations observed during three POMME cruises using a neural network clustering method, *Applied Optics,* Vol. 46, No. 18, 3790-3799, ISSN 0003-6935

Cheng, P. & Wilson, R. E. (2006). Temporal variability of vertical nontidal circulation pattern in a partially mixed estuary: Comparison of self-organizing map and empirical orthogonal functions, *Journal of Geophysical Research*, Vol. 111, No. C12021, doi:10.1029/2005JC003241, ISSN 0148-0227

Corchado, E.; Baruque, B., Mata, A. & Corchado, J. M. (2008). A WeVoS-CBR approach to oil spill problem, *Lecture Notes in Computer Science,* Vol. 5271, 378-384, DOI: 10.1007/978-3-540-87656-4_47, ISSN *0302-9743*, Springer-Verlag Berlin Heidelberg

Crane, R. G. & Hewitson, B.C. (2003). Clustering and upscaling of station precipitation records to regional patterns using self-organizing maps (SOMs). *Climate Research,* Vol. 25, 95-107, ISSN 1616-1572

Ehsani, A.H. & Quiel, F. (2008). Geomorphometric feature analysis using morphometric parametrization and artificial neural networks, *Geomorphology*, Vol. 99, No. 1-4, 1–12, ISSN 0169-555X

Faro, A.; Giordano, D. & Maiorana, F. (2008). Input noise robustness and sensitivity analysis to improve large datasets clustering by using the GRID, J.-F. Boulicaut, M.R. Berthold, and T. Horváth (Eds.), *DS 2008, Lecture Notes in Artificial Intelligence,* Vol. *5255,* pp. 234–245, ISSN 0302-9743, Springer-Verlag Berlin Heidelberg

Fassnacht, S. R. & Derry, J. E. (2010), Defining similar regions of snow in the Colorado River Basin using self-organizing maps, *Water Resources Research*, Vol. 46, W04507, doi:10.1029/2009WR007835, ISSN 0043-1397

Filippi, A.; Dobreva, I., Klein, A.G. & Jensen, J.R. (2010). Self-Organizing Map-based Applications in Remote Sensing, In: *Self-Organizing Maps,* Matsopoulos, G.K. (Ed.), 231-248, ISBN 978-953-307-074-2

Finnis, J.; Cassano, J. J., Holland, M.M. & Serreze, M.C. (2009a). Synoptically forced hydroclimatology of major Arctic watersheds in general circulation models, Part 1: the Mackenzie River basin. *International Journal of Climatology,* Vol. 29, 1226-1243, ISSN 0899-8418

Finnis, J.; Cassano, J. J., Holland, M.M., Serreze, M.C. & Uotila P. (2009b). Synoptically forced hydroclimatology of major Arctic watersheds in general circulation models, Part 2: Eurasian watersheds. *International Journal of Climatology,* Vol. 29, 1244-1261, ISSN 0899-8418

Gutierrez, J.M.; Cano, R., Cofino, A.S. & Sordo, C. (2005). Analysis and downscaling multi-model seasonal forecasts in Peru using self-organizing maps, *Tellus A*, Vol. 57, No. 3, 435-447, ISSN 0280-6495

Hardman-Mountford, N. J.; Richardson, A. J., Boyer, D. C. , Kreiner, A. & Boyer, H. J. (2003), Relating sardine recruitment in the northern Benguela to satellite-derived sea surface height using a neural network pattern recognition approach, *Progress in Oceanography,* Vol. 59, 241– 255, ISSN 0079-6611

Hentati, A.; Kawamura, A., Amaguchi, H. & Iseri, Y. (2010). Evaluation of sedimentation vulnerability at small hillside reservoirs in the semi-arid region of Tunisia using the Self-Organizing Map, *Geomorphology*, Vol. 122, No. 1-2, 56-64, ISSN 0169-555X

Hewitson, B. C. & Crane, R. G. (1994). Neural Nets: Applications in Geography, ISBN 978-0792327462, Springer, New York

Hewitson, B. C. & Crane, R. G. (2002). Self-organizing maps: applications to synoptic climatology. *Climate Research,* Vol. 22, No. 1, 13-26, ISSN 0936-577X

Higgins, M. E. & Cassano, J. J. (2009). Impacts of reduced sea ice on winter Arctic atmospheric circulation, precipitation, and temperature, *Journal of Geophysical Research*, Vol. 114, D16107, doi:10.1029/2009JD011884, ISSN 0148-0227

Hong, Y.; Chiang, Y. M.; Liu, Y.; Hsu, K. L. & Sorooshian, S. (2006). Satellite-based precipitation estimation using watershed segmentation and growing hierarchical self-organizing map. *International Journal of Remote Sensing,* Vol. 27, No. 23-24, 5165-5184, ISSN 0143-1161

Hong, Y.; Hsu, K., Sorooshian, S. & Gao, X. (2004), Precipitation estimation from remotely sensed imagery using an artificial neural network cloud classification system, *Journal of Applied Meteorology,* Vol. 43, 1834–1853, ISSN 1520-0450

Hong, Y.; Hsu, K., Sorooshian, S. & Gao, X. (2005), Self-organizing nonlinear output (SONO): A neural network suitable for cloud patch-based rainfall estimation at small scales, *Water Resources Research,* Vol. 41, No. W03008, doi:10.1029/2004WR003142, ISSN 0043-1397

Hope, P. K.; Drosdowsky, W. & Nicholls, N. (2006). Shifts in the synoptic systems influencing southwest Western Australia, *Climate Dynamics*, Vol. 26, 751-764, ISSN 0930-7575

Hsu, K.-C. & Li, S.-T. (2010). Clustering spatial–temporal precipitation data using wavelet transform and self-organizing map neural network, *Advances in Water Resources*, Vol. 33, No. 2, 190-200, ISSN 0309-1708

Hsu, K.-C. & Li, S.-T. (2010). Clustering spatial-temporal precipitation data using wavelet transform and self-organizing map neural network, *Advances in Water Resources,* Vol. 33, No. 2, 190-200, ISSN 0309-1708

Hsu, K.-L.; Gupta, H. V., Gao, X., Sorooshian, S. & Imam, B. (2002). Self organizing linear output map (SOLO): An artificial neural network suitable for hydrologic modeling and analysis, *Water Resources Research,* Vol. 38, No. 12, 1302, doi:10.1029/2001WR000795, ISSN 0043-1397

Huth, R.; Beck, C., Philipp, A., Demuzere, M., Ustrnul, Z., Cahynová, M., Kyselý, J. & Tveito, O. E. (2008). Classifications of atmospheric circulation patterns, Recent advances and applications, *Annals of the New York Academy of Sciences*, Vol. 1146, No. 1, 105 - 152, ISSN 0077-8923

Iseri, Y.; Matsuura, T., Iizuka, S., Nishiyama, K. & Jinno, K. (2009). Comparison of pattern extraction capability between self-organizing maps and principal component analysis, *Memoirs of the Faculty of Engineering, Kyushu University,* Vol. 69, No. 2, 37–47.

Iskandar, I. (2009). Variability of satellite-observed sea surface height in the tropical Indian Ocean: comparison of EOF and SOM Analysis, *Makara Seri Sains,* Vol. 13, No. 2, 173-179, ISSN 1693-6671

Iskandar, I. (2010). Seasonal and interannual patterns of sea surface temperature in Banda Sea as revealed by self-organizing map, *Continental Shelf Research*, Vol. 30, 1136–1148, ISSN 0278-4343

Iskandar, I., T. Tozuka, Y. Masumoto, and T. Yamagata (2008), Impact of Indian Ocean dipole on intraseasonal zonal currents at 90°E on the equator as revealed by self-organizing map, *Geophysical Research Letters*, 35, L14S03, doi:10.1029/2008GL033468, ISSN 0094-8276

Jin, B.; Wang, G., Liu, Y. & Zhang, R. (2010). Interaction between the East China Sea Kuroshio and the Ryukyu Current as revealed by the self-organizing map. *Journal of Geophysical Research,* (in press)

Johnson, N. C. & Feldstein, S.B. (2010). The Continuum of North Pacific Sea Level Pressure Patterns: Intraseasonal, Interannual, and Interdecadal Variability. *Journal of Climate, Vol.* 23, 851-867, ISSN 0894-8755

Johnson, N. C.; S. B. Feldstein & B. Tremblay (2008). The continuum of Northern Hemisphere teleconnection patterns and a description of the NAO shift with the use of self-organizing maps, *Journal of Climate*, Vol. 21, 6354–6371, ISSN 0894-8755

Khedairia, S. & Khadir, M. T. (2008). Self-organizing map and k-means for meteorological day type identification for the region of Annaba –Algeria, In: *7th Computer Information Systems and Industrial Management Applications,* pp.91-96, 2008, ISBN: 978-0-7695-3184-7, Ostrava

Kropp, J. & Klenke, T. (1997). Phenomenological pattern recognition in the dynamical structures of tidal sediments from the German Wadden Sea, Ecological Modelling, Vol. 103, No. 2-3, 151-170, ISSN 0304-3800

Kohonen, T. (1988). *Self-Organization and Associative Memory,* Springer-Verlag, ISBN 0-387-18314-0, New York, Berlin, Heidelberg

Kohonen, T. (2001). *Self-Organizing Maps.* Springer-Verlag, ISBN 3-540-67921-9, New York, Berlin, Heidelberg

Lee, W.; Kang, S.-H., Montagna, P.A. & Kwak, I.-S. (2003). Temporal dynamics and patterning of meiofauna community by self-organizing artificial neural networks, *Ocean and Polar Research,* Vol. 25, No. 3, 237-247, ISSN 1598-141X

Leloup, J. A.; Lachkar, Z., Boulanger, J. P. & Thiria, S. (2007). Detecting decadal changes in ENSO using neural networks, *Clim*ate *Dynamics*, Vol. 28, 147-162, doi:10.1007/s00382-006-0173-1, ISSN 0930-7575

Leloup, J. A.; Lengaigne, M. & Boulanger, J. P. (2008). Twentieth century ENSO characteristics in the IPCC database, *Climate Dynamics*, Vol. *30*, 277-291, doi:10.1007/s00382-007-0284-3, ISSN 0930-7575

Lin, G.-F. & Chen, L.-H. (2006). Identification of homogeneous regions for regional frequency analysis using the self-organizing map, *Journal of Hydrology,* Vol. 324, 1-9, ISSN 0022-1694

Lin, G.-F. & Wu, M.C. (2007). A SOM-based approach to estimating design hyetographs of ungauged sites. *Journal of Hydrology*, Vol. 339, No. 3-4, 216-226, ISSN 0022-1694

Lin, G.-F. & Wu, M.-C. (2010). A hybrid neural network model for typhoon-rainfall forecasting, *Journal of Hydrology,* Vol. 375, No. 3-4, 450-458, ISSN 0022-1694

Liu, Y. (2006). *Patterns and Dynamics of Ocean Circulation Variability on the West Florida Shelf.* Ph.D. Dissertation, College of Marine Science, University of South Florida.

Liu, Y. & Weisberg, R. (2005). Patterns of ocean current variability on the West Florida Shelf using the self-organizing map*, Journal of Geophysical Research,* Vol. 110, C06003, doi:10.1029/2004JC002786, ISSN 0148-0227

Liu, Y. & Weisberg, R. H. (2007). Ocean currents and sea surface heights estimated across the West Florida Shelf. *Journal of Physical Oceanography,* Vol. 37, 1697-1713, ISSN 0022-3670

Liu, Y.; Weisberg, R. H. & Mooers, C. N. K. (2006a). Performance evaluation of the self-organizing map for feature extraction, *Journal of Geophysical Research,* Vol. 111, C05018, doi:10.1029/2005JC003117, ISSN 0148-0227

Liu, Y.; Weisberg, R. H. & He, R. (2006b). Sea surface temperature patterns on the West Florida Shelf using the growing hierarchical self-organizing maps. *Journal of Atmospheric and Oceanic Technology,* Vol. No. 2, 23, 325-328, ISSN 0739-0572

Liu, Y.; Weisberg, R. H. & Shay, L. K. (2007). Current patterns on the West Florida Shelf from joint self-organizing map analyses of HF radar and ADCP data. *Journal of Atmospheric and Oceanic Technology,* Vol. 24, No. 4, 702-712, ISSN 0739-0572

Liu, Y.; Weisberg, R. H. & Yuan, Y. (2008). Patterns of upper layer circulation variability in the South China Sea from satellite altimetry using the Self-Organizing Map. *Acta Oceanologica Sinica,* Vol. 27(Supp.), 129-144, ISSN 1869-1099

Liu, Y.; MacCready, P. & Hickey, B. M. (2009). Columbia River plume patterns in summer 2004 as revealed by a hindcast coastal ocean circulation model, *Geophysical Research Letters,* Vol. 36, L02601, doi:10.1029/2008GL036447, ISSN 0094-8276

Lobo, V. J.A.S. (2009). Application of Self-Organizing Maps to the Maritime Environment, In: *Information Fusion and Geographic Information Systems, Lecture Notes in Geoinformation and Cartography,* V.V. Popovich et al, (Eds.), pp.19-36, ISSN 1863-2246, Springer-Verlag, Berlin, Heidelberg

Luengo, F.; Cofiño, A.S. & Gutiérrez, J.M. (2004). GRID Oriented Implementation of Self-organizing Maps for Data Mining in Meteorology, *Lecture Notes in Computer Science,* Vol. 2970, 163-170, DOI: 10.1007/978-3-540-24689-3_21, ISSN 0302-9743, Springer-Verlag Berlin Heidelberg

Lynch, A. H.; Uotila, P. & Cassano, J. J. (2006). Changes in synoptic weather patterns in the polar regions in the 20th and 21st centuries, Part 2: Antarctic, *International Journal of Climatology,* doi:10.1002/joc.1305, ISSN 0899-8418

Malmgren, B. A. & Winter, A. (1999). Climate zonation in Puerto Rico based on principal components analysis and an artificial neural network, *Journal of Climate,* Vol. 12, 977–985, ISSN 0894-8755

Marques, N.C. & Chen N. (2003). Border detection on remote sensing satellite data using self-organizing maps, 11th Portuguese Conference on Artificial Intelligence, Beja, Portugal; Springer, Berlin

Mata, A.; Corchado, E., Baruque, B. (2009). Solving the Oil Spill Problem Using a Combination of CBR and a Summarization of SOM Ensembles, *Advances in Soft Computing,* Vol. 50, 658-662, DOI: 10.1007/978-3-540-85863-8_78, ISSN 1860-0794

Mau, J.-C.; Wang, D.-P., Ullman, D. S. & Codiga, D. L. (2007). Comparison of observed (HF radar, ADCP) and model barotropic tidal currents in the New York Bight and Block Island Sound, *Estuarine, Coastal, and Shelf Science,* Vol. 72, 129–137, ISSN 0272-7714

Michaelides, S.C.; Liassidou, F.& Schizas, C.N. (2007). Synoptic classification and establishment of analogues with artificial neural networks, *Pure and Applied Geophysics,* Vol. 164, No.6-7, 1347-1364, ISSN 1420-9136

Morioka, Y.; Tozuka, T. & Yamagata, T. (2010). Climate variability in the southern Indian Ocean as revealed by self-organizing maps, *Climate Dynamics,* DOI 10.1007/s00382-010-0843-x, ISSN 0930-7575

Niang, A; Gross, L., Thiria, L., Badran, F. & Moulin, C. (2003). Automatic neural classification of ocean colour reflectance spectra at the top of the atmosphere with introduction of expert knowledge, *Remote Sensing of Environment*, Vol. 86, No. 2, 257-271, ISSN 0034-4257, DOI: 10.1016/S0034-4257(03)00113-5

Nishiyama, K.; Endo, S., Jinno, K., Uvo, C.B., Olsson, J. & Berndtsson, R. (2007). Identification of typical synoptic patterns causing heavy rainfall in the rainy season in Japan by a Self-Organizing Map, *Atmospheric Research,* Vol. 83, No. 2-4, 185-200, ISSN 0169-8095

Pelletier, G.; Anctil, F. & Filion, M. (2009). Characterization of 1-h rainfall temporal patterns using a Kohonen neural network: a Québec City case study, *Canadian Journal of Civil Engineering*, Vol. 36, No. 6, 980-990, ISSN 0315-1468

Raju, K. S. & Kumar, D. N. (2007). Classification of Indian meteorological stations using cluster and fuzzy cluster analysis, and Kohonen artificial neural networks, *Nordic Hydrology*, Vol. 38 No. 3, 303–314, ISSN 0029-1277

Rauber, A.; Merkl, D. & Dittenbach, M. (2002). The growing hierarchical self-organizing map: Exploratory analysis of high-dimensional data. *IEEE Transactions on Neural Networks*, Vol. 13, 1331–1341, ISSN 1045-9227

Reusch, D. B.; Alley, R. B. & Hewitson, B. C. (2005b). Towards ice-core-based synoptic reconstructions of west antarctic climate with artificial neural networks. *International Journal of Climatology*, Vol. 25, 581-610, ISSN 0899-8418

Reusch, D. B. & Alley, R.B. (2007). Antarctic sea ice: a self-organizing map-based perspective, *Annals of Glaciology*, Vol. 46, 391-396, ISSN 0260-3055

Reusch, D. B.; Alley, R. B. & Hewitson, B. C. (2005a). Relative performance of self-organizing maps and principal component analysis in pattern extraction from synthetic climatological data, *Polar Geography*, Vol. *29*, 188-212, ISSN 1939-0513

Reusch, D.B.; Alley, R. & Hewitson, B. (2007). North Atlantic climate variability from a self-organizing map perspective, *Journal of Geophysical Research*, Vol. 112, D02104, doi:10.1029/2006JD007460, ISSN 0148-0227

Richardson, A. J.; Risien, C. & Shillington, F. A. (2003). Using self-organizing maps to identify patterns in satellite imagery. *Progress in Oceanography*, Vol. 59, No. 2-3, 223-239, ISSN 0079-6611

Richardson, A. J.; Pfaff, M. C., Field, J. G., Silulwane, N. F. & Shillington, F. A. (2002). Identifying characteristic chlorophyll a profiles in the coastal domain using an artificial neural network, *Journal of Plankton Research*, Vol. 24, 1289– 1303, ISSN 0142-7873

Risien, C. M.; Reason, C. J. C., Shillington, F. A. & Chelton, D. B. (2004). Variability in satellite winds over the Benguela upwelling system during 1999-2000, *Journal of Geophysical Research*, Vol. *109 No.* C3, C03010, doi:10.1029/2003JC001880, ISSN 0148-0227

Saraceno, M.; Provost, C. & Lebbah M. (2006). Biophysical regions identification using an artificial neuronal network: A case study in the South Western Atlantic, *Advances in Space Research*, Vol. 37, 793–805, ISSN 0273-1177

Schuenemann, K. C. & Cassano, J. J. (2009). Changes in synoptic weather patterns and Greenland precipitation in the 20th and 21st centuries: 1. Evaluation of late 20th century simulations from IPCC models, *Journal of Geophysical Research*, Vol. 114, D20113, doi:10.1029/2009JD011705, ISSN 0148-0227

Schuenemann, K. C. & Cassano, J. J. (2010). Changes in synoptic weather patterns and Greenland precipitation in the 20th and 21st centuries: 2. Analysis of 21st century atmospheric changes using self-organizing maps, *Journal of Geophysical Research*, Vol. 115, D05108, doi:10.1029/2009JD011706, ISSN 0148-0227

Schuenemann, K. C.; Cassano, J. J. & Finnis, J. (2009). Forcing of precipitation over Greenland: Synoptic Climatology for 1961– 99, *Journal of Hydrometeorology,* Vol. 10, 60–78, doi:10.1175/2008JHM1014.1, ISSN 1525-7541

Sheridan, S. C. & Lee, C. C. (2010). Synoptic climatology and the general circulation model, *Progress in Physical Geography,* Vol. 34, No. 1, 101-109, ISSN 1477-0296

Silulwane, N. F.; Richardson, A. J., Shillington, F. A. & Mitchell-Innes, B. A. (2001), Identification and classification of vertical chlorophyll patterns in the Benguela upwelling system and Angola-Benguela Front using an artificial neural network, in: A Decade of Namibian Fisheries Science, edited by A. I. L. Payne, S. C. Pillar, and R. J. M. Crawford, *South Africa Journal of Marine Science,* Vol. 23, 37– 51, ISSN 0257-7615

Skific, N.; Francis, J. A. & Cassano, J. J. (2009a). Attribution of seasonal and regional changes in Arctic moisture convergence. *Journal of Climate,* Vol. 22, 5115–5134, DOI: 10.1175/2009JCLI2829.1, ISSN 0894-8755

Skific, N.; Francis, J. A. & Cassano, J. J. (2009b). Attribution of projected changes in atmospheric moisture transport in the Arctic: A self-organizing map perspective. *Journal of Climate,* Vol. 22, 4135–4153, DOI: 10.1175/2009JCLI2645.1, ISSN 0894-8755

Skwarzec, B.; Kabat, K. & Astel, A. (2009). Seasonal and spatial variability of 210Po, 238U and 239+240Pu levels in the river catchment area assessed by application of neural-network based classification, *Journal of Environmental Radioactivity,* Vol. 100, No. 2, 167-175, ISSN 0265-931X

Solidoro, C.; Bastianini, M., Bandelj, V., Codermatz, R., Cossarini, G., Melaku Canu, D., Ravagnan, E., Salon S. & Trevisani S. (2009). Current state, scales of variability & trends of biogeochemical properties in the northern Adriatic Sea, *Journal of Geophysical Research*, Vol. 114, C07S91, doi:10.1029/2008JC004838, ISSN 0148-0227

Solidoro, C.; Bandelj, V., Barbieri, P., Cossarini, G. & Fonda Umani, S. (2007). Understanding dynamic of biogeochemical properties in the northern Adriatic Sea by using self-organizing maps and k-means clustering, *Journal of Geophysical Research*, Vol. 112, C07S90, doi:10.1029/2006JC003553, ISSN 0148-0227

Tadross, M. A.; Hewitson, B. C. & Usman, M. T. (2005). The Interannual variability of the onset of the maize growing season over South Africa and Zimbabwe. *Journal of Climate, Vol.* 18, 3356-3372, ISSN 0894-8755

Tambouratzis, T. & Tambouratzis, G. (2008). Meteorological data analysis using Self-Organizing Maps, *International Journal of Intelligent Systems,* VOL. 23, 735–759. DOI 10.1002/int.20294, ISSN 1740-8873

Telszewski, M.; Chazottes, A., Schuster, U., Watson, A. J., Moulin, C., Bakker, D. C. E., Gonzalez-Davila, M., Johannessen, T., Kortzinger, A., Luger, H., Olsen, A., Omar, A., Padin, X. A., Rios, A. F., Steinhoff, T., Santana-Casiano, M., Wallace, D. W. R. & Wanninkhof, R. (2009). Estimating the monthly pCO2 distribution in the North Atlantic using a self-organizing neural network, *Biogeosciences,* Vol. 6, 1405–1421, ISSN 1726-4170

Tian, B.; Shaikh, M.A., Azimi-Sadjadi, M.R., Vonder Haar T. H. & Reinke, D.L. (1999). A study of cloud classification with neural networks using spectral and textural Features, *IEEE Transactions on Neural Networks*, Vol. 10, No. 1, 138-151, ISSN 1045-9227

Tozuka, T.; Luo, J.-J., Masson S. & Yamagata, T. (2008). Tropical Indian Ocean variability revealed by self-organizing maps, *Climate Dynamics,* Vol. 31, No. 2-3, 333-343, DOI 10.1007/s00382-007-0356-4, ISSN 0930-7575

Uotila, P.; Lynch, A. H., Cassano J. J. & Cullather, R.I. (2007). Changes in Antarctic net precipitation in the 21st century based on Intergovernmental Panel on Climate Change (IPCC) model scenarios, *Journal of Geophysical Research*, Vol. 112, D10107, doi:10.1029/2006JD007482, ISSN 0148-0227

Verdon-Kidd, D. & Kiem, A. S. (2008). On the relationship between large-scale climate modes and regional synoptic patterns that drive Victorian rainfall, *Hydrology Earth System Science Discussions,* Vol. 5, 2791–2815, ISSN 1812-2108

Vesanto, J. & Alhoniemi, E. (2000). Clustering of the self-organizing map. *IEEE Transactions on Neural Networks,* Vol. 11, 586–600, ISSN 1045-9227

Walder, P. & MacLaren, I. (2000). Neural network based methods for cloud classification on AVHRR images, *International Journal of Remote Sensing*, Vol. 21, No. 8, 1693-1708, ISSN 0143-1161

Yacoub, M.; Badran, F. & Thiria, S. (2001). A topological hierarchical clustering: Application to ocean color classification, In *Artificial Neural Networks – ICANN 2001, Lecture Notes in Computer Science*, Vol. 2130, 492 -499, ISSN 0302-9743

Zhang, R.; Wang, Y., Liu, W., Zhu, W. & Wang, J. (2006). Cloud classification based on self-organizing feature map and probabilistic neural network, *Proceedings of the 6th World Congress on Intelligent Control and Automation*, June 21 - 23, 2006, Dalian, China, 41-45, ISSN 0272-1708 (in Chinese)

Žibret, G. & Šajn, R. (2010). Hunting for geochemical associations of elements: factor analysis and self-organising maps, *Mathematical Geosciences,* Vol. 42, No. 6, 681-703, DOI: 10.1007/s11004-010-9288-3, ISSN 1874-8961
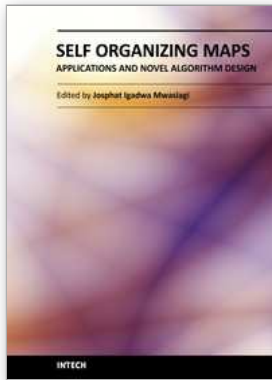
Self Organizing Maps - Applications and Novel Algorithm Design

Edited by Dr Josphat Igadwa Mwasiagi

Kohonen Self Organizing Maps (SOM) has found application in practical all fields, especially those which tend to handle high dimensional data. SOM can be used for the clustering of genes in the medical field, the study of multi-media and web based contents and in the transportation industry, just to name a few. Apart from the aforementioned areas this book also covers the study of complex data found in meteorological and remotely sensed images acquired using satellite sensing. Data management and envelopment analysis has also been covered. The application of SOM in mechanical and manufacturing engineering forms another important area of this book. The final section of this book, addresses the design and application of novel variants of SOM algorithms.

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