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Short communication

# Application of multivariate analysis to determine spatial and temporal changes in water quality after new channel construction in the Chilika Lagoon

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ABSTRACT

Lagoon ecosystems have been severely degraded by anthropogenic activities, which result in ecological and hydrological changes in the system. Detailed understanding of the recovery processes of restored lagoon systems has been impeded by the underlying complexity of integral environmental components. The aim of this study was to understand relationships between water quality variables in a restored lagoon, and temporal and spatial changes at each recovery stage after lagoon restoration. Ten water quality parameters were monitored on a monthly basis at 30 sampling sites in the Chilika Lagoon from 1999 to 2009. Self-Organizing Map and principal component analyses showed that salinity was the dominant factor for the Chilika Lagoon and had maximal component loading in the principal component analysis. Mean salinity level increased after opening of a new mouth in the study site, however, a decreasing trend was observed 4 years after the restoration. The pH and $pCO_2$ exhibited pulse-type resilience after the restoration event. The average nitrate:phosphate ratio increased steadily during the monitoring period. Multivariate analysis of monitoring data of the restoration site provided a deep understanding of its temporal and spatial change. It would be worthwhile to extend multivariate analysis to diverse ecosystems, while considering biological components is recommended in order to evaluate the comprehensive response of the restored system.

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## 1. Introduction

Understanding spatial and temporal changes has long been an area of study in diverse aquatic ecosystems. Because of the complexity of environmental components (i.e., water quality, hydrological parameters, and biological taxa) within the lagoon system, multivariate statistical approaches (Gazzaz et al., 2012; Gharibi et al., 2012; Tobiszewski et al., 2010; Razmkhah et al., 2010) and spatial analyses (Bierman et al., 2011; Lindim et al., 2011) have been widely applied to determine the relative influence of environmental factors and their complex interactions. However, identifying the dominant environmental variables and the relative importance of selected factors in the complex natural environment remains inconclusive. This is especially true in dynamic ecosystems such as estuarine and coastal waters that show changing patterns representing a complicated interaction between several variables in the ecotone.

Chilika Lagoon experienced severe degradation from eutrophication and sediment deposition during the 1990s. A large amount of sediment input from the watershed eventually choked the lagoon mouth and inhibited the hydrological exchange between the lagoon and the ocean. This limited interaction with the ocean further decreased the overall productivity of lagoon biota, including fish, and resulted in proliferation of invasive freshwater aquatic weeds (Mohanty et al., 2009; Patra et al., 2010). Based on an engineering simulation of hydrodynamics (Jayaraman et al., 2007), the Chilika Development Authority (CDA) opened a new mouth (channel connected to the Bay of Bengal) in the year 2000 to enhance the water exchange between the sea and lagoon. This new mouth opening revived fish production, increased seagrass beds, decreased the spread of freshwater weeds, and enhanced recruitment of brackish species from the ocean. However, it is still unclear how this

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hydrological intervention related to spatial and temporal changes in water quality of the restored lagoon.

The goal of the present study was to understand (1) relationships between water quality variables in the restored lagoon and (2) temporal and spatial changes in each recovery stage after lagoon restoration. The relationships between water quality variables were viewed using a novel pattern-recognizing algorithm and by analyzing their decadal trends. Lagoon areas were clustered based on water quality parameters, and the dominant variables were presented spatially to provide a comprehensive evaluation tool to facilitate effective management strategies.

## 2. Materials and methods

### 2.1. Study site

The Chilika Lagoon (N19°43′ E85°19′) covers over 1165 $km^2$. The average length and breadth of the lagoon are approximately 64 km and 20 km, respectively. The lagoon contains a wide range of sub-ecosystems such as freshwater marshes, mudflats, sand dunes, and shallow brackish lakes (avg. depth: 1.4 m). Chilika Lagoon is a warm polymictic lake in which temporary thermal stratification occurs due to seawater intrusion. A tropical monsoon climate prevails over the lagoon's drainage basin. The lagoon experiences southwest and northeast monsoons from May to August and November to December, respectively. The lake initially received seawater through a narrow and shallow 35-km-long zigzag channel. The opening of the new mouth reduced the length of the outer channel by about 18 km, which has improved the flow regime and increased the amount of seawater influx (Sahu et al., 2014). Within 3 months after the opening of the new mouth, the old mouth became inactive due to natural siltation.

### 2.2. Collection and analysis of water quality data

Water sampling was conducted monthly at 30 sampling sites in the lagoon. Hydro-physicochemical parameters were monthly monitored from 1999 to 2009 (132 time points for 11 years). Water temperature, pH, conductivity, and salinity were recorded using a multi-probe Water quality Checker (WMS-24-1-20, TOA-DKK, Japan). Water depth was recorded using a sounding chain at each station. Water transparency was measured using a Secchi disk. Dissolved oxygen was measured using a modified Winkler's titrimetric method. Alkalinity was analyzed titrimetrically with phenolphthalein and methyl orange indicators (APHA, 1992). Water nitrate was measured using a spectrophotometry method with phenol disulfonic acid. Orthophosphate was measured using the ascorbic acid method (APHA, 1992) with a double beam spectrophotometer.

The nitrate:phosphate ratio was calculated using the measured nitrate and phosphate content from the water column (Lenton and Watson, 2000; Redfield, 1958). Partial pressure of $CO_2$ ($pCO_2$) in wet air is defined as the product of the mole fraction of $CO_2$ in wet air and the total pressure. The $pCO_2$ is the gas phase pressure of $CO_2$ that would be in equilibrium with the dissolved $CO_2$. We used the $CO_2$SYS program for $pCO_2$ calculation (Pelletier et al., 2007; Lewis and Wallace, 1998). Water temperature, salinity, pH, alkalinity, and water depth at each sampling time were used as input parameters. Dissociation constants for carbonic acid were calculated according to Millero et al. (2006). $K_2SO_4$ was calculated based on Dickson's method (Dickson, 1990).

### 2.3. Self-Organizing Map (SOM)

The relationships between the input variables were analyzed and visualized using a Self-Organizing Map (SOM), a type of artificial neural network. The SOM visualizes multi-dimensional and complex data in a more comprehensive fashion and a lower dimensional space by approximating the spatial dominance of input data (Chon, 2011; Chon et al., 2013; Kohonen, 2001). For the analysis of large environmental data sets, the SOM has many advantages over traditional projection and classification chemometric techniques (Astel et al., 2007). In this study, 12 variables were selected for characterizing the water quality characteristics of Chilika Lagoon. Other details in training and clustering were performed according to Park et al. (2003) by using the MATLAB 6.1 environment (The Mathworks Inc.). SOM clusters were identified by a hierarchical cluster analysis based on Ward's linkage (Ward, 1963; Wishart, 1969) and the weight vectors of SOM were used for cluster analysis. Mean differences between clusters were determined using one-way ANOVA (Welch *F* test), followed by Games-Howell post hoc test when the main effect or interaction was significant at $p < 0.05$ (SPSS 20.0, IBM).

### 2.4. Principal component analysis (PCA)

Principal component analysis (PCA) is an eigenvector-based multivariate analysis, which converts large data sets of intercorrelated variables into a smaller set of independent variables (Simeonov et al., 2003). PCA is sensitive to the scale of the input variables (Magyar et al., 2013); thus, we standardized all water quality data to the same scale by subtracting the respective mean values from each of the variables and dividing this by the variable's variance. Normalized variables have the same variance, and thus, each variable has the same weight in the PCA matrix.

The principal components (PC) are orthogonal variables obtained by multiplying the original correlated variables with the eigenvector. Based on the loading coefficient and correlation value with the PC, we selected the most highly correlated variables for each PC at the study sites. The variables most highly correlated with PCs were further divided into trend and seasonal patterns with trend–seasonal decomposition using STL function in R (R Development Core Team, 2008). When there were distinct trends over the 11-year period, variables were spatially interpolated and extrapolated with the spline barrier method using the spatial analysis tool in ARCMAP 10.0 (ESRI, USA).

## 3. Results and discussion

### 3.1. SOM clustering of water quality

The vertical gradient of the component map was produced according to the salinity gradient; alkalinity was also highly correlated with this gradient (Fig. 1). Sites with the maximum salinity level appear in the upper portion of the map (Clusters 1 and 4; Supplementary Fig. S.1), while sites with lower salinity levels are grouped in the lower portion (Clusters 2 and 3). Cluster 1 includes sites with high salinity and high alkalinity. The right area in the middle of the map contains sites with medium salinity levels and shallow water. Higher values of lagoon depth and transparency are found at the bottom of the map, while pH and nitrate are higher in Clusters 2 and 3 (bottom section). The nitrate:phosphate ratio was selectively higher in Cluster 4. SOM ordination explained that water quality at the study site were mainly affected by freshwater and seawater exchange. Significant differences were noted for all parameters among the clusters (Supplementary Fig. S.2).

The relative percent composition of Clusters 1 and 4 varied over the study period (Supplementary Fig. S.3). Cluster 1, representing higher salinity levels ($18.8 \pm 8.5$), occupied 38.8%, 48.1%, and 30.9% of the pre-, post-(I) and post-restoration (II), respectively. Cluster 4, which has moderate salinity levels ($8.2 \pm 3.8$), occupied 25.8% of the total SOM clusters in the pre-restoration period, 25.2% in

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