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Investigation of long-term trends in selected physical and chemical parameters of inflows to Everglades National Park, 1977–2005

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Abstract Data of seven water-quality parameters from inflows to the Everglades National Park were collected at three monitoring stations and analyzed for temporal trends. The best-fit models for the existence of trends were evaluated. The Kolmogorov–Smirnov test was used to select the theoretical distribution which best fit the data. Simple regression was used to examine the parameters for concentration–discharge relationships. The power and linear models were found to better describe the concentration–discharge relationships. Loess trend lines indicated a similar trend period of color value change during the selected period at three stations. The sharp decrease in color after 1990 at each station is consistent with the beneficial impacts of control measures, which include Best Management Practices implementation in the Everglades Agricultural Area, water management improvement, and the construction of additional stormwater treatment areas. The existence of trend analysis was performed by using the uncensored seasonal Kendall test. Conductivity and color decreased significantly at two (S12A and S333) of three stations. Alkalinity decreased significantly at S333. A "best-fit" model was selected to describe a trend change with statistical significance; the second-order equation provides a better description of the trend. This study also indicates that by using the routinely measured water-quality parameters, it may be easier to quantify the changes in water quality to aid in making water resources management decisions.

Keywords Everglades · Water quality · Statistics · Trend analysis

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Introduction

The quality of surface water is a major subject of concern throughout the world. Surface water quality has been influenced by anthropogenic factors such as urban, industrial, and agricultural activities and natural processes such as precipitation variation, erosion, and the weathering of crustal minerals (Simeonov et al. 2003; Singh et al.

2004). It is imperative to prevent surface water pollution and to obtain reliable information on water-quality trends for effective management. Long-term monitoring programs have been developed for assessing surface water-quality trends in many countries, generating complex multidimensional datasets due to the analysis of multiple physical–chemical constituents, including the use of different sampling frequencies and the various locations of many monitoring stations. These complex time series datasets often make it difficult to draw meaningful conclusions (Dixon and Chiswell 1996). Monitoring programs may involve large financial costs. Therefore, there is a need to optimize monitoring networks and carefully choose water-quality parameters to minimize repetition without losing essential information. To ensure an efficient and cost-effective monitoring program, multivariate statistical techniques and exploratory data analysis are powerful tools (Singh et al. 2004). Nutrient analyses typically cost more than measuring other chemical and physical parameters. If changes in simple physical and chemical parameters respond to water-quality trends in surface water, it may be possible to lower monitoring costs by focusing on the analysis of selected physical and chemical parameters. To analyze a time series of monthly values of water-quality parameters, the Kolmogorov–Smirnov test (K–S) was used to select the theoretical distribution which gave the best fit of the data and an evaluation of which best-fit models demonstrate the existence of trends (Antonopoulos et al. 2001). Trend analysis using the seasonal Kendall test is a useful tool to examine time series water quality data, to detect trends in water-quality changes over time, and to provide guidance for improving water management (Hirsch et al. 1991; Walker 1991; Qian et al. 2007).

The Everglades is a vast subtropical wetland that dominates the landscape of south Florida and is widely recognized as an ecosystem of great ecological importance (Chimney and Goforth 2001). The Everglades National Park (ENP, established in 1947) was created by Congress to preserve and protect a large area of the south Florida ecosystem, free of agricultural and urban development. It is regarded as an ecosystem of immense regional, national and international importance (Maltby and Dugan 1994). The ENP has been designated as an International Biosphere Reserve, a United Nations World Heritage site and a Wetland of International Importance under the 1987 Ramsar Convention, one of only three wetlands in the world to receive all of these recognitions (Maltby and Dugan 1994). Because the ENP is located at the most downstream portion of Florida, the area is subject to upstream water-management practices. Waters in the ENP are currently designated as both Outstanding Florida Waters and Outstanding Natural Resource Waters and, therefore, must be monitored and protected (McPherson et al. 2001). Water management and Everglades restoration projects have modified the original water flows into the ENP. The question is how these modifications have affected water quality in the ENP.

This paper examines the time series of monthly values of selected physical and chemical water-quality parameters and the discharges at the S12A, S333, and S332 stations. These sites were selected from a total of seven stations using principle component analysis (PCA). The seasonal Kendall test was used to determine the existence of trends, the evaluation of the best fit-trend models, and in the identification of significant trends in selected water-quality physical and chemical parameters.

Materials and methods

Site description

Water-quality samples were collected from multiple sites in three ENP watersheds (Fig. 1). The L29 canal is an East–West canal separating the Water Conservation Area (WCA) 3A from the northernmost part of the ENP. The purpose of the L29 canal is to collect water from lands to the West, North, and East of the ENP. A number of structures (S12A, S12B, S12C, and S12D) along the L29 canal distribute and introduce water into the northern part of the ENP. Structure S333 receives water from the L67 and L67A canals, introducing water directly into the ENP. Lastly, structures S18C and S332 are located on the eastern side of the ENP, approximately 32 km south

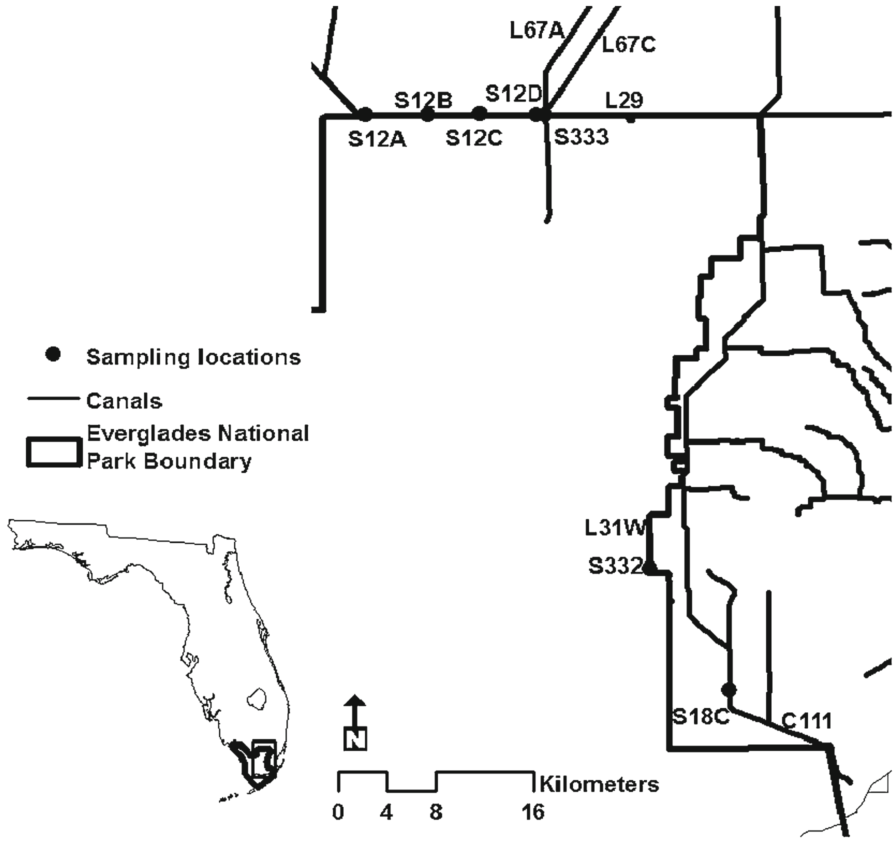

Fig. 1 Location of inflow water quality monitoring stations to the ENP

and east of the structures along the L29 canal. Due to their locations, these structures receive water that has additional filtering, travelling a considerable distance through unlined canals, compared to those along the concrete-lined L29 canal.

Data sources

Water-quality data and hydrogeology parameters collected from the structures described above (Fig. 1) were extracted primarily from the DB-HYDRO data base managed by the South Florida Water Management District (SFWMD). The monitoring sites considered were identified by their structure name and included S12A, S12B, S12C, S12D, S333, S332, and S18C. Water samples were collected using a grab sampling techniques. All data were screened for errors. Water temperature (*T*, degrees Celsius), turbidity (Turb, as NTU), pH (units), specific conductivity (SPC, $\mu S\ cm^{-1}$), dissolved oxygen (DO, mg l^{-1}), color (PCU), and alkalinity (Alk, mg l^{-1} as $CaCO_3$) were used in the statistical evaluations. These selected water quality constitutes were analyzed by the methods from US Environmental Protection Agency (EPA) with EPA method number (turbidity: EPA180.1; pH: EPA 150.2; specific conductivity: EPA120.1; dissolved oxygen: EPA360.1; color: EPA110.2, and alkalinity: EPA310.2). Selected seven water-quality constitutes were based on that they were easily measured and important in water-quality change. Water temperature influences on water chemistry and biological activity. Dissolved oxygen in surface water is used by all forms of aquatic life. Turbidity is the amount of particular matter that is suspended in water. Specific conductivity is highly dependent on the amount of dissolved solids (such as salt). pH is really a measure of the relative amount of free hydrogen and hydroxyl ions in the water. Since pH can be affected by chemicals in the water, pH is an important indicator of water that is changing chemically. Water color is an important index of river TOC and DOC contents. The data for these variables were collected on a monthly basis for the period 1977–2005 (for S12A, S12B, S12C, S12D, and S333) or 1983–2005 (for S332 and S18C).

Data evaluation

All data were analyzed for normality as water-quality data are often characterized by non-normal skewed distributions (Hirsch et al. 1991). If a set of data was found to have a non-normal distribution, the data were transformed using natural logarithms and retested to ensure normality. Data were examined for normality using the Jarque–Bera (Skewness–Kurtosis) test (Jarque and Bera 1980).

Probability distribution of water-quality parameters

Water-quality data do not usually follow convenient probability distributions like the normal and lognormal distributions (Lettenmaier et al. 1991; Antonopoulos et al. 2001). To select the distribution which provided the best fit, 19 theoretical probability distribution functions were examined (Antonopoulos et al. 2001).To select the distribution which provided the best fit, the K–S test was used.

The K–S test is used to test whether the empirical distribution of a set of observations is consistent with a random sample drawn from a specific theoretical distribution. The K–S test is a nonparametric test of the fitting of data to a theoretical distribution using the maximum absolute deviation (D) between the two functions of cumulative distribution (Antonopoulos et al. 2001). It is calculated by

$$D = \max\ \left(F_n(x) - F_o(x)\right)$$

where $F_n(x)$ is the cumulative density function based on n measurements, $F_o(x)$ is the specified theoretical cumulative distribution function under the null hypothesis H_0. The values of $D(n,\alpha)$ are given in tables (Haan 1977).

Trend analysis

In this study, to detect the existence of trends in the time series of the variables involved, the non-parametric (Seasonal Kendall) statistical trend test was used, and different trend models were fitted (Antonopoulos et al. 2001).

The following linear, quadratic, exponential, and mixed type models applied to the time series of the water-quality parameters were used for the trend analysis:

$$F = \alpha + \beta T \tag{1}$$

$$F = \alpha + \beta T + cT^2 \tag{2}$$

$$F = \exp(a + \beta T) \tag{3}$$

$$F = \exp(\alpha + \beta / T) \tag{4}$$

The following statistical criteria of mean error (ME), mean square error (MSE), mean absolute error (MAE), and mean absolute percent error (MAPE) were used to choose the best-fit model of time trend for each variable (Antonopoulos et al. 2001). The closer the average ME is to zero and the smaller the values of MSE, MAE, and MAPE are, the better the fit of the time-series model (Antonopoulos et al. 2001).

Nonparametric (Seasonal Kendall) statistical trend tests were applied to the seven selected water quality components for each station. Trends were evaluated as complete datasets. Measured concentration data were analyzed without flow adjustments since the structures at which all data originated were managed for water control purposes (Lietz 2000). We used the US Geological Survey computerized statistical program Estimate Trend (ESTREND) (Schertz et al. 1991) with SPLUS® software ESTREND. Data points reported at or less than the method detection limit (MDL) were censored by assigning a value of one half that of the MDL (Schertz et al. 1991).

PCA and factor analysis (FA) were applied to the dataset to determine latent variables and to identify possible modifications to the sampling protocol to increase monitoring efficiency. PCA and FA were conducted using SPLUS® software program. A multivariate, principal components method using a covariance matrix was adopted, and varimax rotation was used in the factor analysis.

Results and discussion

PCA and FA analyses

The results of PCA produced a clustering of inflow sites (Fig. 2). Three groups were selected from seven monitoring stations are group 1 (S12A and S12B), group 2 (S12C, S12D and S333), and group 3 (S18C and S332, see Fig. 1), respectively. The water entering the L29 canal originates from WCA-3A and from both parallel canals of L67 and L67A and distributes these waters into the northern portion of the ENP. Structures S12A, S12B, S12C, S12D, and S333 distributed along the L29 from west to east, receiving water from WCA-3A in the L29 canal increasingly from west to east (S12A to S333). The S12A and S12B were influenced less than S12C, S12D, and S333 by the water from WCA-3A. The S332 and S18C cluster is located about 40 km south and on the east side of the ENP. Receiving waters for these structures are canals bordering and in proximity to the eastern ENP boundary. This clustering can be used in designing management practice strategies for targeted water-quality improvements and can be also used in designing water-quality monitoring programs to maximize the amount of variability captured in as few as stations as possible.

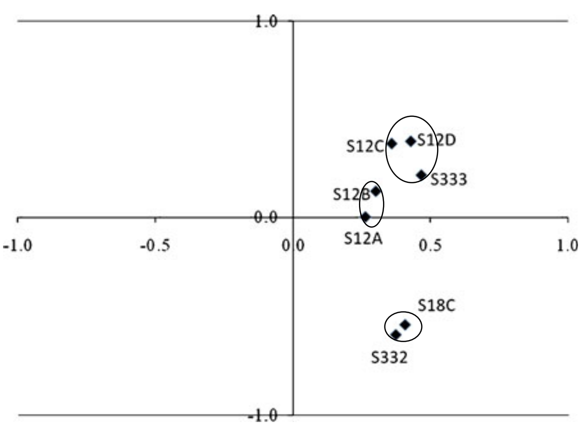

Fig. 2 PCA analyses of seven physical species data by inflow site. Water-quality trends are responding similarly at sites within clusters

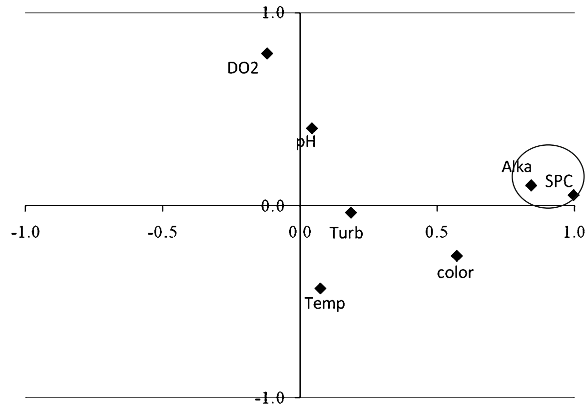

Fig. 3 Factor Loadings for the first factor (Factor 1) and the second factor (Factor 2; seven physical parameters obtained from each station were used for the analysis)

Factor analysis generated a cluster of seven selected physical and chemical parameters (Fig. 3), only alkalinity and specific conductivity demonstrated a close relationship, because specific conductivity depends on alkalinity (Parinet et al. 2004). No other parameters had similar close relationships. Based on PCA, three stations (S12A, S333, and S332) were chosen to be representative of seven monitoring stations. In this paper, water quality related to seven physical and chemical parameters at the three stations was analyzed by different methods.

Statistical analysis of water-quality parameters

Summary statistics of datasets with seven water-quality parameters are presented in Fig. 4.

A comparison of median data among the three stations showed the value of water-quality parameters varied greatly among stations. Structure S12A had the lowest color (25 PCU), SPC (300 μS cm^{-1}), alkalinity (119 $CaCO_3$ mg L^{-1}), and turbidity (0.9 NTU); the S333 station had the highest median value for color (56 PCU) and SPC (622 μS cm^{-1}). The S332 had highest median value for alkalinity (198 mg L^{-1}) and turbidity (2.2 NTU), because canal L31W for the S332 station was influenced by land use for agricultural production. The S332 station had very high concentrations of alkalinity, which may be related to fertilizers applied upon agricultural lands

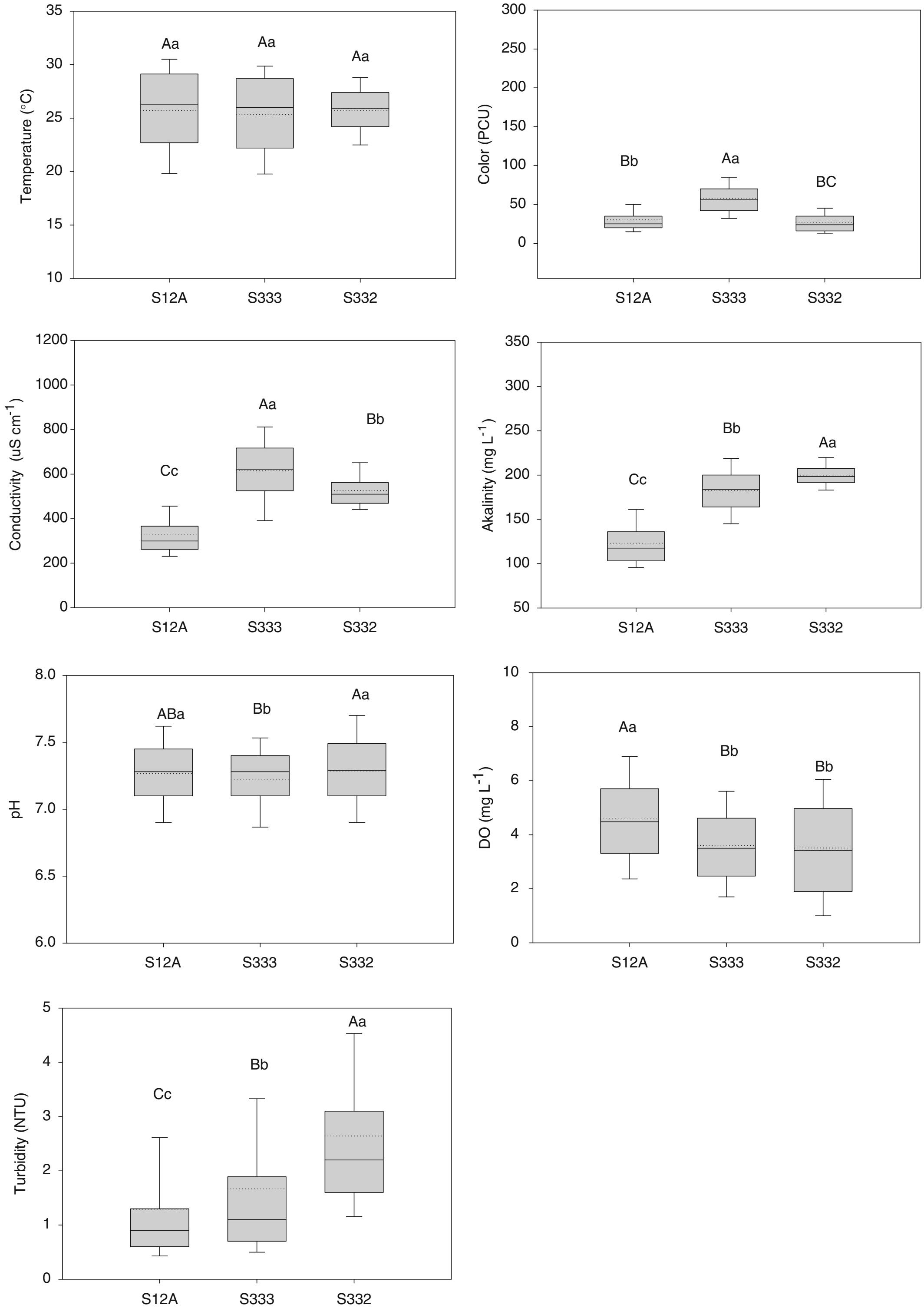

Fig. 4 Boxplots of measured value of water quality physical parameters at S12A, S333, and S332. *Box boundaries* indicate the 25th and 75th percentiles; *whiskers indicate* the 10th and 90th percentiles; the *inner solid horizontal line* is the median; the *dash horizontal line* is mean. *Boxes marked with the same lowercase letters* are not significantly different at $P \leq 0.05$. *Boxes marked with the same capital letters* are not significantly different at $P \leq 0.01$

Table 1 The best fitted distribution parameters and concentration-time relationships of water-quality parameters

Parameters	S12A distribution	K–S test D	S333 distribution	K–S test D	S332 distribution	K–S test test D
Q	Logistic	0.2445	Logistic	0.1589	Logistic	0.2239
T, °C	Triangular	0.0547	Triangular	0.0579	Inv. Gaussian	0.0518
SPC, μS cm^{-1}	Inv. Gaussian	0.0889	Normal	0.0359	Log-Logistic	0.0785
DO, mg L-1	Gamma	0.0443	Weibull	0.0346	Weibull	0.0844
pH	Laplace	0.0621	Weibull	0.0826	Laplace	0.0434
Color	Log-Gamma	0.0857	Gamma	0.0396	Inv. Gaussian	0.0422
Turbidity	Log-Logistic	0.0867	Log-Logistic	0.0683	Log-Logistic	0.0367
Alkalinity	Log-Logistic	0.0697	Logistic	0.0270	Laplace	0.0664

(Muñoz-Carpena et al. 2005). The DO at S12A, S333, and S332 was 4.5, 3.5, and 3.4 mg L^{-1}, respectively. Higher DO may indicate better water quality. These median values at different stations are in agreement with the locations of the sampling stations. The S12A, located west of S333, was influenced less by water from WCA-3A and had superior water quality. The S333 also received water from L67 and L67C and was affected greatly by the water from WCA-3A. Walker (2002) indicated that this phenomenon reflected an increasing influence of channelizing flows that transport flow and nutrients along the L29 and L67 levee. The S332 is located in the L31W canal which received water from an agricultural area. The water-quality parameters varied greatly among the three stations, which may be due to natural variations in geology, hydrology, and vegetation and differences in water management and land uses for the different regions.

The procedure used to fit a theoretical continuous distribution function to the data time series by running a K–S one-sample test for goodness-of-fit with its maximum absolute deviation (D). Table 1 presents the results of the K–S test for the water variables at the S12A, S332, and S333 structures. It has been accepted that the best fit theoretical distribution for each data time series is the one which satisfies K–S test. After thoroughly examining the statistical results, the following conclusions about the distribution of each variable were reached: (1) Discharge (Q) and turbidity at the three stations follow the logistic distribution and log-logistic distribution, respectively; (2) Parameters of T, SPC, DO, pH, color, and Alk at the S12A station follow Triangular, Inv. Gaussian, Gamma, Laplace, Log-Gamma, and Log-Logistic distribution, respectively, (3) Parameters of T, SPC, DO, pH, color, and alkalinity at the S333 station follow Triangular, Normal, Weibull, Weibull, Gamma,

Table 2 Parameter concentration–discharge relationship

Parameters	S12A		S332		S333	
	Model	Equation	Model	Equation	Model	Equation
SPC, μS cm^{-1}	Power	$336.37e^{-3E-04x}$ ($r = -0.2611$)	Linear	$-0.0482x + 30.88$ ($r = -0.0757$)	Power	$577.64e^{8E-05x}$ ($r = 0.0838$)
DO, mg L^{-1}	Power	$4.2502e^{4E-05x}$ ($r = 0.0071$)	Linear	$-0.0057x + .1013$ ($r = -0.4396$)	Linear	$-0.001x + 3.8756$ ($r = -0.2149$)
pH	Power	$7.2284e^{1E-05x}$ ($r = 0.0692$)	Linear	$-0.0004x + .3069$ ($r = -0.1644$)	Linear	$-0.0001x + 7.2705$ ($r = -0.1355$)
Color	Power	$26.95e^{-1E-04x}$ ($r = -0.0590$)	Linear	$-0.0043x + 26.413$ ($r = -0.0465$)	Linear	$0.0066x + 55.749$ ($r = 0.0925$)
Turbidity	Power	$1.1262e^{-5E-04x}$ ($r = -0.1451$)	Power	$2.1463e^{0.0005x}$ ($r = 0.1147$)	Power	$1.1482e^{0.0004x}$ ($r = 0.1738$)
Alkalinity	Power	$129.26e^{-2E-04x}$ ($r = -0.2828$)	Linear	$-0.0159x + 200.7$ ($r = -0.1316$)	Linear	$-0.0088x + 189.1$ ($r = -0.0781$)

and Logistic distribution, respectively; and (4) Parameters of T, SPC, DO, pH, color, and alkalinity at the S332 station follow Inv. Gaussian, Log-Logistic, Weibull, Laplace, Inv. Gaussian, Laplace distribution, respectively. The characteristics of different distribution are described in the e-book by Van Hauwermeiren and Vose (2009).

Table 2 presents the best-fit to the data regression models used to describe the relationship between parameter concentration and discharge. The linear ($Cij = a + b\,Qj$), the power ($Cij = aQjb$), the exponential ($Cij = a \exp(bQj)$), and the logarithmic ($Cij = a + b \ln(Qj)$) models were used for this analysis. The method of least squares for the pairs of monthly measured values of each variable and the discharge was used to determine the constants of these models (Antonopoulos et al. 2001). From the values of Table 2, not one of the applied models describes the parameter concentration–discharge relationships well, or these relationships are very weak. The correlation coefficients are negative, which show a decreasing relationship for all variables at the S332; for SPC and Color at the S12A and for DO, pH, and Alk at the S333. This may be a result of the dilution effects of high flow. The power and linear models describe the concentration–discharge relationships better. The relationship between DO and discharge at the S332 demonstrated a better correlation coefficient value ($r = -0.439$), followed by SPC at the S12A ($r = -0.261$) and then by DO at the S333 ($r = -0.215$), while most of variables show weaker relationships.

Trend analysis of water-quality parameters

The time series of seven water-quality parameters for samples from the S12A, the S332, and the S333 were tested for existence of trend by using the uncensored seasonal Kendall test. According to the results of S–K test (Table 3), during the long-term period, some of the selected parameters (T, DO, pH, SPC, alkalinity, turbidity, color) exhibited significant positive or negative trends ($p < 0.1$) at the three stations. The pattern of the trend was found to be dependent upon the individual parameter species as well as the location of the monitoring stations. More negative trends (31% of total) were observed in comparison with positive trends (14% of total). Only temperature showed a significant upward trend at the three stations (S12A, S333, and S332) with slopes of 0.25%, 0.18%, and 0.33% per year, respectively. The decreasing trends in DO are found at the three stations with only a significant downward trend at S12A. And all three stations showed upward trends in pH with only a significantly increasing trend at S332. Conductivity and color decreased significantly at two (S12A and S333) of three stations. Alkalinity decreased significantly at S333. There were no significant trends in turbidity for the three stations (Table 3).

LOESS trend lines (Fig. 5) identified changing trend in color value change during 1977–2005 or 1983–2005 at the three stations. Color at S12A, S333, and S332 declined greatly after 1990, which demonstrated water quality improved after 1990.

Table 3 Statistical summary and trends of selected water-quality constituents for all data from 1977 to 2005 without flow adjustment

Station	S12A		S333		S332	
Constituent	Trend (%)	P	Trend (%)	P	Trend (%)	P
Temperature	0.25	0.06^{+}	0.18	0.02^{+}	0.33	0.03^{+}
Dissolved oxygen	−0.66	0.01^{-}	−1.15	0.12	−0.26	0.87
pH	0.06	0.74	0.01	0.86	0.23	0.01^{+}
Conductivity	−0.85	0.00^{-}	−1.62	0.00^{-}	−0.05	0.92
Alkalinity	−0.45	0.17	−0.77	0.01^{-}	0.05	0.75
Color	−1.93	0.02^{-}	−1.54	0.01^{-}	−1.64	0.14
Turbidity	−0.81	0.78	0.00	0.96	0.17	0.71

Trend analysis was performed using uncensored Seasonal Kendall procedure
Trend (%), percent change per year; A P value with a + or − sign indicates increasing or decreasing trend at $P < 0.10$

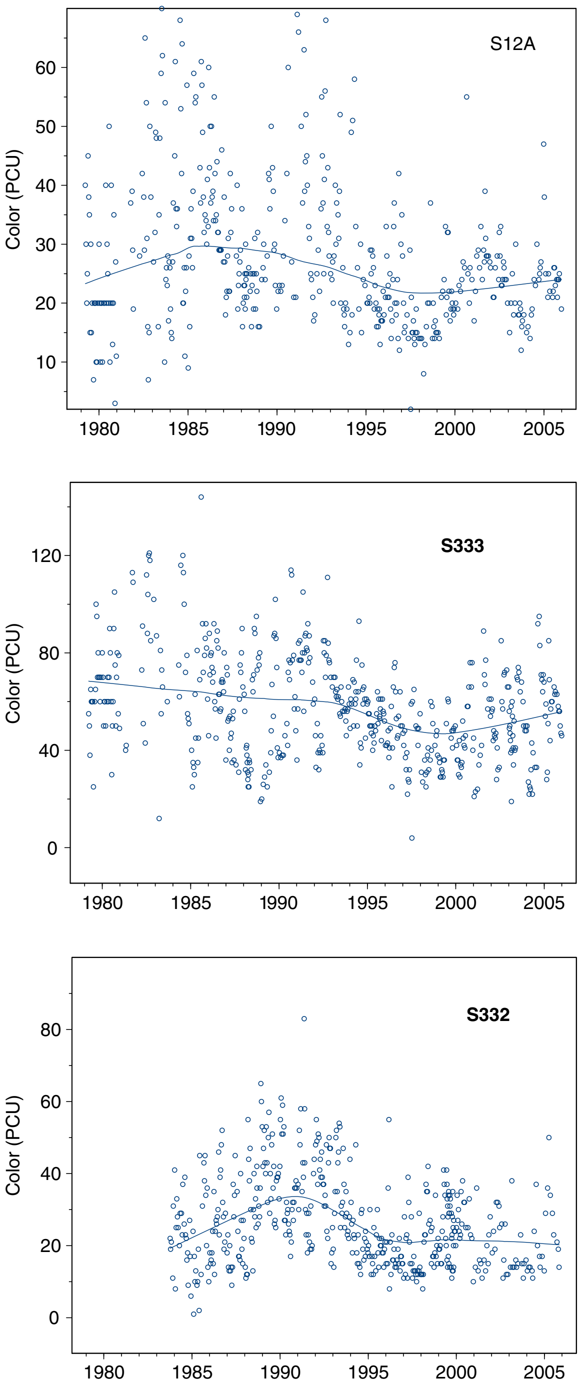

Fig. 5 Time series plot of Color at S12A, S333, and S332 with loess smoothing

This changing pattern is consistent with beneficial impacts of control measures that include Best Management Practices (BMPs) implementation in the Everglades Agricultural Area (EAA), shifts in agricultural crops (away from vegetable crops), Management changes during the early 1990s may not have been the only factor influence water quality. Because the entire system is dynamic, several management changes were made during this time. For example, the Army Corps of Engineers and the SFWMD made selected operational changes to Lake Okeechobee water control, the EAA implemented BMPs, which became mandatory for all EAA farms in 1995, and both stormwater treatment areas and WCA management, including construction projects, were implemented. One of the most effective BMPs in the EAA has been control of water movement, specifically discharge of drainage due to rainfall from the farm. Daroub et al. (2009) indicated that trend analysis on P concentrations and loads out of EAA basin and sub-basins showed a decreasing trend from 1992 to 2002, which is consistent with our results of water quality improvement of inflow to ENP after 1990. Sediment BMPs include laser leveling of fields, constructing ditch and canal sumps to trap sediments contribute to improve water quality of inflow to ENP also (Daroub et al. 2004; Van Horn et al. 2008).Other mechanisms in particular, high flows and stage heights in the WCAs may have also contributed to the apparent water quality improvements (Walker 1997, 2002).

Water quality parameters analysis by Ouyang et al. (2006) revealed that there was a very strong correlation between water color and the organic related parameters such as TKN, TOC, and DOC; he indicated that water color is an important index of river TKN, TOC, and DOC contents. The correlation analysis (Table 4) showed that there were a significant relationship between water color and chemical parameters (TKN, TP, and PO_4). Both of water pH and DO had significant negative correlations with TP; DO had a significant negative correlation with PO_4 also. Data in Table 4 also showed that SPC and Turb had significant correlations with TP and PO_4; SPC had significant correlation with TKN also. Comparing the correlation coefficient among the selected physical parameters and the selected chemical parameters, water color had higher correlation coefficients with the chemical parameters (TKN, TP, and PO_4) than other physical parameters. Ouyang et al. (2006)

Table 4 Trend models which describe better the trends of water-quality variables at three stations, with the values of the statistical tests for the goodness-of-fit

Station	Constituent	Model	ME	MSE	MAE
S12A	Color	$5E-06x^2-0.0674x+41.263$	0	269.13	10.48
S12A	Temperature	$-4E-05x^2+0.0169x+24.129$	0	15.03	3.37
S12A	Dissolved oxygen	$-2E-05x^2+0.0025x+4.9286$	0	2.35	1.19
S12A	Conductivity	$-0.0026x^2+0.6824x+315.36$	0	10397.2	73.96
S333	pH	$7E-06x^2-0.0015x+7.2526$	0	0.06	0.18
S333	Temperature	$-2E-05x^2+0.0066x+24.797$	0	13.9	3.27
S332	Color	$-0.0005x^2+0.0855x+25.712$	0	129.47	8.89
S332	Temperature	$-9E-06x^2+0.0061x+24.952$	0	5.06	1.86
S332	Conductivity	$-0.0043x^2+1.0274x+490.52$	0	6014.32	58.83
S332	Alkalinity	$-0.0002x^2+0.0461x+197.21$	0	251.61	11.14

x time in month from Dec. 1977

indicated the organic-related parameters (i.e., water color, DOC, and TOC) as well as the mineral-related parameters (i.e., alkalinity, EC, and salinity) are the most important parameters in contribution to water-quality variations in the lower St. Johns River. Our study indicated simple physical and chemical parameters (such as water color and SPC) can be used to predicate the trend of water quality change.

In order to describe water parameter changes, an attempt was made to fit one of the known trend models (Eqs. 1–4) to each data time series at the parameter trend with statistical significance. The selection of the "best-fit" model was based on the values of the statistical tests described and are given in Table 5. The results showed that the second order equation (Eq. 2) does a better job of describing the trend of the data time series.

Conclusions

In this study, different multivariate statistical techniques were used to evaluate spatial and temporal variations in selected water-quality parameters from inflows to the ENP. PCA showed that seven sampling stations can be grouped into three clusters of similar water quality characteristics. Data of discharge (Q) and turbidity at the three stations follow the logistic distribution and log-logistic distribution respectively; data of T, SPC, DO, pH, color, and Alk follow the probability distribution which varied stations, respectively.

A comparison of median data among the three stations showed the water-quality parameters varied greatly among the three stations, which may be due to natural variations in geology, hydrology, and vegetation and differences in water management and land uses for the different regions.

Table 5 Pearson product-moment correlations of water quality variables monitored in seven stations

	Temp	Color	SPC	pH	TKN	TP	PO_4	Turb	DO	Alk
Temp	1									
Color	0.138*	1								
SPC	0.042	0.441*	1							
pH	−0.046	−0.148*	0.059*	1						
TKN	−0.006	0.485*	0.090*	−0.048	1					
TP	0.186*	0.268*	0.123*	−0.066*	0.268*	1				
PO_4	0.088*	0.142*	0.131*	−0.025	0.062	0.289*	1			
Turb	0.216*	−0.056	0.255*	0.003	−0.114*	0.237*	0.129*	1		
DO	−0.368*	−0.197*	−0.132*	0.297*	0.012	−0.057*	−0.090*	−0.148*	1	
Alk	−0.029	0.224*	0.879*	0.071*	−0.032	0.062	0.075*	0.319*	−0.117*	1

*$p < 0.0001$ correlation coefficient statistically significant

The best-fit to the data regression models used to describe the relationship between parameter concentration and discharge indicated the power and linear models describe better. The fitting one of the known trend models showed that the second-order equation does a better job of describing the trend of the data time series.

The uncensored seasonal Kendall test showed significantly decreasing in conductivity and color at two (S12A and S333) of three stations and in alkalinity at S333. LOESS trend lines identified that color at S12A, S333, and S332 declined greatly after 1990, which demonstrated water quality improved after 1990.

The correlation matrix showed that there were significant positive relationship between water color, SPC, and chemical parameters (TKN, TP, and PO_4), significant negative correlations with between DO and TP, PO_4; significant positive correlations between Turb and TP, PO_4. Water color had higher correlation coefficients with the chemical parameters (TKN, TP, and PO_4) than other physical parameters.

This study also showed that it was possible to select simple physical and chemical parameters for evaluating water quality change influenced by management practice. Further study is to evaluate the reliability of selected simple physical and chemical parameters to describe water quality change over different hydrogeological condition.

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References

Antonopoulos, V., Papamichail, D., & Mitsiou, K. (2001). Statistical and trend analysis of water quality and quantity data for the Strymon river in Greece. *Hydrology and Earth System Sciences, 5*, 679–691.

Chimney, M. J., & Goforth, G. (2001). Environmental impacts to everglades ecosystem: A historical perspective and restoration strategies. *Water Science and Technology, 44*, 93–100.

Daroub, S. H., Lang, T. A. Diaz, O. A., Chen, M., & Stuck, J. D. (2004). *Annual report phase XII: Implementation and verification of BMPs for reducing P loading in the EAA and Everglades Agricultural Area BMPs for reducing particulate phosphorus transport*. Submitted to the Everglades Agric. Area Environ. Protection District and The Florida Dep. of Environ. Protection. Univ. of Florida, Everglades Res. and Education Ctr., Belle Glade, FL. Available at http://erec.ifas.ufl.edu/WQ/WQ-ReportSum.htm (verified 16 July 2010).

Daroub, S. H., Lang, T. A., Diaz, O. A., & Grunwald, S. (2009). Long-term water quality trends after implementing best management practices in south Florida. *Journal of Environmental Quality, 38*, 1683–1693.

Dixon, W., & Chiswell, B. (1996). Review of aquatic monitoring program design. *Water Research, 30*, 1935–1948.

Haan, C. T. (1977). *Statistical methods in hydrology*. Iowa: The Iowa University Press.

Hirsch, R. M., Alexander, R. B., & Smith, R. A. (1991). Selection of methods for the detection and estimation of trends in water quality. *Water Resources Research, 29*, 803–813.

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters, 6*, 255–259.

Lettenmaier, R. P., Hooper, E. R., Wagoner, C., & Fans, K. B. (1991). Trends in stream quality in continental United States, 1978–1987. *Water Resources Research, 27*, 327–339.

Lietz, A. C. (2000). *Analysis of water-quality trends at two discharge stations—One within Big Cypress National Preserve and one near Biscyane Bay—Southern Florida, 1966–94*. Tallahassee: US Geological Survey.

Maltby, E., & Dugan, P. J. (1994). Wetland ecosystem protection, management, and restoration: An international perspective. In S. M. Davis, & J. C. Ogden (Eds.), *Everglades: The ecosystem and its restoration* (pp. 29–46). Delray Beach: St. Lucie.

McPherson, B. F, Miller, R. L., Sobczak, R., & Clark, C. (2001). *Water quality in big cypress national preserve and Everglades National Park, 1960–2000*. U.S. Geol. Survey Fact sheet FS-097–03.

Muñoz-Carpena, R., Ritter, A., & Li, Y. C. (2005). Dynamic factor analysis of groundwater quality trends in an agricultural area adjacent to Everglades National Park. *Journal of Contaminant Hydrology, 80*, 49–70.

Ouyang, Y., Nkedi-Kizza, P., Wu, Q. T., Shinde, D., & Huang, C. H. (2006). Assessment of seasonal variations in surface water quality. *Water Research, 40*, 3800–3810.

Parinet, B., Lhote, A., & Legube, B. (2004). Principal analysis: An appropriate tool for waterquality evaluation and management-application to a tropical lake system. *Ecological Modelling, 178*, 295–311.

Qian, Y., Migliaccio, K. W., Wan, Y., Li, Y. C., & Chin, D. (2007). Seasonality of selected surface water constituents in south Indian River Lagoon, Florida. *Journal of Environmental Quality, 36*, 416–425.

Schertz, T. L., Alexander, R .B., & Ohe, D. J. (1991). The computer program Estimate Trend (ESTREND), a system for the detection of trends in water-quality data: U.S. Geological Survey Water-Resources Investigations Rpt. 91–4040.

Simeonov, V., Stratis, J. A., Samara, C., Zachariadis, G., Voutsa, D., Anthemidis, A., et al. (2003). Assessment of the surface water quality in Northern Greece. *Water Research, 37*, 4119–4124.

Singh, K. P., Malik, A., Mohan, D., & Sinha, S. (2004). Multivariate statistical techniques for the evaluation of spatial and temporal variations in water quality of Gomti River (India): A case study. *Water Research, 38*, 3980–3992.

Van Hauwermeiren, M., & Vose, D. (2009). *A compendium of distributions* (ebook). Vose Software, Ghent, Belgium. Available from www.vosesoftware.com. Accessed 06/07/2010.

Van Horn, S., Adorisio, C., Bedregal, C., Gomez, J., & Madden, J. (2008). Phosphorus source controls for basin tributary to the Everglades Protection Area. South Florida Environ. Rep., South Florida Water Management District, West Palm Beach, FL. Available at https://my.sfwmd.gov/portal/page?_pageid=2714,14424186&_dad=portal&_schema=PORTAL (verified 16 July 2010).

Walker, W. W. (1991). Water quality trends at inflows to everglades national park. *Water Resources Bulletin, 27*, 59–72.

Walker, W. W. Jr. (1997). *Long-term water-quality in the Everglades: Symposium on phosphorus biogeochemistry in Florida ecosystems: Clearwater Beach, FL, July 13–16, 1997*.

Walker, W. W. (2002). *Analysis of recent phosphorus data from shark river slough inflows to Everglades National Park DRAFT* (pp. 1–16). For Discussion at TOC Meeting, August 1 2002 for U.S. Department of the Interior.