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TIME-SCALE ANALYSIS OF WATER QUALITY INDICATORS

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ABSTRACT

The sustainable management of water resources is very important for the survival of humans. Most of the signals from freshwater resources are non-stationary in time structure. In this paper, water quality signals monitored in a freshwater ecosystem are investigated by classical and modern time series analysis methods. The classical methods revealed the presence of trends and long-term memories in the signals. The modern method revealed the presence of long-term cycling processes rather than linear trends in the signals which could not be detected by the classical methods. Investigating long term water quality signals (water temperature, dissolved oxygen and chlorophyll-a) by these methods was found necessary.

Index Terms **–** Water quality, time series analysis, wavelet analysis

1. INTRODUCTION

The necessity to efficiently conserve and manage freshwater resources in the world is becoming more and more urgent. There is a growing concern that the rapidly rising demand of freshwater resources is likely to double or even triple the global consumption of water before 2050 [6]. At the same time, floods are taking an increasing toll of life; droughts are becoming wide spread, while pollution of surface and ground water is greatly diminishing the resources available for use. This is as a result of growing world population and economic activities with the subsequent degradation of freshwater resources as a result of anthropogenic pollution [13]. In order to effectively assess the state of a freshwater body and develop an understanding of the interrelationship between the components for sustainable management, freshwater quality data of water quality indicators (WQI) collected by monitoring programs is extremely important.

From the point of view of information theory, monitored water quality data series represent full process information. These signals are usually non-stationary as a result of internal and external driving forces, the most significant being induced by humans.

Signal analysis methods enable the extraction of information from these variables by projecting them in the time, frequency, time-frequency and time-scale domains [9]. Using wavelet method in studying the long term evolution and variations, the structural characteristics of the variables as well as the relationships that exist between them at different time scale reveals information necessary in the diagnosing of water quality problems and in choosing an appropriate management strategy. Investigating the dependencies of freshwater ecosystem indicators on natural external driving forces as well as natural and anthropogenic internal and external stressors is necessary.

In this paper, water temperature, dissolved oxygen and algal biomass (measured as chlorophyll-a content) from the river Havel from 1998 to 2002 at the Potsdam monitoring station will be analyzed. The analysis will first consist of detecting non-stationarity in the data set by means of the cumulative sum and trend analysis methods. Next, the autocorrelation structure of the signals will be investigated. Finally, wavelet decomposition will be applied to it so as to investigate their long term dynamics.

2. WATER QUALITY INDICATORS

Water quality indicators (WQI) consist of physical, chemical and biological variables designed to provide clear signals about the status and changes of an ecosystem [8]. The variable recorded may be of different origins and will be denoted as stressors to the ecosystem (e.g. nutrients), state variable of the ecosystem (e.g. biomass) or driving force of the ecosystem (water temperature). These give rise to stressor indicators, ecological state indicators and driving force indicators [11]. Some variables can both be stressors and state variables depending on the specific situation. In table1 some essential freshwater quality indicators are given.

Table 1 Water quality indication and their indicators

Indicator	Indication	Type	Category
Water temperature	Energy	Phys.	Driving force
Solar radiation	Light	Phys.	Driving force
Secchi disk transparency	Transparency	Phys.	Ecological state
Turbidity	Transparency	Phys.	Ecological state
Suspended solids	Transparency	Phys.	Ecological state
Nitrogen, Phosphorus	Nutrients	Chem.	Stressor
BOD	Pollution	Chem.	Stressor
Conductivity	Pollution	Chem.	Stressor
Dissolved oxygen	Productivity, respiration	Chem.	Ecological state
pH	Acidity, alkalinity, respiration	Chem.	Stressor
Chlorophyll-a	Algal biomass	Biol.	Ecological state
Faecal coliform	Faecal material	Biol.	Stressor

The measurements of the indicators obtained depend on both natural and anthropogenic driving forces. Fluctuations from the mean value over time may be as a result of parallel acting internal and external driving forces. Seasonal and periodic processes influence the variable causing most of them to exhibit a cycling behaviour over time [1].

3. TIME SERIES ANALYSIS OF WQI

The cumulative sum method enables a water manager to recognize changes in the general tendency of a specific WQI [7]. It is very sensitive to changes in the mean value of a signal. The advantage of the graphical plot of the values obtained is that all local mean is immediately deducted from the slope. Given a signal x(t) sampled at regular intervals t, varying between 1 to N and a reference value r (for example the mean). This reference value is subtracted from all the estimations of the series:

$$S_q = \sum_{i=1}^{q} X_i - qr \quad .$$

If two points Xi and Xj being the respective lower and upper limits of a relatively monotonous series are given, then the slope p between these two values separated by k intervals of time (j – i = k), results in $p = \frac{X_j - X_i}{k}$. The local mean between the two distant points of k is equal to the slope of the graphic of the cumulative sum plus the chosen reference value r.

This approach was applied to the water temperature (top), dissolved oxygen (middle) and chlorophyll-a (down) signal (fig. 1).

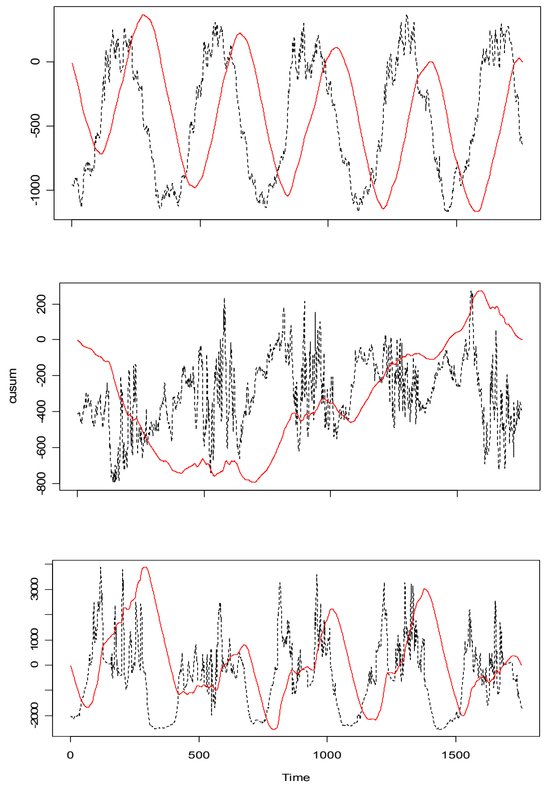

Figure 1 Detection of local changes of means (water temperature (top), dissolved oxygen (middle) and chlorophyll-a (bottom)

The cumulative sum of water temperature changes slowly from one period to the other indicating a relatively weak non-stationary behaviour. The observation made from the dissolved oxygen signal is that the change from one interval to the next is much stronger, revealing a stronger deviation from stationarity. Finally, the chlorophyll-a signal, portrays a change in the mean value across time, though not as strong as that of dissolved oxygen. It can be noted from these observations that the nonstationarity as a result of a change in the mean value of the signals across time is more pronounced in the chemical indicator as compared to the physical and biological indicator. Hence, any subsequent analysis has to take this into consideration either by ignoring or rendering the data stationary.

4. TREND ANALYSIS OF WQI

The presence of trends in the WQI signals can analyzed using simple linear regression. The time series of values are related to time by an equation of the form:

$$Y = B0 + B1(T)$$

where Y is the water quality indicator such as chlorophyll-a, T is the time in years, B0 and B1 are the least-square estimates of the intercept and slope coefficients.

The slope B1, indicates the average rate of change in the water quality indicator during each day of the time period. If the slope is significantly different from zero, the trend in the water quality indicator is equal to the magnitude of the slope. If the slope is not significantly different from zero, there is no trend in the water quality indicator. An advantage of this technique is that it is easy to apply to a large number of data series. Unfortunately, the method may fail to detect trends that are nonlinear but still monotonic (in one direction). Other approaches such as the Mann-Kendall test can equally be used for detecting monotonic and nonlinear trends, but it only indicates the direction and not the significance of the trends.

Figure 2 provides a graphical representation of the linear trends present in each of these three signals. The regression equation for water temperature gives

$$Yt = 11{,}800 + 0{,}00167t$$

representing an upward trend in the signal as indicated by the positive sign in front of the value of the slope.

The equation obtained for the regression of dissolved oxygen is represented by

$$Yt = 8{,}935 + 0{,}00129t$$

denoting the presence of a slow upward linear trend in the signal.

The biological indicator, chlorophyll-a gives the following regression equation representing a very slow downward trend.

$$Yt = 50{,}37 - 0{,}00033t$$

The negative sign in front of the value of the slope confirms the downward trend observed in figure 2.

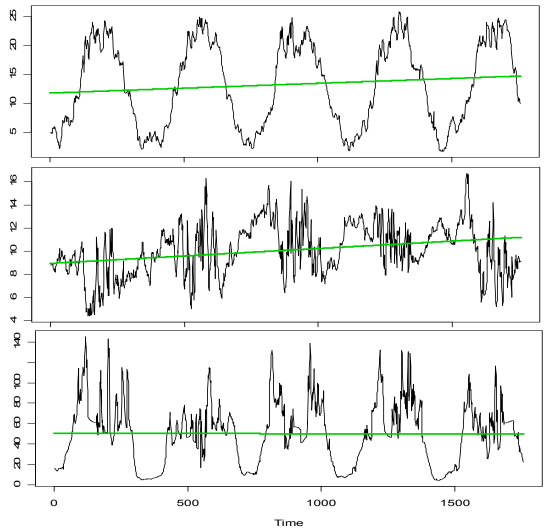

Figure 2 Linear trend model of water temperature (top), dissolved oxygen (middle) and chlorophyll-a (bottom).

5. CORRELATION ANALYSIS OF WQI

The autocorrelation refers to the correlation of the signal with its past and future values. In other words, it is a method for characterizing the correlation within a signal over time and is given by

$$\gamma_k = \frac{\sum_{i=1}^{N-k}(Y_i - \bar{Y})(Y_{i+k} - \bar{Y})}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2}$$

where the measurements are denoted by Y1, Y2, ..., YN, and k is the time lag. The autocorrelation function is used to detect non-randomness in the data, extract information on dependence and for the identification of an appropriate model for a non-random data (AR, MA, ARIMA, SARIMA models) [2]. Correlograms are very practical for the determination of the dependence between successive observations of a time series. If the correlogram indicates the existence of correlation between successive terms x(t) and x(t + k), the signal is assumed dependent or said to exhibit long memory [3].

The correlogram of the water temperature signal clearly shows the presence of a strong dependence of the future values on the present ones. The signal exhibits long memory with the absence of any form of randomness. The signal of the chemical indicator dissolved oxygen equally portrays persistence as shown in the correlogram, though not as strong as in the case of water temperature. This as well means that the future values of the signal are strongly influenced by the present values. The signal of the biological indicator chlorophyll-a also reveals the presence of dependence of the future values on the present ones. As is shown in figure 3, all three signals have long memories with the signal of the physical water quality indicator having the strongest autocorrelation compared to the other two.

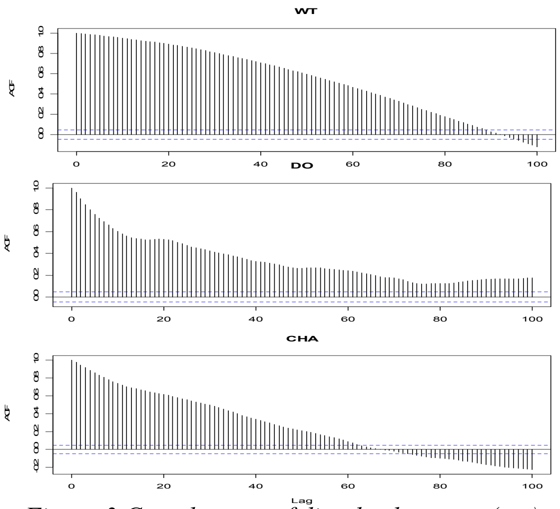

Figure 3 Correlogram of dissolved oxygen (top), chlorophyll-a (middle) and water temperature (bottom)

6. WAVELET ANALYSIS OF WQI

The main idea behind wavelet analysis is to imitate the windowed Fourier analysis, but using basis functions (wavelets) that are better suited to capture local behaviour of non-stationary signals [12].

Wavelet analysis makes use of the different wavelet basis function in the wavelet transform to project a signal from the time domain into the time-scale domain. It decomposes a signal into its constituents at different time scales [10].

A wavelet ψ(t) is a function of time that obeys the following wavelet admissibility condition [5]:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0$$

and

$$\int_{-\infty}^{\infty} \phi \ (t)dt = 1$$

Wavelets come in families generated by the father wavelet denoted by Φ and a mother wavelet denoted by ψ. Father wavelets, used to represent the long scale smooth or low frequency component of a signal integrates to one while the mother wavelet, used to capture the detailed and high frequency components or deviations from the smooth components, integrates to zero. The wavelet transform uses a basis function (mother wavelet) which dilates and translates to capture features which are local in time and frequency [4].

Wavelet analysis serves as a mathematical tool acting as a lens for inspecting the time varying structure of WQI signals and relationships between signals. It decomposes signals on a scale by scale basis by projecting them onto a basis function and can be expressed by

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)$$

where s is the scale parameter, t is the location parameter. Changing s produces dilating effects (s > 1) or contracting effects (s < 1) of the function ψ(t). Changing u analysis the signal f(t) around different points of u.

Wavelet decomposition was applied to time series of WQI. The water temperature signal and the approximations from the analysis are provided in figure 4. The figure reveals a progressively smoother version of the signal, taking off the high frequency fluctuations in a progressive manner. This reveals the underlying general tendency of the signal.

The original signal shows the presence of yearly cycles in the signal. When the wavelet approach is used to decompose it till level eight, it is observed that a longer cycle was actually hidden within the yearly cycles. When the signal is further decomposed to level nine, it reveals an approximately three year cycle. Extending it to level ten portrays what may be interpreted as an upward trend which may in reality turn out to be an even longer cycle. This shows the need for analyzing longer ecological signals so as to unravel long cycles hidden in signals. Investigating the reason for these cycles may be greatly relevant for the sustainable management of freshwater bodies.

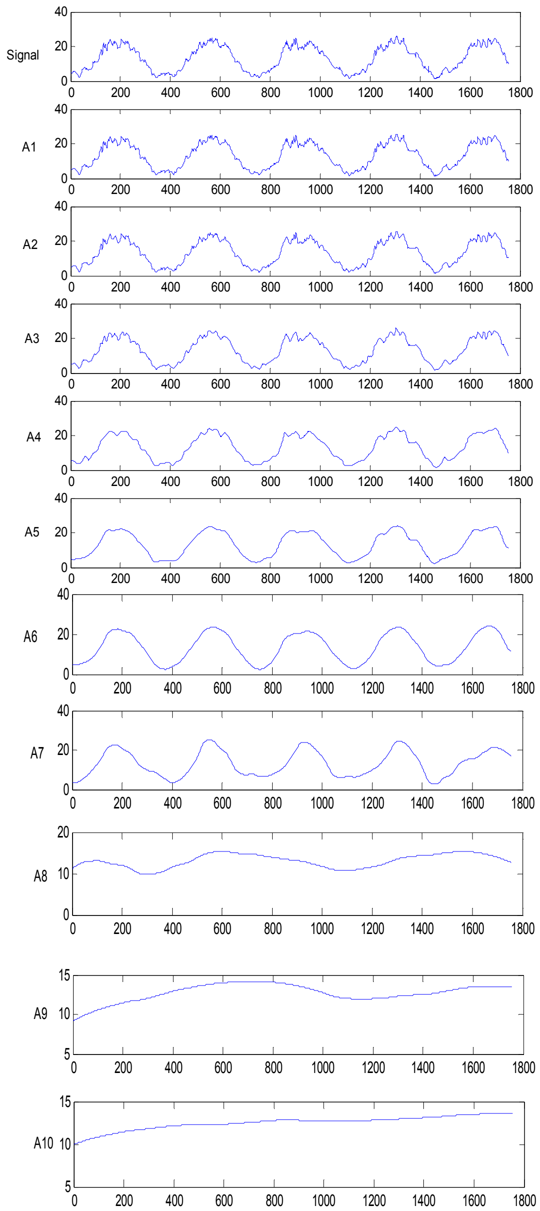

Figure 4 Approximations of water temperature

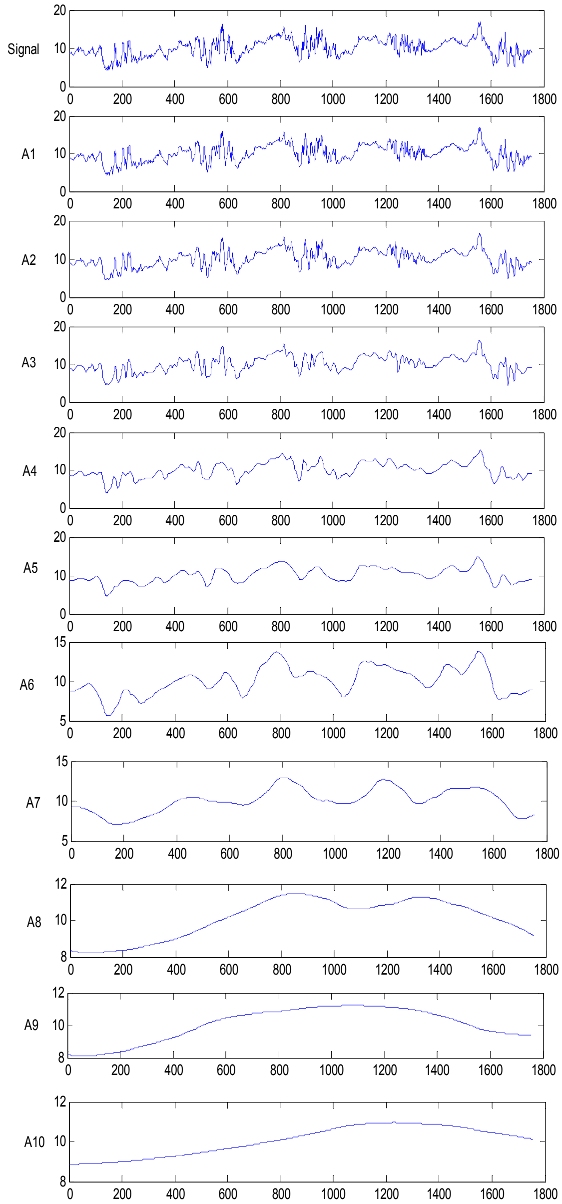

Figure 5 Approximations of dissolved oxygen

The approximations from the wavelet decomposition of chemical WQI dissolved oxygen are presented in figure 5. Acting as a lens which progressively reveals a clearer version of the signal, the micro structure and the long term dynamics of the signal at different time scales is unraveled. As can be observed, the approximations at level one clearly shows yearly cycles in the signal. As the signals are progressively decomposed till level 10, longer cycles which were not visible are progressively revealed. The dissolved oxygen signal which seem to contain a slow upward trend is rather found to contain different cyclic components of different lengths as observed at levels 8, 9 and 10.

Approximations from the wavelet decomposition of chlorophyll-a are presented in figure 6. Analogously to the chemical WQI the biological WQI for algal biomass expressed by the chlorophyll-a content of the water body portrays the presence of long cycles as shown at level 8, 9 and 10 of figure 6. These levels represent a time scale of 4 months, 8 months and 16 months respectively.

There is a necessity for investigating the driving forces behind these observed cycling behaviors at the higher time scales as well as an investigation of the signals over longer periods of time as it will be done by the Long Term Ecological research Project in Germany (LTER-D).

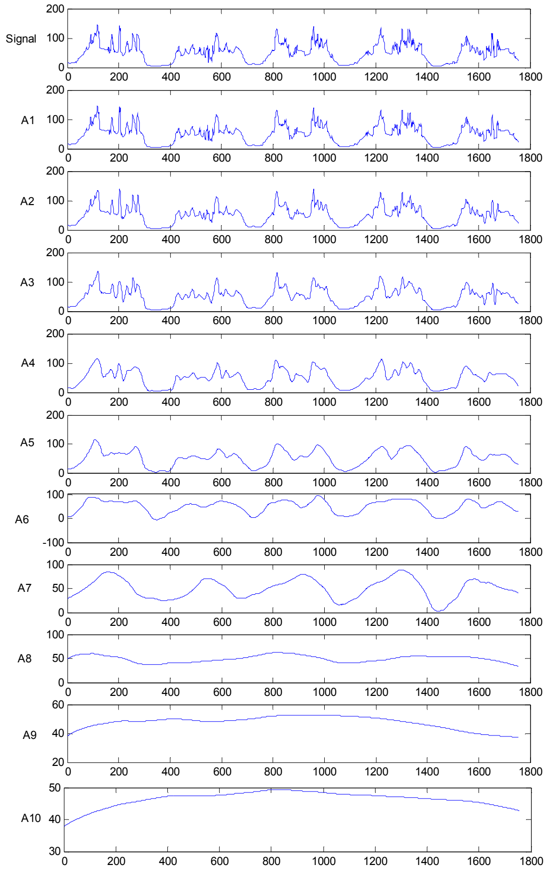

Figure 6 Approximations of chlorophyll-a

7. CONCLUSION

Time series analysis of WQI is necessary for extracting information required for a sustainable management of freshwater bodies. This can be done using classical time series analysis methods with different levels of success. The structural characteristics of the signals such as the presence of trends, dependence, and long memory can be detected by techniques such as the cumulative sum, trend analysis, and the autocorrelation function. These techniques reveal that the water quality signals are nonstationary and have to be rendered stationary before applying time series models like the Box-Jenkins and the Fourier approximation modeling approaches. The non stationary structure due to internal and external driving forces in the freshwater body poses no problems to wavelet analysis which reveals the basic variation present in the signals. In so doing, it unravels any hidden long term cycles which seem to be present in all the investigated water quality signals. It is of great importance to analyze the signals over longer periods of time so as to extract the underlying general tendency.

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