Evaluation of Salinity by Using Wavelet Modeling

Funda Dökmen (f_dokmen@hotmail.com)
Kocaeli University

Zafer ASLAN
İstanbul Aydın Üniversitesi: Istanbul Aydin Universitesi

Research Article

Keywords: Cations, groundwater, soil salinity, quality of irrigation water, wavelet analyses

Posted Date: January 13th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1225991/v1

Abstract

Every year, due to the salinity resulting from improper irrigation practices, almost 10 billion ha of agricultural lands across the world cannot be used. Among the main elements (cations) for salinity in regions with dry or semi-dry climate are potassium (K^+), sodium (Na^+), calcium (Ca^{+2}) and magnesium ($Mg^{+'2}$). Using proper irrigation methods as well as ensuring the quality of irrigation water are of great importance in terms of the salinity of agricultural soils. In this study, laboratory analyses of ground water resources for salinity parameters were conducted in the province of Yalova (Taşköprü, Çiftlikköy, and Altınova regions). In the explanation of the analysis results, variations and effects based on the level of salinity were taken into account and the role of small, meso and large scale factors were determined through the use of the wavelet model. The study results would be of use in the estimation of salinity contents of soils with respect to groundwater irrigation in agricultural areas.

1 Introduction

The quality of water is determined by the surrounding natural elements and phenomena including soils, plant covers and flora, in addition to the meteorological, hydrological, and geological properties of the area. The quality of surface and groundwater resources is inevitably impacted by any changes that may occur in these properties as a result of global climate change, as well as any changes in precipitation quality that may occur in different seasons. The amount of precipitation varies not only temporally, but also spatially (Dökmen and Kurtuluş, 2009; Kalteh, 2015; Dökmen and Duru 2019; Dökmen and Aslan, 2020).

Within the past ten years, wavelet theory has begun to be used in signal processing analysis. The wavelet transform has been successfully applied to wave data analysis, as well as other engineering applications, in recent years (Massel, 2001; Teisseire at al. 2002; Huang, 2004; Anctil and Paulin, 2004; Brutsuert, 2005; Blackburn and Ferwerda, 2008).

One of the important contributors to the water quality problems are storm water in urbanized areas. As indicated by the results of the time series prediction competition results Models such as ANN, recurrent neural networks, wavelet neural networks, particle swarm optimization methods, and fuzzy neural networks, etc. are among the best options to be used in the prediction of time series, which is a generalized form of run off quality prediction. These models can be expected to yield the best results in the prediction of specific run off quality as well.

Recently, wavelet analysis (also known as ‘wavelet theory’ or ‘wavelets’) has received considerable interest in signal processing. Having been employed in various applications including transient signal analysis, image analysis, communications systems with success, it is still open to further development in terms of both the mathematical understanding and various applications in science and engineering (Massel, 2001; Zhang, et.al. 2004; Reum and Zhang, 2007; Moosavi, et.al. 2013; Moosavi, et.al. 2017).

In recent years, wavelet techniques have been widely applied to various water resources research because of their time-frequency representation. The aim of this work was to study the influence of precipitation/rainfall events and quantity on the ground water resources in terms of potassium (K^+), sodium (Na^+), calcium (Ca^{+2}) and magnesium (Mg^{+2}) by using wavelet techniques. And also, As main elements (cations) and sampling parameters, spatio-tempora variations of potassium (K^+), sodium (Na^+), calcium (Ca^{+2}) and magnesium ($Mg^{+'2}$) for salinity in dry and semi-dry climatic regions have been analyzed.

2 Material And Methods

2.1.Materials

In this study, five different ground water resources located in the vicinity of Yalova (at three study areas; Taşköprü, Çiftlikköy and Altınova) in Turkey were investigated (Fig. 1).The content of potassium (K^+), sodium (Na^+), calcium (Ca^{+2}) and magnesium (Mg^{+2}) were examined for the relation to amount of rainfall. This work was accomplished analyzing five different ground water samples every month in the period of over all the 10 years (June 2010-August 2020).

In the research area, annual mean temperature is 23.6 ^{0}C and annual mean of precipitation is 808.4 mm year^{-1}. In the long period years (1975-2020), total annual potential evaporation is 540.5 mm water year^{-1} and total annual real evaporation of research area is 476.9 mm water (TSM, 2019; TSM, 2020).

2.2.Methods

2.2.1.Chemical analysis

Standard sampling methods were used in the work, and the samples were analyzed according to standard methods (APHA, 1985). Chemical analysis were used of potassium (K^+), sodium (Na^+), calcium (Ca^{+2}) and magnesium (Mg^{+2}).

2.2.2.Wavelet analysis

Having received considerable attention since it was theoretically developed, the wavelet analysis is a sophisticated tool employed in signal processing (Grossmann and Morlet, 1984). As an alternative to the Fourier transform in the preservation of local, non-periodic, and multi-scaled phenomena, it has been increasingly used in communications, image processing and optical engineering applications. Wavelet transforms, which can generally be used in exploring, denoising, and smoothening time series, are of help in forecasting and other empirical analyses (Sehgal, et.al. 2014; Sang, et.al. 2015; Shafaei, 2016).

In wavelet analysis, which breaks up a signal into shifted and scaled versions of the original (or mother) wavelet, the signal-cutting problem is solved through the use of a fully scalable modulated window. By shifting the window along the signal, the spectrum for each position is calculated. After repeating this

process many times using a slightly shorter (or longer) window for each new cycle, a collection of time-frequency representations of the signal, all of which will have different resolutions, will be obtained. This collection of representations allows us to speak of a multi-resolution analysis. Both the dominant modes of variability and how those modes vary in time can be determined through the decomposition of a time series into time-frequency-space. Proven to be a powerful tool for the analysis and synthesis of data from long memory processes, wavelets are strongly associated with such processes as the same shapes repeat in different orders of magnitude. By simultaneously localizing a process in time and scale domain, wavelets enable the representation of many dense matrices in a sparse form (Ramana et al. 2013; Parmar and Bahrdwaj, 2012; Sing and Rashmi, 2014).

A sufficient condition for f(t) to qualify as a mother wavelet is given as below (Meyer, 2000; Siddiqi, 2010; Dökmen and Aslan, 2013; Nourani, 2015; Daubechies, 1992).

$$\int_{-\infty}^{\infty} |f(t)|^2 \, dt < \infty \qquad (1a)$$

The Fourier transform F of f(t) is defined as

$$F(w) = \int_{-\infty}^{\infty} f(t) e^{iwt} \, dt \qquad (1b)$$

A function ψ(t) satisfying the following condition is called a continuous wavelet:

$$\int_{-\infty}^{\infty} |\psi(t)|^2 \, dt = 1 \qquad (2a)$$

and

$$\int_{-\infty}^{\infty} |\psi(t)| \, dt = 0 \qquad (2b)$$

Where $$\psi_{a,b}^{(u)} = \frac{1}{\sqrt{a}} \psi((u-b)/a) \qquad (3)$$

Here *a* is a scaling parameter, *b* is a location parameter and $\psi_{a,b}^{(u)}$ is often called continuous wavelet (or daughter wavelet) while ψ(u) is the mother wavelet. For 1D continuous wavelet analyses the Mexican hat wavelet `upside-down', with a central trough (top of the hat) and two symmetric bumps on either side (the curled rim) was used in (Fig. 2).

In this paper as a wavelet function, f(t) temporal variations of potassium (K^+), sodium (Na^+), calcium (Ca^{+2}) and magnesium (Mg^{+2}) have been considered.

Continuous wavelet transform using Db Wavelet at level 8 have been analyzed for each water parameter. Continuous Wavelet analyses analysis decomposes each data in 10 parts namely, s, a3, d1, d2, d3, d4, d5, d6, d7, d8. The first part “s” represents signal or raw data, second part “a3” correspond to amplitude of signal for Db Waelet at level 3. d1.d8 represents details of signal or raw data at eight different levels. 1D Continuous wavelet analysis has three parts; first part on top represents the analyzed signal or raw data, second part contains the scalogarms value.

3 Results And Discussion

3.1.Temporal and Spatial Variations of Potassium (K^+) Elements

Results of this study would be helpful for estimation of salinity contents on soils by using irrigation of five different groundwater resources at agricultural areas.

Fig. 3a-c show wavelet analyses of K^+ elements variations in Yalova Province (regions of Taşköprü, Çiftlikköy and Altınova). Small scale fluctuations play an important role at the study areas of Taşköprü and Altınova (Fig. 3a). Large scale factors have higher impact at Altınova, but the effective role of meso scale fluctuations have been observed at Çiftlikköy. Mean value K^+ element is 5,133 mg L^{-1} at study area. Range is changing between 2 and 13. Its frequency histogram has a positive skewness (Fig. 3b).

Fig. 3(c) shows, 1D wavelet analyses of K^+ element at study area. Based on these analyses, it is concluded that, Taşköprü and Altınova are under the affects of small – meso and large scale factors. But Çiftlikköy is affected by small and meso scale factors.

3.2.Temporal and Spatial Variations of (Na^+) Elements

Figs. 4a-c show wavelet analyses of Na^+ elements variations in Yalova Province (regions of Taşköprü, Çiftlikköy and Altınova). Small scale fluctuations play more important role at Altınova (Fig. 4a). This variation is associated with sea-water (Marmara Sea) intrusion. Meso and large scale factors have same impacts at all sudy areas. Mean value Na^+ element is 1,373 mg L^{-1} at study area. Range is changing between 0 and 4. Its frequency histogram has a positive skewness (Fig. 4b).

Fig. 4(c) shows, 1D wavelet analyses of Na^+ element at study area. Based on these analyses, it is concluded that, all three study areas are under the affects of small – meso and large scale factors.

3.3.Temporal and Spatial Variations of Calcium (Ca^{+2}) Elements

Figures 5a-c show wavelet analyses of Ca^{+2} elements variations in Yalova Province (regions of Taşköprü, Çiftlikköy and Altınova). High frequency variations have been observed at all stations in study area (Fig. 5a). Role of large scale factors are associated with artificial fertilization at Çiftlikköy. Mean value Ca^{+2} element is 5,133 mg L^{-1} at study area. Range is changing between 1 and 8. Its frequency histogram has a negative skewness (Fig. 5b).

Fig. 5(c) shows, 1D wavelet analyses of Ca^{+2} element at study area. Based on these analyses, it is concluded that, all three study areas are under the affects of small – meso and large scale factors. On the other words, the main influence on temporal variations of Ca^{+2} elements at the study area is accompanied with combined factors of small, meso and large scale fluctuations with frequencies of 1-8 months. But the role of large scale factors play more important role at Çiftlikköy than the other stations.

3.4.Temporal and Spatial Variations of Magnesium (Mg^{+2}) Elements

Figures 6a-c show wavelet analyses of Mg^{+2} elements variations in Yalova Province (regions of Taşköprü, Çiftlikköy and Altınova). Low frequency variations have been observed at all stations in study area (Fig. 6a). Role of large scale factors are associated with artificial fertilization and sea water intrusion at all three study areas. Mean value Mg^{+2} element is 1,92 mg L^{-1} at study area. Range is changing between 1 and 6 mg L^{-1}. Its frequency histogram has a positive skewness (Fig. 6b).

Fig. 6(c) shows, 1D wavelet analyses of Mg^{+2} element at study area. Based on these analyses, it is concluded that, all three study areas are under the affects of small – meso and large scale factors. The main influence on temporal variations of Mg^{+2} elements at Taşköprü and Çiftlikköy is accompanied with combined factors of small, meso and large scale fluctuations with frequencies of 1-5 months. But in Altınova, periodicities of these fluctuations change between 1-5 months in 2010, and also it changes between 1-10 months in 2020. This result may be attributed to the lower affects of large scale factors at Altınova in 2020.

3.5. Wavelet analyses of rainfall rate

The influence of rainfall events and quantity on the ground water resources have been analyzed by using wavelet techniques. The results of analyses explained that relationship for salinity parameters in terms of drought climatic conditions in research area.

Figures 7 (a and b) show Wavelet 1D and Continuous Wavelet 1D analyses of monthly total rainfall rates. Small and meso scale factors have an important role on rainfall rate. Their role show less importance effects during summer period. Their periodicity lasts for a couple of months. Large scale fluctuations are important on total rainfall rate variations in autumn.

5 Conclusions

Wavelet analyses of extreme events show the role of seasonal oscillations, and small-, meso- and large-scale effects on water quality parameters. Wavelet analysis helps us to interpret the frequency dependent changes of time series due to regional and large scale factors. Based on this fact, contents of parameters were determined for suitability of underground water to different using activities.

The time series of groundwater resources and levels of salinity are analyzed by using continuous wavelet transforms. These analyses help to improve the monitoring of water quality, the modeling and

determining of salinity strategies concerning water resources. In addition, this analysis can provide information on the causative impact of groundwater resources on the salinity concentrations, as well as their phase relationship in time frequency domain.

Declarations

Authors Contributions All the contributions are by two authors.

Funding There is no funding source for the article.

Availability of Data and Materials Authors are ready to respond to any request.

Ethical Approval Authors approve all the ethical rules stated by WRM journal.

Consent to Participate These are two authors article.

Consent to Publish From our side we give the permission to publish this work.

Competing Interest There is no competing interest and no conflict.

References

1. Anctil F, Paulin C (2004) Wavelet analysis of the interannual variability in southern québec streamflow. J Climate, 17, 163–173.
2. APHA (1985) Standart Methods for the Examination of Water and Wastewater American Public Health Association, Washington.
3. Blackburn GA, Ferwerda JG (2008) Retrieval of chlorophyll concentration from leaf reflectance spectra using wavelet analysis. Remote Sense Environmen. 112, 1614-1632.
4. Brutsaert W (2005) Hydrology: An Introduction. Cambridge University, Press, N.Y. 605 pp. England.
5. Daubechies I (1992) Ten Lectures on Wavelets SIAM, Philadelphia.
6. Dökmen F, Kurtuluş C (2009) Temporal Variation of Nitrate, Chlorine and pH Values in Surface Waters, Journal of Food, Agriculture & Environment, Vol.7 (2): 689-691, WLF Publisher, Finland.
7. Dökmen F, Aslan Z (2013) Evaluation of the parameters of water quality with wavelet techniques, Water Resources Management, 27:4977- 4988, DOI 10.1007/s11269-013-0454-5, Springer.
8. Dökmen F, Duru N (2019) Assessment of water quality model using fuzzy logic system: A case study of surface water resources in Yalova of Turkey. Mathematical of Real World Problems, Interdisciplinary Studies in Applied Mathematics, Eds: Aslan, Z., Dökmen, F., Feoli, E., Siddiqi, A.H., chapter:6, 103-117, Nova Science Publishers, New York.
9. Dökmen F, Aslan Z (2020) Evaluation of Oxygen Demand in Water Resources with Wavelet Modelling. Fresenius Environmental Bulletin. 29 (11), 10078-10087.

10. Grossmann A, Morlet J (1984) Decomposition of Hardy Functions into Square Integrable Wavelets of Constant Shape. SIAM J Math Anal 15(4):723–736.
11. Huang MC (2004) Wave Parameters and Functions in Wavelet Analysis. Ocean Eng 31(1):111–125.
12. Kalteh AM (2015) Wavelet genetic algorithm–support vector regression (wavelet GA-SVR) for monthly flow forecasting. Water Resources Management**,** *29*: 1283-1293.
13. Massel SR (2001) Wavelet analysis for processing of ocean surface wave records. Ocean Eng**,** 28*,* 957–987.
14. Meyer Y (2000) The role of oscillation in some nonlinear problems, school on mathematical problems in image processing. ICTP, SMR 1237/4, pp. 4-22.
15. Moosavi V, Vafakhah M, Shirmohammadi B, Behnia N (2013) A wavelet–ANFIS hybrid model for groundwater level forecasting for different prediction periods”*,* Water Resources Management*,* 27: 1301-1321.
16. Moosavi V, Talebi A, Hadian MR (2017) Development of a hybrid wavelet packet-group medhod of data handling (WPGMDH) model for runoff forecasting”, Water Resources Management**,** 31: 43-59.
17. Nourani V, Alami MT, Vousoughi FD (2015) Wavelet-entropy data pre-processing approach for ANN-based groundwater level modeling, Journal of Hydrology, Vol. 524, P. 255-269.
18. Parmar KS, Bhardwaj R (2012) Analysis of water parameters using Haar wavelet (Level 3). Int. Journal of Current Eng. And Tech, *2* (1), 166-171.
19. Ramana RV, Krisna B, Kumar SR, Pandey NG (2013) Monthly Rainfall Prediction Using Wavelet Neural Network Analysis. Water Resources Management, An International Journal-Published for the European Water Resources Association (EWRA), 10.1007/s11269-013-0374-4.
20. Reum D, Zhang Q (2007) Wavelet based multi-spectral image analysis of maize leaf chlorophyll content. Computer Electronic Agriculture, 56, 60-7.
21. Sang Y, Wang Z, Lin C (2015) Wavelet neural modeling for hydrologic time series forecasting with uncertainty evaluation. Water Resources Management, *29*: 1789-1801.
22. Sehgal V, Sahay RR, Chatterjee C (2014) Effect of utilization of discrete wavelet components ob flood forecasting performance of wavelet based ANFIS models*.* Water Resources Management*, 28*: 1733-1749.
23. Shafaei M, Kişi Ö (2016) Lake level forecasting using wavelet-SVR, wavelet–ANFIS and wavelet-ARMA conjuction models. Water Resources Management, 30: 79-97.
24. Singh PK, Rashmi B (2014) Time Series, Trend and Wavelet Analysis of Water Parameters, Indian Journal of Industrial and Applied Mathematics, Volume : **5**, Issue : 1, 1-9, DOI : 10.5958/1945-919X.2014.00203.5
25. Siddiqi AH (2010) Some recent developments in wavelets theory. Proceeding of the IVth International Workshop on Applications of Wavelets to Real World Problems, IWW2009, June 5-7, 2009, *Eds:* A.H. Siddiqi, Z. Aslan, F. Dökmen, N. Duru, H. K. Sevindir, N. P. Özer, ISBN: 978-605-4158-12-6, Publication Number: KOU-354, Kocaeli, Turkey, p:391.

26. Teisseire LM, Delafoy MG, Jordan DA, Miksad RW, Weggel DC (2002) Measurement of the Instantaneous Characteristics of Natural Response Modes of a Spar Platform Subjected to Irregular Wave Loading. J Offshore Polar Eng 12(1):16–24.
27. TSM, Turkish State Meteorolojical Service (2019) Recorders of Kocaeli Forecasting Station, Kocaeli, Turkey.
28. TSM, Turkish State Meteorolojical Service (2020) Recorders of Yalova Wheather Station, Yalova, Turkey.
29. Zhang J, Yuan L, Pu R, Loraamm RW, Yang G, Wang J (2004) Comparison between wavelet spectral features and conventional spectral features in detecting yellow rust for winter wheat. Computers Electronic Agriculture, 100, 79-87.

Figures

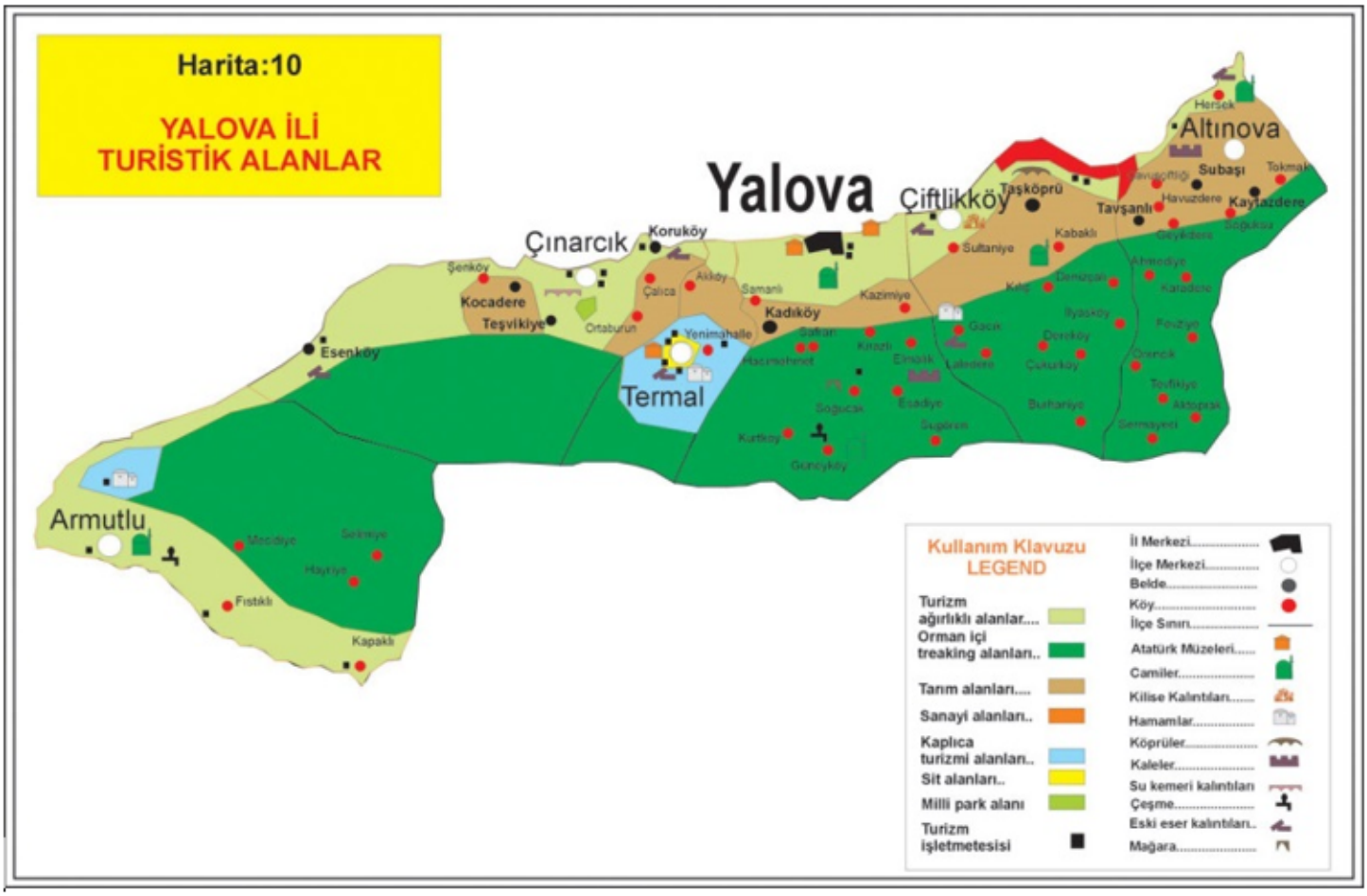

Figure 1

Map of three study areas as Taşköprü, Çiftlikköy and Altınova in the vicinity of Yalova Province in Turkey

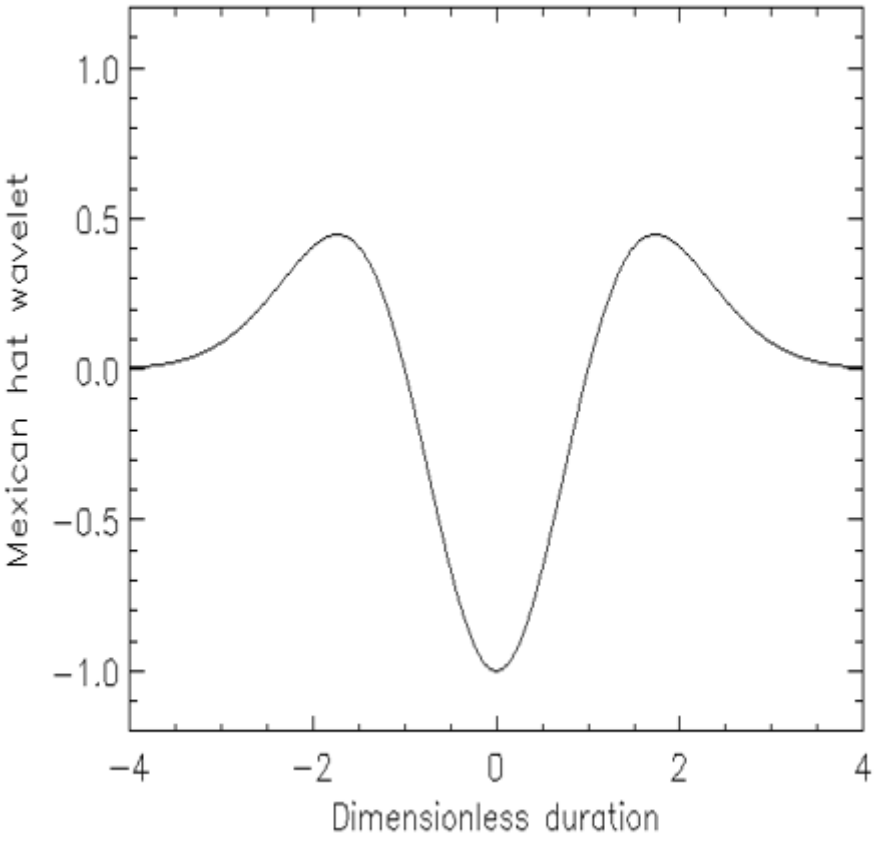

Figure 2

Maxican hat wavelet (Meyer, 2010).

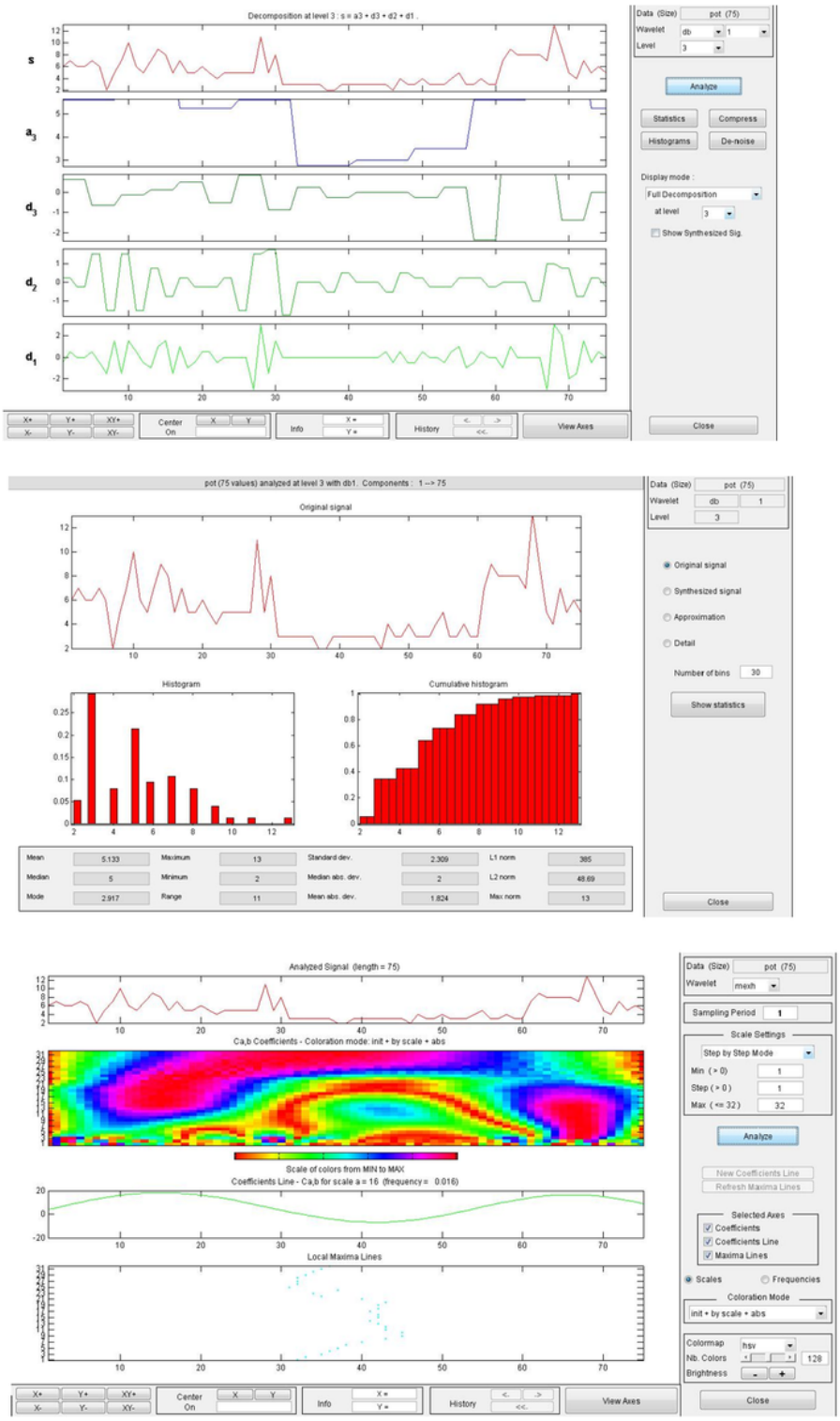

Figure 3

a- Wavelet analyses of K^+, Db, Level 3, (June 2010-August 2020).

b- Statistical analyses of K^+, Db, Level 3, (June 2010-August 2020).

c- 1D continuous wavelet analyses of K^+, Mexh, (June 2010-August 2020).

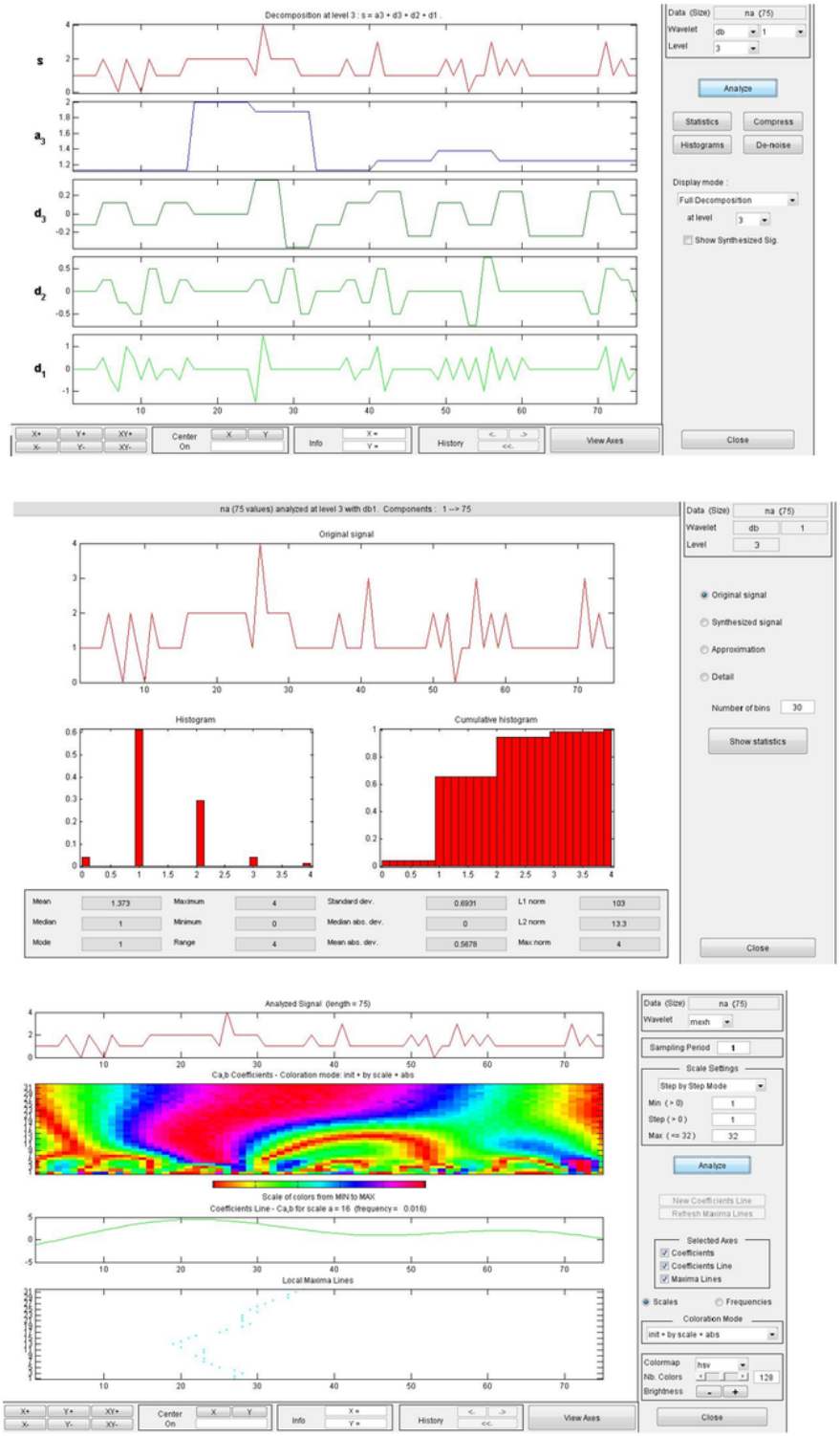

Figure 4

a- Wavelet analyses of Na^+, Db, Level 3, (June 2010-August 2020).

b- Statistical analyses of Na^+, Db, Level 3, (June 2010-August 2020).

c-1D Continuous wavelet analyses of Na^{+}, Mexh, (June 2010-August 2020).

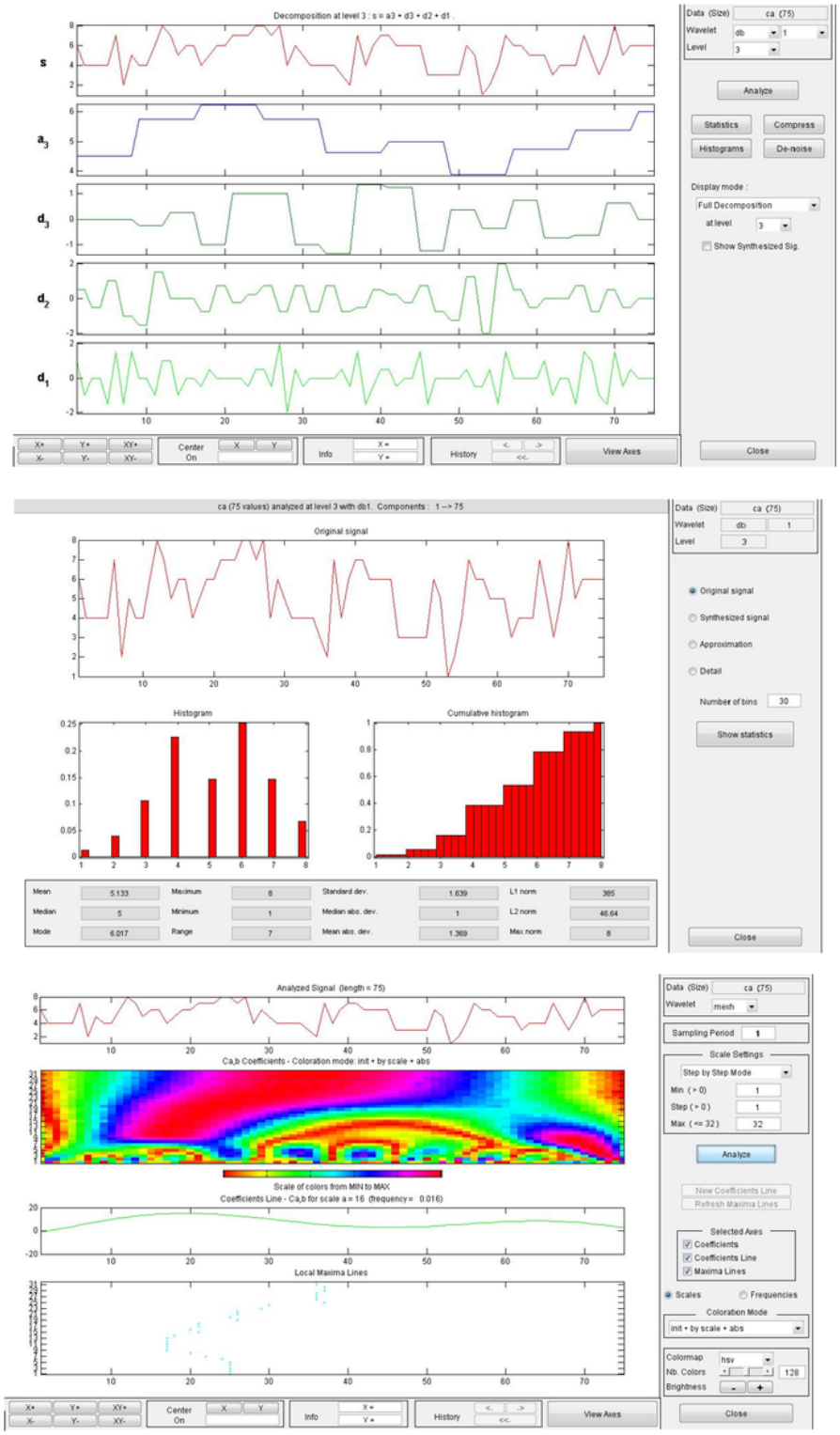

Figure 5

a- 1D wavelet analyses of Ca^{+2}, Db, Level 3, (June 2010-August 2020).

b- Statistical analyses of Ca^{+2}, Db, Level 3, (June 2010-August 2020).

c- 1D continuous wavelet analyses of Ca^{+2}, Mexh, (June 2010-August 2020).

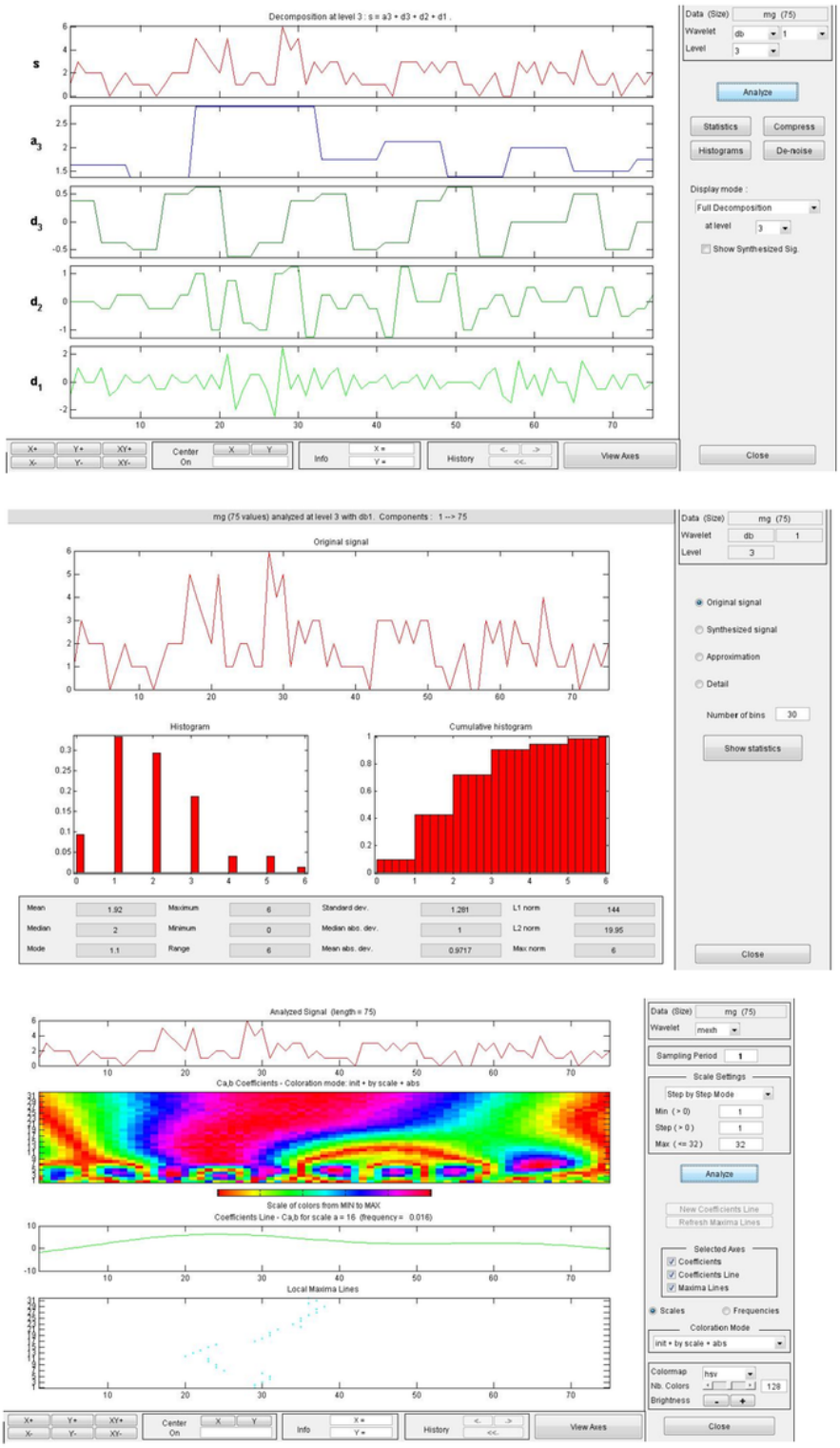

Figure 6

a-1D wavelet analyses of Mg^{+2}, Db, Level 3, (June 2010-August 2020).

b-Statistical analyses of Mg^{+2}, Db, Level 3, (June 2010-August 2020).

c-1D continuous wavelet analyses of Mg^{+2}, Mexh, (June 2010-August 2020).

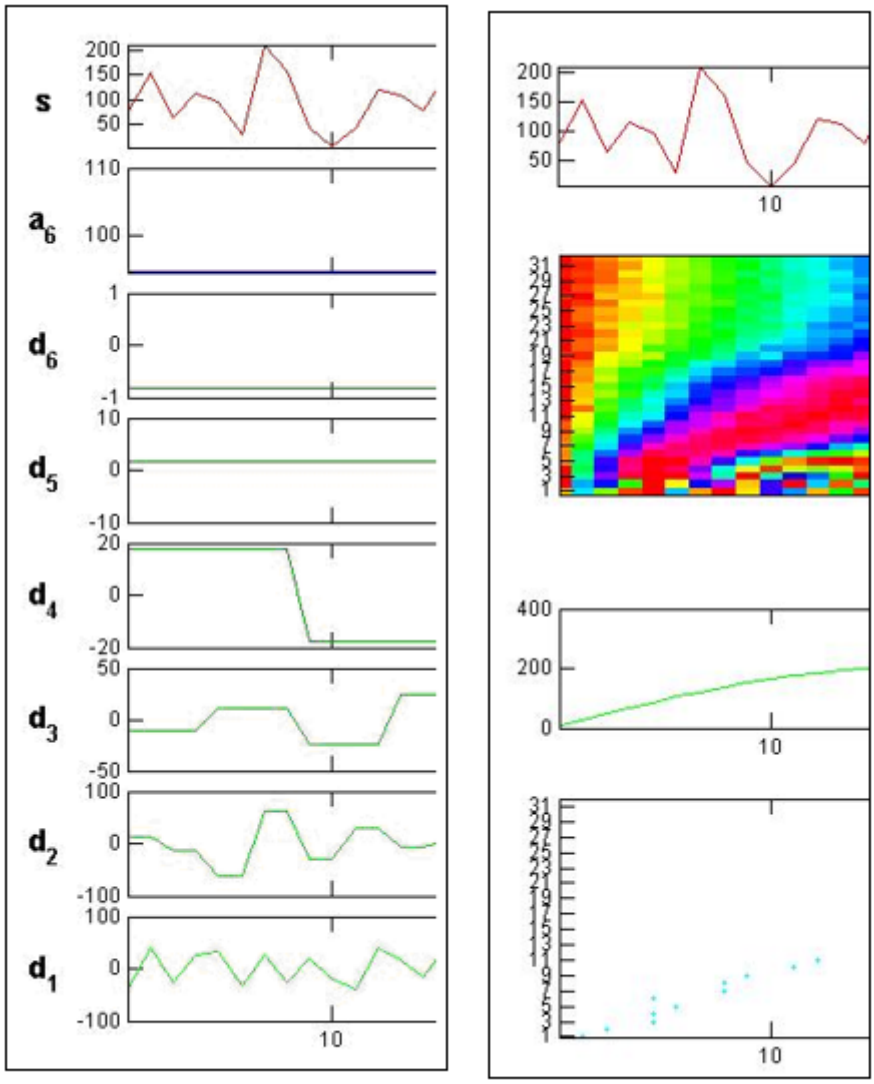

Figure 7

(a)- Monthly total rainfall rate, wavelet 1D, db, level 6,

(b)-Monthly total rainfall rate, continuous wavelet 1D, Mexh, sampling period:1