Master Thesis TVVR-13/5012
ISSN-1101-9824

Nonlinear Chaotic and Trend Analyses of Water Level at Urmia Lake, Iran

Does Climate Variability Explain Urmia Lake Depletion?

Sina Khatami

Water Resources Engineering Department
Lund Institute of Technology (LTH)
Lund University
Spring 2013

Avd för Teknisk Vattenresurslära
TVVR-13/5012
ISSN 1101-9824

Nonlinear Chaotic and Trend Analyses of Water Level at Urmia Lake, Iran

Does Climate Variability Explain Urmia Lake Depletion?

By: **Sina Khatami**

Supervisors: **Prof. Ronny Berndtsson**
Prof. Cintia B. Uvo

Examiner: **Prof. Magnus Persson**

Department of Water Resources Engineering
Lund University
Spring 2013

Visiting Address: **John Ericssons väg 1, V-huset, SE-223 63, Lund, Sweden**
Postal Address: **Box 118, S-221 00 Lund, Sweden**
Telephone: **+46 (0)46-222 4009; +46 (0)46-222 7398; +46 (0)46-222 8987**
Web page: http://www.tvrl.lth.se
E-mail: tvrl@tvrl.lth.se

Abstract

Urmia Lake is the largest habitat of *Artemia Urmiana* in the world located in an endorheic basin in northwest Iran. This shallow terminal lake has been designated as a Biosphere Reserve by UNESCO and a National Park under the 1971 Ramsar Convention. Currently, the entire lake's watershed is threatened due to its abrupt desiccation of more than 50% of its surface area and the concomitant increase of salinity during the last two decades. As the rapidly declining eco-environmental conditions have serious impacts on the socio-economy of the whole region, the drying of the lake is considered as a national threat. In light of the above, within the present study a holistic hydroclimatic analysis of the lake is conducted. The principal hypothesis of this research is that 'during *the recent years (1996-2012)*, there has been an *intrinsic change* in the dynamic of the lake water level *mainly due to human activities* which has had *deteriorating impacts* on the lake and its entire basin'. Therefore, water level variations, as the eco-hydrological indicator of this basin, are compared for the two periods of natural and anthropogenically intervened i.e. 1966-1995 and 1996-2012, respectively. The result of Mann-Kendall trend test, which has been used to identify the changes, shows that there is a unique decreasing trend of about -0.25 m/yr in average during the recent period of 1996-2012. Further, the nonlinear chaotic analysis of Correlation Dimension Method is employed in order to investigate the underlying dynamic of water level oscillations. The correlation exponent has decreased from 3 during the period of 1966-1995 to 2 during 1966-2012 implying that 1 governing variable of the lake's dynamic is missing! Pursuing the major cause of the recent desiccations, a multiple linear regression model is made based on the standardized monthly anomalies of the lake water level during 1966-1995 and the influencing teleconnection indices as predictors. For the months March and April as high season months and December as a low season month, water level variations have been modeled. Comparing modeled and observation time series shows that climate variability could explain about 35-40% of water level variations in the 1st period. For the 2nd period, nonetheless, only 11-14% of the variations in the high season (i.e. March and April) and 35% in December (low season) could be explained by climate variability i.e. natural causes. In view of the above and alluding to fact that extensive human activities in terms of climate change, land use changes, groundwater withdrawals, causeway, dam and other water diversion projects have occurred or have been intensified during the 2nd period, it could *inductively* be concluded that human activities are the major cause for the recent depletion of the lake. This result has been confirmed by previous paleolimnological studies as well. Afterwards, the salinity of the lake is modeled by means of regressions and the current salinity level of the lake is obtained to be more than 360 g/l. Eventual ecological consequences of the ongoing deteriorating conditions on the whole basin are discussed. Finally, after the critical review of previously proposed solutions, the project is closed by suggesting plausible possibilities for the restoration of the lake and its watershed towards a sustainable eco-socio-economic state, in terms of short- and long-term measurements.

Keywords: Hypersaline lake, Urmia Lake, Artemia Urmiana, Nonlinear time series analysis, Chaos Theory, Correlation Dimension Method, Man-Kendall trend test, Trend, Climate Variability, Hydroclimatology, Salinity, Secondary Salinization, Regressions

Recommended Citation

Khatami, S. (2013). Nonlinear Chaotic and Trend Analyses of Water Level at Urmia Lake, Iran. M.Sc. Thesis report: TVVR-13/5012, ISSN:1101-9824, Lund University, Lund, Sweden.

Acknowledgment

You realize how lucky you are when you come to know there are plenty of people that you need to acknowledge.

I would like to express my sincerest gratitude to my great advisers, Professors Ronny Berndtsson and Cintia B. Uvo. I enjoyed working with Ronny, not only because of his encyclopedic knowledge and his brilliant works on Chaos Theory but also for a far greater matter, his humble personality which I tried to learn from. Working with Cintia was also a delight. I am thankful for her motherly support all the way, the passion she gave me and her wonderful data analysis course where I learned critical thinking. I would also like to thank my examiner Professor Magnus Persson for his valuable comments and suggestions.

I am grateful for the time I have spent at Lund University and the chance of meeting great academics. I strongly believe that knowing Professors Rolf Larsson and Kaveh Madani was a huge turning point in my life. Rolf was the most influential teacher I ever had and he was an incredible mentor to me when it came to the philosophy of life. Kaveh's remarkable guidance and endless support not only improved this research but has also broadened my horizon in many ways.

I am thankful to my lovely friends and family in Sweden for their help, insights, and company during my journey in Lund. I would also like to thank my old buddies Meead Saberi, Hamidreza Hajinejad, Farhad Toosi, Siroos Raouf, Bahram Khazaee and Shahin Nik-Ayin for their endless support, motivation and presence even from kilometers away. They never let me feel far from home by energizing me with their calls and emails.

I would like to warmly thank my old hydrology teacher, Professor M.B. Sharifi back at home. I'm also thankful to Professors Mahdi Zarghami and Saeed Morid for their generous support in providing all the data and information I needed.

Last, but definitely not least, I'd like to heartily and deeply thank my greatest loves of my life, my parents, Hadi Khatami, Haleh Sharifi, my beloved brother, Kasra Khatami, and my dear Uncle, Hamed Sharifi, for bearing with me in all the ups and downs in my chaotic life and for their continuous love, patience, presence, and support which mean the world to me. I am nothing without you.

Sina

14 June 2013, Lund

Acronyms and Abbreviations

AMR	Annual Mean Runoff
ANN	Artificial Neural Network
ARMA	AutoRegressive Moving Average method
BCM	Billion Cubic Meters
CDM	Correlation Dimension Method
CV	Climate Variability
DOF	Degree of Freedom
GPA	Grassberger-Procaccia Algorithm
LSR	Least-Squares Regression
MASL	Meters Above mean Sea Level
MCM	Million Cubic Meters
MFE	Multistage Flash Evaporation
ODE	Ordinary Differential Equation
OLS	Ordinary Least Squares
PCC	Pearson Correlation Coefficient
RO	Reverse Osmosis
SA	Standardized Anomalies
SD	Standard Deviation
SL	Salinity Level
SMA	Standardized Monthly Anomalies
SMA-WL	Standardized Monthly Anomalies of the lake Water Level
SRCC	Spearman Rank Correlation Coefficient
SSA	Standardized Seasonal Anomalies
SSE	Square Sum of Errors
SSR	Regression Sum of Squares
SST	Sum of Square Errors
TDS	Total Dissolved Solids
TI	Teleconnection Indices
UL	Urmia Lake
WL	Water Level

Table of Contents

List of Figures

List of Tables

List of Equations

1 INTRODUCTION

Lakes as natural systems are sensitive indicators and recorders of the impact of natural and anthropogenic disturbances inside, or even outside, their drainage basins. In addition to their function as storage bodies, they are dynamic ecosystems in which a large range of dissolved and particulate substances sink. Therefore, they are one of the most fragile aquatic ecosystems. Beside their storage function, they provide a foundation for people's livelihoods as they support a great extent of biodiversity and are the source of food and recreation for humans. In view of the above, studying the impact of natural factors (e.g. climate variability) as well as human's interventions (e.g. water diversion and pollution) on these vulnerable systems are of high importance (Waiser & Robarts, 2009).

Saline lakes, nonetheless, have been perceived to be less important, of less utility and less abundant than their freshwater counterparts. Despite such misperceptions, they are distributed worldwide and as it is presented in Figure 1, saline lakes are counter-intuitively accounted for possessing only slightly a lower percentage of water level volume (0.008%) than fresh waters (0.009%) (Waiser & Robarts, 2009).

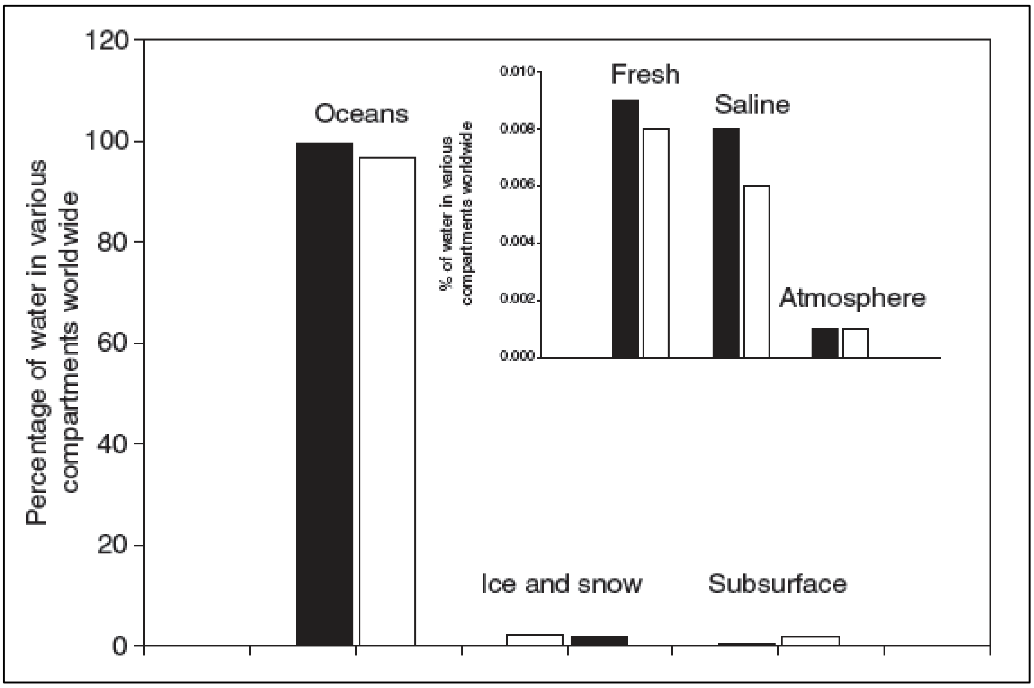


Figure 1. *Water percentage in various compartments worldwide (Waiser & Robarts, 2009)*

Based on two different sources presented as black bars (Wetzel, 1983) and white bars (Shiklomanov, 1990) in Figure 1, it could be seen that in terms of water volume, saline waters are inappreciably less than fresh waters. Except for drinking water purposes, due to their salinity rate, salt lakes are mainly of a high value as they have important uses for both society and their environment in semi-arid and arid regions of the world (Waiser & Robarts, 2009).

Urmia Lake (UL) as one the top-ten largest saline lakes in the world (Waiser & Robarts, 2009) is located in northwest Iran. It is, in fact, a hypersaline lake with a unique aquatic ecosystem for which it has been designated as a Biosphere Reserve by UNESCO and a National Park under the 1971 Ramsar Convention. The lake Water Level (WL) has plummeted about more than 6 m during the last 17 years due to a dramatic decline of its inflows which lead to a consequent increase in the salinity of the lake (from 166 g/l in 1995 to about 340 g/l in 2008) (Khatami & Berndtsson, 2013). Generally, freshwater species have a limited flexibility for outranged salinity level and there are not many species that can survive saline systems especially extreme ones e.g. hypersaline lakes. Therefore, salinity level in saline systems is a determining ecological indicator (Waiser & Robarts, 2009). As a result, the entire lake's ecology is threatened by its recent changes.

Desiccation of Urmia Lake is, indeed, a socio-economic-hydrologic-ecologic problem (Khatami & Berndtsson, 2013). The lake has a significant sociologic feature in the region due to its cultural and recreational value for the residents adjacent to the lake. The lake could also be seen as an economic resource since it is a rich source of shrimps. Moreover, it could be utilized for tourism and recreational purposes. Saline lakes are sources of evaporitic minerals such as NaCl which are widely used in chemical industries, agricultural activities, manufacturing, construction and medicine (Waiser & Robarts, 2009). Urmia Lake is the ecological indicator of its own basin for its unique but fragile ecosystem which is due to the sensitive pyramid food chain of this hypersaline system. And finally it is a vital hydrological subsystem since it is the terminal in which all inflowing rivers sinks.

The issue of desiccation due to anthropogenic interventions is an ongoing global challenge which has affected different environmental systems in different scales and to different extents. Comparing the current status of the lake to the 80s (see Figure 2) markedly shows the extent of this unfortunate but ongoing environmental disaster and the importance of a comprehensive study. Prior to its depletion, Urmia Lake was the 6th largest saline lake in the world (Waiser & Robarts, 2009) by the average surface area of about 5500 km^2 (UNEP and GEAS, 2012). Landsat satellite observations, however, show that more than 50% of the lake surface area has been desiccated during the last two decades and its surface area has shrunk to less than 2500 km^2 (UNEP and GEAS, 2012). It well elaborates the importance of this issue and why such a strong emphasis has been placed on this issue as a motivation for this project.

Figure 2. *Satellite images of recent changes in Urmia Lake's surface area and its surroundings, comparing 1984 with 2012 (Google Earth Engine, 2012)*

1.1. Objectives & Scope

Drought and desiccation of closed water bodies – lakes – are serious global issues. Anthropogenic interventions such as water diversion, damming and overwhelming groundwater withdrawals have intensified the impact of climate change and global warming. There are plenty of different examples both in saline and freshwater lakes that are subjected to serious drought. This has led to their desiccation and the consequent change of the socio-economy and ecology of their sensitive environments.

Essentially, this project is intended to answer the following questions:

1. Are there significant changes in the lake WL fluctuations?
2. How crucial are these changes and therefore the current condition of the lake?
3. What is the major cause of these changes, human activities or natural causes?
4. What are the consequences of the lake water level changes on its basin and ecosystem?

Although the general outline of this study is presented here, the description of the research hypotheses and their testability are comprehensively discussed in Methods section (see Chapter 4).

In a nutshell, this study attempts to review the state of the art of knowledge for the lake's background. In order to be able to analyze the current state of UL basin or to propose realistic and feasible solutions for mitigating the ongoing crisis, a comprehensive study on the lake's background is required. Although state-of-the-art-reviews are the founding block of any research project, such studies have not been done on this basin. After the background review, water level fluctuations of the lake will be examined from the viewpoint of both nonlinear chaotic and trends analysis. Finding the origin of the recent changes is of utmost importance for the policy making and water management of the basin. As there is an ongoing debate on the role of climate variability on WL variations, a climatic analysis is also conducted investigating the relationship between the lake water level and teleconnection indices in order to see whether climate variability has a significant role in the recent changes, and if so, to what extent. Afterwards, due to the lack of access to salinity data and its immense ecological importance, monthly salinity rate is modeled by means of regressions in order to estimate its current level. The project is closed by discussing the restoration measures that have been suggested so far and then proposing plausible solutions that have been applied in other similar cases.

2 STUDY AREA & BACKGROUND

Urmia or Oroumieh Lake (formerly known as Lake Rezaiyeh) is a shallow terminal lake located in northwest Iran, near Turkey, and is one of the largest permanent lakes in the Middle East, a region with arid and hot climate. It is situated in the heart of two neighboring provinces of West Azarbaijan and East Azarbaijan at latitude 37°00' to 38°12' N, and longitude 44°40' to 45°50' E (UNESCO, 2001) in the west of the Iranian Plateau (see Figure 3).

Figure 3. *Iran located in the Middle East region (Google Maps, 2012)*

Urmia Lake is the largest permanent lake, in terms of surface area, in Middle East (excluding Caspian Sea) with a total catchment area of about 51762 km^2 including the lake itself covering about 3% of the country. Prior to its desiccation, the surface area of the lake used to be about 5822 km^2, comprising about 7% of total surface water in Iran (Eimanifar & Mohebbi, 2007) which has depleted to about less than 2500 km^2 during the last 17 years (UNEP and GEAS, 2012). Its length is varying between 130 to 146 km and its width between 58 to 15 km. The surface area of the lake is directly related to its depth which varies in the range of 5-16 m and its volume is about 25 km^3 (Waiser & Robarts, 2009). However, the depth of the lake has decreased for about 6 m during the last 17 years.

2.1. Climatic Zone

Saline lakes are mainly between 30°N to 53°N in the Northern Hemisphere and 3°N to 42°S in the Southern Hemisphere. They often occur in arid and semi-arid climatic zones with the mean annual precipitation of 25-200 mm and 200-500 mm, respectively, where net evaporation exceeds precipitation. Hydrologically speaking, these lakes are located in endorheic or closed basins. Therefore, they are the termini of inland drainage basins i.e. there is no outflow but evaporation. As Figure 4 shows, such endorheic drainage basins cover approximately 10% of the Earth surface area (Waiser & Robarts, 2009).

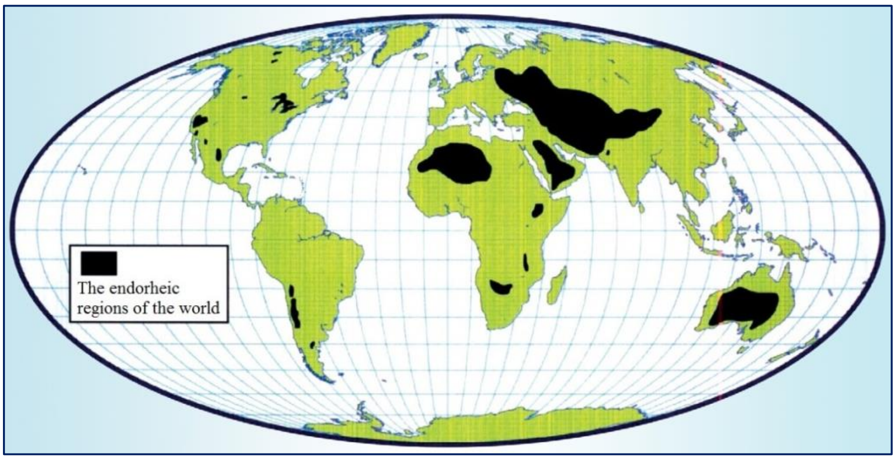


Figure 4. *Endorheic drainage basins of the world (Waiser & Robarts, 2009)*

Urmia Lake catchment, according to the Global Bioclimatic Classification System, is in a Mediterranean pluviseasonal–continental climate (Rivas-Martínez, et al., 1999). Mean annual precipitation and temperature in this watershed are 341 mm and 11.2 $°C$, respectively, while mean maximum and minimum temperatures occur in July (23.9 $°C$) and January (-2.5 $°C$), respectively (Djamali, et al., 2008). The Lake is located in an arid and semi-arid climatic zone where the extreme temperature observed during the last 30 years are -33 $°C$ and +44 $°C$ with the annual mean temperature of 11 $°C$ (West Azarbaijan Regional Water Authority, 2013b). In view of the above, being situated in arid and semi-arid endorheic basins make UL as a saline lake to be extremely responsive to climate. That is, during low seasons and/or drought, the water level declines and consequently, the lake volume decreases markedly. These series of events concomitantly raise the salinity rate.

2.2. Topography

Saline lakes are mostly found between about 400 to 1500 $masl$ (Waiser & Robarts, 2009). As it could be seen in Figure 5, lake basin's elevation is varying between 1270 to 1278 $masl$ (Iran's wetlands data base, 2013). Topography together with climate has a determining role in the hydrology of the lake and its whole basin. Moreover, topography of the basin plays an important role in its climatic condition as the continental climate of this basin is affected by its surrounding mountains (Kelts & Shahrabi, 1986).

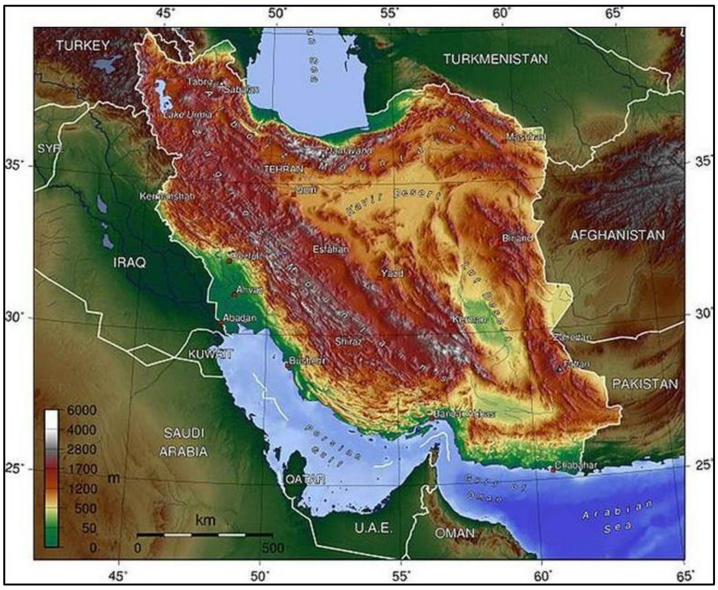


Figure 5. *Topography of Iran*

Being subjected to air mass coming from Black Sea, Mediterranean Sea and Atlantic Ocean along with the existence of Zagros Mountains in the south and southwest and Mountains of Ararat at its northern parts, cause great deals of precipitation in this region. It eventually gives rise to large permanent rivers in this basin (West Azarbaijan Regional Water Authority, 2013b).

2.3. Population

Saline lakes are often close to large population centers (Waiser & Robarts, 2009). Northwest Iran, where the Urmia Lake is located, is rather densely populated by the population density of about 71-88 persons per square kilometers (see Figure 6).

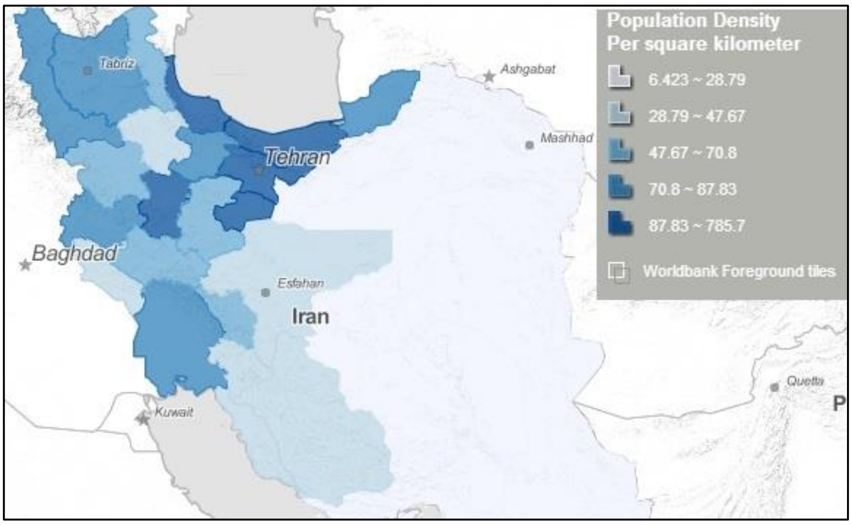


Figure 6. *Population density of Iran (The World Bank, 2012)*

This catchment has a population of more than two million (West Azarbaijan Regional Water Authority, 2012a; Statistical Centre of Iran, 2012) residing in two provinces of West and East Azarbaijan. Urmia, capital of West Azarbaijan province, is the closest city to the lake, with the population of about 667,499 on the west shore of the lake. Tabriz, the capital of East Azarbaijan, located on the eastern side of the lake, is the second largest city close to the lake with a population of about 1,494,998 (Statistical Centre of Iran, 2012).

2.4. Rivers

In order to collect information on rivers and dams, multiple sources have been used. These sources have been compared for the verification of their information and finally the most important ones are presented synthesizing these sources (Ghaheri et al., 1999; MPO, 2005; Ministry of Energy, 2007; Eimanifar & Mohebbi, 2007; Karbassi et al., 2010; Jame Jam, 2010; Khabar Online, 2011; WARW Information System, 2012; West Azarbaijan Regional Water Authority, 2013a; West Azarbaijan Regional Water Authority, 2013c; Iran Water Resources Management Company, 2013).

It has been admitted that the inflowing rivers are the vital life lines of the lake and its basin (West Azarbaijan Provincial Government, 2011). The lake is fed by 14 permanent and 7 seasonal rivers together with about 39 episodic streams. Prior to the lake's drying, annually about 5500 million cubic meters (MCM) of the lake's water came from 14 major rivers, 1500 MCM from precipitation, and 500 MCM from floodwaters which were flowing to the lake; hence the total inflow to the lake was about 6900 MCM/yr. There are about 11 major rivers (see Table 1) in the lake catchment among which Zarrineh Rood and Simineh Rood are respectively the largest rivers in this basin in terms of annual mean runoff (AMR) with the corresponding annual discharge of 1642 and 503 MCM.

Table 1. *Major rivers in Urmia Lake watershed*

River	River Length (km)	River Basin Area (km^2)	Annual Mean Runoff (MCM)
Zarrineh Rood	340	11897	1642
Simineh Rood	145	3656	503
Aji Chai	77	7432	434
Gadar Rood	100	2137	425
Nazlou River	85	2267	399
Mahabad Chai	80	152	351
Barandouz Rood	70	1318	268
Shahar Chai	70	720	260
Zola River	84	2090	140
Sofi Chai	55	754	135
Rowzeh River	51	453	41

Contrary to most regions in Iran, which suffer from fresh water scarcity, northwest and in particular West Azarbaijan province possess rich sources of fresh water. These rivers are the main water supply for agricultural activities in the region. Most rivers in this catchment flow in its southern part (see Figure 7). Thus, there is an expected continuous flow from its south end to the north.

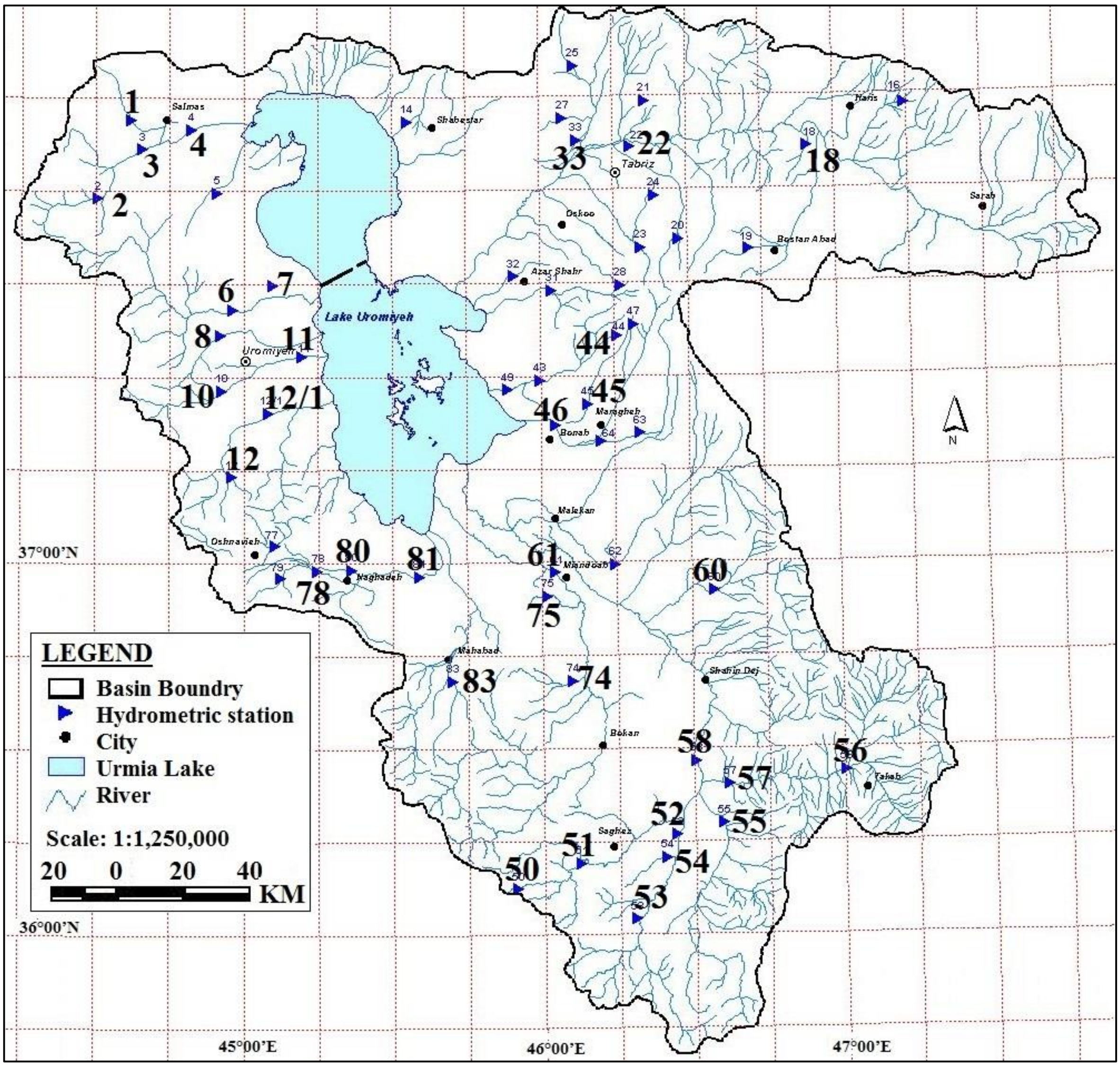


Figure 7. *Main Rivers in the Urmia Lake watershed (MPO, 2005)*

As it could be seen from the Figure 7, southern inflowing rivers such as Zarrineh Rood (58 & 61) and Simineh Rood (74 & 75) have larger drainage basins as well as discharges (see Table 1). As Figure 7 presents, there are more than 80 rivers in the lake basin. Information on annual mean discharge, total dissolved solid (TDS) and sediment load for Major rivers in this watershed – with the annual discharge greater than about 40 MCM – are presented in Table 2. Also, the complete information on almost all the rivers of this watershed could be found in Table 20 (see Appendix 1).

Table 2. *Major rivers in Urmia Lake catchment (MPO, 2005)*

River	Code	Station	Annual Mean Runoff (*MCM*)	TDS (*g/l*)		Sediment Load (*Ton/yr*)
				Min	Max	
Derik Chai	1	Nazar Abad	39	_	_	19700
Zola River (Zola Chai)	2	Chahriq Olia	142	199	363	185000
	3	Yalghouz Aghaj	63	_	_	_
	4	Pol-darvish	58	_	_	_
Nazlou River (Nazlou Chai)	6	Tapic	399	214	400	574500
	7	Abajaloo	243	_	_	_
Rowzeh Chai	8	Kalhor	39	208	365	66000
Shahar Chai	10	Mirabad	184	90	310	320000
	11	Keshteeban	91	_	_	_
Barandooz Cahi	12	Dizaj	293	175	230	295600
	12/1	Babarood	265	_	_	_
Aji Chai	18	Saransar	141	210	3242	47000
	22	Veniar	444	780	20560	2512000
	33	Pol-e-Davazdah	434	_	_	_
Sofi Chai	44	Tazeh Kand	135	75	405	147800
	45	Maragheh	96	85	410	180200
	46	Bonab	47	120	411	37500
Saghez Chai	50	Ghabghabloo	326	115	295	116500
	51	Dash-Aloochely	366	126	295	_
	52	Panbehdan	407	115	386	341000
Jighato Chai	53	Pol-e-Hasan	470	150	420	_
	54	Pol-e-Anian	627	115	225	299000
Khorkhoreh Chai	55	Karim Abad	278	150	285	150000
Saroogh Chai	56	Pol-e-Sarouq	226	183	488	115400
	57	Safakhaneh	368	230	507	919000
Zarrineh Rood	58	Sari Ghamish	1729	165	325	344000
	61	Pol-e-Miandoab	1996	145	795	_
Ajorloo Chai	60	162	195	390	238100	
Simineh Rood	74	Dashband	555	132	618	839460
	75	Pol-e-Miandoab	630	161	500	_
Gadar Chai	78	Pay Ghaleh	295	100	205	164300
	80	Naghadeh	389	105	378	553100
	81	Pol-e-Bahramlou	385	185	595	_
Mahabad Chai	83	Baitass	56	155	285	57100

It has to be noted that the values of annual mean runoff presented in Table 2 have a slight difference from values in Table 1. It is due to the fact that different sources consider different historical records in their calculations.

2.5. Dams

In total, there are 107 dams in Urmia Lake basin, among which 57 are in operation, 9 under construction and the other 41 under study for future planning (Iran Water Resources Management Company, 2013). The main reason for damming the inflowing rivers to the lake is to supply irrigation water for agricultural activities as the growing population in this area raises the need for food.

As agricultural activities are the main source of income in the region and in order to address the future demands of the increasing population, dam construction and water diversion projects are increasing. There are numerous ongoing projects together with many other projects, which will be soon initiated, addressing the growing population and its need for water and food (see Figure 8).

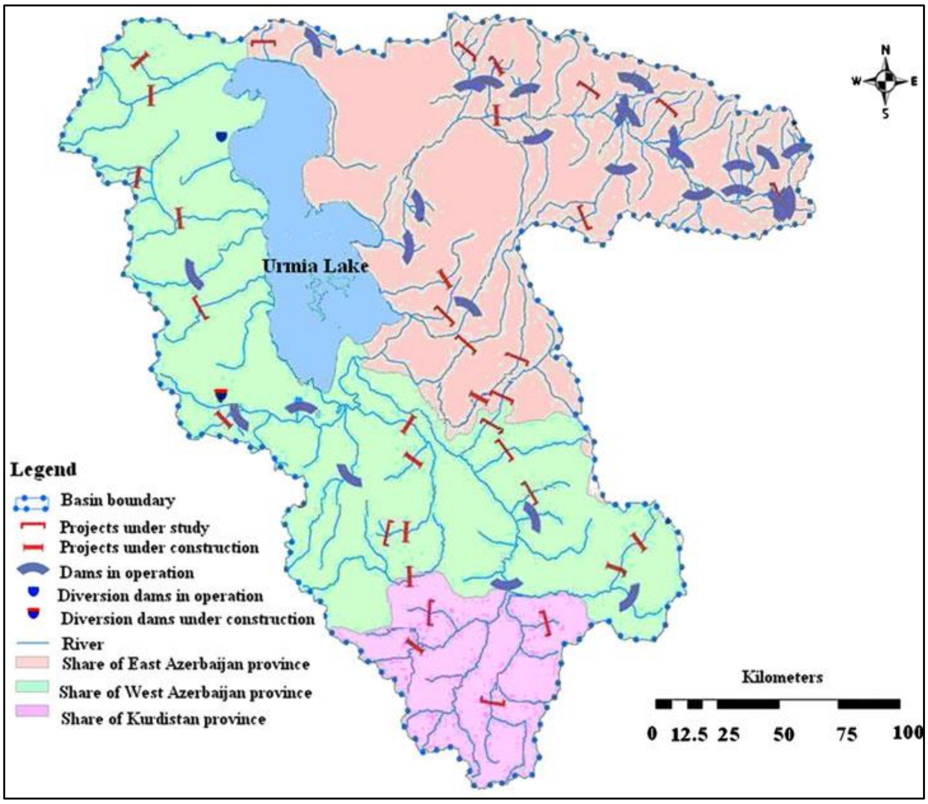


Figure 8. *Schematic map of inflowing rivers and most important water diversion projects in Urmia Lake's catchment (Hassanzadeh, et al., 2011)*

Detailed information of the main operating and construing dam projects within the Urmia Lake basin is presented in Table 3. Projects which are located in West and East Azarbaijan provinces are denoted respectively as (WA) and (EA) in the last column. Also, the name of the river on which the dam has been built, is bolded in the same column.

Table 3. *Major dams at Urmia Lake watershed*

Dam name	Starting	Ending	Physical progress (%) 2011	Physical progress (%) 2012	Storage Capacity (*MCM/yr*)	Irrigation (*MCM/yr*)	Drinking & industry (*MCM/yr*)	Irrigation & drainage network (*ha*)	Purpose/Notes
Martyr Kazemi	1968 2002	1971 2005	–	–	650 +232	–	–	55000	(WA) On **Zarrineh Rood** and close to Bukan City providing drinking water for Bukan, Miandoab and part of Tabriz cities together with fishing and irrigation purposes; The capacity of the dam has been increased by increasing its height for electricity production purposes
Simineh Rood	2005	2017	_	10	364	269	37.5	31300	(WA) On **Simineh Rood** close to Bukan City for irrigation, drinking and electricity production purposes
Martyr Madani	1995	2011	_	_	361.2	_	_	25000	(EA) On **Aji Chai River** behind hills of Tabriz City for irrigation purposes
Shahar Chai	1994	2012	99	99	220.3	132	67	12500	(WA) Constructing a reservoir on **Shahar Chai River**, 12 *km* to the southwest of Urmia City, for the purposes of drinking water and irrigation water for about 12500 *ha* farm fields
Mahabad	1968	1971	_	_	197.8	_	_	_	(WA) On **Mahabad River** and close to Mahabad City for irrigation, drinking and electricity production purposes
Nazlou	2005	2017	11	31.3	170	317	38	43100	(WA) Constructing a reservoir on **Nazlou River**, 26 *km* to the Northwest of Urmia city, for irrigation, drinking and electricity production purposes at northern parts of Urmia Plain
Dirik	2004	2010	87	99	170	34.2	_	6000	(WA) Constructing a reservoir on **Dirik River**, 12 *km* to the west of Salmas County
Chir Abad (Oshnavieh)	2002	2013	69	77.4	127	137	_	19200	(WA) Constructing a reservoir on **Kanirash Rood**, an upper tributaries of the Gadar Rood, for irrigation purposes at Oshnavieh County
Hasanlou	1990	1999	_	_	94.4	_	_	16627	Close to Naghdeh City and on **Gadar Chai** for irrigational purposes
Barandooz	2009	2016	_	74.6	91.5	_	30	_	(WA) On **Barandooz Chai** close to Mahabad City for drinking and irrigation purposes; Adjusting 270 *MCM/yr*
Zola dam	2000	2009	68	99	85	132	13	15800	(WA) Constructing a reservoir on **Zola River** for irrigation and drinking purposes at Salmas County
Silveh	2007	2014	45.5	71.2	74.6	183	10.8	9400	(WA) Constructing a reservoir on **Lavin River** for irrigation and drinking water purposes at Piranshahr County, also transferring about 95.2 *MCM/year* to to Chir Abad dam
Alavian	1990	1995	_	_	60	_	_	1100	(EA)On **Sofi Chai River** close to Maragheh City for irrigation, drinking and electricity production purposes
Saroogh	2003	2012	95	99	40.1	41.2	10.3	5500	(WA) Constructing a reservoir on **Saroogh River**, a tributary of Zarineh Rood rises from Takab County hills, for irrigation, drinking water and industry at Takab County purposes
Martyr Ghanbari	2000	2012	99.9	99.9	26.5	28.7	_	5000	(WA) Constructing a reservoir on **Sariso International River** (between Iran and Turkey) for irrigation purposes at Maku County
Tabriz Amand Amand I Baftan Gavdosh Abad	1983 1994 1989 1981	1985 1999 1993 1982	–	–	6 2.5 2.4 0.25	–	–	–	(EA) All dams are on **Aji Chai**, mainly for irrigation purposes

Major dams with storage capacities of more than 90 MCM/yr have been constructed on the southern and south-western sides of the lake where there has been an expansion in agricultural fields and activities (see Section 2.6) during the last decades. Nevertheless, there are plenty but smaller dams constructed on the eastern side i.e. East Azarbaijan Province. Although the storage capacities of these dams are not usually greater than 5 $MCM/yr,$ the water balance of the lake is apparently disturbed since there are plenty of these dams on the inflows. Such overwhelming pressure on the lake and its related water resources has a great impact on the whole basin.

Massive dam constructions in this basin, as the main source of the lake drying, have been reported in many official news agencies interviewing several environmental experts (Tabnak, 2011). Apart from what is mentioned in Table 3 as only the major projects, there are numerous other water diversion projects funded by local farmers. There are, also, several other projects which are planned by water management authorities within this basin for the future. For instance, at present, there are 275 projects under study and 231 of these have been approved and will be initiated in near future (see Figure 8) (Hassanzadeh, et al., 2011).

2.6. Land Use

Land use changes from rangeland and forest to agriculture and orchard and their consequential hydrologic and environmental impacts in different basins in Iran have been widely studied (e.g. Emadi et al., 2008; Emadi et al., 2009; Ghaffari et al., 2010; Khalighi Sigaroodi & Ebrahimi, 2010). Being subjected to such changes, UL basin was no exception. For example, satellite images, historical aerial photos and field observations have been used to investigate Barandooz Chai basin which comprises 7 sub-basins as presented in Figure 9 (Khalighi & Ebrahimi, 2010).

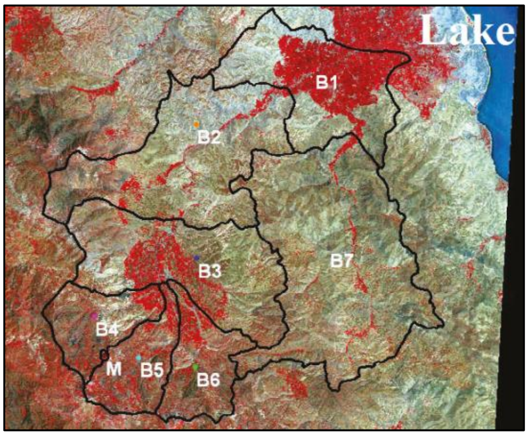


Figure 9. *Barandooz Chai basin (Khalighi & Ebrahimi, 2010)*

The study by Khalighi & Ebrahimi (2010) demonstrates that from 1955 to 2006 about 14% of rangeland is changed into dry-farming area and about 7% of irrigated farming is transformed to orchards (see Figure 10).

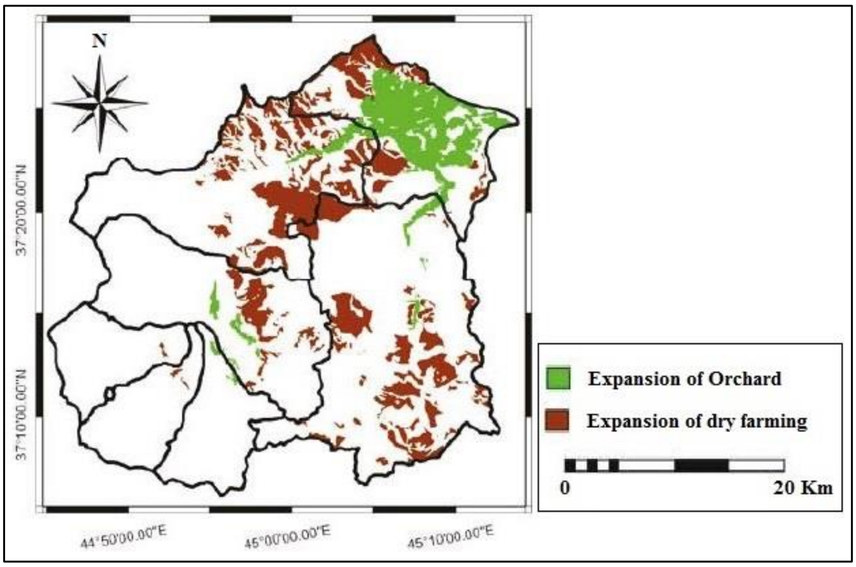


Figure 10. *Land use changes in Barandooz Chai sub-basins (Khalighi & Ebrahimi, 2010)*

Although their result shows that the mentioned land use changes have not affected the mean annual discharge but the maximum and minimum daily discharges have increased and decreased, correspondingly. And they concluded that continuing this situation may cause the ground water level to decay, and it ultimately increases water salinity of the Lake. This study is only an instance of several land use changes in UL catchment. Despite the fact that there is an intense pressure on the lake and the river systems within its basin, agricultural lands are increasing (Figure 11) due to a short-sighted management.

Figure 11. *Urmia Lake and schematic land use in its basin (ISS EarthKAM, 2007)*

Saline lakes are sensitive systems where changes in land use patterns within their basin, can remarkably decrease their water level (Waiser & Robarts, 2009). Although land use changes may not seemingly affect the surface water regime as it is discussed by Khalighi & Ebrahimi (2010), but it will definitely change the water demand in the basin; the more agricultural land you have, the more water will be needed. This increases the stress on the limited water supply in this region and consequently, intensifies the crucial ongoing situation. Not just the ecosystem could be damaged by an unthoughtful and inconsiderate land use change but the socio-economy of the region will also be impacted by such changes as they are interrelated systems.

2.7. Causeway

The lake is divided into southern and northern parts by the 15-km Martyr Kalantari causeway with an unbridged gap of 1276 m (see Figure 11). It is, so far, the largest and longest bridge project in Iran. The causeway is constructed across the lake, facilitating communication between east (Tabriz City) and west (Urmia City) of the lake by reducing the driving distance between these two major cities to approximately 130 km (West Azarbaijan Province Portal, 2012). The project was initiated in 1979 (Teimouri, 1998) and a floating bridge was constructed in 1980. On January 21st 2004, ground operations were started and on January 21st 2005, in-lake operations were launched and the project was finally completed in 2008. Table 4 presents the project's timeline:

Table 4. *Martyr Kalantari causeway (West Azarbaijan Province Portal, 2012)*

Construction Stage	Filling Activities	Floating Bridge	Onshore Activities	Offshore Activities	Completed
Starting Date	1979	1989	2004	2005	Nov. 2008

Although, simulation studies (Zeinoddini, et al., 2009) claim that the causeway has no significant influence on the lake's flow and salinity regime, such results have never been verified by any other studies. Opposing to this result, it has been stated (Khosravifard, 2010) that the 1276-m gap in the causeway is not sufficiently wide to allow adequate flow between the two parts of the lake; the embankment created for the causeway prevents the natural flow of water in the lake. Therefore, lake circulation needs more sophisticated modeling to study the effect of the causeway in the lake's salinity regime and rates in order to see whether further openings are needed or not.

2.8. Groundwater

The groundwater situation in this watershed is rather unclear. Although it is one of the major uncertainties in this region, it is probably an influential factor as groundwater, in general, discharges from the catchment areas to the lake. Pumping is also extensive over the catchment and that possibly affects the total inflow of groundwater to the lake. Groundwater withdrawal is estimated to be around

1200 MCM/yr. Due to such intense withdrawals, permission to drill new wells and groundwater pumping has been ceased in many regions within the lake's basin (West Azarbaijan Regional Water Authority, 2012b).However, still about 20,000 illegal wells in the lake basin have been reported (Hamshahri, 2013).

2.9. Evaporation

Inflows to the lake are precipitation and inflowing rivers and as a terminal lake, there are no outflows from the lake other than evaporation (excluding possible groundwater exchanges). In Urmia Lake basin, annual evaporation rate is about 1500 mm/yr while the annual precipitation rate is less than 300 mm/yr (West Azarbaijan Regional Water Authority, 2013a). During the past two decades, massive dam construction and water diversion projects on the one hand and decrease in precipitation for about 17% together with increase in temperature by about 7% (Hassanzadeh, et al., 2011) on the other hand, had a decisive impact on the lake water level. However, no study has so far investigated the influence of these factors on the lake WL separately.

Evaporation as the only output of the system – excluding groundwater exchange – plays an important role in the lake's WL fluctuations. The underlying dynamic of the lake evaporation has been investigated (Farzin, et al., 2012) and evidence of low-dimensional correlation (2.47) as a sign of chaotic behavior has been reported.

Nevertheless, Farzin et al. (2012) ignores the distinction between freshwater and salt water evaporation in their prediction of the lake evaporation. Theoretically, under given meteorological conditions, the evaporation rate of salt water descends as the salinity increases. Dissolved solids i.e. salinity, lower the water vapour pressure. The evaporation process is governed by its energy balance. Vapour pressure decreases as less energy is permitted to escape as latent heat of vaporization due to salinity. It, therefore, causes the sensible heat to rise, i.e., the temperature increases. Warmer saline water will adversely exchange sensible heat and long-wave radiation between atmosphere and its surface. The consequent shift in energy balance towards greater losses makes the evaporation rate of brines lower than fresh or less saline waters exposed to the same meteorological conditions (Bonython, 1965).

Moreover, in case of Urmia Lake, the extent to which evaporation contributes to water level depletion during recent years in comparison with other involving factors e.g. dam construction, water diversion projects and the causeway, is under question. A comprehensive hydroclimatic study is highly needed in order to rank the aforementioned factors in terms of their influence on the water level decline considering low and high seasons together with future scenarios investigating the impact of climate change on these factors and ultimately on the lake WL. Such studies could be highly beneficial for the restoration of the lake or future water resources allocation and management in this basin.

2.10. Water Level

Water Level data used in the present study are observed at Golmankhane station (37°36 'N, 45°16'E). Average daily water level fluctuations from January 1966 to July 2012 are presented in Figure 12:

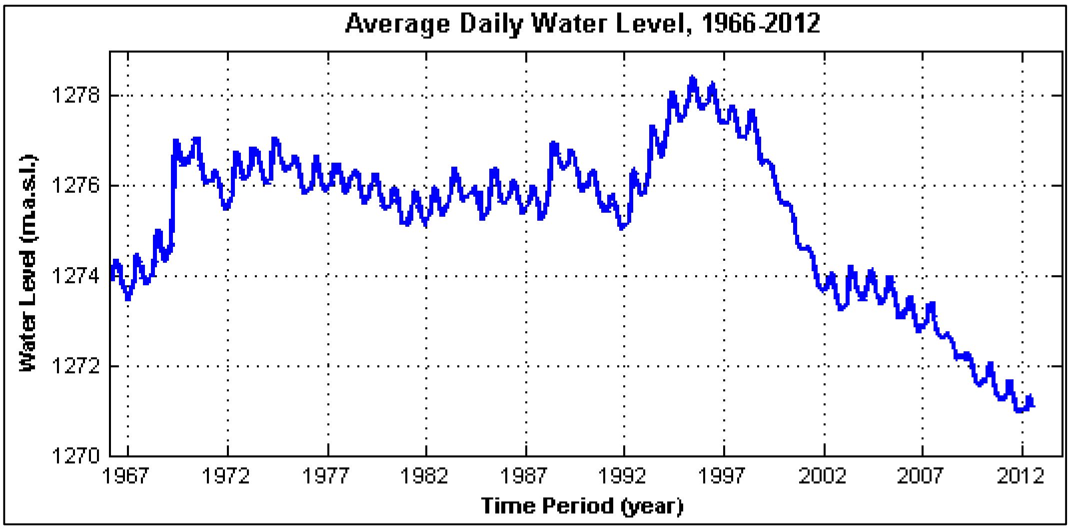


Figure 12. *Daily Water Level, measured at Golmankhaneh station, 1966-2012*

It is quite evident that there is a significant decreasing trend during the past 17 years (1966-2012) in the lake WL. Generally, during this period, water level has declined about 7 m which is quite a substantial decrease value for a shallow lake with a depth ranging between 5-15 m. WL in the lake has fallen about 2.5 m below the 30-year historical daily minimum (i.e. 1273.47 $masl$ in Dec. 1966). The lowest WL recorded is 1270.95 $masl$ in July 2012. Due to such dramatic decline, the surface area of the lake has decreased from 5500 km^2 in the past century to less than 2500 km^2 during the past two decades. This simply but sadly means that more than 50% of the lake surface area has been desiccated during the past two decades (UNEP and GEAS, 2012).

A simple frequency analysis on the monthly WL values during the period of 1966-2011 has been done in order to identify months in which low and high lake level has been recorded in each year.

Table 5. *Frequency analysis of low & high monthly WL during the 46 years of 1966-2011*

	Max lake WL				**Min lake WL**			
Month	March	April	May	June	October	November	December	January
1st period	0	1	14	15	3	5	7	15
2nd period	2	3	10	1	4	1	10	1
Total	2	4	24	16	7	6	17	16

As it could be understood from Table 5, low WL season is from October to January (mid-Fall to mid-Winter) and high WL season is from March to June (Spring to mid-Summer). From Table 5, it is obvious that during the first period lake's low WL occurs from mid- Fall to mid-Winter with having a climax in January. Interestingly, during the second period, there is a shift from January to December in terms of the most frequent low WL occurrence. There is the same shift in the high level season comparing the same two periods from June to May. It has to be noted that year 2012 is excluded from the frequency analysis presented in Table 5 since the available data only comprises the records of WL during the first 6 months in 2012.

Water level in the lake oscillates between the two extremes of low and high (usually in Spring and Summer, respectively) levels. In the most extreme case in 1969, water level varied about 2.32 m between low and high months. In average, however, WL varies for about 0.86 m between extreme months during a year. Annual range of this variation throughout the period of 1966-2012 is presented below in Figure 13:

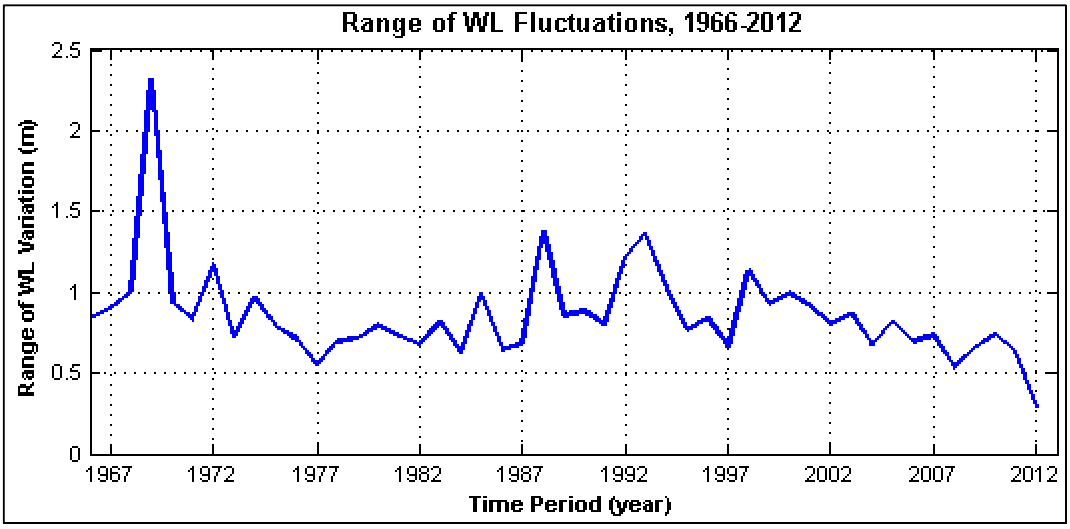


Figure 13. *Range of water level variations between max and min WL in each year, 1966-2012*

It could be understood from Figure 13 that during the early decades, there were more variation in the range with no observable trend. However, during the recent years, the range of water level fluctuations has had a decreasing trend (starting from 1998) with less variation between following years. This could be seen as an indication of a more regulated water level at the lake due to human activities such as dammed inflows and water diversion projects. Therefore, the natural seasonality – variation between low and high water levels – of the inflows is not reflected in the lake water level oscillations as it used to be the case in the historical records.

2.11. Ecology

Generally, few species could be found in saline environments with a salinity greater than 1000 mg/l. At lower concentrations, organisms show flexibility and tend to adapt to various ion combinations.

Nevertheless, as salinity rises, such flexibilities disappear. This is due to the fact that *osmoregulatory* stress on endemic organisms will be exerted at higher salinity levels. Osmotic regulation or osmoregulation refers to the internal regulation of the cell environment corresponding to the concentration in the external environment across a semi-permeable membrane known as cell membrane. Therefore, organisms adapt to life in saline environments by accumulating organic solutes within their cells. In order to maintain properly functioning tissues, a great deal of energy should be expended. If cell tissues fail to function properly, cells would ultimately die as the water moves across the cell membrane to the surrounding saline water (osmosis) attempting to equalize the salt concentration. Due to such a high energy consumption in osmoregulation halophiles – organisms need a salt-rich environment to grow in – can survive saline lakes which can produce energy in other ways (e.g., through photosynthesis). The green alga *Dunaliella*, for instance, is present in hypersaline environments worldwide as the main or sole primary producer (Waiser & Robarts, 2009).

Saline lakes, despite such crucially sensitive environments, are important nesting, feeding, breeding and staging areas for all types of waterbirds around the world. They are renowned seasonal habitats for pink flamingoes during their migration season. Lake Natron, for example, has the highest concentration of flamingos in East Africa (Waiser & Robarts, 2009).

After Anzali lagoon, Urmia Lake National Park is the most important natural fauna habitat in Iran (see Figure 14). There are about 102 islands within the lake (West Azarbaijan Regional Water Authority, 2012b) and its wildlife is composed of about 27 mammal species, 212 bird species, 41 reptile species, 7 amphibian species, and 26 fish species (Rezvantalab & Amrollahi, 2011). They are all dependent on the lake and the surrounding wetlands. These values are apparently outdated as the lake desiccation has affected its entire ecosystem. For one thing, many of these islands are not any more within the lake due to its substantial shrinkage in recent years.

Also, Urmia Lake is one of the largest natural habitats of a unique brine shrimp, a crustacean, called *Artemia Urmiana*. The most predominant eco-environmental feature of the lake is the dependence of migratory birds such as flamingoes and pelicans on the lake as their seasonal habitat. These migratory birds feed to a major extent on *Artemia Urmiana* (Ghaheri, et al., 1999). The lake has been designated as a Biosphere Reserve by UNESCO and a National Park under the 1971 Ramsar Convention due to its unique ecological environment and biodiversity (UNESCO, 2009). Urmia Lake is also one of the 610 Biosphere reserves in 117 countries recognized in 1976 under UNESCO's Man and the Biosphere (MAB) Program (UNESCO, 2012a).

Figure 14. *Iran's National Parks*

Although designated biosphere reserves remain under national sovereign jurisdiction, they should share their experience and ideas nationally, regionally, and internationally within the World Network of Biosphere Reserves (WNBR) (UNESCO, 2012b). Unfortunately, there is only a general international discussion regarding the Urmia Lake ongoing deterioration. Much of the recent research related to the lake has only been reported in Farsi that indirectly limits the international awareness about this environmental crisis. Even for national scholars, it is not easy to access data about the lake. Locally, East Azarbaijan State Water and Wastewater Company and West Azarbaijan Regional Water Authority, are the responsible authorities regarding the lake's condition. These organizations are operating under the supervision of Ministry of Energy. Accessing data such as climate, water level, salinity, pollutants, etc., requires intense bureaucratic procedures that are time consuming and exhausting. On the other hand, free access to lake's data could contribute to a better knowledge regarding the lake's state of art and possible remediation (Khatami & Berndtsson, 2013).

2.11.1. Food Chain & Brine Shrimp

As salinity level increases, the food chain becomes simpler since less species could survive high rates of salinity. Urmia Lake food chain is an extremely simple ecological pyramid (Abbaspour & Nazaridoust, 2007). Migratory birds such as flamingoes and pelicans feed to a major extent on *Artemia Urmiana* (see Figure 15). The shrimp itself, feeds on diatoms and the green algae (Ghaheri, et al., 1999). *Artemia*, as the dominant invertebrate, is the only primary consumer and the center of food chain. Playing this centric important role, *Artemia*, hence, is the key element in the lake's aquatic food chain (Abbaspour & Nazaridoust, 2007).

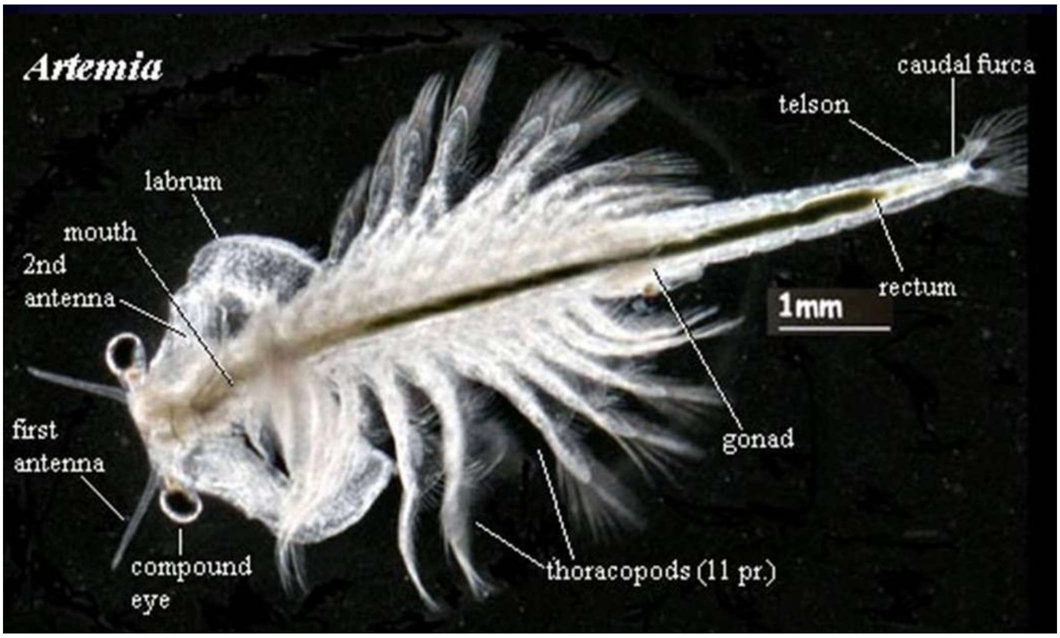


Figure 15. *Artemia Urmiana*

As it was mentioned earlier, the dependence of migratory birds solely on *Artemia* and its simple food chain make the lake highly sensitive and ecologically fragile since there would be no other aquatic fauna as a substitute for energy pathway to higher levels of the ecosystem but *Artemia*. Therefore, any change in *Artemia* biology or ecology in the lake that can impact *Artemia*, will consequently affect the biodiversity of the entire ecosystem and therefore its sustainability.

During the past years, agricultural activities in this region have been increased. Agricultural lands have been expanded from about 300,000 ha to about 650,000 ha (West Azarbaijan Provincial Government, 2011). This overdevelopment of agricultural activities has deteriorated the natural ecosystem of the lake basin. Massive land use changes from natural to agricultural ecosystems and orchards is, indirectly, influencing the lake's conditions negatively as it gives rise to water demand for irrigation purposes. This consequently has decreased the water level in the lake and the salinity has risen dramatically. Although the tolerance range of the brine shrimps against salinity level is not known, there are clear signs of their decline. For instance, it has been previously studied (Khalili, et al., 2007) that the escalation of salinity level over 300 g/l, extensively reduces the percentage of survival of the brine shrimp. Therefore, the current condition of the lake, in terms of its salinity level (more than 340 g/l), should be accounted as a severe threat to *Artemia* and thereupon this ecosystem. The increase in salinity due to the drying of the lake along with the consequent disruption of the food chain have ultimately resulted in the red tide phenomenon (Khatami & Berndtsson, 2013).

2.11.2. Red Tide

As colonies of algae grow out of control Harmful Algal Blooms (HABs), popularly known as "*red tide*", occurs. This phenomenon produces toxics which have harmful effects on people, fish, shellfish, marine mammals, birds and simply put, it has serious impacts on the entire ecosystem. Although human illnesses caused by HABs are rare, they can be debilitating or even fatal. The rise of HABs in many U.S. coastal areas have been reported and are now accounted as a national concern due to their serious impacts not only on the health of people and marine ecosystems, but also the "health" of local and regional economies (NOAA, 2013).

Unfortunately, during the years, due to an increase in salinity and its resulting impacts on the brine shrimp, and also the increase of pollutants in the lake, UL has been subjected to this environmental deteriorating phenomenon (Najafi, et al., 2011). Temperature escalation and water saturation caused a large growth of *halophilic* bacteria in this lake. It is reported (Mohebbi, et al., 2011) that the presence of these bacteria plays a more important role in the red coloration of Urmia Lake than the green alga *Dunaliella*. Whatever the origin and root cause might be, there is no doubt that due to the increase in salinity, the lake is literally turned reddish which is more evident during low seasons. This is another indication of the intensification of the ongoing environmental crisis of the lake.

2.12. Lake Salinity

Terminal lakes are usually saline and measuring salinity level (SL) is usually difficult and time taking. However, salinity rate is vitally important since the ecosystem of such lakes is highly sensitive to their salinity rate; for one thing, at a salinity above 3000 mg/l, freshwater species start to disappear (Waiser & Robarts, 2009). In terms of hydrochemistry, the lake is a sodium-chloride-sulfate type oceanic lake (Eugster & Hardie, 1978). Salinity is defined as the total sum of ionic compounds dissolved in water (Waiser & Robarts, 2009). As it is presented in Table 6, Urmia Lake is accounted as hypersaline due to its high salinity level (higher than 300 g/l).

Table 6. *Classification of saline waters according to TDS (Waiser & Robarts, 2009)*

Lake type	TDS (*mg/l*)	Salinity (*ppt, ‰*)
Fresh	< 500	< 0.5
Sub-saline	500 - 3000	0.5 - 3
Hyposaline	3000 - 20000	3 - 20
Mesohaline	20000 - 50000	20 - 50
Hypersaline	> 50000	> 50
Seawater	35000	35

During the past decade, the ecology of the entire lake's watershed has been threatened due to drought and the consequent increase of salinity. Salinity fluctuations of the lake's water are not a recent phenomenon. During 1967 to 1995, the salinity of the lake varied between 166 and 280 g/l (Karbassi, et al., 2010). From 1995 to 2008, however, the mean salinity of the lake started to increase from 166 g/l to 340 g/l due to an abrupt decline of the lake water level. Average concentrations of the major substances measured in June 2008 in the lake are presented in Table 7.

Table 7. *Average concentration (C) of lake's different substances (Karbassi, et al., 2010)*

Substance	Average C *(g/l)*
Na	125
Mg	11.3
K	2.63
Ca	0.55
Cl	216
SO_4	22.4
HCO_3	1.38

Since the Saturation Index (SI) of all major salts in the lake is greater than zero (dolomite 4.49, calcite 1.29, aragonite 1.14, anhydrite 0.19, gypsum 0.17 and halite 0.09), lake's water is supersaturated and salt precipitation is likely (Karbassi, et al., 2010). Because of this, crystallized salt are visible across the lake's shore.

The direct and most predominant impact of water level changes is on the salinity rate which itself affects the percentage of survival of *Artemia Urmiana*. In other words, water level fluctuations will consequently disturb the food chain since *Artemia Urmiana* cannot survive high salinity levels. Despite its utmost importance, there is no accessible time series of salinity level except for 7 monthly values presented in Table 8.

Table 8. *Observed average monthly salinity in different years (MOE, 2009)*

Year	Salinity *(g/l)*	Elevation *(m)*
1967	280	1273.8
1975	228	1276.1
1987	230	1276
1995	166	1277.8
2001	292	1273.6
2003	290	1273.7
2008	340	1272.1

2.13. Urmia Lake WL & Teleconnection Indices (TI)

Substantial variability of atmospheric circulation reflects circulation systems and weather patterns occurring on different temporal scales. Such systems/patterns could last from a few days (such as a normal storm system), to a few weeks (like the characteristic of a mid-winter warm-up or a mid-summer wet period), to a few months (e.g. cold winters or hot summers), to several years (such as abnormal winters for several years in a row), or even to several centuries e.g. long-term climate change. According to NOAA (2012), *teleconnection pattern* pertains to "a recurring and persistent, large-scale pattern of pressure and circulation anomalies that spans vast geographical areas". In others terms, these patterns refer to "preferred modes of low-frequency or long time scale variability". They reflect a significant part of both the interannual and interdecadal variability of the atmospheric circulation (NOAA, 2012).

Teleconnection patterns as a naturally occurring aspect of our chaotic atmospheric system, influence variation and intensity of temperature, rainfall, storms etc. and also their location. Therefore, they are often accounted to be responsible for abnormal weather patterns occurring simultaneously over ostensibly vast distances (NOAA, 2012). Many of these patterns are planetary-scale in nature among which El Niño–Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), East Atlantic (EA), East Atlantic/Western Russia (EA/WR), Scandinavia (SCA), West Pacific (WP), Pacific/North American (PNA), Polar/Eurasia (POL) and Pacific Decadal Oscillation (PDO) are the renowned ones.

Connection of Urmia Lake Level fluctuations with ENSO and NAO Climate Signals has been reported previously (Abrishamchi, et al., 2006), nonetheless, a detailed study involving other climatic signals has not been conducted yet. Therefore, the influence of the 9 aforementioned teleconnection indices on the lake water level will be studied. However, due to the limited scope of this study and thorough descriptions of this teleconnection on authentic sources (such as NOAA, 2012), only important Figures of these indices are presented in this report.

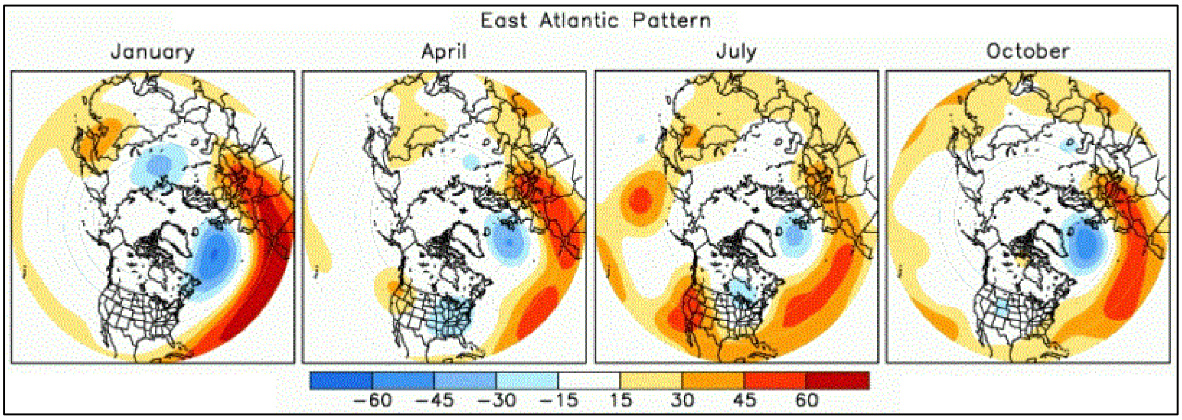


Figure 16. *EA patterns for Jan., Apr., Jul., and Oct. representing the temporal correlation between the monthly standardized height anomalies at that point and the teleconnection pattern time series (NOAA, 2012)*

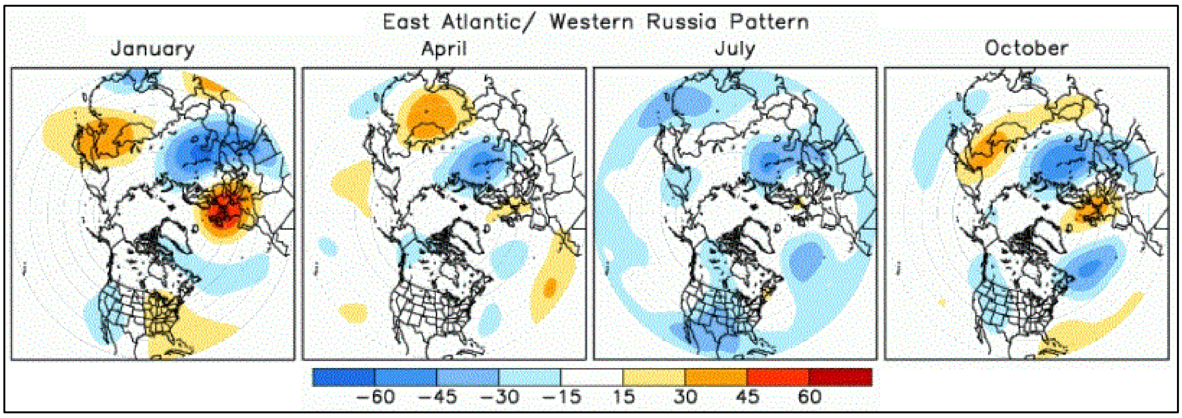


Figure 17. *EA/WR patterns for Jan., Apr., Jul., and Oct. representing the temporal correlation between the monthly standardized height anomalies at that point and the teleconnection pattern time series (NOAA, 2012)*

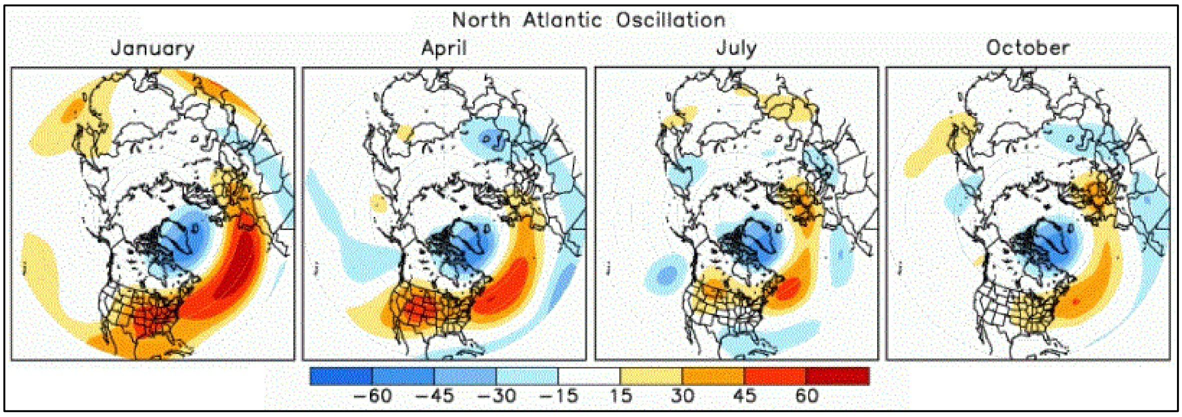


Figure 18. *NAO patterns for Jan., Apr., Jul., and Oct. representing the temporal correlation between the monthly standardized height anomalies at that point and the teleconnection pattern time series (NOAA, 2012)*

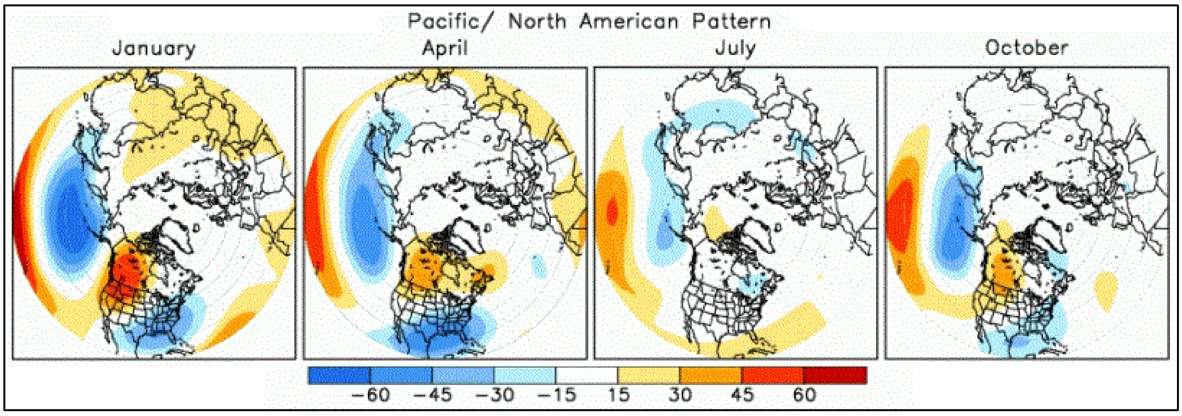


Figure 19. *PNA patterns for Jan., Apr., Jul., and Oct. representing the temporal correlation between the monthly standardized height anomalies at that point and the teleconnection pattern time series (NOAA, 2012)*

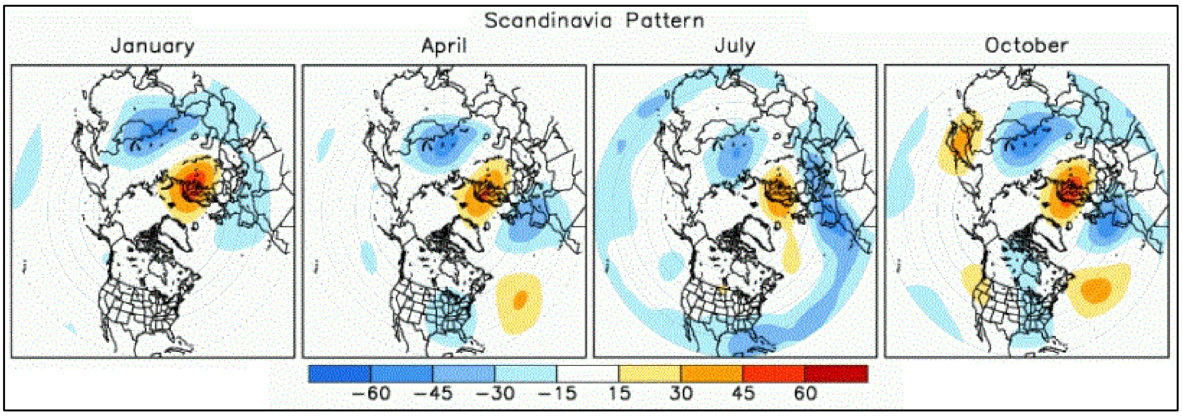


Figure 20. *SCA patterns for Jan., Apr., Jul., and Oct. representing the temporal correlation between the monthly standardized height anomalies at that point and the teleconnection pattern time series (NOAA, 2012)*

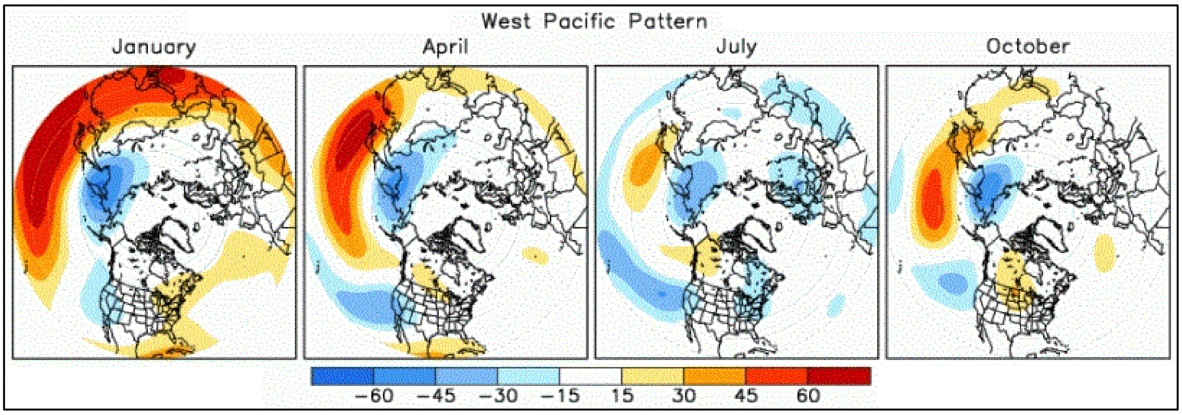


Figure 21. *WP patterns for Jan., Apr., Jul., and Oct. representing the temporal correlation between the monthly standardized height anomalies at that point and the teleconnection pattern time series (NOAA, 2012)*

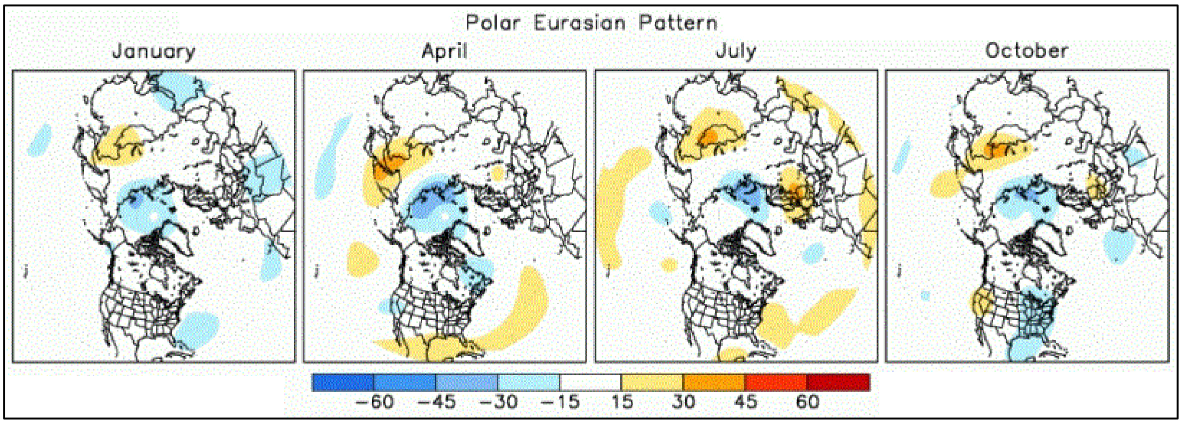


Figure 22. *POL patterns for Jan., Apr., Jul., and Oct. representing the temporal correlation between the monthly standardized height anomalies at that point and the teleconnection pattern time series (NOAA, 2012)*

As it could be seen from Figures 16-22, these teleconnections have a significant influence on the lake basin at least in some moths throughout the year.

3 CHAOS THEORY

There are indications that the hydrology of the lake could be described by a chaotic climate and a low-dimensional dynamical system (Khatami & Berndtsson, 2013). Therefore, a chaotic analysis of the underlying dynamic of the lake water level could reveal valuable information on its recent changes. For doing so, a thorough background review on Chaos Theory and its application in hydrology, as the first stage, is necessary due to its complex concept and the sophisticated mathematics behind it.

In the time scale of mathematical science, Chaos Theory is a newly-born filed. Due to its burgeoning developments in different areas such as economy, quantum physics, biology, neuroscience, atmospheric science, philosophy, psychology and even political sciences, it has received a lot of attention not only from scientists but also the public sphere.

Chaos Theory attempts to study dynamical systems and how they behave with their highly dependence on initial conditions – dynamical instability. From the historical point of view, an early explainer of the Chaos Theory was Henri Poincaré who studied the three-body problem in the 1880s (Diacu & Holmes, 1999). Others had come across chaotic behavior in different studies but none of them studied the concept as Edward N. Lorenz did. Despite other scientists, Lorenz, American mathematician and meteorologist at MIT, investigated the nonlinear behavior and discovered the strange attractor and coined the term *butterfly effect* (Lorenz, 1972). As the principal advocator of this theory, he was named the Father of Chaos Theory.

3.1. Lorenz's Studies

Lack of periodicity as a common factor in many natural systems such as turbulent flow raised Lorenz's interest in his studies. Therefore, his main interest was non-periodic solutions (solutions that never repeat their past history). As a result, his work was involved with the ultimate behavior of the solutions. This was opposed to the transient behavior of the system depending on arbitrary initial conditions. Non-periodic solutions could not be determined by analytical methods but by numerical ones (Lorenz, 1963).

Generally, viscous and thermal dissipation always occur in any (real) hydrodynamical system. In many cases, plenty of systems are treated as conservative systems, i.e. total energy does not vary with time for specific purposes. Due to the fact that the final value of any conservative system has to be equal to the arbitrarily initial conditions, using conservative equations in pursuing the ultimate behavior of hydrodynamical system is inadequate (Lorenz, 1963). Lorenz (1963) dealt specifically with finite systems of deterministic Ordinary Differential Equations (ODE) which were designed to portray forced dissipative hydrodynamical systems. It should be noted that equations are idealizations of a hydrodynamical system.

Lorenz (1963) attempted to model the atmosphere convection by a set of three ODEs (Equation 1) which are a simplification of the system derived by Saltzman (1962) to investigate finite-amplitude convection. He obtained the equations as follow:

$$\begin{cases} \dot{X} = -\sigma X + \sigma Y \\ \dot{Y} = -XZ + rX - Y \\ \dot{Z} = XY - bZ \end{cases} \qquad \textit{(Equation 1)}$$

where X, Y and Z are only functions of time and defined as follow:

- X is proportional to the intensity of the convection motion (speed of motion of fluid due to convection).
- Y is proportional to the temperature difference between the warmer rising and the cooler falling currents (measure of horizontal temperature difference).
- Z is proportional to the vertical temperature profile distortion from linearity (measure of vertical temperature difference).

In Equation 1, dots above the X, Y and Z variables symbolize a derivative with respect to the dimensionless time. X, Y and Z variables in Lorenz's set of equations are the same as the Saltzman's variable A, D and G, nevertheless, the multiplicative constant, σ, b and r, were not the same and defined as follow:

- σ is proportional to the value of "Prantdl number" based on physical parameters of the involved fluid. ($\sigma = 10$ in the original work)
- b is the measure of the area size being represented. ($b = 8/3$ in the original work)
- r is the "Rayleigh number". This is simply a parameter which shows the point at which convection starts in a particular system.

Through a recursive procedure and then by plotting the data after the transient died out, Lorenz, accidentally, Figured out that a small change in the initial conditions – due to rounding up errors or whatsoever – is not only cancelled out after long-term iterations as commonsensically expected, but also gives rise to substantial differences in the results; it is nowadays known as chaotic behavior.

In simple words, the principal result of Lorenz's study – which later became widely popular after his lecture "Predictability; Does the Flap of a Butterfly's wings in Brazil Set off a Tornado in Texas?" (Lorenz, 1972) –is a disappointing fact that the precise prediction of the sufficiently distant future is impossible no matter what the method is. This is simply due to the fact that Lorenz's main results involve instability of non-periodic solutions.

These dynamical systems, which could even be deterministic systems described by ostensibly straightforward equations, are highly sensitive to initial conditions that even an extremely minute difference in the initial value – metaphorically the flap of a butterfly's wing – could yield a vast difference in the future state of the system. Achieving exact initial conditions, for example in weather observations, is not possible, because there are inevitable inaccuracies in our measurements.

In view of the above and considering the present technology in data collecting, Lorenz's work put an end to Newtonian classical mechanics and the dream of accurate forecasting as P. Laplace (1749-1827) once said that "*Give me the past and present co-ordinates of any system and I will tell you its future*".

3.2. Phase-space

In the late 19th century, Ludwig Boltzmann, Henri Poincaré, and Willard Gibbs developed the concept of phase-space (Nolte, 2010). Phase-space, phase plot or phase diagram[1], is simply an n-dimensional space of all possible states of a dynamical system. Each point in the phase-space is corresponding to a unique possible state of the system. The dimension of the phase-space is infinite where the system state is defined by a field. Each dimension of the phase-space corresponds to an independent variable determining the state of the system. In other words, every degree of freedom (DOF) or parameter of the system is represented in the phase-space as an axis of a multidimensional space. And each DOF stands for an autonomous ODE (Ivancevic & Ivancevic, 2008). For instance, Lorenz's system (Equation 1) is a 3-dimensional system as it is described by three autonomous ODEs, hence, it has a 3D phase-space.

A well-known example of a simple dynamical system is pendulum. In the case of the free pendulum, the phase-space is 2-dimensional as this system has 2 DOF. Strictly speaking, the pendulum's state could be described by two variables of position y and velocity $\dot{y}$ (see Figure 23).

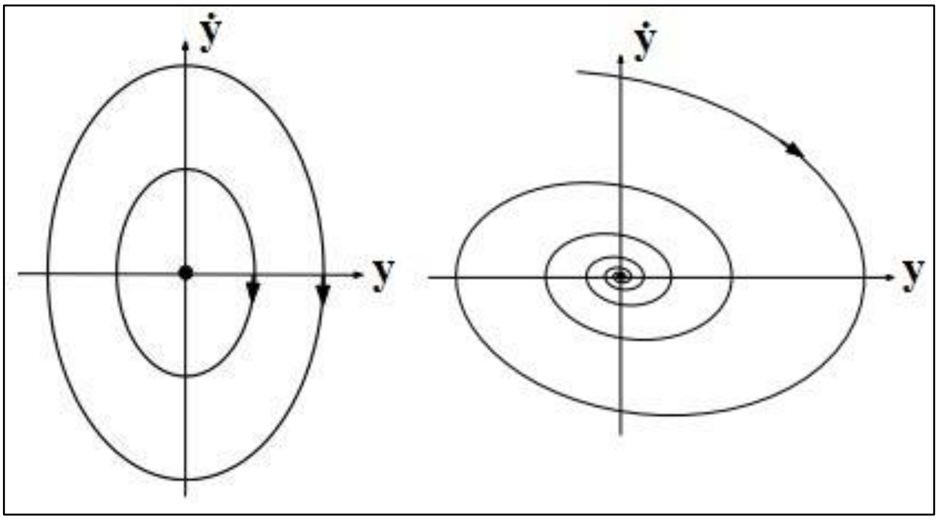


Figure 23. *2D phase-space of pendulum, undamped (left) and damped (right) (Gidea & Niculescu, 2002)*

[1] It is relevant to note that although phase diagram is also used as a synonym for phase-space in mathematics and physics, in physical chemistry and material science, phase diagram, in fact, refers to a type of chart used to show conditions at which thermodynamically distinct phases can occur at equilibrium. Therefore, these two should not be confused in that sense.

The concept of phase-space is an invaluable and powerful tool by which one can study the nonlinear behavior of dynamical systems. A real-world system similar to a dynamical system can be portrayed as the geometry of a single moving point with a model and a set of appropriate variables.

3.2.1. Trajectory

Mathematically speaking, a trajectory can be described either by the geometry of the path, or as the position of the object over time. In dynamical systems, trajectory is a time-ordered set of a dynamical system's states or in other words, a solution of the equation of motion. By way of explanation, it is a curve in the phase-space, in the matter of continuous time, which is parametrized by the time variable. Regarding discrete systems, it is an ordered-set of points in the phase-space (Ivancevic & Ivancevic, 2008).

3.2.2. Phase-line

Phase-line is a low dimension example of phase-space. In fact, it is the specific case of phase-space for a system with one DOF i.e. 1-dimensional phase-space. One DOF occurs when one has an autonomous ODE in a single variable. The qualitative behavior of the system would be visible from its phase-line.

3.2.3. Phase-plane

It is the two-dimensional case of the general n-dimensional phase-space. It is the traditional case in classical mechanics for 1-dimensional motion of a single particle where the two variables are only position and velocity (see Figure 23).

3.2.3.1. Phase Portrait

A geometric representation of the trajectories of a dynamical system in the phase-plane is called phase portrait. Due to the fact that each set of initial conditions is represented by a different curve, or point, the entire phase plane is filled with trajectories (Ivancevic & Ivancevic, 2008).

For sufficiently small amplitudes, the equation of motion for the simple pendulum is:

$$\frac{d^2\theta}{dt^2} + \frac{g}{l}\theta = 0 \qquad \textit{(Equation 2)}$$

where θ and l are presented in Figure 24.

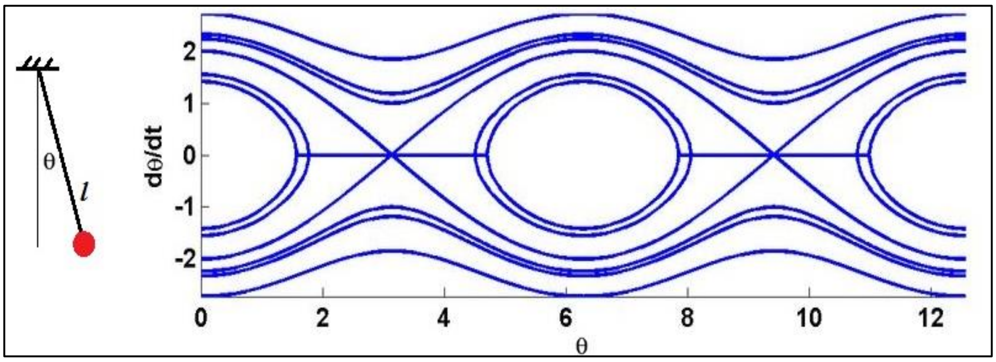


Figure 24. *Phase portrait of the motion of a simple pendulum (MATHEMATICS, 2012)*

Since phase portrait consists of a plot of typical trajectories in the state space, they reveal information such as whether an attractor, a repellor or limit cycle is present for the chosen parameter value. Therefore, they are important tools in studying the behavior of dynamical systems.

3.3. Attractor

Dissipative systems are those which lose energy by friction or diffusion. These systems are often associated with the presence of an attractor in their phase-space (Gidea & Niculescu, 2002). Roughly speaking, attractor is an invariant set in the system's phase-space to which all neighboring trajectories converge (Ivancevic & Ivancevic, 2008). For instance, the point $(0,0)$ of the pendulum's phase plane (Figure 23) is called an attractor.

3.3.1. Definition

Attractor A, is a nonempty subset of phase-space M. A would be an *attracting set* for Φ if it satisfies the following conditions (Ivancevic & Ivancevic, 2008; Gidea & Niculescu, 2002):

1. A is closed and invariant;
2. It is minimal (It cannot contain one or more smaller attractors).
3. A possesses an open neighborhood U, such that

$$\lim_{t\to\infty} d(\Phi_t(x), A) \to 0 \; for\ every\ x \in U \qquad \textit{(Equation 3)}$$

Adding to the mathematical definition, a more comprehensible description from the viewpoint of dynamical system theory is that an attractor is a set or region in an n-dimensional space towards which a variable evolves throughout time. The variable evolves/moves based upon the function of the dynamical system that dictates such evolution. This evolving variable could be represented, algebraically, as an n-dimensional vector.

Investigating the long-term behavior of a dynamical system is of high importance as it assists not just the understanding of the nature of such systems but also providing more reliable predictions. Attractor is a geometric object which characterizes the long-term behavior of a dynamical system in its phase-space (Sivakumar & Jayawardena, 2002). That being said, describing the attractors of dynamical systems and in particular chaotic dynamical systems has been one of the significant achievements of Chaos Theory.

3.3.2. Strange Attractor

An attractor can be a point (see Figure 23), a finite set of points, a curve, a manifold, or even a complicated set with a fractal structure known as a *strange attractor* or *chaotic attractor*. Strange attractors are also called *fractal attractors* as they have a non-integer dimension. They are strange in the sense that either their dynamics is unpredictable or their structure is fractal. The importance of attractors in dynamical systems is due to the discovery that the presence of attractor causes the turbulence phenomenon (Ruelle & Takens, 1971). Strange attractors are the most important geometrical object in chaotic dynamics which are special attractors that exhibit sensitive dependence on initial conditions (Ivancevic & Ivancevic, 2008).

Originally, Lorenz (1963) illustrated how very simple low-dimensional systems could display turbulent or chaotic behaviors. “Strange attractors” – coined by Ruelle and Takens (1971) – are attractors which display such behaviors. Therefore, in view of the above, a strange attractor is an attracting set that has zero measure in the embedding phase-space and has fractal dimension. Trajectories within them appear to skip around randomly (Ivancevic & Ivancevic, 2008). Ruelle and Takens (1971) hypothesized that the strange attractor is the cause of turbulent behavior in fluid flow; a hypothesis that has been backed up by later experiments (Gollub & Swinney, 1975).

Figure 25 shows the phase-space of the Lorenz (1963) model. As Lorenz model has 3 DOF, the attractor of this dynamic system could geometrically be represented in a 3D space i.e. by 3 axes.

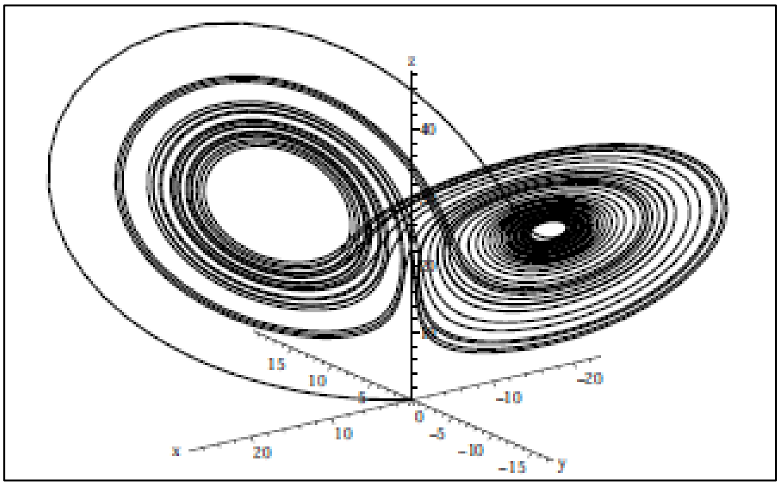


Figure 25. *The Lorenz strange attractor (Lorenz, 1972)*

As it can be seen, the Lorenz's strange attractor is quite similar to a butterfly. Due to such resemblance and the fact that strange attractors are highly sensitive to initial conditions, Lorenz has coined the term *butterfly effect* representing such systems metaphorically (Lorenz, 1972).

3.4. Chaos Theory in Hydrological Studies

One of the main aspects of hydrological studies, e.g. rainfall or runoff dynamics, which has received a great deal of attention by many hydrologists, is the characterization of the dynamics of hydrological processes and exploring their underlying structures in order to have a reliable tool for predicting them (Sivakumar, 2009; Islam & Sivakumar, 2002). The main limitations for this goal are spatial and temporal variability of the processes, and also lack of "appropriate" mathematical tools for these investigations. Traditionally, it was thought that these variabilities stem from a large number of influencing variables in these processes (stochasticity). However, considering the advent of deterministic chaos, it is known that even simple deterministic systems involving a few variables could yield puzzling and complex structures (Sivakumar, 2000). The main parameters, which play a significant role in chaotic systems, are nonlinear iterative (differential) equations or large time series (observed data of a phenomenon). These equations show high sensitivity to initial conditions.

As it is summarized in the Table 9, a number of studies concerning Chaos Theory approach in hydrological processes are presented in an informative classified way. It is possible to roughly classify the hydrological studies with regard to Chaos Theory in four main categories of (1) investigation of the existence of chaos, (2) prediction by implementation of Chaos Theory, (3) existence of noise in recorded data, and finally (4) approaches to noise reduction. It should be noted that early studies in this realm were severely influenced by lack of data and restricted computational power (Sivakumar, 2009). As the goal of the present study could be identified as group (1), the emphasis of the present literature review is then placed on the studies that claimed the existence of low-dimensional (three to eight) dynamic in hydrological processes.

3.4.1. Chaotic Methods for Hydrological Time Series

So far, different methods have been employed in order to investigate the deterministic chaos in hydrological processes. The simplest tool is the phase diagram plot of a dynamical system which is in fact a visual evaluation of the process investigating preliminary evidence on deterministic chaotic behavior (for further explanation read Section 3.2 & Section 3.4.3). Sophisticated methods are namely Correlation Dimension Method (CDM), Lyapunov Exponent Method (LEM), Kolmogorov Entropy Method (KEM), Nonlinear Prediction Method (NPM), Gaussian Kernel Algorithm (GKA), and False Neighbors Algorithm (FNA) or False Nearest Neighbors (FNN). In principle, these methods are tests examining whether a given system/process is deterministic chaotic or stochastic. As it mentioned earlier, since CDM is the fundamental approach and the most celebrated one in hydrological studies, only implications and challenges of this very method are discussed in this study (read Section 4.7).

Table 9. *Classified summary of hydrological studies regarding Chaos Theory (values presented in method(s) are approximations)*

Process	Research	Category	Method(s)	Notes
Rainfall	(Hense, 1987)	1	CDM (2.5-4.5)	1008-point monthly rainfall, in Nauru Island
	(Rodriguez-Iturbe, et al., 1989)	1	CDM (3.78) LEM	148-year weekly rainfall, in Genoa; and 1990-point single storm event, in Boston, USA
	(Sharifi, et al., 1990)	1	CDM (3.35, 3.75, 3.60)	4000-, 3991- and 3316-point storm events, Boston, USA
	(Tsonis, et al., 1993)	1	CDM (2.4)	Time between rain signals
	(Islam, et al., 1993)	1	CDM (1.5)	10-sec time-step simulated rainfall intensity from a 3D cloud model, 7200 point data
	(Jayawardena & Lai, 1994)	1,2	CDM, LEM & KEM NPM, found to be superior to ARMA	4015-point daily rainfall, and 7300- & 6025- point stream flow data, in Hong Kong
	(Puente & Obregón, 1996)	1	CDM, KEM, FNA & LEM	1990-point storm events, in Boston
	(Porporato & Ridolfi, 1997)	1	CDM & NPM	14,246 point daily flow data, Dora Baltea, Italy
	(Sivakumar, et al., 1999)	1,3,4	CDM & NPM	Rainfall phenomenon
	(Sivakumar, et al., 2001)	1	CDM (6.4)	131-year monthly record, Göta River basin in the south of Sweden
	(Sivakumar, et al., 2013)	1	CDM (4.63-8.29)	804-point monthly rainfall, from 62 gaging stations, investigating rainfall dynamics across Western Australia
River flow/runoff	(Sivakumar, et al., 2001)	1	CDM (5.5)	131-year monthly record, Göta River basin in the south of Sweden
	(Sivakumar & Jayawardena, 2002)	1	CDM (2.32)	21-year daily discharge, Mississippi River basin, St. Louis, USA
	(Islam & Sivakumar, 2002)	1, 2	CDM (3.76) FNN (low global dimension of 4 or 5) NPM (optimal E_m of 3)	19-year daily observed runoff (January 1, 1975–December 31, 1993) at the Lindenborg catchment in Denmark
Rainfall-runoff	(Sivakumar, et al., 2001)	1	CDM (7.8)	131-year monthly record, Göta River basin in the south of Sweden
Lake	(Sangoyomi, et al., 1996)	1	CDM (3.4)	144-year biweekly time series of GSL lake volume, USA
	(Lall, et al., 1996)	2	CDM	Forecasting the Great Salt Lake volume
Solute transport	(Sivakumar, et al., 2005)	1	CDM (1.33 & 2.12)	Simulated solute transport through the two and three facies media in a heterogeneous aquifer medium
Groundwater	(Hossain & Sivakumar, 2005)	1	CDM (8-11), medium-to-high dimensional chaotic pattern	Investigation of the existence of chaotic behavior in arsenic contamination in shallow tube wells of Bangladesh
Sediment transport	(Sivakumar & Jayawardena, 2002)	1	CDM (2.55), suspended sediment concentration, CDM (2.41), bed load	21-year daily suspended sediment concentration and bed load data from the Mississippi River basin at St. Louis, USA
	(Sivakumar, 2002)	2	Phase-space reconstruction	21-year daily observed suspended sediment concentration, Mississippi River basin at St. Louis, USA

3.4.2. CDM: Issues & the Reliability of Dimension Estimate

In a nutshell, CDM attempts to calculate the dimension of the attractor of a dynamic process/system. If the dimension is low (three to eight) and non-integer, it means that the attractor of the process is a strange attractor i.e. it is a deterministic chaotic system. This dimension will be measured as the slope of a particular plot ($log\big(C(r)\big)\ vs.\ log(r)$ plot) which is called the correlation exponent denoted as ν. The first integer after the correlation exponent refers to the number of independent parameters determining the dynamic of the process i.e. the number of autonomous ODEs describing the underlying dynamic of the given process/system. This integer value, from the standpoint of time series geometry, is the minimum number of dimensions (axes) needed to unfold the strange attractor and hence the structure of the underlying dynamic.

In light of the CDM limitations and considerations which will be discussed in the following subsections, if this method succeeds in measuring the correlation exponent as its result, it could be seen as a promising evidence of low-dimensional deterministic chaos within the given process. Nevertheless, it should be revisited with other methods verifying the findings of CDM in order to claim solid evidence of deterministic chaos. If CDM fails to measure the correlation exponent, it does not necessarily mean the system is not chaotic. Manipulation of the temporal resolution or using a longer time series might improve the chance for getting evidence for low-dimensional chaos by means of CDM. Otherwise, other approaches or manipulations should be taken.

3.4.2.1. Proper Delay Time

It is relevant to note that although τ is related to the dynamic of the process while the autocorrelation lag is connected to the time series statistic, τ could vary depending on the data size. (Rodriguez-Iturbe, et al., 1989; Sivakumar, 2005). In this context, it has been debated (Schertzer, et al., 2002) that due to the inappropriate selection of delay time τ, the correlation dimension, for example in river flow time series, is underestimated. In spite of that, it has been demonstrated (Sivakumar, 2005) that the use of large τ values usually results only in an overestimation rather than underestimation. On that ground, any argument regarding the underestimation of correlation dimension, due to inappropriate selection of delay time, may be largely baseless. For further explanations and examples on this issue Sivakumar (2000), Sivakumar et al. (2002a) and Sivakumar (2005) are recommended.

3.4.2.2. Data size

Although the infinite length of data is a fundamental assumption in the GPA (Grassberger & Procaccia, 1983) it would lead to nowhere in “practical” problems where time series are not just finite but also small. The assumption of infinite time series would lead to a larger scaling region – where you can measure the dimension of the strange attractor – as it includes a large number of points (or vectors) on the reconstructed phase-space. For a finite (end especially limited) time series, however, the determination of the dimension is difficult since there would only be a few points on the reconstructed phase-space (Sivakumar, 2000). Numerous attempts have been made providing practical guidelines regarding the “minimum data size”, N_{min}, required for estimating a “reliable” correlation dimension.

It has been comprehensively argued (e.g. Lorenz, 1991; Sivakumar et al., 2002a; Sivakumar et al., 2002b; Sivakumar, 2005) why the determination of the minimum data size proposed previously (e.g. Smith, 1988; Nerenberg & Essex, 1990; Ramsey & Yuan, 1990; Schertzer et al., 2002) could be misleading; proposed guidelines underestimate or overestimate the required data size, for small and large embedding dimensions, respectively. Regarding the application of Chaos Theory in hydrology, previous studies (Sivakumar, 2000; Sivakumar, et al., 2002a; Sivakumar, 2005) have addressed this issue and it was revealed that the data length, in terms of the sheer number of values, is not as decisive as it was thought to be (Schertzer, et al., 2002).

Discussion on the minimum data size (Sivakumar, et al., 2002a) has lead reasonably to the conclusion that the data size, practically, is neither a requisite for applying CDM nor a limitation. Data needs to be considered with other factors related to the dynamic of the given process. The crucial problem is to assess the time series regarding the period of coverage and sampling time, to be long and representative enough so that it could capture the essentials of the process/system evolution (Sivakumar, et al., 2013). Choosing the temporal scale appropriately, even with a time series with a few hundred data points, can provide a reliable dimension estimate. For example, correlation dimension could be estimated even with about 300 data points for flow time series (Sivakumar, 2005).

3.4.3. Why Not Stochastic but Deterministic?

There could be a suspicion of stochastic chaos when one deals with a low-length finite data (Schertzer, et al., 2002). Phase-space – or better say pseudophase-space (Rodriguez-Iturbe, et al., 1989) – could be a helpful tool for providing reliable evidence that the system is not stochastic indeed. In case of a stochastic time series, one would expect a space-filling phase-space diagram in all embedding dimensions m. Nonetheless, Figure 26 vividly represents that despite the phase-space of a purely stochastic time series (Figure 26-a), when phase-space of a chaotic time series is embedded in a 2-dimensional space (Figure 26-b), it fills up the space only partially. As it was mentioned earlier, for measuring the dimension of the strange attractor i.e. correlation exponent, $log\big(C(r)\big)\ vs.\ log(r)$ plot should be plotted. As it could be seen from Figure 26, in case of a stochastic process (Figure 26-c), the correlation exponent is increasing as the embedding dimension increases. However, for a chaotic process (Figure 26-d), correlation exponent saturates beyond a certain embedding dimension.

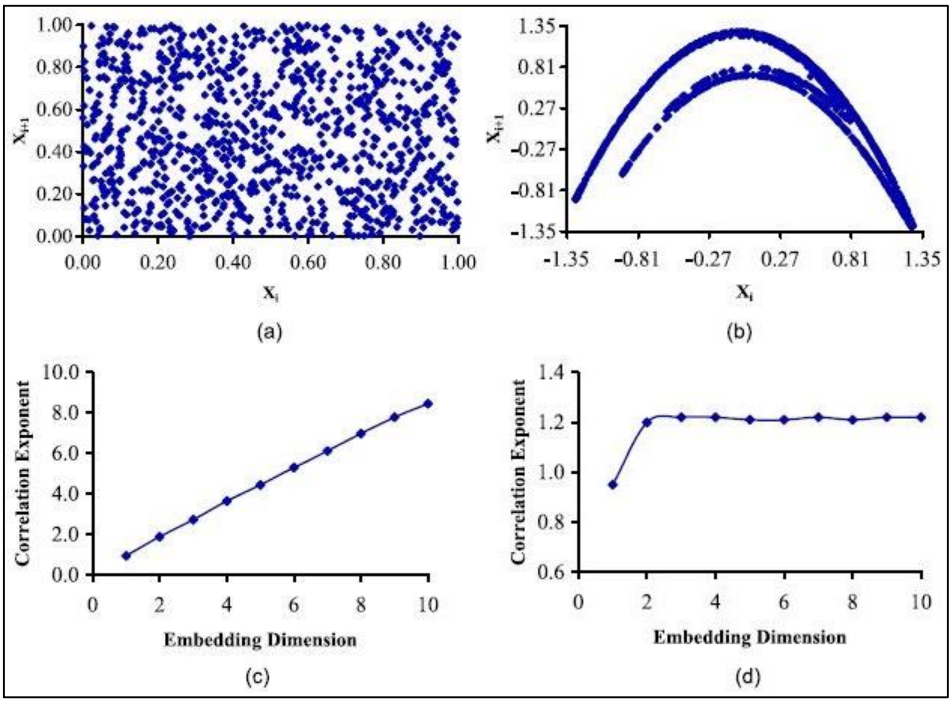


Figure 26. *Random vs. chaotic data: (a) and (c) are, respectively, phase-space and correlation dimension of a random/stochastic data set; (b) and (d) are, respectively, phase-space and correlation dimension of a chaotic time series (Sivakumar, 2012)*

3.4.4. The Verification of Correlation Exponent (ν) Accuracy

In general, for further verification of CDM results, they should be revisited by other nonlinear approaches and in particular other investigative tools of chaos. As it could be understood from Table 9, while a few studies did such verifications, many of them most commonly used solely CDM. In view of that, verification of the correlation exponent estimation is argued when only CDM is employed.

Due to the fact that the characteristics of stochastic and chaotic time series are known *a priori*, the verification could be easily done using a relationship between ν and m. Comparing stochastic, chaotic and hydrological time series (Sivakumar, 2005) has revealed substantial clues in this regard. In case of a stochastic time series, there is a linear relationship of $\nu = m$ for any m (see Figure 26-c).However, for a chaotic time series which has been artificially generated by Sivakumar (2005) using the Henon map Equation, it is given by $\nu = m$ for $m = 1$ and $\nu = 1.22$ for $m > 1$. In other words, for a chaotic time series, the ν is increasing as m increases on the basis of $\nu = m$ until a certain m from which ν will be saturated i.e. correlation exponent.

It has been found that the estimations of ν for data lengths above 300 data units for stochastic as well as chaotic time series respect the aforementioned relationships accordingly. On this ground Sivakumar (2005) argued that a data length of 300 could be reliably sufficient for the estimation of ν for these two time series. This study has also argued the reliability of scaling region. The scaling regimes and exponents may not be a function of data length, especially if the duration of process evolution could be considered long enough (e.g. about 300 points).

Comparatively speaking, hydrological time series are different from the other two as their characteristics in terms of their generating mechanisms are not known *a prior*. Sivakumar (2005) has discussed why N_{min} is not a function of m, and why no other guidelines could be defined in this regard. In light of that, in case of hydrological time series, N_{min} is quite dependent on the background nature of the time series. For example even a data length of 360 or even 240 could be reliably sufficient for the estimation of correlation exponent for the flow time series of the Göta River (Sivakumar, 2005).

3.4.5. The Limitations of CDM for Interpreting the Results

Sivakumar et al. (2002) has comprehensively discussed the considerations and limitations of CDM in an argumentary paper, answering the suspicions (Schertzer, et al., 2002) about practicality and limitatoins of this method. Therefore, in the present study, only the conclusion of the mentioned studies are presented.

Dealing with CDM, one has to pay a careful attention to the following. In general – unless the data size is extremely small:

a) "not all processes yielding finite and low correlation dimensions are stochastic";
b) "all low-dimensional chaotic systems yield low correlation dimensions"; and
c) "many stochastic processes yield infinite correlation dimensions."

Therefore, on the condition that the dynamic characteristics of a real hydrological time series are not known *a priori*, the interpretation of the dimension results requires delicate cautions.

For extremely small stochastic series finite and low correlation dimensions might result. In view of that, a more reliable approach in examining hydrological time series is required to support the CDM results. Some previous studies (e.g. Sangoyomi et al., 1996; Sivakumar et al., 2002) have also employed methods other than CDM for the sake of confirmation and verification of CDM results. It is important to note that if the application of the CDM fails to discern the indication of the existence of chaos in a process for a particular temporal resolution, it does not necessarily mean that the system could not be chaotic (Rodriguez-Iturbe, et al., 1989).

Apart from the existence of noise that can influence the estimation of correlation dimension, there are other factors that have such influences as well. For instance, as it is common in hydrological time series, the presence of a large number of zeros in data could cause an underestimation of correlation dimension (Sivakumar, et al., 2002a).

3.4.6. The Advantages of CDM for Hydrological Time Series

By a quick look at Table 9, it is obvious that many studies have solely employed CDM. The main reason is its feature of being straightforward and quick for calculation. Also, this method is often in agreement with other methods.

The purpose of characterizing a system is to identify an appropriate mathematical model describing main feature of the system adequately. Comparing low-dimensional chaotic approaches to stochastic ones (e.g. Jayawardena & Gurung, 2000; Lisi & Villi, 2001) or other data driven approaches (Sivakumar, et al., 2002b), it has been revealed that low-dimensional chaotic approaches may provide more accurate predictions. In addition to that, the reliability of CDM as an indicator of low-dimensional chaos for short-term hydrological time series has been investigated (Sivakumar, et al., 2002b) previously. It has been shown (Sivakumar, et al., 2002b) that even for a monthly runoff time series as short as 48 years i.e. 576 data points, despite theoretical limitations (e.g. Grassberger & Procaccia, 1983; Schertzer et al., 2002), CDM could still be a reliable tool as it was compared with Artificial Neural Networks (ANN) using an inverse approach.

From the view point of noise existence in the series, the presence of noise even in small levels, influences the prediction accuracy significantly. Nevertheless, the estimation of correlation dimension by means of CDM does not seem to be influenced notably even when the noise levels are high (Sivakumar 1999 & 2000).

3.4.7. The Discussion of Previous Studies

Previous studies concerning chaos in hydrology, presented in Table 9, are only the main ones in this realm. Therefore, this table needs to be updated both on the matter of time and the matter of contents. However, as it presents an encapsulated version of the history of chaos in hydrology, it would be easy to elicit a lot of information from this table and get instant inspirations as well. Such literature review presentations could be beneficial for both beginners and experts in this field as it concisely lights up the history of the application of Chaos Theory in hydrology.

Due to the limited scope of the present report, only the most significant studies are discussed here. As it can be seen from Table 9, the study by Hense (1987) was the first that investigated the possible existence of chaos in hydrological processes. The second one by Rodriguez-Iturbe et al. (1989) is one of the most influential studies (greatly cited by other scientists) analyzed two rainfall records by two different methods of CDM and LEM. First, weekly rainfall data for a 148-year period and second, a set of 1990 rainfall records with 8 Hz sampling frequencies.

Jayawardena & Lai (1994) employed various approaches of CDM, LEM, KEM and NPM to a daily rainfall time series of 4015 data points and two streamflow time data sets of 7300 and 6025 data points. They have reported convincing evidence for the existence of chaos. In spite of their low prediction accuracy, they showed the superiority of the nonlinear prediction method (NPM) over traditional methods. Regardless of the method, two main issues of Chaos Theory approach to hydrological studies were the issue of data size and the issue of noise. Previous studies show that the presence of noise does not have a significant influence on CDM than it has on the nonlinear prediction method (Sivakumar, 2000). Therefore, the issue of noise in time series has been neglected in the present study as it only employs CDM.

Sivakumar (2000) showed that low prediction accuracy in studies such as Jayawardena & Lai (1994), could be mainly due to the presence of noise as it can improve significantly in the case of noise removal. Further studies by Sivakumar et al. (2002b) suggested that CDM could be a reliable indicator of low-dimensional chaos. They presented that the results of the correlation dimension method are in conceivably good agreement with other methods such as phase-space method and ANNs. They also addressed the aforementioned issues (noise and data size) and demonstrated that small data size would not cause any underestimation in correlation dimension, but there seems to be even a slight overestimation because of the noise in the data.

As it can be seen, most of the earlier studies were concerned with the investigation of chaos in rainfall (or storm). This simply shows that rainfall is the most obvious phenomenon suspected to be chaotic. Another common point in all studies is that they have referred to a low-correlation dimension either as a proof or as a preliminary evidence of the existence of chaos in their studies. Most of the studies during the period of 1987-1999 attempted to investigate the existence of chaos in hydrological processes while by approaching the 21st century, there is a rising trend in shifting the focus of these studies from the investigation of chaos in such processes (investigation phase) to other issues such as determining the noise level or reduction of noise. Also, during the recent years, the implementation of Chaos Theory in solving the hydrological problems such as ground water contamination, rainfall-runoff modeling and so on has been gaining considerable momentum (Sivakumar, 2009).

Having what has been said in Section 3.4.2 , another relevant critique to chaos existence investigations is that there is no single reliable method available to determine whether a system is stochastic or chaotic (investigation phase) (Sivakumar, 2000). Furthermore, there is no reliable model or tool for solving hydrological problems (implementation phase). For instance, there is no decent model to capture the hydrologic extreme events at any given location (with a good level of trust). Alluding to this inadequacy of determination and solving tools, there is a serious need for an integrative approach towards hydrological problems. Integration of different methods and models in a way that can be complementary to each other and can also incorporate in the direction of necessary and unanswered hydrological problems could be one of the current challenges for hydrologists. (Sivakumar, 2009)

4 METHODS

In this chapter, the principal hypothesis of this study and its sub-hypotheses are thoroughly argued. As the Scientific Method requires, a hypothesis will not be accounted valid if it cannot be tested. Therefore, the ability of each hypothesis should be tested in order to see if it can adequately answer the question under investigation. In view of the above, in the present chapter, the testability of the hypotheses and their appropriate measures are presented, discussing the presuppositions and conditions under which each hypothesis will be verified or rejected. Afterwards, different methods used pursuing the validity of the hypotheses are explained.

4.1. The Principal Hypothesis & Assumptions

The principal hypothesis of this study is that 'during *the recent years (1996-2012)* there has been an *intrinsic change* in the dynamic of the lake water level *mainly due to human activities* which has had *deteriorating impacts* on the lake and its entire basin'. As it could be understood, there are 4 sub-hypotheses embedded; (1) there is a uniquely significant change in the lake water level during the recent years of 1996-2012 comparing to historical records (1966-1995) (Hypothesis I), (2) the changes have intrinsically altered the underlying dynamic of water level fluctuations (Hypothesis II), (3) the major cause of such changes is anthropogenic interventions and not natural causes (Hypothesis III), and (4) these changes have a serious negative effect on the lake's condition (Hypothesis IV).

Each of these 4 sub-hypotheses (Hypothesis I-IV) will be discussed thoroughly in the following subsections. It has to be mentioned that as it is already discussed in the background review (see Chapter 2), extensive and burgeoning human activities during the recent years in terms of climate change, dam construction and water diversion projects, and land use changes are the supporting bedrock based on which this hypothesis is postulated.

There are two major assumptions based upon which the principal hypothesis is grounded. Due to the fact that Urmia Lake is a terminal lake, its water level can be seen as an eco-hydrological indicator and recorder reflecting the combination of all influencing factors. These factors, influencing the lake water level, could be categorized as natural (climate variability) and anthropogenic (e.g. dam construction, water diversion, climate change, groundwater withdrawals and etc.). Therefore, studying the lake water level fluctuations could be *assumed* to be a reasonable approach in order to test the aforementioned hypotheses.

Having a 47-year daily water level time series in hand, the time period of 1966-2012 of the lake water level fluctuations is divided into two distinct periods of 1966-1995 and 1996-2012. Such a division as another *assumption* of the principal hypothesis, is based on the facts that there are not so many dam construction projects or other human activities in the period of 1966-1995 (see Table 3) and also lake water level in this period is fluctuating quite distinctively from the period of 1996-2012 (see Figure 12) where there is an obvious declining trend in the water level. Moreover, a period of 30 years (1966-1995) is traditionally the standard period for climatic analysis as all possible climate variability could be seen in about 30 years (WMO, 2012). Therefore, the first period, 1966-1995, period is *assumed* to be the pre-disturbance period i.e. the natural period of the lake. And the period of 1996-2012, is *assumed* to be the disturbed or anthropogenically intervened period due to overwhelming human activities in terms of water diversion projects and damming the inflowing rivers, construction of Kalantari Martyr causeway and climate change – reduction of precipitation by 17% and increase of temperature by 7% (Hassanzadeh, et al., 2011) – on the one hand, and an abrupt declination of water level on the other hand.

For the principal hypothesis to be verified or validated (*testability*), it has to be identified that there was a significant declining trend in the lake WL during the recent years of 1996-2012 distinguishable from all other periods with the same length throughout the historical record. Further, it should be demonstrated how or to what extent such declinations have impacted the WL dynamic claiming an intrinsic/substantial change comparing the two periods of natural and anthropogenically intervened. Moreover, for the sake of hypothesis validity, climate variability should fail to explain the major portion of water level variations during the second period while it explains the variability during the first period quite clearly. Then, it could be concluded that human activities are the major cause of lake depletion in this case. And finally, it has to be shown how recent changes in the lake water level could influence its entire ecosystem as a major threat.

4.1.1. Hypothesis I

There is a uniquely-significant change (declining trend) in the lake water level during the recent years of 1996-2012 compared to historical period of 1966-1995.

In order to test this hypothesis, changes in the pattern of water level oscillations should be identified. The whole period of 1966-2012 needs to be investigated in order to see if declinations during the last 16.5 years (the second period from January 1996 to July 2012 i.e. 198 months) are uniquely different from all other 198-month periods. Establishing the existence of a substantially unique change, Mann-Kendall trend test (see Section 4.4 & Section 5.1) is used.

If a statistically significant trend could not be observed during the 2nd period or if other periods with such declinations are found, the significance of recent changes in terms of its historical uniqueness will be under question, otherwise, this hypothesis will be verified.

4.1.2. Hypothesis II

The changes, i.e. the depletion of the lake during 1996-2012, have intrinsically altered the underlying dynamic of water level fluctuations.

Establishing the existence of a unique significant change (Hypothesis I), its seriousness in terms of its impact on the underlying dynamic of water level variations should be studied. Since Chaos Theory is investigating the underlying structure of dynamical systems assessing their qualitative behavior, it is well fitted for testing this hypothesis. Therefore, Correlation Dimension Method (CDM) as the most common method of nonlinear chaotic analysis is employed (see Section 4.7 & Section 5.2) in order to examine the extent of the changes. Therefore the two periods of natural and anthropogenically intervened will be compared from the viewpoint of Chaos Theory.

If the result of this analysis could show that the dynamic of the lake WL oscillations, in terms of the number of parameters governing its dynamic, is changed during the 2nd period while there is an identifiable dynamic constantly governing the water level variations during the first period, then the hypothesis is verified. Otherwise, CDM will fail to verify the hypothesis but its validity would still remain as a question.

4.1.3. Hypothesis III

The major cause of the recent depletion of the lake and its concomitant intrinsic changes in the lake WL dynamic is anthropogenic interventions and not natural causes.

Physical background of the lake suggests that there are different factors contributing to the water level fluctuations namely climate variability, climate change, land use changes, groundwater withdrawals, causeway and dam constructions – which are the most significant causes in this case study. These contributing factors could be exclusively categorized to (a) anthropogenic and (b) natural causes. It could simply be assumed that climate variability is the only significant natural cause while the rest of aforementioned factors are counted to be anthropogenic.

Due to lack of data on all human activities and its direct consequences – i.e. groundwater withdrawals, dam construction, land use changes and climate change – detailed enough for examining whether the root cause of the mentioned changes is anthropogenic or not, or the problem of accessibility to certain data (e.g. details of dam construction projects), another angle has to be taken in order to examine the root cause. In other words, alluding to the fact that climate variability is the only known natural factor affecting the WL fluctuations, in order to answer the elusive question of the connection between human activities and WL depletion, based on the available data, the link between climate variability and WL should be examined instead. In view of the above, climatic analysis could clarify to what extent the oscillations can be explained by natural causes – climate variability – and therefore the unexplained portion of the variations are, presumably, associated with anthropogenic interventions.

For testing the hypothesis, standardized monthly anomalies of WL during the first period have been compared to the teleconnection indices by means of the Spearman Rank Correlation test (see Section 4.3.5) in order to find the influential climate signals for each month in this period. This is an indirect method for studying the influence of hydrometeorological variables such as precipitation, temperature etc. that are influencing the lake. Afterwards, by means of multiple linear regressions, the lake water level is modeled and validated for the first period to predict the second period variations based on the influential teleconnections (see Section 4.6 & Section 5.3).

For the hypothesis to be verified, climate variability should fail to explain the major portion of water level variations during the second period while it explains the oscillations during the first period quite clearly. If so, one can convincingly claim that there are significant changes during the second period that not only cannot be explained by climate variability but are also well in accordance with the expected consequences of the recent human activity in that region. Otherwise the mentioned climatic analysis will fail to examine the validity of this hypothesis.

4.1.4. Hypothesis IV

Depletion of the lake has a serious deteriorating impact on the lake's condition and its entire ecosystem.

As it was discussed earlier, the lake's hydrological condition is important for its entire basin's environment and ecosystem. Interrelation of the lake WL as the hydrological indicator and its salinity rate as the ecological indicator of this basin shows how the lake's hydrology and ecology are strictly tied together. Due to the fact that the lake water level determines its salinity rate, which is the major factor governing the ecosystem's biodiversity and food chain, thus, extreme changes in the lake water level could be highly crucial for the whole basin's ecosystem.

In order to examine this very last hypothesis, salinity level of the lake is modeled evaluating the current salinity rate of the lake (see Section 4.5 & Section 5.4) to see whether the recent salinity level is imposing an intense pressure on this ecosystem. If the salinity level is beyond the affordable rates, it is obvious that the whole catchment is threatened due to the lake's drying.

4.2. The Uncertainties of the Present Study

Alluding to the facts that the UL is relatively a large lake (in terms of its surface area) and due to the variety of factors influencing the lake nonlinearly and on different spatial and temporal scales, this natural system is quite complicated. One of the main uncertainties of this study is the short length of water level data for such hydroclimatic analyses; whether it is representative enough. Further, for studying the climate variability, only 9 TIs are employed.

Regarding the lake water level, only one observation time series is used. Alluding to the fact that the lake has a rather large surface area and it is divided into two separate parts by the causeway, the reliability of this single data set might be under question since it has not been compared with any other observation stations. Moreover, modeling the lake water level variations by means of a linear multiple regression method is indeed problematic as it is quite obvious that the relationship between the lake and teleconnection indices is indeed nonlinear. Moreover, the existence of noise in the data and its short length in analysis such as CDM is certainly a challenging issue for which further investigation applying other methods such as noise reduction and other chaos investigative approaches are necessary for verifying the results of the present study.

4.3. Statistical Methods

In order to test the aforementioned hypotheses, different statistical methods are employed, namely, Scatterplot, Mean, Standard Deviation (SD), Pearson Correlation Coefficient (PCC) and Spearman Rank Correlation Coefficient (SRCC). Each of these methods are defined and discussed below.

4.3.1. Scatterplot

An important aspect of the data structure is the relationship between different variables within the data set. If for each observation in one batch of the data set, there is a corresponding observation in another one, then these data are *paired*. Important insights could be achieved by elucidating relationships between sets of data pairs (Wilks, 2011).

The most common and probably universal exploratory technique for graphically displaying paired data is the scatterplot or the *x-y plot*. Geometrically, in a scatterplot, a collection of data pairs are presented in a plane where the values of each member of the data pair correspond to the two Cartesian coordinates of that plane. Scatterplots allow one to easily and visually examine features of the data such as trends, curvature in the relationship, clustering of one or both variables, changes of the spread of one variable as a function of the other, and extraordinary points or outliers (Wilks, 2011).

4.3.2. Mean

Sample mean is a measure of central tendency for an n-point dataset of x_i. It could be calculated as follow:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad \textit{(Equation 4)}$$

4.3.3. Standard Deviation & Variance

Sample standard deviation is a conventional measure of scale of a dataset which could be calculated as follow for the same dataset:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad \textit{(Equation 5)}$$

Sample standard deviation, s, simply shows the square root of the squared difference between data points and their corresponding sample mean. As it is comprehensible from Equation 5, standard deviation s, has the same physical dimensions as the underlying data.

It is also relevant to note that in Equation 5, the division by $\mathrm{n} - 1$ is often more frequent rather than dividing by n. This is to compensate for the fact that the x_i are on average closer to their sample mean $\bar{x}$ than to the true population mean μ. On this basis, dividing by $n - 1$ exactly counters this tendency for the sample standard deviation s to be, on average, too small (Wilks, 2011). The square of the sample standard deviation is known as the *sample variance*, s^2. In simple words, variance as a measure of spread or dispersion describes how far data points lie from their mean.

4.3.4. Pearson (Ordinary) Correlation

Pearson correlation coefficient is a dimensionless single-valued measure of association between two variables, say x and y that could be calculated as below (Wilks, 2011):

$$r_{xy} = \frac{Cov(x,y)}{s_x s_y} = \frac{\sum_{i=1}^{n}[(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad , -1 \le r_{xy} \le 1 \qquad \textit{(Equation 6)}$$

It is simply the ratio of the sample covariance of two variables to the product of their standard deviations that shows how two variables are varying together *linearly*. If PCC is close to +1, it implies a strong linearly-direct relationship between the two variables and if close to -1, it indicates an adverse linear relationship. PCC being close to zero shows that no linear relation between the two variables could be identified.

4.3.5. Spearman Rank Correlation

As PCC is not *robust* – i.e. nonlinear relationships between the two variables are not recognized – nor *resistant* – i.e. it is extremely sensitive to one or a few outliers – and hydroclimatology usually deals with nonlinearly-interrelated variables, hence, *Spearman Rank Correlation Coefficient* is often used.

It is basically the Pearson Correlation Coefficient but computed for the ranks of data instead of the sheer values. Therefore, it is both robust and resistant (Wilks, 2011). It is important to note that in all statistical methods employed in this research, the statistical significance of the method is used by computing the p-values on the two-tailed test (MathWorks, 2012).

4.4. Trend Analysis

4.4.1. Time Series Analysis & Stationarity

Although it is not expected for past and future values of hydroclimatic time series data to be identical, in some cases it is reasonable to assume similarities between their statistical properties. Roughly speaking, the idea of such statistical similarity between the past and the future of the data values of a time series is called *stationarity*. There are two types of stationarity. *Weak stationarity* or *covariance stationarity* simply implies that the mean of the data series does not change throughout the time. The more restrictive one, however, is *strict stationarity* which means that the full joint distribution of the variables in the series does not change throughout time (Wilks, 2011).

Without demonstrating any further details of stationarity, its implications in time series analysis will be discussed. One of the main concerns in time series analysis and in particular in hydroclimatic data analysis is that the stationarity of the data is presupposedly assumed for most methods. Nevertheless, many atmospheric and climatic processes are distinctly not stationary. For instance, temperature or wind speeds often exhibit annual or diurnal cycles (Wilks, 2011). Therefore, dealing with stationarity is an elemental challenge in time series analysis.

There are two approaches for dealing with nonstationary in data, both of which aim to process the data in a way that stationarity could be reasonably assumed. Transforming the nonstationary data mathematically to approximate stationarity is the first method; for example, projecting anomalies from data having an annual cycle. This could be easily done by subtracting the periodic sample mean from the given data and a transformed data series with a constant (zero) mean will be produced. *Standardization* of anomalies, as further but necessary manipulation, is needed in order to generate a series with both constant mean and variance (Equation 7).

$$z_i = \frac{x_i - \bar{x}}{s_x} = \frac{x'_i}{s_x} \qquad \textit{(Equation 7)}$$

where x_i is the raw data (e.g. in this study monthly WL), $\bar{x}$ is the sample mean, z_i is the standardized anomaly and s_x is the corresponding sample standard deviation that vary through the annual cycle. x'_i is the non-standardized anomaly where only the seasonality, $\bar{x}$, has been excluded. After removing such (e.g. annual) cycle, the resultant stationary data is said to be *cyclostationarity* (Wilks, 2011). It has to be noted that the result of Man-Kendall trend test for both standardized and non-standardized anomalies will be the same.

The alternative to the aforementioned approach is to stratify the data. In other words, one can conduct separate analyses on short-enough subsets of the data which could be regarded as nearly stationary. As an example, one might analyze daily observations for all available records at a given location in March, assuming that each 31-day data record in March for any given period of time is a sample from the same physical process. It implies that one is not necessarily assuming such process is the same as for July or even for February (Wilks, 2011). In this research this approach of data stratification is used.

4.4.2. Mann-Kendall Trend Test

The Mann-Kendall, as a hypothesis test, is a nonparametric, rank-based – the data is ranked according to time – method for evaluating the presence of trends in time series data. Each and every data point is sequentially treated as a reference point and is compared to all the following data points (Douglasa, et al., 31 December 2000). In the context of examining the possibility of the trend underlying a time series $x_i = 1, 2, 3, \ldots, n$, the time index i (e.g. the year, month etc. of observation of each datum) is, by definition, monotonically increasing, which simplifies the calculations. The test statistic, Kendall's S (Kendall, 1962), is calculated as

$$S = \sum_{i=2}^{n} \sum_{j=1}^{i-1} sign(x_i - x_j) \qquad \textit{(Equation 8)}$$

where the $sign$ function is defined as

$$sign(a) = \begin{cases} -1 & ,a < 0 \\ 0 & ,a = 0 \\ +1 & ,a < 0 \end{cases} \qquad \textit{(Equation 9)}$$

The sampling distribution of the test statistic, for moderate (n about 10) or larger lengths of data series, is approximately Gaussian. If the null hypothesis – no trend – is true, this Gaussian null distribution will then have a zero mean. In other words, for independent and identically distributed random variables – a series of values in a random order –, the S is expected to be zero:

$$E(s) = 0 \qquad \textit{(Equation 10)}$$

If all the x_i are distinct – random variable with no tied data – the variance of this sampling distribution is:

$$Var(S) = \frac{n(n-1)(2n+5)}{18} = \sigma^2 \qquad \textit{(Equation 11)}$$

Otherwise, for some x_i repeated values – some data values are tied –, the correction to $Var(S)$ is:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{n} t_i(i)(i-1)(2i+5)}{18} \qquad \textit{(Equation 12)}$$

where t_i indicates the number of ties of extent i. For instance, a dataset with two tied values have one extent two i.e. $i = 2$ and $t_2 = 1$.

For $n > 10$ (e.g. the present study), the test statistic follows a standard normal distribution calculating as below (Kendall, 1962):

$$Z_s = \begin{cases} \frac{S-1}{\sigma} & ,S > 0 \\ \frac{S+1}{\sigma} & ,S < 0 \\ 0 & ,S = 0 \end{cases} \qquad \textit{(Equation 13)}$$

Statistical significance level i.e. p-values for each test could be achieved as follow:

$$\Phi = 2[1 - \Phi(|Z_s|)] \qquad \textit{(Equation 14)}$$

where Φ is the cdf (cumulative distribution function) of a standard normal variable (Douglasa, et al., 31 December 2000).

4.5. Simple Linear Regression & Salinity Level (SL)

Since there is not accessible data on the salinity rate of the lake, and it is comprehensible that there is a linear relationship between WL and SL, the salinity rate of the lake could be modeled by means of regressions.

Simple linear regression is intended to summarize the relationship between two given variables. Conventionally, the *independent variable* or *predictor* is symbolized by x and the *dependent variable* or *predictand* is represented by y. The essence of this method is to find the line producing the least error for predicting y based on observations, x. In other words, as it is illustrated in Figure 27, the line minimizing a specific measure of the vertical distances between the data points and the line itself (the residuals e) is defined as the best-fitting line or the regression line, $\hat{y} = a + bx$ (Wilks, 2011).

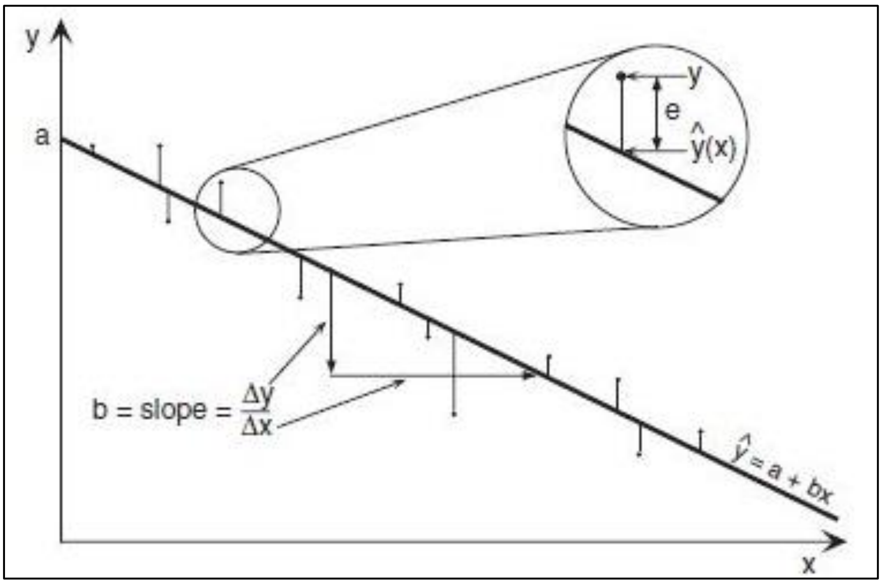


Figure 27. *Schematic illustration of simple linear regression or the best-fitting line (Wilks, 2011)*

Although the concept of least error is quite open to interpretation, the most common approach is to minimize the sum or equivalently, the average of the squared errors. On this basis, it is named as *least-squares regression* (LSR) or *ordinary least squares* (OLS) regression. In LSR method, the sum of the squared vertical distances between each data point and the regression line would be minimized.

For a given data set of $(x\ , y)$ pairs, regression aims to forecast/model y values.

$$\hat{y} = a + bx \qquad \textit{(Equation 15)}$$

where a is the least-squares intercept or regression constant and b is the line slope (see Figure 27). The circumflex accent "^" (called hat or roof) denotes predicted values of y. Therefore, *error* or *residuals*, e, are defined as the difference or distance between the sample values y_i and the forecasted values $\hat{y}(x_i)$:

$$e_i = y_i - \hat{y}(x_i) \qquad \textit{(Equation 16)}$$

As it can be understood from the Equation 16, there is a separate error, e_i, for each pair of (x_i, y_i). Generally, in the usual statistics convention, points above the regression line are regarded as positive errors and points below it are considered to be negative. In the atmospheric sciences, nevertheless, forecasts smaller than the observations – where the line is below the data points – are considered as having negative errors and vice versa (underestimation and overestimation, respectively). But in general, the issue of sign for residuals is trivial (Wilks, 2011).

4.5.1. Fitting the Line

In order to fit the regression line to data points, the least-squares intercept, a, and the line slope, b, need to be calculated. Finding analytic expressions for a and b is straightforward.

$$\sum_{i=1}^{n}(e_i)^2 = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n}(y_i - [a + bx_i])^2 \qquad \textit{(Equation 17)}$$

In order to minimize the sum of squared residuals, one needs to simply set the derivatives of Equation 17 with respect to the parameters a and b to zero.

$$\frac{\partial \sum_{i=1}^{n}(e_i)^2}{\partial a} = \frac{\partial \sum_{i=1}^{n}(y_i - a - bx_i)^2}{\partial a} = -2\sum_{i=1}^{n}(y_i - a - bx_i) = 0 \qquad \textit{(Equation 18)}$$

$$\frac{\partial \sum_{i=1}^{n}(e_i)^2}{\partial b} = \frac{\partial \sum_{i=1}^{n}(y_i - a - bx_i)^2}{\partial b} = -2\sum_{i=1}^{n}x_i[(y_i - a - bx_i)] = 0 \qquad \textit{(Equation 19)}$$

This solution would lead to the so-called *normal equation* (Wilks, 2011):

$$\sum_{i=1}^{n} y_i = na + b\sum_{i=1}^{n} x_i \qquad \textit{(Equation 20)}$$

$$\sum_{i=1}^{n} x_i y_i = a\sum_{i=1}^{n} x_i + b\sum_{i=1}^{n}(x_i)^2 \qquad \textit{(Equation 21)}$$

And finally, solving the normal equation for the regression parameters would yield a and b:

$$b = \frac{\sum_{i=1}^{n}[(x_i - \bar{x})(y_i - \bar{y})]}{\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{n\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{n\sum_{i=1}^{n}(x_i)^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \qquad \textit{(Equation 22)}$$

$$a = \overline{y} - b\overline{x} \qquad \textit{(Equation 23)}$$

Equation 22, calculating the slope (b), is similar in form to Equation 6 for the Pearson Correlation Coefficient.

4.5.2. Examination of Residuals

In order to measure the quality of the regression i.e. the forecast, residuals should be examined statistically. The statistical idea behind regression relies on two important assumptions that residuals,

e_i, are independent random variables, therefore, with (1) zero mean (Equation 24) and (2) constant variance. The additional assumption that these residuals/errors follow a Gaussian distribution is often made (Wilks, 2011).

$$\sum_{i=1}^{n} e_i = 0 \qquad \textit{(Equation 24)}$$

The idea of a constant variance implies that the residuals scatter randomly about the mean value i.e. 0. In other words, it is the regression line around which the residuals are scattered. According to Equations 5 and Equation 16, the variance of residuals could be calculated:

$$s_e^2 = \frac{1}{n-2}\sum_{i=1}^{n} {e_i}^2 = \frac{1}{n-2}\sum_{i=1}^{n}[y_i - \hat{y}(x_i)]^2 \qquad \textit{(Equation 25)}$$

Since the two parameters of the regression, a and b, are known, the sum of squared residuals is divided by n – 2. However, in practical problems, rather than computing the estimated residual variance using Equation 25, it is common to apply a computational form as follow (Wilks, 2011):

$$SST = SSR + SSE \qquad \textit{(Equation 26)}$$

SST (the Total Sum of Squares) denotes the variation in the predictand y i.e. the sum of squared deviations of the quantities y_i around their mean $\bar{y}$. A partitioning of SST is represented by the Regression Sum of Squares (SSR), and its unrepresented portion is attributed to the variation of residuals i.e. Sum of Square Errors (SSE). Each of the mentioned acronyms is mathematically defined as follow:

$$SST = \sum_{i=1}^{n}(y_i - \bar{y})^2 = \sum_{i=1}^{n} {y_i}^2 - n\bar{y}^2 \qquad \textit{(Equation 27)}$$

$$SSR = \sum_{i=1}^{n}[\hat{y}(x_i) - \bar{y}]^2 = b^2\sum_{i=1}^{n}(x_i - \bar{x})^2 = b^2\left[\sum_{i=1}^{n} {x_i}^2 - n\bar{x}^2\right] \qquad \textit{(Equation 28)}$$

$$SSE = \sum_{i=1}^{n} {e_i}^2 \qquad \textit{(Equation 29)}$$

Therefore, the Equation 25 could be reformulated as follow:

$$s_e^2 = \frac{1}{n-2}\{SST - SSR\} = \frac{1}{n-2}\{\sum_{i=1}^{n} {y_i}^2 - n\bar{y}^2 - b^2[\sum_{i=1}^{n} {x_i}^2 - n\bar{x}^2]\} \qquad \textit{(Equation 30)}$$

s_e^2 indicates the degree to which the distributions of residuals cluster tightly or spread widely around the regression line.

For the better understanding of the discussed issue of constant variance, Figure 28 is presented in order to visually illustrate different possible cases of residuals.

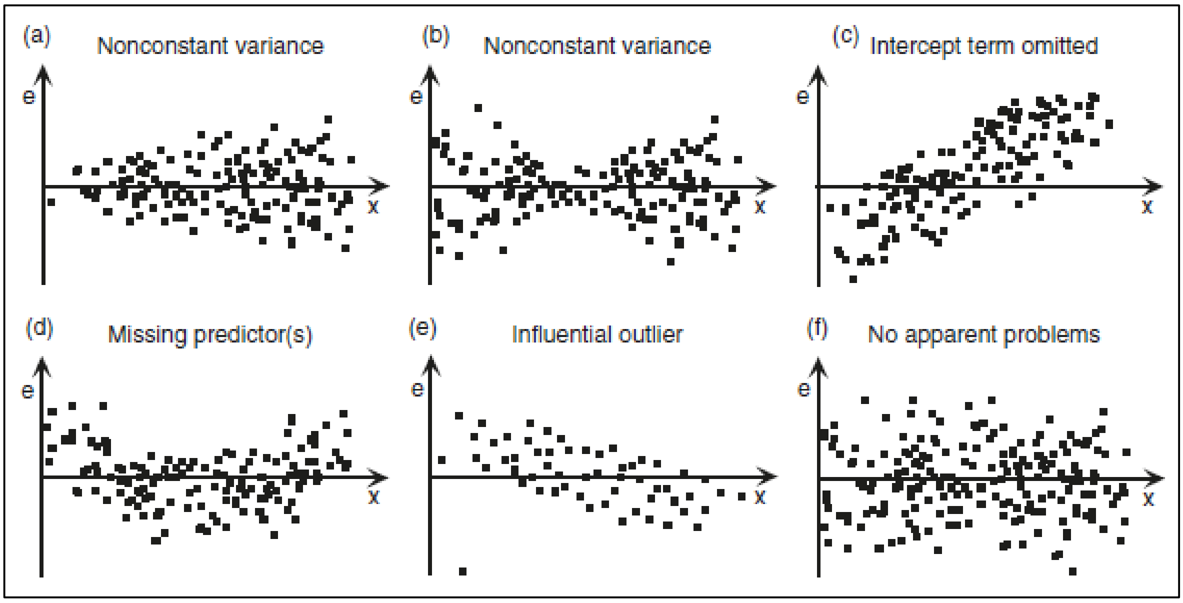


Figure 28. *Schematic scatterplots of idealized residuals vs. predictor x for a hypothetical regression, with corresponding diagnostic interpretations (Wilks, 2011)*

As it could be seen from Figure 28, the acceptable scatter of residuals in a visual manner is case (f) where there is no deductible information left in the residuals.

4.5.3. Goodness-of-Fit Measures

The common measure of the fit of a regression is the coefficient of determination, R^2, which could be simply computed for the case of a simple linear regression as follow:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} = \frac{\sum_{i=1}^{n}(\hat{y}(x_i) - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad , 0 \le R^2 \le 1 \qquad \textit{(Equation 31)}$$

R^2 could be seen as a way of expressing the closeness or discrepancy between SST and SSR. The closer SSR is to SST – i.e. each predicted value $\hat{y}$ is closer to its respective y – the closer its corresponding residual is to zero. In other terms, R^2 could be interpreted as the proportion of the predictand variation, SST, described or accounted for by the regression, SSR (Wilks, 2011).

In the particular case of simple linear regression, R^2 equals the absolute value of the Pearson correlation coefficient between the predictand y and forecasted $\hat{y}$. It is important to note that similar to correlation coefficient, R^2 does not reveal any information about the causal relationship between the predictor and predictand.

4.6. Multiple Linear Regression & Climatic Variability (CV)

In order to see to what extent WL fluctuations in Urmia Lake are related to climatic variability in the two periods, a multiple linear regression is needed. WL in the first period could be modeled by selected TI as predictors. The validated regression model could be used to generate the WL in the second period to be compared by the observed values.

In practical forecast problems, very often, more than one variable or predictor is needed for a single predictand. Therefore, multiple linear regression is the more common case. Generally, most of what was presented in simple linear regression (Section 4.5) could be generalized to the case of multiple linear regression. Supposing k number of predictor variables, the prediction equation for the case of multiple linear regression becomes:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_k x_k \qquad \textit{(Equation 32)}$$

For each of the k predictors, $x_1, \ldots, x_k$, there is a coefficient, $b_1, \ldots, b_k$, analogous to the slope b in Equation 22. It is obvious that simple linear regression is the special case of $k = 1$. The k coefficients, $b_1, \ldots, b_k$, together with the regression intercept or constant, b_0, are often called the *regression parameters* (Wilks, 2011).

Equation 16 is similarly valid for residuals considering that the predicted value $\hat{y}$ is not a function of a single predictor but a function of a vector of predictors, $x_k, k = 1, 2, \ldots, k$. Also, the average residual is zero, meaning that the residual distributions are centered on the predicted values $\hat{y}_i$. Therefore, the $k + 1$ regression parameters could be found, as before, by minimizing the sum of squared residuals. Due to the fact that such minimizations are most conveniently done using matrix algebra, regression parameters could be achieved by simultaneously solving $k + 1$ minimization equations analogous to Equation 18 and Equation 19. Measuring the quality of forecast in the case of multiple linear regression is exactly the same as what has been explained for simple linear regression (see Section 4.5.2 & Section 4.5.3).

4.7. Correlation Dimension Method

From the view point of dynamical systems, the behavior a lake in terms of its WL fluctuations could be characterized as either chaotic or stochastic. In order to represent the underlying dynamics of the Urmia Lake, the concept of phase-space diagram, and phase-space reconstruction and correlation dimension method (CDM) are employed as celebrated nonlinear methods in hydrological studies.

As it can be visually understood from Figure 12, Urmia Lake WL exhibits some degrees of nonlinearity. Therefore, nonlinear analysis of its time series is of high interest for the two following reasons: (a) By analyzing how the WL has evolved through the last few decades, one could understand the dynamical characteristics of the lake. It is significantly important due to the fact that lake is an important terrestrial component of the hydrologic cycle and understanding its dynamical properties could be seen as a valuable input for the better comprehension of more complex systems, i.e. hydroclimatic processes, in a larger scheme. (b) Nonlinear analysis of WL changes could open a new doorway for a more advanced approach in assessing the recent decline in the lake WL. Such an investigation by comparing the two historical period (1966-1995) and recent period (1996-2012) has not been done and the author believes it could reveal useful clues regarding the abrupt depletion of the lake during the past two decades.

An encapsulated description of Chaos Theory, its history and its important components namely phase diagram and strange attractor, was explained earlier (see Chapter 3). Due to the sophisticated mathematics behind this theory, which has been explained thoroughly in several authentic sources (e.g. Broer & Takens, 2011; Ivancevic & Ivancevic, 2008; Gidea & Niculescu, 2002), the present study only scratches the surface by an attempt of providing more explanatory description of the theory than its fundamental mathematics. Subsequently, CDM which is the popular approach for the chaotic analysis of the lake's hydrology in the resent study is explained.

4.7.1. Phase-space Reconstruction

The reconstruction of the phase-space of a scalar time series and, hence, its attractor is the first important step in any chaos identification approach. Such a reconstruction approach uses the concept of embedding a single-variable series in a multi-dimensional phase-space to represent the underlying dynamic (Sivakumar & Jayawardena, 2002). As the present study aims to analyze the WLs discrete time series, hence, the phase-space reconstruction method is explained for discrete scalar time series.

For an autonomous system characterized by d interacting state variables (a d-dimensional state space $\boldsymbol{z}$) the associated dynamics could be represented as:

$$\frac{d\boldsymbol{z}(t)}{dt} = F(\boldsymbol{z}(t)) \qquad \textit{(Equation 33)}$$

Assume a scalar univariate time series $x(t), t = 1, 2, \ldots, N$ for one of the d state variables (e.g. lake WL), generated by this system. This system can be rewritten as a high-ordered differential equation in terms of the single state variable x as follow:

$$x^{(d)} = f(x, x', \ldots, x^{(d-1)}) \qquad \textit{(Equation 34)}$$

Based upon the notion of phase-space reconstruction (Packard et al., 1980; Taken, 1981) a pseudophase-space could be defined using delay coordinates by defining a delay vector Y_t:

$$Y_t = \{\, x(t), x(t-\tau), \ldots, x(t-(m-1)\tau)\} \qquad \textit{(Equation 35)}$$

where τ is delay time, appropriately chosen as an integere multiple of simpling time Δt, and m is an integer embedding dimension. If the solution of the equations lies on an attractor of dimension d_A ($d_A < d$), choosing the integer m ($m > 2d_A$) is a sufficient condition for unfolding the attractor from time series $x(t)$. Subjecting to generic assumptions on F and Δt, for any delay time τ and forecast period T, the underlying dynamics could be represented by a smooth (i.e. differentiable) map:

$$Y_{t+T} = f^T\big(x(t), x(t-\tau), x(t-2\tau), \ldots, x(t-(m-1)\tau)\big) = f^T(Y_t)$$
$$f^T: \mathbb{R}^m \to \mathbb{R} \qquad \textit{(Equation 36)}$$

Where Y_t and Y_{t+T} are vectors of dimension m, describing the system state at current state t and future state $t+T$, respectively. Equation 36 is a basis for reconstructing the phase-space of the underlying dynamic of a given scalar time series by providing the map f^T if appropriate values of τ and m are chosen.

Simply put, the phase-space reconstruction from a discrete time series (pseudophase-space) can be achieved with the help of an m-dimensional "embedding space", E_m, which is spanned by delay vectors for any given (integer) time delay τ. For a scalar univariate time series X_i (e.g. lake WL), where $i = 1, 2, \ldots, N$ the phase-space could be reconstructed according to (Sivakumar, et al., 2001):

$$Y_j = (\, X_j, X_{j+\tau}, X_{j+2\tau}, \ldots, X_{j+(m-1)\tau}\,) \qquad \textit{(Equation 37)}$$

where $j = 1, 2, \ldots, N-(m-1)\tau/\Delta t, m$ is the embedding dimension (dimension of vector Y_j) and τ is delay time. τ is almost an 'arbitrary', but fixed time delay for an infinite amount of noise-free data (Taken, 1981). τ should be a suitable integer multiple of the sampling time Δt (Packard et al., 1980; Taken, 1981). m is the number of coordinate of the embedding space.

Despite the basic assumption of phase-space reconstruction method that for an infinite noise-free time series, τ is an almost 'arbitrary', there is no such time series in real life problems and hydrological time series are no exceptions to this. Therefore, there has been a quest finding the optimal delay time for practical problems.

4.7.1.1. Finding the Proper Delay Time

Primarily, the lag at which the autocorrelation function crosses the zero line, has been chosen as the delay time τ (Mpitsos, et al., 1987). Fraser & Swinney (1986), nonetheless, explained why mutual criterion is the better choice for τ in most systems. Mutual information has been suggested (Shaw, 1985) as a suitable criterion for time delay τ in phase portrait reconstruction. Shaw (1985) has proposed that when the value of τ produces the first local minimum in the mutual information, it is best to be used for phase portraits. Further studies (Fraser & Swinney, 1986) have investigated this criterion on Belousov-Zhabotinskii reaction and the Rössler system. It has been shown (Fraser & Swinney, 1986) that mutual information is a superior criterion comparing to autocorrelation, the traditional one.

Roughly speaking, mutual information measures the *general* dependence of two variables while autocorrelation assesses *linear* dependence among successive values of the process. Hence, it offers a better qualified option for τ (Fraser & Swinney, 1986). However, in the case of time series with strong periodic contents, a minimum of mutual information between two measurements is approximately equal to the first zero-crossing of the autocorrelation function (Holzfuss & Mayer-Kress, 1986).

In practical problems and in particular hydrological studies investigating the existence of chaos in hydrological time series (e.g. Rodriguez-Iturbe et al., 1989; Sharifi et al., 1990; Jayawardena & Lai, 1994; Puente & Obregón, 1996; Sivakumar et al., 1999; Sivakumar et al., 2001; Sivakumar et al., 2005; Sivakumar et al., 2013), for the sake of simplicity, the autocorrelation criterion has been commonly used. For example, Sharifi et al. (1990), for selecting τ, has taken the lag at which the autocorrelation function falls below the value of 0.5 while Tsonis & Elsner (1988) defined and proposed the threshold as $1/e$ specially for cases that autocorrelation function is approximately exponential. Nevertheless, another common threshold is the zero line (Mpitsos, et al., 1987) that has been used widely in more recent studies (e.g. Sivakumar et al., 1999; Sivakumar et al., 2001; Sivakumar et al., 2005; Sivakumar et al., 2013).

Equation 38 could be an instance of computing the autocorrelation function $r(\tau)$ for different lag times τ (Tsonis, 1992):

$$r(\tau) = \frac{\sum_{i=1}^{N-\tau} X_i X_{i+\tau} - \frac{1}{N-\tau}\sum_{i=1}^{N-\tau} X_{i+\tau} \sum_{i=1}^{N-\tau} X_i}{\left[\sum_{i=1}^{N-\tau} X_i^2 - \frac{1}{N-\tau}\left(\sum_{i=1}^{N-\tau} X_i\right)^2\right]^{\frac{1}{2}} \left[\sum_{i=1}^{N-\tau} X_{i+\tau}^2 - \frac{1}{N-\tau}\left(\sum_{i=1}^{N-\tau} X_{i+\tau}\right)^2\right]^{\frac{1}{2}}} \quad \textit{(Equation 38)}$$

where X_i, is the discrete time series, with $i = 1, 2, \ldots, N$.

Autocorrelation function is beneficial in other ways as well. It is also applicable in identifying the time series behavior by determining the present degree of linear dependence in the data. In the case of a purely random process, the autocorrelation function $r(\tau)$ varies around zero. It indicates that the process has no "memory" of its past at any given instance. For a periodic system, nonetheless, the autocorrelation function $r(\tau)$ is periodic likewise, suggesting a strong relationship between the repeating values. Despite the two previous cases, for chaotic processes, the autocorrelation function decays exponentially as the lag increases. It is due to the fact that a chaotic process is neither completely deterministic (therefore dependent) nor stochastic (therefore independent of each other) (Tsonis, 1992; Sivakumar et al., 2001).

4.7.2. Correlation Dimension Method

There are different methods discerning low-order deterministic chaotic processes from stochastic ones. Among those, CDM is almost certainly the most fundamental one that has been used in a wide range of subjects from traffic time series (Shang, et al., 2005) to hydrological time series.

In simple words, CDM attempts to estimate the attractor dimension. CDM is established upon the concept of the *correlation integral* (or function). The concept is that an ostensibly irregular phenomenon could arise from deterministic dynamic. Such systems will have a limited number of DOF equal to the smallest number of first order differential equations that capture the most important features of their dynamic. From different approaches in estimating the correlation dimension, the present study utilizes the Grassberger-Procaccia Algorithm (GPA) (Grassberger & Procaccia, 1983).

Based upon Equation 37, a trajectory in an m-dimensional space can be constructed. Therefore, moving along with time t, a series of m-dimensional will be obtained which represent the m-dimensional phase-space of the system. Suppose a circle (a sphere for $m = 3$ or a hypersphere for $m \geq 4$) of radius r centered about an arbitrary point of the m-dimensional set of vectors (see Figure 29) and count the number of points $N(r)$ located inside the circle. Normalizing such a count, the so called *correlation integral* $C(r)$ of the process will be obtained (Rodriguez-Iturbe, et al., 1989).

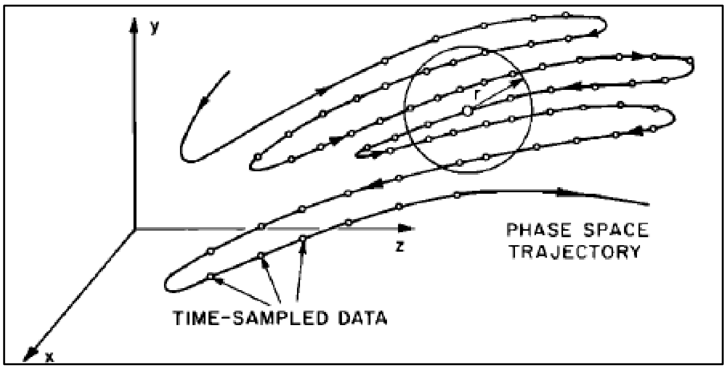


Figure 29. T*he counting sphere in a longtime trajectory in phase-space (Rodriguez-Iturbe, et al., 1989)*

The GPA uses the described concept of phase-space reconstruction to represent the system's dynamic. According to GPA, for an m-dimensional phase-space (m is an integer), the correlation function $C(r)$ of an infinite time series is (Grassberger & Procaccia, 1983):

$$C(r) = \lim_{N \to \infty} \frac{2}{N(N-1)} \sum_{\substack{i,j \\ 1 \le i < j \le N}} H\left(r - \| Y_i - Y_j \|\right) \qquad i \neq j \qquad \textit{(Equation 39)}$$

where N is the number of data point, r is the vector norm (radius of a sphere) centered on Y_i or Y_j and H is the Heaviside step function or the unit step function defined as below:

$$H(u) = \begin{cases} 0, & u < 0 \\ 1, & u \ge 0 \end{cases} \qquad \textit{(Equation 40)}$$

$C(r)$ is also called the correlation dimension or correlation integral. The correlation integral $C(r)$ is used to describe the dimension of the attractor (Berndtsson, et al., 2001). It defines the density of points around a specific coordinate x_i. In other words, it measures how densely the trajectories populate phase-space. If the time series is characterized by an attractor, according to Equation 41, the correlation function $C(r)$ and radius r for positive values, are related:

$$\underset{\substack{r \to \infty \\ N \to \infty}}{C(r)} \approx \alpha\, r^{\nu} \qquad \textit{(Equation 41)}$$

where α is constant and υ is the *correlation exponent*. In case the values of υ are not integers, it is implied that the attractor is fractal and thus chaotic (Berndtsson, et al., 2001). Correlation exponent υ, as the slope of $logC(r)\ vs\ logr$ plot, could be simply obtained as follow:

$$\upsilon = \lim_{\substack{r \to \infty \\ N \to \infty}} \frac{\log C(r)}{\log r} \qquad \textit{(Equation 42)}$$

Generally, the slope is estimated by a least-squares fit of a straight line over a certain range of r known as the *scaling region* or *scaling regime* (Rodriguez-Iturbe et al., 1989; Sangoyomi et al., 1996; Sivakumar et al., 2001). This will be explained in the following section.

For a random process, correlation exponent υ varies linearly as m increases without reaching a saturation value; on the contrary, in case of a determinisitic processes, the estimated correlation dimension of the reconstructed attractor (i.e. correlation exponent υ) reaches a plateau from which the dimension estimate υ is relatively constant for a large range of embedding dimensions m. It is assumed that the plateau dimension υ is an estimate of the attractor dimension d_A in the original full phase-space (Ding, et al., 1993). It is due to fact that a widely fluctuating and seemingly irregular process stems from a deterministic dynamic which has a limited number of DOF. Hence in constructing the phase-space of higher dimensions, a point will be reached at which the dimension equals the DOF and increasing the dimension will not affect the relation $N(r) \sim r^{\nu}$ for an infinite time series. In other words, the saturation value d_A (attractor dimension) is defined as the correlation dimension of the attractor (or the time series) (Rodriguez-Iturbe, et al., 1989). Therefore, d – the nearestt integer above d_A – suggests the the minimum number of variables essential to understand/capture the dynamic of the system i.e. minimum number of embedding dimensions required to unfold the attractor and subsequently, the dynamic of the system (Jayawardena & Lai, 1994). In other words, the smallest number of first-order differential equations that capture the main feature of the process dynamics may be determined.

4.7.2.1. The Scaling Region

The correlation dimension $C(r)$ is defined with the limit that r approaches zero. If the data is extremely noisy, $C(r)$ behaves poorly as r approaches zero. Below some radius r, the number of available pairs of points can be too few and for very large r, correspondingly, all the neighbors that get counted will be counted with reference to a few vectors that are near the edges of the domain. As the m increases the edge effect grows. Ultimately, the applicable r values will be in an intermediate range called the scaling region (Sangoyomi, et al., 1996).

For each m, the correlation exponent and hence the correlation dimension are computed from the slope of the $\log\big(\mathrm{C(r)}\big)$ vs. $\log(\mathrm{r})$ plot in the linear scaling region (Ding, et al., 1993). It is always desirable to have a larger scaling region to determine the slope, since the determination of the slope for a smaller scaling region may be difficult and could possibly give rise to errors.

The scaling region is not visually obvious, thus to make it easier, the local slope of the curve $log\big(C(r)\big)\ vs.\ log(r)$ should be calculated:

$$\Delta_t = \frac{log[\,C(r)]_{t+1} - log[\,C(r)]_{t-1}}{log(r)_{t+1} - log\,(r)_{t-1}} \qquad \textit{(Equation 43)}$$

The local slopes, then, should be plotted versus $log(r)$ so that scaling region could be seen.

For the better illustration of the above explanations, the scaling region of an earlier hydrological study (Sangoyomi, et al., 1996) is presented in Figure 30.

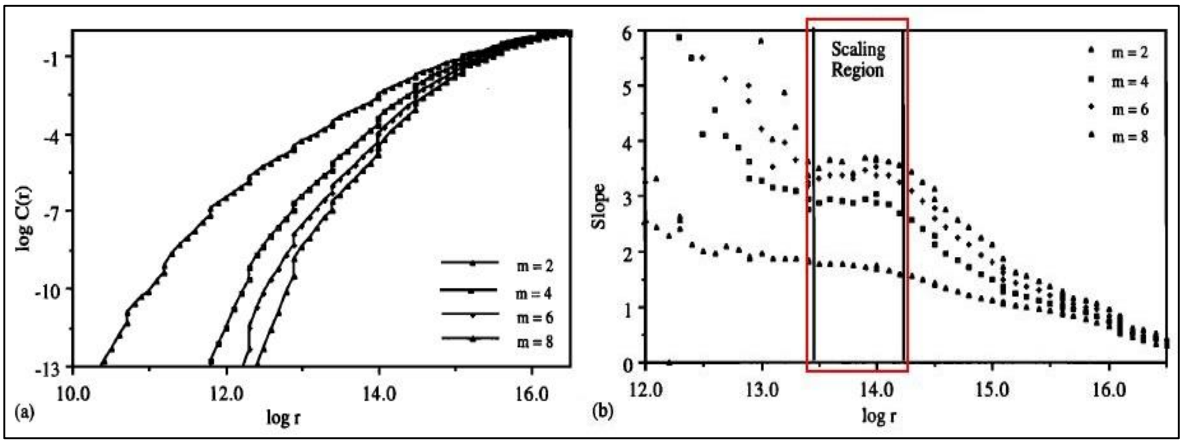


Figure 30. *(a) $\boldsymbol{log(C(r))}$ $\boldsymbol{vs.log(r)}$ for the time series of Great Salt Lake (GSL) volume and (b) Local slope of the curve (a) vs.* $\boldsymbol{log(r)}$ *(Sangoyomi, et al., 1996)*

It has to be noted that Lai & Lemer (1998) have probed the dependency of the scaling region on fundamental parameters τ, m and $m\tau$. The results suggested that the effective linear scaling region used for reliably estimating correlation dimension, is highly sensitive to the choice of delay time employed in the phase-space reconstruction (Lai & Lerner, 1998).

5 RESULTS & DISCUSSIONS

5.1. Trends in Urmia Lake WL

The celebrated method of Mann-Kendall trend test has been widely used by other contemporary hydrologists (e.g. Douglasa et al., 2000; Burn & Hag Elnur, 2002) and climatologists (e.g. Gadgil and Dhorde 2005;Tomozeiu et al. 2006; Rana et al., 2012). With regard to its broad application, the two following advantages of this method could be cited (Ríoa, et al., 2005):

1. It is not a presuppositional method in terms of data distribution i.e. there are no necessary assumptions about the data distribution as the prerequisite of this method – known as nonparametric method. Therefore, there is no uncertainty in this method in terms of the data distribution.
2. It is directly applicable to climate data for a given month or season.

As it has been explained previously, the very first step in hydroclimatic analyses such as trend test is to derive the Standardized Monthly Anomalies of the lake Water Level (SMA-WL).

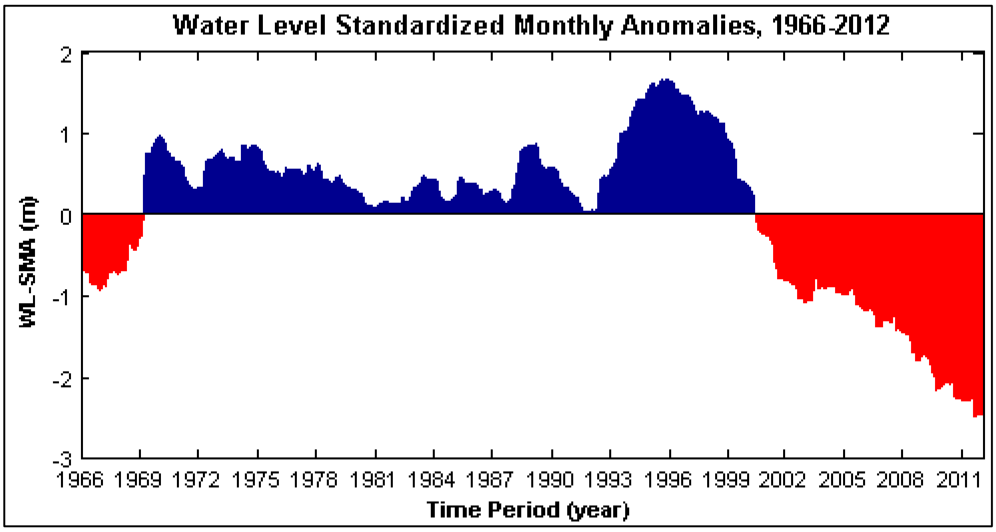


Figure 31. *Standardized anomalies of monthly water level, 1966-2012*

As it could be seen from Figure 31, it is a realistic hypothesis that the changes have begun around 1996. Therefore, Mann-Kendall trend test has been applied on SMA-WL to find the critical period in terms of the most extreme decreasing trend. In order to be able to statistically prove that the changes in the last 16.5 years are unique, all consecutive 16.5-year periods (i.e. 198 months) in the time series have been analyzed. First, all months are indexed respectively as it is presented in Table 10.

Table 10. *Indexing months subjected to Mann-Kendall trend test*

Date	Month index
January, 1966	1
February, 1966	2
…	…
May, 1995	353
January, 1996	361

The results of the trend test presented in Figure 32 clearly show that the lowest Mann-Kendall's S is around 1996 implying that the critical 198-month period throughout 1966-2012 begins around this year.

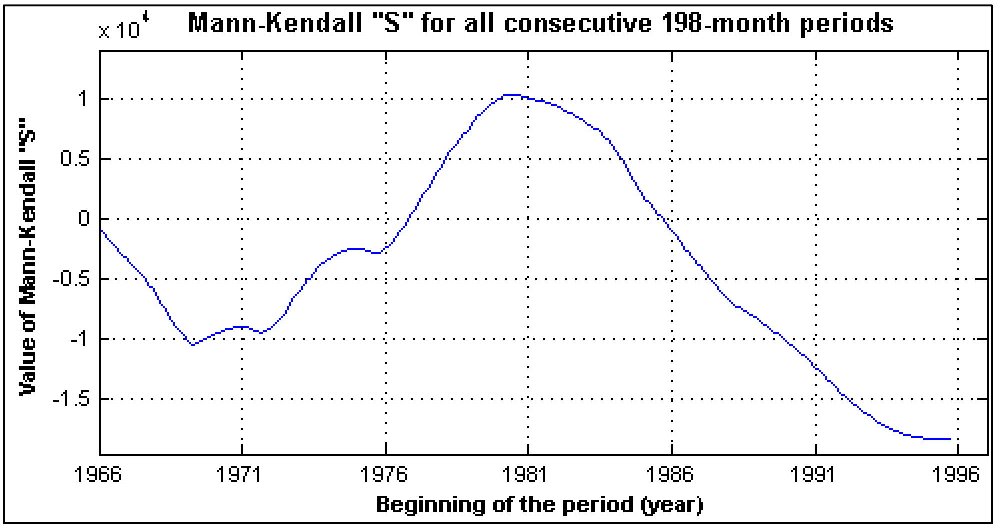


Figure 32. *The value of "S" from Mann-Kendall test for all possible consecutive 198-month periods*

As it is presented in Table 11, the critical period, in fact, begins at month 355, i.e. August 1995, 5 months prior to the period proposed by hypothesis I. Due to the fact that all critical periods of decreasing trends are consecutively occurring after month 355, therefore, one could say, with a great degree of certainty, that they are sharing the same reason(s) for such negative S i.e. dramatic declination. Therefore, assuming the critical period starting from month 361 instead of month 353, with less than 0.1% difference in Mann-Kendall's S, will not harm the logical consistency for further analyses.

Table 11. *Finding critical period in terms of steepest trend regardless of its sign*

Month index	353	354	355	356	357	358	359	360	361
p-value	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Z	-19.57	-19.58	-19.59	-19.58	-19.58	-19.58	-19.58	-19.57	-19.57
S	-18241	-18253	-18259	-18257	-18251	-18257	-18257	-18243	-18241

Figure 33 shows how SMA-WL is fluctuating during these two periods together with their linear trend lines.

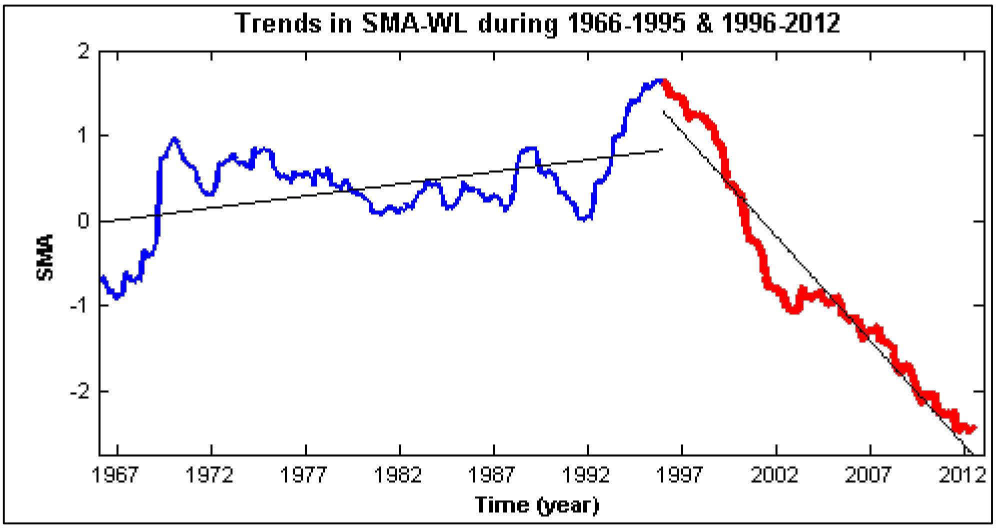


Figure 33. *Trends in Standardized Monthly Anomalies of Water Level (SMA-WL) during 1966-1995(blue) and 1996-2012 (red)*

Detailed results of the trend test comparing these two periods is presented in Table 12, indicating that both results are statistically significant (p-values < 0.05), therefore, reliable:

Table 12. *Mann-Kendall trend test results comparing two periods*

	1st period, 1966-1995	**2nd period, 1996-2012**
Month index	1	361
P-value	0.00014	0.0
Z	3.81	-19.57
S	8686	-18241

Equations of the linear trend lines in Figure 32 are presented in Table 13:

Table 13. *Trend line equations comparing the two periods*

Period	**Trend Line Equation**	
1st	$y = 0.028\ SMA - 55.88$	*(Equation 44)*
2nd	$y = -0.246\ SMA + 491.49$	*(Equation 45)*

As it could be understood from these equations, during the 1st period, there was a mild but increasing trend in the lake water level of about 0.03 m/yr increase in average while during the 2nd period, there was a strong but declining trend of about -0.25 m/yr in average.

In order to check the aforementioned results on a more detailed scale, the same approach has been taken to find the critical year for each month separately (see Table 14).

Table 14. *Critical annual index as a result of Mann-Kendall trend test for each particular month*

Month	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
Critical index	31	31	30, 31				30, 31					
S	-132	-132	-132				-162					

As Table 14 vividly represents, for each separate month subjected to Mann-Kendall trend test, the critical period equally begins by year 30 or 31 i.e. 1995 or 996, respectively. Figure 34 presents the comparison of trend lines for the periods of natural (1st period) and anthropogenically intervened (2nd period) on a monthly resolution for each month separately.

As it has been discussed above, the critical period of the declining trend begins by year 1996 for all months as it was proposed by hypothesis I (see Section 4.1.1). In other words, the period of 1966-2012 is the critical period as it was expected. Therefore, the hypothesis I is tested by Mann-Kendall trend test and has been verified.

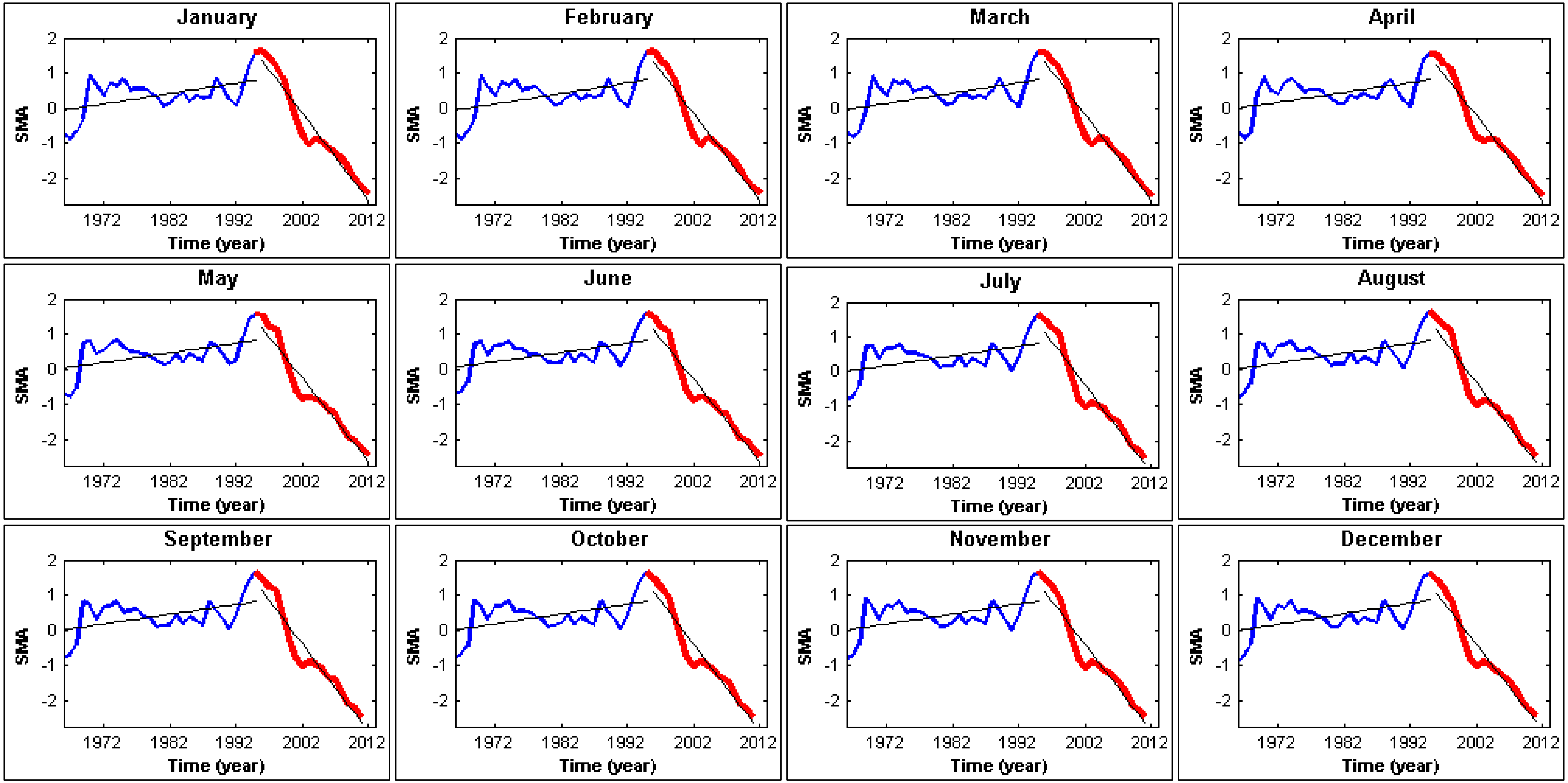


Figure 34. *Results of Mann-Kendall trend test on monthly water level value during comparing two periods of 1966-1995to 1996-2012*

5.2. Chaotic Analysis of Urmia Lake WL

This section aims to examine the structure of the hydrological process of the Urmia Lake WL fluctuations. There is a necessity of bridging the gap between the theoretical notions of deterministic chaos on the one hand, and practical hydrology on the other (Sivakumar, 2000). Despite all the previous studies that used CDM for investigating evidence for low-dimensional dynamic in hydrological processes, this study put a step further, and apart from such investigations, applies CDM for assessing the changes in the underlying dynamic of a system comparing two periods of the same dynamical system.

In order to investigate the possible presence of low-dimensional chaotic behavior in WL variations and due to the issue of data size (see Section 3.4.2.2), direct comparison of the period of 1966-1995 and 1996-2012 is not possible. However comparing the two periods of 1966-1995 (natural period) with the whole period of 1966-2012 which holds a great deal of changes in its fluctuations is quite reasonable regarding the logical consistency needed for testing the hypothesis II. However, in order to verify the results of the first period, an auxiliary period of 1966-1985 is employed; in order to see whether the underlying dynamic during 1966-1995 is governing the earlier periods (i.e. 1966-1985) as well. Therefore, only in this section, in order to test the hypothesis II, three periods with the respective lengths of (i) 500 biweekly data points i.e. about 19.2 years (the auxiliary period), (ii) 782 data points i.e. 30 years (the natural period), and (iii) 1213 data points of about 46.5 years (the whole period) are studied.

5.2.1. Phase-space Reconstruction & CDM

As it has been discussed previously, the temporal resolution of the data is a challenging issue using CDM. The experience of the author with the lake's data suggests that biweekly WL variations are properly suited for this method. It is relevant to note that chaotic analysis of Great Salt Lake in Utah was conducted with the same temporal resolution (Sangoyomi, et al., 1996).

In view of the above, firstly, biweekly water level fluctuations are mapped on the phase diagram. Since the Urmia Lake WL time series is a 1-DOF system, its phase-plane can be simply reconstructed by plotting the WL signal $x(t)$ versus itself, delayed by a fixed time constant T i.e. the $x(t)\ vs.\ x(t+T)$ (pseudophase-space) (Rodriguez-Iturbe, et al., 1989). It is due to the fact that for systems with small DOF, if a sufficiently long T is chosen, the properties of the system in its pseudophase-space are analogous to the properties of the original systems in the classic phase-plane $(x(t), dx/dt)$ describing the deterministic dynamic of the 1-DOF system (Packard, et al., 1980). Urmia Lake attractor is presented in Figure 35 as an indication of the deterministic behavior of the lake WL variations. It has to be noted that it is difficult to see strange attractors in hydrological time series; it is not as distinguishable as the Lorenz strange attractor (Figure 25).

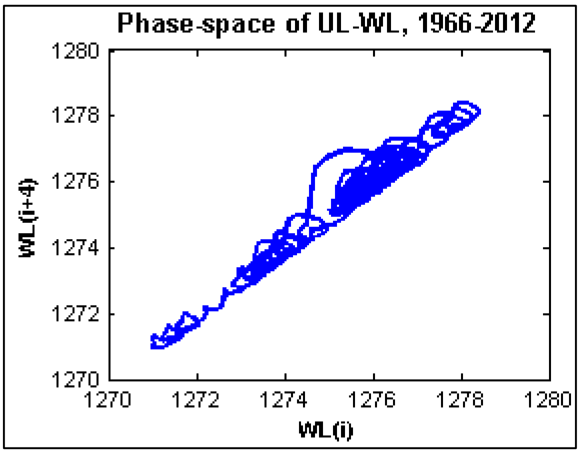


Figure 35. *Attractor of biweekly WL at Urmia Lake with lag 4, 1966-2012*

Figure 35 shows a biweekly lake WL phase diagram for the period 1965-2012 with a lag 4 (about 2 months). As it shows, biweekly lake WLs from 1965 to 2012 varies between about 1271.01 to 1278.4 $masl$. Regarding the investigation of Urmia Lake's attractor, a closer look on the evolution of this attractor might be helpful for understating its dynamic and recent changes (see Figure 36).

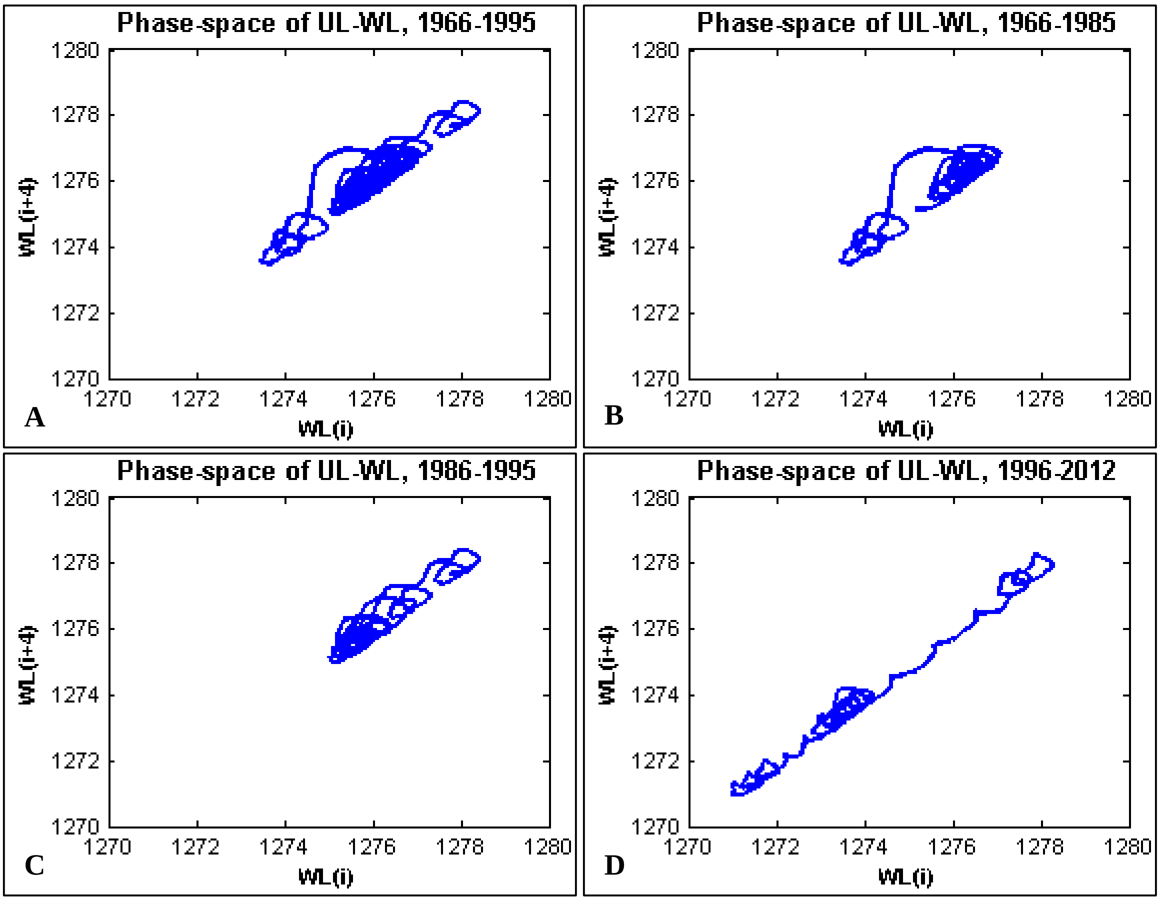
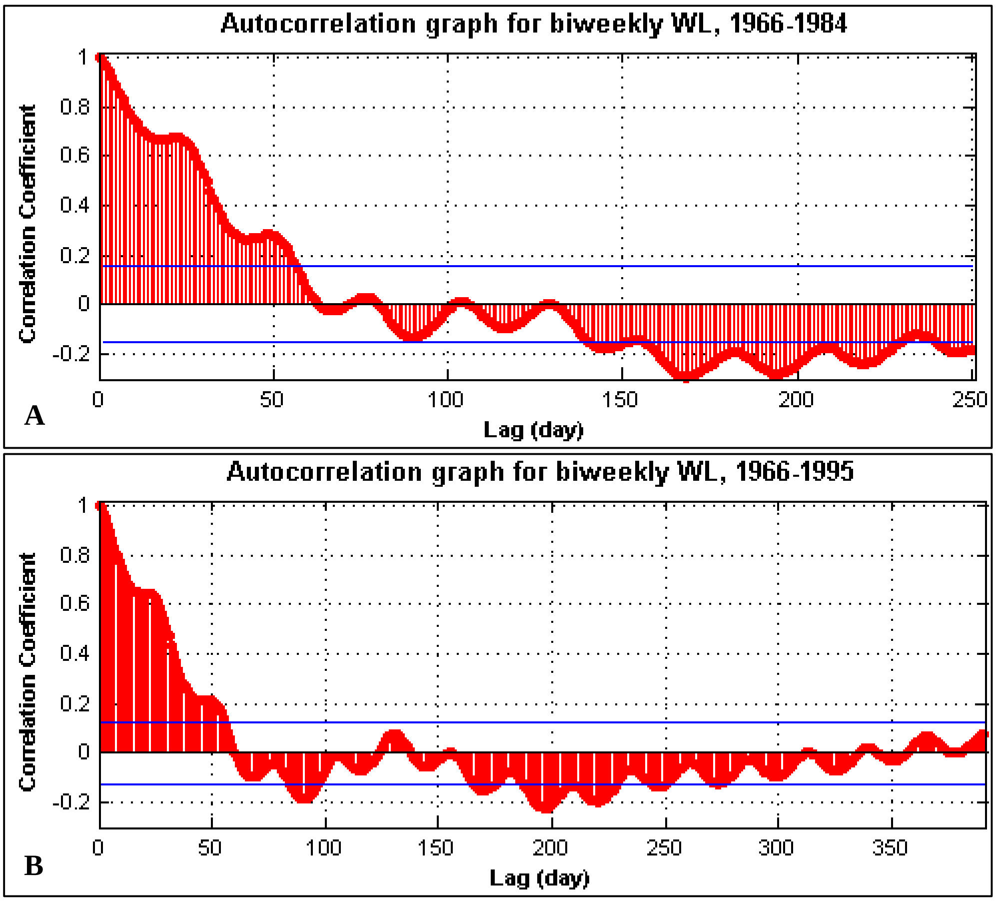


Figure 36. *Evolution of Urmia Lake Attractor of biweekly WL with lag 4 during (A) 1966-1980, (B) 1981-1995, (C) 1966-1995(i.e. natural period) and (D) 1996-2012(i.e. anthropogenically intervened period)*

As it can be understood from the Figures, the historical climatic influence has made the water level fluctuate between two states, namely a wet higher lake water level and a dry low lake water level. As it could be seen from Figure 36, during the first period (A) water levels are oscillating due to natural fluctuations quite closely to each other at higher levels compared to the second period (D). (C) and (D) quite clearly show how closely water levels are fluctuating comparing the period 1966-1985 and 1986-1995 within the first period. However, during the second period (1996-2012), a significant shift from higher levels to lower ones could be seen. It implies that within this period, there is a time when no oscillation has occurred in WL fluctuations which is totally unexpected. This could be interpreted as a preliminary indication of an unnatural change in the dynamic of the lake as such an irregular abrupt change in the evolution of Urmia Lake's attractor could significantly influence its dynamic.

The first step for estimating the correlation exponent is to find the proper delay time by means of the autocorrelation function as discussed previously (see Section 3.4.2.1). Thus, the autocorrelation plots of the three aforementioned periods of *i*, *ii*, and *iii* are presented below.



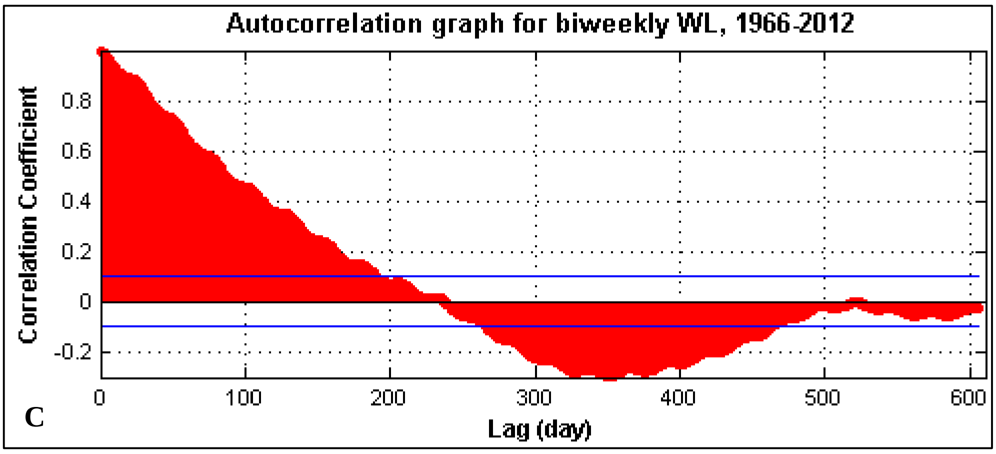
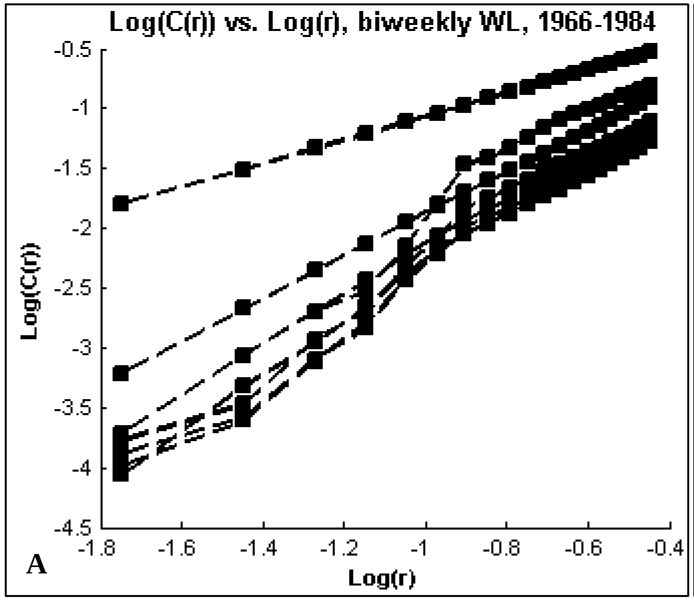


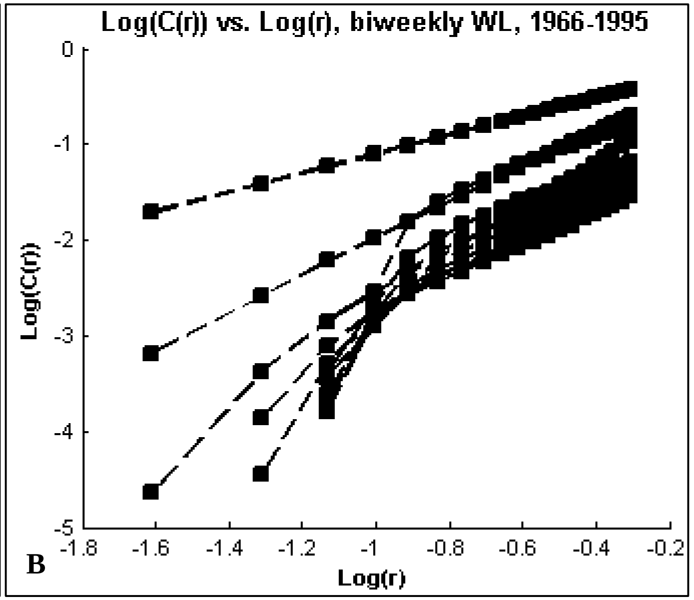
Figure 37. *Autocorrelations of biweekly WL for 3 periods of (i) 1966-1984, (ii) 1966-1995 and (iii) 1966-2012, respectively (the blue bands are indicating statistical significance of p-value<0.05)*

The first zero values that the autocorrelation function attains are the proper delay times for the periods of *i*, *ii* and *iii* are 65, 62 and 240, respectively. As is it could be seen from Figure 37, there is a semi-regular behavior in the autocorrelation function after its initial behavior of abrupt decline, especially in A and B. Generally, this smooth seasonal, but certainly not periodic, characteristic of the process may be an indication that one is dealing with a process which is neither completely deterministic nor completely stochastic, but chaotic. Moreover, larger variations in the autocorrelation plot of the period *i* and *ii* show that they are more variable than the whole period (C). It suggests that the correlation dimension of these two periods might be higher than the whole period. Nevertheless, it is important to note that autocorrelation is neither a necessary nor a sufficient method characterizing a system to be stochastic or chaotic (Sivakumar, et al., 2001).

In contrast to the 1st period (periods *i* and *ii*), the autocorrelation of the whole period (1966-2012) not just has a more significant decline in the abrupt behavior, but also does not represent the seasonal behavior as it is expected – similar to the autocorrelation graphs of the periods *i* and *ii*. This could be seen as another indicator of how the recent decline in water level fluctuations does not follow the seasonal variations influenced by climate variability.

Afterwards, by constructing the phase-space, the $log\big(C(r)\big)\ vs.\ log(r)$ plot for biweekly water level of the lake for the periods of *i*, *ii*, and *iii* are presented in Figure 38. And finally the plots of correlation exponent vs. the embedding dimensions for the same periods are presented in Figure 39.





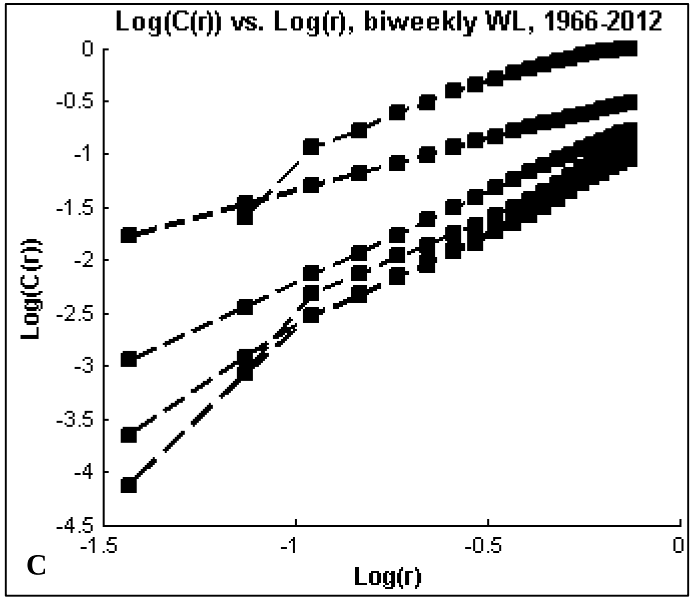


Figure 38. *Plots of* $\boldsymbol{log}\left(\boldsymbol{C}(\boldsymbol{r})\right)\ \boldsymbol{vs}.\boldsymbol{log}(\boldsymbol{r})$ *of biweekly WL, for 3 periods of (i) 1966-1984, (ii) 1966-1995 and (iii) 1966-2012*

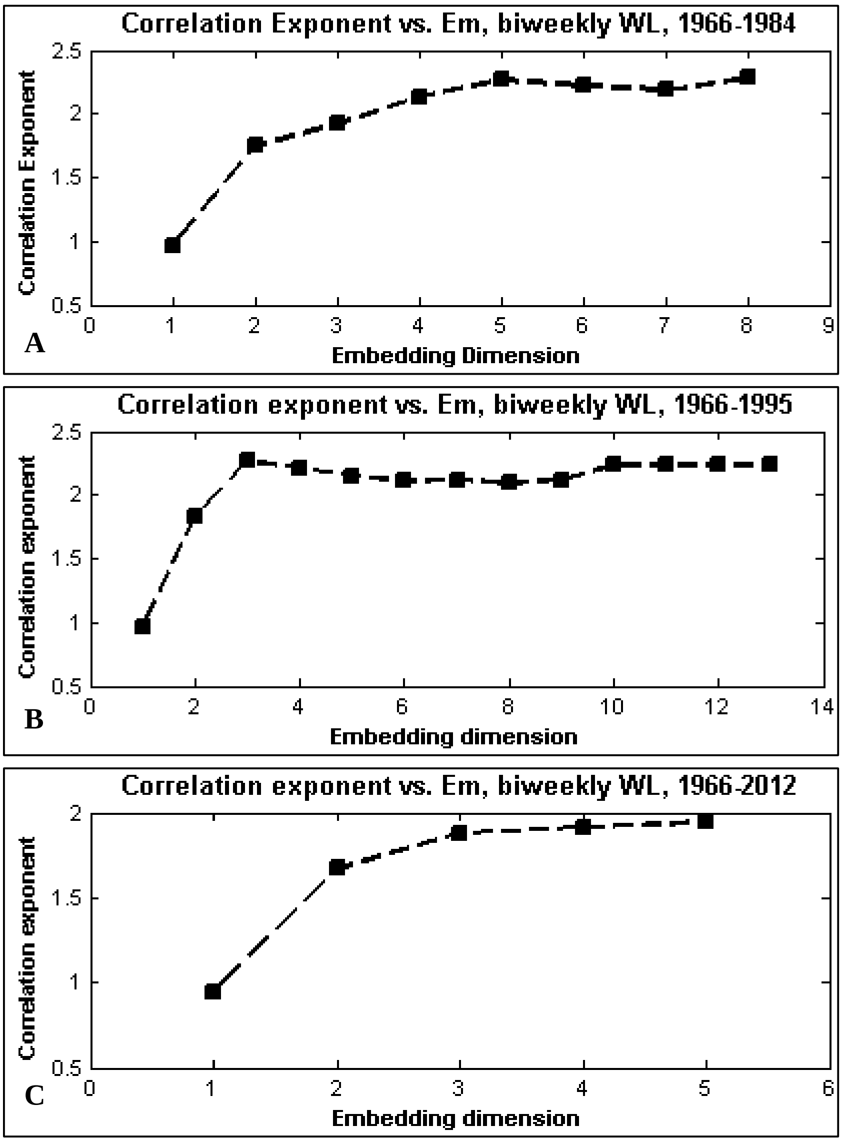


Figure 39. *Correlation Exponent vs. Embedding Dimension (E_m) for biweekly WL, for 3 periods of (i) 1966-1984, (ii) 1966-1995 and (iii) 1966-2012*

As it could be seen from Figure 39, correlation exponents are saturated beyond a certain embedding dimension increasing the embedding dimensions. It indicates the possible existence of low-dimensionality i.e. chaos in the lake WL. However, for the period *iii*, the phase-space could not be reconstructed as properly as periods *i* and *ii*; beyond the embedding dimension of 5 the CDM fails to construct the phase-space (see Figure 39 C). More importantly, Figure 39 shows that for periods *i* and *ii* (i.e. the first period 1966-1995), correlation exponents saturate between 2 and 3, indicating that the dynamic of the lake is governed by 3 independent variables (i.e. 3 ordinary differential equations). For the period *iii* i.e. the whole period, on the other hand, this value is 2 meaning that one of the governing variables of the lake is "missing" in the 2nd period. It could be said that the chaotic characteristic of the dynamical system has been vanished due to the abrupt declination of water level in the recent years. In light of the above, one can conclude that there has been a substantial/intrinsic change in the underlying dynamic of the lake; therefore, the hypothesis II has been verified.

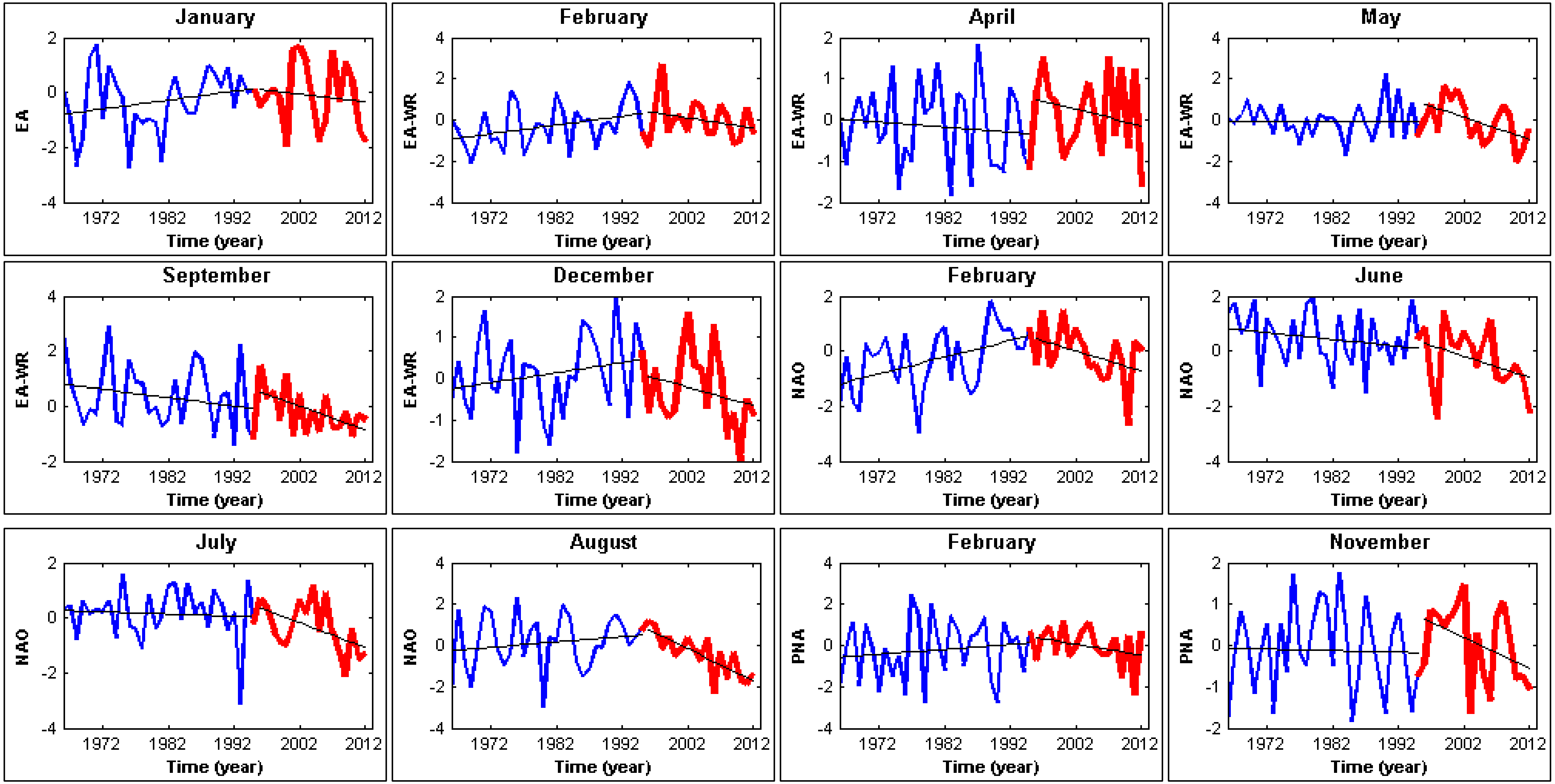
The results from the present study are not definitive and need to be revisited by longer records of water level and also other methods than CDM. The available data indicate that the lake water level is chaotic in nature and thus cannot be predicted in the long-term. However, the recent trend implies that the lake water level is changed into a state that has no historical similarity (Khatami & Berndtsson, 2013). As discussed in the previous sections, the recent decline of the lake water level has both climatic and human influences. However, which of these factors has a greater impact on pushing the lake water level well below the two high/low level extremes is under question (hypothesis III). This will be answered in the following section.

5.3. Climate Variability & Urmia Lake WL

In order to see to what extent climate variability, as the only natural source, is influencing water level fluctuations, a multiple regression model is needed comparing the capability of TIs in explaining/predicting WL variations in the first period to the second period. Therefore, for finding the most influencing TIs, SMA-WLs in the first period are compared to TIs by means of a Spearman Rank Correlation test. It should be noted that since the complete WL records of the year 2012 is not at hand, this year has been excluded from the analyses in this section.

5.3.1. Trends in TIs

Prior to finding the TI predictors for the multiple regression model, in order to have an understating on the variations of climatic signals, the Mann-Kendall trend test is applied comparing the two periods (see Figures 40 and 41). Such graphs provide a larger scheme on the variations of different climatic signals in terms of their increasing/decreasing trends comparing the two periods of this study.


January
February
April
May
September
December
February
June
July
August
February
November
EA
EA-WR
NAO
PNA
Time (year)
1972
1982
1992
2002
2012

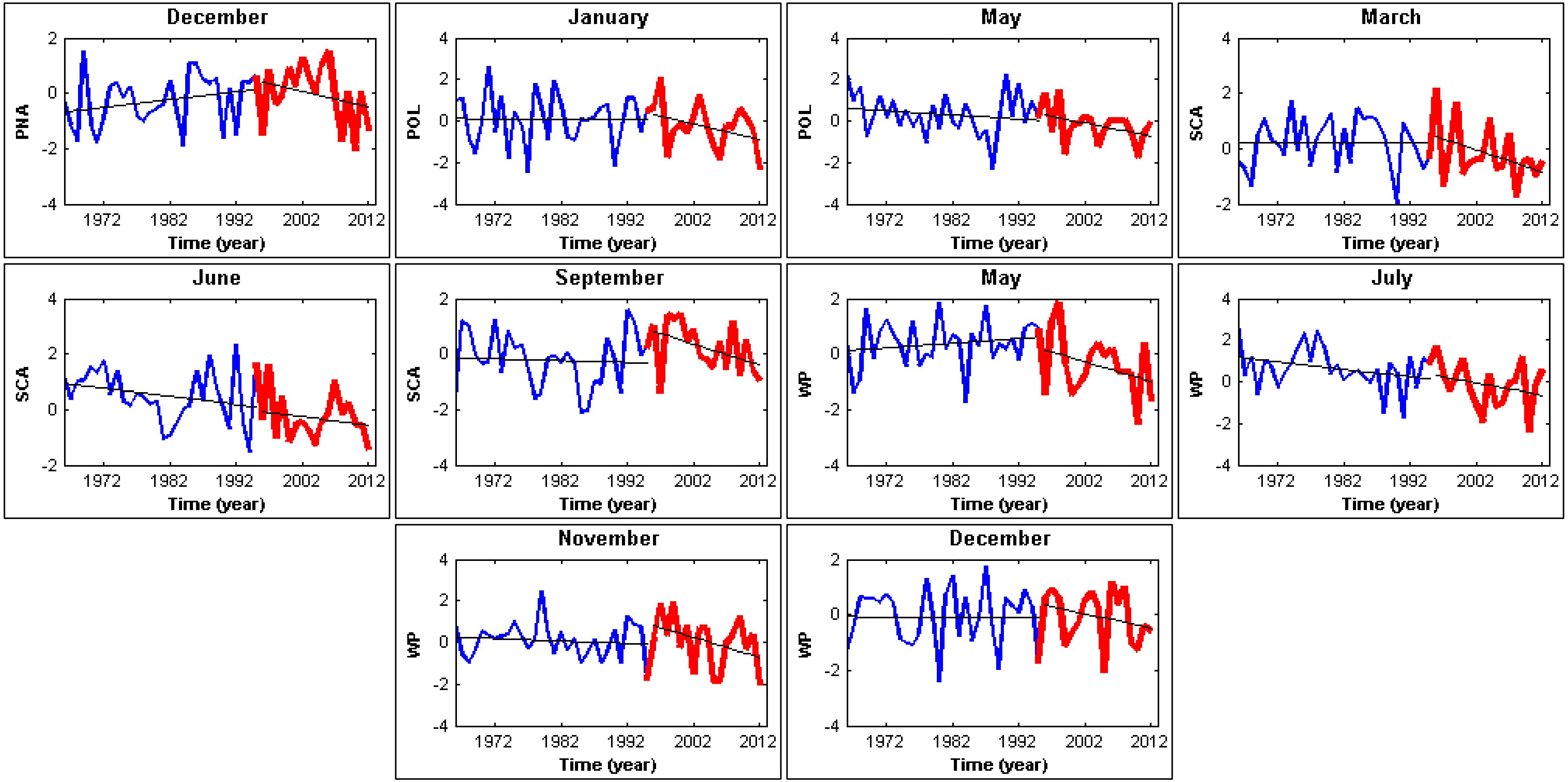
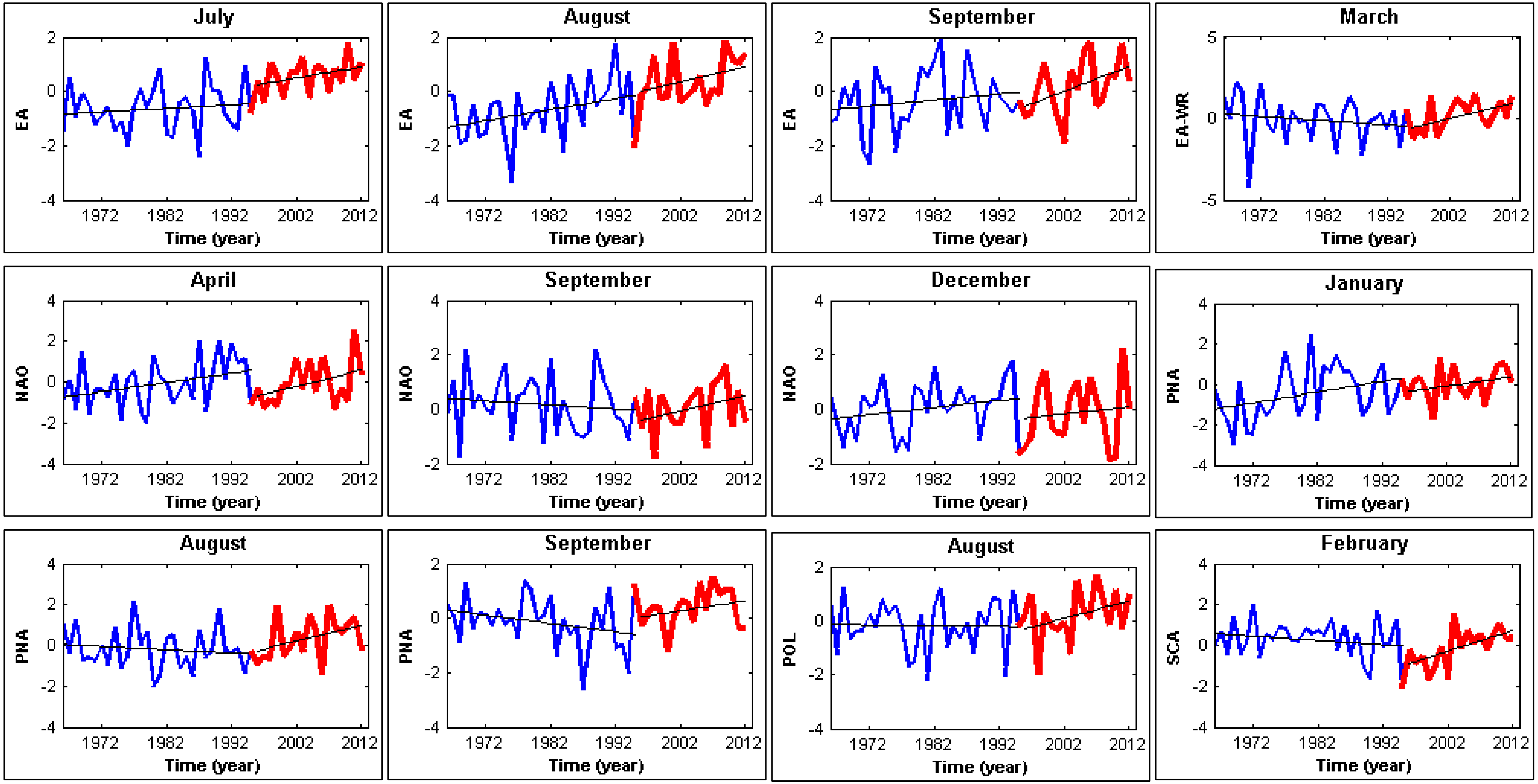


Figure 40. *Teleconnection indices with significant decreasing trends during the year*


July
EA
August
EA
September
EA
March
EA-WR
April
NAO
September
NAO
December
NAO
January
PNA
August
PNA
September
PNA
August
POL
February
SCA
1972
1982
1992
2002
2012
Time (year)

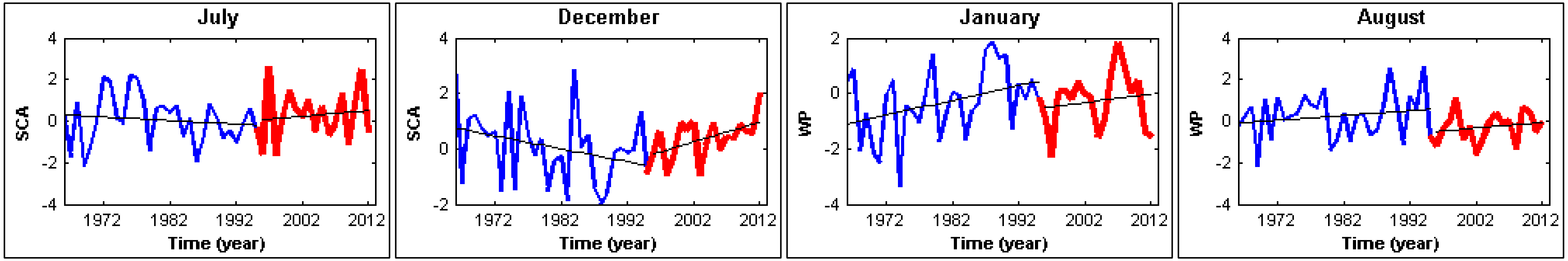


Figure 41. *Teleconnection indices with significant increasing trends during the year*

As it could be seen from Figures 40 and 41, there is no constant declining trend in all the TIs during the year. In other words, there are ups and downs in climatic signals which would lead to a seasonal variation or perhaps a mild decreasing trend if the lake is highly connected to a TI with a strong decline in several months per year.

There are more decreasing trends than increasing trends observed in TIs in several months of the year, which could be seen as a sign of a possible influence from TIs on the recent declinations of the lake. Generally, however, the effect of TIs on the lake is highly nonlinear and cannot be discussed in terms of such simplistic and visual linear analyses. Therefore, more detailed analyses are conducted investigating the nonlinear correlation of the lake WL fluctuations with TIs on a monthly scale, each month dependently and considering the lags between climate signals and lake WL in order to find the predictors for the multiple regression model.

5.3.2. Urmia Lake TI predictors

On all temporal resolutions of annual, seasonal and monthly data, standardized anomalies (SA) of the lake WL for each given resolution have been analyzed with respect to the teleconnection indices (with the same temporal resolutions) identifying significant correlations.

Therefore, by means of Spearman Rank Correlation, the relationship between the lake and climate variability has been studied (with no lags on seasonal and annual resolutions). As it was expected, no significant correlation has been found on the annual scale. On a seasonal resolution, nonetheless, promising correlations have been observed between the lake's Standardized Seasonal Anomalies (SSA-WL) and climatic signals.

Table 15. *SRCC comparing TIs and SSA-WL during 1966-2011*

	Winter		Spring	Summer	Fall
Indices	NAO	EA	EA/WR	SCA	EA
SRCC (r_{rank})	0.35	0.31	-0.41	0.30	-0.35
p-value	0.06	0.10	0.02	0.11	0.06

As it is presented in Table 15, most of SRCC values are statistically significant (p-value$\leq$ 0.05). This reveals that there is a promising chance of finding an even more detailed relationship in monthly scale. Therefore, the same approach has been applied for monthly values but considering 0-4 lags. The results are presented as follow:

Table 16. *SRCC comparing TIs and SMA-WL during 1966-201, the underlined months are the candidates for the multiple linear regression models as they have more TI predictors, and the subscripts of the TIs denotes the lag between WL and TI*

Month	Indices	SRCC	p-value	Month	Indices	SRCC	p-value
March	WP_0	-0.44	0.016	September	WP_1	0.37	0.045
	EA/WR_0	-0.46	0.011		PNA_4	0.32	0.085
	NAO_2	0.37	0.045	October	EA_0	-0.31	0.092
	EA_2	0.50	0.005		WP_2	0.33	0.075
	PNA_3	0.43	0.020	November	EA_1	-0.33	0.078
April	WP_1	-0.33	0.074		WP_3	0.35	0.056
	EA/WR_1	-0.38	0.037	December	PNA_0	0.40	0.029
	NAO_3	0.31	0.100		EA_2	-0.33	0.071
	EA_3	0.45	0.012		SCA_3	0.31	0.098
	PNA_4	0.43	0.020		WP_4	0.35	0.056
May	POL_0	-0.31	0.100	January	NAO_0	0.34	0.06
	EA_4	0.37	0.044		EA_0	0.45	0.013
June	POL_1	-0.33	0.071		PNA_1	0.43	0.019
	EA/WR_3	-0.33	0.077	February	NAO_1	0.35	0.057
July	PNA_2	0.33	0.077		EA_1	0.44	0.015
August	WP_0	0.37	0.047		PNA_2	0.43	0.020
	PNA_3	0.32	0.088				

As it could be seen from Table 16, indices that have a distinct influence on the lake WL are WP, EA/WR, POL, PNA, EA, NAO and SCA among which WP, PNA and EA have a distinguishably larger and more frequent effect. It has to be noted that despite the previous studies (Abrishamchi, et al., 2006) which have reported the connection of WL fluctuations to ENSO climate signal, no significant correlations have been observed in this study. Also, no strong decreasing trend in Nino3.4 signal has been observed (see Appendix 2) during this study which is alluding to the point that the recent decline in WL could apparently not be connected to this very teleconnection.

As it can be comprehended from Table 16, there is a strong relationship between climate indices and low level season (mid-Fall to mid-Winter) during the 1st period, 1966-1995. It is also important to note that successive existence of statistically significant WL vs. TI correlations in almost all months implies a strong relationship between climate variability and the lake WL for which lake has a rather long memory especially during the extreme months of December and January where the WL is at its lowest levels.

5.3.3. Multiple Regression Model of Urmia Lake WL

For three months March, April and December (underlined in Table 16) which have a greater number of predictors than other months, multiple regression models are created (see Table 17).

Table 17. *Multiple regression climate models for studied months*

Month	The Equation of Prediction Model	
Mar.	$\hat{y}_{mar} = -0.67WP_0 - 0.26EA/WR_0 + 0.19NAO_2 + 0.18EA_2 + 0.77PNA_3 + 0.01$	*(Equation 46)*
Apr.	$\hat{y}_{apr} = -0.02WP_1 - 0.24EA/WR_1 + 0.23NAO_3 - 0.16EA_3 - 0.04PNA_4 - 0.02$	*(Equation 47)*
Dec.	$\hat{y}_{dec} = 0.54PNA_0 - 0.13EA_2 + 0.20SCA_3 - 0.25WP_4 - 0.02$	*(Equation 48)*

It should be noted that these regression models do not predict the WL directly but the variations of the SMAs. This means that for calculating the WL, one needs to simply multiply the predicted anomalies by the standard deviation of the given months, and then, add the resulted values to the monthly means. However, due to the fact that the purpose of this model was not to predict the water level but to investigate its connection to climate variability, only SMAs are predicted.

In order to be able to validate the calculated models, 20% of the SMA data points in the first period have been excluded for generating the model. In other words, from each 5 consecutive data points, the last one has been reserved for the validation and the regression models presented in table 18 are calculated based on the other 4 throughout the first period. After validating the models, SMA-WLs are predicted for the 2nd period based on TI predictors presented in Table 16. Table 18 presents the coefficient of determination (R^2) for the three stages of modeling, validating and predicting for each candidate month.

Table 18. *Coefficient of determination (R^2) in different stages of climate modeling for candidate months*

	R^2, Modeling	**R^2, Validation**	**R^2, Prediction**
March	0.415	0.932	0.143
April	0.351	0.887	0.110
December	0.375	0.541	0.350

It has to be noted that all the values have been checked to be statistically significant. It could be seen that the regression models are able to explain about 35-40% of WL variations in the 1st period (column 2, Modeling). They have been verified obtaining high R^2 in the validation stage except for December. However, comparing the forecasted SMA-WL with the observed ones in the 2nd period (column 4, Prediction) quite clearly shows climate variability cannot explain the recent variations in the lake WL while it could do so during the 1st period. More accurately, during the 2nd period, only 11-14% of the variations in the high season (i.e. March and April) could be explained by natural causes i.e. TIs. However, for December (as a low season month) climate variability could still explain about 35% of the variations in the 2nd period as it did similarly during the 1st period.

Therefore, it could be *inductively* concluded that only one third of the variations in low seasons and about 10% in high seasons could be explained by climate variability i.e. natural causes. Therefore, it could be said that at least in these months/seasons, the major cause contributing to the decline of the WL is not natural i.e. it is anthropogenic. On this ground, it would be reasonable to conclude *inductively* that it is very unlikely for the recent depletion of the lake to have a significant root cause in the climate variability. In other words, human activities are the major cause of the UL drying; thus the hypothesis IV is also tested finding highly supportive evidence in its favor.

5.3.3.1. Further Discussion

Apart from the fact that climate variability failed to explain the recent depletion of the lake, overwhelming dam constructions in this basin – as discussed thoroughly in previous sections (see Section 2.5) – together with dramatic land use changes from natural rangeland to agricultural lands have substantially influenced the lake WL fluctuations and majorly caused the declining trends. For instance, the main inflowing river to the lake is Zarrineh Rood which regularly fed the lake by the mean annual flow of about 2200 MCM/yr. This inflowing rate has decreased to only 1.3 MCM/yr which has clearly affected the lake dramatically (West Azarbaijan Provincial Government, 2011).

Figure 42 presents dam construction projects vs. WL variations of the lake, comparing the two periods of natural (blue) and anthropogenically intervened (red). Each horizontal black line represents the timeline of a major dam construction project (presented in Table 3). These timelines are weighted based on the total storage capacity of the dam categorized into five groups of 0-10, 10-75, 85-170, 200-400 and over 500 MCM/yr. The orange one refers to the timeline of the causeway construction.

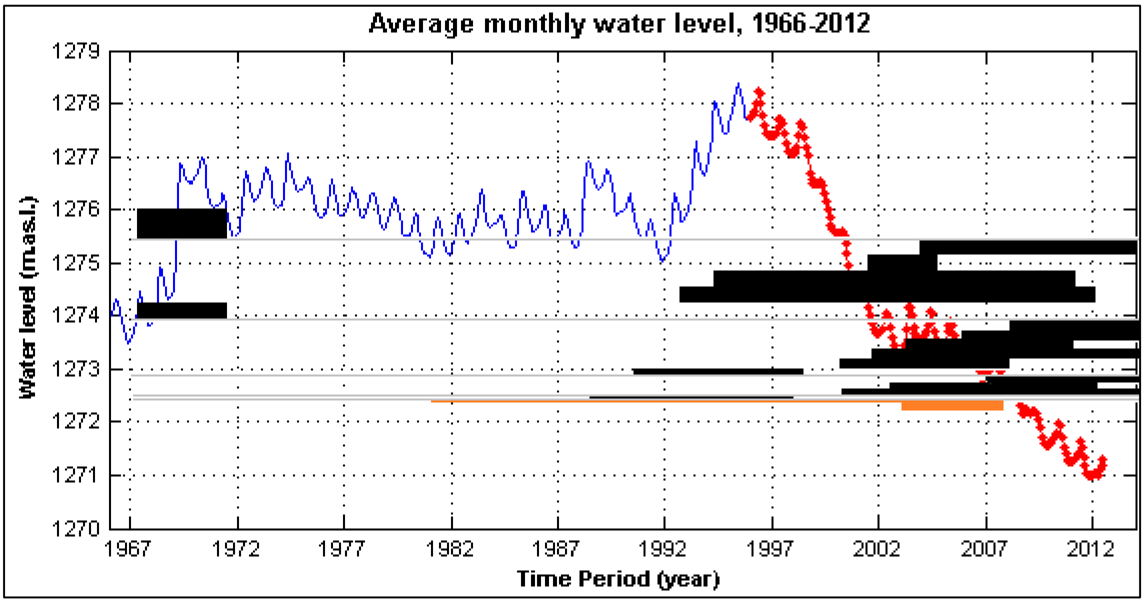


Figure 42. *Water level fluctuation vs. dam construction projects, comparing periods 1966-1995 and 1996-2012. Black lines represent the timeline of dam construction projects on the inflows of the lake, categorized into five categories of 0-10, 10-75, 85-170, 200-400 and larger than 500* $\boldsymbol{MCM/yr}$. *And the orange line shows the causeway construction timeline.*

It is quite clear that major dam projects occur during the 2nd period. Further, having a closer look at Figure 12 and Figure 42 reveals that no seasonality in WL fluctuations could be seen during the period 1999- 2002. As it could be seen, WL variations have a semi-cyclic annual pattern i.e. during low season months WL is at its lowest and in high seasons at its highest; therefore, throughout each year WL is varying between these two extremes. During the period 1999-2002, nonetheless, such seasonal variations cannot be observed, and in this very period WL has decreased about 4 m. Due to lack of seasonality, such declinations cannot be caused by climate variability; thus, it is most probably related to dam construction activities such as lake filling. Furthermore, paleolimnological studies (Lak, et al., 2012) also show that climate change and particularly the increase in evaporation are significant factors in the lake WL declination but are not the main causes for the lake's drying. Although Iran is experiencing a long-term drought of about 13000 years, Urmia Lake has never experienced drought but in its coastal areas. Lak et al. (2012) have concluded that the main factor contributing to the recent decrease of the lake WL is anthropogenic interventions is terms of damming the inflowing rivers.

5.4. The Salinity Level of Urmia Lake

In this study, the term "salinity" refers to TDS in the lake which has a major impact on the lake's ecology and biodiversity as discussed earlier. However, in this section, the focus is on the variations of the lake's salinity. Figure 43 presents the monthly salinity and water level variations in the past 7 years. Based upon only these 7 data points, a regression model should be created in order to predict the salinity rate of the lake.

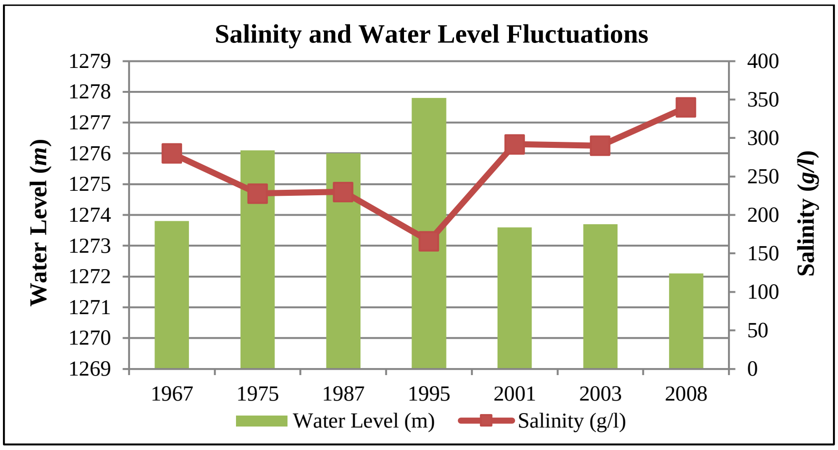


Figure 43. *Plot of water level and salinity rate based on monthly observations*

In order to create the linear regression model, first, the scatterplot of WL vs. SL is presented in Figure 44. As it can be seen from the Figure, there is a linear but inverse correlation between water level (WL) and salinity level (SL).

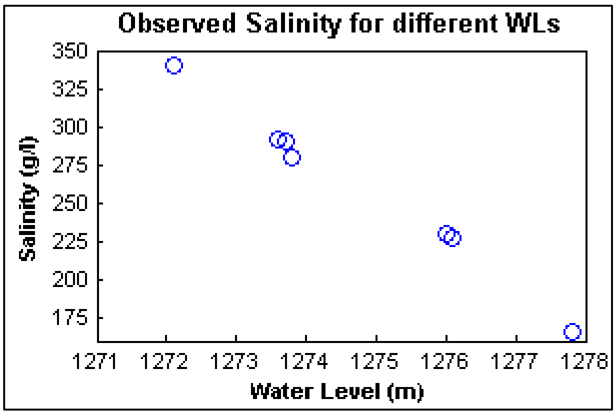


Figure 44. *Scatterplot of the 7 measured data pairs of monthly salinity & WL*

PCCs and SRCCs between the WL and SL are confirming the mentioned linear relationship:

Table 19. *Correlation coefficients between SL and WL for the 7 monthly data points*

	Correlation coefficient	P-value (%)
Pearson	-0.995	0.0003
Spearman	-1.000	0.0400

A high value of PCC (close to 1) verifies that a simple linear regression model is properly suited for predicting the salinity level in the lake. The equation for the regression model is calculated:

$$\hat{Y} = -28.938X + 37149.244 \qquad \textit{(Equation 49)}$$

Figure 45 shows how perfectly ($R^2 \cong 1$) this model fits the observed data pairs of WL and SL.

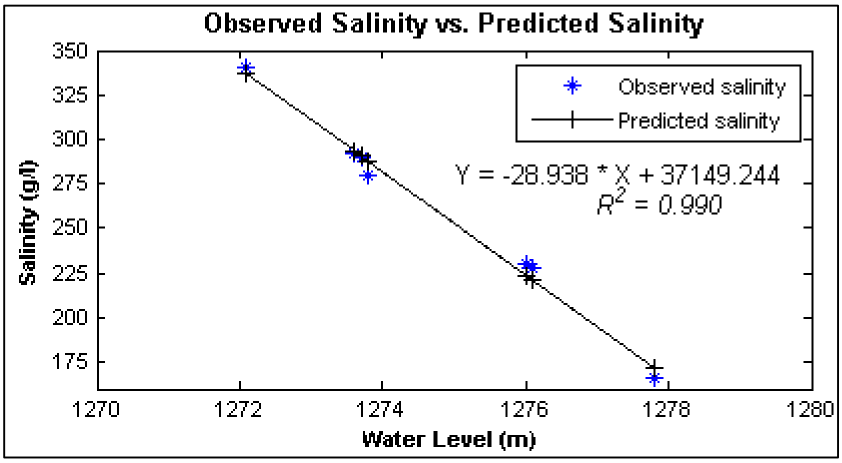


Figure 45. *Linear regression model forecasting the monthly salinity level of Urmia Lake during the whole period based uopn the 7 monthly data points*

Figure 46 shows residuals/errors indicating that residuals are approximate independent random errors i.e. there is no discernible pattern in residuals.

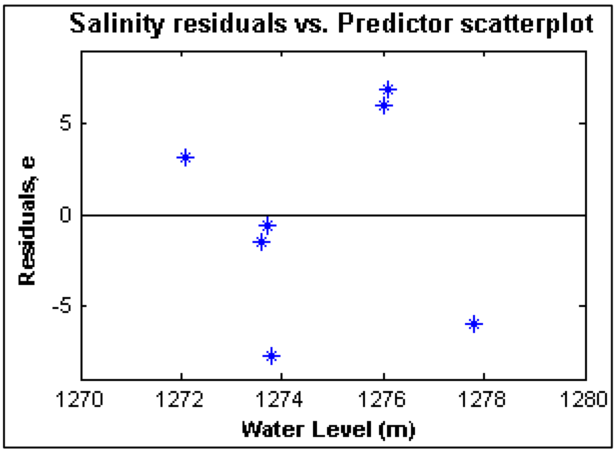


Figure 46. *Scatterplot of salinity residuals vs. predictor variale (water level)*

Finally, the estimation of monthly mean salinity during 1966 to 2012 is presented in Figure 47.

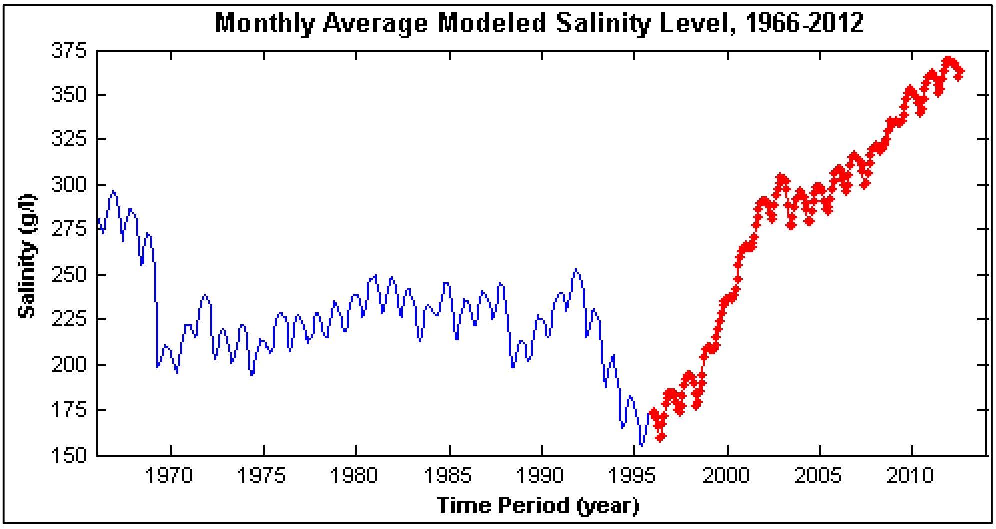


Figure 47. *Prediction of monthly SLs during two periods of natural i.e. 1966-1995 (blue) and anthropogenically intervened i.e. 1996-2012 (red)*

As the model suggests the salinity of the lake is currently around 360 g/l which puts it as one the saltiest bodies of water in the world, after Don Juan Pond in Antarctica with the salinity of around 400 g/l (Marion, 1997). This could simply imply how serious the issue of Urmia Lake is in terms of its deteriorating salinity level for its basin's ecosystem. It is quite obvious that the months that have the lowest salinity levels are the ones that have the highest water level and vice versa. Therefore, the highest salinity levels are expected during the recent years and in low water level seasons.

It could also be perceived from the Figure 47 and above discussions that the ongoing conditions of the lake's salinity could be counted as extreme for the survival of *Artemia Urmiana*. If the current conditions continue, they could irreversibly lead to the elimination of *Artemia Urmiana* and consequently a failure of the food chain and the ecosystem. On this ground, the last hypothesis is also examined and has been verified finding such extreme saline conditions.

5.4.1. Further Discussion

The human activities have decreased the water level below its historical records. A decrease in the mean annual precipitation by 17% during 1997 to 2006 and an increase of 17% in the mean annual temperature during 1996 to 2006 have been recorded (Hassanzadeh, et al., 2011). At the same time, human withdrawal of water from groundwater and inflowing rivers for agriculture purposes has escalated. In line with future water withdrawal and diversion projects, the water level is expected to continue to decrease in the near future. Thus, the current mismanagement of water allocation and the uncontrollable increasing demand for irrigation and potable water that authorities are over-seeing will eventually backlash in terms of a degraded eco-environment which will damage the economy of the region as well (Khatami & Berndtsson, 2013).

Anthropogenic salinization is perhaps the greatest threat to saline lakes. Anthropogenic or secondary salinization is the result of human activities in the lake basin in terms of construction, agriculture and industrial activities. The significance of this threat is to such extents that it has been discussed that "anthropogenic salinization, in some countries, represents the most important threat to water resources" (Williams, 2001). Disturbance of hydrological cycle due to mentioned human activities would lead to freshwaters becoming saline and saline waters becoming even more saline (Waiser & Robarts, 2009).

For instance, land irrigation and agricultural activities, at Murray River floodplain in Australia, have caused the saline aquifer to rise. Due to the consequent salinization of floodplain wetlands, macrophytes and riparian trees disappeared. Their disappearance clearly shows that even small increases in the salinity level could have large effects (*chaotic*) on biota due to the fact that freshwater organisms have a narrow tolerance range for salinity. It has been estimated that anthropogenic salinization in Australia annually costs more than $50 million US (Waiser & Robarts, 2009). It well shows the importance of environment and ecosystem protection not, only for ecosystem sustainability but for its interconnection with socio-economy of the given basin.

At Urmia Lake basin, until 2006, the total amount of regulated water by dams, pump stations, flood control, weirs and conduction facilities, etc. was about 1712 MCM. Within the next 20 years about 2157 MCM will be added to the current regulated water due to the newly-approved projects (Ministry of Energy, 2007). It is evident that these projects will intensify the ongoing environmental crisis if authorities do not consider water for the ecosystem and living organisms existing in a certain area as well as human beings. These projects will probably have a major impact on the natural circulation of water in this basin and more specifically desiccation of the lake. Therefore, within the next chapter, plausible and feasible restoration measures for the current conditions are proposed and discussed.

6 WATERSHED RESTORATION

As it was discussed in the previous chapter, the desiccation of the lake is majorly due to human activities. Therefore, according to the investigation of the hydro-climatic nature of the lake, it could be said that the ultimate solution to the lake's problem is watershed management via a multidisciplinary (holistic) approach towards the sustainability of the eco-socio-economy of the entire basin (Khatami & Berndtsson, 2012). In this study, there is no time for deep analyses of watershed management. However, just by scratching the surface, previous proposals/solutions for UL drying are critically reviewed and new plausible restoration measures are suggested. Given measures are certainly preliminary and their feasibility and applicability for the specific case of Urmia Lake need further investigations by means of different modelings and simulations.

It is evident that the continued decline of water level in the lake will lead to an irreversible damage to the environment and the possible collapse of the regional ecosystem (specifically *Artemia Urmiana* as the key link of the food chain and consequently fauna and migratory birds). The decline of the water level may lead to the migration of the major part of the local and rural population to urban areas, since their life is mainly dependent on agricultural activity. Thus, the ongoing environmental decline will also negatively affect the socio-economy of the region (Hassanzadeh, et al., 2011; Delju, et al., 2012; Khatami & Berndtsson, 2013). The extent and concrete effects of the continued desiccation of the lake are still under debate. However, regardless of its details, the current situation calls for an extensive national and even international discussion on how to improve the current situation.

6.1. Previously Proposed Solutions

Three main solutions have been suggested by previous studies in order to tackle the current crisis, namely; desalination, inter-basin water transfer (specifically water transfer from Caspian Sea), and releasing water from dams to inflowing rivers.

Two major desalination methods that have been considered for desalination of the lake's water are Reverse Osmosis (RO) and Multistage Flash Evaporation (MSF). In general, costs of desalination depend on various site-specific variables. Considering the size of the lake and the fact that it is a hypersaline lake with the SL more than 360 g/l, costs associated with desalination will be high. Karbassi et al. (2010) estimated that the cost for the desalination of Urmia Lake by a combination of the RO and MSF would equal about US\$ 6.7/m^3. It has to be noted that the performance of these desalination methods has not been tested for hypersaline waters and their potential performance is regarded for desalination measures. Together with the high costs of desalination, another important environmental challenge would be the disposal problems of the brines. Thus, desalination does not seem to be a viable restoration measure at present (Karbassi, et al., 2010).

Although some previous studies have suggested the inter-basin transfer of water as a promising solution (Golabian, 2010; UNEP and GEAS, 2012), it is not an eco-friendly plausible solution. Water transfer from the Caspian Sea is not economically plausible due to a large height difference (1316 m). In addition, common sense would suggest that for solving a problem, one should not introduce new ones. Transferring water from Caspian Sea through a man-made river is likely to cause international tension. Further, the transfer of water from Caspian Sea would affect the whole ecosystem through its path to Urmia Lake. Previous experiences from large-scale water transfers have resulted in several issues such as water logging, increased salinization, and water intrusion to groundwater aquifers (Mamaev, V.; Woods Hole Group, Inc., 2002).

The most realistic and plausible suggestion from the previous studies for addressing the issue of Urmia Lake drought, is water allocation adjustment i.e. increase in discharge from dammed inflow rivers to the lake. One study (Abbaspour & Nazaridoust, 2007) estimated the ecologically-required water for the restoration of Urmia Lake as 3085 MCM of inflow per year. Despite the fact that this study is fairly outdated due to changes of salinity and other conditions during the past few years, and also considering the extent of the problem and the lake's size, this volume does not seem to be a sustainable volume of water needed for the lake. Probably instead, it has to be seen as a minimum amount of water needed for the restoration of the lake. Fortunately, the Ministry of Energy has agreed on the allocation of 2000 to 3000 MCM/yr to restore the lake's salinity to the previous condition of 166 g/l (Karbassi, et al., 2010). As it was discussed, despite the fact that this volume is fairly low regarding a sustainable perspective, it is a promising start for the restoration of the lake. It has to be noted that a more comprehensive study is needed in order to calculate the required amount of water based on the updated conditions of the lake and through a holistic approach.

Also, it is highly recommended to initiate a new research and simulation studies in order to investigate different uncertainties about the lake; most importantly, groundwater interaction with the lake and its circulation patterns which is anticipated to have a significant influence on the lake's water level. Therefore, it has to be investigated from different aspects and of course with the updated conditions of the lake which as it is a serious drawback of all previous research in this area. Also comparative studies between Urmia Lake and similar lakes could also be of interest for future studies.

6.2. Short-term Measures

Suggested short-term measures include cloud seeding and weather modification, cessation of dam construction (ongoing projects and newly planned), and release of at least 3 MCM/yr (required water to attain a salinity of 166 g/l). Since precipitation and the inflowing rivers are the only source of inflow to this terminal lake, cloud seeding and weather modification together with release of water from dams could enhance the eco-hydrological situation of the lake significantly. The main objective of cloud seeding or in general weather modification (WM) programs is to reduce the impact of drought and the consequent water shortage, and enhance reservoir storage within the subjected area. Recent evaluation of different regions exposed to WM programs reveals positive responses for precipitation intensification in most cases (Ryan, et al., 2005). Cloud seeding and WM could be seen as an acceptable but short-term solution for modifying and improving the precipitation conditions within the basin and consequently mitigating the climate changes affecting the region. A study (Acharya, et al., 2011) in the arid region of North Platte River Watershed evaluated the impacts of WM programs by developing a hydrological model. The impacts were assessed in terms of streamflow changes. An increase of 0.3% to 1.5% in the annual streamflow was the result of an anticipated increase of 1 to 5% in precipitation rate. Beside precipitation enhancement and snowpack increase, WM could lead to other environmental improvements beyond precipitation enhancement. Exploratory analysis of case studies in North Dakota has identified a 6% growth in agricultural wheat production together with a decrease of 45% in crop hail loss than what would be expected on the basis of prior experience during the operational period (Smith Jr., P.L.; Johnson, L.R.; Priegnitz, D.L.; Boe, B.A.; Mielke, P.W., 1997).

Climatic studies on Urmia Lake shows that during 1997 to 2006 annual average precipitation (204.6 mm) on the lake's basin decreased nearly 17% in comparison with the 30 year average from 1967 to 1996 (246.6 mm) (Hassanzadeh, et al., 2011). Other studies (Delju, et al., 2012) claim a 9% decrease in the mean annual precipitation during the period 1964-2005. The effectiveness of cloud seeding, 5 to 20%, could help deal with the climate change in terms of precipitation (Acharya, et al., 2011). Due to the fact that cloud seeding may change individual or a group of clouds but not the weather patterns (since they are determined by large-scale atmospheric processes) (Langerud, 2011), it has to be seen only as a short-term solution.

It is evident that effective WM programs with the aim of precipitation augmentation need to be studied based on regional and local conditions and generalization of previous studies at other locations (climate and time period). Hence it is necessary to evaluate and analyze hydrological impact for different scenarios in the given catchment. It should be considered that spatial and temporal variation in annual precipitation distribution is a factor in the changes of simulated streamflow that have to be taken into account. Apart from the fact that cloud seeding and WM in general are environmentally friendly, they are also cost effective (Weather Modification Inc., 2005). For instance, KWO (2001) estimated the cost in the range of \$0.8–12 per 1000 m^3 of additional runoff from snowpack in Kansas, which could be considered inexpensive in comparison with building a new infrastructure or desalination.

Together with cloud seeding and other mitigating measures, the Ministry of Environment could design an urgent Environmental Protection Law for this specific region.

6.3. Long-term Measures

The ultimate goal for solving the current issue of the lake and its watershed is a long-term integrated approach towards sustainability. Eco-friendly solutions are needed that contain a set of actions done in parallel and under a greater plan of restoration. It is important to stress solutions that are integrated with all parts of society and where local participation can guarantee sustainable solutions in the long term.

6.3.1. New Sources of Income

A major local economic issue is a sustainable agricultural activity as the main consumer of water. The escalating population that increases the demand for food on the one hand, and traditional methods of irrigation on the other hand, intensify the threats to water resources and environment deterioration in the region. New sources of income have to be introduced within the lake's catchment in order to control the water demand in the agricultural sector. For example, the lake's salinity has a potential for salt industry or other manufacturing minerals. In addition, its unique ecosystem has a great potential for tourism industry – ecotourism. Previous initiatives in this direction from private sector have mainly failed. However, new initiatives with the support from authorities may lead to successful results.

6.3.2. Sustainable Energy Development

Another example of a long-term required measure is sustainable energy development that both improves the economy of the region and could also be seen as an environmental protection measure. Due to the fact that about 50% of algae weight is lipid oil that can be used in biodiesel production and its capability of yielding oil is about 30 times more than the currently used crops in biodiesel production, it has a good chance to be considered in a longer term. The recent phenomenon of red tide has a potential for a new source of energy. Algae could be directly converted into energy like biodiesel, bioethanol, and biomethanol (Najafi, et al., 2011). This high potential of biofuel energy has to be more investigated in future studies in terms of its feasibility for this specific catchment.

6.3.3. Water Infrastructure

Currently, there is a great need for improving water infrastructure in the watershed. For example, within the province of East Azarbaijan, there are 8 running wastewater treatment plants with the annual capacity of 94.96 MCM that is operating for 71.23 MCM. First of all, this capacity is not even capable of addressing the current population of the province (3.6 million) nor is it for the future population. In addition, the efficiency of 74% is not satisfactory. Also, these treatment plants have the potential of improvement in terms of chemical and biological treatment processes (East Azarbaijan State Water and Wastewater Company, 2012).

Authorities have initiated different water infrastructure projects including water and wastewater treatment plants. For instance, there are four wastewater treatment plants with the annual nominal capacity of 14.32 MCM under construction in the province of East Azarbaijan (East Azarbaijan State Water and Wastewater Company, 2012). Similar projects could be of a great positive influence for the environmental conditions of the basin in the long run, but it seems that these types of projects are quite slow in implementation. Moreover, the efficiency of these plants is always a matter of discussion. It is very important that authorities prioritize these projects and put their best effort to speed up the physical progress together with the improvement of their efficiency. There are 6 cities in the province of East Azarbaijan that are adjacent to the lake with the total population of about 0.62 million. It simply shows that an increasing population would directly and indirectly influence the lake's environmental conditions.

6.3.4. Social Sustainability

For social sustainability, which is widely neglected by scholars and authorities, the most significant issue is the participatory approach that has a great potential influence on environmental systems as well. For example, according to a national news agency, consumption patterns show that a typical resident of this watershed is consuming about 183 *L* per capita and day (Mehr News Agency, 2009). This shows that the demand is too high in comparison with the supply and so measures are needed to improve the efficiency of the distribution systems. Hence, for approaching a more sustainable consumption pattern, it is necessary to improve the public awareness and sense of responsibility for water, *hydromorality*, together with – or perhaps prior to – the improvement of irrigation efficiency and implementing advanced irrigation methods together with waste water treatment, and stormwater management and re-use in agriculture that requires larger investment and support from authorities.

As mentioned above, sustainable development is the essence of a long-term perspective. It is necessary to integrate factors affecting the environment in order to enable the improvement of the region towards a more sustainable position. Researchers and scholars dealing with the lake play a central role in providing authorities and society with the real image of the lake's condition. A greater consideration from authorities and government is required in terms of environmental support and access to data bases. Hydrological and hydraulic data for the area are quite limited with short records and are not easily accessible for researchers. Providing a comprehensive database, both in Farsi and English, would catch the attention of international researchers for further studies and better interdisciplinary solutions. Further hydrological modeling studies are highly needed to study the combined effect of climate change, groundwater exchange, and dam construction on the lake's ecology. The output of these studies would be the basis for long-term management and decision making of the authorities.

7 CONCLUSION

Urmia Lake is a shallow terminal lake located in an endorheic basin in northwest Iran and is one of the largest saline lakes in the world. Due to its biodiversity as the largest habitat of *Artemia Urmiana* in the world, it has been designated as a Biosphere Reserve by UNESCO and a National Park under the 1971 Ramsar Convention. Currently, the entire lake's watershed is threatened due to drought and an abrupt decline of the lake water level and the concomitant increase of salinity. Landsat satellite observations show that more than 50% of the lake's surface area has been desiccated during the past two decades. The rapidly declining eco-environmental conditions have had serious impacts on the socio-economy of the whole region and therefore, this situation should be considered as a national threat.

There are indications that the hydrology of the area could be described by a chaotic climate and a low-dimensional dynamical system. However, the human impact in terms of the mismanagement of water resources has also had serious repercussions. Therefore, within the present study, a holistic hydroclimatic analysis of the lake is conducted. In light of the above, the principal hypothesis of this study is that 'during *the recent years (1996-2012,)* there has been an *intrinsic change* in the dynamic of the lake water level *mainly due to human activities* which has had *deteriorating impacts* on the lake and its entire basin'. Having the data at hand, water level variations of the two periods of 1966-1995 and 1996-2012 are compared considering the first period as the natural period and the second one as the anthropogenically intervened.

In order to identify the changes, Mann-Kendall trend test has been used comparing different periods of 1966-2012. The results show that there has been a unique decreasing trend of about -0.25 m/yr in average during the recent period of 1996-2012. In addition, for investigating the changes in the underlying dynamic of water level fluctuations, the nonlinear chaotic analysis of Correlation Dimension Method is employed. The result implies the missing of 1 governing variable of the lake's dynamic; the correlation exponent has decreased from 3 during the period of 1966-1995 to 2 during 1966-2012.

Pursuing the major cause of the recent desiccations, a multiple linear regression model based is made based on the standardized monthly anomalies of the period 1966-1995 and the influencing teleconnection indices as predictors. Water level variations of the lake during the second period i.e. 1996-2012, for months March and April as high seasons months and December as a low season month have been modeled. Comparing modeled and observation time series shows that climate variability could explain about 35-40% of WL variations in the 1st period while during the 2nd period, only 11-14% of the variations in the high season (i.e. March and April) and 35% of the variations in December (low season) could be explained by natural causes. Hence, it could be *inductively* concluded that only one third of the variations in low seasons and about 10% in high seasons could be explained by climate variability i.e. natural causes. Also, it has been observed that extensive human activities in terms of climate change, land use changes, groundwater withdrawals, causeway, dam and other water diversion projects have occurred or have been intensified during the 2nd period. On this ground, it would be reasonable to conclude that human activities are the major cause for the recent depletion of the lake. This result has been confirmed by previous paleolimnological studies as well.

Afterwards, the salinity of the lake is modeled by means of regressions and the current salinity level of the lake is obtained to be more than 360 g/l. Eventual ecological consequences of continuing the ongoing deteriorating conditions on the whole basin are discussed. Finally, after the critical review of previously proposed solutions, the project is closed by suggesting plausible possibilities for the restoration of the lake and its watershed towards a sustainable eco-socio-economic state, in terms of short- and long-term measurements.

7.1. Suggestions for Future Studies

It is suggested that for future studies, groundwater, as an important but unknown factor in this region, should be studied in order to examine its interaction with the lake during both dry and wet seasons comparing these two periods. Also, further analyses of the meteorological factors namely precipitation and temperature, influencing this basin, could be of interest. This could be extended by studying the effects of climate changes independently and comparing it to other human activities such as dam construction of groundwater withdrawals. Results of chaotic analysis should also be revisited by other chaotic and nonlinear methods in order to verify the obtained results. Any other studies involving hydroclimatological analyses and modeling is also interesting and definitely important.

REFERENCES

Abbaspour, M. & Nazaridoust, A., 2007. Determination of environmental water requirement of Lake Urmia, Iran: an ecological approach. *International Journal of Environmental Studies*, Volume 64 (2), pp. 161-169.

Abrishamchi, A., Hazrati, S., Tajrishy, M. & Marino, M. A., 2006. *ENSO and NAO Influences on the Urmia Lake Basin Meteorology and Hydrology*. s.l., American Geophysical Union.

Acharya, A., Piechota, T. C., Stephen, H. & Tootle, G., 2011. Modeled streamflow response under cloud seeding in the North Platte River watershed. *Journal of Hydrology*, Volume 409, pp. 305-314.

Berndtsson, R. et al., 2001. Solar-climatic relationship and implications for hydrology. *Nordic Hydrology*, 32(2), pp. 65-84.

Bonython, C. W., 1965. *Factors determining the rate of solar evaporation in the production of salt*. s.l., s.n., pp. 152-167.

Broer, H. & Takens, F., 2011. *Dynamical Systems and Chaos Applied Mathematical Sciences*. s.l.:Springer.

Burn, D. H. & Hag Elnur, M. A., 2002. Detection of hydrologic trends and variability. *Journal of Hydrology*, 255(1–4), p. 107–122.

Delju, A. H., Ceylan, A., Piguet, E. & Rebetez, M., 2012. Observed climate variability and change in Urmia Lake Basin, Iran. *Theoretical and Applied Climatology*, Volume doi: 10.1007/s00704-012-0651-9.

Diacu, F. & Holmes, P., 1999. *Celestial Encounters: The Origins of Chaos and Stability*. s.l.:Princeton University Press.

Ding, M. et al., 1993. Estimating correlation dimension from a chaotic time series: when does plateau onset occur?. *Physica D: Nonlinear Phenomena*, 69(3-4), pp. 404-424.

Djamali, M. et al., 2008. A late Pleistocene long pollen record from Lake Urmia, NW Iran. *Quaternary Research*, 69(3), pp. 413-420.

Douglasa, E., Vogela, R. & Krollb, C., 31 December 2000. Trends in floods and low flows in the United States: impact of spatial correlation. *Journal of Hydrology*, 240(1–2), p. 90–105.

East Azarbaijan State Water and Wastewater Company, 2012. [Online] Available at: http://www.abfa-azarbaijan.com/fa/index.php?page_id=215&menu_id=7&menu_item_id=198
[Accessed 18 09 2012].

Eimanifar, A. & Mohebbi, F., 2007. Urmia Lake(Northwest Iran): a brief review. *Saline Systems*, 3(5).

Emadi, M., Baghernejad, M. & Memarian, H. R., 2009. Effect of land-use change on soil fertility characteristics within water-stable aggregates of two cultivated soils in northern Iran. *Land Use Policy*, 26(2), pp. 452-457.

Emadi, M. et al., 2008. Effect of land use change on selected soil physical and chemical properties in North Highlands of Iran. *Journal of Applied Sciences*, 8(3), pp. 496-502.

Eugster, H. & Hardie, L., 1978. *Saline lakes. In Lakes, Chemistry, Geology, Physics*. New York: Spriger.

Farzin, S. et al., 2012. An Investigation on Changes and Prediction of Urmia Lake water Surface Evaporation by Chaos Theory. *International Journal of Environmental Research,* 6(3), pp. 815-824.

Fraser, A. M. & Swinney, H. L., 1986. Independent coordinates for strange attractors from mutual information. *Physical Review A,* 33(2), pp. 1134-1140.

Gadgil, A. & Dhorde, A., 2005. Temperature trends in twentieth century at Pune, India. *Atmospheric Environment,* 39(35), pp. 6550-6556.

Ghaffari, G., Keesstra, S., Ghodousi, J. & Ahmadi, H., 2010. SWAT-simulated hydrological impact of land-use change in the Zanjanrood basin, Northwest Iran. *Hydrological Processes,* 24(7), pp. 892-903.

Ghaheri, M., Baghal-Vayjooee, M. & Naziri, J., 1999. Lake Urmia, Iran: A summary Review. *International Journal of Salt Lake Research,* Volume 8, pp. 19-22.

Gidea, M. & Niculescu, C. P., 2002. *Chaotic Dynamical Systems: An Introduction.* Craiova: Universitaria Press.

Golabian, H., 2010. Urumia Lake: Hydro-Ecological Stabilization and Permanence Macro-engineering Seawater in Unique Environments. Volume (pp. 365-397). Berlin: Springer-Verlag. doi: 10.1007/978-3-642-14779-1_18.

Gollub, J. P. & Swinney, H. L., 1975. Onset of Turbulence in a Rotating Fluid. *Physical Review Letters,* 35(14), pp. 927-930.

Google Earth Engine, 2012. *Drying of Lake Urmia, Iran.* [Online] Available at: http://earthengine.google.org/#intro/LakeUrmia [Accessed 03 05 2013].

Google Maps, 2012. [Online] Available at: https://maps.google.com/maps?num=100&q=urmia+lake&ie=UTF-8&hq=&hnear=0x401ab691484226e9:0xa3bcb751ad9dec7a,Lake+Urmia&ei=4NiTUeHTNsnDPIvdgcAL&ved=0CIsFELYD
[Accessed 20 09 2012].

Grassberger, P. & Procaccia, I., 1983. Measuring the strangeness of strange attractors. *Physica D: Nonlinear Phenomena*, 9(1-2), p. 189–208.

Hamshahri, 2013. [Online] Available at: http://hamshahrionline.ir/details/209122 [Accessed 05 04 2013].

Hassanzadeh, E., Zarghami, M. & Hassanzadeh, Y., 2011. Determining the Main Factors in Declining the Urmia Lake Level by Using Dynamics Modeling. *Water Resources Management,* Volume 26(1), pp. 129-145, doi: 10.1007/s11269-011-9909-8.

Hense, A., 1987. On the possible existence of a strange attractor for the southern oscillation. *Beitraege zur Physik der Atmosphaere*, Volume 60, pp. 34-47.

Holzfuss, J. & Mayer-Kress, G., 1986. An Approach to Error-Estimation in the Application of Dimension Algorithms. In: G. Mayer-Kress, ed. *Dimensions and Entropies in Chaotic Systems.* New York: Springer Series in Synergetics, pp. 114-122.

Hossain, F. & Sivakumar, B., 2005. Spatial pattern of arsenic contamination in shallow wells of Bangladesh: regional geology and nonlinear dynamics. *Stochastic Environmental Research and Risk Assessment*, 20(1-2), pp. 66-76.

Iran Water Resources Management Company, 2013. *IWRMC Information System.* [Online] Available at: http://daminfo.wrm.ir/fa/home [Accessed 05 04 2013].

Iran's wetlands data base, 2013. *Urmia Lake wetland.* [Online] Available at: http://wetland.doe.ir/ViewGeneralTalab.aspx?Talab=38&ZHoze=29 [Accessed 09 03 2013].

Islam, M. & Sivakumar, B., 2002. Characterization and prediction of runoff dynamics: a nonlinear dynamical view. *Advances in Water Resources,* Volume 25, pp. 179-190.

Islam, S., Bras, R. & Rodriguez-Iturbe, I., 1993. A possible explanation for low correlation dimension estimates for the atmosphere. *Journal of Applied Meteorology,* Volume 32, pp. 203-208.

ISS EarthKAM, 2007. *Lake Urmia, Iran.* [Online] Available at: https://earthkam.ucsd.edu/images/Iran_and_Lake_Urmia_LARGE.jpg [Accessed 13 05 2013].

Ivancevic, V. G. & Ivancevic, T. T., 2008. *Complex Nonlinearity: Chaos, Phase Transitions, Topology Change and Path Integrals.* Verlag Berlin Heidelberg: Springer.

Jame Jam, 2010. *Martyr Madani Dam.* [Online] Available at: http://jamejamtabriz.com/index.php?option=com_flexicontent&view=items&cid=131:1390-04-08&id=703:-17- [Accessed 05 04 2013].

Jayawardena, A. & Gurung, A., 2000. Noise reduction and prediction of hydrometeorological time series: dynamical systems approach vs. stochastic approach. *Journal of Hydrology,* 228(3-4), pp. 242-264.

Jayawardena, A. & Lai, F., 1994. Analysis and prediction of chaos in rainfall and stream flow time series. *Journal of Hydrology,* Volume 153, pp. 23-52.

Karbassi, A., Nabi Bidhendi, G., Pejman, A. & Esmaeili Bidhendi, M., 2010. Environmental Impacts of Desalination on the Ecology of Lake Urmia. *Journal of Great Lakes Research,* Volume 36(3), pp. 419-424.

Kelts, K. & Shahrabi, M., 1986. Holocene sedimentalogy of hypersaline Lake Urmia, northwestern Iran. *Paleogeography, Paleoclimatology and Paleoecology,* Volume 54, pp. 105-130.

Kendall, M., 1962. *Rank Correlation Methods.* 3rd ed. New York: Hafner Publishing Company.

Khabar Online, 2011. *Dam Construction on Urmia Lake.* [Online] Available at: http://www.khabaronline.ir/detail/173085/ [Accessed 05 03 2013].

Khalighi, S. & Ebrahimi, S., 2010. Effects of land use change on surface water regime (case study Orumieh Lake of Iran). *Procedia Environmental Sciences,* Volume 2, p. 256–261.

Khalili, N., Emadi, H. & Negarestan, H., 2007. Assessing the impact of high salinity levels on the growth and reproduction of Artemia in Urmia Lake and Qom wetlands. *Journal of Environmental Science and Technology (JEST),* 9(1), pp. 65-70.

Khatami, S. & Berndtsson, R., 2012. *Integrated Watershed Management to Save the UNESCO Biosphere Reserve Lake Urmia, Iran.* AWRA Annual Water Resources Conference, Jacksonville, Florida.

Khatami, S. & Berndtsson, R., 2013. *Urmia Lake Watershed Restoration in Iran: Short- and Long-Term Perspectives.* Proceedings of the 6th International Perspective on Water Resources & the Environment (IPWE), Izmir, Turkey.

Khosravifard, S., 2010. *Campaigners Fear Lake Urmia Drying Up.* [Online] Available at: http://iwpr.net/report-news/campaigners-fear-lake-urmia-drying [Accessed 19 01 2013].

KWO (Kansas Water Office), 2001. *Weather Modification Program, Fact Sheet No. 18,* s.l.: (access NAIWMC FAQs, www.naiwmc.org).

Lai, Y.-C. & Lerner, D., 1998. Effective scaling regime for computing the correlation dimension from chaotic time series. *Physica D: Nonlinear Phenomena,* 115(1-2), pp. 1-18.

Lak, R., Darvishi khatooni, J., Mohammadi, A. & Salehipuor Milani, A., 2012. *Paleolimnology study and causes of Sudden decrease in water level of Urmia Lake.* Bern, Switzerland, s.n.

Lall, U., Sangoyomi, T. & Abarbanel, H., 1996. Nonlinear Dynamics of the Great Salt Lake: Nonparametric Short-Term Forecasting. *Water Resources Research,* Volume 32(4), pp. 975–985, doi:10.1029/95WR03402.

Langerud, D., 2011. *North American Interstate Weather Modification Council.* [Online] Available at: http://agriculturedefensecoalition.org/sites/default/files/file/plumas_co/71W_2011_NAIWMC_Cloud_Seeding_Facts_Brochure_Q_A_Website_April_4_2011.pdf
[Accessed 18 09 2012].

Lisi, F. & Villi, V., 2001. Chaotic forecasting of discharge time series: A case study. *Journal of the American Water Resources Association,* 37(2), p. 271–279.

Lorenz, E. N., 1963. Deterministic nonperiodic flow. *Atmospheric Science,* Volume 20, pp. 130-141.

Lorenz, E. N., 1972. *Predictability; Does the Flap of a Butterfly's wings in Brazil Set off a Tornado in Texas?,* s.l.: American Association for the advancement of science, 139th meeting.

Lorenz, E. N., 1991. Dimension of weather and climate attractors. *Nature,* Volume 353, pp. 241 - 244 .

Mamaev, V.; Woods Hole Group, Inc., 2002. *Seas around Europe, The Caspian Sea.* [Online] Available at: www.eea.europa.eu/publications/report_2002_0524_154909/regional-seas-around-europe/CaspianSea.pdf/at_download/file
[Accessed 13 08 2012].

Marion, G., 1997. A theoretical evaluation of mineral stability in Don Juan Pond, Wright Valley, Victoria Land. *Antarctic Science,* 9(1), pp. 92-99.

MATHEMATICS, 2012. [Online] Available at: http://math.stackexchange.com/questions/220418/why-are-the-phase-portrait-of-the-simple-plane-pendulum-and-a-domain-coloring-of
[Accessed 06 05 2013].

MathWorks, 2012. *Linear Regression.* [Online] Available at: http://www.mathworks.se/help/matlab/data_analysis/linear-regression.html
[Accessed 29 01 2013].

Mehr News Agency, 2009. *Water Use per capita in West Azarbaijan.* [Online] Available at: http://www.mehrnews.com/fa/newsdetail.aspx?NewsID=854091
[Accessed 16 09 2012].

Ministry of Energy, 2007. Water allocation for the development projects in Urmia Lake basin. *Technical report of Water and Wastewater Planning Office.*

MOE, 2009. *Water Balance Report of the Country,* Tehran, Iran: Ministry of Energy.

Mohebbi, F. et al., 2011. On the red coloration of Urmia Lake (Northwest Iran). *International Journal of Aquatic Science* , 2(1), pp. 88-92.

Mpitsos, G., Creech, H., Cohan, C. & Mendelson, M., 1987. Variability and chaos: neurointegrative principles in self-organization of motor patterns. In: H. Bai-Lin, ed. *Directions in Chaos, Vol. 1.* s.l.:World Scientific, p. 162 190.

MPO, 2005. *Current State and Future of Water Resources at Urmia Lake Basin,* Iran: Section of Water, Agriculture and Natural Resources.

Najafi, G., Ghobadiana, B. & Yusaf, T., 2011. Algae as a sustainable energy source for biofuel production in Iran: A case study. *Renewable and Sustainable Energy Reviews,* 15(8), p. 3870–3876.

Nerenberg, M. A. H. & Essex, C., 1990. Correlation dimension and systematic geometric effects. *Physical Review A,* 42(12), p. 7065–7074.

NOAA, 2012. *Northern Hemisphere Teleconnection Patterns.* [Online] Available at: http://www.cpc.ncep.noaa.gov/data/teledoc/telecontents.shtml [Accessed 05 05 2013].

NOAA, 2013. *A "red tide" is a common term used for a harmful algal bloom.* [Online] Available at: http://oceanservice.noaa.gov/facts/redtide.html [Accessed 05 04 2013].

Nolte, D. D., 2010. The tangled tale of phase space. *Physics Today,* 63(4), pp. 33-38.

Packard, N. H., Crutchfield, J. P., Farmer, J. D. & Shaw, R. S., 1980. Geometry from a Time Series. *Physical Review Letters,* 45(9), p. 712–716.

Porporato, A. & Ridolfi, L., 1997. Nonlinear analysis of river flow time sequences. *Water Resources Research,* Volume 33, p. 1353–1367.

Puente, C. E. & Obregón, N., 1996. A Deterministic Geometric Representation of Temporal Rainfall; Results for a Storm in Boston. *Water Resources Research,* 32(9), p. 2825–2839.

Ramsey, J. B. & Yuan, H. J., 1990. The statistical properties of dimension calculations using small data sets. *Nonlinearity,* 3(1), pp. 155-176.

Rana, A., Uvo, C. B., Bengtsson, L. & Sarthi, P. P., 2012. Trend analysis for rainfall in Delhi and Mumbai, India. *Climate Dynamics,* 38(1-2), pp. 45 - 56.

Rezvantalab, S. & Amrollahi, M. H., 2011. Investigation of Recent Changes in Urmia Salt Lake. *International Journal of Chemical and Environmental Engineering,* Volume 2, No.3, pp. 168-171.

Ríoa, S. d., Penasa, Á. & Fraileb, R., 2005. Analysis of recent climatic variations in Castile and Leon (Spain). *Atmospheric Research,* 73(1-2), pp. 69-85.

Rivas-Martínez, S., Sánchez-Mata, D. & Costa, M., 1999. North American boreal and western temperate forest vegetation (Syntaxonomical synopsis of the potential natural plant communities of North America, II). *Itinera Geobotanica,* Volume 12, pp. 5-316.

Rodriguez-Iturbe, I., Power, F. D., Sharifi, M. & Georgakakos, K., 1989. Chaos in rainfall. *Water Resources Research,* Volume 25, pp. 1667-1675.

Ruelle, D. & Takens, F., 1971. On the Nature of Turbulence. *Communications in Mathematical Physics,* 20(3), pp. 167-192.

Ryan, T., Busto, J., Huggins, A. & Hunter, S., 2005. Weather modification for precipitation augmentation and its potential usefulness to the Colorado River Basin States. *A report for Metropolitan Water District of Southern California.*

Saltzman, B., 1962. Finite amplitude free convection as an initial value problem. *Atmospheric Science,* Volume 19, pp. 329-341.

Sangoyomi, T., Lall, U. & Abarbanel, H., 1996. Nonlinear dynamics of the Great Salt Lake: dimension estimation. *Water Resources Research,* Volume 32, pp. 149-159.

Schertzer, D. et al., 2002. Which Chaos In The Rainfall-runoff Process? Discussion of "Evidence of chaos in the rainfall–runoff process". *Hydrological Sciences Journal,* 47(1), pp. 139-148.

Shang, P., Li, X. & Kamae, S., 2005. Chaotic analysis of traffic time series. *Chaos, Solitons & Fractals,* 25(1), p. 121–128.

Sharifi, M., Georgakakos, K. & Rodriguez-Iturbe, I., 1990. Evidence of deterministic chaos in the pulse of storm rainfall. *Atmospheric Science*, Volume 47, pp. 888-893.

Shaw, R. S., 1985. *The Dripping Faucet as a Model Chaotic System.* Santa Cruz, CA: Aerial Press.

Shiklomanov, I., 1990. Global water resources. *Natural Resources,* Volume 26, pp. 34-43.

Sivakumar, B., 2000. Chaos theory in hydrology: important issues and interpretations. *Journal of Hydrology,* Volume 227, pp. 1-20.

Sivakumar, B., 2002. A phase-space reconstruction approach to prediction of suspended sediment concentration in rivers. *Journal of Hydrology*, 258(1-4), pp. 149-162.

Sivakumar, B., 2005. Correlation dimension estimation of hydrological series and data size requirement: myth and reality. *Hydrological Sciences Journal,* 50(4), pp. 591-603.

Sivakumar, B., 2009. Nonlinear dynamics and chaos in hydrologic systems: latest developments and a look forward. *Stochastic Environmental Research and Risk Assessment,* Volume 23, pp. 1027-1036.

Sivakumar, B., 2012. Chaos Theory for Modeling Environmental Systems: Philosophy and Pragmatism. In: L. Wang & H. Garnier, eds. *System Identification, Environmental Modelling, and Control System Design.* Verlag London: Springer, pp. 533-555.

Sivakumar, B., Berndtsson, R., Olsson, J. & Jinno, K., 2001. Evidence of chaos in the rainfall-runoff process. *Hydrological Sciences Journal,* 46(1), pp. 131-145.

Sivakumar, B., Berndtsson, R., Olsson, J. & Jinno, K., 2002a. Reply to "Which chaos in the rainfall-runoff process?". *Hydrological Sciences Journal,* 47(1), pp. 149-158.

Sivakumar, B., Harter, T. & Zhang, H., 2005. Solute transport in a heterogeneous aquifer: a search for nonlinear deterministic dynamics. *Nonlinear Processes in Geophysics*, 12(2), pp. 211-218.

Sivakumar, B. & Jayawardena, A., 2002. An investigation of the presence of low-dimensional chaotic behaviour in the sediment transport phenomenon. *Hydrological Sciences Journal,* 47(3), pp. 405-416.

Sivakumar, B., Liong, S.-Y., Liaw, C.-Y. & Phoon, K.-K., 1999. Singapore rainfall behavior: chaotic?. *Journal of Hydrologic Engineering,* 4(1), pp. 38-48, (doi: http://dx.doi.org/10.1061/(ASCE)1084-0699(1999)4:1(38)).

Sivakumar, B., Persson, M., Berndtsson, R. & Uvo, C., 2002b. Is correlation dimension a reliable indicator of low-dimensional chaos in short hydrological time series?. *Water Resources Research,* Volume 38.

Sivakumar, B., Woldemeskel, F. M. & Puente, C. E., 2013. Nonlinear analysis of rainfall variability in Australia. *Stochastic Environmental Research and Risk Assessment,* Volume doi: 10.1007/s00477-013-0689-y.

Smith Jr., P.L.; Johnson, L.R.; Priegnitz, D.L.; Boe, B.A.; Mielke, P.W., 1997. An Exploratory Analysis of Crop Hail Insurance Data for Evidence of Cloud Seeding Effects in North Dakota. *Journal of Applied Meteorology,* Volume 36, p. 463–473.

Smith, L. A., 1988. Intrinsic limits on dimension calculations. *Physics Letters A,* 133(6), p. 283–288.

Statistical Centre of Iran, 2012. *Population.* [Online] Available at: http://www.amar.org.ir/Portals/2/pdf/jamiat_shahrestan_keshvar.pdf [Accessed 11 12 2012].

Tabnak, 2011. *What is the main cause of Urmia Lake drying?.* [Online] Available at: http://www.tabnak.ir/fa/news/159105/%D8%B9%D8%A7%D9%85%D9%84-%D8%A7%D8%B5%D9%84%DB%8C-%D8%AE%D8%B4%DA%A9%DB%8C-%D8%AF%D8%B1%DB%8C%D8%A7%DA%86%D9%87-%D8%A7%D8%B1%D9%88%D9%85%DB%8C%D9%87-%DA%86%DB%8C%D8%B3%D8%AA%D8%9F [Accessed 06 10 2012].

Taken, F., 1981. Detecting strange attractors in turbulence. *Dynamical Systems and Turbulence, Lecture Notes in Mathematics,* Volume 898, pp. 366-381.

Teimouri, B., 1998. Urmia golden gate highway (known as Martyr Kalantari Highway) after two decades of uncertainty. *Sanat Haml-o Naql (Transportation Industry)* , Volume 173, pp. 18-23.

The World Bank, 2012. *Iran, Islamic Republic of.* [Online] Available at: http://maps.worldbank.org/mena/iran-islamic-republic [Accessed 03 12 2012].

Tomozeiu, R., Pavan, V., Cacciamani, C. & Amici, M., 2006. Observed temperature changes in Emilia-Romagna: mean values and extremes. *Climate Research,* Volume 31, pp. 217-225.

Tsonis, A. A., 1992. *Chaos: from Theory to Applications.* New York, USA.: Plenum Press.

Tsonis, A. A. & Elsner, J. B., 1988. The weather attractor over very short timescales. *Nature,* 333(6173), pp. 545-547.

Tsonis, A., Elsner, J. & Georgakakos, K., 1993. Estimating the dimension of weather and climate attractors: important issues about the procedure and interpretation. *Atmospheric Science,* Volume 50, pp. 2549-2555.

UNEP and GEAS, 2012. The drying of Iran's Lake Urmia and its environmental consequences. *Environmenta lDevelopment,* Volume 2, pp. 128-137.

UNESCO, 2001. *MAB Biosphere Reserves Directory, Lake Oromeeh.* [Online] Available at: http://www.unesco.org/mabdb/br/brdir/directory/biores.asp?code=IRA+07&mode=all [Accessed 18 09 2012].

UNESCO, 2009. *List of Biosphere Reserves which are wholly or partially RAMSAR Wetlands.* [Online] Available at: http://www.unesco.org/mab/doc/brs/brs_ramsar.pdf [Accessed 18 09 2012].

UNESCO, 2012a. *Global list of Biosphere reserves.* [Online] Available at: http://www.unesco.org/new/fileadmin/MULTIMEDIA/HQ/SC/pdf/sc_mab_BR2012.pdf [Accessed 18 09 2012].

UNESCO, 2012b. *Ecological Sciences for Sustainable Development.* [Online] Available at: http://www.unesco.org/new/en/natural-sciences/environment/ecological-sciences/biosphere-reserves/ [Accessed 18 09 2012].

Waiser, M. & Robarts, R., 2009. Saline Inland Waters. *Encyclopedia of Inland Waters,* p. Pages 634–644.

WARW Information System, 2012. *Water Resources Development Projects.* [Online] Available at: http://www.tarh-agrw.ir/Default.aspx?tabid=4209 [Accessed 05 03 2013].

Weather Modification Inc., 2005. *Wyoming level II weather modification feasibility study: Executive summary,* s.l.: Wyoming Water Development Commission.

West Azarbaijan Province Portal, 2012. *Urmia Lake Causeway.* [Online] Available at: http://www.omran-ag.ir/tabid/1930/Default.aspx [Accessed 06 11 2012].

West Azarbaijan Provincial Government, 2011. *Urmia Lake News.* [Online] Available at: http://ostan-ag.gov.ir/tabid/807/articleType/ArticleView/articleId/8312/-----.aspx [Accessed 07 03 2013].

West Azarbaijan Regional Water Authority, 2012a. [Online] Available at: http://www.agrw.ir/Farsi/AreaF.asp?Id=3 [Accessed 16 09 2012].

West Azarbaijan Regional Water Authority, 2012b. [Online] Available at: http://www.agrw.ir/Farsi/UsageF.asp?Id=5 [Accessed 29 09 2012].

West Azarbaijan Regional Water Authority, 2013a. *Urmia Lake.* [Online] Available at: http://www.agrw.ir/fa/lake [Accessed 03 04 2013].

West Azarbaijan Regional Water Authority, 2013b. *Jurisdiction.* [Online] Available at: http://www.agrw.ir/fa/scope [Accessed 08 03 2013].

West Azarbaijan Regional Water Authority, 2013c. [Online] Available at: http://www.agrw.ir/fa/%D8%B7%D8%B1%D8%AD%D9%87%D8%A7%DB%8C-%D8%AA%D9%88%D8%B3%D8%B9%D9%87-%D9%85%D9%86%D8%A7%D8%A8%D8%B9-%D8%A2%D8%A8 [Accessed 07 04 2013].

Wetzel, R., 1983. *Limnology.* 2nd ed. Philadelphia: Saunders.

Wilks, D. S., 2011. *Statistical methods in the atmospheric sciences.* s.l.:Academic Press.

Williams, W., 2001. Anthropogenic salinisation of inland waters. *Hydrobiologia,* 466(1-3), pp. 329-337.

WMO, 2012. [Online] Available at: http://www.wmo.int/pages/prog/wcp/ccl/faqs.html [Accessed 05 05 2013].

Zeinoddini, M., Tofighi, M. & Vafaee, F., 2009. Evaluation of Dike-Type Causeway Impacts on the Flow and Salinity Regimes in Urmia Lake, Iran. *Journal of Great Lakes Research,* Volume 35, pp. 13-22.

Appendix 1

Table 20. *List of all rivers in Urmia Lake watershed basin, bold ones are the major ones in terms of annual mean flow* **(MPO, 2005)**

#	River	Station	MAR *(MCM)*	TDS *(g/l)*		SL *(Ton/yr)*
				min	max	
1	**Derik Chai**	**Nazar Abad**	**39**	**_**	**_**	**19700**
2	**Zola Chai**	**Chahriq Olia**	**142**	**199**	**363**	**185000**
3	**Zola Chai**	**Yalghouz Aghaj**	**63**	**_**	**_**	**_**
4	**Zola Chai**	**Pol-darvish**	**58**	**_**	**_**	**_**
5	Khorkhoreh Chai	Tamer	8	210	442	35600
6	**Nazlou Chai**	**Tapic**	**399**	**214**	**400**	**574500**
7	**Nazlou Chai**	**Abajaloo**	**243**	**_**	**_**	**_**
8	**Rowzeh Chai**	**Kalhor**	**39**	**208**	**365**	**66000**
9	Rowzeh Chai	Pol-e-Ozbak	_	_	_	44600
10	**Shahar Chai**	**Mirabad**	**184**	**90**	**310**	**320000**
11	**Shahar Chai**	**Keshteeban**	**91**	**_**	**_**	**_**
12	**Barandooz Cahi**	**Dizaj**	**293**	**175**	**230**	**295600**
12/1	**Barandooz Cahi**	**Babarood**	**265**	**_**	**_**	**_**
13	Balanch Chai	Ghassemloo	_	220	288	23100
14	Daryan Chai	Daryan	15	125	295	92560
15	Sofian Chai	Sofian	_	255	389	_
16	Aghmioon Chai	Sohrab	28	88	180	3900
17	Tajlar	Sarab	_	80	204	_
18	**Aji Chai**	**Saransar**	**141**	**210**	**3242**	**47000**
19	Ojan Chai	Bostan-Abad	67	265	1875	79600
20	Saeed Chai	Saeed-Abad	13	195	893	4450
21	Nahand Chai	Nahand	45	1010	15610	186000
22	**Aji Chai**	**Veniar**	**444**	**780**	**20560**	**2512000**
23	Lighvan Chai	Lighvan	25	72	200	7500
24	Lighvan Chai	Heravi	23	84	240	4750
25	Gamnab	Anakhatoon	38	945	5880	210200
26	Abshoor	Pardil	_	434	24627	_
27	Senikh Chai	Pol-e-Senikh	30	198	21110	153500
28	Sard Rood	Zinjanab	9	72	505	4000
29	Sard Rood	Sard Rood	_	140	490	_
30	Onsor Rood	Esfanjan	_	88	185	_
31	Gambar Chai	Ghermezi Gol	33	100	395	21100
32	Azar Shahr Chai	Azar Shahr	29	145	300	10100
33	**Aji Chai**	**Pol-e-Davazdah**	**434**	**_**	**_**	**_**
34	Aji Chai	Akhooleh	_	975	7925	161350
35	Mehran Rood	Mehran	_	250	635	_
36	Sabri Chai	Sabri	_	290	481	_
37	Aji Chai	Markabad	_	780	7471	_
38	Baz Chai	Pol-e-Khajoo	_	795	2268	_
39	Saeed Abad Chai	Toyghooni	_	640	5517	_
40	Tajlar Chai	Tajlar	_	105	143	_
41	Nahand Chai	Sad	_	1880	7928	_

42	Arjan Chai	Diznab	_	208	225	_
43	Mahpari	Khorma Zard	10	115	435	_
44	**Sofi Chai**	**Tazeh Kand**	**135**	**75**	**405**	**147800**
45	**Sofi Chai**	**Maragheh**	**96**	**85**	**410**	**180200**
46	**Sofi Chai**	**Bonab**	**47**	**120**	**411**	**37500**
47	Chekani Chai	Chekan	22	130	416	56680
48	Aspiran Chai	Aspiran	_	92	134	_
49	Ghaleh Chai	Ghaleh Chai	_	255	329	28100
50	**Saghez Chai**	**Ghabghabloo**	**326**	**115**	**295**	**116500**
51	**Saghez Chai**	**Dash-Aloochely**	**366**	**126**	**295**	**_**
52	**Saghez Chai**	**Panbehdan**	**407**	**115**	**386**	**341000**
53	**Jighato Chai**	**Pol-e-Hasan**	**470**	**150**	**420**	**_**
54	**Jighato Chai**	**Pol-e-Anian**	**627**	**115**	**225**	**299000**
55	**Khorkhoreh Chai**	**Karim Abad**	**278**	**150**	**285**	**150000**
56	**Saroogh Chai**	**Pol-e-Sarouq**	**226**	**183**	**488**	**115400**
57	**Saroogh Chai**	**Safakhaneh**	**368**	**230**	**507**	**919000**
58	**Zarrineh Rood**	**Sari Ghamish**	**1729**	**165**	**325**	**344000**
59	Zarrineh Rood	Ghez Korpi	_	125	280	_
60	**Ajorloo Chai**	**Choobloocheh**	**162**	**195**	**390**	**238100**
61	**Zarrineh Rood**	**Pol-e-Miandoab**	**1996**	**145**	**795**	**_**
62	Leylan Chai	Shirin Kandi	53	295	1085	133800
63	Moghanjigh Chai	Moghanjigh	26	155	525	34300
64	Mardoogh Chai	Gheshlagh Amir	86	141	999	95900
65	Ajorloo Chai	Janagha	_	161	390	_
66	Zarrineh Rood	Nezam Abad	_	221	330	201600
67	Saroogh Chai	Alaasofl-e-rast	_	408	500	_
68	Saroogh Chai	Alaasofl-e-chap	_	332	462	_
69	Saroogh Chai	Alaasolf-e-assl	_	250	503	_
70	Khorkhoreh Chai	Santeh	_	170	649	_
71	Jighato Chai	Gheshlagh Pol	_	157	194	299000
72	Cham Ghoozeh	Mahmood Abad	_	260	364	_
73	Cham Ghoozeh	Chalekhmaz	_	216	546	_
74	**Simineh Rood**	**Dashband**	**555**	**132**	**618**	**839460**
75	**Simineh Rood**	**Pol-e-Miandoab**	**630**	**161**	**500**	**_**
76	Simineh Rood	Zanjir Abad	_	230	400	_
77	Kelaz Chai	Oshnavieh	54	125	260	24000
78	**Gadar Chai**	**Pay Ghaleh**	**295**	**100**	**205**	**164300**
79	Gadar Chai	Chehrabad	37	110	330	9000
80	**Gadar Chai**	**Naghadeh**	**389**	**105**	**378**	**553100**
81	**Gadar Chai**	**Pol-e-Bahramlou**	**385**	**185**	**595**	**_**
82	Mahabad Chai	Kootar	_	120	339	157000
83	Mahabad Chai	Baitass	56	155	285	57100
84	Mahabad Chai	Sad	_	180	295	_
85	Balekhchi Chai	Balekhchi	_	274	360	17300
86	Shaikhan Chai	Doroud	_	110	193	_
87	Bayram Bolag	Mohammad Shahr	_	159	592	_
88	Balekhchi Chai	Bayazid Abad	_	165	381	_
89	Mahabad Chai	Gerd Yaghoob	_	229	468	_

Appendix 2

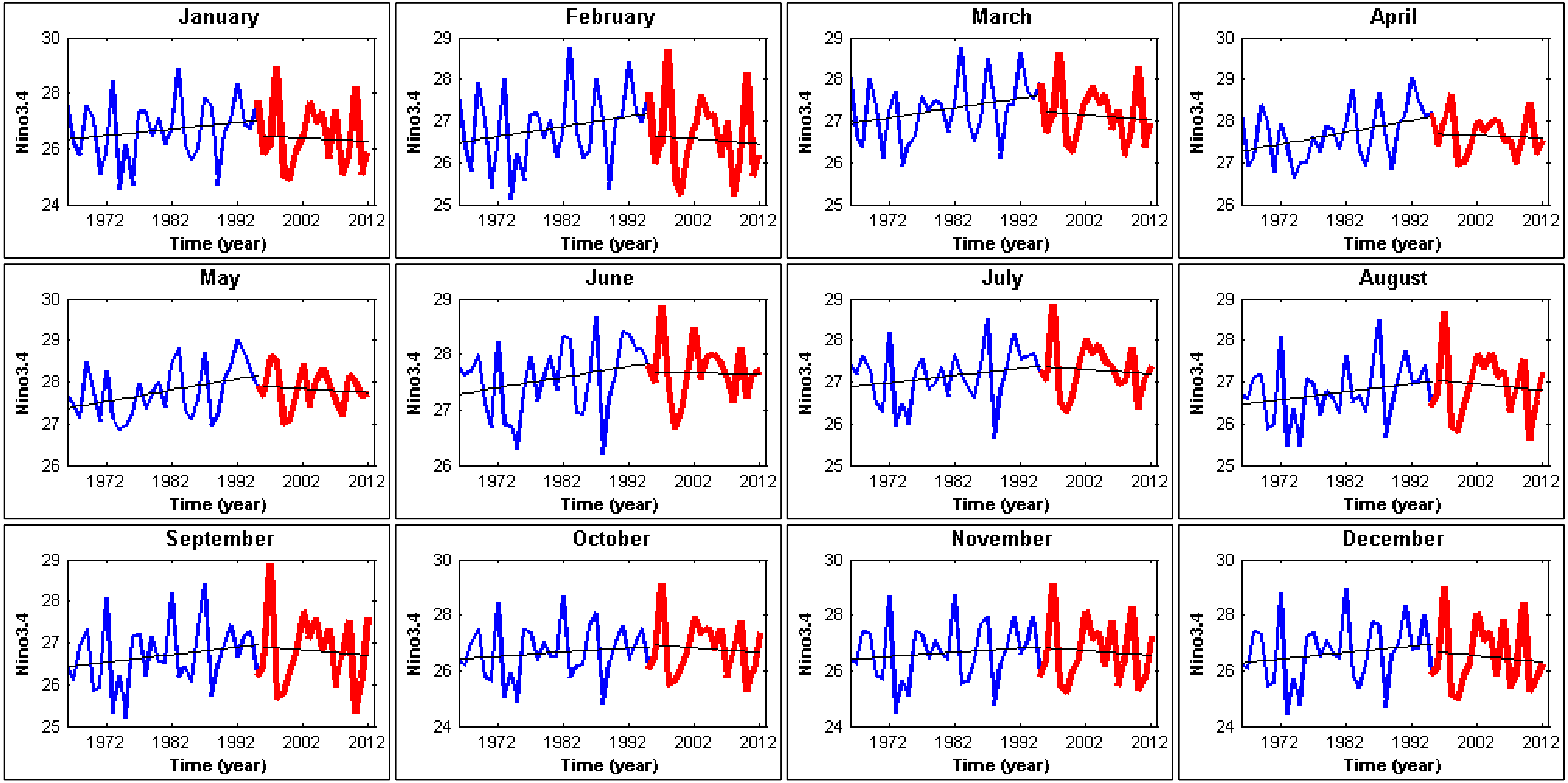


Figure 48. *Trend in Nino3.4 teleconnection index*