Hydrol. Earth Syst. Sci. Discuss., 10, 2353–2371, 2013
www.hydrol-earth-syst-sci-discuss.net/10/2353/2013/
doi:10.5194/hessd-10-2353-2013

Hydrology and Earth System Sciences
Open Access
Discussions

# Stochastic modeling of Lake Van water level time series with jumps and multiple trends

**H. Aksoy**[1], **N. E. Unal**[1], **E. Eris**[2], **and M. I. Yuce**[3]

[1]Istanbul Technical University, Istanbul, Turkey
[2]Ege University, Izmir, Turkey
[3]University of Gaziantep, Gaziantep, Turkey

Received: 31 January 2013 – Accepted: 11 February 2013 – Published: 22 February 2013

Correspondence to: E. Eris (ebru.eris@ege.edu.tr)

Published by Copernicus Publications on behalf of the European Geosciences Union.

## Abstract

In 1990s, water level in the closed-basin Lake Van located in the Eastern Anatolia, Turkey has risen up about 2 m. Analysis of the hydrometeorological shows that change in the water level is related to the water budget of the lake. In this study, a stochastic model is generated using the measured monthly water level data of the lake. The model is derived after removal of trend and periodicity in the data set. Trend observed in the lake water level time series is fitted by mono- and multiple-trend lines. For the multiple-trend, the time series is first divided into homogeneous segments by means of SEGMENTER, segmentation software. Four segments are found meaningful practically each fitted with a trend line. Two models considering mono- and multiple-trend time series are developed. The multiple-trend model is found better for planning future development in surrounding areas of the lake.

## 1 Introduction

Closed-basin lake ecosystems have been important issues in the world since decades. A very dramatic example is the Aral Sea from Central Asia that has repeatedly filled and dried under the effect of both natural and human forces. The most recent dry period started in the early 1960s due mainly to the expansion of irrigation that has drained the tributary rivers, fallen the lake level by 23 m, shrunk the lake surface area by 74 %, decreased its volume by 90 %, and grew its salinity from 10 $\mathrm{g\,L^{-1}}$ to more than 100 $\mathrm{g\,L^{-1}}$, causing negative ecological changes as well as social problems with impacts on the population residing around the lake (Micklin, 2007). Another example is Lake Urmia from northwestern Iran, one of the largest hypersaline lakes in the world. Due to drought and increased demands for agricultural water in the lake's basin, the salinity of the lake has risen to more than 300 $\mathrm{g\,L^{-1}}$ during recent years, and large areas of the lake bed have been desiccated (Eimanifar and Mohebbi, 2007). The instrumental record of the water level oscillations in the Caspian Sea that covers a period starting from 1900s showed a progressive and dramatic decrease during the 1940s which continued up to 1977 after which the surface water level has shown a continuous rise that has resulted in tremendous costs to its surrounding countries. According to Vaziri (1994), the reasons for the recent increase can be categorized from the implementation of the former Soviet Union's projects to the earth tectonic movements, from the occurrence of a wet period for the region resulting in increase of river inflows to global warming, and reduction of surface evaporation. Another example of water level decline was observed in Lake Toba, Indonesia, due to use of water for power generation (Acreman et al., 1993).

As water resources become more limited due to higher demand; the significance of investigation on the changes in water bodies increases vastly. Thus, modeling lake water level fluctuations and storage possibilities of closed-basin water areas have gained particular attention. Water level in closed-basin lakes depends on the balance between precipitation and evaporation. Such lakes with large areas contain large volume of water and can effectively filter climatic noises, and may serve as a good indicator of climate change through the change observed in their water levels over a period of time (Rodinov, 1994). In addition, future water lake level change scenarios can be used for long-term planning of water resources. Observations and measurements in water bodies provide important information about hydrology of the interested water system. However, observations and measurements are not all the time available to the users due to their time consuming and expensive nature. Therefore, modeling approaches are developed for understanding the hydrology of the water bodies, including lakes.

Several studies are available to model and evaluate lake water level fluctuations. Examples selected from the literature are as follows: a study by Khavich and Ben-zvi (1995) presents a model based on the water budget to forecast daily changes in water level in Lake Kinneret, Israel during flood periods. The water balance of the Aral Sea was simulated by Small et al. (1999) with a lake model coupled to NCAR's regional climate model (RegCM2). Multi-source satellite-driven data such as satellite-based rainfall estimates, modeled runoff, evapotranspiration, and a digital elevation dataset were used to model Lake Turkana, East Africa water levels from 1998 to 2009 (Velpuri et al., 2012). Support Vector Machine (SVM), Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models were developed to predict water levels for Lake Erie, North America (Khan and Coulibaly, 2006), for Lake Urmia, Iran (Talebizadeh and Moridnejad, 2011), and for Lakes Egirdir and Iznik, Turkey (Guldal and Tongal, 2010; Kisi et al., 2012).

Similarly, water level fluctuations of Lake Van have been studied. Due to high salinity of its water, changes in the deep closed-basin Lake Van water level have been important to analyze in order to investigate the mixing conditions (Kaden et al., 2010). A method based on the water balance equation with an added cumulative departures concept to show additional water level increments along the time axis was applied by Kadioglu et al. (1999). Monthly water level of the lake was studied with a stochastic model providing a basis for the assessment of the expected extreme water levels at different risk percentages (Sen et al., 2000). In order to predict the lake water level fluctuations, models based on the triple diagram, ANN and SVMs were developed for Lake Van (Altunkaynak et al., 2003; Cimen and Kisi, 2009).

In this study, precipitation data obtained from meteorological stations surrounding the Lake Van are first analyzed. Water budget of the lake based on the input and output variables (precipitation and evaporation) is established. A stochastic model is then generated at annual scale using the lake water level data recorded at the gauging station in Tatvan at monthly time scale. The lake water level time series is divided into homogeneous periods by using a segmentation software (SEGMENTER by Gedikli et al., 2008, 2010a,b). With SEGMENTER, up to four trend lines were fitted to the existing data instead of adopting one single tendency as usually used in previous studies (Sen et al., 2000). Data used in the application are defined, water budget is explained below, after which the mono- and multiple-trend autoregressive models are detailed. Results and conclusions come later.

## 2 Lake Van and water level data

Lake Van is a saline closed-basin lake located in Eastern Anatolia, Turkey, between the coordinates 37° 43′–39° 26′ North and 42° 40′–44° 31′ East (Fig. 1a). It is the largest lake in Turkey and the largest soda lake in the world. The surface area and drainage area of the lake are approximately 3502 km$^2$ and 12 956 km$^2$, respectively. Its elevation above the mean sea level is 1646 m with a deepest point of 451 m, and a water volume of 576 km$^3$. The lake is fed by direct precipitation on the lake, runoff from contributing rivers and snowmelt. Lake Van does not have any natural outlet, water discharges by evaporation only. The lack of outflows causes the accumulation of salts in the lake and increases the salinity (Thiel et al., 1997). Therefore, water in the lake cannot be used for drinking or irrigation because of its high salinity, and only limited species of fresh water fish can live.

Water level rises after spring with melting of snow from surrounding mountains whereas lake has the lowest level during winter months due to terrestrial climate. Under normal climate conditions, 50–60 cm of fluctuation is observed in the lake water level at annual scale. Monthly lake water level data recorded from 1944 to 2007 (768-month data) in Tatvan gauging station (Fig. 1b) are used in this study. As seen from Fig. 2, water level in the lake stays at an almost constant level after which a sudden upward jump is recorded. The water level shows a persistency at the increased level until another upward jump after which an increasing gradual trend is observed in 1990s to reach its maximum level. A gradually decreasing water level followed by an increasing trend is recorded at the end of the time series. Lake water level data in Fig. 2 correspond to differences between measured water level relative to the limnograph base level (1646.59 m). Minimum and maximum lake water levels were recorded as 1646.68 m and 1650.53 m, respectively. During the observation period mean lake water level is 1648.31 m. Standard deviation of annual difference in the lake water level is 92 cm.

## 3 Water budget

As no outlet other than evaporation exists for discharging water out of the lake, the sudden and gradual changes (jumps and trends) observed in the lake water level (Fig. 2) should be linked to the water budget of the lake balanced by the change in the lake water level between precipitation, runoff and evaporation. Water budget of the lake was established at annual scale based on precipitation data obtained from 11 meteorological stations surrounding the lake (Fig. 1b). Evaporation data were extracted from Batur et al. (2008). As inflows, direct precipitation falling on the lake surface was taken together with runoff flowing through the river system to the lake. The runoff was calculated as that portion of precipitation over the drainage basin turning into runoff depending on an average runoff coefficient 0.26 determined for the Lake Van hydrological basin (Bayazit, 1999). The three components, precipitation, runoff, and evaporation, are balanced with change in the lake water level. Therefore, a comparison between lake water level calculated through the water budget and that measured at the gauging station is made. In Fig. 3, change in the water level of the lake was referenced to the previous year; i.e. change can either be positive or negative depending on if an increase or a decrease is observed or calculated relative to the previous year's water level. It is seen that calculated and measured lake water levels match each other; maximum levels in 1988 and 1993, and minimum level in 2000 show this clear match. As a result, any sudden or gradual change (upward or downward jump, increasing or decreasing trend) in the lake water level is due to the response of the lake to the imbalanced effect of inflow and outflow. No delay is observed in the lake response probably because of the coarse time scale used in this study. If the analysis is made at a shorter time interval (say monthly) a delay in the lake response can be meaningful. For example; Gencsoy (1997) discovered a 2-month delay in the lake response based on monthly inflow and outflow data. Another water balance study (Landmann et al., 1996) suggests that rivers add 2.1 $\mathrm{km^3\,yr^{-1}}$ and that direct precipitation adds another 1.7 $\mathrm{km^3\,yr^{-1}}$ to the lake while evaporation from the lake amounts to 3.8 $\text{km}^3\,\text{yr}^{-1}$ under stationary lake level conditions.

## 4 Mono- and multiple-trend model

Considering a stationary time series $\ldots, x_{t-1}, x_t, x_{t+1}, \ldots$ normally distributed with mean $\mu$ and variance $\sigma^2$, observed at equally spaced times $\ldots, t_{t-1}, t_t, t_{t_{+}1}, \ldots$ autoregressive moving average (ARMA) models (Box and Jenkins, 1970) are widely used in hydrology and water resources studies (Yevjevich, 1972). In the model construction, the variable of the time series is transformed by standardization of

$$y_t = (x_t - \mu)/\sigma \tag{1}$$

with which the time series is converted to $\ldots$, $y_{t-1}$, $y_t$, $y_{t+1}, \ldots$ of a variable with zero mean and unit variance The ARMA-type models are well established in the literature (Salas et al., 1980). Therefore, only very brief information is provided below.

For the sake of obtaining a parsimonious model, AR(1), AR(2) and ARMA(1,1) models are commonly used in the literature when water-related data are concerned. In this study, these models were tested as alternative to each other. After the partial correlation test and the Akaike Information Criterion, the most suitable model was found as AR(2) which is given by

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varepsilon_t \tag{2}$$

with coefficients,

$$\varphi_1 = \frac{r_1 - r_1 r_2}{1 - r_1^2} \tag{3a}$$

$$\varphi_2 = \frac{r_2 - r_1^2}{1 - r_1^2} \tag{3b}$$

where $r_1$ and $r_2$ are lag-1 and lag-2 correlation coefficients, respectively. This type of models is applied to stationary time series free of deterministic components; trends and periodicities. Therefore, any trend and periodicity disrupting the homogeneous structure of the water level data of Lake Van should be determined and removed from the time series to obtain the stochastic components of the time series. The trend can be represented by a first-order polynomial function as:

$$y_t = at + b \tag{4}$$

while the periodicity which corresponds to cycles or periodic changes with time can be fitted by a Fourier series.

In this study, modeling the lake water level was performed in two different ways. It is obvious from Fig. 4a that the water level time series has an increasing trend which can be fitted by Eq. (4) when the whole time series is taken at once. It is clear, at the same time, that the time series can be divided into segments each with its own statistical characteristics. Considering that the time series depicts a number of different segments, it was decided, in this study, to fit multiple trend lines to each segment within the time series. A software called SEGMENTER (Aksoy et al., 2007, 2008; Gedikli et al., 2008, 2010a,b) is used for this purpose. The segmentation of a time series simply divides a given number of observations into subseries with statistical characteristics that are similar within each subseries and different between subseries. This is called jump analysis and can also be considered a change point detection problem. The simplest case is the segmentation-by-constant in which it is aimed to determine the change points where the average of the current segment is statistically different than the averages of the next segment as well as that of the previous one. Not only segmentation-by-constant but also segmentation with regression-by-lines or higher order polynomials can be used. In this study, segmentation with regression-by-lines was used due to the linear trend fit in Eq. (4). When the linear segmentation is concerned, a time series can be segmented into as many linear pieces as half the number of items in the time series. This information might be useful in many cases. For instance, one might be interested in dividing a time series into six segments and fitting linear equations to each segment. Such information is important in particular when the inner trends might behave differently than the trend taken over the whole dataset, which was the case in Fig. 4b. It is seen that the increasing mono-trend fitted to the whole time series in Fig. 4a can have different behavior when multiple inner trends are taken into account as in Fig. 4b.

Two models were developed in this study. In the first model, the time series was treated as a whole under the hypothesis that the time series has an increasing trend as in Fig. 2. In the second model, the time series was divided into a number of segments to each a linear trend was fitted. The former was called mono-trend model while the latter was defined as the multiple-trend model. Both the mono- and multiple-trend models were used for simulation of synthetic lake water level time series under the hypothesis that the observed mono- and multiple-trend structure of the lake water level will persist during the simulation period. The mono-trend hypothesis can be accepted while the repeatability of the multiple-trend structure of the time series during the simulation period can be questioned. Investigations on the Lake Van water level (Landman et al., 1996) showed that the lake had experienced such changes (increase and decrease in the lake water level) in its history, and the highest lake terrace was about 70 m above its present level. As referenced by Sen et al. (2000), the water level fluctuations in the order of few meters were reported in the 19th century. Based on this information, it is therefore possible to assume that the multiple-trend hypothesis of the water level time series is likely to occur during the simulation period although the order, length and steepness might change.

Parameters of the AR(2) model were determined for the mono- and multiple-trend models. In the multiple-trend models, the lake water level data were divided into a number of segments changing between 2 and 30 (Teltik, 2008). Among the multiple-trend models tested the four-trend model was taken into account. This is mainly based on the obvious segmentation in Fig. 4b. It is seen that the first trend is fitted to an almost constant segment followed by a negative trend after which two increasing trends more severe than the mono-trend in Fig. 4a are observed. Not only because of this, but also due to the observation that more extreme water levels were obtained by the use of the four-trend model among the multiple-trend models selected. The periodic component of the water level data was treated by Fourier series in mono- and multiple-trend models.

Both mono- and multiple-trend models well simulated the Lake Van water levels. 1000-yr long synthetic series are generated by each model. Maximum lake water levels of different return periods were calculated from the synthetic sequences. Table 1 shows maximum lake water levels for given probabilities together with their observed counterparts. Synthetic and observed lake water levels are very close to each other for both models such that all relative errors are less than 3 %.

As seen from Table 1, the probable maximum lake water level for the multiple-trend model is higher than that of the mono-trend model levels except for the return period of 5 and 10 yr. Maximum water level for 50-yr frequency is simulated as 391.8 cm by using the mono-trend model while it was calculated as 400.3 cm in the multiple-trend model. The former model gave a lower water level than the observed value of 393.9 cm whereas the latter model resulted in a higher water level for this particular return period. For 20, 25 and 50-yr return periods; maximum levels using the multiple-trend model are higher than the levels of the mono-trend model. The same circumstance is valid for the return periods of 100, 500 and 1000 yr. The multiple-trend model represents more extreme conditions than those observed in the past for the return periods of 25 and 50 yr. In this context, the multiple-trend model is assumed to be more appropriate for planners and practitioners who want to be on the safe side particularly for the long-term planning of the lakeshore infrastructure planning and development projects.

## 5 Conclusions

In this study, changes in the water level of the closed-basin Lake Van were analyzed by establishing the water budget between the inflow to and outflow from the lake. The inflow into the lake is composed of precipitation in the form of either rainfall or snow. It can fall on the lake directly or arrives later at the lake as runoff. The only outflow from the lake is evaporation. Inflow and outflow of the lake were balanced by increasing or decreasing lake water levels that can be observed in sudden or gradual changes. Water budget of Lake Van showed that any sudden or gradual change in the lake water level was due to the response of the lake to the imbalanced precipitation, runoff and evaporation.

Also two stochastic models were developed for the simulation of the water level time series of the lake. Mono-trend and multiple-trend cases were evaluated. In the mono-trend case, a linear trend line was fitted to the whole time series of the lake water level at once. In the second case, differently from previous studies, a multiple-trend case was used, in which the time series was divided into a number of segments each represented by its own linear trend. Periodicity in both cases was represented by Fourier series. After the time series was made trend- and periodicity-free, autoregressive type stochastic model was developed for both mono-trend and multiple-trend cases. 1000-yr synthetic series were generated by using each model.

It was seen from the results of the mono- and multiple-trend models that maximum lake water level hardly reached to the value of 400 cm corresponding to the 50-yr return period for the mono-trend model while it exceeded that threshold by the multiple-trend model. Therefore, in engineering point of view, the synthetic lake water level time series generated by the multiple-trend model is more suitable and safer compared to the mono-trend model for the planning of coastal infrastructural projects in the lakeshore.

*Acknowledgements.* This study is based on MSc thesis of Ilkay Teltik co-supervised by H. Aksoy and N. E. Unal. The study has been extended by contribution of E. Eris and M. I. Yuce on Water Budget of Study Area, Data Analysis and Discussion of Results.

## References

Acreman, M. C., Meigh, J. R., and Sene, K. J.: Modelling the decline in water level of Lake Toba, Indonesia, Adv. Water Resour., 16, 207–222, 1993.

Aksoy, H., Unal, N. E., and Gedikli, A.: Letter to the editor, Stoch. Env. Res. Risk A., 21, 447–449, 2007.

Aksoy, H., Gedikli, A., Unal, N. E., and Kehagias, A.: Fast segmentation algorithms for long hydrometeorological time series, Hydrol. Process., 28, 1047–1060, 2008.

Altunkaynak, A., Özger, M., and Sen, Z.: Triple diagram model of level fluctuations in Lake Van, Turkey, Hydrol. Earth Syst. Sci., 7, 235–244, doi:10.5194/hess-7-235-2003, 2003.

Batur, E., Kadioglu, M., Ozkaya, M., Saban M., Akin, I., Kaya, Y.: Water level of Lake Van and estimation of extreme levels, in: Proceedings of Lake Van Hydrology of Pollution Conference, 12–28, Van, Turkey, 2008 (in Turkish).

Bayazit, M.: Hydrology, Istanbul Technical University, Istanbul, Turkey, 1999.

Box, G. E. P. and Jenkins, G. M.: Time Series Analysis, Forecasting and Control, Holden-Day Series in Time Series Analysis, Oakland, CA, 1970.

Cimen, M. and Kisi, O.: Comparison of two different data-driven techniques in modeling lake level fluctuations in Turkey, J. Hydrol., 378, 253–262, 2009.

Eimanifar, A. and Mohebbi, F.: Urmia Lake (Northwestern Iran): a brief review, Saline Syst., 3, doi:10.1186/1746-1448-3-5, 2007.

Gedikli, A., Aksoy, H., and Unal, N. E.: Segmentation algorithm for long time series analysis, Stoch. Env. Res. Risk A, 22, 291–302, 2008.

Gedikli, A., Aksoy, H., and Unal, N. E.: AUG-segmenter: a user-friendly tool for segmentation of long time series, J. Hydroinf., 12, 318–328, 2010a.

Gedikli, A., Aksoy, H., Unal, N. E., and Kehagias, A.: Modified dynamic programming approach for offline segmentation of long hydrometeorological time series, Stoch. Env. Res. Risk A, 24, 547–557, 2010b.

Gencsoy, I.: Relation of Lake Van water level fluctuations with hydrometeorological parameters, M.Sc. Thesis, Institute of Science and Technology, Istanbul technical University (in Turkish), 1997.

Guldal, V. and Tongal, H.: Comparison of recurrent neural network, adaptive neuro-fuzzy inference system and stochastic models in Eğirdir Lake level forecasting, Water Resour. Manag., 24, 105–128, 2010.

Kaden, H., Peeters, A., Lorke, A., Kipfer, R., Tomonaga, Y., and Karabiyikoglu, M.: Impact of lake level change on deep-water renewal and oxic conditions in deep saline Lake Van, Turkey, Water Resour. Res., 46, W11508, doi:10.1029/2009WR008555, 2010.

Kadioglu, M., Sen, Z., and Batur, E.: Cumulative departures model for lake-water fluctuations, J. Hydrol. Eng., 4, 245–250, 1999.

Khan, M. S. and Coulibaly, P.: Application of support vector machine in lake level prediction, J. Hydrol. Eng., 11, 199–205, 2006.

Khavich, V. and Ben-zvi, A.: Forecast of daily water Levels for Lake Kinneret, Israel, Hydrolog. Sci. J., 40, 133–143, 1995.

Kisi, O., Shiri, J., and Nikoofar, B.: Forecasting daily lake levels using artificial intelligence approaches, Comput. Geosci., 41, 169–180, 2012.

Landmann, G., Reimer, A., and Kempe, S.: Climatically induced lake level changes at Lake Van, Turkey, during the Pleistocene/Holocene transition, Global Biochem. Cy., 10, 797–808, 1996

Micklin, P.: The Aral Sea disaster, Annu. Rev. Earth Planet. Sci., 35, 47–72, 2007.

Rodinov, S. N.: Global and Regional Climate Interaction: The Caspian Sea Experience, Kluwer Academic Publisher, Dordrecht, The Netherlands, 1994.

Salas, J. D., Delleur, J. W., Yevjevich, V., and Lane, W. L.: Applied Modeling of Hydrologic Time Series, Water Resources Pub., Littleton, Colo., 1980.

Small, E. E., Sloan, L. C., Hostetler, S., and Giorgi, F.: Simulating the water balance of the Aral Sea with a coupled regional climate-lake model, J. Geophys. Res., 104, 6583–6602, 1999.

Sen, Z., Kadıoğlu, M., and Batur, E.: Stochastic modeling of the Van Lake monthly level fluctuations in Turkey, Theor. Appl. Climatol., 65, 99–110, 2000.

Talebizadeh, M. and Moridnejad, A.: Uncertainty analysis for the forecast of lake level fluctuations using ensembles of ANN and ANFIS models, Expert Syst. Appl., 38, 4126–4135, 2011.

Teltik, I.: Stochastic modeling of Lake Van water level, M.Sc. Thesis, Institute of Science and Technology, Istanbul Technical University, 2008 (in Turkish).

Thiel, V., Jenish, A., Landmann, G., Reimer, A., and Michaelis, W.: Unusual distributions of long-chain alkenones and tetrahymanol from the highly alkaline Lake Van, Turkey, Geochim. Cosmochim. Ac., 61, 2053–2064, 1997.

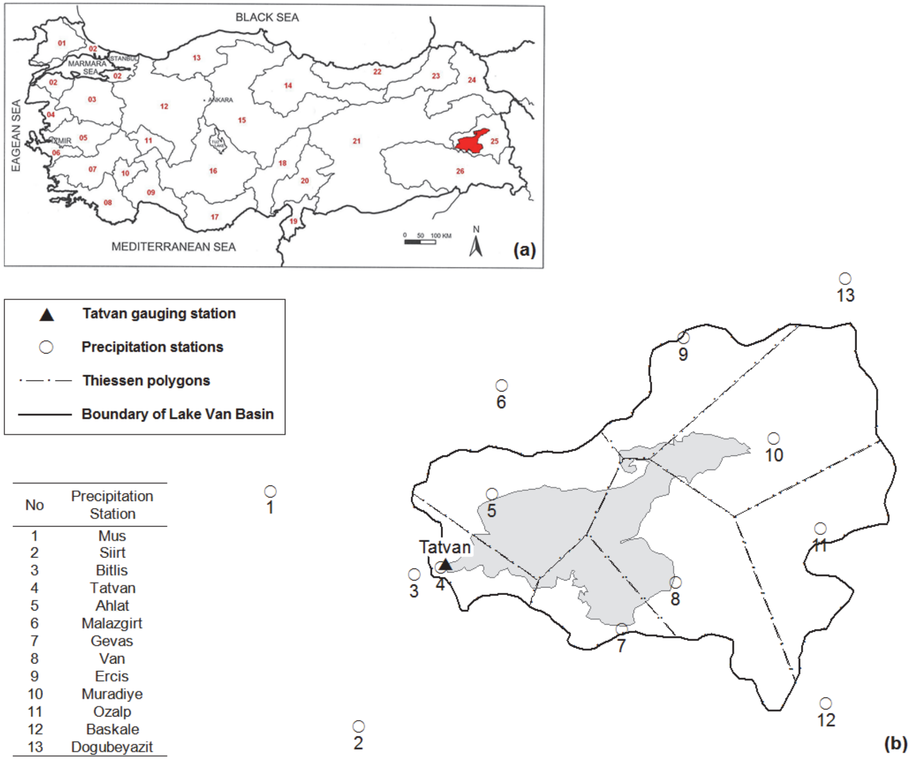
Vaziri, M.: Predicting Caspian Sea surface water level by ANN and ARIMA models, J. Waterw. Port C.-ASCE, 123, 158–162, 1997.

Velpuri, N. M., Senay, G. B., and Asante, K. O.: A multi-source satellite data approach for modelling Lake Turkana water level: calibration and validation using satellite altimetry data, Hydrol. Earth Syst. Sci., 16, 1–18, doi:10.5194/hess-16-1-2012, 2012.

Yevjevich, V.: Probability and Statistics in Hydrology, Water Resources Pub., Colorado, 1972.

**Table 1.** Observed and synthetic maximum lake water levels.

| Return period (year) | Probability | Observed water level (cm) | Synthetic water level (cm) | |
|---|---|---|---|---|
| | | | Mono-trend | Multiple-trend |
| 2 | 0.50 | 190.6 | 189.9 | 190.5 |
| 5 | 0.20 | 275.4 | 275.7 | 271.4 |
| 10 | 0.10 | 323.2 | 326.7 | 319.8 |
| 20 | 0.05 | 378.2 | 372.6 | 375.8 |
| 25 | 0.04 | 387.2 | 378.6 | 389.5 |
| 50 | 0.02 | 393.9 | 391.8 | 400.3 |
| 100 | 0.01 | | 394.4 | 402.0 |
| 500 | 0.002 | | 395.5 | 403.3 |
| 1000 | 0.001 | | 395.9 | 404.5 |



| No | Precipitation Station |
|---|---|
| 1 | Mus |
| 2 | Siirt |
| 3 | Bitlis |
| 4 | Tatvan |
| 5 | Ahlat |
| 6 | Malazgirt |
| 7 | Gevas |
| 8 | Van |
| 9 | Ercis |
| 10 | Muradiye |
| 11 | Ozalp |
| 12 | Baskale |
| 13 | Dogubeyazit |

**Fig. 1. (a)** Location of Lake Van in Turkey, **(b)** lake water level gauging station in Tatvan and precipitation stations surrounding the lake.

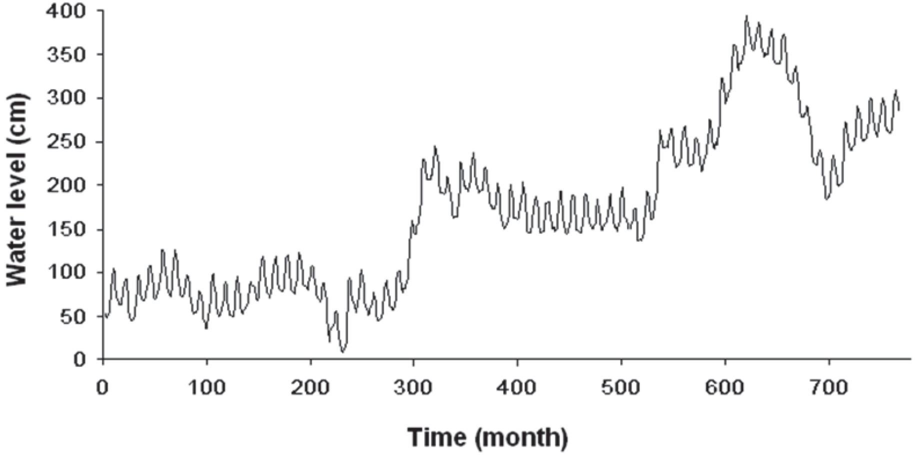


**Fig. 2.** Monthly lake water level time series.

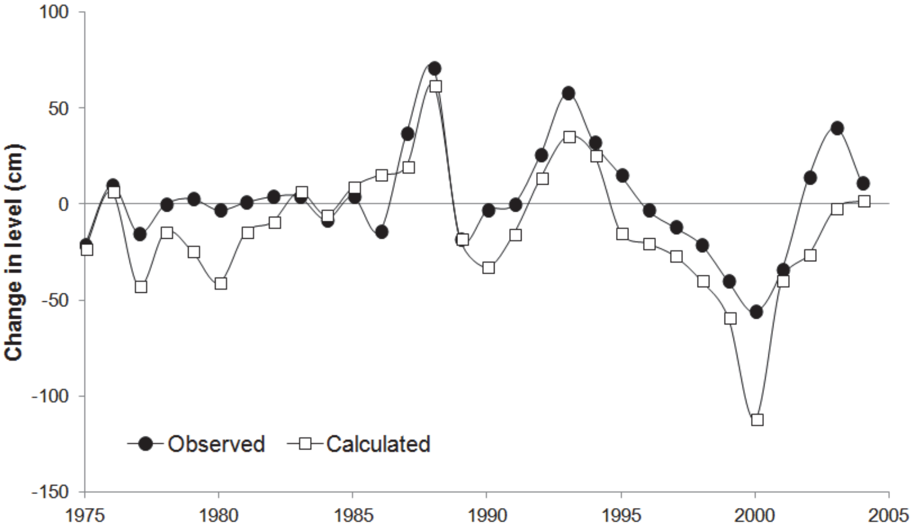


**Fig. 3.** Observed and calculated change in the lake water level relative to previous year.

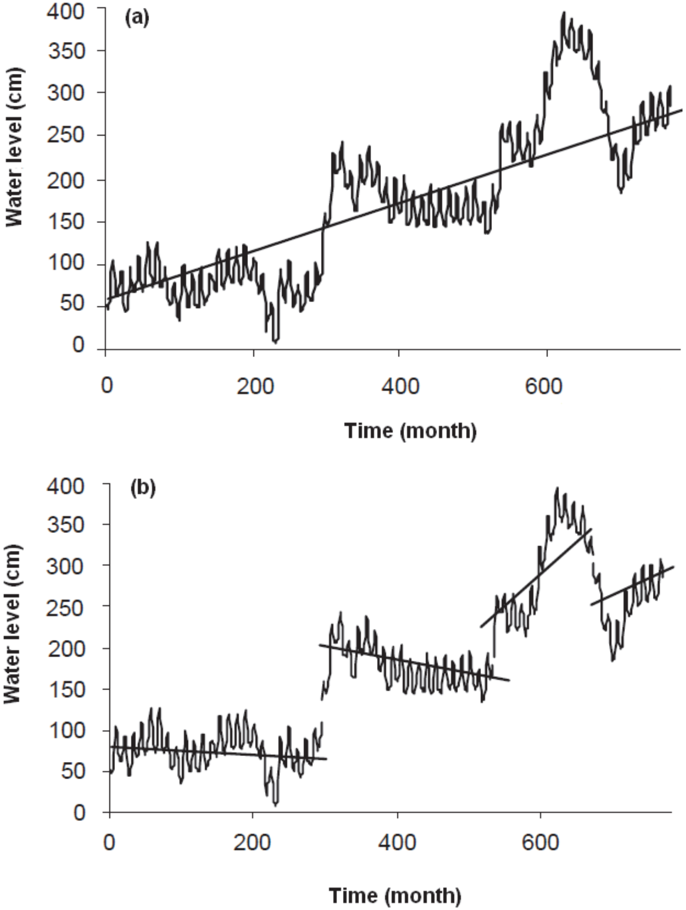


**Fig. 4.** Lake water level time series fitted by **(a)** mono-trend line, and **(b)** multiple-trend lines.