

# IMPACTS OF DRYING UP OF URMIA LAKE, THE SECOND LARGEST HYPERSALINE LAKE IN THE WORLD, ON PARTICULATE MATTER CONCENTRATION IN THE NORTHWESTERN IRAN

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## 1. INTRODUCTION

In recent decades, some of the world's water bodies, such as the Aral Sea, Dead Sea, Lake Poopó, Lake Eyre and Lake Mead have been shrinking mostly due to human-induced activities and climate change. Desertification caused by the drying up of these lakes have led to soil degradation and dust storms which have negative impacts on people's health and the environment as well (Barnett and Pierce., 2008; Indoitu et al., 2015; Izdebski et al., 2016; Satgé et al., 2017; Farebrother et al., 2017). Urmia Lake in the northwest of Iran has lost most of its water surface area over the past 2 decades mainly due to agricultural development and misguided water policies in the basin (Hassanzadeh et al., 2012; Chaudhari et al., 2018; Alizade Govarchin Ghale et al., 2018; Khazaei et al., 2019; Alizade Govarchin Ghale et al., 2019). This lake is known as the second largest hypersaline lake worldwide and its basin covers 3% of the area of Iran (Eimanifar and Mohebbi, 2007). The maximum water surface area of the lake was observed (i.e., 6000 km<sup>2</sup>) in the 1990s, while more than 90% of this area was lost in 2015 (Alizade Govarchin Ghale et al 2019). The dried bottom of Urmia Lake can be the source of dust storms and air pollution. Despite the importance of the effects of the lake desiccation on the air quality, few studies have been conducted in this area. Gholampour et al. (2017) concluded that the crustal soils around the lake are the main source of aerosol emissions. Sotoudeheian et al. (2016) used ground-level PM<sub>10</sub> data and Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model during the dust episodes to estimate the impacts of dried lake bed on PM<sub>10</sub> in the northwest of Iran. Their results indicated that emitted dust from the dried bottom of the lake can lead to ~30–60% increase in PM<sub>10</sub>

of cities around the lake. In a recent study, Effati et al. (2019) used MODIS data to estimate the dust emission probability in Urmia Lake Basin. They found high correlation between dust emission probability and wind speed, soil texture together with the surface soil moisture. Previous studies have not examined the relationship between ground-level PM<sub>10</sub> and AOD derived from satellite in the northwestern Iran. In this study, hourly ground observation PM<sub>10</sub> data of Urmia station, the closest station to the lake, AOD data of Terra MODIS and Aqua MODIS observed between 2010 and 2017 were used to investigate the spatio-temporal aerosol pollution in the northwestern Iran. AOD data derived from MODIS, daily meteorological data of Urmia station and statistical methods including Multiple Linear Regression (MLR) and Linear Mixed Effect (LME) were used to predict PM<sub>10</sub> concentration in the northwestern Iran.

## 2. MATERIALS AND METHODS

### 2.1. STUDY AREA

Urmia Lake (N 37.5°, E 45.5°) with a surface area ranging between 5000 and 6000 km<sup>2</sup> is located between West Azerbaijan and East Azerbaijan provinces of Iran (Eimanifar and Mohebbi, 2007). It is the largest inland lake of Iran and one of the largest hypersaline lakes in the world, at an altitude of 1250 m above sea level (Zarghami, 2011). Fig. 1. (a) indicates the location map of Urmia Lake and its basin in the northwestern Iran and Fig. 1. (b) indicates the 2° × 2° box covering Urmia Lake and its vicinity. The lake is an internationally protected area and it is home for different species of birds and mammals. More than 5 million people live in the regions close to the lake and agricultural sector accounts for 30% of employment around the lake (ULRP, 2019).

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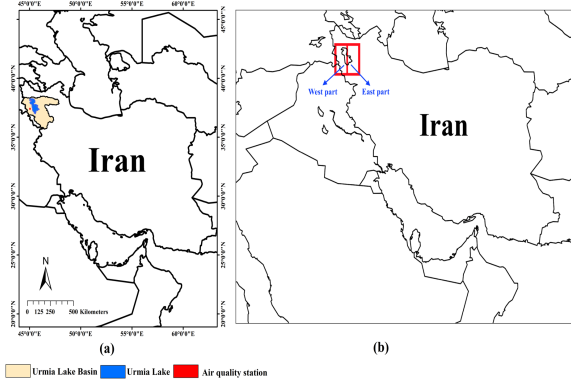


Fig. 1. (a) The location map of Urmia Lake and its basin in the northwestern Iran. (b) Box covering Urmia Lake.

## 2.2. METHODOLOGY

This study used the hourly ground-level PM<sub>10</sub> data of Urmia station in the northwestern Iran conducted by Department of Environment. PM<sub>10</sub> represents inhalable particles with diameters that are generally 10 micrometers and smaller (You et al., 2015). The hourly data were converted to daily average PM<sub>10</sub> data and statistical methods such as trend analysis were performed month by month on daily data to find episodes with same trends. In the next step, daily level 2 Aerosol Optical Depth data (at 550 nm) of Aqua MODIS (MYD04) and Terra MODIS (MOD04), collection 6.1, at 10 \*10 km spatial resolution were used as a columnar proxy of aerosol abundance. An optical depth of less than 0.1 indicates a clear sky with maximum visibility, while a value of 1 indicates dust and very hazy conditions (NASA earth observatory., 2019). The daily average AODs in a 2° × 2° box (covering Urmia Lake and its vicinity) were used to understand the aerosol concentration in the western and eastern parts of the lake. The monthly average AODs were calculated using the daily AODs to evaluate the seasonal optical depths changes around Urmia Lake.

Meteorological data especially Temperature (Tem), Relative Humidity (RH) and Wind Speed (WS) impact the relationship between AOD and PM<sub>10</sub> by affecting physical features and chemical compositions of particles (Ghotbi et al., 2016; Soni et al., 2018).

Particles formation and photochemical reactions between precursors can be affected by RH and temperature. RH variations influence on the particles size and their distribution due to photochemistry phenomena and hygroscopic particles growth (Soni et al., 2018). WS can transfer different particulate matters from different

sources and cause diluting the concentration of pollutants, which affect the mixing of aerosols. Therefore, in addition to AOD, meteorological parameters should also be used in estimation of PM<sub>10</sub>. Many researchers used different kinds of statistical models such as Simple Linear Regression, Empirical Linear Regression, Multiple Linear Regression, Log-linear Regression and Linear Mixed Effect (LME) models to explore the relationship between daily average PM and AOD (Dinoi et al., 2010; You et al., 2015; Ghotbi et al., 2016; Soni et al., 2018). Among these models, the multi-variable LME model has performed better (Lee et al., 2011; Kloog et al., 2011; Nordio et al., 2013; Ghotbi et al., 2016). The MLR and multi-variable LME models were used in this study to explore the relationship between PM<sub>10</sub> and AOD in the northwestern Iran. The daily metrological data of Urmia station and daily average AOD values in the western Urmia Lake (west box) were used to estimate ground-level PM<sub>10</sub>. The Equations of MLR and LME are shown below, respectively:

$$PM = a + (b_1) \times AOD + (b_2) \times Tem + (b_3) \times RH + (b_4) \times WS + e \quad (1)$$

where, all variables are averaged daily. PM indicates the PM<sub>10</sub> concentration at Urmia station (dependent variable). AOD, Tem, RH and WS are independent variables, a is intercept, b<sub>1</sub>, b<sub>2</sub>, b<sub>3</sub> and b<sub>4</sub> are regression coefficients and e represents the error term.

$$PM_{ij} = (c + U_j) + (d) \times Tem_{ij} + (V_j) \times AOD_{ij} + (W_j) \times RH_{ij} + (Z_j) \times WS_{ij} + e_{ij} \quad (2)$$

where, PM<sub>ij</sub> indicates the PM<sub>10</sub> concentration (dependent variable) at the i-th site on the j-th day, c and U<sub>j</sub> are the fixed and random intercepts, respectively, d and V<sub>j</sub>/ W<sub>j</sub>/ Z<sub>j</sub> are the fixed and random slopes, respectively and e<sub>ij</sub> indicates the error term in i-th site and j-th day. Tem<sub>ij</sub>, AOD<sub>ij</sub>, RH<sub>ij</sub> and WS<sub>ij</sub> are independent variables in i-th site and j-th day.

## 3. RESULTS AND DISCUSSION

Analyzing the daily mean (24-hour mean) PM<sub>10</sub> concentration is necessary for understanding the air quality changes and air pollution category in the study area. The United States Environmental Protection Agency (EPA) has classified 24-hour mean PM<sub>10</sub> (µg/m<sup>3</sup>) values to 4 categories including; very good (0 – 16.4), good (16.5 – 32.9), fair (33 – 49.9), poor (50 – 74.9) and very poor (75 or greater) (EPA., 2019). The

maximum 24-hour mean PM<sub>10</sub> concentration was observed in Urmia station at December 16 2015, which was 876.13 µg/m<sup>3</sup>. The maximum monthly mean PM<sub>10</sub> concentration in Urmia station was 174.96 µg/m<sup>3</sup>, observed in May 2015. There was no significant seasonal difference between PM<sub>10</sub> variations in the northwestern Iran. In this area, winter and summer seasons accounted for high level (93.65 µg/m<sup>3</sup>) and low level (89.02 µg/m<sup>3</sup>) PM<sub>10</sub> concentrations, respectively. High levels of PM<sub>10</sub> during the winter were expected due to the atmospheric conditions and the existence of local and regional air pollution sources during this season. The annual mean PM<sub>10</sub> concentration significantly increased after 2013. It should be noted that the water level of Urmia lake dramatically dropped from 2013 to 2015 and more than 5000 km<sup>2</sup> of its area changed to saline bodies.

The results of satellite data processing showed that the negative impacts of Urmia Lake desiccation on the local and regional air quality is undeniable. In the next step, the daily AOD values were obtained by averaging the AOD data of Terra MODIS and Aqua MODIS. The mean value of AODs were calculated in the west box (covering west part of the lake), east box (covering east part of the lake) and the box, covering both west and east parts of the lake to have a detailed spatio-temporal analysis.

Based on the results of this study, in total, 129 days with mean AOD values more than 1 were observed in box covering all parts of the lake, which indicated the severity of air pollution and dust emission from the dried bottom of the lake. The daily mean AOD in the west box and east box was estimated about 0.348 and 0.508, respectively. The extensive of salinization and desertification in the eastern part of the lake can be the source of high AODs concentration in this part. The monthly mean AOD values were calculated using daily mean values. Based on the results of this study, the eastern part of the lake was more affected by the emitted dust from the dried bottom of the lake and winter accounts for higher AOD levels in the study period. In the next step, MLR and LME models were used to estimate the ground-level PM<sub>10</sub> variations in Urmia station. Estimation of ground-level PM<sub>10</sub> using AODs and meteorological variables (Tem, RH and WS) is very important to map PM<sub>10</sub> concentrations in places, where there is no air quality station.

Fig. 2. shows the scatter plot of AOD-PM<sub>10</sub> relationship and the scatter plot of predicted PM<sub>10</sub> by two statistical models versus observed PM<sub>10</sub> concentrations at Urmia station.

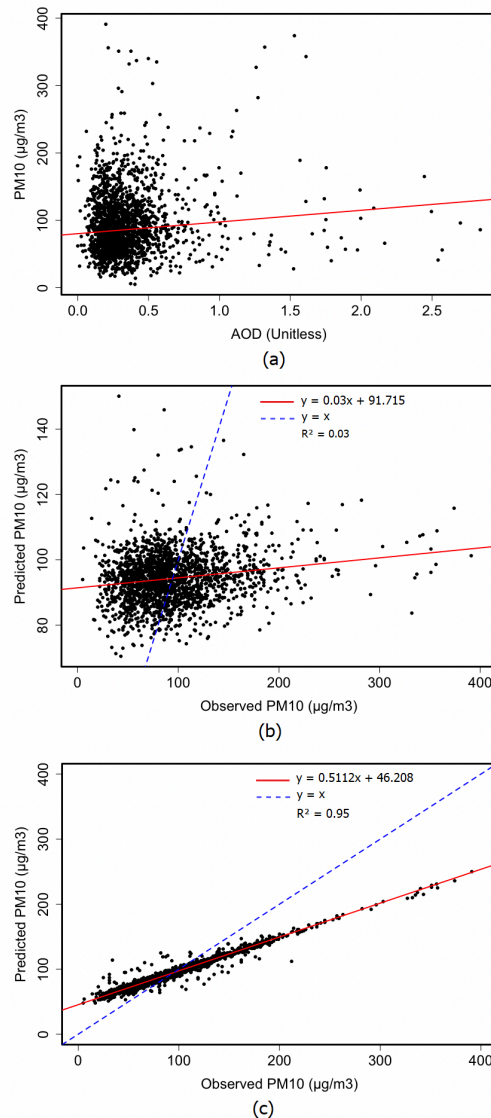


Fig. 2. (a) Scatter plot of AOD-PM<sub>10</sub> relationship (b) Scatter plot of predicted PM<sub>10</sub> by MLR model versus observed PM<sub>10</sub> concentrations (c) Scatter plot of predicted PM<sub>10</sub> by LME model versus observed PM<sub>10</sub> concentrations.

The results of LME were better than MLR. The RMSE and AME values of MLR were 45.60 µg/m<sup>3</sup> and 33.09 µg/m<sup>3</sup>, respectively, while, the RMSE and AME values of LME were 23.22 µg/m<sup>3</sup> and 16.59 µg/m<sup>3</sup>, respectively. The R<sup>2</sup> of LME was 0.95 and this model performed better than MLR. Moreover, the seasonal analysis of LME indicated that the summer and winter seasons account for higher (0.98) and lower (0.86) values of R<sup>2</sup>. The R<sup>2</sup> of MLR in summer and winter seasons was 0.14 and 0.06, respectively.

Fig. 3. shows the monthly variations of observed and predicted PM<sub>10</sub> concentrations by

LME. There is a good match between the monthly mean observed and monthly mean predicted PM<sub>10</sub> concentrations. The predicted values given by red dashed line follow the trend of the observation especially when the observations are below 100 µg/m<sup>3</sup> as the smaller picks especially for example around 2014 the model predicts pretty good. There are a few cases where there is an overestimation and most of the time it is following the observation line, but in the area highlighted by circles, the model is underestimating significantly.

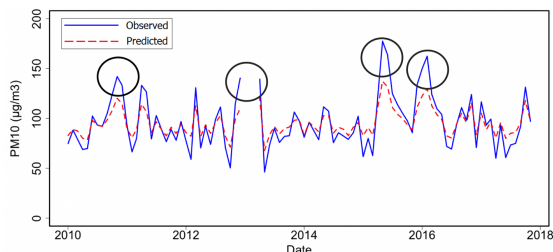


Fig. 3. Monthly variations of observed and predicted PM<sub>10</sub> concentrations by LME.

So, from this figure it can be conclude that although the overall trend is estimated by model the extreme values of the observations cannot be modeled by LME model. The future work can focus on the use of atmospheric transportation model (CMAQ) to understand the mechanics of dust transportation in the region. In addition to northwestern Iran, the high levels of PM<sub>10</sub> values and aerosol concentration were observed in the eastern and southeastern Turkey. Investigation of the possible transportation of dust from Urmia Lake to neighbouring regions and countries is an interesting topic too.

The results of this study emphasized the importance of using the multi-variable Linear Mixed Effect (LME) model in estimation of PM<sub>10</sub> concentrations.

#### 4. CONCLUSION

The Shrinkage of Urmia Lake has caused many environmental problems in the northwestern Iran such as salinization, desertification and air pollution. Dust emission from the dried bottom of the lake and its negative impacts on people's life has attracted the attention of government in recent years. Urmia Lake Restoration Program (ULRP) has contributed to reduce the severity of this environmental problem by providing scientific solutions, but still 3000 km<sup>2</sup> of lake bed has potential to be the source of dust. Although, the eastern part of the lake is mostly affected by dust

emission, other parts of the lake are also at risk. According to the UNEP studies (UNEP, 2012), the lake desiccation affects a region with a radius of 500 km. In total, 129 days with mean AOD values more than 1 were observed in box covering all parts of the lake between 2010 and 2017, which indicated the severity of air pollution and dust emission from the dried bottom of the lake. The daily mean AOD in the west part of the lake and east part of the lake was 0.348 and 0.508, respectively. The extensive of salinization and desertification in the eastern part of the lake can be the source of high level AODs in this part. Two statistical models including MLR and LME were used for estimation of PM<sub>10</sub> concentrations in Urmia station. The RMSE and AME values of MLR were 45.60 µg/m<sup>3</sup> and 33.09 µg/m<sup>3</sup>, respectively, while, the RMSE and AME values of LME were 23.22 µg/m<sup>3</sup> and 16.59 µg/m<sup>3</sup>, respectively. The R<sup>2</sup> of LME was 0.95 and this model performed better than MLR model. Moreover, the seasonal analysis of LME indicated that the summer and winter seasons account for higher (0.98) and lower (0.86) values of R<sup>2</sup>.

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