The role of new-emerging lands on sources of aeolian sand deposits driven by shrinking of the Urmia salt lake

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Abstract

Urmia Lake, the largest saline lake in Iran and the Middle East, in the northwest of Iran, has shrunk over the past decades. The reduced water level has increased the area of dry land around the lake allowing new environmental hazard such as sand dunes encroachment, particularly on the western side of the lake. New land has emerged as a consequence of lake shrinkage, and this new land is a major sediment source for the creation of sand dunes around the lake. This shrinking of the lake has created emerging lands. These lands play a major role in creating sand dunes around the lake. There are five terrain types that could contribute sediment to the dunes, and it is the main aim of this research to identify the contributions to the dunes of each terrain type. Fifteen surface samples were collected from the five most erodible terrain types, and eight samples were collected from the dunes both downwind and upwind from the lake, and major element components were measured using X-ray fluorescence. According to the Besler classification, all samples are in the saline class. Also, the chemical index of alteration values in all samples were less than 50, indicating weak weathering. Based on multivariate statistical analysis, suitable tracers were selected and were imported to the sourcing equations. Quantification of uncertainty and the creation of two new fingerprinting models for aeolian sediments based on both Bayesian and GLUE procedures were used. The highest proportion comes from the salty and puffy lands (44.2%) followed by salty polygon land (23.5%), clay-salty areas, puffy-flaky lands (7.01%), the terminus of the fine sandy alluvial fan (13.2%) and clay-salty abandoned lands (12.1%). It is concluded that if land managers use these results, they can more efficiently decrease the hazards posed by dune formation, reactivation and migration through implementation of soil conservation on the affected lands around the dried lake.

Keywords Aeolian hazard · Emerging geomorphological units · Sand provenance uncertainty · Mixing model

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1 Introduction

Wind erosion is one of the most important and complex geomorphic processes that causes land degradation in arid, semi-arid and hyper-arid areas (Chappell et al. 2019; Kasper-Zubillaga et al. 2007). About one-sixth of the world’s population (Skidmore 2000) lives in areas where there are mobile sand dunes with destructive effects on infrastructure and human activities. Sand dunes are easy to identify, but the recognition of sand dune sources, for the design of soil conservation to slow dune construction and reduce mobility, requires detailed information (Gholami et al. 2017). By recognizing the geomorphological terrains of sand dune source areas and determining their contribution to sediment production, the control of sediment production can be planned. Sourcing methods were developed in the late 1980s and 1990s based on various quantitative approaches (Walling 2005) including the use of quantitative hybrid models (Collins and Walling 2002).

In the field of dust sediment monitoring and provenance, various techniques have been used such as remote sensing (Long et al. 2016; Cherboudj et al. 2016; Schepanski et al. 2012), mineral and chemical properties (Behrooz et al. 2019; Shen et al. 2009), isotopes (Grousset and Biscaye 2005; Chen et al. 2007; Cao et al. 2008; Wang et al. 2005; Del Rio-Salas et al. 2012), combined methods (Yan et al. 2015; Cao et al. 2015). Although the application of these methods to fluvial sediment fingerprinting has been widely used (e.g., Collins et al. 1996; Mukundan et al. 2010; Cooper et al. 2015), they have not been applied widely to aeolian sediments, although their use is increasing (e.g., Liu et al. 2016; Gholami et al. 2017a, b). Recent studies such as (Yu and Oldfield 1989; Walling and Woodward 1992; Collins et al. 1996) and Collins et al. (2017, 2020) in recent years have led to the methodological decision-tree for end-users of the fingerprinting technique. However, each study conducted in the world, individually, has helped to improve part of the fingerprinting methodology. Improvements in the methodology of this technique include: selection of new study areas with new complex features, innovation in the selection of a wider range of tracer properties, new sampling protocols for sediments and sources, diversity in the selection of grain size fractions for analysis, assessment of tracer conservatism, source apportionment modeling, use of artificial sediment mixtures to assess the accuracy of source apportionment modeling, and particle size and organic matter content correction methods.

The fingerprinting sourcing method has two main aspects: (1) determining the best tracers in both sediments and potential source units; (2) solving multiple fingerprinting equations for determining sediment contributions from each geomorphologic mapping unit (GMU) (Adabi 2004). Most investigations of aeolian sediment sources have used mixing models that have included isotopes and geochemical properties (Collins et al. 2010; Honda et al. 2004; Saye and Pye 2006; Wang et al. 2012). But here only major elements are used as they are easier to obtain and, it will be shown, produce reliable results.

In recent decades, Lake Urmia has been affected by human activities such as dam construction in its upland catchment (AghaKouchak et al. 2015), water level lowering by climatic change (by decreased rainfall, increased evaporation, and increased wind speed), and land use changes have led to shrinkage of the lake. Together with vegetation loss but dune encroachment, new geomorphologic terrains have been created on the exposed lake floor. The creation of sand dunes from the newly exposed terrain (Boroughani et al. 2020), including salty particles, has led to undesirable conditions for agriculture, human health, with the creation of threats to socio-economic conditions and the environment, affecting two provinces in northwestern Iran (Katebi et al. 2018).
The main aim of this study is to link the newly formed sand dunes to their sediment sources that have been exposed by drying of Urmia Lake, through multiple fingerprinting models as well as assessment of uncertainty through statistical analysis. This approach involved the following steps: (1) measurement of the chemical composition of sediments and corresponding GMU by X-ray fluorescence (XRF) and calculation of the chemical index of alteration (CIA) (Motha et al. 2003; Honda et al. 2004); (2) calculation of the contribution of each GMU to the dominant sand fraction though multiple fingerprinting equations and a Bayesian approach; and (3) estimation of the uncertainty related to each contribution using GLUE and Bayesian approaches.

2 Materials and methods

2.1 Study area

The study area is located on the western margin of Urmia Lake in the northwest of Iran. The lake and newly exposed dry bed cover an area of approximately 10km², between 37°45′ and 37°57′ N latitude and 45°01′ to 45°57′ E longitude (Fig. 1). A study of the wind regime at Urmia Station (Fig. 1) showed that southwest winds (15.4%) prevail, and the sand drift potential is 63 VU (Nazari Samani et al. 2018) which causes sand to move to the northeast (Fig. 2). The major sediments of the study area are of the Quaternary period. When Urmia Lake began to dry up in 2003 (Fig. 3), new geomorphologic units appeared (Fig. 4). On this newly exposed surface, vegetation is sparse and scattered and mainly

Fig. 1 Location of the study area in the northwest of Iran (a) geology map (b) and sand dune location
consists of halophyte and hydro-halophyte species such as *Nitraria schoberi* and *Haloxylon* spp. *Tamarix* spp. have been established in the riparian zones along the ephemeral wadis that feed the lake.

### 2.2 Sample collection and geochemical analysis

The geomorphological mapping units (GMUs) were identified from interpretations of satellite images, slope condition and lithological information as well as field studies (Fig. 5). Based on the terrain map, 23 samples were collected, including 15 samples from potential geomorphic sources, and eight samples from sand dunes (windward and leeward sides of dunes). A random sampling strategy was used to collect samples from
the upper 0–5 cm of surface soil of each GMU and the sand dunes. During the field sampling, we tried to keep 500 m distance between two points along a sampling transect line.

All the samples were sieved, and particle size distributions determined by drawing granulometric curves. The particle size fraction with > 50% frequency is 125–500 µm; therefore, this fraction was selected for chemical analysis. The samples were analyzed by XRF (in ppm) to provide estimates of the major elements: Cl, S, As, Ba, Ce, Co, Cr, Cu, Nb, Ni, Pb, Rb, Sr, V, Y, Zr, Zn, Mo. And the following compounds of Earth’s crust were also determined: SiO₂, Al₂O₃, Fe₂O₃, CaO, Na₂O, MgO, K₂O, TiO₂, MnO, P₂O₅, as well as LOI.

The CIA (McLennan 1993) is an indicator of the degree of weathering of the alumino–silicate minerals (Eq. 1) (Honda et al. 2004):

\[
\text{CIA} = \left[ \frac{\text{Al}_2\text{O}_3}{(\text{Al}_2\text{O}_3 + \text{CaO} + \text{Na}_2\text{O} + \text{K}_2\text{O})} \right] \times 100
\]  

The CIA value indicates the degree to which minerals have been converted to clay, and in the present case range from 45 to 55 indicating minimal weathering. A value of 100 indicates complete weathering (Motha et al. 2003).

The salinity levels of the sands were determined and classified according to the scheme of Besler (2008). The salinity status of the sand dunes has been determined based on their salt content, which has been combined with other information to produce the following classification: allowing the distinction between sand dunes (not saline (< 102 mS/cm), mega dune sands (saline: > 102 mS/cm), aeolian sediments subjected to surface-water
infiltration and evaporation during long timespans (strongly saline: > 103 mS/cm), and littoral sands influenced by sea salt water (extremely saline: > 104 ms/cm) (Besler 2008).

2.3 Optimum tracing composite and sand provenance

Multiple tracers were selected based on a pre-sourcing study (Boroughani et al. 2020) and geochemical variation. The 125–500 μm fraction was used for analysis because it is the
dominant size fraction. All elemental data were used as a starter list of tracers and through simple and multivariate data analysis the tracers that can distinguish different sources were identified. A principal assumption for selection of appropriate tracers is related to their conservative behavior. In this research, those traces that their minimum and maximum as well as the mean value in sediment samples were in associated sources range were considered as conservative tracers (Collins et al. 2020) to assess conservatism. All the tracers showed conservative behavior except: Zn, Y, V, Sr, MnO, Ba, As and P₂O₅.

Small differences among the source groups were not used for the final tracer list. A combined statistical analysis was used to discriminate the most suitable set of tracers (Fatahi et al. 2022). A principal component analysis (PCA) was applied to condense the information of the original variables into a smaller set of factors. The results of the PCA revealed that for all tracers the communalities value is more than 0.9, indicating that the extracted factors can explain more that 90% of total variation. Based on the eigenvalues, the first three components (factors) account for more than 85% of total variance. However, the correlation matrix indicates a high significant correlation between tracers and to decrease this multicollinearity effect those tracers with significant correlation with others that have been removed. Therefore, taking account of both multicollinearity and between-group variance, the tracers with high loading factor and low correlation value were selected for the next statistical step. Finally, a stepwise multivariate discriminant function analysis (DFA) was applied to the data to extract a suitable set of properties for predicting source

Fig. 5 Geomorphological mapping units and the locations of sampling points
membership. Tests for outliers and normality were performed using box plots and the Kolmogorov–Smirnov test, respectively.

### 2.4 Relative source contribution estimation using a Bayesian mixing model

Suppose $Y$ is an $n \times k$ matrix representing $n$ measured tracers in $k$ sediment samples and $S$ is an $n \times m$ matrix of $n$ measured tracers in $m$ sources; each column represents $n$ measured tracers in each source. Let $B$ be an $m \times k$ matrix of $m$ fractional source contributions to $k$ sediment samples. Note that all elements in this vector are non-negative and sum to unity. The mixing problem can be expressed using a multivariate linear model (Eq. 2):

$$ Y = SB + E $$

where $E$ is an $n \times k$ error matrix.

When the number of tracers is equal to or more than the number of sources, the system of linear equations is mathematically over determined and there are infinite solutions. To estimate the source contribution matrix ($B$), frequentist statisticians employ an optimizing algorithm to minimize objective functions such as the root mean square of relative errors (Motha et al. 2003). Problems arise from a limited number of samples used to represent tracer concentrations in sources, the optimization algorithm used to minimize an objective function, the number of selected tracers, the use of a single value of tracers for each source in the mixing model, and analytical errors of the tracers, and combine to produce uncertainty in estimated source contributions (Franks and Rowan 2000; Small et al. 2002; Collins et al. 2010; Walling 2013). Knowledge of uncertainty ranges enables a realistic assessment of sediment fingerprinting results.

To quantify uncertainty associated with variability of the fingerprint properties in the sources and sediment, many researchers couple Monte Carlo simulation with a mixing model (Franks and Rowan 2000; Martínez Carreras et al. 2010; Collins et al. 2010). The Monte Carlo approach ignores correlation between tracers in modeling and it has insufficient flexibility to take account of all sources of uncertainty (Cooper et al. 2015). Recently different Bayesian mixing models have been developed to deal with the drawbacks of the Monte Carlo technique and to estimate uncertainty in sediment fingerprinting (Douglas et al. 2009; Stewart et al. 2015; Mabit et al. 2018).

### 2.5 Uncertainty estimation based on a Bayesian mixing model

In this study, we used a hierarchical Bayesian end-member model (BEMMA) to estimate the uncertainty in sediment fingerprinting. This model was originally developed by Yu et al. (2016) to unmix sediment sources and determine their contributions to sinks from sediment grain-size data.

Based on Bayes’ theorem, the probability of event $A$ given event $B$ is proportional to the probability of event $B$ given event $A$ multiplied by its prior probability (Eq. 3):

$$ p(A|B) \propto P(B|A)p(A) $$

The Bayesian theorem states that the initial belief (i.e., prior knowledge) about parameter $A$ can be updated by observational data to find the posterior distribution of parameter $A$.

Within the Bayesian framework, we assume that the likelihood follows the multivariate normal distribution with covariance matrix $\Sigma$ (Eq. 4):
where $T$ denotes the transpose of a matrix or a vector, $||$ is the determinant, and $\text{tr}(.)$ denotes the tracer matrix.

An important component of Bayesian modeling is to define a suitable prior distribution for parameters and hyper-parameters. Depending on prior knowledge and the complexity of a model, one can select informative and non-informative parameters, or some parameters and hyper-parameters that are directly estimated using measured data (Carlin and Louis 1996).

For source fractional contributions, we adopted the non-informative Dirichlet distribution as a prior to ensure that fractional source contributions are positive and sum to one.

$$y_i \sim \text{Dirichlet}(\lambda_i)$$

where $y_i$ is an $m$ dimensional vector of the fractional source contribution to sediment sample $i$ and $\lambda_i$ is the Dirichlet distribution parameter.

For the inverse covariance matrix ($\Sigma^{-1}$), the Wishart distribution ($\psi, \nu$) was selected as the prior distribution, where the hyper-parameter $\nu > n - 1$ is the degrees of freedom and the hyper-parameter $\psi$ is a $n \times n$ positive definite scale matrix. In this study, $\nu$ was set to $n$ and for $\psi$ we assume the Wishart distribution ($\Omega, p$), due to lack of prior knowledge, and $P$ was set to $n$ and $\Omega$ was set to $PI_n$.

Due to the complexity of the posterior distribution, an analytical method cannot be used to infer the unknown parameters; therefore, we used the reversible-jump Markov chain Monte Carlo algorithm in conjunction with the Gibbs samplers to sample the posterior distributions to generate random numbers that mimic the posterior distribution of the parameters.

### 2.6 Uncertainty estimation based on the GLUE method

The generalized likelihood uncertainty estimation (GLUE) method is based on the equifi-nality concept and was originally developed by Beven (2006) to estimate uncertainties in hydrological models. This method rejects a single optimum parameter set and states that there are several and different parameter sets that provide a good fit to observed data (Blasone et al. 2008).

Because it is a simple concept, is relatively easy to implement and is flexible, this method is widely used in many areas of environmental modeling (Vrugt et al. 2009; Blasone et al. 2008). This method does not make any assumptions about input and error distributions (Dotto et al. 2012). To conduct the GLUE method to estimate uncertainty, we used the following steps.

Select a prior distribution to sample feasible parameter sets. Note that in the mixing model the source contributions are the parameters. Due to lack of prior knowledge about parameter sets, a uniform distribution was selected as the prior distribution for sample parameter sets (Yang et al. 2008; Fathabadi et al. 2017).
Select a likelihood function and threshold value to split all parameter sets into behavioral and non-behavioral parameter sets. In this study, the Nash–Sutcliffe coefficient (Nse) was selected as the likelihood function (Eq. 6).

\[
Nse = 1 - \frac{\sum (y_{obs} - y_{sim})^2}{\sum (y_{obs} - \bar{y}_{obs})^2}
\]  

(6)

where \(\bar{y}_{obs}\) represents mean values of observed tracer concentrations in the sediment; \(y_{sim}\) are the estimated values of tracer concentrations in sediment samples; and \(y_{obs}\) are observed tracer concentrations in the sediment.

The Nse values range from \(-\infty\) to 1. The value of Nse equaling 1 indicates perfect correspondence between observed and simulated values and minus values indicate poor performance of the model.

Latin hypercube sampling was employed to generate random parameter sets from the prior distribution. Then the mixing model was run with sampled parameter sets and Nse was calculated for each parameter set. Here parameter sets were sampled 200,000 times (Behrooz et al. 2019).

Parameter sets were divided into behavioral and non-behavioral with respect to selected thresholds and calculated likelihood values for each parameter set. For the next step, non-behavioral parameter sets were discarded.

For all parameter sets, likelihood weights were rescaled to cumulatively sum to 1. For each source, fractional contributions were sorted in ascending order and, using assigned weights, the cumulative distribution was calculated, and finally different quintiles were estimated.

Furthermore, to above mention, the reliability of modeling outputs was assessed though a goodness of fit (GOF) index (Eq. 7).

\[
GOF = 1 - \frac{\sum_{i=1}^{n} \left| b_i - \sum_{j=1}^{m} p_j a_{ij} \right|}{b_i}
\]  

(7)

where \(a_{ij}\) is the \(i\)th tracer \((i = 1, \ldots, n)\) in source \(j\) \((j = 1, \ldots, m)\), \(p_j\) indicates the relative contribution of the \(j\)th source, \(b_i\) is the \(i\)th tracer in a sediment sample, \(m\) indicates the number of potential sources, and \(n\) is the number of selected tracers. A GOF value of 1 indicates that the fingerprint property values predicted by the model for the estimated source contributions match the measured values.

3 Results

The CIA index, the enrichment ratio and the amount of salinity are shown in Table 1, showing that weathering is low. The main reason for the low weathering status is the very dry climate (and youth of the exposed source materials exposed by the drawdown of the lake) that has allowed the preservation of unstable minerals. Maximum electrical conductivity was found in the Salty Polygon GMU (9333 \(\mu\)S/cm, > 10^3), and sand dunes have values between 270 and 950 \(\mu\)S/cm in sand dune 7 and sand dune 4, respectively. Also, the results of normalization of elements in all terrains are shown in Fig. 6a, b.

In the study area, most of the rare elements are As, Sr, Pb, Mo and Cl. The high presence of these elements is because of the acidic environment caused by oxidation.
of igneous and metamorphic rocks in the catchment. Also, a large amount of Cl is due to the presence of salty polygon land caused by the drying of Urmia Lake (Fig. 6). The pre-statistical analysis for testing the normality and outlier cases and variables was performed by the Kolmogorov–Smirnov test and box plot diagram, respectively (Table 2). The descriptive statistics show that the maximum element is Cl (53,791) and the minimum is MnO (0.02), and the skewness index for all tracers (except, LOI, CaO, Mo and Zr) is positive.

Considering both PCA results together with the correlation matrix indicates that in the first factor Mo and Zr have no significant correlation, while in the second factor Na₂O and Cl have the lowest significant correlation (and the smallest number of significant correlations with other variables). However, in the third factor, S has the highest loading factor (0.92) and minimum number of significant correlations with other variables. Based on the Wilks’ Lambda criteria (Table 3) and stepwise DFA, the optimal tracers are Mo, Na₂O and S. Based on the applied procedure, the variance ratio of the between-group was increased rather than for within-group, which can enhance the precision of the mixing model solution. According to the mixing model, the relative contributions of each GMU are as follows: (1) salty polygon lands (A, 23.5%); (2) Salty and puffy lands (B, 44.2%); (3) clay, salty areas, puffy and flaky lands (C, 7.01%); (4) terminus of the fine sandy alluvial fan (D, 13.2%); and (5) clay, salty and abandoned lands (E, 12.1%) (Table 4).

Figure 7 depicts the relative contribution to the sand dunes of sediments from the various sources with their variability according to the GLUE and Bayesian approaches. Source B and then source A have the highest contribution to the sand dunes compared to the other sources. Sand dune samples 1 to 4 are in the southern sand dunes, 5–8 are located in the northern part of the region, but the sources and their proportions, however, remain the same for both sets of dunes.

For a closer examination of the estimated source contributions and associated uncertainties, three quintiles of source contributions (0.025%, 0.5% and 0.975% quintiles) have been estimated using the GLUE and Bayesian methods for each sediment sample (Table 5).

### Table 1 The CIA index, enrichment ratio and salinity

| GMU                               | SiO₂ | Al₂O₃ | Fe₂O₃ | CaO  | Na₂O | K₂O | CIA (%) | Salinity µS/cm |
|-----------------------------------|------|-------|-------|------|------|-----|---------|----------------|
| Sand dune1 (Stoss)                | 12.76| 1.89  | 1.32  | 41.39| 0.38 | 0.81| 4.3     | 420            |
| Sand dune2 (Lee ward)             | 13.29| 2.04  | 1.42  | 40.69| 0.41 | 0.87| 4.63    | 880            |
| Sand dune3 (Stoss)                | 13.65| 2.18  | 1.47  | 40.37| 0.42 | 0.86| 4.96    | 570            |
| Sand dune4 (Lee ward)             | 10.73| 1.55  | 1.35  | 42.65| 0.46 | 0.63| 3.42    | 950            |
| Sand dune5 (Stoss)                | 9.98 | 1.32  | 1.09  | 43.19| 0.31 | 0.47| 2.91    | 260            |
| Sand dune6 (Lee ward)             | 9.53 | 1.50  | 1.10  | 44.71| 0.54 | 0.47| 3.18    | 350            |
| Sand dune7 (Stoss)                | 9.89 | 1.45  | 1.13  | 43.46| 0.35 | 0.57| 3.16    | 270            |
| Sand dune8 (Lee ward)             | 9.20 | 1.66  | 1.29  | 42.45| 0.26 | 0.62| 3.68    | 300            |
| Salty polygon (A)                 | 0.86 | 0.7   | 1.4   | 23.18| 2.37 | 0.95| 10.1    | 9333           |
| Salty and puffy lands (B)         | 0.55 | 0.4   | 0.95  | 26.44| 2.85 | 0.63| 4.8     | 7800           |
| Clay, salty areas, puffy and flaky lands (C) | 1.84 | 1.7   | 2.55  | 11.86| 0.76 | 2.20| 31.2    | 1356           |
| Terminus of the fine sandy alluvial fan (D) | 1.19 | 0.9   | 2.21  | 13.41| 0.32 | 1.19| 18.0    | 397            |
| Clay, salty and abandoned lands (E) | 0.93 | 1.03  | 2.06  | 22.64| 1.28 | 1.29| 18.9    | 2503           |
Fig. 6 The normalization of elements in the sand dunes (a, b) and source sediment (c)
The accuracy of the mixing model solution is presented in Table 6. The GOF value for all of sediment samples is about 85. The mean of the GOF index for Bayesian and GLUE analyses is 84.5 and 85.6, respectively. It can be concluded that solving of the mixing model using both methods is similar and low variation is found within the same method.
Therefore, it would be difficult to determine the best model and sediment samples though the GOF results. This finding can be related to Fig. 7 where the calculated contribution for each sediment sample is almost the same.

4 Discussion

The measured data and the Basler method have shown that the maximum salinity is in the Salty polygon and salty and puffy terrains and the maximum salinity in the sand dunes is in the leeward samples. These source terrains have played a major role in the salinization of the sand dunes showing that the strongly saline (> $10^3$ mS/cm) terrain is an important source for the highly saline dunes (> $10^2$ mS/cm). Also, research in the Qarhan Desert, China, showed that cohesion of saline sand when water was present increased the threshold shear velocity (Li et al. 2019). Drying of Urmia Lake over the past decade has created new, salty terrains on the exposed bed allowing fine particles of salt to be carried by the wind, causing the sand dunes to become salty. Also, one study based on remote sensing found new dust sources for the period 2000–2017 in Urmia Lake (Boroughani et al. 2020). Through multitemporal image processing they tracked the effects of both dam construction and frequent droughts on the increasing of the newly exposed dry littoral area of the Lake and concluded that newly generated dust can affect a large area surrounding the lake (> 100 km).

The results of normalizing the elements showed that the high concentrations of As, Sr, Pb, Mo elements are a result of an acidic environment resulting from the oxidation of igneous rocks (Boroughani et al. 2020), dolomite, calcite, aragonite and gypsum, and the high level of Cl is due to salinity (Table 2). The high levels of Co and Ni in potential sources is a result of being in a zone of volcanic rocks and close to industrial centers and residential areas. Also, the high presence of iron in the terminus of the fine sandy alluvial fan terrain is likely linked to agricultural activity and the use of pesticides (Boroughani et al. 2020).

In general, CIA values ranging from 80 to 100 imply that limited chemical weathering has occurred under the hot and humid conditions (Ding et al. 2016), but the maximum value of 31.2% is in the Clay, salty areas, puffy and flaky lands, mainly due to the presence of large amounts of clay, and puffy lands has a minimum value of 4.8% due to its high salt content. Furthermore, CIA values decreased from the west to the east of the study area, which indicates that the western sediments are more sensitive to weathering than the eastern sediments.
Fig. 7 Relative contribution to the supply of sand to the dunes from the different sources: GLUE approach (Blue) and Bayesian approach (be pale brown)
The enrichment ratio of CaO (10–30%) is explained by a high level of calcite in all samples. Also, relationships between Fe$_2$O$_3$ and Al$_2$O$_3$ and between Al$_2$O$_3$ and SiO$_2$ have been used to separate granite-derived soils from basalt-derived soils (Dyer et al. 1999) and generally coexist in soils (Taylor McLennan 1985). The high concentration of these elements in the potential sources indicates a dominant contribution from weathering of acidic igneous and metamorphic rocks but the amount of these elements is low in all samples. This apparent contradiction may be a result of elements in the source sediments, which low-energy prevailing winds (DP = 63, UDI = 0.52) could not transport.

The maximum Na$_2$O concentration is in the Salty and puffy lands (2.85%) and is mainly due to the high evaporation of surface water and the presence of abundant salt. The maximum K$_2$O in the clay, salty areas, puffy and flaky lands (2.20%) is mostly due to the high content of salt and clay. Also, in all terrains the maximum amount of Fe$_2$O$_3$, Al$_2$O$_3$ and SiO$_2$ is associated with granite and gabbro. Boroughani et al. (2020) also noted that the presence of metamorphic and igneous rocks in the western upland catchments of the Lake has increase the content of Al, Fe and SiO$_2$ in the dunes.

In general, the presence of Al, Fe and SiO$_2$ may be attributed to the existence of igneous and metamorphic rocks in the catchment and their mineralization, a conclusion supported
Table 5  The uncertainties of sediment source terrains using the Bayesian and GLUE approaches

| Sand dunes | Uncertainty estimation (average %) | Bayesian model | GLUE model |
|------------|-----------------------------------|----------------|-------------|
|            |                                   | Sources        | Sources     |
|            |                                   | A   B   C   D   E | A   B   C   D   E |
| SD1        | 0.025                             | 0.79 3.78 0.19 0.40 0.36 | 1.86 29.95 0.07 0.46 0.40 |
|            | 0.5                               | 19.68 43.62 5.07 10.28 9.39 | 29.77 46.08 2.65 9.75 8.03 |
|            | 0.975                             | 69.01 80.18 23.73 45.16 41.93 | 53.92 71.78 10.59 29.91 26.64 |
|            | 95% credible interval              | 68.22 76.40 23.54 44.76 41.57 | 52.07 41.83 10.52 29.45 26.25 |
| SD2        | 0.025                             | 0.79 3.55 0.20 0.41 0.37 | 2.80 28.42 0.09 0.46 0.29 |
|            | 0.5                               | 19.73 42.36 5.24 10.73 9.72 | 30.04 44.71 2.81 10.25 8.22 |
|            | 0.975                             | 68.88 79.46 24.23 45.69 43.15 | 53.49 68.95 11.29 32.59 28.04 |
|            | 95% credible interval              | 68.09 75.91 24.03 45.27 42.77 | 50.69 40.53 11.20 32.14 27.75 |
| SD3        | 0.025                             | 0.80 3.36 0.20 0.43 0.39 | 2.89 25.40 0.15 0.56 0.47 |
|            | 0.5                               | 20.15 41.71 5.37 10.78 9.76 | 29.57 41.39 3.16 11.85 9.19 |
|            | 0.975                             | 69.03 78.90 24.65 46.13 43.38 | 53.42 66.15 13.09 34.58 30.31 |
|            | 95% credible interval              | 68.23 75.54 24.45 45.70 42.99 | 50.53 40.75 12.95 34.02 29.85 |
| SD4        | 0.025                             | 0.76 4.23 0.18 0.37 0.33 | 2.08 27.31 0.10 0.47 0.26 |
|            | 0.5                               | 19.24 46.09 4.73 9.66 8.84 | 29.91 44.13 3.06 9.76 8.33 |
|            | 0.975                             | 68.93 81.63 22.59 43.05 40.44 | 56.04 68.60 11.89 31.55 26.76 |
|            | 95% credible interval              | 68.17 77.40 22.41 42.68 40.11 | 53.96 41.29 11.78 31.08 26.50 |
| SD5        | 0.025                             | 0.72 4.70 0.17 0.35 0.33 | 1.33 30.51 0.05 0.40 0.24 |
|            | 0.5                               | 18.87 47.45 4.57 9.42 8.85 | 30.05 47.19 2.63 8.96 7.27 |
|            | 0.975                             | 68.52 82.32 21.93 42.58 39.79 | 54.64 70.99 10.50 28.00 25.09 |
|            | 95% credible interval              | 67.80 77.62 21.76 42.23 39.46 | 53.31 40.48 10.45 27.60 24.86 |
| SD6        | 0.025                             | 0.74 4.37 0.18 0.38 0.35 | 1.84 31.05 0.14 0.46 0.35 |
|            | 0.5                               | 18.86 46.52 4.73 9.68 8.86 | 29.46 47.47 2.88 8.71 7.30 |
|            | 0.975                             | 68.65 81.89 22.57 43.08 40.48 | 53.37 72.33 10.75 29.46 26.81 |
|            | 95% credible interval              | 67.91 77.52 22.39 42.70 40.14 | 51.54 41.27 10.61 29.00 26.46 |
Table 5  (continued)

| Sand dunes | Uncertainty estimation (average %) | Bayesian model | GLUE model |
|------------|-----------------------------------|----------------|------------|
|            | Sources                           | A   | B   | C   | D   | E   | A   | B   | C   | D   | E   |
| SD7        | 0.025                             | 0.73 | 4.45 | 0.17 | 0.38 | 0.33 | 2.08 | 30.81 | 0.08 | 0.36 | 0.24 |
|            | 0.5                               | 18.89 | 46.53 | 4.66 | 9.73 | 8.84 | 31.54 | 46.82 | 2.81 | 8.75 | 7.12 |
|            | 0.975                             | 68.43 | 81.94 | 22.36 | 43.38 | 40.53 | 53.97 | 70.82 | 11.02 | 29.23 | 25.02 |
|            | 95% credible interval             | 67.71 | 77.49 | 22.18 | 43.01 | 40.20 | 51.88 | 40.01 | 10.93 | 28.87 | 24.78 |
| SD8        | 0.025                             | 0.63 | 3.27 | 0.16 | 0.33 | 0.29 | 3.48 | 26.08 | 0.15 | 0.54 | 0.35 |
|            | 0.5                               | 17.33 | 49.02 | 4.43 | 8.67 | 7.94 | 31.11 | 42.69 | 2.99 | 10.39 | 8.93 |
|            | 0.975                             | 66.75 | 86.50 | 27.74 | 45.16 | 42.81 | 55.28 | 66.22 | 12.53 | 33.44 | 27.79 |
|            | 95% credible interval             | 66.12 | 83.23 | 27.58 | 44.83 | 42.52 | 51.80 | 40.14 | 12.38 | 32.90 | 27.44 |
by the positive skewness index. The high content of these elements is due to the presence of naturally occurring pyroxene, amphibolite, mica, in the rocks (granite and magnetite). Therefore, these natural elements do not threaten human health. Intense human, agricultural, and industrial activities have taken place in the area in the past few decades, leading to pollution by pesticides and other chemicals. These pollutants can be dangerous to humans and cause health problems and may be needed to be investigated more in detailed in the future research.

Based on the distance between the dunes and the GMUs, the Salty and puffy lands terrains are the closest and therefore the most important sources according to the tracers. Therefore, considering the importance of this terrain for the sand supply to the sand dunes, revegetation involving, for example, *Nitraria schoberi*, which is a salt-tolerant species, could prevent the surface detachment of soil in this area (Jafari Takhtinajad et al. 2019). This shrub and other hydro halophyte species could prevent desertification in the sand dune and source regions (Li et al. 2016, 2017; Zareian et al. 2018).

The clay, salty and abandoned lands terrain, despite being across the path of the prevailing winds and upwind of the dunes, has not played a role in the production of sediment for the sand dunes due to its long distance from the sand dunes and its stabilization by being built over.

The terminus of the fine sandy alluvial fan and clay, salty areas, puffy and flaky lands terrains are also susceptible to erosion by the prevailing wind, and windbreaks and enclosure of land have prevented fine particles from moving through these geomorphic terrains; and the same thing has happened in the salty and puffy lands terrain. Furthermore, in the terminus of the fine sandy alluvial fan terrain, biological planning, including the construction of biotic windbreaks including the planting of shrubs, has prevented the movement of sediment. Although the sand dunes were in different locations (north and south of the region), the relative contribution of sand sources are similar over the study area, so the relative contributions from the potential sources are not significantly different regionally. However as mentioned before, the relative important of each source terrain is related to its area.

The Kolmogorov–Smirnov test revealed that the geochemical data deviate from a normal distribution (Reimann and Filzmoser 2000) and therefore for statistical analysis non-parametric tests should be applied. The positive skewness of chemical results can be used to address problems of mineralization and environmental pollution due to mineral alteration processes related to litho-climatic conditions in contrast to human activities. Such processes may lead to either an increase or decrease in the concentration of elements (Reimann et al. 2005 quoted by Nazari Samani et al. 2011). Generally, in the study area industrial and

| Sample | GLUE  | Bayesian |
|--------|-------|----------|
| SD1    | 85.57 | 84.61    |
| SD2    | 85.00 | 84.09    |
| SD3    | 85.55 | 84.63    |
| SD4    | 86.01 | 85.10    |
| SD5    | 86.20 | 85.27    |
| SD6    | 85.30 | 84.35    |
| SD7    | 85.40 | 84.52    |
| SD8    | 85.34 | 84.39    |
mining activities may have produced skewness in the data, along with the presence of igneous and metamorphic rocks in the upland catchments of the lake.

Comparing the results of Bayesian and GLUE sourcing revealed that although the results are not identical, both methods produced the same relative estimates of contributions: Salty and puffy lands (B) are the main sources. According to the results of the Bayesian method, the three most important GMUs that produce sand dune sediments are, respectively, salty and puffy lands-B (44.2%), salty polygon terrain-A (23.5%) and terminus of the fine sandy alluvial fan-D (13.2%). While the GLUE results indicate salty and puffy lands-B (45.8%), Salty polygon terrain-A (30.9%) and the terminus of the fine sandy alluvial fan-D (10.8%), and the same pattern for sediment supply by GMU is observed. It is noticeable that the importance of each GMU as a source is dependent on their relative areas, and the relative importance for each GUM should be determined by dividing sediment contribution by the relative area.

The results of the models show that the maximum contribution of sediments is from the salty and puffy lands and salty polygon terrain, but the exact values of the contributions are different. Unlike previous work (e.g., Gholami et al. 2019; Gholami et al. 2019), that used a Monte Carlo method, none of the applied methods provided a full uncertainty band range (0–100). But for the salty and puffy lands source both methods (GLUE and Bayesian methods) provided a wide uncertainty band range in contrast to the other GMUs (Fig. 7b). The main reason for this result is related to the effects of both drying of the saline surface of the Lake on one hand and the effect of loose and fine-grained salty sediment terrain on the other hand, related to haloturbation processes. In other words, the structure of the laminated salt surface can be complex due to evaporative crystallization of salt and therefore their surface properties have spatio-temporal variability (Reynolds et al. 2007).

Overall, across all sources and sediment samples the GLUE method estimated a narrower CI uncertainty bound that can be attributed to the structure of the model. In the GLUE method an important CI tracer that has influenced the width of the uncertainty bound acts as a cutoff threshold that is used to identify behavioral parameter sets. This cutoff threshold is selected by the user and is inserted subjectively in the GLUE method. An example is the estimation of uncertainty from the WASMOD hydrological model by Jin et al. (2010) where a lower threshold results in a wider uncertainty bound. In the Bayesian method an uninformative distribution was used for the parameters. Incorporating prior knowledge and using an informative prior distribution can reduce estimated uncertainty. Cooper et al. (2015) found that using a narrower hyper-parameter distribution can reduce estimated uncertainty associated with source contributions. Therefore, in the Bayesian method a multivariate distribution should be used to infer the posterior and can be used to model correlation between parameters better than GLUE.

5 Conclusion

In the western part of the newly exposed floor of Lake Urmia, people are currently faced by an increasing area of sand dunes. These sand dunes have fine, loose salty and non-saline sediments. In some seasons of the year (especially in spring and summer) sand and dust are raised and moved far away from the dried lake floor, affecting the whole province. Also, the movement of dunes has created a serious threat to the economic, social, health, and environmental resources on the edge of the lake. Therefore, it is important to study the origin of the sand dunes to provide information to reduce their creation and mobility. In
this paper, a Bayesian mixing model was used to fingerprint the sediment sources of the sand dunes. The aeolian sediment source tracing method has been successfully used to determine the relative importance of regional terrains as contributors to the dunes. The findings of this study are as follows: (1) In order to determine the relative contribution of sediments to the sand dunes of Urmia Lake, the potential sources have been classified into five geomorphologic map units (GMU). (2) Storm roses and sand rose graphs for the area have revealed that the prevailing and erosive winds blow from the west–southwest and the movement of sand dunes is therefore to the east–northeast. (3) Geochemical results for all samples using XRF have been provided. (4) The CIA index has revealed that the study area is subject to very low rates of weathering because it is located in a zone of igneous rocks. (5) The enrichment ratio based on the upper the elements in the continental crust revealed that elements in the sediments are enriched, because the environment is acidic. (6) The drying of Urmia Lake in recent decades has led to the emergence of saline and salt terrains which have played the most important role in the creation and salinity of the sand dunes. (7) The main elements used as tracers of the sand dune sediment sources, selected as the optimum composite tracers, and used in mixing models are Mo, Na₂O, S and Cl. (8) The study of sediment tracing sources using a Bayesian mixing model shows that the largest contributions to the dunes are from the Salty and puffy lands (B) followed by the Salty polygon terrain (A). (9) Because of similar variation of tracer concentrations in both the salty polygon and salty and puffy lands the Bayesian model results had large uncertainties for these GMUs. This result indicates that although the use of salt content as an informative tracer can help the tracing of salty sand dunes, the use of salty ions can increase the uncertainty of the final quantitative results. (10) Moreover, the wide uncertainty bounds for the two salty sources indicate that increasing the number of tracers helps to separate geochemical characteristics of the source areas, thereby reducing the uncertainty level. According to the findings, to understand the undesirable effects of a lake drawdown in a dry land environment, more examples are needed to better control deflation from the areas left after drying of the lake floor so that similar effects on the surrounding area of Urmia Lake are not repeated.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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