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# Uncertainty Estimation in Stream Bed Sediment Fingerprinting Based on Mixing Model

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**Abstract**

Uncertainty associated with mixing models is often substantial, but has not yet been fully incorporated in models. The objective of this study is to develop and apply a Bayesian-mixing model that estimates probability distributions of source contributions to a mixture associated with multiple sources for assessing the uncertainty estimation in sediment fingerprinting in Zidasht catchment, Iran. In view of this, 31 geochemical tracers were measured in 35 different sampling sites of three sediment sources (rangelands, crop fields and stream banks) and 14 sediment samples from stream bed deposition. Based upon statistical analysis, the best 20 composition subsets of tracers (e. g. 2, 3, 4 …21) were then selected. Sediment source fingerprinting was used to explore the uncertainty in the contributions of sediment from the three sources. The results showed that the main source of uncertainty was the number of tracers included in the model and the higher number of tracer in the model the lower deviation in uncertainty. However, differences between the ranges of uncertainty values from subset 5 to subset 21 of tracers are not statistically significant. In the study area, mean of relative contributions associated with uncertainty from rangeland, crop field and stream bank sources (mean of subset 5 to 21) were 0.526, 0.059, and 0.411 respectively. These results can be useful as a scientific basis of sediment management and selecting the soil erosion control methods for decision makers of natural resources.

*Keywords:* Sediment source; Discriminat analysis; Uncertainty; Bayesian-mixing model; Zidasht catchment

## 1. Introduction

Soil erosion is a natural hazard, which threatens the world in many different aspects and is one of the today's world problems. Soil erosion is also a serious problem in degradation of natural resources of Iran such as degradation of soil and water resources, pollution of fishery habitats, recurring floods, reduction of soil fertility, sedimentation in dam reservoirs, desertification, destruction of range lands and agricultural lands, etc. When the occurrence of floods is studied in a period of 42 years (1951 to 1993) in Iran, it is shown that in addition to life and financial losses, a huge volume of fertile soil have been eroded, so that in 1951, 1961, 1981 and 1993 about 500 million tons, 750 million tons, 1.5 and 2.5 billion tons of soil have been eroded, respectively and they were transported into dam reservoirs, lakes and seas (www.wrm.ir). Therefore, there has been an increase of 440 % in soil erosion from 1951 to 1993 (Ahmadi, 1999). This trend represents a great disaster in Iran, which should be prevented

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by studying the sediment sources and using soil erosion control measures.

Source fingerprinting techniques are being increasingly used to establish the relative importance of the main sediment sources in a catchment in many different areas of the world (Brown et al., 2009; Collins and Walling, 2007; Minella et al., 2008; Walling, 2005). Fingerprinting techniques have been applied over a range of timescales spanning from the event (Kevin et al., 2008) to extended reconstructions involving sediment sinks such as floodplains (Owens et al., 1999), reservoirs and estuaries (Juracek and Ziegler, 2009). However, while the range of fingerprinting properties and application has grown, relatively limited attention has been paid to the quality of the statistical models developed (Lees, 1997) and to the methodological uncertainties approach (Collins and Walling, 2002). It is important that methods for identifying and quantifying the contributions of individual sediment sources should provide an indication of the uncertainty associated with the result obtained (Minella et al., 2008). The uncertainty assessment should therefore be incorporated into the fingerprinting approach (Martinez-Carreras, 2008), even though any uncertainty assessment will always be conditional on the possibilities considered and the assumption made (Beven, 2007).

There are a few studies that have clearly considered the resulting uncertainty estimation when using the fingerprinting approach to establish the relative contributions from a number of potential sediment sources. As a result there is little guidance available to select an appropriate approach to incorporate consideration of uncertainty. Recent sediment source studies using mixing models have undertaken uncertainty analysis due to the spatial variability of source tracer properties to determine confidence limits of model estimates based on Monte-Carlo estimation approach (Krause et al., 2003; Motha et al., 2003; 2004; Wallbrink et al., 2003; Collins and Walling, 2007; Smith and Dragovich, 2008), or Bayesian uncertainty estimation (Small et al., 2002). In Monte-Carlo approach tracer property values randomly are selected from the cumulative normal distribution for each tracer, in order to establish a range of mean values for the tracer property to characterize a particular source. This enables assessment of the effect of uncertainty in tracer means on estimates of source contributions.

Rowan et al., (2000) and Martinez-Carreras (2008) considered uncertainty associated with the numerical solutions provided by the current generation of multivariate fingerprinting mixing models based on GLUE approach (Generalized Likelihood Uncertainty Estimation) developed by Beven and Binley (1992). This approach incorporates a user-specified efficiency tolerance which can reflect measurement error and population variability uncertainties.

The main objectives of this paper are to develop a reliable and statistical-based model for assessing the uncertainty estimation in sediment fingerprinting and to identify the relative contribution to the uncertainty associated with the number and type of tracers.

## 2. Material and Methods

### *2.1. Study area*

The study area is Zidasht catchment in Taleghan River Basin, which is located in 50º 37´ 46´´ and 50º 44´ 56´´ eastern longitude and between 36º 5´ 35´´ and 36º 11´ 46´´ northern latitude, in southern Alborz Mountains, 90 kilometers Northwest of Tehran, Iran (Figure 1).

The total area of Zidasht catchment is 64.9 $km^2$. Long-term (1975-2003) mean annual precipitation of the study area is 650 mm. The drainage area has a verity of lithology materials, with outcrops of Pre-Cambrian to Quaternary Formations

### *2.2. Sampling and data collection*

Potential sediment sources were identified by observing the main land use types and soil erosion features within the study catchment and were dominated by three main groups; the rangelands, crop fields and stream banks. 35 representative samples were collected from these potential sources at different locations within the study area.

The samples of potential sediment sources were collected using a trowel, by obtaining a representative sample of the uppermost layer of the source material (0–5 cm). In order to ensure that the source material samples were representative of the potential heterogeneity of the individual sources, composite samples, made up of 5 sub-samples, were collected over an area of approximately 100 $m^2$. For eroding stream banks a composite of 5 sub-samples were collected in the vicinity of the sampling point.

Sediment samples were collected from stream deposits to provide an indication of the source contributions to sediment. Sampling of deposits occurred in the study catchment with a total of 14 samples collected from different locations (Figure 1). Each of the 14 samples consisted of approximately 7 small samples of deposited sediment collected through the stream bed; these were combined to form deposited sediment samples for analysis.

In order to remove bias associated with grain-size effects, only the < 63 µm soil and sediment fraction, obtained by dry sieving, was taken for tracer analysis (Collins et al., 1997). A 3 gr of the soil sample, after removing organic carbon by loss on ignition at 550 °C for 2 hr, was digested on water bath at 95 °C using aqua regia ($HCl–HNO_3$; 3:1) for 2 hr and $HClO_4$ for 1 hr. After digestion, all samples were filtered through S&S ME24 (0.2 µm) filter paper and made up to final 50 ml with bidistilled water, and stored in sterile polythene tubes prior to analysis. the solutions were analysed by ICP-OES (GBC Integra) for Al, B, Ba, Be, Bi, Ca, Cd, Co, Cr, Cu, Fe, Ga, K, Li, Mg, Mn, Mo, Na, Ni, P, Pb, Se, Sr, Te, Tl and Zn. Total N was determined by the Kjeldahl method (Rutherford et al., 2008) and the total organic C was measured by the Walkley-Black method (Skjemstad and Baldock, 2008). In addition, several elemental ratios (Fe/Mn, Fe/P and Pb/Ni) were calculated.

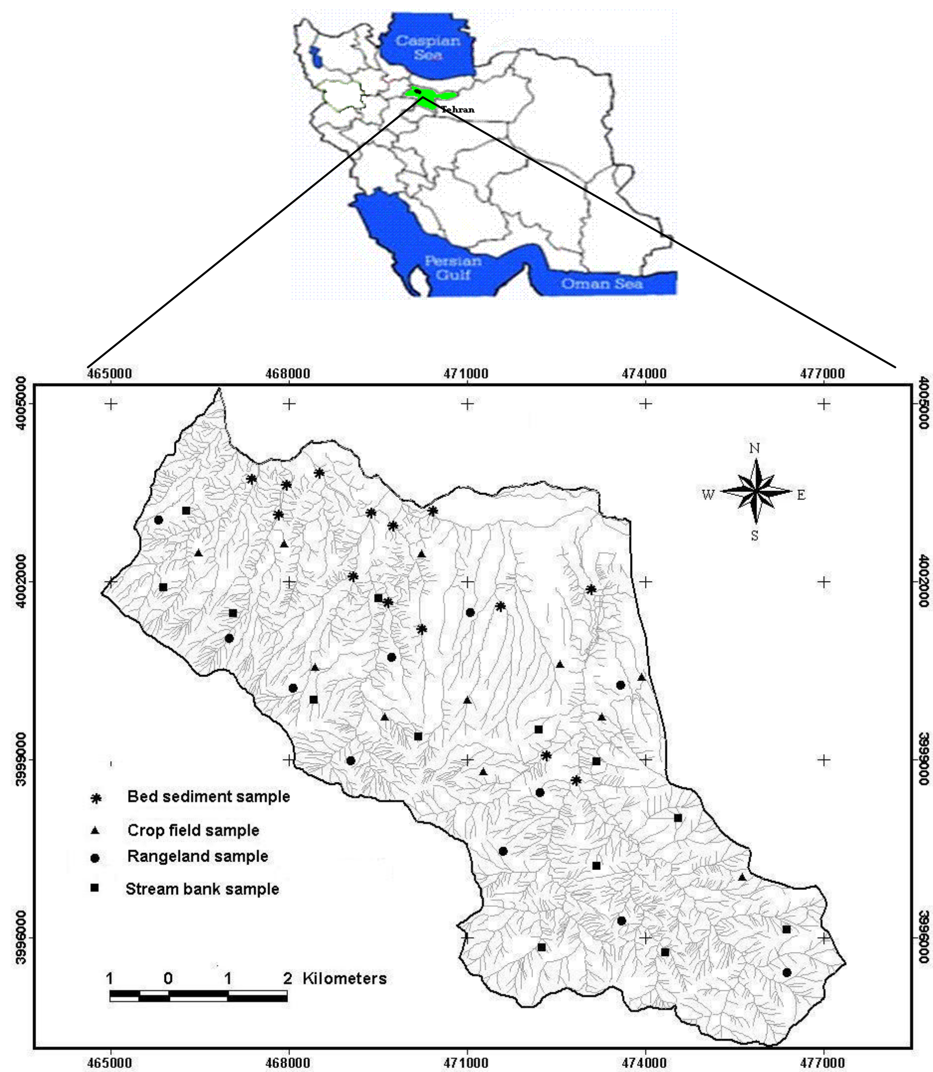


Fig. 1. Location map of the Zidasht catchment and sampling sites used in this analysis

*2.2. Source discrimination/Discriminant analysis*

A key requirement of any sediment source fingerprinting exercise is the need to use statistical tests to identify a composite fingerprint or set of source material properties that is capable of discriminating between the potential sources. In this study, a two stage procedure proposed by Collins et al. (1997) was used to identify composite fingerprints capable of discriminating the samples collected to represent individual source types. In the first stage, the Kruskall–Wallis non-parametric test is used to identify those fingerprint properties (from 31 tracers) which were able to discriminate between the three potential sources.

In the second stage, a backward stepwise multivariate discriminant function analysis is undertaken, in order to select the optimum subset composition of geochemical tracers (i.e. 2, 3 …21) to investigate the effect of the number of tracers in contribution of sediment sources to the uncertainty of the Zidasht catchment. The main use of DA is to assess the adequacy of a classification, given the group memberships of the objects under study. DA consists of finding a transform which gives the maximum ratio of difference between a pair of group multivariate means to the multivariate variance within the two groups (Davis, 1986). DA is used to classify cases into the values of a categorical dependent, usually a dichotomy. If DA is effective for a data set, the classification table of correct and incorrect estimates will indicate a high percentage of correct estimates. Discriminant coefficients maximize the distance between the means of the dependent variable. A discriminant functions table relates the number of important functions through a variety of tests such as eigenvalues, Canonical-R, Wilks' Lambda, Chi-Square and p-value. A chi-square transformation of Wilks' Lambda is used along with the degrees of freedom to determine significance. (Davis, 1986; Härdle and Simar, 2007). All statistical analyses were performed using STATISTICA V. 6.0 (StatSoft Inc., 2001).

*2.3. Treatment of uncertainty in the modeling procedure*

The uncertainty for the relative contribution of sediment sources was determined using a Bayesian-mixing model proposed by Moore and Semmens (2008); Moore et al. (2009). Bayesian statistical methods quantify uncertainty by calculating the probability distributions for the proportional contribution ($f_i$) of each source i to the mixture in three stages: 1) determination of the prior probability distribution for model parameters, 2) construction of a likelihood function for the statistical model, and 3) derivation of the posterior probability distribution for the parameters using the Bayes rule to adjust the prior distribution based on the observed data (Bolstad, 2007). The Bayes rule states that the posterior probability distribution for all $f_i$ is proportional to the prior probability distribution multiplied by the likelihood, and then dividing by their sum.

$$P(f_q|data) = \frac{L(data|f_q) \times p(f_q)}{\sum L(data|f_q) \times p(f_q)} \quad (1)$$

Where L (data|fq) is the likelihood of the data given $f_q$, p ($f_q$) represents the prior probability of the given state of nature being true based on prior information and $f_q$ is proportional source contributions of q proposed vectors.

Uncertainty in source tracer values are factored into the model by defining mean and variance parameters for each sediment source i and concentration of tracer property j. The proposed tracer distributions for the sediment mixture are determined by solving for the proposed means $\hat{\mu}_j$ and standard deviations $\hat{\sigma}_j$ of the sediment mixture based on the randomly drawn $f_i$ values comprising a vector $f_q$:

$$\hat{\mu}_j = \sum_{i=1}^{n} (f_i \times m_{j_{Source_i}}) \quad (2)$$

$$\hat{\sigma}_j = \sqrt{\sum_{i=1}^{n} (f_i^2 \times S^2_{j_{Source_i}})} \quad (3)$$

Where $m_{j_{Source_i}}$ is the mean of the jth tracer of the ith source and $S^2_{j_{Source_i}}$ the variance of the jth tracer property of the ith source. Based on the $\hat{\mu}_j$ and $\hat{\sigma}_j$, the likelihood of the data given the proposed sediment mixture is calculated as:

$$L(x|\hat{\mu}_j, \hat{\sigma}_j) = \prod_{k=1}^{n}\prod_{j=1}^{n}\left[\frac{1}{\hat{\sigma}_j \times \sqrt{2\times\pi}} \times \exp\left(-\frac{(X_{kj}-\hat{\mu}_j)^2}{2\times\hat{\sigma}_j^{\,2}}\right)\right] \quad (4)$$

Where $X_{kj}$ represents the jth tracer property of the kth sediment sample. The likelihood of $f_q$ given prior information (user-specified α and β for each source) is calculated according to a beta distribution:

$$L(f_q|\alpha_i, \beta_i) = \prod_{i=1}^{n} \frac{f_i^{\alpha_i - 1} \times (1-f_i)^{\beta_i - 1}}{B(\alpha_i, \beta_i)} \quad (5)$$

The model is based on the following constraints: $0 \le f_i \le 1$; the percentage source contributions must lie between 0 and 1; and $\sum_{i=1}^{n} f_i = 1$ ; the percentage source contributions must sum to 1.

## 3. Results and Discussion

### *3.1. Source discrimination*

The results of the two stage statistical analysis provided clear verification that it was possible to use a subset of different fingerprints to discriminate the three potential sediment sources in the study catchment. Individual tracers were tested for their ability to discriminate the potential sediment sources using the Kruskal-Wallis test. Table 1 presents the results of applying the Kruskall–Wallis test to the sediment source samples and indicated that 21 properties showed a statistically significant difference between the sources. Tracers unable to discriminate the sources were discarded (i. e. Ca, Cr, Cu, Ga, Na, Ni, Se, Fe/Mn, Fe/P and Pb/Ni).

Table 1. The result of the Kruskall-Wallis H test for the sediment source discrimination in Zidasht catchment

| Tracer | Chi-Square | p-value |
|---|---|---|
| Al | 21.1 | 0.000 |
| B | 20.6 | 0.000 |
| Ba | 20.0 | 0.000 |
| Be | 21.4 | 0.000 |
| Bi | 14.5 | 0.002 |
| C | 21.9 | 0.000 |
| Ca | 6.8 | 0.077 |
| Cd | 30.0 | 0.000 |
| Co | 20.3 | 0.000 |
| Cr | 7.2 | 0.067 |
| Cu | 5.4 | 0.142 |
| Fe | 26.2 | 0.000 |
| Ga | 3.8 | 0.281 |
| K | 21.9 | 0.000 |
| Li | 21.5 | 0.000 |
| Mg | 22.3 | 0.000 |
| Mn | 22.9 | 0.000 |
| Mo | 34.9 | 0.000 |
| N | 23.1 | 0.000 |
| Na | 2.3 | 0.515 |
| Ni | 1.3 | 0.728 |
| P | 23.2 | 0.000 |
| Pb | 33.1 | 0.000 |
| Se | 7.7 | 0.052 |
| Sr | 23.2 | 0.000 |
| Te | 13.1 | 0.004 |
| Tl | 32.7 | 0.000 |
| Zn | 27.6 | 0.000 |
| Fe/Mn | 2.8 | 0.431 |
| Fe/P | 2.1 | 0.545 |
| Pb/Ni | 3.3 | 0.343 |

* Statistically significant (p-value=0.05)

The 21 tracers remaining were retained to estimate the uncertainty of the contribution of the potential sediment sources to the sediment samples from the study catchment. Previous studies have used stepwise DA to select a set of tracers that provides the best discrimination between the potential sediment sources (Collins et al., 1997; Minella et al., 2008), Whereas we used DA to select the best 20 composition subset of different tracers (i. e. 2, 3, 4 ….21) as input of the uncertainty model.

In order to select the optimum composition subset of the tracers for maximising discrimination 21 tracers resulting from first stage were entered into DA. Classification matrices obtained from the DA are shown in Table 2.

There are some tests to determine whether discriminant functions (roots) are statistically significant. Chi-Square tests with successive roots removed for DA of sediment source tracers are shown in Table 3. The largest eigenvalue corresponds to the eigenvector in the direction of the maximum spread of the groups' means. The canonical correlation measures the association between the discriminant scores and the groups. Values close to 1 indicate a strong correlation between the discriminant scores and the groups. Wilks' Lambda is the proportion of the total variance in the discriminant scores not explained by differences among the groups. Wilks' Lambda ranges between 0 and 1. Values close to 0 indicate the group means are different. A chi-square transformation of Wilks' Lambda is used along with the degrees of freedom to determine significance. If the significance value is small (less than 0.10) group means differ (Table 3). Therefore the best 21 composition subset of different tracers resulted from DA are significant.

*3.2. Uncertainty in source apportionment*

The significance of the number of tracers in the mixing model to the uncertainty was assessed by solving the model with different of the best subset of tracers from 2 to 21. The model run of $10^6$ iterations and the maximum importance ratio was below 0.001. The model was run for mixture of sediment samples and the uncertainty ranges associated with the mean source contributions are shown in Figure 2. The results show that the uncertainty ranges for rangeland and crop field sources decrease when the number of tracers in the model is increased, whereas for stream bank source from the second subset of tracer the graph follows constant values. The study conducted by Martinez-Carreras et al. (2008) also supports the idea that the main source of uncertainty was the number of tracers included in the model. In addition for all three sources from fifth best subset of tracers provided similar uncertainty ranges (Figure 2).

Furthermore, the relative contribution of each source dose not affect on uncertainty ranges (Table 4). However the most certain source attribution are not expected to be obtained when contributions of the individual potential sources are similar, but rather when the sediment sample tracers values are close to one source values that source dominates. In addition source contribution also depends on the tracer property values for sediment samples, since the location of the tracer values would hamper the output uncertainty (Martinez-Carreras et al., 2008).

The 90% confidence limits of total source contributions of different subset of tracers for three sediment sources have been shown in Figure 3. The result showed that the more increase in the best subset of tracers, the more decrease in confidence limits of uncertainty. If the mean source contribution is equated with the median 50th percentile result obtained from the subset of tracers, it would be possible to indicate that the mean of subset 5 to 21 of tracers ranged between rangeland contributed 0.526, stream bank 0.411 and crop field 0.059 to the sediment samples (Table 4).

Table 2. Classification matrix resulting from discriminant analysis applied to the best subset of tracers

| Subset of tracers | Rangelands | Crop fields | Stream banks | Total |
|---|---|---|---|---|
| 2 | 100.0 | 55.6 | 100.0 | 90.5 |
| 3 | 100.0 | 55.6 | 100.0 | 90.5 |
| 4 | 100.0 | 66.7 | 100.0 | 92.9 |
| 5 | 100.0 | 66.7 | 100.0 | 92.9 |
| 6 | 100.0 | 66.7 | 100.0 | 92.9 |
| 7 | 100.0 | 66.7 | 100.0 | 92.9 |
| 8 | 100.0 | 77.8 | 100.0 | 95.2 |
| 9 | 100.0 | 77.8 | 100.0 | 95.2 |
| 10 | 100.0 | 88.9 | 100.0 | 97.6 |
| 11 | 100.0 | 88.9 | 100.0 | 97.6 |
| 12 | 100.0 | 88.9 | 100.0 | 97.6 |
| 13 | 100.0 | 88.9 | 100.0 | 97.6 |
| 14 | 100.0 | 88.9 | 100.0 | 97.6 |
| 15 | 100.0 | 88.9 | 100.0 | 97.6 |
| 16 | 100.0 | 88.9 | 100.0 | 97.6 |
| 17 | 100.0 | 88.9 | 100.0 | 97.6 |
| 18 | 100.0 | 88.9 | 100.0 | 97.6 |
| 19 | 100.0 | 88.9 | 100.0 | 97.6 |
| 20 | 100.0 | 88.9 | 100.0 | 97.6 |
| 21 | 100.0 | 88.9 | 100.0 | 97.6 |

Table 3. Chi-Square tests with successive roots removed for discriminant analysis applied to the best subset of tracers

| Subset of tracers | Root | Eigenvalue | Canonical-R | Wilks' Lambda | Chi-Square | df | P-value |
|---|---|---|---|---|---|---|---|
| 2 | 0 | 2.70 | 0.85 | 0.19 | 64.59 | 4.0 | 0.0000 |
| | 1 | 0.45 | 0.56 | 0.69 | 14.23 | 1.0 | 0.0002 |
| 3 | 0 | 3.40 | 0.88 | 0.15 | 71.99 | 6.0 | 0.0000 |
| | 1 | 0.51 | 0.58 | 0.66 | 15.69 | 2.0 | 0.0004 |
| 4 | 0 | 5.99 | 0.93 | 0.09 | 89.18 | 8.0 | 0.0000 |
| | 1 | 0.54 | 0.59 | 0.65 | 16.28 | 3.0 | 0.0010 |
| 5 | 0 | 7.01 | 0.94 | 0.07 | 97.60 | 10.0 | 0.0000 |
| | 1 | 0.75 | 0.65 | 0.57 | 20.61 | 4.0 | 0.0004 |
| 6 | 0 | 7.98 | 0.94 | 0.06 | 103.51 | 12.0 | 0.0000 |
| | 1 | 0.90 | 0.69 | 0.53 | 23.40 | 5.0 | 0.0003 |
| 7 | 0 | 8.58 | 0.95 | 0.05 | 106.10 | 14.0 | 0.0000 |
| | 1 | 0.99 | 0.71 | 0.50 | 24.75 | 6.0 | 0.0004 |
| 8 | 0 | 9.41 | 0.95 | 0.05 | 108.11 | 16.0 | 0.0000 |
| | 1 | 1.02 | 0.71 | 0.50 | 24.94 | 7.0 | 0.0008 |
| 9 | 0 | 10.43 | 0.96 | 0.04 | 110.42 | 18.0 | 0.0000 |
| | 1 | 1.05 | 0.72 | 0.49 | 25.16 | 8.0 | 0.0015 |
| 10 | 0 | 10.45 | 0.96 | 0.04 | 112.51 | 20.0 | 0.0000 |
| | 1 | 1.28 | 0.75 | 0.44 | 28.39 | 9.0 | 0.0008 |
| 11 | 0 | 11.48 | 0.96 | 0.04 | 113.84 | 22.0 | 0.0000 |
| | 1 | 1.28 | 0.75 | 0.44 | 28.01 | 10.0 | 0.0018 |
| 12 | 0 | 12.07 | 0.96 | 0.03 | 113.86 | 24.0 | 0.0000 |
| | 1 | 1.29 | 0.75 | 0.44 | 27.74 | 11.0 | 0.0035 |
| 13 | 0 | 12.73 | 0.96 | 0.03 | 114.14 | 26.0 | 0.0000 |
| | 1 | 1.32 | 0.75 | 0.43 | 27.71 | 12.0 | 0.0061 |
| 14 | 0 | 12.76 | 0.96 | 0.03 | 114.11 | 28.0 | 0.0000 |
| | 1 | 1.43 | 0.77 | 0.41 | 28.90 | 13.0 | 0.0068 |
| 15 | 0 | 13.06 | 0.96 | 0.03 | 114.00 | 30.0 | 0.0000 |
| | 1 | 1.51 | 0.78 | 0.40 | 29.42 | 14.0 | 0.0092 |
| 16 | 0 | 13.11 | 0.96 | 0.03 | 113.50 | 32.0 | 0.0000 |
| | 1 | 1.60 | 0.78 | 0.38 | 30.12 | 15.0 | 0.0115 |
| 17 | 0 | 13.15 | 0.96 | 0.03 | 112.14 | 34.0 | 0.0000 |
| | 1 | 1.63 | 0.79 | 0.38 | 30.01 | 16.0 | 0.0180 |
| 18 | 0 | 13.25 | 0.96 | 0.03 | 110.60 | 36.0 | 0.0000 |
| | 1 | 1.64 | 0.79 | 0.38 | 29.58 | 17.0 | 0.0295 |
| 19 | 0 | 13.35 | 0.96 | 0.03 | 113.60 | 38.0 | 0.0000 |
| | 1 | 1.65 | 0.79 | 0.38 | 31.58 | 18.0 | 0.0095 |
| 20 | 0 | 13.55 | 0.96 | 0.03 | 110.78 | 38.0 | 0.0000 |
| | 1 | 1.73 | 0.80 | 0.38 | 29.60 | 18.0 | 0.0055 |
| 21 | 0 | 13.72 | 0.96 | 0.03 | 110.28 | 39.0 | 0.0000 |
| | 1 | 1.85 | 0.83 | 0.38 | 29.48 | 19.0 | 0.0045 |

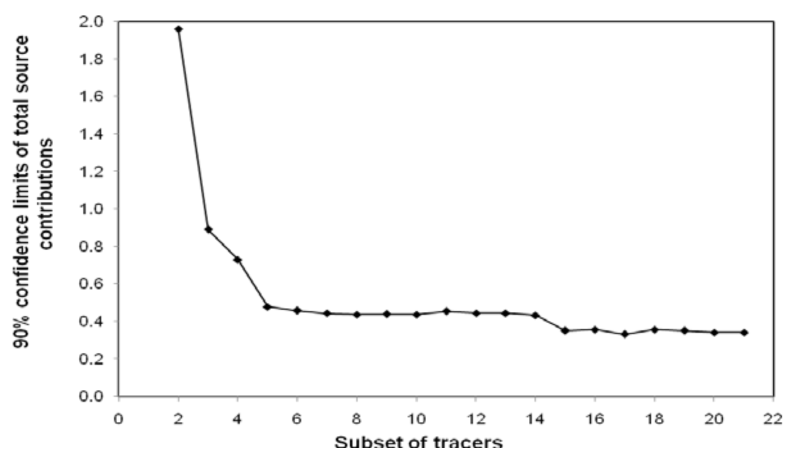


Fig. 2. 90% confidence limits of total source contributions of different subset of tracers in Zidasht catchment

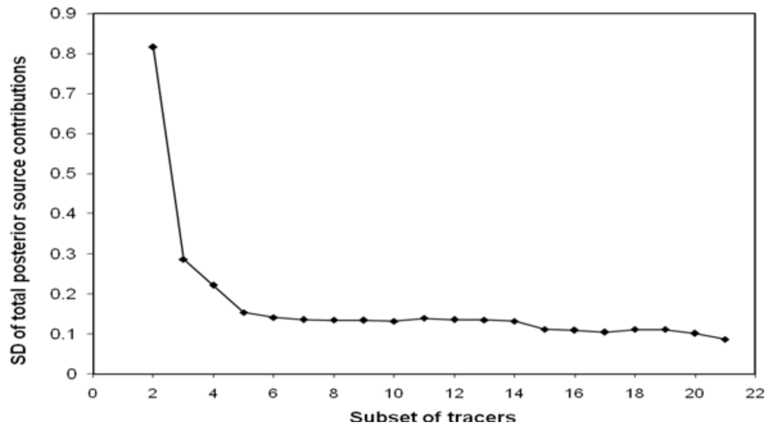


Fig. 3. SD of total posterior source contributions of different subset of tracers in Zidasht catchment

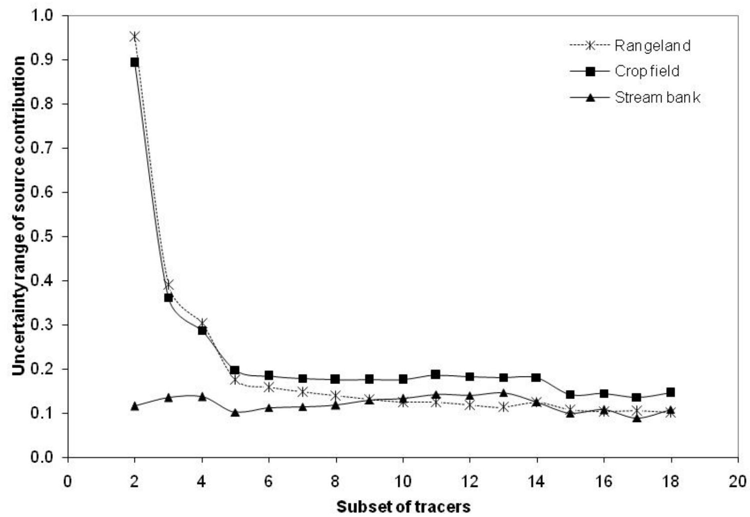


Fig. 4. Source contribution uncertainty ranges associated with the best subset of tracers in Zidasht catchment.

Smith and Dragovich (2008) have reported a 25% surface and 75% subsurface contribution of in-channel deposits using the mixing model that has used Monte Carlo approach with a 15.1 uncertainty 95% confidence limits. Collins and Walling (2007) used a composite fingerprinting technique, incorporating uncertainty analysis in Dorset, UK, and reported the mean relative contributions from areas of woodland, pasture and cultivation, and from channel banks sources ranged between 1±1%–6±2%, 10±2%–42± 2%, 44±4%–81±2% and 7±2%–19±4%, respectively. Such large uncertainty limitation levels have obvious inferences for the usefulness of the fingerprinting scheme, particularly where these data may be important for catchment management purposes (Rowan et al., 2000).

In order to investigate the uncertainty variation of the subset number of tracers the SD of total posterior source contributions was determined (Figure 4). The results demonstrate that the uncertainty ranges decrease when the numbers of the best subset increase to 5 and after this subset the line continue in constant values.

Plots of the proportional contribution of sources and relative likelihood histogram associated to 3, 8, 13 and 18 subset tracers have shown in Figure 5. The results demonstrate that when the number of tracer increases the uncertainty ranges decreases. Wallbrink et al. (2003) optimized the contributions using taking into account their relative uncertainties that the result showed that subsoil erosion dominates (70 ± 13%) compared to surface erosion (30 ± 13%) at the catchment outlet. In addition, Krause et al. (2003) incorporates a Bayesian Monte Carlo modeling framework approach to sediment source ascription interpreted the complex sediment fingerprint of the pasture and gully wall sources. Motha et al. (2004) presented same results in the relative contributions associated to the uncertainties in source and sediment tracer properties using a Monte-Carlo approach. They reported that relative contributions from gravel-surfaced roads, grouped lands (un-graveled roads, pasturelands and cultivated lands on basalt-derived soils), cultivated lands on granite-derived soils, and forest to sediments in the falling limbs of event hydrographs were 0.41±0.17, 0.18±0.13, 0.13±0.11 and 0.14±0.07, respectively (Figure 5).

## 4. Conclusion

In this case study, different multivariate statistical techniques and Bayesian-mixing model were used to evaluate spatial variations of the uncertainty estimation in sediment fingerprinting in Zidasht catchment. The model incorporates tracer uncertainty to characterize the posterior probability distributions of source contributions and produces source contribution estimates with explicit probability distributions. The Kruskall–Wallis non-parametric test was used for 31 tracers in 35 sediment sources to identify those fingerprint properties which were able to discriminate between the three potential sources namely rangeland, crop field and stream banks, that indicated 21 properties showed a statistically significant difference between the sources. The stepwise multivariate DA aided in extraction and identification of optimum subset composition of geochemical tracers (i.e. 2, 3 …21) is undertaken. The uncertainty for the relative contribution of sediment sources was determined using a Bayesian-mixing model. The results obtained indicate that, for the study area the main sources of uncertainty were associated with the number of individual source.

This study illustrates the usefulness of multivariate statistical techniques for analysis and interpretation of complex data sets in sediment fingerprinting assessment, and the spatial variability of relative contributions associated with uncertainty for effective land management. Therefore, it can be concluded that this model can be used as sediment fingerprinting associated with uncertainty in Zidasht catchment and these methods can be tested in other regions. Consequently, the improvement of the exiting uncertainty model by considering the grain size and organic matter corrections should contribute to better assessment of sediment fingerprinting as well in reducing sediment mobilization and transfer using effective land management and soil erosion control methods.

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Table 4. Model estimates of the contribution sediment sources associated with the best subset of tracers in Zidasht catchment

| | Sediment sources | | |
|---|---|---|---|
| Subset of tracers | Rangeland | Crop field | Stream bank |
| 2 | 0.90 (0.04-0.99) | 0.04 (0.00-0.12) | 0.04 (0.00-0.89) |
| 3 | 0.26 (0.07-0.47) | 0.06 (0.01-0.14) | 0.67 (0.48-0.85) |
| 4 | 0.29 (0.14-0.44) | 0.07 (0.01-0.15) | 0.63 (0.49-0.78) |
| 5 | 0.50 (0.41-0.59) | 0.04 (0.00-0.11) | 0.46 (0.35-0.55) |
| 6 | 0.47 (0.40-0.56) | 0.05 (0.01-0.12) | 0.47 (0.37-0.56) |
| 7 | 0.47 (0.40-0.55) | 0.05 (0.01-0.12) | 0.47 (0.38-0.56) |
| 8 | 0.47 (0.40-0.54) | 0.06 (0.01-0.13) | 0.47 (0.38-0.56) |
| 9 | 0.46 (0.39-0.52) | 0.08 (0.02-0.15) | 0.47 (0.38-0.55) |
| 10 | 0.42 (0.36-0.48) | 0.09 (0.02-0.16) | 0.49 (0.40-0.58) |
| 11 | 0.41 (0.35-0.48) | 0.08 (0.01-0.16) | 0.51 (0.41-0.60) |
| 12 | 0.42 (0.36-0.48) | 0.08 (0.02-0.16) | 0.50 (0.41-0.59) |
| 13 | 0.42 (0.37-0.48) | 0.11 (0.04-0.18) | 0.47 (0.38-0.56) |
| 14 | 0.43 (0.37-0.50) | 0.07 (0.01-0.14) | 0.49 (0.40-0.58) |
| 15 | 0.58 (0.53-0.64) | 0.04 (0.00-0.10) | 0.38 (0.30-0.44) |
| 16 | 0.58 (0.53-0.63) | 0.05 (0.01-0.11) | 0.37 (0.30-0.44) |
| 17 | 0.60 (0.55-0.65) | 0.03 (0.00-0.09) | 0.36 (0.29-0.43) |
| 18 | 0.60 (0.55-0.65) | 0.05 (0.01-0.11) | 0.35 (0.27-0.42) |
| 19 | 0.75(0.72-0.85) | 0.04 (0.00-0.10) | 0.21 (0.17-0.23) |
| 20 | 0.75(0.69-0.79) | 0.05 (0.01-0.10) | 0.20 (0.17-0.22) |
| 21 | 0.75(0.68-0.79) | 0.05 (0.01-0.09) | 0.21 (0.17-0.22) |

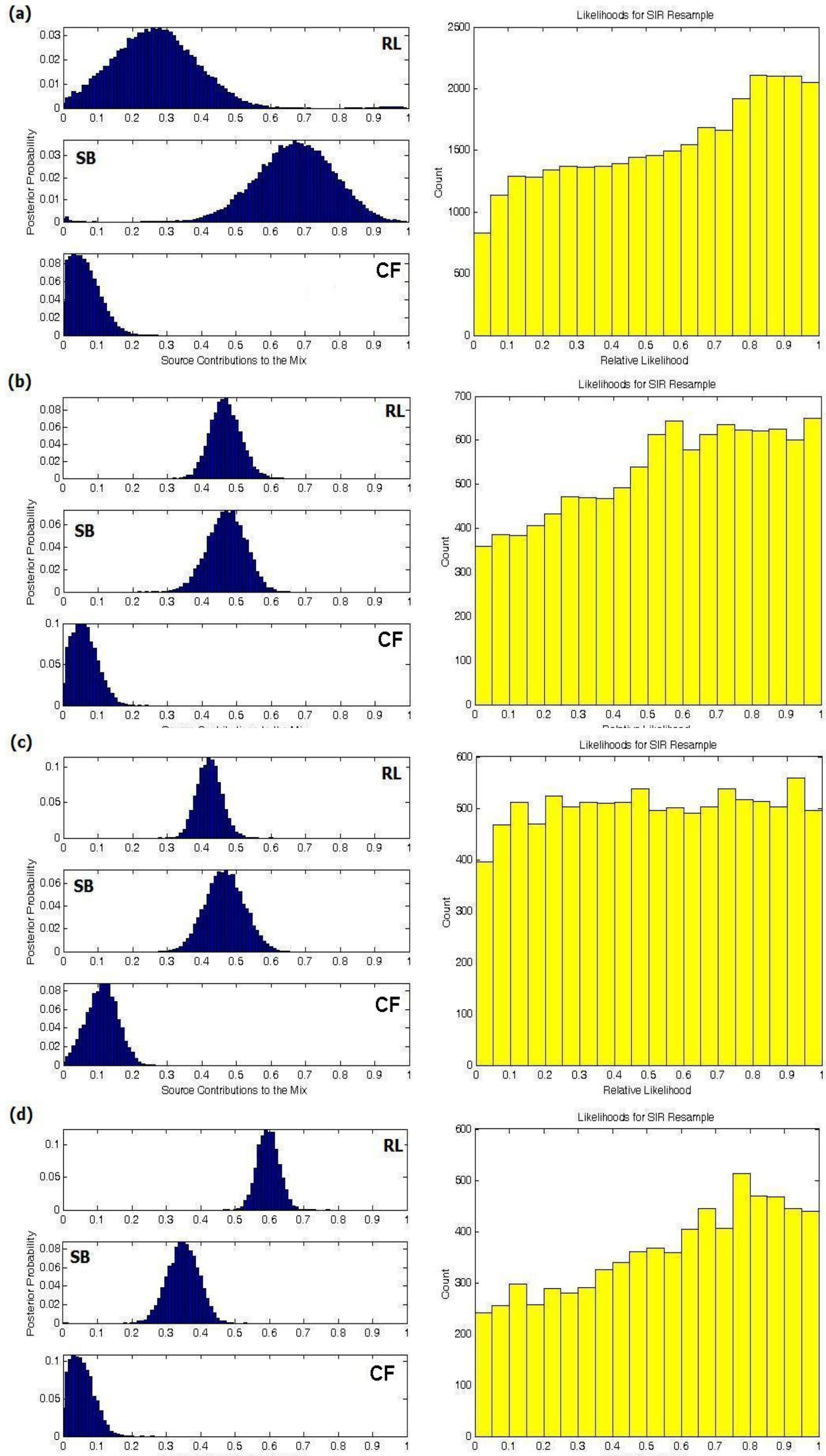


Fig. 5. Estimation of source contributions using model in Zidasht catchment with associated relative likelihood histogram. (a), (b), (c) and (d): 3, 8, 13 and 18 subset of tracers, respectively; RL: rangeland; CF: crop field; SB: stream bank

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