How much dust? And which dust?

From grain-size data (and bulk density) to aeolian mass fractions

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A (more or less) typical loess section

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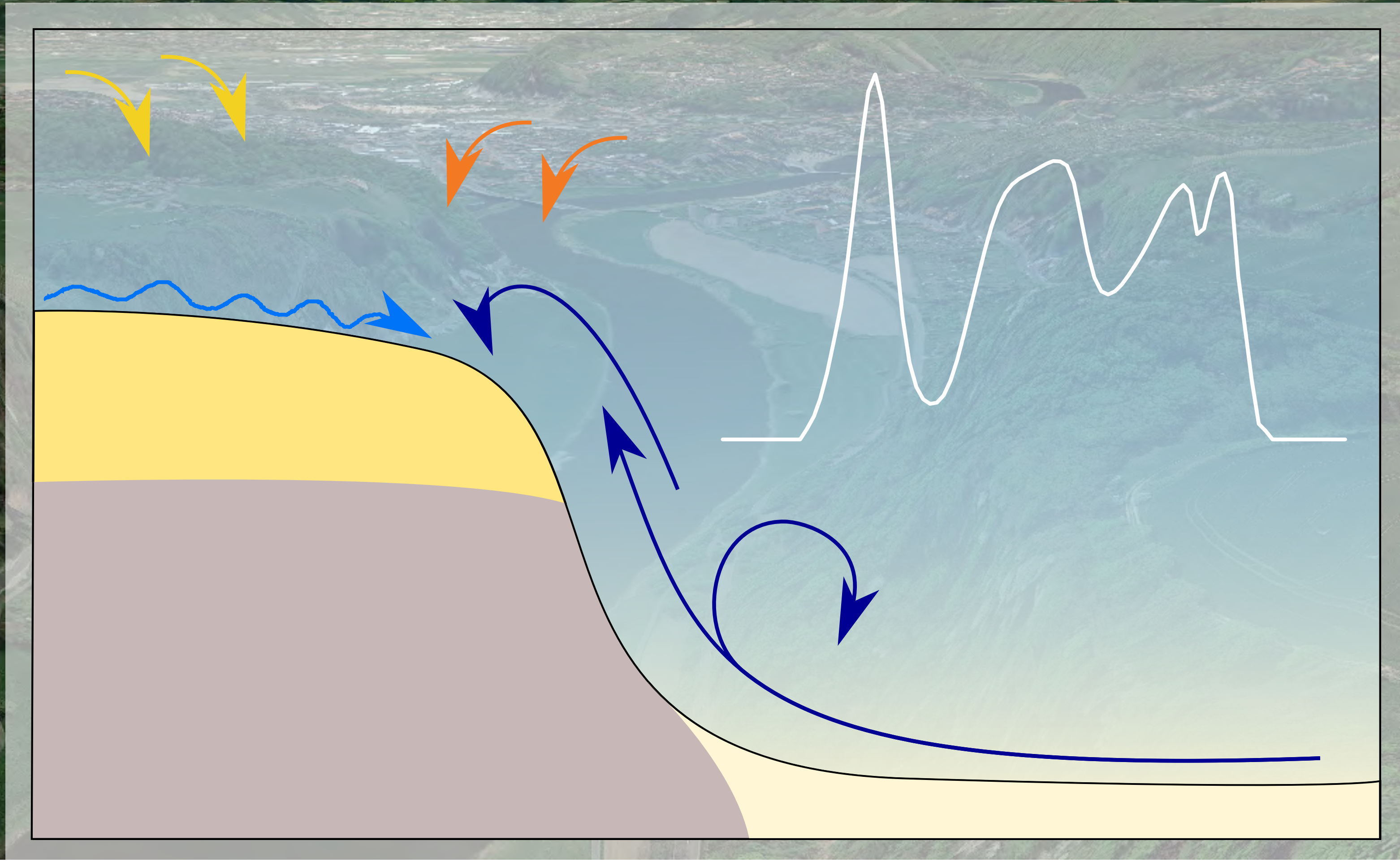
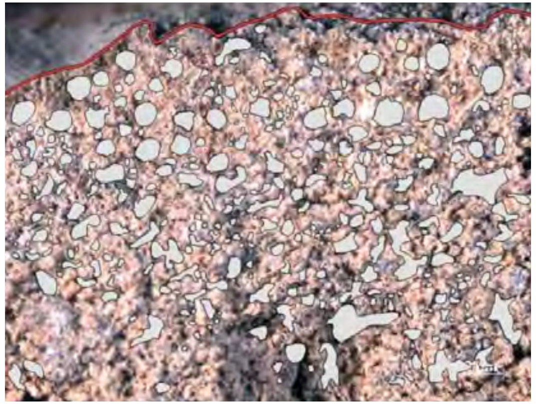
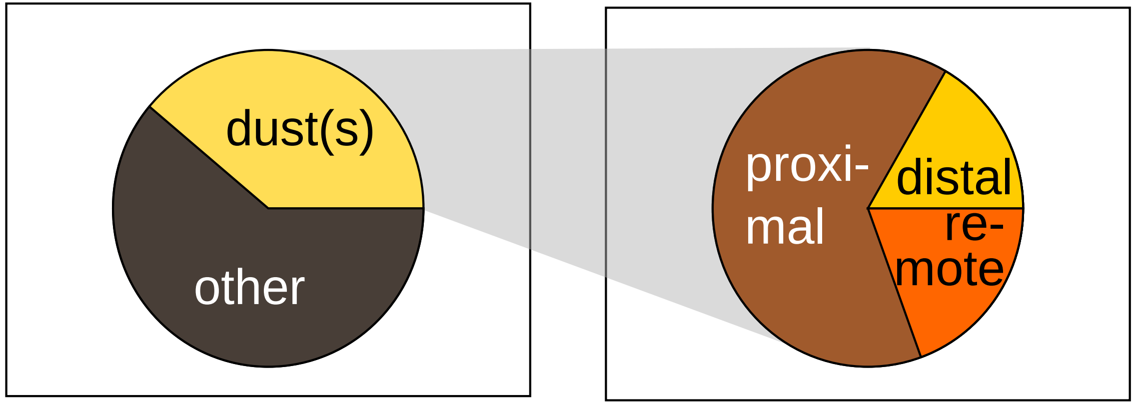


A more conceptual formulation of the problem





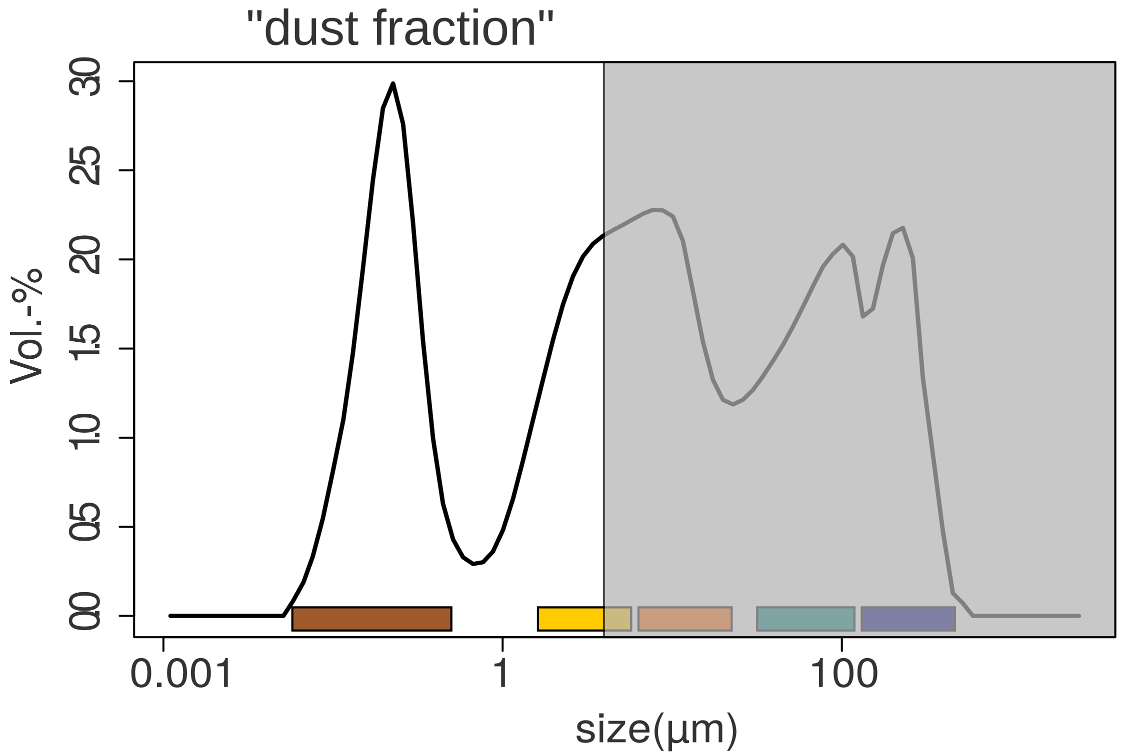
1. How much solid is there?

2. How much of it is "dust"?

3. Which types/sources are there?

4. What are its average densities?

A conceptual estimate of potential consequences



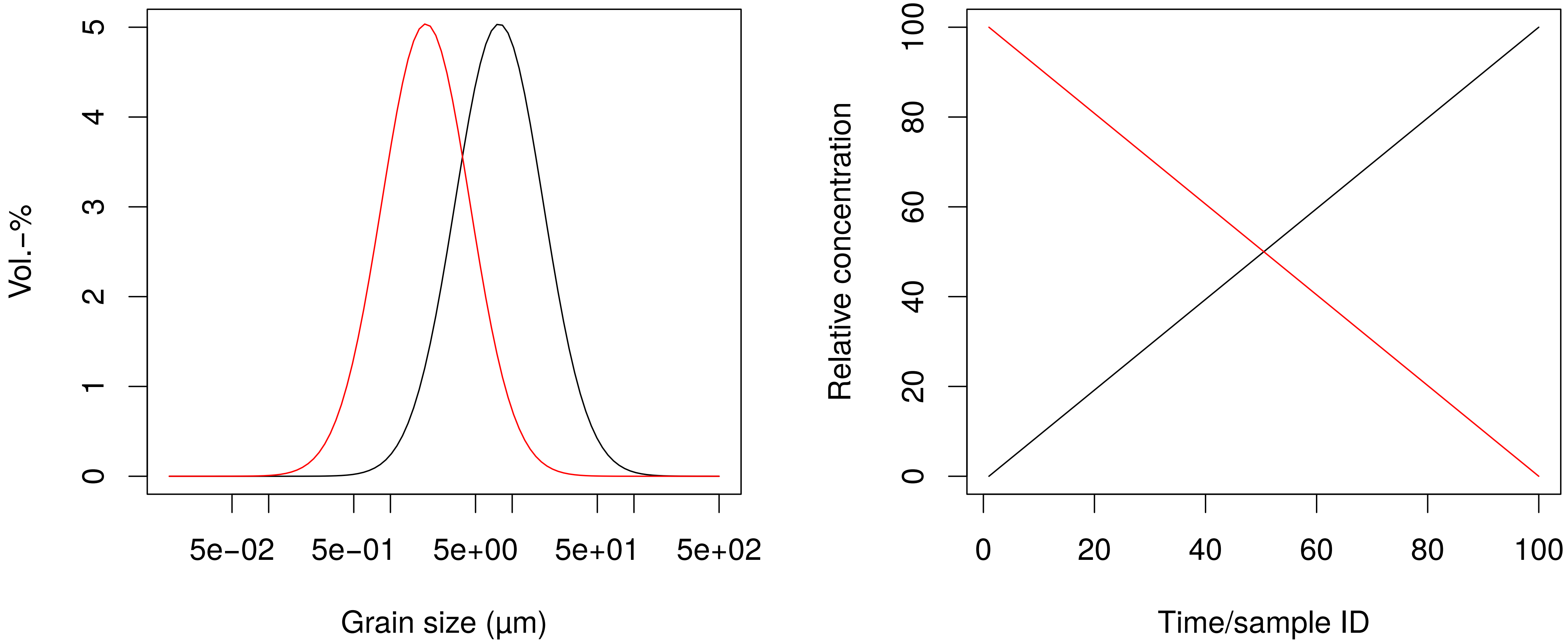
Cutting off at fixed boundaries may lead to:

- underestimation of the target fraction's total vol.-%

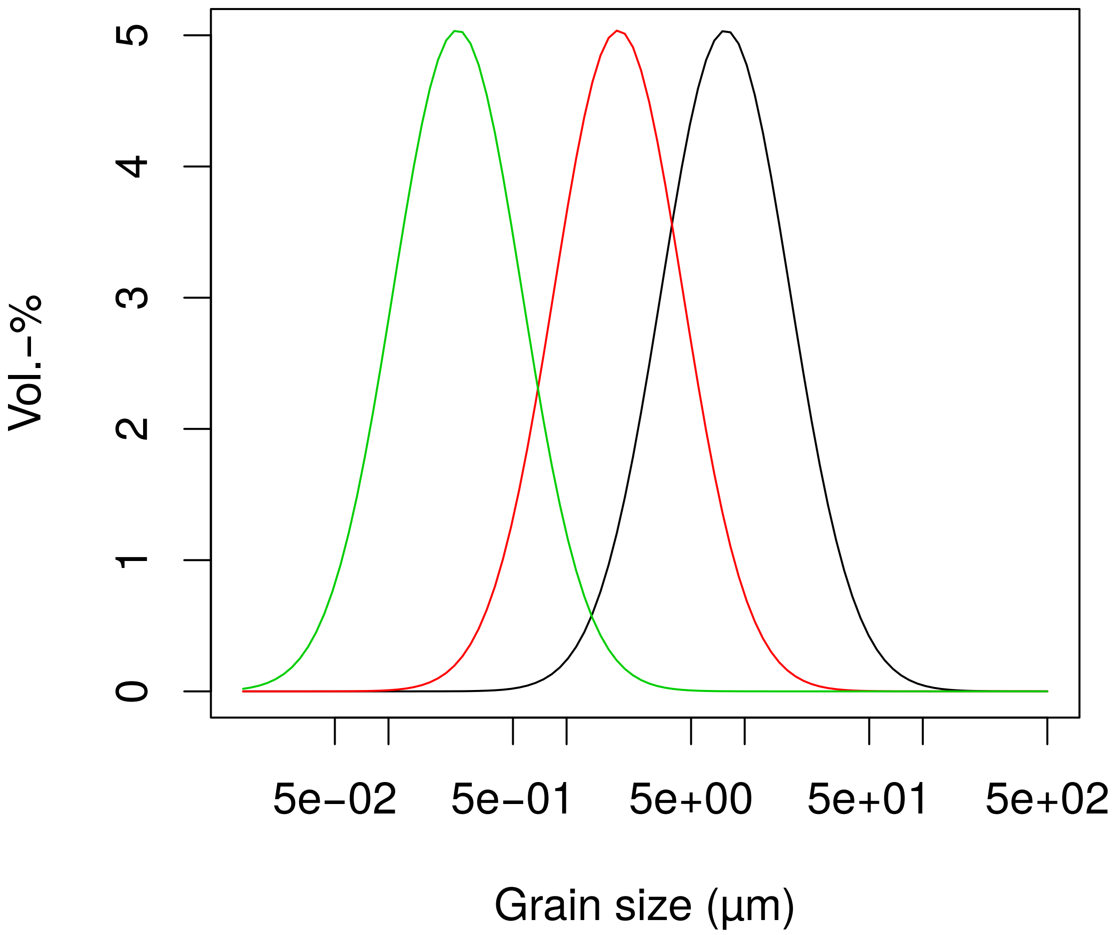
- contamination of the target fraction, by
  - tail(s) of coarser fractions
  - contribution of smaller fractions

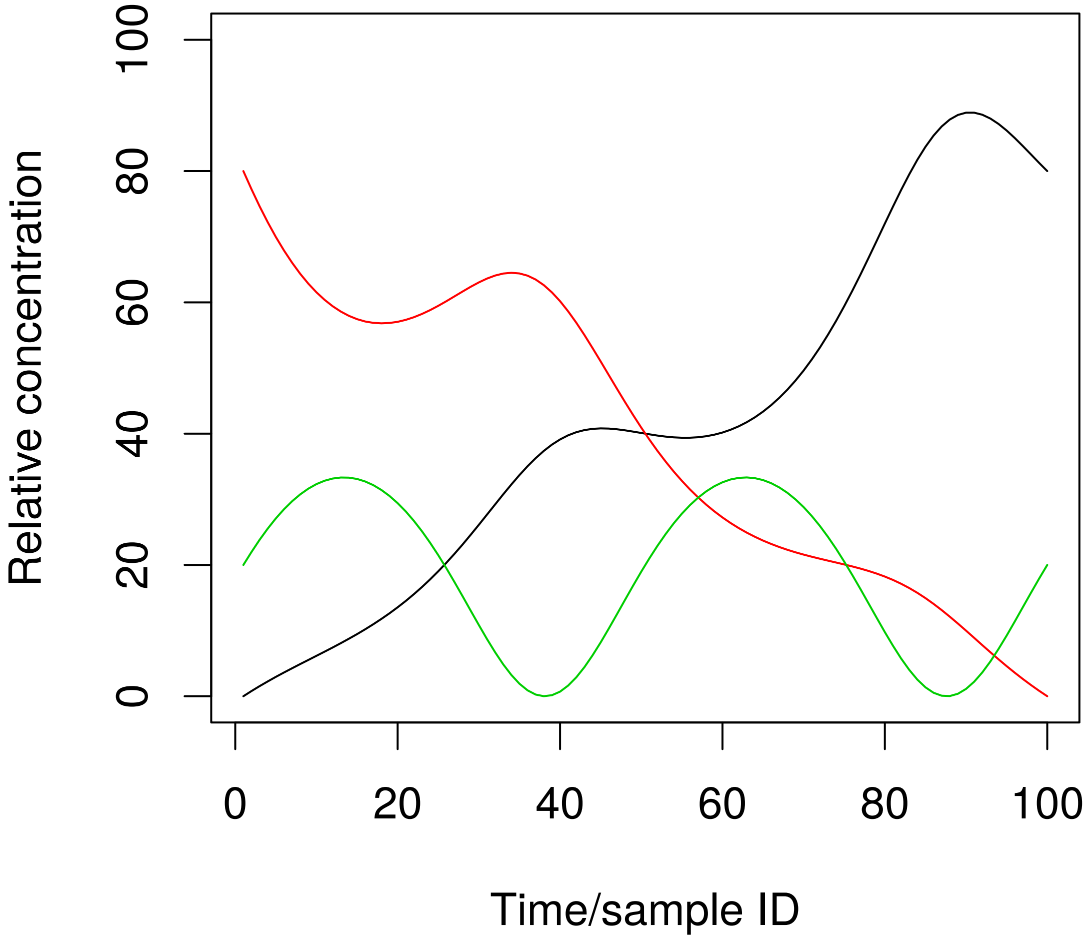
- bias in the resulting time series of dust

A simple test of the contamination hypothesis – Setup A

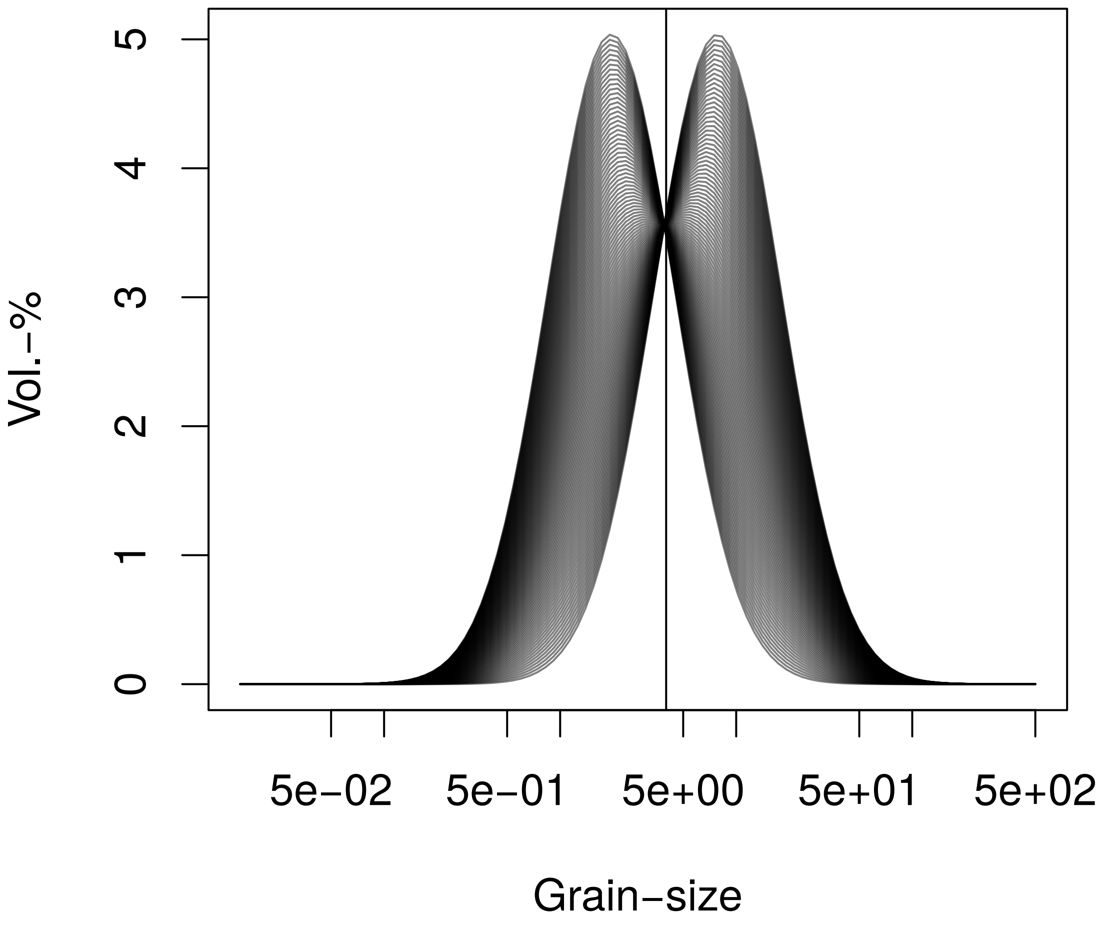


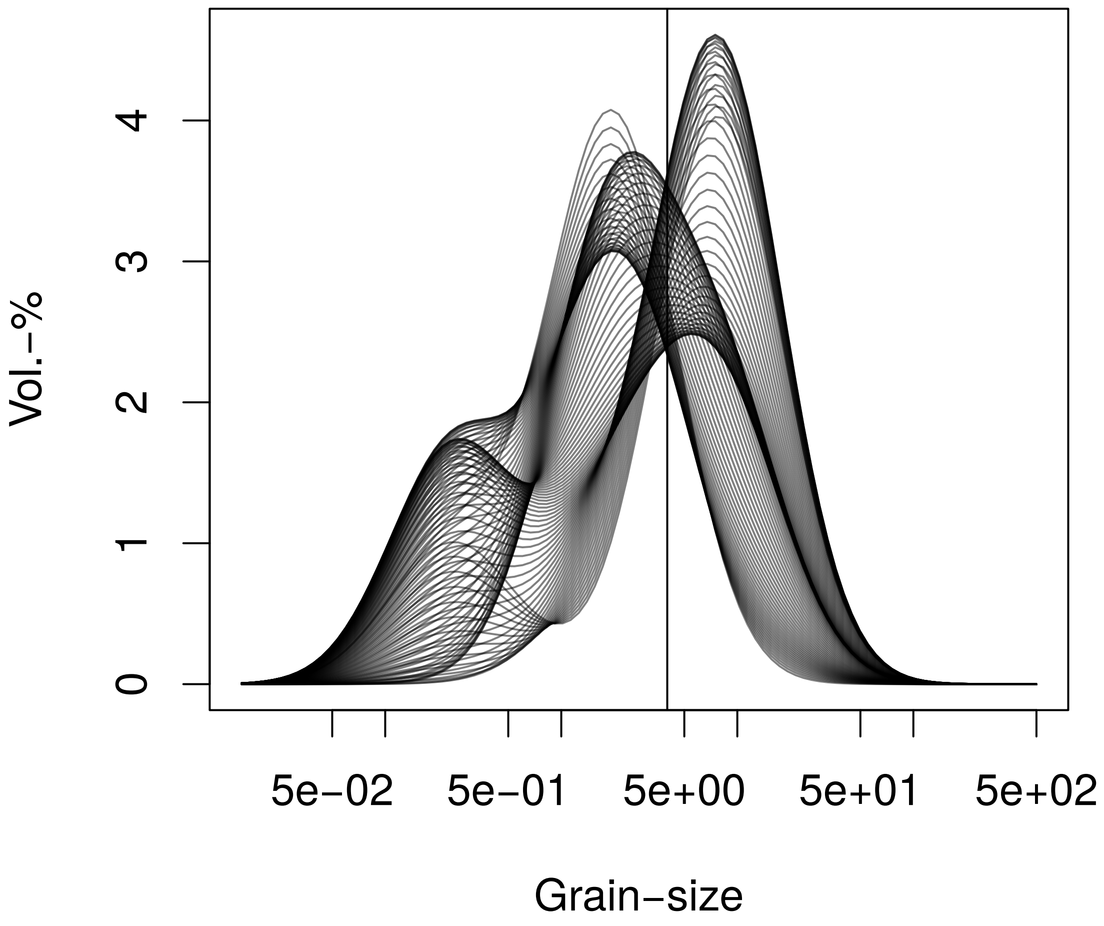
A simple test of the contamination hypothesis – Setup B



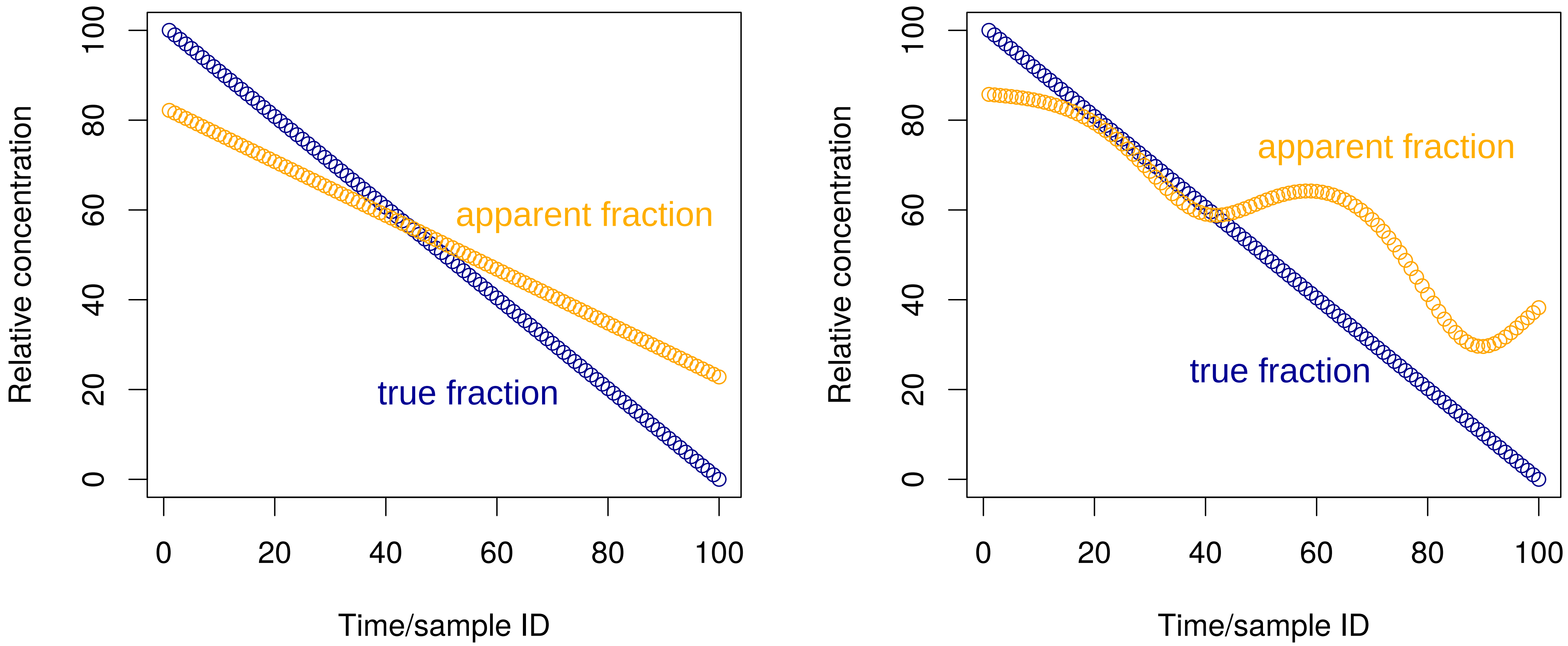


A simple test of the contamination hypothesis – Resulting mixed data sets

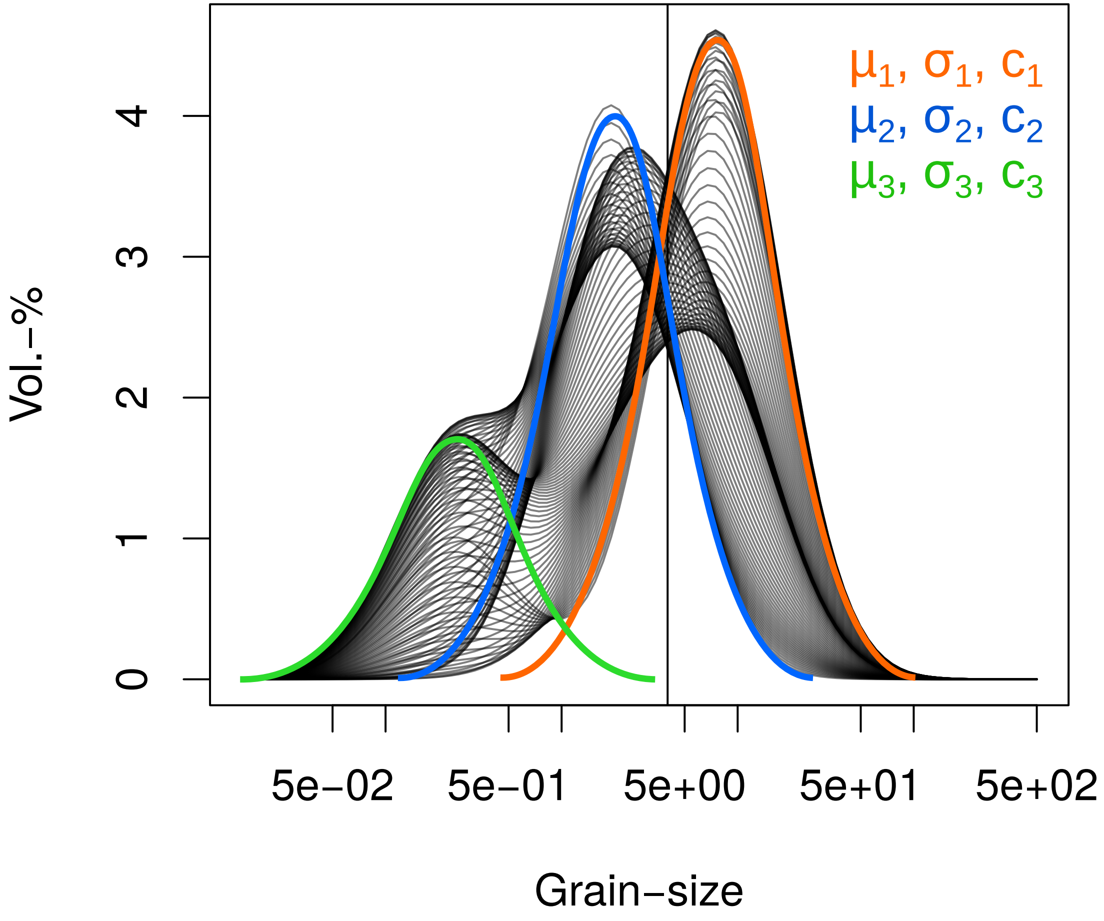




A simple test of the contamination hypothesis – Resulting "dust" fractions (< 4 µm)



One approach to tackling the problem – parametric curve fitting



Fitting n parametric distributions (log-normal, Weibull, Gamma, ...)

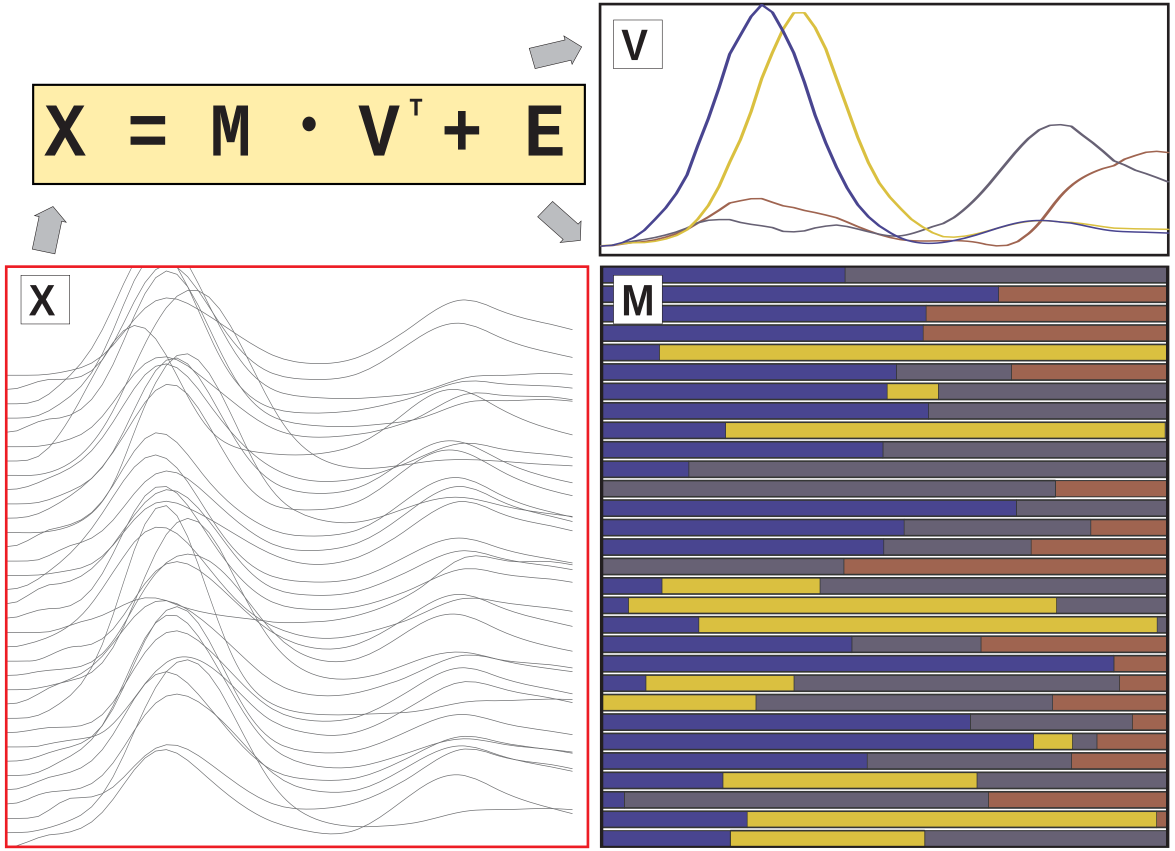
Attractive, because we get unmixed time series and parametric end-member definition

But, for each sample we can get different μ, σ. So which one is the right one?

What if a sample has more than n components, or less?

Another approach to tackling the problem – eigen space based decomposition (EMMA)

$$X = M \cdot V^T + E$$

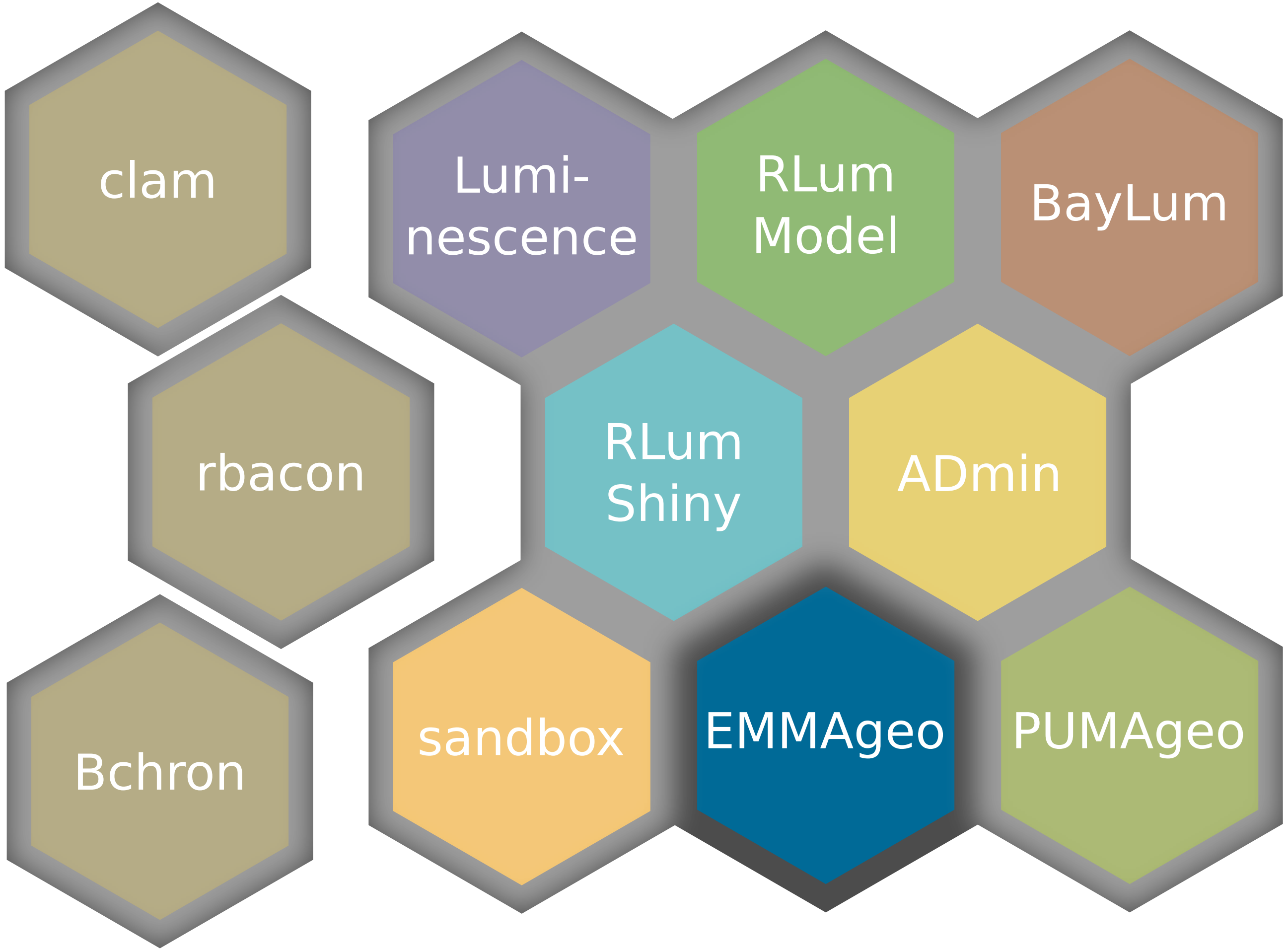


Considers an entire data set as input and describes it as linear combination of eigen vectors (V) and their scores (M) plus an error matrix (E).

Based on eigen space decomposition (PCA), extended to optimisation and reduction (FA), framed by scaling to real units (EMMA).

Attractive, because we get unmixed time series and unconstrained end-member definition

Another approach to tackling the problem – eigen space based decomposition (EMMA)



Basic and advanced data analysis

Luminescence model implementation

Bayesian age calculations

Bayesian age depth models

Advanced age data visualisation

Age error type separation

Virtual sediment section modelling

Compositional data analysis

Age-depth to proxy uncertainty propagation

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Another approach to tackling the problem – eigen space based decomposition (EMMA)

Rescale data matrix X to constant sum c.

```
X  <- X / apply(X, 1, sum) * c
```

Weight tranformation after Miesch (1970).

```
qts <- function(X, lw) quantile(X, c(lw, 1-lw), type = 5)
ls <- t(apply(X, 2, qts, lw = lw))
W <- t((t(X) - ls[,1]) / (ls[,2] - ls[,1]))
```

Similarity matrix calculation (major product).

```
A <- t(W) %*% W
```

Eigen space extraction.

```
EIG <- eigen(A)

V <- EIG$vectors[,order(seq(ncol(A), 1, -1))]
Vf <- V[,order(seq(ncol(A), 1, -1))]
L <- EIG$values[order(seq(ncol(A), 1, -1))]
Lv <- cumsum(sort(L / sum(L), decreasing = TRUE))
```

Varimax rotation of the eigen vector matrix Vf.

```
Vr <- do.call(rotation, list(Vf[,1:q]))
```

Extract and sort (decreasing) factor loadings and write them to matrix Vq. Rescale (Vqr) and normalise (Vqn) the factor loadings column-wise.

```
Vq <- Vr$loadings[,order(seq(q, 1, -1))]
Vqr <- t(t(Vq) / apply(Vq, 2, sum)) * c
Vqr <- t(Vqr)
Vqn <- t((Vqr - apply(Vqr, 1, min)) / (
  apply(Vqr, 1, max) - apply(Vqr, 1, min)))
```

Calculate factor scores matrix (Mq) by non-negative least square fitting of Vqn and transposed row-wise weight-transformed data W.

```
Mq <- matrix(nrow = nrow(X), ncol = q)
for (i in 1:nrow(X)) {Mq[i,] = nnls(Vqn, as.vector(t(W[i,])))$X}
```

Model the dataset (Wm) as the minor product

```
Wm <- Mq %*% t(Vqn)
```

Rescale the factor loadings matrix Vqn to Vqsn.

```
s <- (c - sum(ls[,1])) / apply(Vqn * unname(ls[,2] - ls[,1]), 2, sum)
Vqs <- Vqn
for(i in 1:q) {Vqs[,i] <- t(s[i] * t(Vqn[,i]) * (ls[,2] - ls[,1]) + ls[,1])}
Vqsn <- t(t(Vqs)/ apply(Vqs, 2, sum)) * c
```

Rescale factor scores (Mq) to matrix Mqs and calculate variance explanied by scores.

```
Mqs <- t(t(Mq) / s) / apply(t(t(Mq) / s), 1, sum)
Mqs.var <- diag(var(Mqs)) / sum(diag(var(Mqs))) * 100
```

Evaluate measures of model goodness.

```
Em <- as.vector(apply(X - Xm, 1, mean))
En <- as.vector(apply(X - Xm, 2, mean))
Rm <- diag(cor(t(X), t(Xm))^2)
Rn <- diag(cor(X, Xm)^2)
```

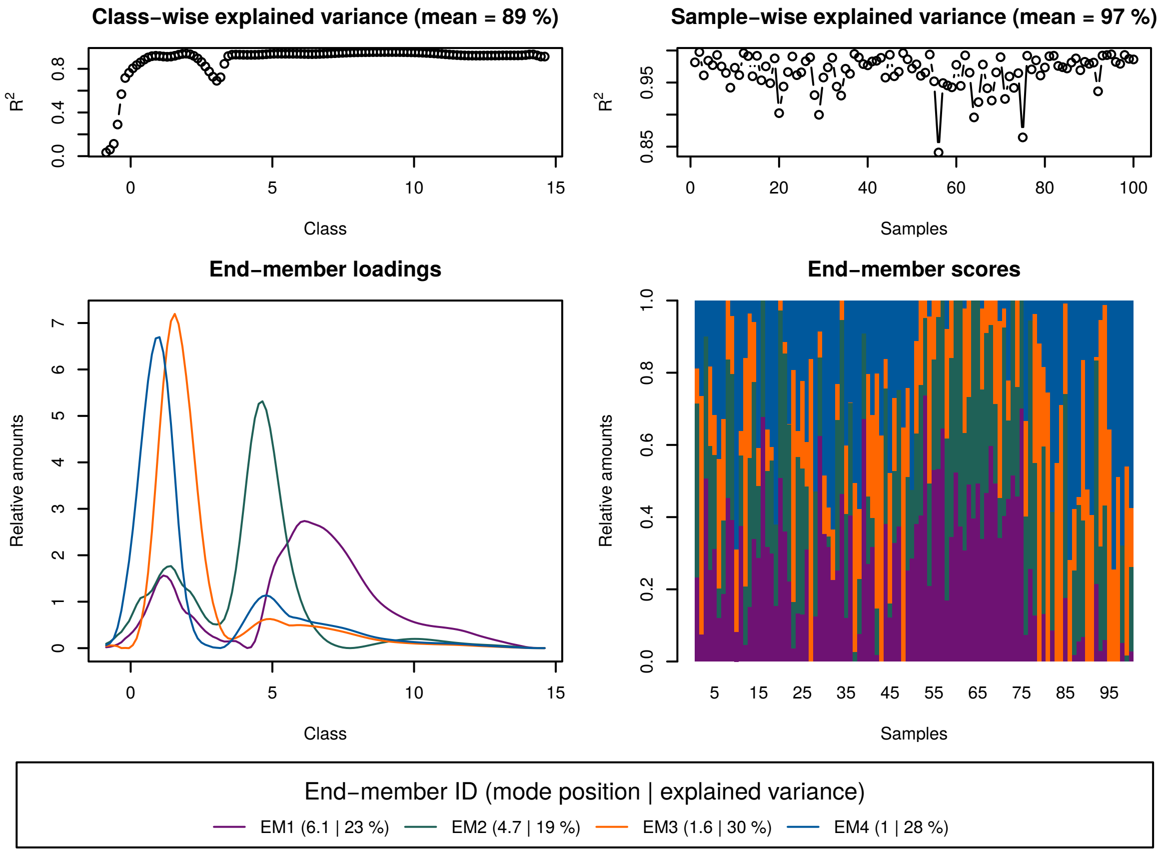
PCA

FA

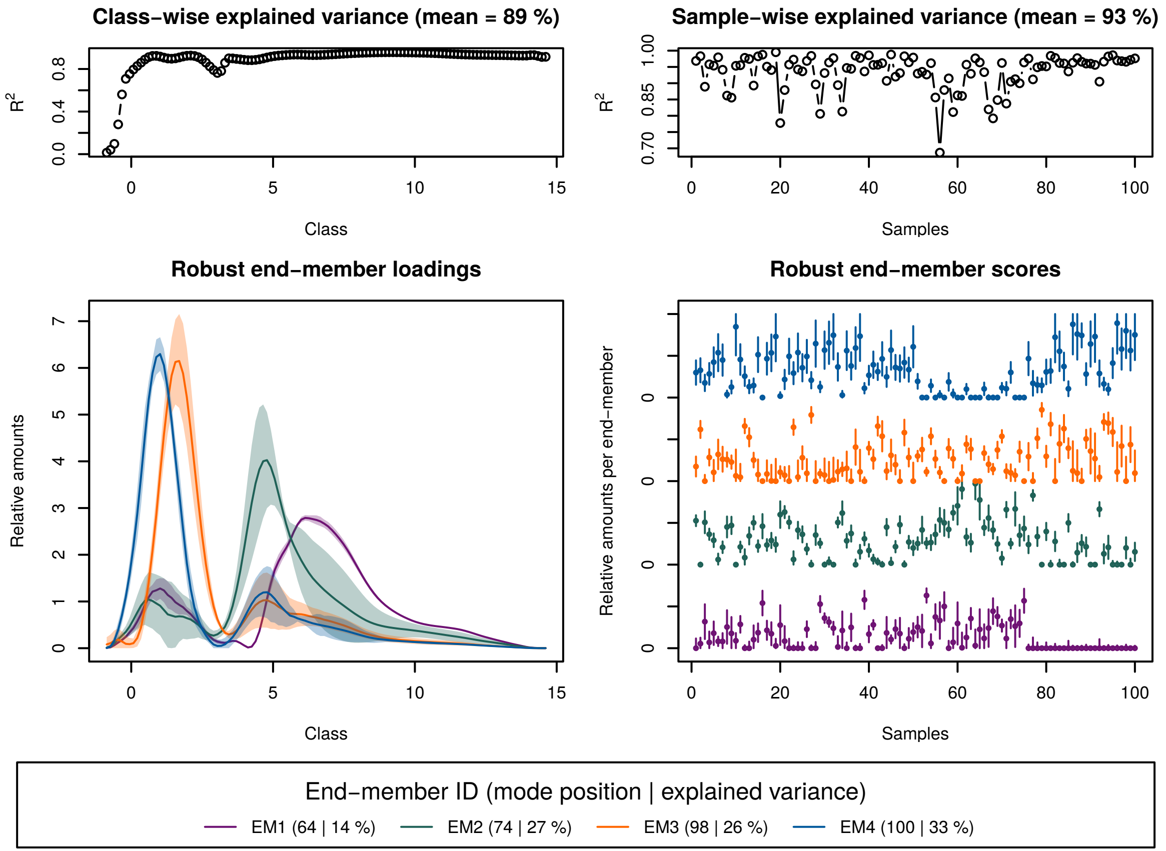
EMMA

Another approach to tackling the problem – eigen space based decomposition (EMMA)

Deterministic mode ("I know the number of components")



Robust mode ("I fully allow for parameter uncertainty")



Let's apply the technique – Welcome to a special kind of dusty deposit

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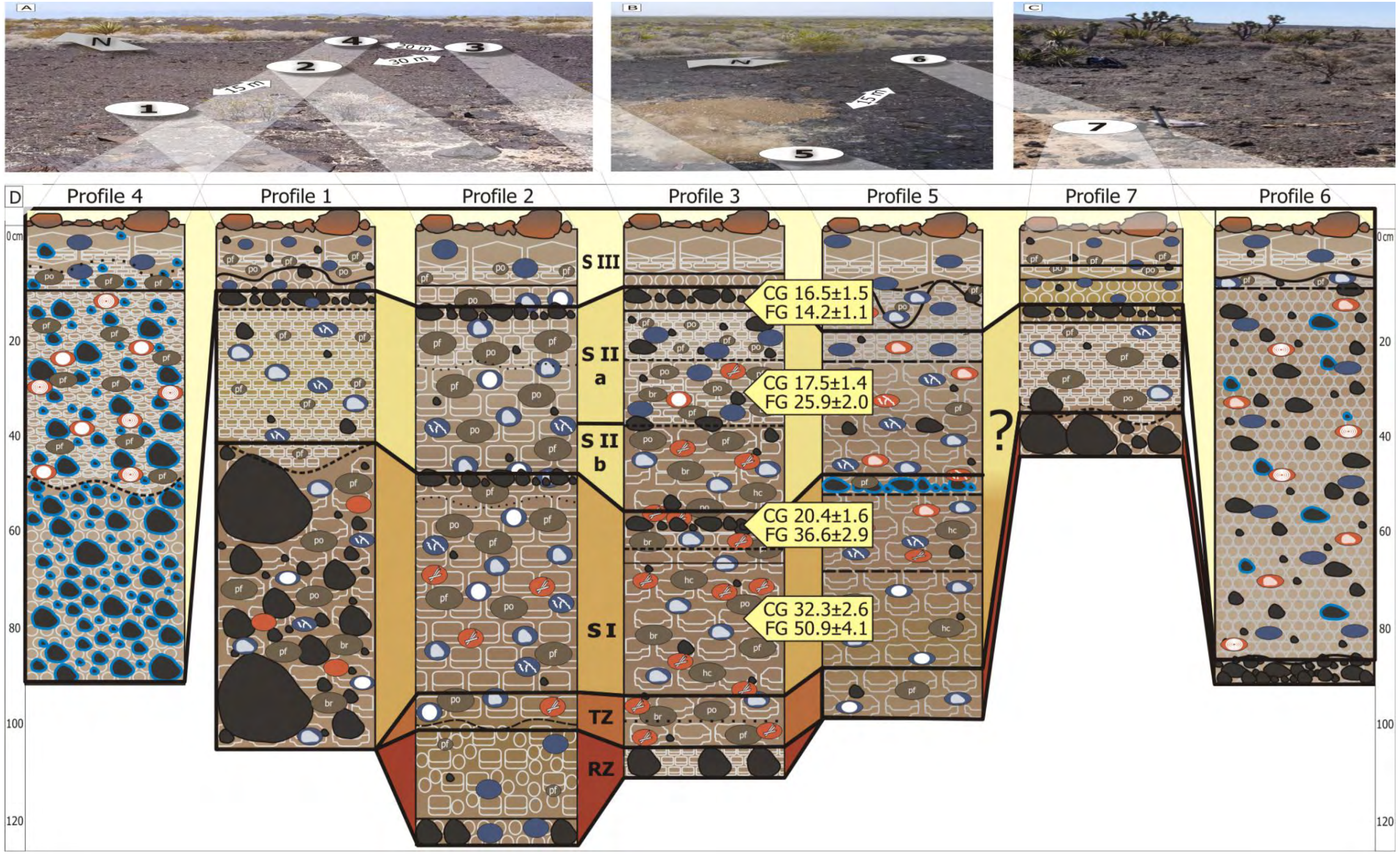

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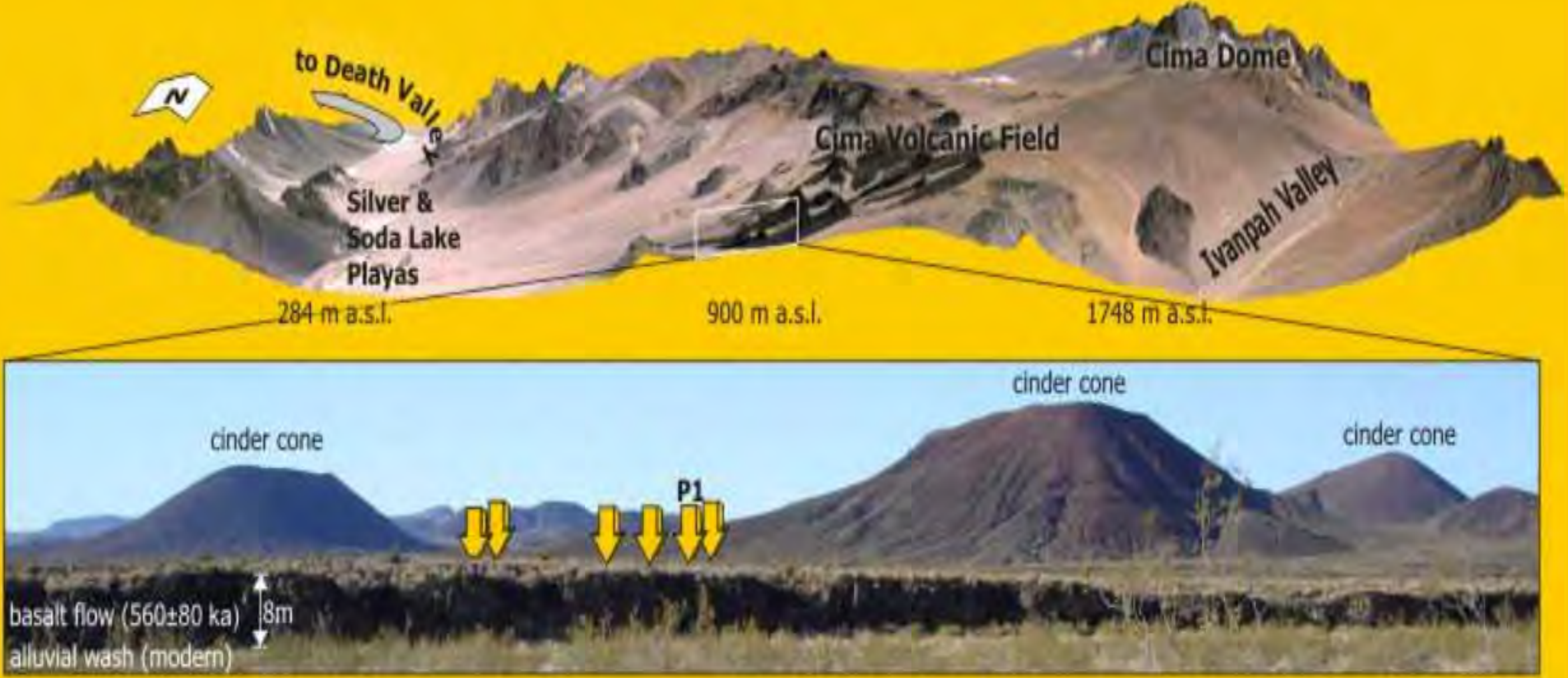

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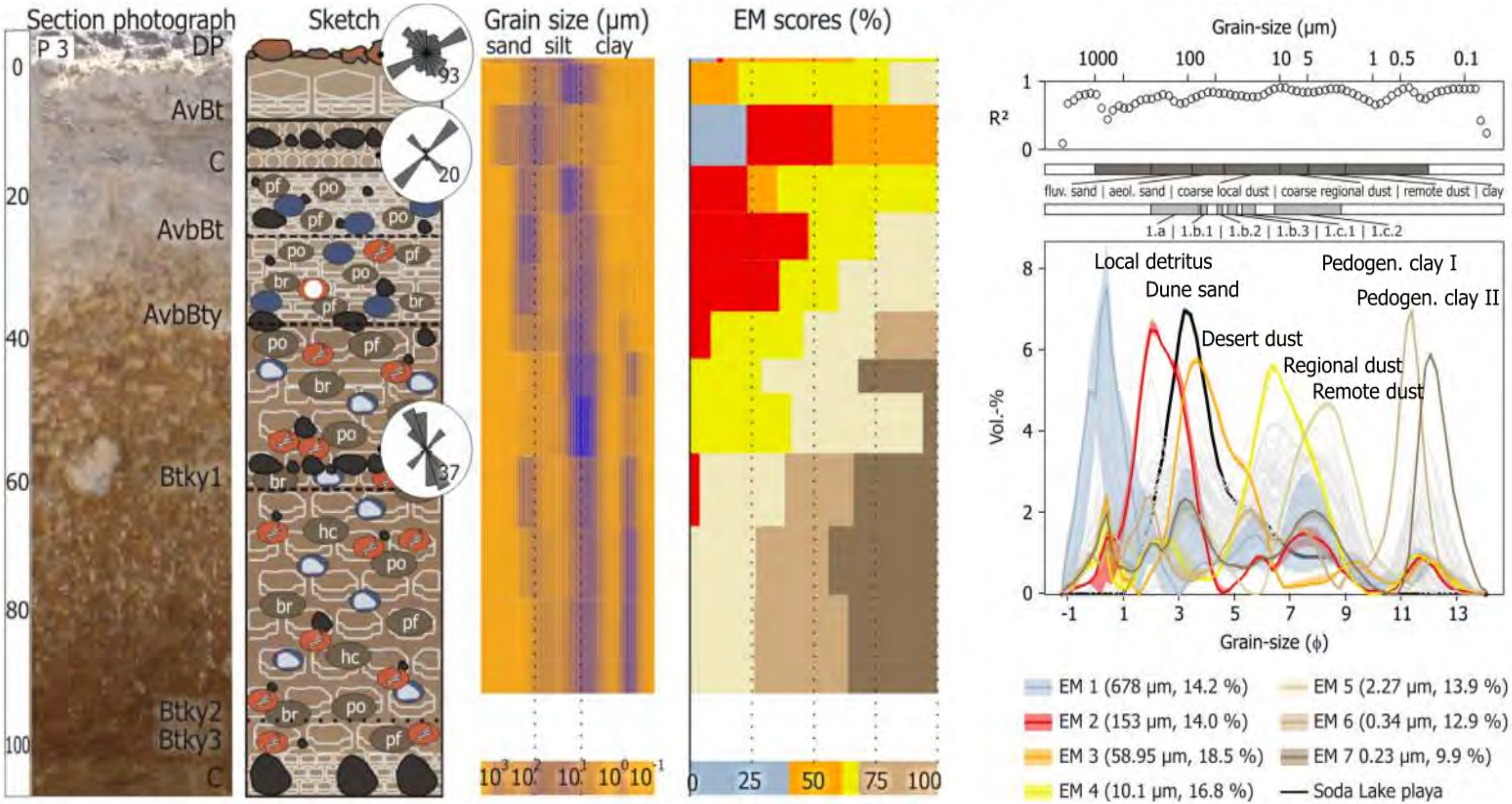

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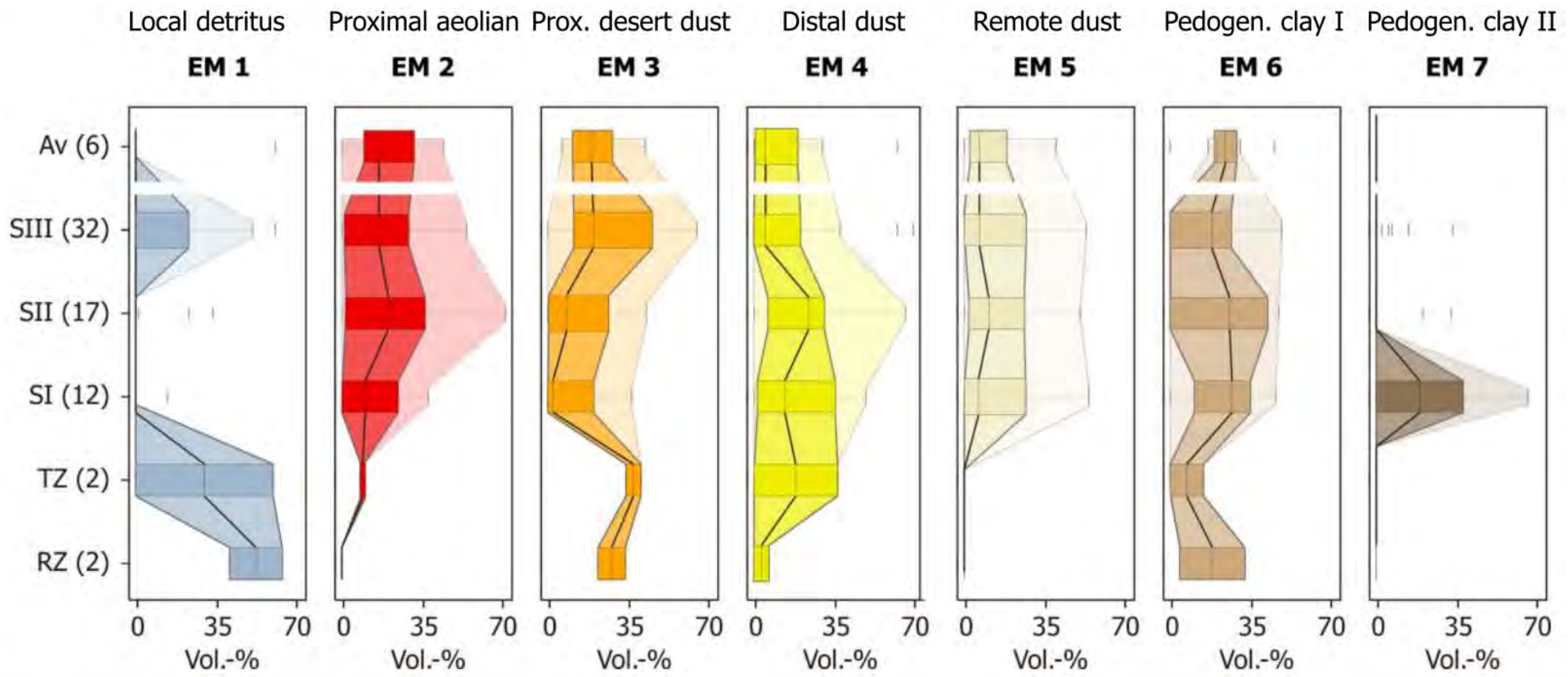

So?... Some recapitulation ... And a look ahead

Aeolian deposits usually comprise a mixture of components from different sources, transport pathways and transport processes, and have undergone syn- and postdepositional alteration.

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With spatially "scaled" volume percentages of distinct dust fractions, one can engage with
i) removing the non-solid volume fractions (water, air),
ii) propagating solid volumes to age-depth-space, and
iii) robustly estimating size- and component-specific material density,
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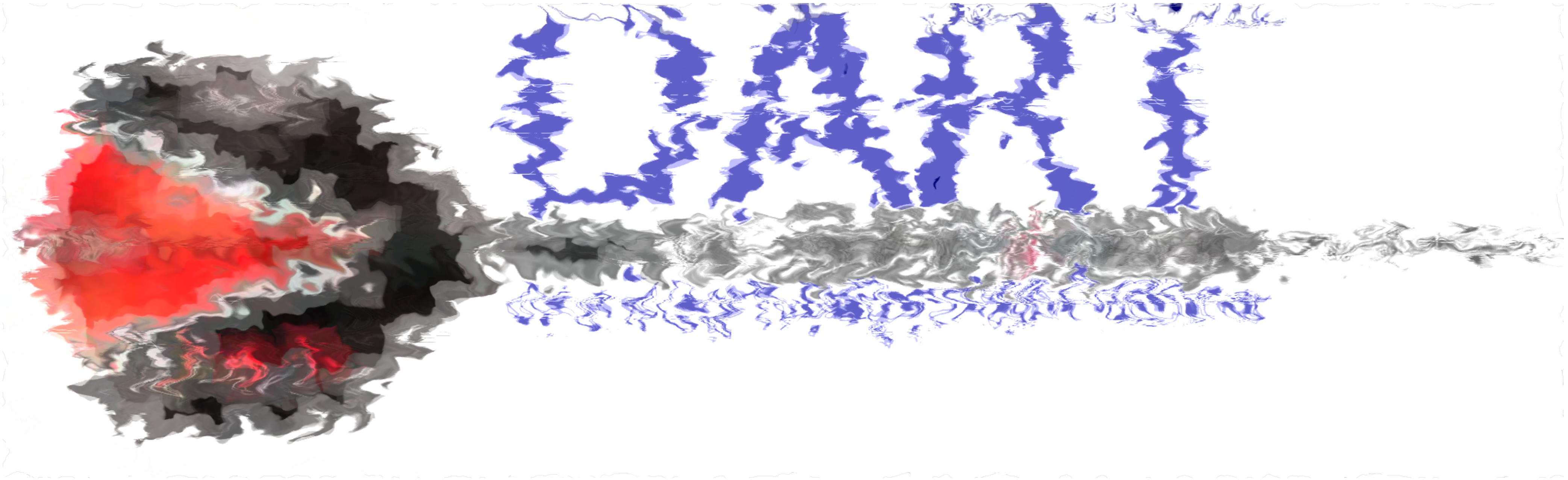

Thanks

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