

## Overview

Grain size analysis

Method of moments

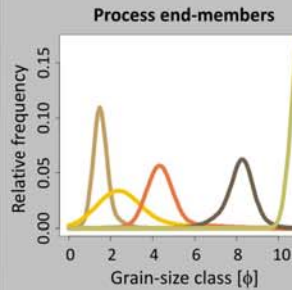
Principle component analysis

Factor analysis

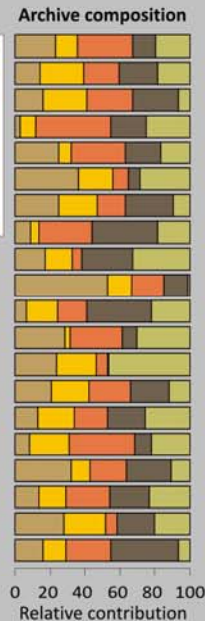
**End-member modelling**

Finite-mixture modelling

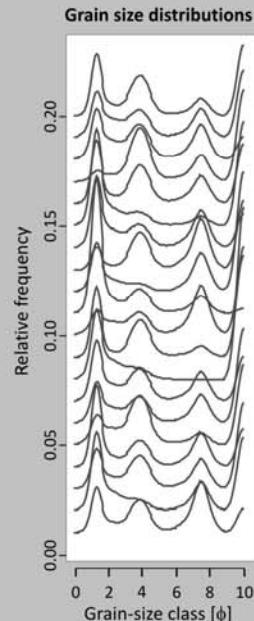
### Processes sort



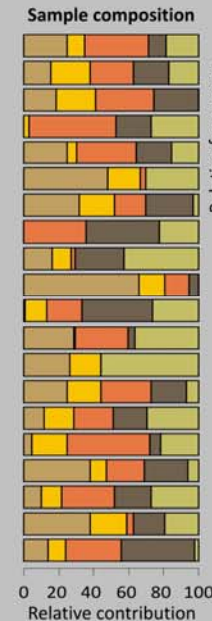
### Archives mix



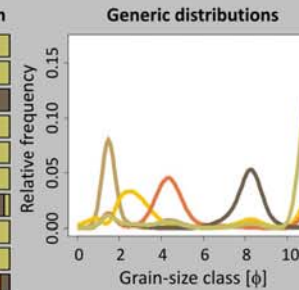
### The scientist's dilemma



### EMMA scores



### EMMA loadings



from process to archive

from archive to process

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## Why EMMA

- Meaningful interpretation of polymodal data
- Infer processes and their relative importance

## Constraints

- Stationarity in processes
- Processes create non-overlapping spectrae
- Sufficient samples with respect to resolution

## Strengths

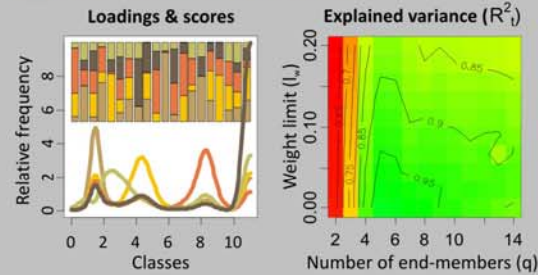
- Process quantification
- Robustness and uncertainty estimation
- Open source, flexible code

Dietze et al. (2012)

## Package & applications

### The R-package EMMAgeo

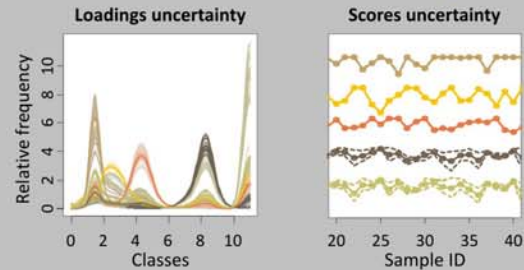
#### Optimisations and tests



#### Features

- check data consistency
- test weight limits
- test factor explanatory power
- work with user-defined loadings
- Infer model robustness
- Several measures of goodness

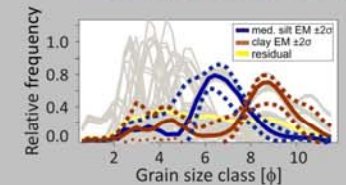
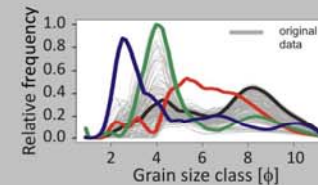
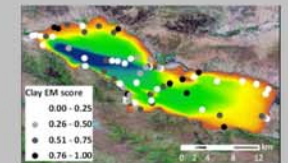
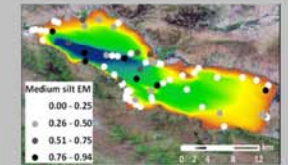
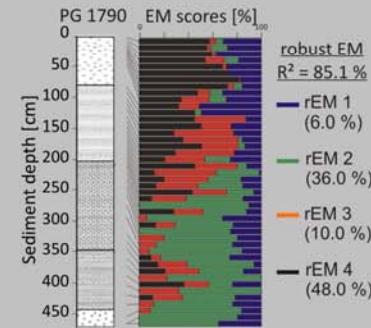
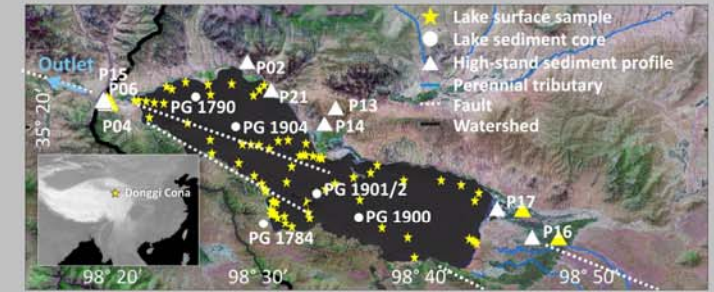
#### Robustness and uncertainty



#### Work with the package

```
install.packages("EMMAgeo")
library(EMMAgeo)
```

### An example from the Tibetan Plateau





## The way of EMMA



```
check.data(X = DC.data, q = q, lw = lw, c = 100)
[1] "Data matrix passed test... OK"
[2] "End-member vector passed test... OK"
[3] "Weight transformation limit vector
passed test... OK"
[4] "Scaling parameter passed test... OK"
[5] "Maximum weight transformation limit value
passed test... OK"
[6] " Note: the following rows do not sum up
to the specified c: 1, 42, 250."
[7] "No columns contain only zero values... OK"
```

### Check the input data

- check appropriate data structure
- check for columns with only zero-values
- check for rows with NA-values

### Package functions

```
mu.phi()
phi.mu()
interpolate.classes()
check.data()
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```

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## The way of EMMA



```
lw.test <- seq(0, 0.5, length.out = 100)  
test.lw(X = DC.data, lw = lw.test)
```

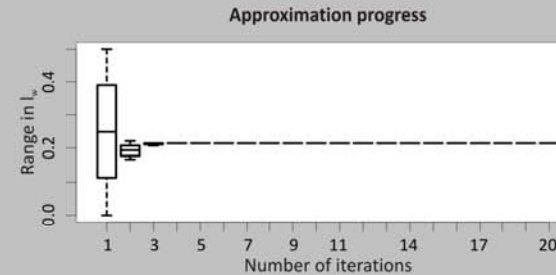
```
$step  
[1] 43  
$lw.max  
[1] 0.2121
```

```
lw.0 <- 0 # lowest lw  
lw.n <- 0.5 # highest lw  
n = 10 # length of the lw-vector
```

```
for(i in 1:20) {  
  lw.test <- test.lw(X = X,  
                    lw = seq(from = lw.0,  
                             to = lw.n,  
                             length.out = n))  
  
  lw.new = seq(lw.0, lw.n, length.out = n)[c(  
    lw.test$step, lw.test$step + 1)]  
  lw.0 <- lw.new[1]  
  lw.n <- lw.new[2]  
}
```

### Test weight tranformation limits

- Weight-transformation of input data handles sample outliers, cf. Miesch (1970)
- EMMA crashes when limits set too high
- The function evaluates the last valid weight transformation limit  $l_w$
- Use a loop to iteratively approximate  $l_w$  max



### Package functions

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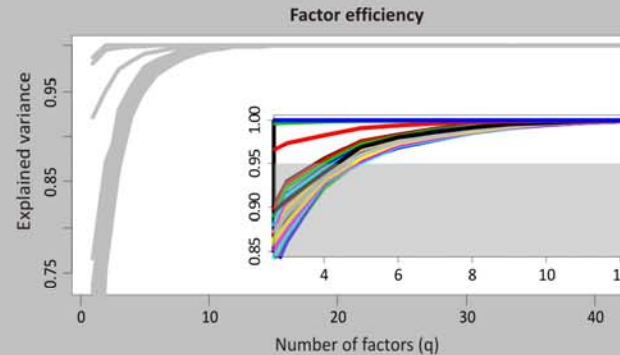
## The way of EMMA



```
lw = seq(0, lw.max, length.out = 20)  
Lv.test <- test.Lv(X = DC.data, lw = lwplot = TRUE)  
q.min <- Lv.test$q.min  
q.min  
[1] 4 4 4 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 2 1 1
```

### Test explained variance & get $q_{\min}$

- Finding the minimum number of factors/potential end-members relies on the Kaiser criterion (i.e.  $R^2 > 0.95$ )
- The function returns the number of factors necessary to pass an  $R^2 > 0.95$



### Package functions

```
mu.phi()  
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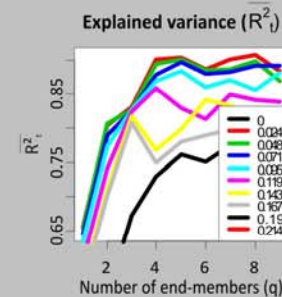
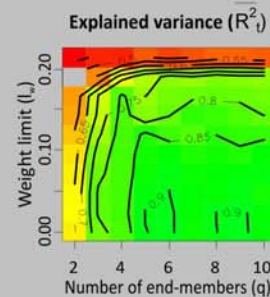
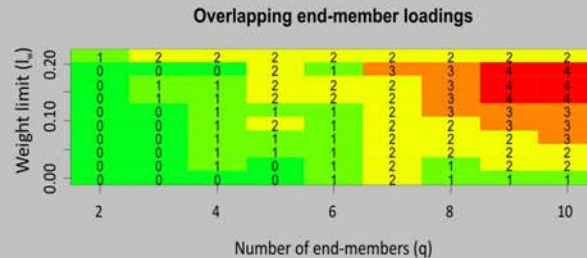
## The way of EMMA



```
q.seq <- seq(from = 2,  
            to = 10)  
  
lw.seq <- seq(from = 0,  
            to = lw.max,  
            length.out = 10)  
  
params.test <- test.parameters(X = DC.data,  
                              q = q.seq,  
                              lw = lw.seq,  
                              plot = "mRt",  
                              legend = TRUE,  
                              cex = 0.7)
```

### Infer parameter influence & get $q_{\max}$

- Test influence of combinations of  $q$  and  $l_w$  on diverse measures of model goodness (e.g. mRt, mRn, mEn, mEm, mEn).
- Infer number of overlapping end-member loadings
- Infer maximum number of end-members



### Package functions

```
mu.phi()  
phi.mu()  
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```

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## The way of EMMA



```
q.min <- ifelse(q.min < 2, 2, q.min)
q.max <- ifelse(q.max < q.min, q.min, q.max)
input.matrix <- cbind(q.min, q.max, lw.seq)
input.matrix <- input.matrix[complete.cases(
  input.matrix),]

TR <- test.robustness(X = DC.data,
  P = input.matrix,
  plot = TRUE,
  ol_rej = 1,
  mRt_rej = 0.95)

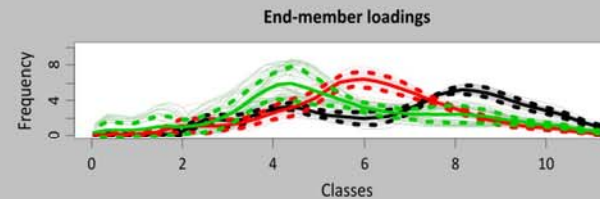
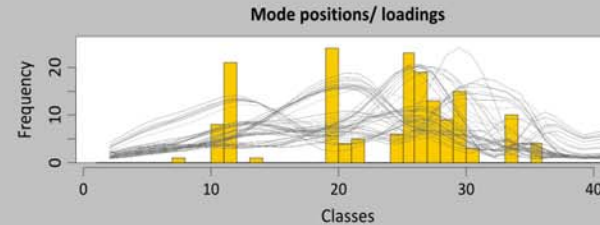
l.min <- c(10, 17, 25)
l.max <- c(15, 22, 28)
limits = cbind(l.min, l.max)

REM <- robust.EM(Vqsn = TR$Vqsn,
  limits = limits,
  Vqn = TR$Vqn,
  classunits = DC.units,
  plot = TRUE)

Vqn.mean <- REM$Vqn.mean
Vqn.sd <- REM$Vqn.sd
```

### Test and extract robust end-members

- Run all parameter combinations and extract only robust ones (given by mode limits)
- Further threshold parameters:  $ol$  and  $R^2$



### Package functions

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## The way of EMMA



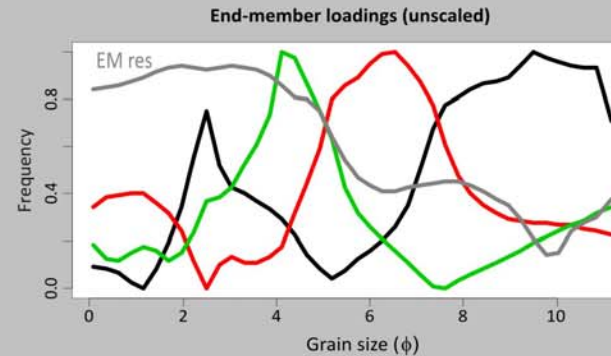
```
Vqn.res <- residual.EM(Vqn.mean)

plot(NA,
     main = "End-member loadings",
     xlab = expression(paste("Grain size (",
                             phi, ")"), sep = "")),
     ylab = "Loadings [Vol.-%]",
     xlim = range(DC.units),
     ylim = c(0, 1))

for(i in 1:nrow(Vqn.mean)) {
  lines(DC.units,
        Vqn[i,],
        col = i)
}
lines(DC.units, Vqn.res, col = "grey")
```

### Retrieve the residual end-member

- Robust, unscaled end-members (Vqn) are not able to cover the entire data variance
- The residual end-member aims to describe this portion of "open" variance



### Package functions

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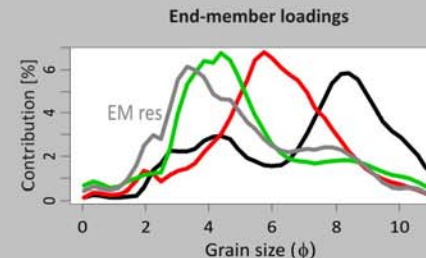
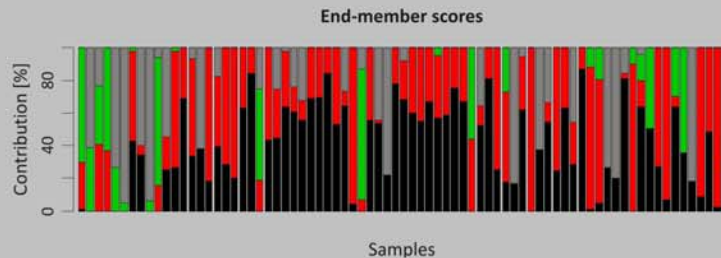
## The way of EMMA



```
Vqn.rob.res <- rbind(Vqn.mean, Vqn.res)  
  
EM.rob <- EMMA(X = DC.data,  
              q = nrow(Vqn.rob.res),  
              lw = 0.012,  
              Vqn = Vqn.rob.res,  
              classunits = DC.units,  
              plot = TRUE)
```

### Model the data with robust loadings

- EMMA() can be run with intrinsic or user-defined end-members (Vqn).
- This allows to include both, robust and residual end-member loadings.



### Package functions

```
mu.phi()  
phi.mu()  
interpolate.classes()  
check.data()  
test.lw()  
test.Lv()  
test.parameters()  
  
EMMA()  
test.robustness()  
robust.EM()  
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```

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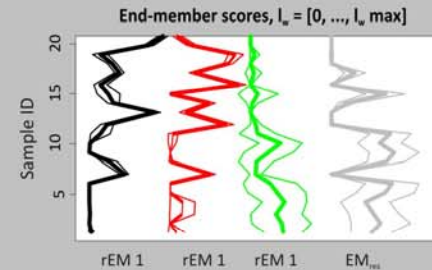
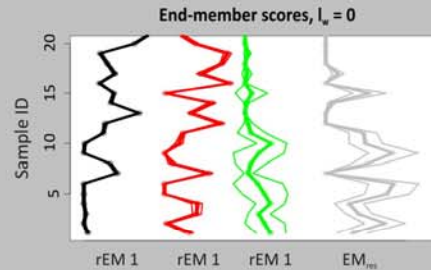
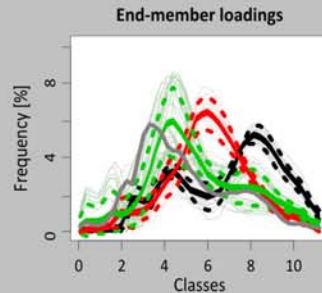
## The way of EMMA



```
Vqn.rob.res.sd <- rbind(Vqn.sd,  
                      rep(0, nrow(Vqn.sd)))  
lw.test <- c(0, lw.max)  
  
M <- Mqs.uncertainty(X = DC.data,  
                   q = 4, lw = lw.test,  
                   runs = 200,  
                   Vqn = Vqn.rob.res.mean,  
                   Vqn.sd = Vqn.rob.res.sd,  
                   type.lw = "runif",  
                   autocorrelation = 3)
```

### Estimate uncertainty of Mqs and Vqsn

- Monte Carlo runs allow to estimate end-member scores uncertainty, varying number of end-members and weight transformation limits.
- The robustness test contributes uncertainty estimation for end-member loadings.
- data autocorrelation can be implemented



### Package functions

- `mu.phi()`
- `phi.mu()`
- `interpolate.classes()`
- `check.data()`
- `test.lw()`
- `test.Lv()`
- `test.parameters()`
- `EMMA()`
- `test.robustness()`
- `robust.EM()`
- `residual.EM()`
- `Mqs.uncertainty()`
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## The EMMA algorithm

Rescale data matrix X to constant sum c.

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

Weight transformation 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 (outer 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 inner 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 explained by scores.

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

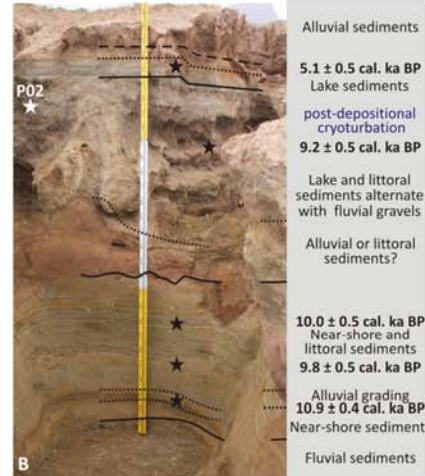
Evaluate measures of model goodness.

```
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)
```

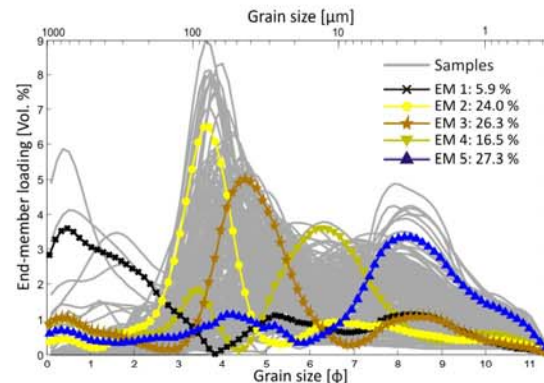
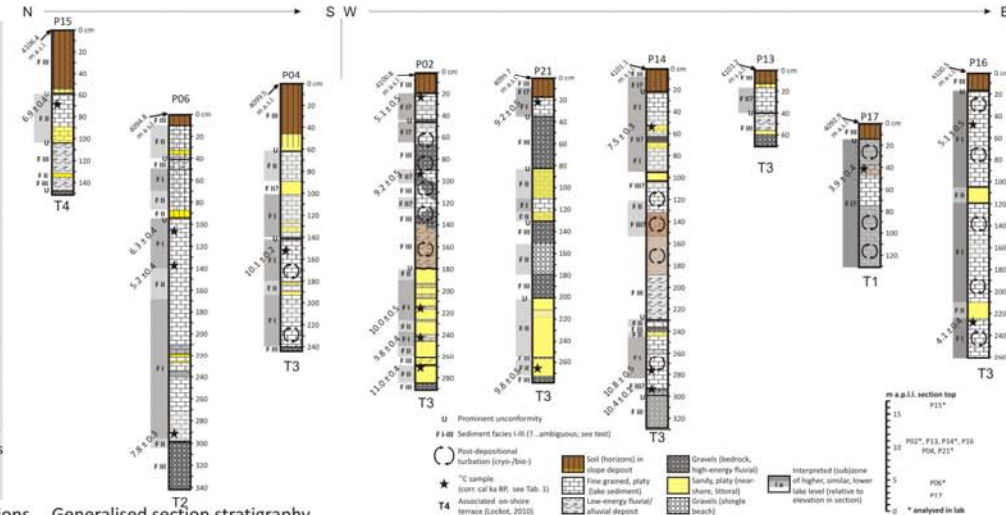


## Lake high-stand deposits

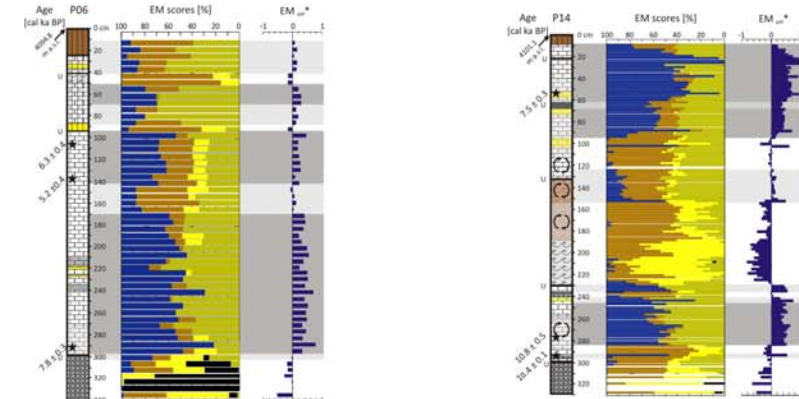
Lake high-stand sediments in onshore terraces at Lake Donggi Cona, north-eastern Tibetan Plateau allow a detailed view into the lake history. End-member modelling of grain-size samples allowed identification and quantification of sediment delivering processes. A normalized difference between the finest and coarsest end-members was calculated as a proxy for relative lake-level change. The interpreted processes are high-energy fluvial transport, low-energy unconfined flow, proximal dust, remote dust and lacustrine suspension load (EM 1 to 5, respectively).



Complex stratigraphy with post-depositional alterations. Generalised section stratigraphy.



End-member loadings of high-stand sediment grain size samples.



End-member scores and normalized difference of EM 2 and EM 5 in relation to section characteristics.

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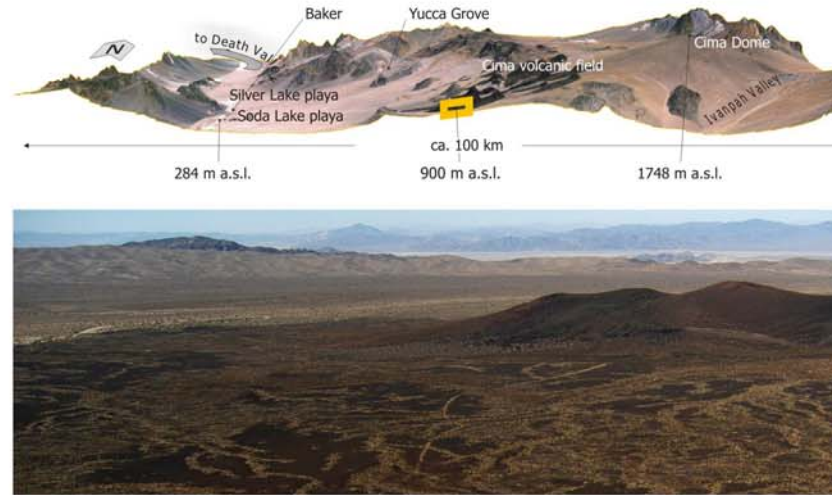




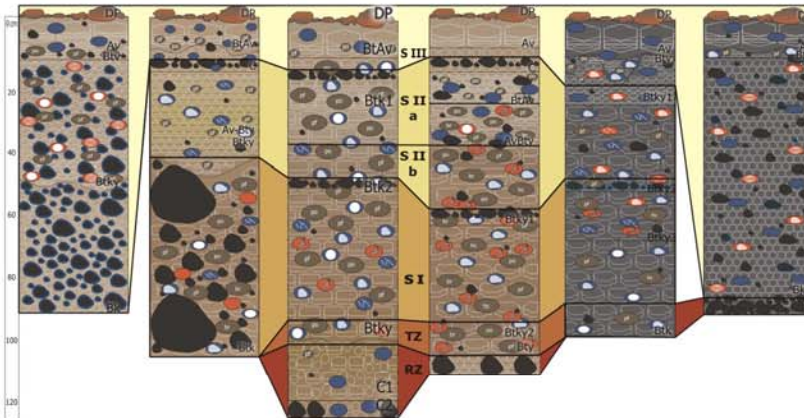
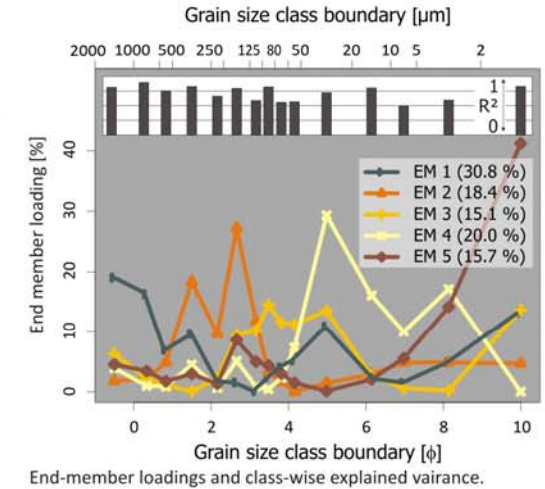
## Accretionary soils

Cima volcanic field, eastern Mojave Desert, USA, hosts dissected lava flows with soil-sediment-complexes of aeolian origin, covered by stone pavements.

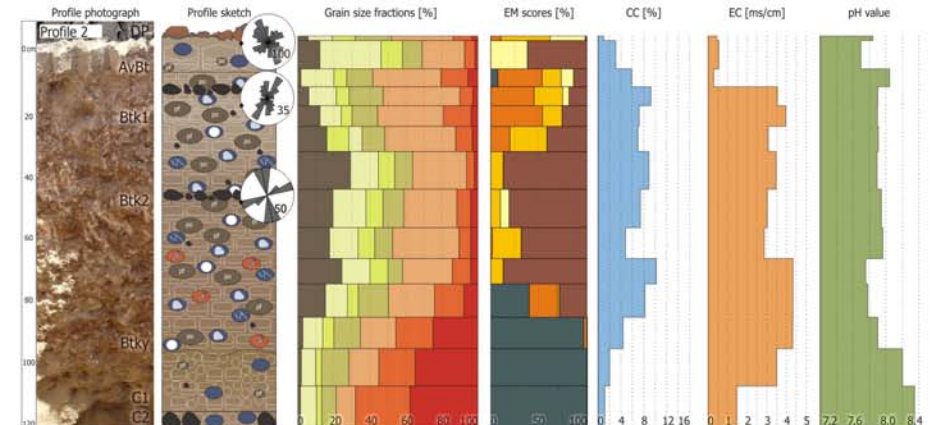
Relevant processes contributing to profile thickening are accumulation of dune sand, proximal dust and remote dust as well as admixture of local detritus and enrichment of pedogenic clay (EM 1 to 5, respectively). These processes are identified by EMMAgeo, based on 104 samples with 16 classes and show a robust result even for a comparably poor sample resolution.



Cima volcanic field, a set of 40 cinder cones and lava flows downwind a prominent dust source.



Stratigraphy of six soil-sediment complexes with 3 accretionary units, covered by a stone pavement.



Photo, sketch, grain-size data, end-member scores and soil-chemical data for on accretionary section.

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## Outlook & Resources

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### How to access the R-package EMMAgeo

- <http://tu-dresden.de/Members/micha.dietze/EMMAgeo>

### The foundations of the package

- Weltje GJ. 1997. End-member modeling of compositional data: numerical–statistical algorithms for solving the explicit mixing problem. *Mathematical Geology* 29: 503-549.
- Dietze E, Hartmann K, Diekmann B, Ilmker J, Lehmkuhl F, Opitz S, Stauch G, Wünnemann B, Borchers A. 2012. An end-member algorithm for deciphering modern detrital processes from lake sediments of Lake Donggi Cona, NE Tibetan Plateau, China. *Sedimentary Geology* 243-244: 149-180.

TECHNISCHE UNIVERSITÄT DRESDEN

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MICHA.DIETZE - HOMEPAGE

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EMMAGEO

OVERVIEW

EMMAgeo is a selection of functions to allow flexible and robust end-member modelling analysis of multidimensional earth science data. For detailed descriptions of the algorithm and related information please see Dietze et al. (2012) and Weltje (1997).

The primary field of interest for EMMAgeo are multimodal, high resolution grain size data sets, typically resulting from laser particle size analysis. In the case of multimodal data, classic approaches of sediment descriptions such as the method of moments (eg. Folk & Ward, 1957) fall by definition. Furthermore, it is desired to reduce redundant information in multivariate data (laser grain size data provide more than 100 classes, each of them usually autocorrelated).

End-member modelling analysis is a statistical approach to unmix or decompose mixed grain size distributions and reduce them to a few, meaningful, genetically seasoned grain size distributions (end-member loadings). To do so, there are several approaches (cf. Dietze et al., 2012). EMMAgeo uses eigen space decomposition and several scaling procedures to return model output in the same scale like the input data.

Process and members Archive composition Grain size distributions Sample composition Generic distributions