



How well does end-member modelling analysis of grain size data work?

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End-member modelling analysis (EMMA) is a powerful and flexible statistic approach to identify and quantify generic sediment transport processes from multimodal grain-size distributions. EMMA has been introduced over 15 years ago and is now available in different approaches as encapsulated FORTRAN code (Weltje, 1997), Matlab-script (Dietze et al., 2012) and the R-package EMMAgeo (Dietze and Dietze, 2013). EMMA was mainly used to reconstruct past sedimentation processes in a variety of sedimentary environments (marine, aeolian, lacustrine).

Typically, it is rather difficult to assess how meaningful and well the model performs in a certain environment, since neither the actual process end-members (generic grain-size distributions sorted by a certain sediment transport) nor their individual contributions to each sample are known a priori. To allow a comprehensive performance test, we sampled a set of four known process end-members: alluvial sand (main mode: $0.70 \pm 0.55 \phi$), dune sand (main mode: $1.35 \pm 0.60 \phi$), loess (main mode: $4.71 \pm 0.65 \phi$) and overbank deposit (main mode: $5.81 \pm 1.62 \phi$). High resolution grain-size information is based on laser-diffraction analysis (116 classes). The four process end-members were artificially mixed with random, but known proportions to yield 100 samples. This mixed data set was measured again with the laser particle size analyser and served as input for EMMA within the R-package EMMAgeo.

This contribution discusses the ability of EMMA to identify and characterise the four distinct process end-members and quantify their contributions to each sample. Different ways to estimate uncertainties are presented. Further evaluations focus on the influence of numbers of included samples, numbers of grain-size classes, vertical mixing of samples (simulating turbation) and self-similarity of process end-members.

Dietze E, et al. 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: 169-180.

Dietze M, Dietze E. 2013. EMMAgeo: End-member modelling algorithm and supporting functions for grain-size analysis. R package version 0.9.1. <http://CRAN.R-project.org/package=EMMAgeo>

Weltje GJ. 1997. End-member modeling of compositional data: numerical–statistical algorithms for solving the explicit mixing problem. *Mathematical Geology* 29, 503–549.