

# Additional functions for transforming soil particlesize distributions

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March 8, 2012

## 1 Load the `soiltexture` package

The `soiltexture` package can be installed from CRAN with the following commands:

```
install.packages("soiltexture")
```

And loaded with the following commands:

```
require("soiltexture")  
require("drc")
```

'drc' has been loaded.

Please cite R and 'drc' if used for a publication,  
for references type 'citation()' and 'citation('drc')'.

## 2 Transforming soil texture data using many Particle- Size Distribution models (from 3 or more particle size classes)

`TT.text.transf.Xm()` is used to transform soil texture data from 3 or more particle size classes using various Particle-Size Distribution (PSD) models. The `drc` package and its associate packages(`lattice`,`magic`,`nlme`, `plotrix`) are required in the PSD model fitting. Compared to `TT.text.transf()`, the following check is not needed (and not done) :

- When the 1st value of input `tri.data` and output particle size classes limits is 0, The 2nd value of the output particle size classes limits must be higher or equal to the 2nd value of the input particle size classes limits."

We need first to create a dummy dataset with more than 3 particle size classes:

```
my.text4 <- data.frame(  
  "CLAY" = c(05,60,15,05,25,05,25,45,65,75,13,47),  
  "FSILT" = c(02,04,10,15,25,40,35,20,10,05,10,20),
```

```

"CSILT" = c(03,04,05,10,30,45,30,25,05,10,07,23),
"SAND"  = c(90,32,70,70,20,10,10,10,20,10,70,10)
) #

```

Transform this data frame from 4 particle size classes to 3 particle size classes:

```

res <- TT.text.transf.Xm(
  tri.data      = my.text4,
  base.ps.lim  = c(0,1,50,2000),
  dat.ps.lim   = c(0,2,30,60,2000),
  psdmodel     ="AD"
) #
#
round( res[,1:6], 3 )

```

	0-1	1-50	50-2000	f0:(Intercept)	b:(Intercept)	c:(Intercept)
[1,]	4.338	4.653	91.008	0.587	0.366	4.222
[2,]	59.656	6.932	33.410	0.807	0.148	3.208
[3,]	13.609	14.906	71.486	0.789	0.497	1.281
[4,]	3.408	23.472	73.119	0.571	0.412	1.629
[5,]	24.117	49.479	26.405	0.619	0.265	4.298
[6,]	4.476	81.339	14.253	0.521	0.318	9.100
[7,]	24.366	62.039	13.598	0.620	0.255	6.744
[8,]	44.507	41.646	13.847	0.721	0.189	5.920
[9,]	63.849	14.739	21.412	0.833	0.171	1.102
[10,]	74.779	11.980	13.241	0.874	0.087	4.801
[11,]	11.933	15.827	72.239	0.611	0.361	1.988
[12,]	46.492	39.848	13.658	0.731	0.183	5.538

```

#
round( res[,7:ncol(res)], 3 )

```

	r0:(Intercept)	dev
[1,]	0.634	0.796
[2,]	0.138	0.000
[3,]	0.888	0.000
[4,]	0.179	0.000
[5,]	0.039	0.000
[6,]	0.032	0.014
[7,]	0.031	0.000
[8,]	0.035	0.000
[9,]	0.090	0.000
[10,]	0.052	0.000
[11,]	0.231	0.000
[12,]	0.035	0.000

The first 3 columns are the predicted values with a sum not equal to 100% (can be normalised by `TT.normalise.sum.X()`). The following 4 columns are the fitted PSD model parameters. And the last column is the Residual Sum of Squares (deviance). Note that the transforming results may be slightly different even with the same function parameters. This is caused by the nature of `drc`

package in fitting dose-response models.

Sometimes, the fitting will failed for the iteration is not converged or some errors and warnings happened. These can be ignored, as you can get the transforming results.

The following PSD models are implemented: Anderson (AD), Fredlund4P (F4P), Fredlund3P (F3P), modified logistic growth (ML), Offset-Nonrenormalized Lognormal (ONL), Offset-Renormalized Lognormal (ORL), Skaggs (S), van Genuchten type(VG),van Genuchten modified, Weibull (W), Logarithm(L), Logistic growth (LG), Simple Lognormal (SL),Shiozawa and Compbell (SC). The performance of PSD models is influenced by many aspects like soil texture class, number and position (or closeness) of observation points, clay content etc. The latter four PSD models perform worse than the former ten. The AD, F4P, S, and W model is recommended for most of texture classes. And it will be even better to compare several different PSD models and using the results of the model with the minimum residual sum of squares. Except S and W models, all the PSD models could be used to predict the content below the minimum input limit. The "psdmodel" option could be changed to any other of the above models:

```
res <- TT.text.transf.Xm(
  tri.data      = my.text4,
  base.ps.lim  = c(0,1,50,2000),
  dat.ps.lim   = c(0,2,30,60,2000),
  psdmodel     = "ML"
) #
#
round( res[,1:6], 3 )

      0-1    1-50  50-2000  a:(Intercept)  b:(Intercept)  c:(Intercept)
[1,]  4.929  3.965  91.106      19.543        12.805         0.997
[2,] 59.849  6.848  33.302       0.675         5.741         0.983
[3,] 14.721 13.805  70.984       6.473         4.911         0.549
[4,]  4.413 22.512  72.510      53.879         7.420         0.304
[5,] 24.466 46.833  28.700       3.162        62.765         1.140
[6,]  4.269 76.354  19.377      27.028        56.061         0.826
[7,] 24.185 58.851  16.964       3.259        72.589         1.090
[8,] 44.788 38.541  16.671       1.238       180.296         1.534
[9,] 64.027 14.559  21.321       0.615         4.399         0.563
[10,] 74.978 11.682  13.340       0.334       249.107         1.927
[11,] 12.406 15.396  71.926       8.170         5.554         0.527
[12,] 46.747 37.139  16.114       1.146       144.534         1.467

#
round( res[,7:ncol(res)], 3 )

[1] 0.000 0.000 1.669 1.071 0.000 0.012 0.000 0.000 0.011 0.000 0.205 0.000
```

Because the current PSD model fitting is quite time-consuming and some models are not always successful for all soils, you can change the PSD model,

or optimization method potentially at the cost of some accuracy. The default "omethod" option (i.e. "all") is to run all methods and choose the best results with minimum residual sum of squares. The optional methods are "Nelder-Mead", "BFGS", "CG", "L-BFGS-B", "SANN" (see `optim()` for details.)

```
res <- TT.text.transf.Xm(
  tri.data      = my.text4,
  base.ps.lim  = c(0,1,50,2000),
  dat.ps.lim   = c(0,2,30,60,2000),
  psdmodel     = "ML",
  omethod      = "SANN"
) #
#
round( res[,1:6], 3 )

      0-1   1-50 50-2000 a:(Intercept) b:(Intercept) c:(Intercept)
[1,]  4.942  3.946  91.112      19.470      13.390      1.014
[2,] 59.849  6.848  33.302       0.675       5.741       0.983
[3,] 14.721 13.805  70.984       6.473       4.911       0.549
[4,]  4.414 22.512  72.510      53.854       7.420       0.304
[5,] 24.468 46.832  28.701       3.161      62.782       1.140
[6,]  4.299 76.329  19.372      26.776      56.349       0.828
[7,] 24.185 58.851  16.964       3.259      72.584       1.090
[8,] 44.788 38.541  16.671       1.238     180.289       1.534
[9,] 64.022 14.566  21.319       0.615       4.395       0.563
[10,] 74.977 11.683  13.340       0.334     248.871       1.927
[11,] 12.405 15.397  71.925       8.172       5.553       0.527
[12,] 46.747 37.139  16.114       1.146     144.520       1.467

#
round( res[,7:ncol(res)], 3 )

[1] 0.000 0.000 1.669 1.071 0.000 0.006 0.000 0.000 0.011 0.000 0.205 0.000
```

### 3 Normalizing soil texture data (sum of X texture classes)

`TT.normalise.sum.X()` is similar to `TT.normalise.sum()`. But it normalize the sum of the X ( $X > 1$ ) texture classes instead of 3. The option `tri.data` should be a `data.frame` with only soil texture data (no additional extra columns should be present).

```
my.text5 <- data.frame(
  "CLAY"   = c(05,60,15,04.9,25,05,25,45,65,75,13,47),
  "FSILT"  = c(02,04.3,10,15,25,40,35,20,10,05,10,20),
  "CSILT"  = c(03,04,05,10,30,45,30,25,05,10,07.2,23.3),
  "SAND"   = c(90.5,32,70,70,20.3,10.9,9.3,9.4,20,10,70,10)
) #
#
res <- TT.normalise.sum.X(
```

```

    tri.data    = my.text5,
    residuals   = TRUE
) #

[1] 100.5 100.3 100.0 99.9 100.3 100.9 99.3 99.4 100.0 100.0 100.2 100.3

#
res

```

	CLAY	FSILT	CSILT	SAND	residuals
[1,]	4.975124	1.990050	2.985075	90.049751	0.5
[2,]	59.820538	4.287139	3.988036	31.904287	0.3
[3,]	15.000000	10.000000	5.000000	70.000000	0.0
[4,]	4.904905	15.015015	10.010010	70.070070	-0.1
[5,]	24.925224	24.925224	29.910269	20.239282	0.3
[6,]	4.955401	39.643211	44.598612	10.802775	0.9
[7,]	25.176234	35.246727	30.211480	9.365559	-0.7
[8,]	45.271630	20.120724	25.150905	9.456740	-0.6
[9,]	65.000000	10.000000	5.000000	20.000000	0.0
[10,]	75.000000	5.000000	10.000000	10.000000	0.0
[11,]	12.974052	9.980040	7.185629	69.860279	0.2
[12,]	46.859422	19.940179	23.230309	9.970090	0.3