Clim. Past Discuss., 10, C19–C26, 2014
www.clim-past-discuss.net/10/C19/2014/
© Author(s) 2014. This work is distributed under
the Creative Commons Attribute 3.0 License.

Climate of the Past Discussions

Interactive comment on "Paleoclimate and weathering of the Tokaj (NE Hungary) loess-paleosol sequence: a comparison of geochemical weathering indices and paleoclimate parameters" *by* A.-K. Schatz et al.

G. Ujvari

ujvari.gabor@csfk.mta.hu

Received and published: 20 February 2014

Dear Authors,

First of all, congratulations for your paper. This is a really systematic study on the Tokaj sequence with many important results and observations. It is well-written and the results and conclusions are presented in a logical manner. I particularly like the chapter(s) dealing with the weathering indices. So, I personally suggest that it should be published in CP. Despite the fact that my impression is favorable, I can't help re-

vealing my concerns and criticism regarding some issues. I hope this will help further improving the paper (and sorry, but I won't focus on its strengths).

1) You write in chapter 5.2. (page 482, line 7) that 'Both MS and grain size distribution are commonly applied as indicators of weathering intensity (Buggle et al., 2009; Marković et al., 2008; Terhorst et al., 2014)'.

I simply question here that grain size would be a first-order proxy of weathering. Of course, weathering has an effect on grain size, but GS can be regarded as an integrated 'index' being affected by wind (or transport medium) strength, dust source distance, water availability in the source region and also weathering, if we are talking about paleosols and not just loess. However, atmospheric circulation changes, ratios of wet and dry deposition, dust source distance and also sediment availability will define the GS signal and it seems to be quite hard to decipher the effect of weathering on grain size. Also you demonstrate a strong correlation between grain size (>30 micron) and Rb/Sr ratios and explain this by weathering. By having a look at Fig. 1, that displays ICP-MS data of three loess samples from Hungary, it is immediately clear that Rb and Sr concentrations are heavily grain size dependent (finer grain size→more clays, micas→higher Rb concentrations). This means there is a strong covariance between GS and the Rb/Sr ratio in loess samples. Thus, if grain size varies owing to wind strength or dust source distance or whatever this will heavily affect the Rb/Sr ratio too, so the strong correlation is not surprising and may not be purely due to weathering. This should be noted somewhere.

2) My second criticism is related to the mean annual temperature (MAT), and mean annual precipitation (MAP) reconstructions that were based on geochemical transfer functions by Sheldon et al. (2002) and Gallagher et al. (2013). In my view, these estimates can only be regarded as semi-quantitative data at most, and I deem as one of the most important results of your study that has not been emphasized, but should be, that these values of MAT or MAP should be treated with extreme caution. I believe that for reconstructing MAP and MAT other approaches are much more reliable

(MAP: magnetic susceptibility, MAT: tooth enamel δ18O or groundwater noble gases). Regarding PWI-based MAP reconstructions, the regression equation of Gallagher et al. (2013) have an R2 value of 0.20, clearly showing that there is no correlation between PWI and MAP. As for MAT, they did a logarithmic regression that has an R2 of 0.57, quite low too. But why don't we do a linear regression that have an R2 value of 0.50 (see Fig. 2)? (One could play a lot with regressions, but at the end we conclude that such PWI-based estimates of MAT will be very uncertain.) The major problem here is that the dataset by Gallagher et al. (2013) have a huge scatter and their regression model simply does not describe the dataset well (if we suppose that there is a one-by-one relationship between PWI and MAT, at all). To prove this, I performed the regression based on their data and calculated all the necessary parameters to gain insight into how well their regression model works. They have given an error estimate on their y values (MAT) which is 2.1. This value is exactly the root mean squared error (RMSE, σ0) of the regression, but from a mathematical statistical point of view, this cannot be used for estimating the errors of y, i.e. MAT values. In general, for defining the uncertainties one has to calculate the 95% confidence bands, but for any independent estimation of MAT and its uncertainties one has to use the 95% prediction intervals (see Fig. 3 and the equations given below in the 'Appendix'). If you have a look at this figure it is visible that any of your MAT estimates will have an error of ca. ±4-5 °C, twice as high as it was specified by Gallagher et al. (2013). This, of course, can be calculated rigorously, so I have provided an Excel spreadsheet for this (hope I could upload). In my view, these more conservative uncertainty estimates should be used in your work when you compare your MAT estimates with the literature data.

Again, hope I could help to foster your interpretations and I look forward to seeing your final paper in Climate of the Past.

Best regards, Gabor Ujvari PhD senior research fellow Geodetic and Geophysical Institute, Research Centre for Astronomy and Earth Sciences Hungarian Academy of Sciences Email: ujvari.gabor@csfk.mta.hu

Figure captions

Fig. 1. Rb vs. Sr and Rb vs. Rb/Sr ratio plot of three LGM loess samples (Me-L1, Me-L2, Pa-L1) as a function of grain size. Lines in color define Rb/Sr ratios.

Fig. 2. Linear and logarithmic regression of forest soil data from Gallagher et al. (2013) (alfisols, ultisols, and inceptisols, excluding data below 6 °C). X-axis: PWI, Y-axis: MAT (in °C).

Fig. 3. Logarithmic regression on data from Gallagher et al. (2013) with lower and upper 95% confidence (blue) and prediction bounds (red). Note that the X-axis is logarithmic here.

Appendix (please find it as a pdf supplement!)

To calculate the uncertainties of y (MAT) (σy): σ_yˆ2=AMAˆT

where

A=[âŰă(∂y/∂a&∂y/∂b&∂y/∂x)]

and

M=[âŰă(σ_aˆ2&ãĂŰcovãĂŮ_ab&0@ãĂŰcovãĂŮ_ab&σ_bˆ2&0@0&0&σ_xˆ2)]

, i.e. M is the variance-covariance matrix, and AT is transpose of matrix A.

σ_y=√((∂y/∂a)ˆ2 σ_aˆ2+(∂y/∂b)ˆ2 σ_bˆ2+(∂y/∂x)ˆ2 σ_xˆ2+2 ∂y/∂a ∂y/∂b ãĂŰcov-ãĂŮ_ab)=√(xˆ2 σ_aˆ2+σ_bˆ2+aˆ2 σ_xˆ2+2x_ab σ_a σ_b)

From this, we can calculate the confidence and prediction bands by using

σ_(y_(CI 95%))=t_((1-âĹİ/2,n-2)) σ_y and σ_(y_(PI 95%))=t_((1-âĹİ/2,n-2)) √(σ_yˆ2+σ_0ˆ2) , where t is the t score equal to N-2 degrees of freedom from the Student's distribution, α=1-(confidence level/100) (confidence level is 95% here), and σ0 (RMSE of the regression) is

$\sigma_0=\sqrt{\left(\sum_{k=1}^{N}((y_i-y_p)^2)_k\right)/(N-2)}$, where N is the number of independent x_i-y

Interactive comment on Clim. Past Discuss., 10, 469, 2014.

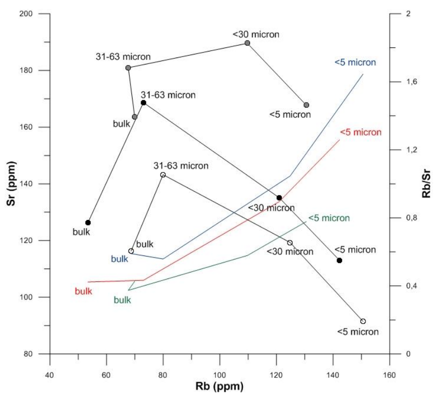

Fig. 1.

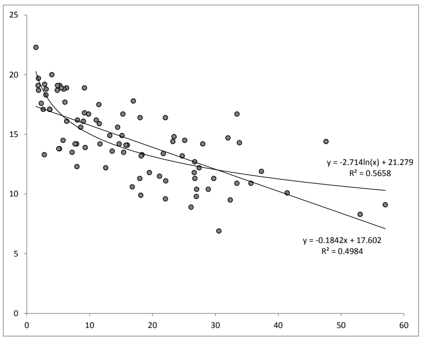
y = -2.714ln(x) + 21.279
R² = 0.5658
y = -0.1842x + 17.602
R² = 0.4984

Fig. 2.

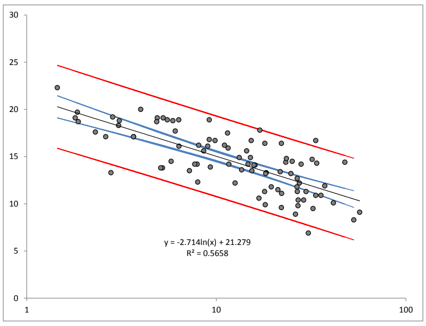
y = -2.714ln(x) + 21.279
R² = 0.5658

Fig. 3.