Soto-Kerans, G., Stockli, D., Janson, X., Lawton, T.F., and Covault, J.A., 2019, Orogen proximal sedimentation in the Permian foreland basin: Geosphere, https://doi.org/10.1130/GES02108.1

SUPPLEMENTAL FILE 1

Plotting Software

DetritalPy (Sharman et al., 2018) was employed in plotting all DZ U-Pb data of this study. This Python-based plotting software uses the Jupyter Notebook interface and allows for quick plotting of detrital age distributions using multiple visualization types such as Kernel Density Estimation (KDE) plots, Probability Density Plots (PDP), pie charts, and MDA. Here, we utilize the KDE plots for visualization of a large number of data points and MDA to track transport lag time and volcanic activity in the source regions. We used a Matlab script by Vermeesch (2013) for Multi-Dimensional Scaling (MDS) plots (discussed below). An MDS plot can be seen as a simplification of intersample dissimilarity by plotting pairwise sample comparisons in relation to all samples as opposed to single sample comparison (Vermeesch, 2013). In this way, broad trends can be visualized and interpreted.

Data Representation

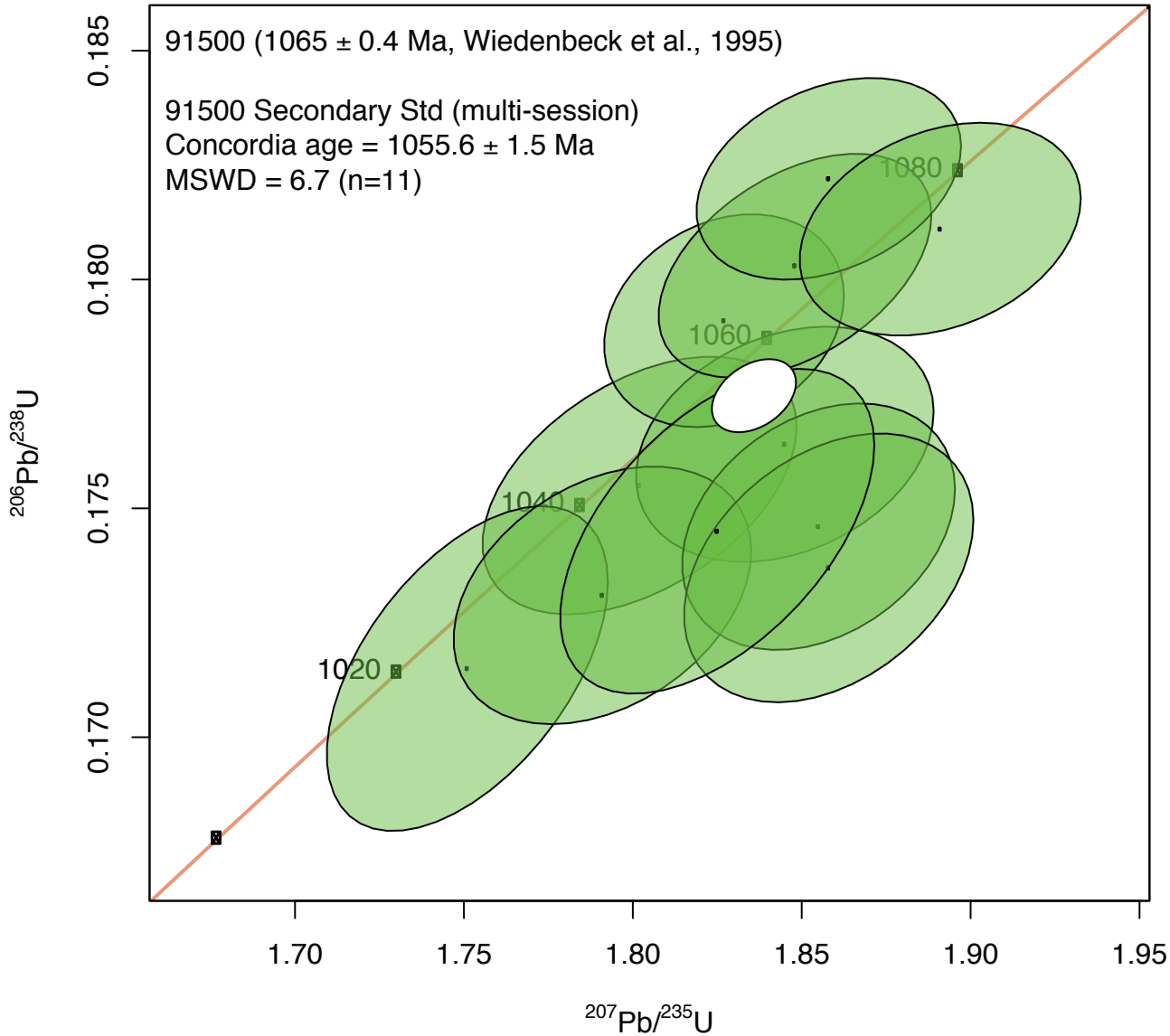
A Kernel Density Estimation (KDE) is produced by arranging detrital zircon age measurements along a line and stacking a 'kernel' (e.g., fit of box, triangle, or Gaussian distribution) of a specified width ('bandwidth') on top of them (Vermeesch, 2012). Given a set of n measurements x_i (I = 1 → n), the KDE can be written as:

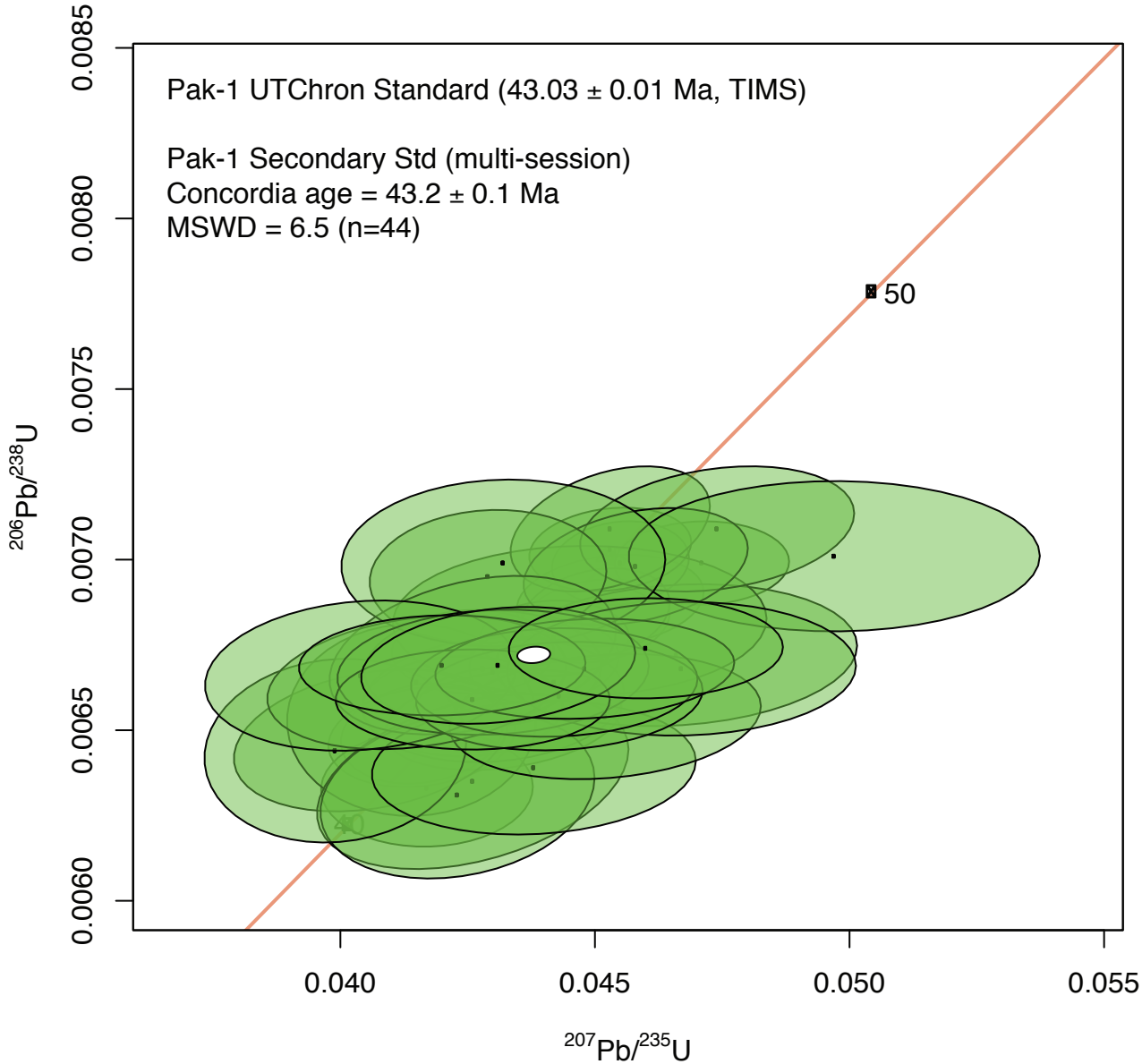
$$KDE(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

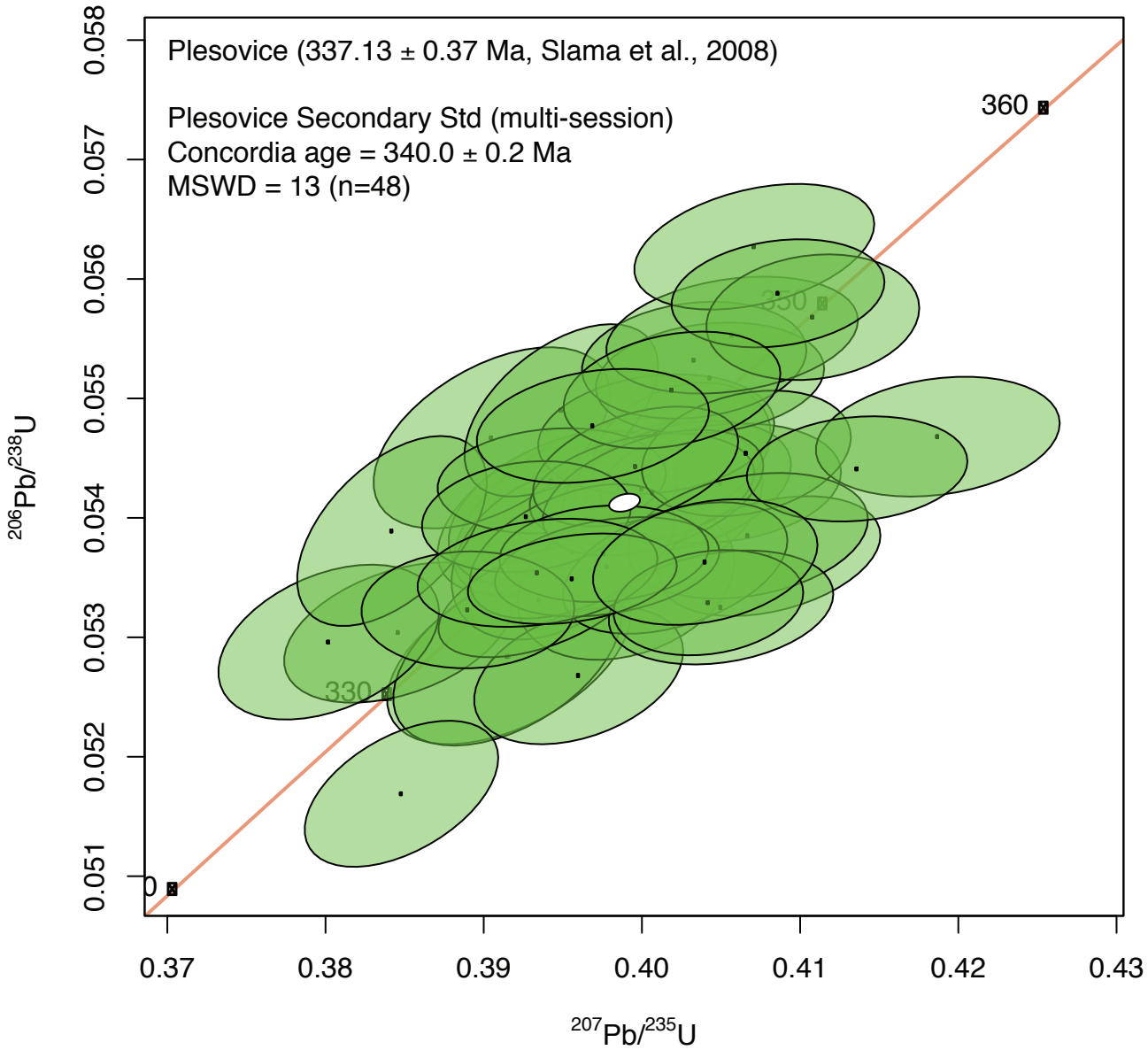
where K is the 'kernel' and h is the 'bandwidth' (Vermeesch, 2012).

Application of KDEs helps to negate probability biases by determining density of measurements as opposed to distribution weighted by analytical precision of measurements as seen in Probability Density Plots (PDPs). However, visual inspection of DZ datasets through PDPs and KDEs potentially evokes natural bias by a researcher (Satkoski et al., 2013). These plotting methods have great utility when looking at big-picture trends across the sample space and provide a visual aid that represents the data well in publication. However, meticulous inspection of the 1720 DZ ages presented in this study becomes too much information for the human eye to accurately process (Vermeesch, 2013). To correct for this, application of multiple statistical analyses provides inter-sample trend comparisons, which may otherwise be overlooked or misinterpreted. By use of a table of pairwise K-S dissimilarity measurements of a given sample set, Vermeesch (2013) formatted the statistical technique of Multi-Dimensional Scaling (MDS). MDS produces a two dimensional 'map' of points on which samples with similar total DZ age spectra cluster and dissimilar samples plot at distance (Figs. 11 and 14). The output plot can be seen as a simplification of a complex matrix of QQ plots which take each individual sample and compare its similarity along a 1:1 line with each other sample in the study. Q-Q plotting forms an upper triangular matrix of n(n-1)/2 individual plots (where n is the number of samples in a study) whereas MDS gives each sample a unique value in relation to all other samples in the study. Using a dissimilarity metric to plot the points at distance yields a 'map' of points in which points that plot at distance reflect a relatively high dissimilarity and vice versa for those that plot in proximity (Vermeesch, 2013).

11)


91500 (1065 ± 0.4 Ma, Wiedenbeck et al., 1995)
91500 Secondary Std (multi-session)
Concordia age = 1055.6 ± 1.5 Ma
MSWD = 6.7 (n=11)
1020
1040
1060
1080
0.170
0.175
0.180
0.185
1.70
1.75
1.80
1.85
1.90
1.95
206Pb/238U
207Pb/235U


Pak-1 UTChron Standard (43.03 ± 0.01 Ma, TIMS)
Pak-1 Secondary Std (multi-session)
Concordia age = 43.2 ± 0.1 Ma
MSWD = 6.5 (n=44)
50
40
0.0060
0.0065
0.0070
0.0075
0.0080
0.0085
$^{206}Pb/^{238}U$
0.040
0.045
0.050
0.055
$^{207}Pb/^{235}U$


Plesovice (337.13 ± 0.37 Ma, Slama et al., 2008)
Plesovice Secondary Std (multi-session)
Concordia age = 340.0 ± 0.2 Ma
MSWD = 13 (n=48)
360
350
330
0
0.051
0.052
0.053
0.054
0.055
0.056
0.057
0.058
0.37
0.38
0.39
0.40
0.41
0.42
0.43
206Pb/238U
207Pb/235U