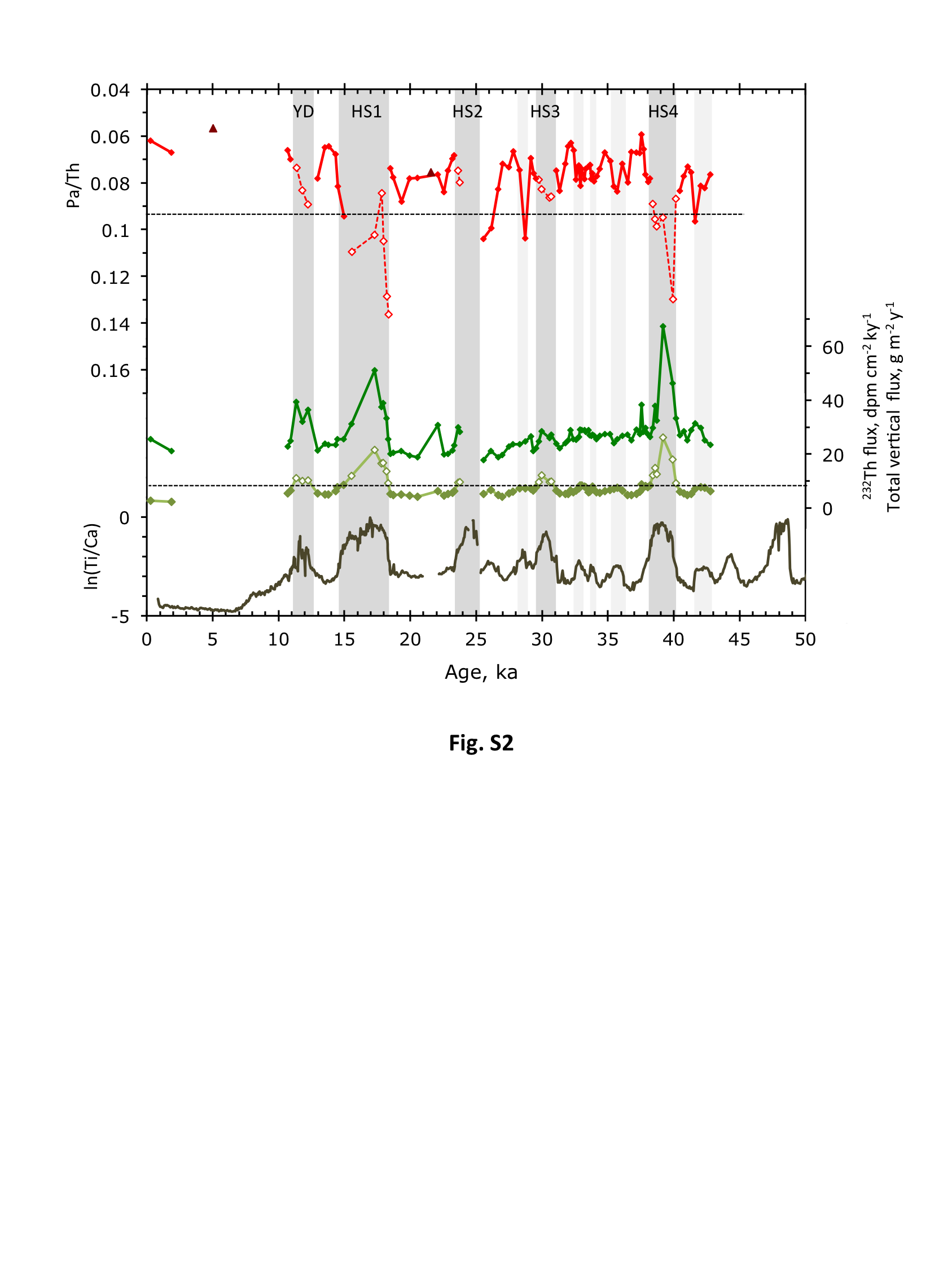
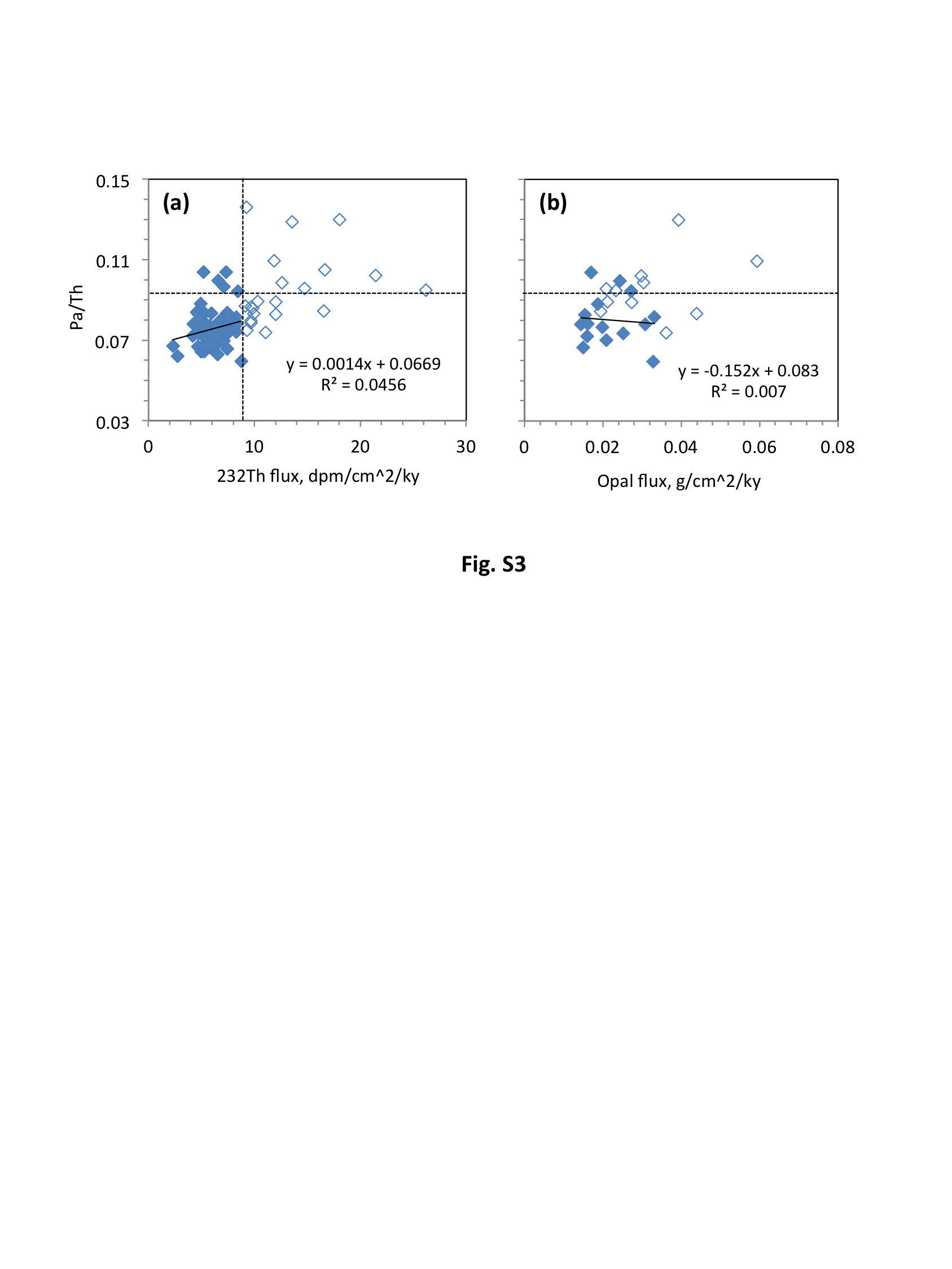


**Figure S1.** Alignment of GeoB3910-2 ln(Ti/Ca) to MD09-3257 ln(Ti/Ca) signal over the time interval 32-50 ka, i.e. the portion of the *C. wuellerstorfi* δ13C (δ13CCw) record consisting in GeoB3910 measurements. From top to bottom: GeoB3910-2 δ13CCw, GeoB3910-2 and MD09-3257 ln(Ti/Ca) (both multiplied by 0.3 for graphic purposes), GeoB3910-2 sedimentation rate. Triangles denote alignment pointers between GeoB3910-2 and MD09-3257 ln(Ti/Ca) signals.

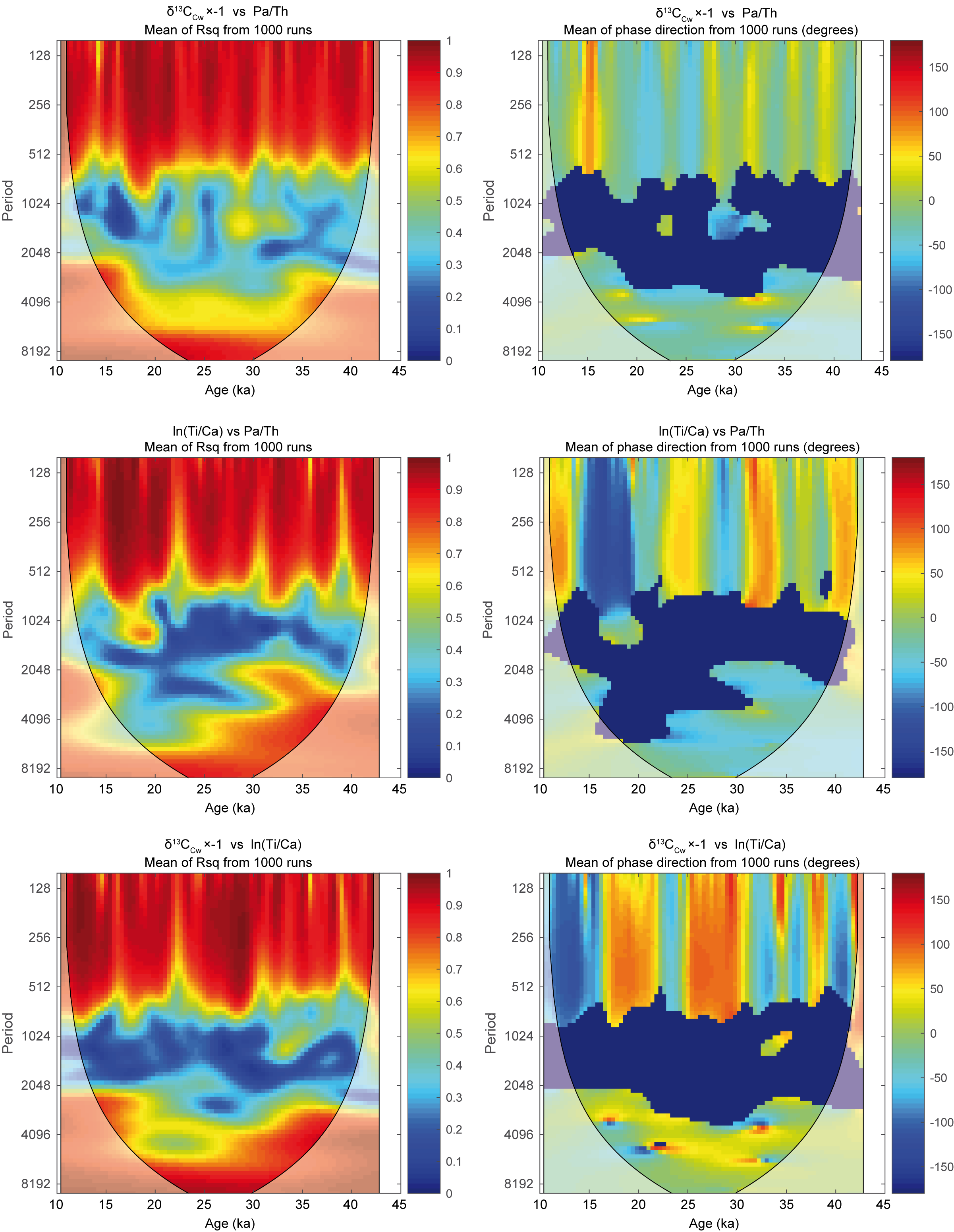
The uncertainty on the tie points relative timing ranges from 70 to 150 y (mean uncertainty = 102 y) over the time interval 32-50 ka. NB: It is lower and ranges from 80 to 110 y (mean uncertainty = 90 y) over the time interval 32-38 ka, over which the cross-wavelet analysis yields a mean relative phase of 247 ± 89 y between δ13CCw and Pa/Th.



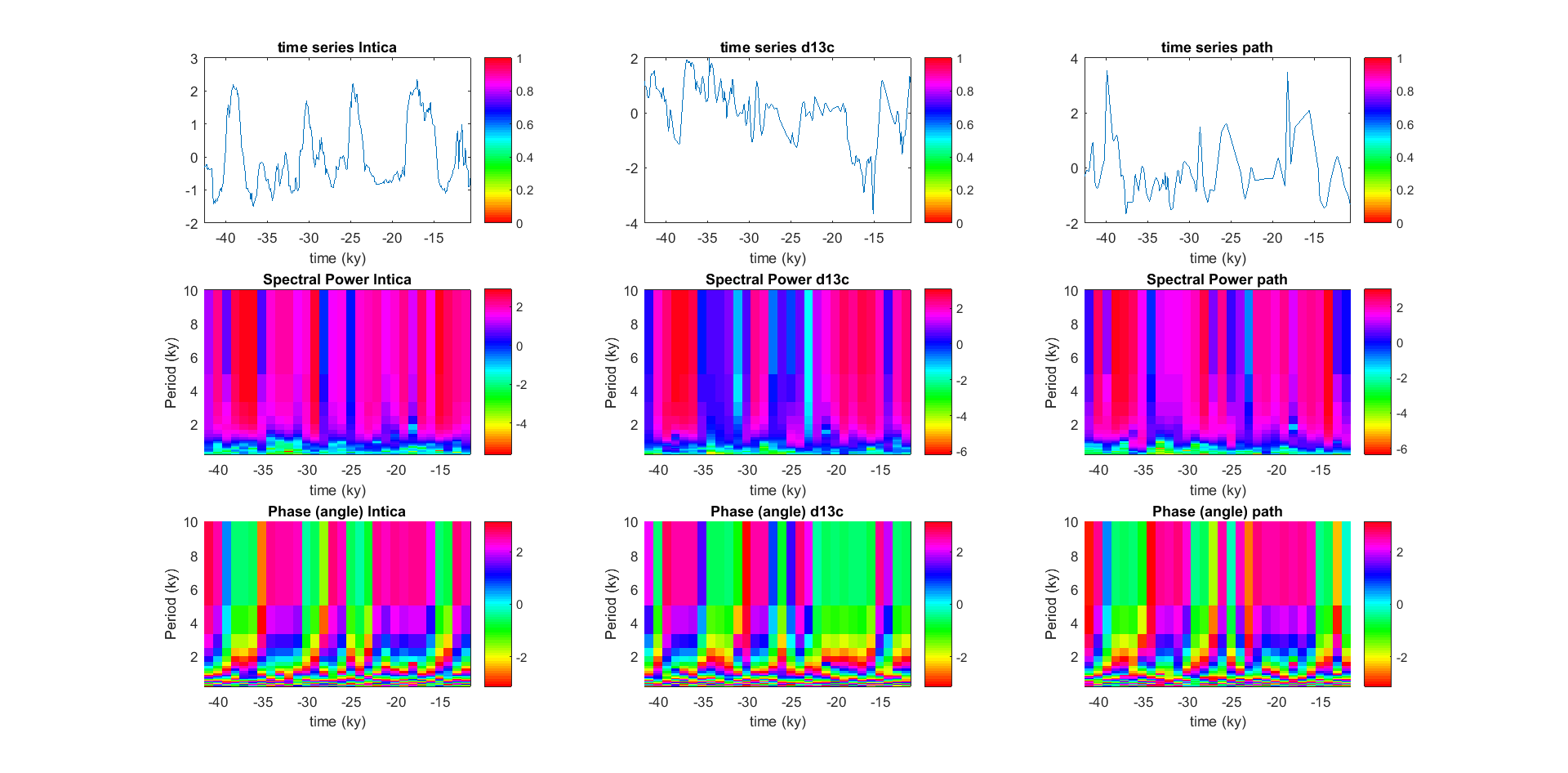
**Figure S2.** MD09-3257 sedimentary Pa/Th, 230Th-normalized 232Th flux (olive green), total vertical flux (green), and ln(Ti/Ca) versus calendar age. Dark triangles denote two sedimentary Pa/Th data points that were measured on core GeoB3910 by J. Lippold (all data given in Table S1). Olive green empty symbols denote 232Th flux values larger than 9 dpm cm-2 ky-1 (black dotted line) and correspond to samples within the main precipitation events PE0 to PE4. Horizontal black dotted lines indicate the Pa/Th production ratio (0.093) and 232Th flux threshold of 9 dpm cm-2 ky-1.



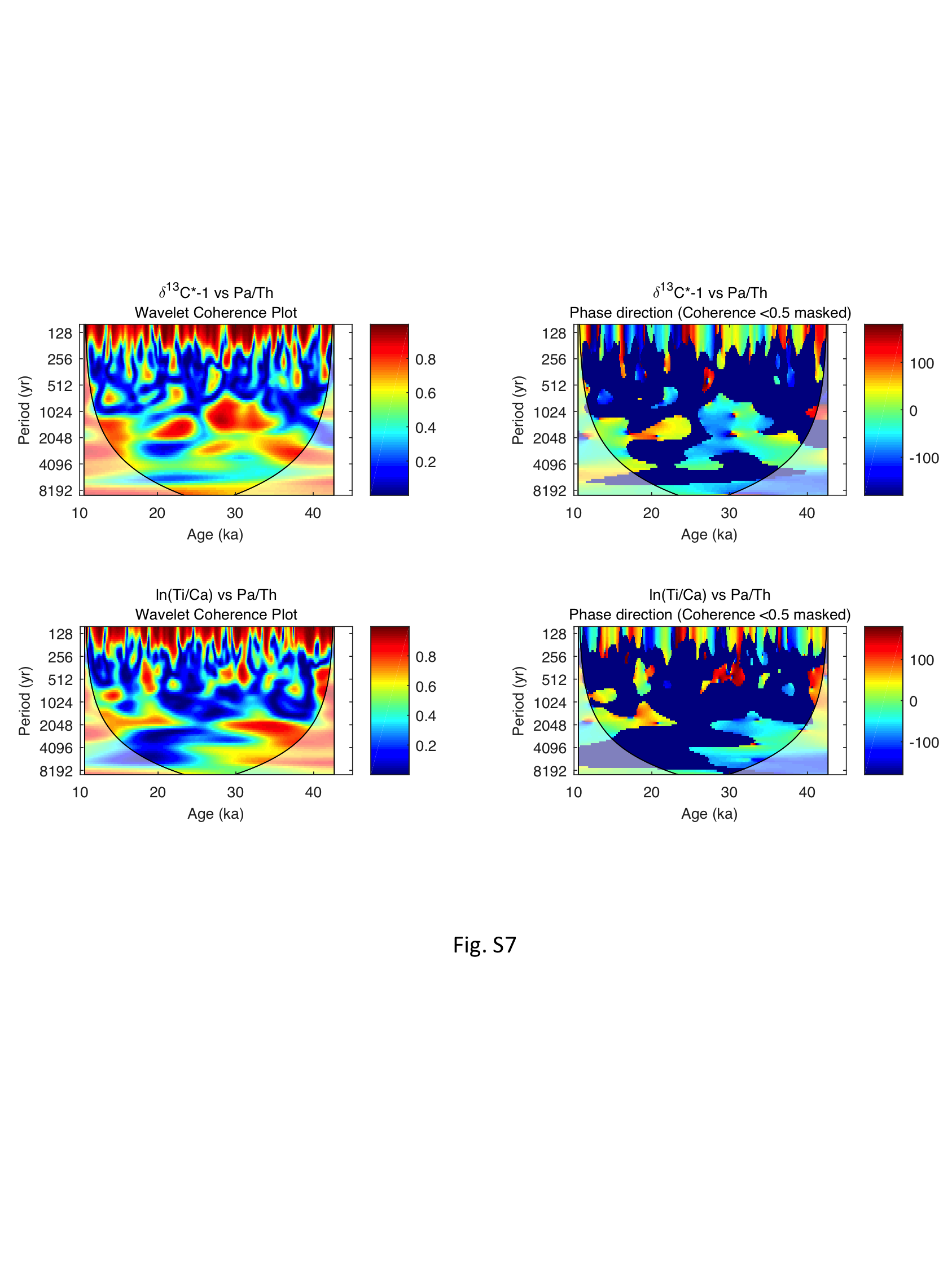
**Figure S3.** MD09-3257 sedimentary Pa/Th versus **(a)** 230Th-normalized 232Th flux, and **(b)** opal flux. Empty symbols denote 232Th flux values larger than 9 dpm cm-2 ky-1. Empty symbols correspond to samples within the main precipitation events PE0 to PE4 (Fig. S2). New opal measurements were added to the ones published in ([Burckel et al., 2015](#_ENREF_1)). The new opal measurements were generated by Fourier transform infrared spectroscopy, as described in ([Vogel et al., 2016](#_ENREF_3)) (all data are given in Table S2). The black dotted lines correspond to those of Fig. S2.

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**Figure S4.** Cross-wavelet results obtained when the time series are resampled with a time step of 400 y. Results are meaningful for periods > 800 y (corresponding to a Nyquist frequency = 1/(2\*400 y)).

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**Figure S5.** Spectrograms of MD09-3257 ln(Ti/Ca), sedimentary Pa/Th, and composite δ13CCw records obtained computing finite time Fourier transforms dividing the signal in 20 windows, with 10 overlaps and using 100 frequencies. Upper panels: normalized signals. Middle and lower panels: power spectra and absolute phases, respectively, of each signal taken separately. Spectral amplitude is mostly concentrated in periods longer than 2 ky and decreases with the period. This kind of power spectral density is typical of turbulent climate time series ([Lovejoy and Schertzer, 1990](#_ENREF_2)). Sensitivity (not shown) suggest that results for periods larger than 6 ky are not interpretable due to the short duration of the analyzed records.

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**Figure S6.** Cross-wavelet results obtained for the subset of Pa/Th data points not affected by large particle fluxes.

**References**

Burckel, P., Waelbroeck, C., Gherardi, J.-M., Pichat, S., Arz, H., Lippold, J., Dokken, T., and Thil, F.: Atlantic Ocean circulation changes preceded millennial tropical South America rainfall events during the last glacial, Geophys. Res. Lett., 42, 411-418, 2015.

Lovejoy, S., and Schertzer, D.: Multifractals, universality classes and satellite and radar measurements of cloud and rain fields, Journal of Geophysical Research: Atmospheres, 95, 2021-2034, 1990.

Vogel, H., Meyer‐Jacob, C., Thöle, L., Lippold, J. A., and Jaccard, S. L.: Quantification of biogenic silica by means of Fourier transform infrared spectroscopy (FTIRS) in marine sediments, Limnology and oceanography: methods, 14, 828-838, 2016.

**R script**

library(readxl)

library(writexl)

# imports three time series (d13C, PaTh, and ln\_TiCa)

mydata = read\_xlsx("./input/MD09-3257\_data\_100y\_norm.xlsx")

nline<-length(mydata$Age)

# initializes variables

r13C\_vs\_PaTh<-NULL

r13C\_vs\_TiCa<-NULL

rPaTh\_vs\_TiCa<-NULL

pval13C\_vs\_PaTh<-NULL

pval13C\_vs\_TiCa<-NULL

pvalPaTh\_vs\_TiCa<-NULL

lagm<-NULL

dummy<-NULL

d13C<-matrix(data=NA,nrow=nline,ncol=1)

shiftd13C<-matrix(data=NA,nrow=nline,ncol=length(-10:10))

PaTh<-matrix(data=NA,nrow=nline,ncol=1)

shiftPaTh<-matrix(data=NA,nrow=nline,ncol=length(-10:10))

ln\_TiCa<-matrix(data=NA,nrow=nline,ncol=1)

# computes correlation coefficient r[m] for lag = -m\*100 --> -100

for (m in -10:-1) {

j=m+11

for (i in 1:(nline+m)) {

d13C[i]<-mydata$d13C[i]

shiftd13C[i,j]<-mydata$d13C[i-m]

PaTh[i]<-mydata$PaTh[i]

shiftPaTh[i,j]<-mydata$PaTh[i-m]

ln\_TiCa[i]<-mydata$ln\_TiCa[i]

}

# computes r for d13C vs PaTh ct=cor.test(PaTh,shiftd13C[,j],alternative=c("two.sided"),method=c("spearman"),exact=NULL,conf.level=0.95,continuity=FALSE)

r13C\_vs\_PaTh[j]<-ct$estimate

pval13C\_vs\_PaTh[j]<-ct$p.value

# computes r for d13C vs ln\_TiCa ct=cor.test(ln\_TiCa,shiftd13C[,j],alternative=c("two.sided"),method=c("spearman"),exact=NULL,

conf.level=0.95,continuity=FALSE)

r13C\_vs\_TiCa[j]<-ct$estimate

pval13C\_vs\_TiCa[j]<-ct$p.value

# computes r for PaTh vs ln\_TiCa ct=cor.test(ln\_TiCa,shiftPaTh[,j],alternative=c("two.sided"),method=c("spearman"),exact=NULL,

conf.level=0.95,continuity=FALSE)

rPaTh\_vs\_TiCa[j]<-ct$estimate

pvalPaTh\_vs\_TiCa[j]<-ct$p.value

lagm[j]<-m\*100

}

# computes correlation coefficient r[m] for lag = 0 --> m\*100

for (m in 0:10) {

j=m+11

for (i in (1+m):nline) {

d13C[i]<-mydata$d13C[i]

shiftd13C[i,j]<-mydata$d13C[i-m]

PaTh[i]<-mydata$PaTh[i]

shiftPaTh[i,j]<-mydata$PaTh[i-m]

ln\_TiCa[i]<-mydata$ln\_TiCa[i]

}

# computes r for d13C vs PaTh

ct=cor.test(PaTh,shiftd13C[,j],alternative=c("two.sided"),method=c("spearman"),exact=NULL,conf.level=0.95,continuity=FALSE)

r13C\_vs\_PaTh[j]<-ct$estimate

pval13C\_vs\_PaTh[j]<-ct$p.value

# computes r for d13C vs ln\_TiCa

ct=cor.test(ln\_TiCa,shiftd13C[,j],alternative=c("two.sided"),method=c("spearman"),exact=NULL,

conf.level=0.95,continuity=FALSE)

r13C\_vs\_TiCa[j]<-ct$estimate

pval13C\_vs\_TiCa[j]<-ct$p.value

# computes r for PaTh vs ln\_TiCa

ct=cor.test(ln\_TiCa,shiftPaTh[,j],alternative=c("two.sided"),method=c("spearman"),exact=NULL,

conf.level=0.95,continuity=FALSE)

rPaTh\_vs\_TiCa[j]<-ct$estimate

pvalPaTh\_vs\_TiCa[j]<-ct$p.value

lagm[j]<-m\*100

}

dummy<-data.frame(lagm=lagm,r13C\_vs\_PaTh=r13C\_vs\_PaTh,pval13C\_vs\_PaTh=pval13C\_vs\_PaTh,

r13C\_vs\_TiCa=r13C\_vs\_TiCa,pval13C\_vs\_TiCa=pval13C\_vs\_TiCa,rPaTh\_vs\_TiCa=rPaTh\_vs\_TiCa,

pvalPaTh\_vs\_TiCa=pvalPaTh\_vs\_TiCa)

write\_xlsx(dummy,"./output/output\_100y.xlsx")

matplot (lagm, cbind (r13C\_vs\_PaTh,r13C\_vs\_TiCa,rPaTh\_vs\_TiCa), pch = 19)