Milankovitch forcing and Cambrian climate dynamics: Integrated stratigraphy of the Miaolingian Epoch in Baltica

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Work environment, packages and data loading

```
#Setting of the work environment
setwd("C:/Users/vjamart/OneDrive - Université de Lausanne/Bureau/Draft Alum Shale/R code/html")

#Loading of the packages that will be used in this study
library(WaverideR)
library(astrochron)
```

```
Welcome to astrochron v1.5 (2025-04-28)
```

```
library(matrixStats)
```

```
Warning: le package 'matrixStats' a été compilé avec la version R 4.2.3
```

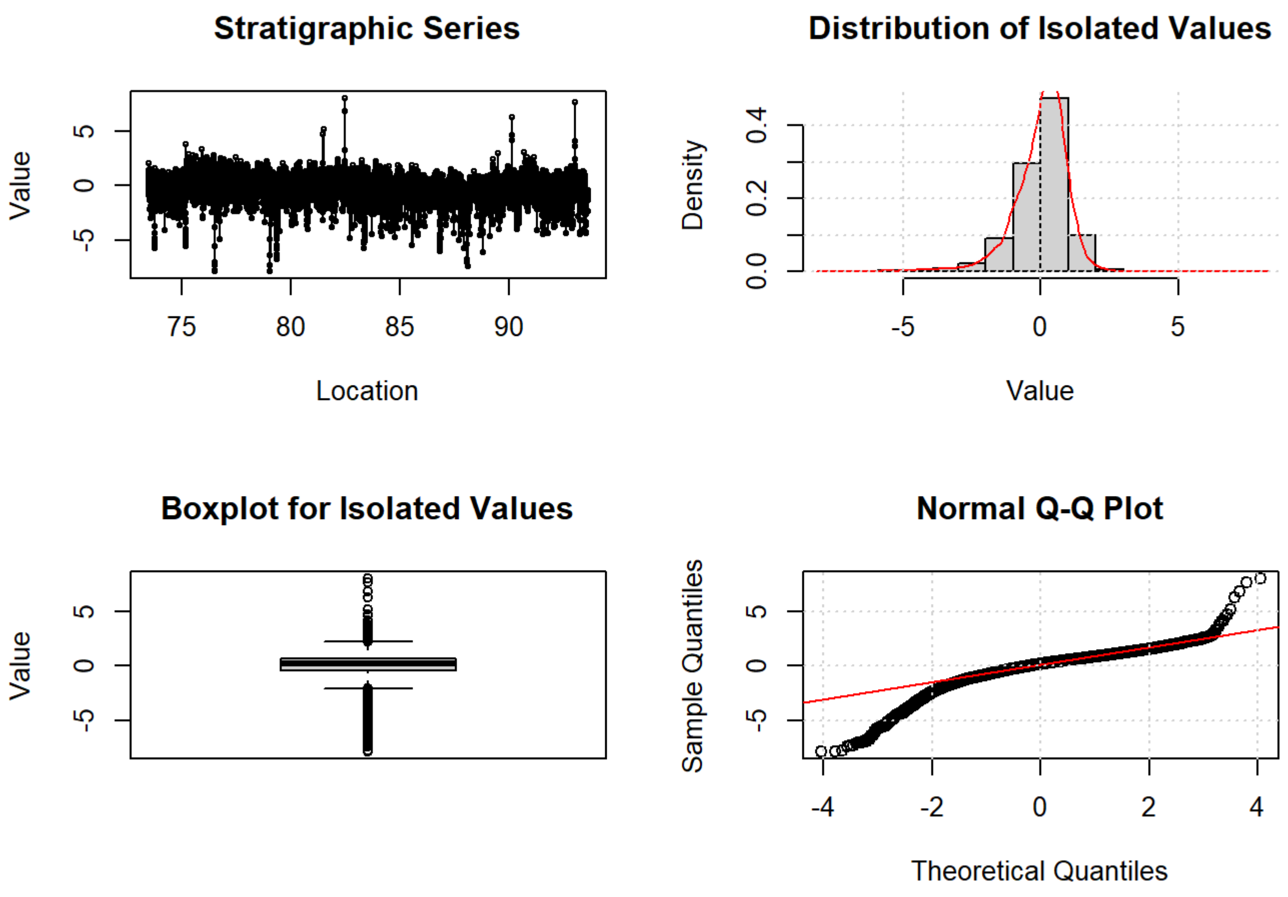
```
#Loading of the dataset file
Alb <- read.csv("Z score.csv", sep=";")
```

Step 1: Data selection, resampling and detrending

1.1. Selecting Titanium data

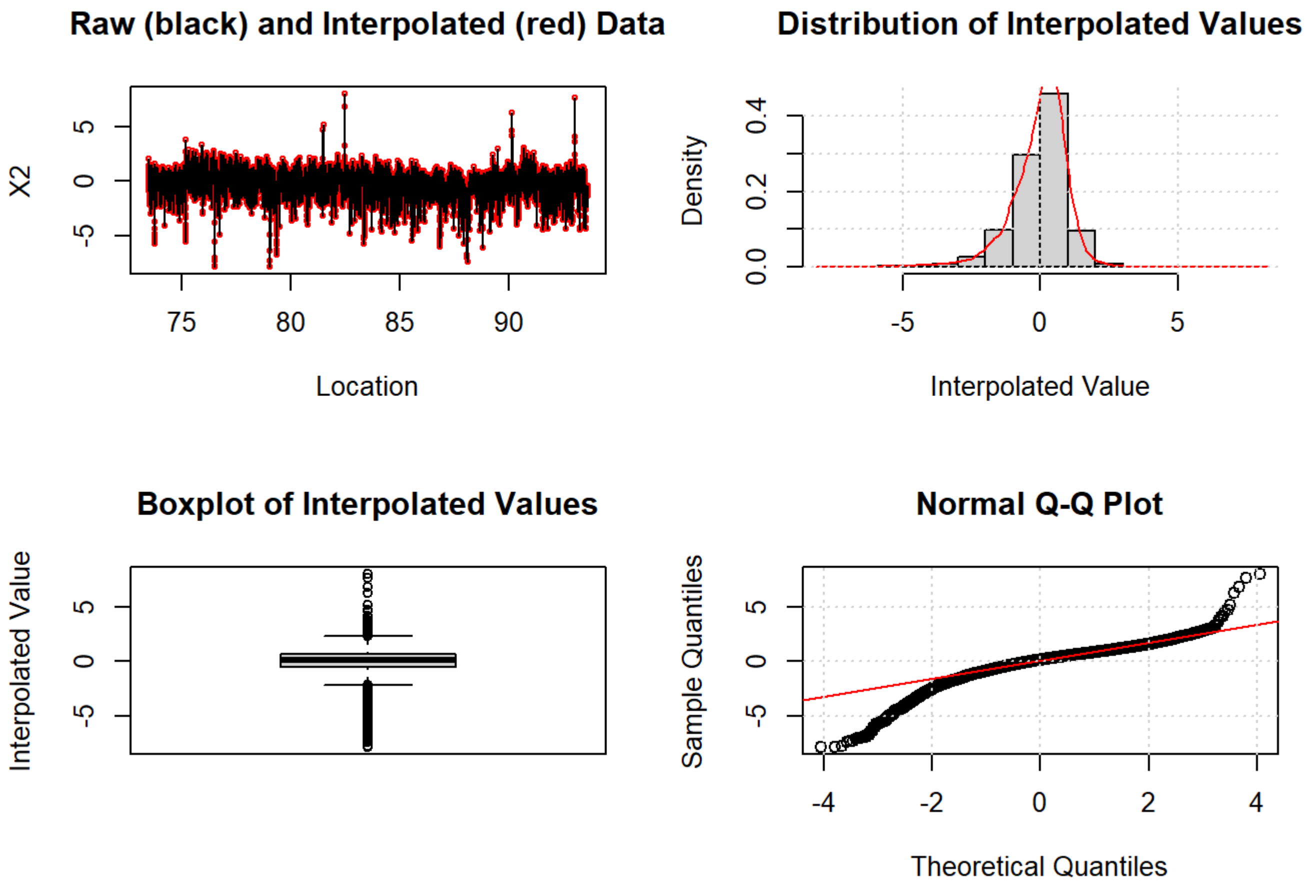
```
# Selection of the data
alb_Ti <- cbind(Alb$DepthAdj,Alb$Ti)
alb_Ti <- na.omit(alb_Ti)
alb_Ti[!is.finite(alb_Ti)] <- NA
alb_Ti <- na.omit(alb_Ti)

#Isolation of the studied time interval
alb_Ti <- iso(dat=alb_Ti, xmin=73.452, xmax=100)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30577
 * Number of columns= 2
 * Minimum= 62.111 , Maximum= 93.61
 * Isolating data between 73.452 and 100
 * Number of data points following culling= 19312
```



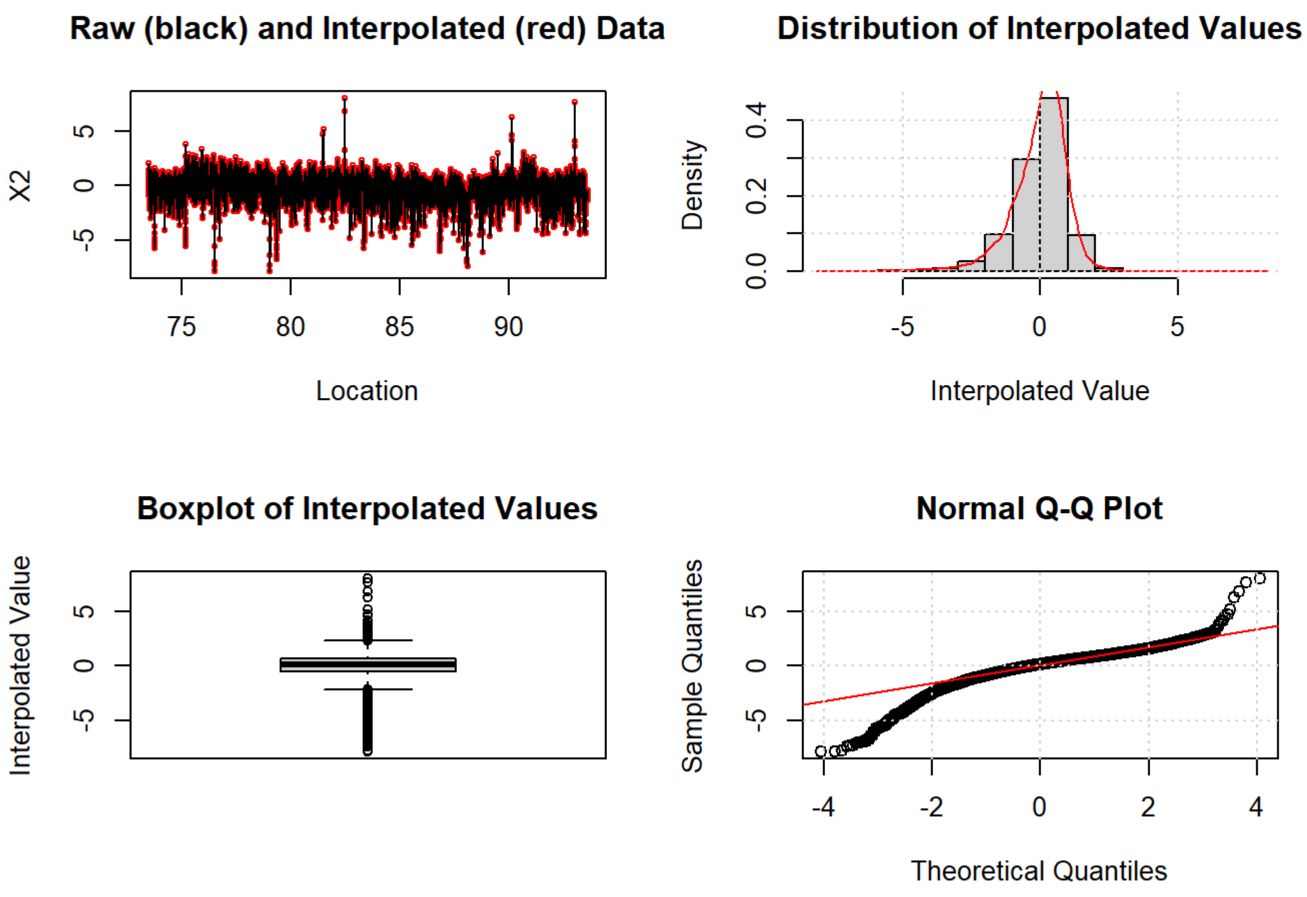

```
alb_Ti <- linterp(alb_Ti, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 19312
 * Determining median sampling interval for series
 * Will interpolate to median sampling interval of 0.001
 * New number of samples= 20158
```



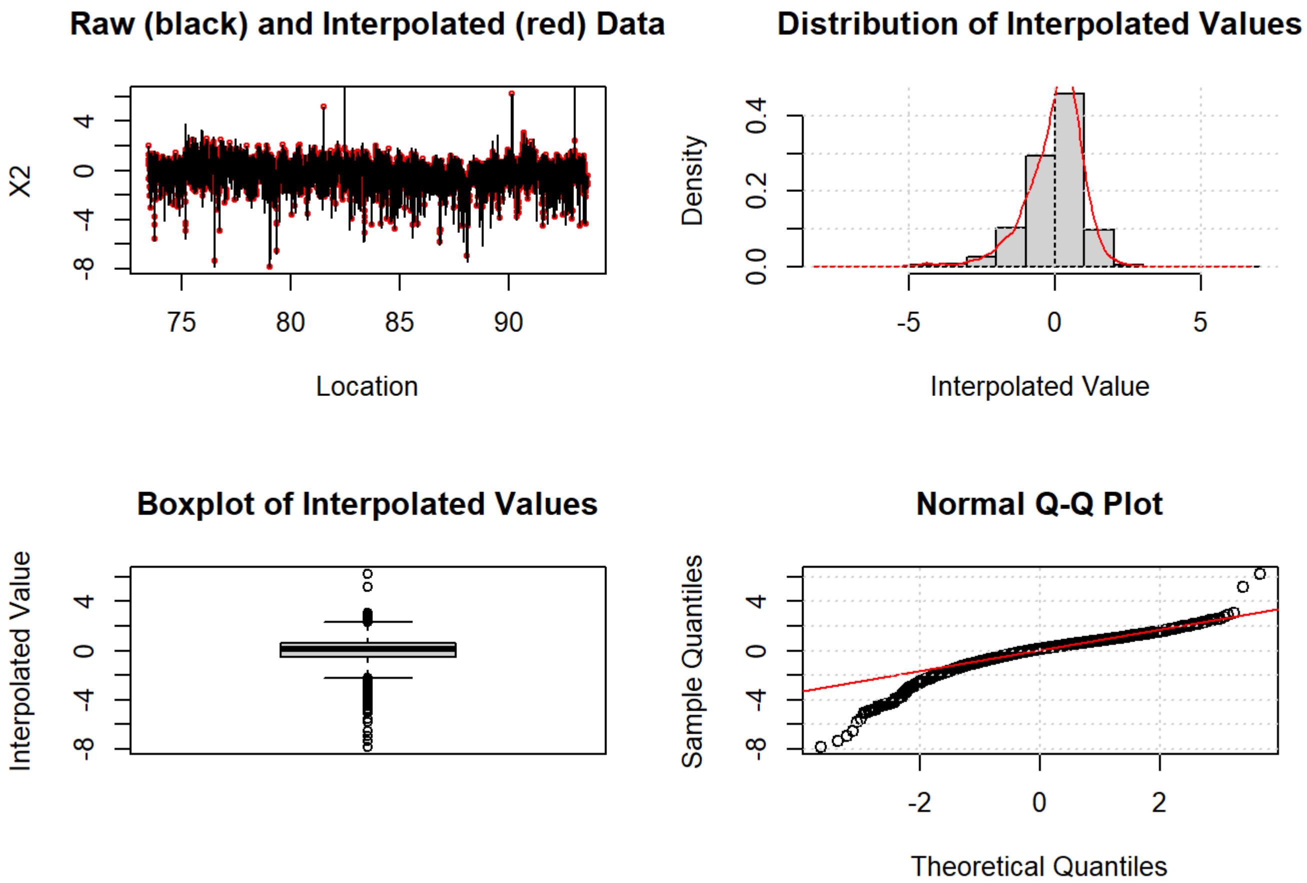

```
#Saving of the 1 mm (non resampled) Ti series
alb_Ti_1mm<-linterp(alb_Ti, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 20158
 * Determining median sampling interval for series
 * Will interpolate to median sampling interval of 0.001
 * New number of samples= 20158
```



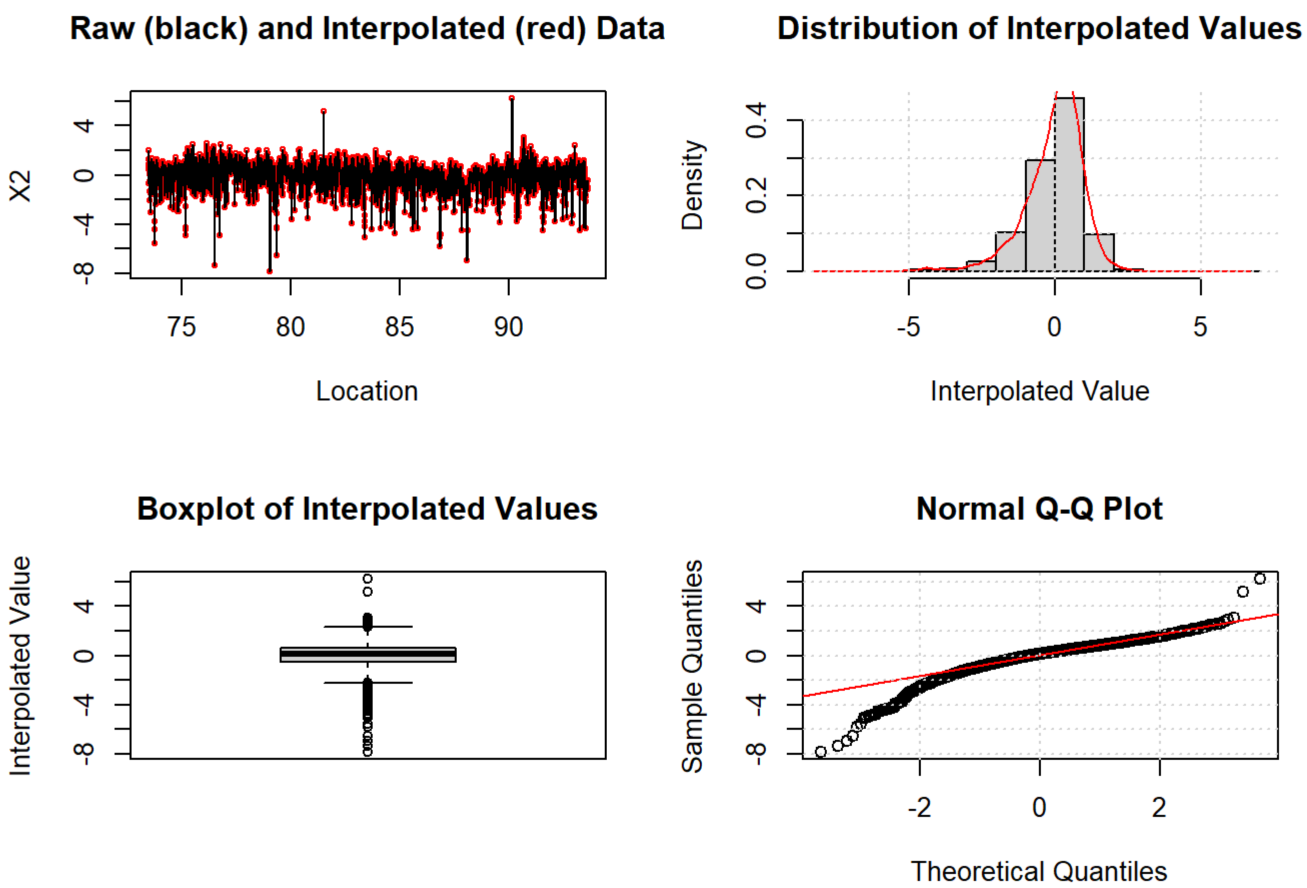

```
#Resampling of the Ti series every 5 mm
alb_Ti <-  linterp(alb_Ti, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 20158
 * New number of samples= 4032
```

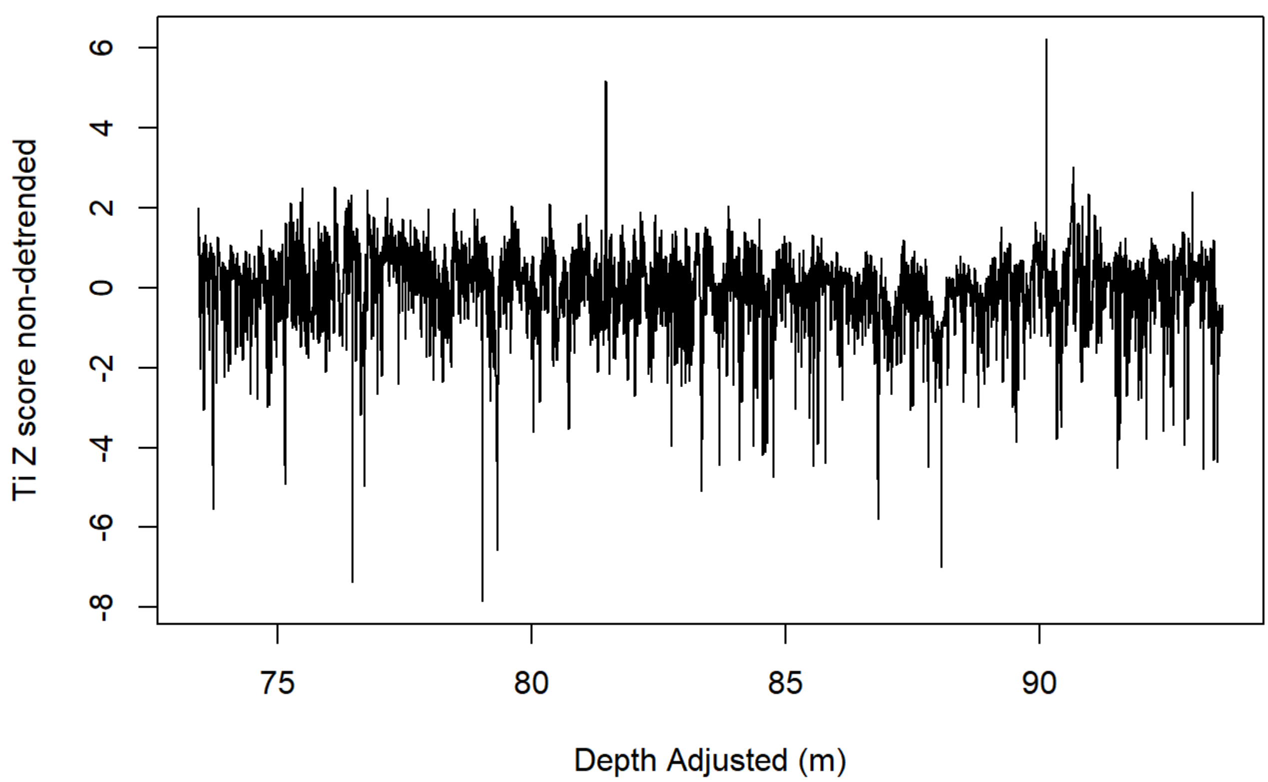



```
#Saving of the non detrended Ti series resampled every 5 mm
alb_Ti_ndet <-  linterp(alb_Ti, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * Determining median sampling interval for series
 * Will interpolate to median sampling interval of 0.005
 * New number of samples= 4032
```




```r
#Plotting of the non detrended 5mm Ti series
plot(alb_Ti_ndet, type = "l", xlab = "Depth Adjusted (m)", ylab = "Ti Z score non-detrended")
```

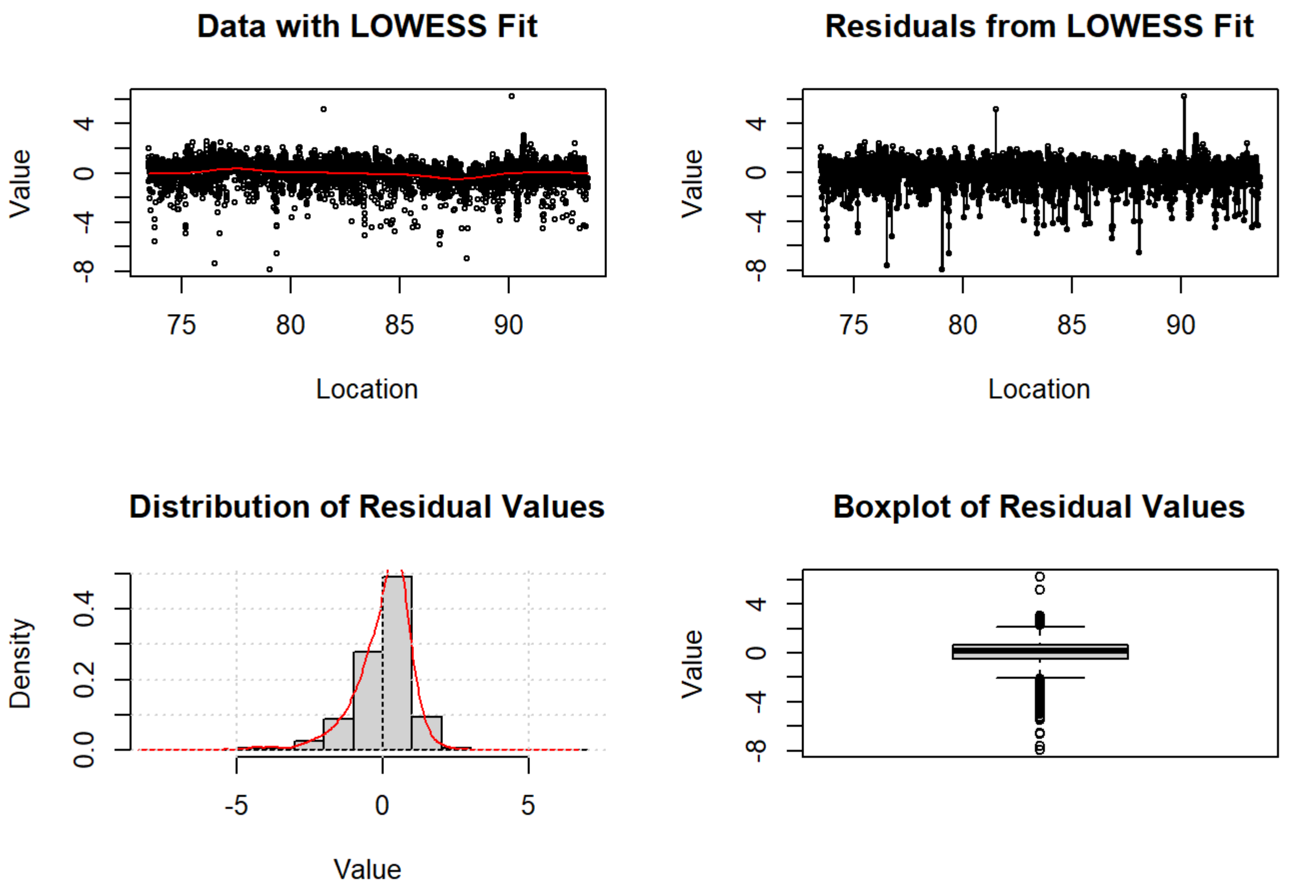


The Ti data have been selected, from the composite core, extending from 73.452 m (= anchoring depth with Zhao et al (2022b) dataset) to 93.609 m (= end of the Alum Shale Formation). Then the data are interpolated to ensure continuity of the Ti record every 5 mm. These data are not detrended and will be used in the Continuous Wavelet analysis (CWT).

1.2. Detrending of the Ti data

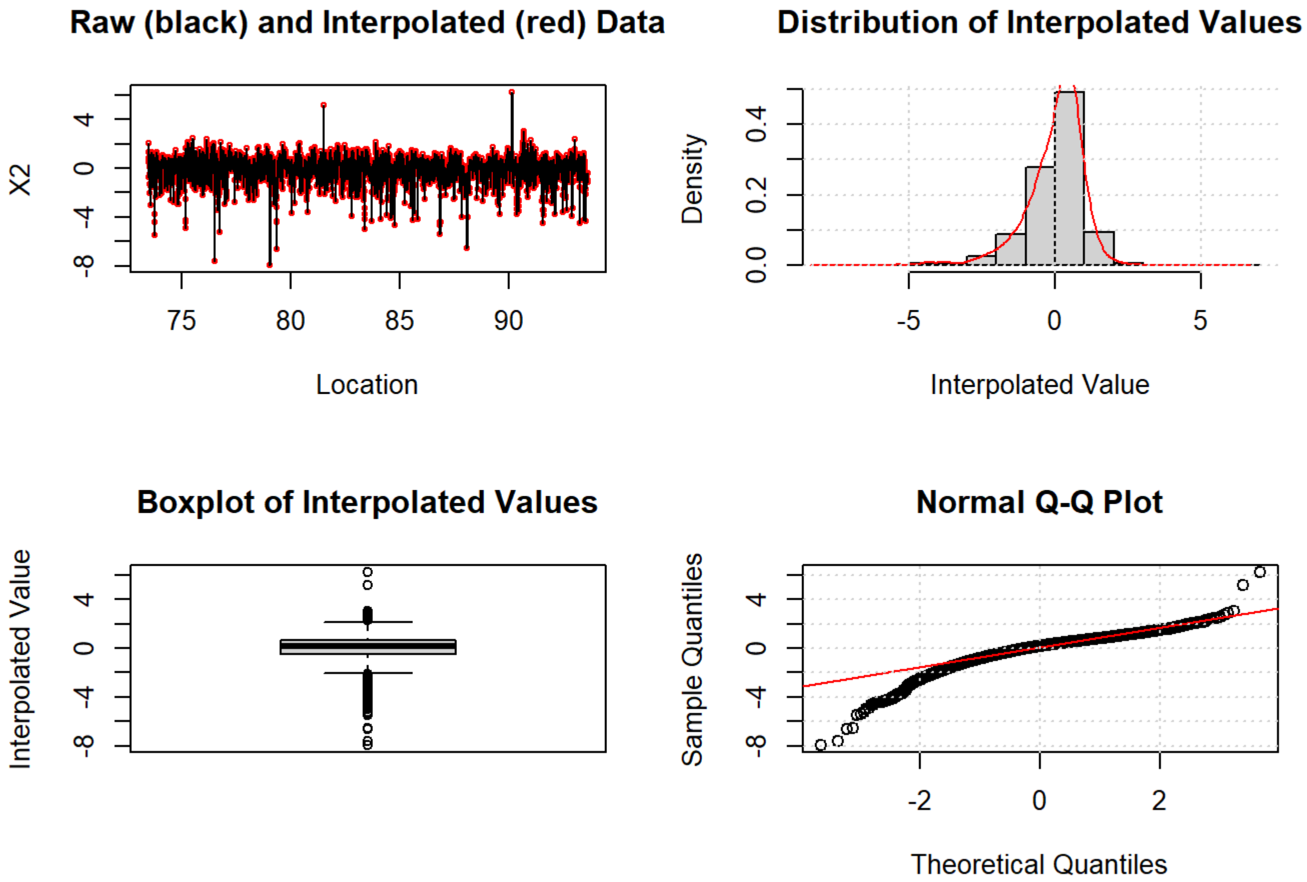
```
#Detrending (20% LOWESS) of the Ti series resampled every 5 mm
alb_Ti <- noLow(alb_Ti, smooth = 0.2, output = 1, genplot = T)
```

```
----- REMOVING LOWESS SMOOTHER FROM STRATIGRAPHIC SERIES -----
Call:
loess(formula = (dat[, 2]) ~ dat[, 1], span = smooth, degree = 1)

Number of Observations: 4032
Equivalent Number of Parameters: 8.17
Residual Standard Error: 1.015
Trace of smoother matrix: 9.68  (exact)

Control settings:
  span      :  0.2
  degree    :  1
  family    :  gaussian
  surface   :  interpolate     cell = 0.2
  normalize:  TRUE
 parametric:  FALSE
drop.square:  FALSE
```

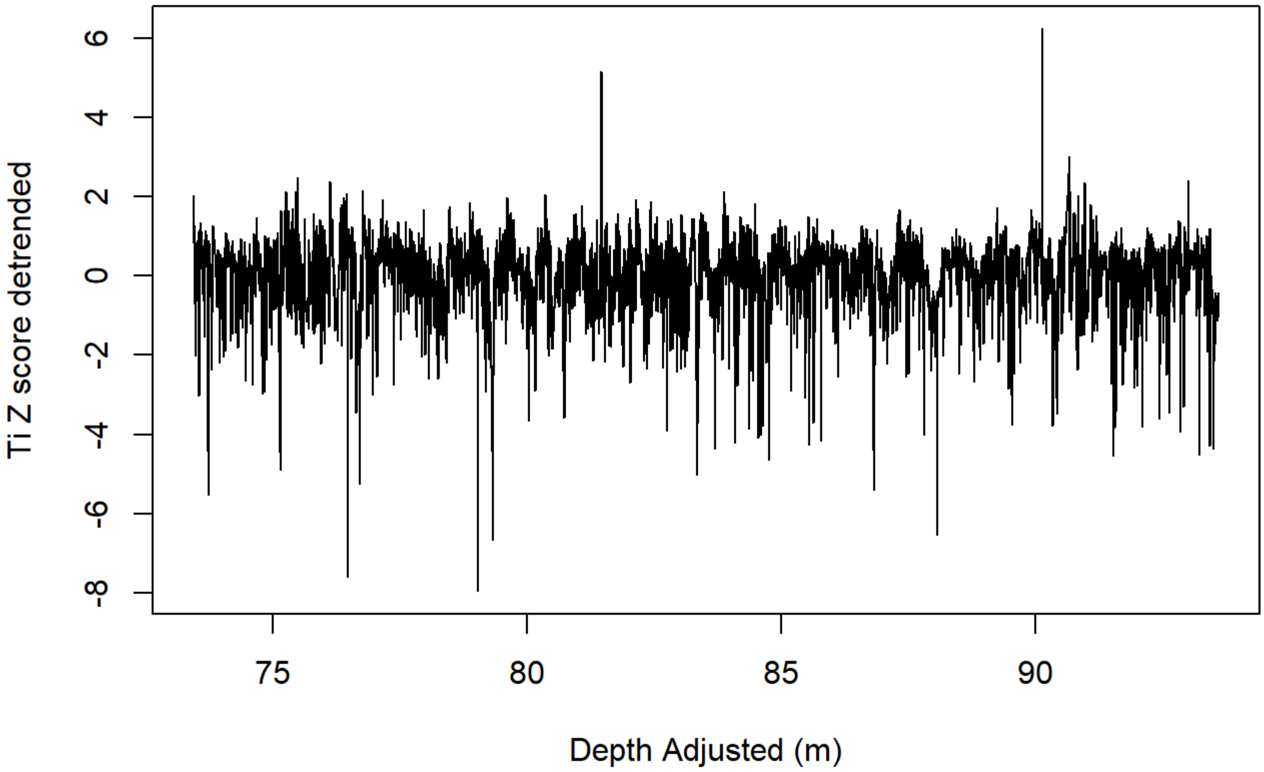



```
alb_Ti <- linterp(alb_Ti, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * Determining median sampling interval for series
 * Will interpolate to median sampling interval of 0.005
 * New number of samples= 4032
```




```r
plot(alb_Ti, type = "l", xlab = "Depth Adjusted (m)", ylab = "Ti Z score detrended")
```



The 5mm spaced Ti series is detrended using a 20% LOWESS regression. These data will be used for step 2 to 10 of the protocol. The step 1 of the protocol was also performed for the other detrital elements (Al, Si, K and Zr)

Step 2: MTM in depth domain

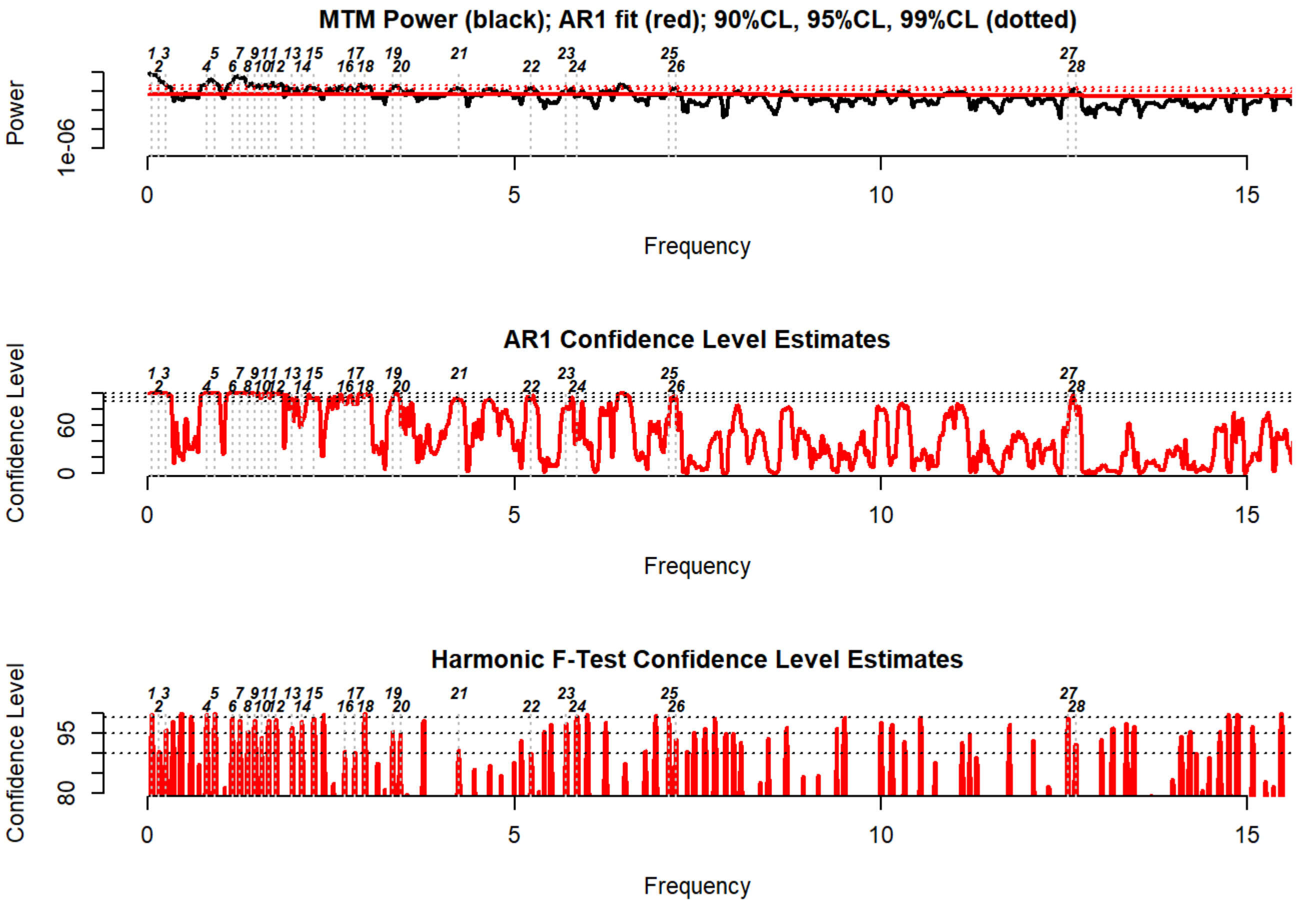
2.1. MTM on the non-detrened dataset

```
alb_Ti_MTM_ndet<-mtm(alb_Ti_ndet, xmax=15, siglevel = 0.9,ar1 = T, tbw= 2, output = 1)
```

```
----- PERFORMING Multitaper Spectral Analysis -----
 * Number of data points in stratigraphic series: 4032
 * Stratigraphic series length (space or time): 20.155
 * Sampling interval (space or time): 0.005
 * Will use default setting of 3 DPSS tapers
 * Mean value subtracted= -0.03819509
 * Linear trend NOT subtracted
 * Nyquist frequency: 100
 * Rayleigh frequency: 0.04960317
 * MTM Power spectrum bandwidth resolution (halfwidth): 0.09920635
 * Padded to 20160 points
 * Estimated AR1 coefficient = 0.4678053

 * Searching for significant spectral peaks that satisfy 90 % CL
   requirements outlined in Meyers (2012):
 * Number of significant F-test peaks identified = 92
```

ID	Frequency	Period	Harmonic_CL	Rednoise_CL
1	0.04960317	20.16	99.59413	100
2	0.1488095	6.72	90.52508	99.99988
3	0.2380952	4.2	95.77769	99.63641
4	0.7936508	1.26	99.6483	99.72414
5	0.9126984	1.095652	99.90369	99.76809
6	1.150794	0.8689655	99.02863	99.96726
7	1.25	0.8	98.28226	100
8	1.359127	0.7357664	95.51838	98.69361
9	1.458333	0.6857143	98.10039	97.33287
10	1.547619	0.6461538	93.83247	94.56589
11	1.646825	0.6072289	98.11976	95.44981
12	1.746032	0.5727273	98.2977	98.37743
13	1.964286	0.5090909	96.41317	89.16807
14	2.093254	0.4777251	98.02182	61.40152
15	2.261905	0.4421053	98.61392	94.04487
16	2.678571	0.3733333	90.52717	87.76271
17	2.81746	0.3549296	90.21642	89.00479
18	2.956349	0.338255	99.80688	97.86445
19	3.333333	0.3	95.41258	94.92955
20	3.44246	0.2904899	94.96416	72.0446
21	4.236111	0.2360656	90.59066	92.04306
22	5.228175	0.1912713	90.0769	95.19748
23	5.704365	0.1753043	97.37866	82.19038
24	5.853175	0.1708475	99.11178	61.88645
25	7.103175	0.1407821	98.71909	58.91435
26	7.202381	0.138843	93.36762	93.5992
27	12.5496	0.07968379	98.55084	64.87143
28	12.65873	0.07899687	92.19144	77.36012
29	25	0.04	97.3433	98.71976
30	28.75	0.03478261	99.35968	81.04829
31	36.37897	0.02748841	93.34859	66.00714
32	36.49802	0.02739875	96.30149	67.03294
33	43.29365	0.02309808	99.42692	86.20213
34	44.6627	0.02239005	91.44214	93.32972
35	50.90278	0.01964529	94.31977	88.83037
36	53.5119	0.01868743	95.83838	91.38573
37	54.4246	0.01837404	93.35112	99.1812
38	56.4881	0.01770285	97.75266	89.76485
39	57.39087	0.01742437	90.87104	57.77427
40	57.60913	0.01735836	94.16765	73.1126
41	57.95635	0.01725436	98.8449	88.00713
42	58.11508	0.01720724	97.76301	96.51954
43	58.22421	0.01717499	96.76889	79.12464
44	59.31548	0.01685901	92.31114	83.25253
45	59.51389	0.0168028	92.95096	83.08796
46	60.66468	0.01648406	95.20887	97.91906
47	61.06151	0.01637693	97.26079	59.79055
48	61.21032	0.01633712	96.41056	70.3925
49	61.33929	0.01630277	99.90043	91.64441
50	61.43849	0.01627644	97.27363	93.0498
51	64.62302	0.01547436	92.17849	96.06461
52	65.87302	0.01518072	94.95824	61.38345
53	67.86706	0.01473469	91.52643	98.95389
54	67.98611	0.01470889	96.36932	91.70161
55	70.82341	0.01411962	92.4982	93.21737
56	71.00198	0.01408411	95.82177	80.20875
57	73.15476	0.01366965	92.54873	73.90308

58	74.89087	0.01335276	99.1105	95.01699
59	75.77381	0.01319717	98.99207	97.37065
60	77.07341	0.01297464	97.10868	73.67353
61	78.65079	0.01271443	93.08389	96.35031
62	79.89087	0.01251707	98.51305	88.55408
63	80.17857	0.01247216	96.8899	84.18897
64	80.60516	0.01240615	96.57845	85.75422
65	80.77381	0.01238025	94.00894	81.35132
66	81.875	0.01221374	94.37419	65.41283
67	81.99405	0.01219601	97.83034	63.22457
68	82.2123	0.01216363	99.6475	74.23975
69	82.33135	0.01214604	91.42259	88.0338
70	82.61905	0.01210375	94.18016	99.50291
71	83.80952	0.01193182	92.76588	98.59736
72	84.59325	0.01182127	94.44594	96.96859
73	85.5754	0.0116856	96.13289	58.66473
74	86.8254	0.01151737	93.10324	99.01141
75	87.14286	0.01147541	94.39685	85.69028
76	87.29167	0.01145585	95.07262	72.84607
77	87.48016	0.01143116	93.38032	63.57838
78	88.10516	0.01135007	97.96073	99.82218
79	89.33532	0.01119378	91.81732	96.05213
80	91.25992	0.01095771	99.14639	82.01627
81	91.51786	0.01092683	99.20717	98.70252
82	91.72619	0.01090201	99.51691	94.60788
83	93.03571	0.01074856	99.57182	86.93861
84	93.64087	0.0106791	92.99375	96.96892
85	93.95833	0.01064302	94.8374	98.20012
86	94.09722	0.01062731	94.58227	95.31293
87	94.40476	0.01059269	90.78054	79.38122
88	95.13889	0.01051095	93.32935	94.5039
89	95.50595	0.01047055	90.6481	96.25297
90	97.66865	0.0102387	97.14167	72.0247
91	98.90873	0.01011033	90.62833	59.48612
92	99.00794	0.0101002	90.26233	79.78084

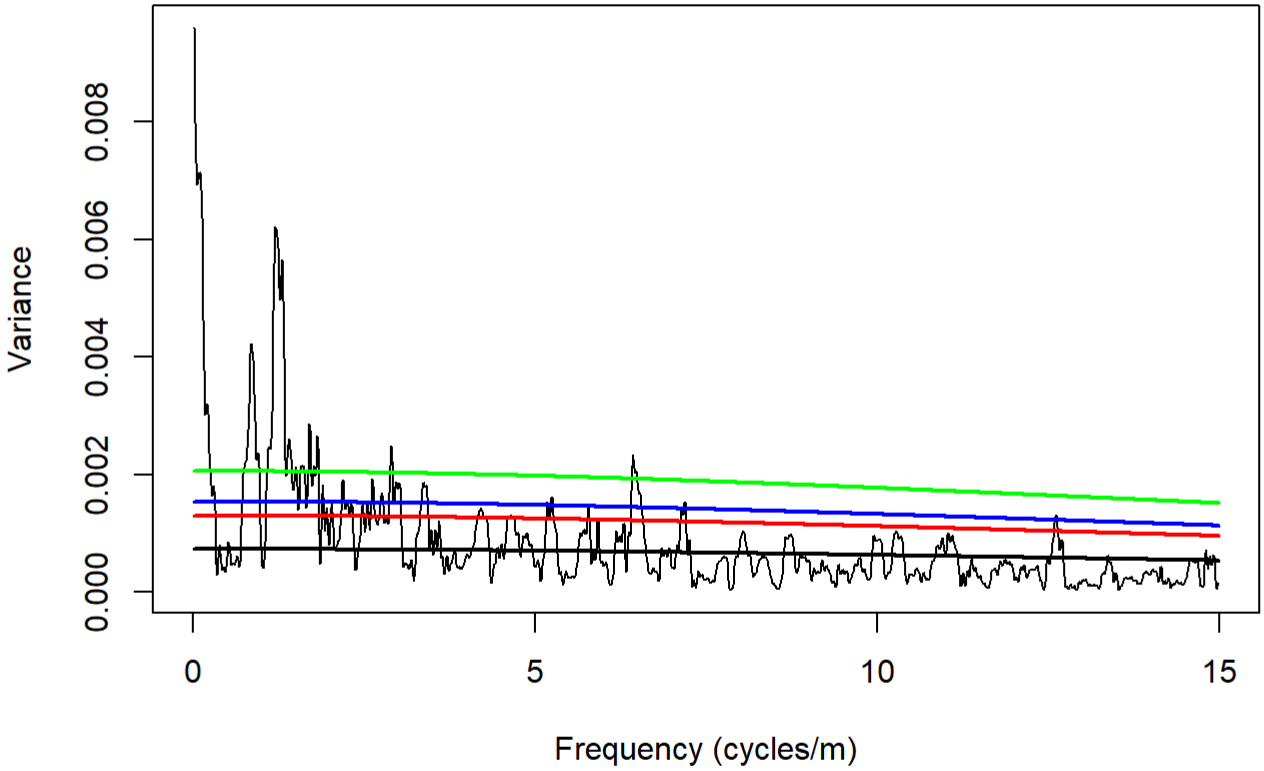



```
alb_Ti_MTM_ndet <- iso(dat=alb_Ti_MTM_ndet,xmin=0,xmax=15, genplot=F)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 10079
 * Number of columns= 8
 * Minimum= 0.009920635 , Maximum= 99.99008
 * Isolating data between 0 and 15
 * Number of data points following culling= 1511
```

```
plot(alb_Ti_MTM_ndet$Frequency,
     alb_Ti_MTM_ndet$Power,
     type = 'l',
     xlab = "Frequency (cycles/m)",
     ylab = "Variance"
     )

lines(alb_Ti_MTM_ndet$Frequency,
      alb_Ti_MTM_ndet$AR1_fit,
      type = 'l',
      col = 'black',
      lwd = 2
      )

lines(alb_Ti_MTM_ndet$Frequency,
      alb_Ti_MTM_ndet$AR1_90_power,
      type = 'l',
      col = 'red',
      lwd = 2
      )
```

```
lines(alb_Ti_MTM_ndet$Frequency,
      alb_Ti_MTM_ndet$AR1_95_power,
      type = 'l',
      col = 'blue',
      lwd = 2
      )

lines(alb_Ti_MTM_ndet$Frequency,
      alb_Ti_MTM_ndet$AR1_99_power,
      type = 'l',
      col = 'green',
      lwd = 2
      )
```



The 2 pi-MTM on the non-detrended data is performed to show the entire range of cyclicities in the signal. This MTM is not used afterward.

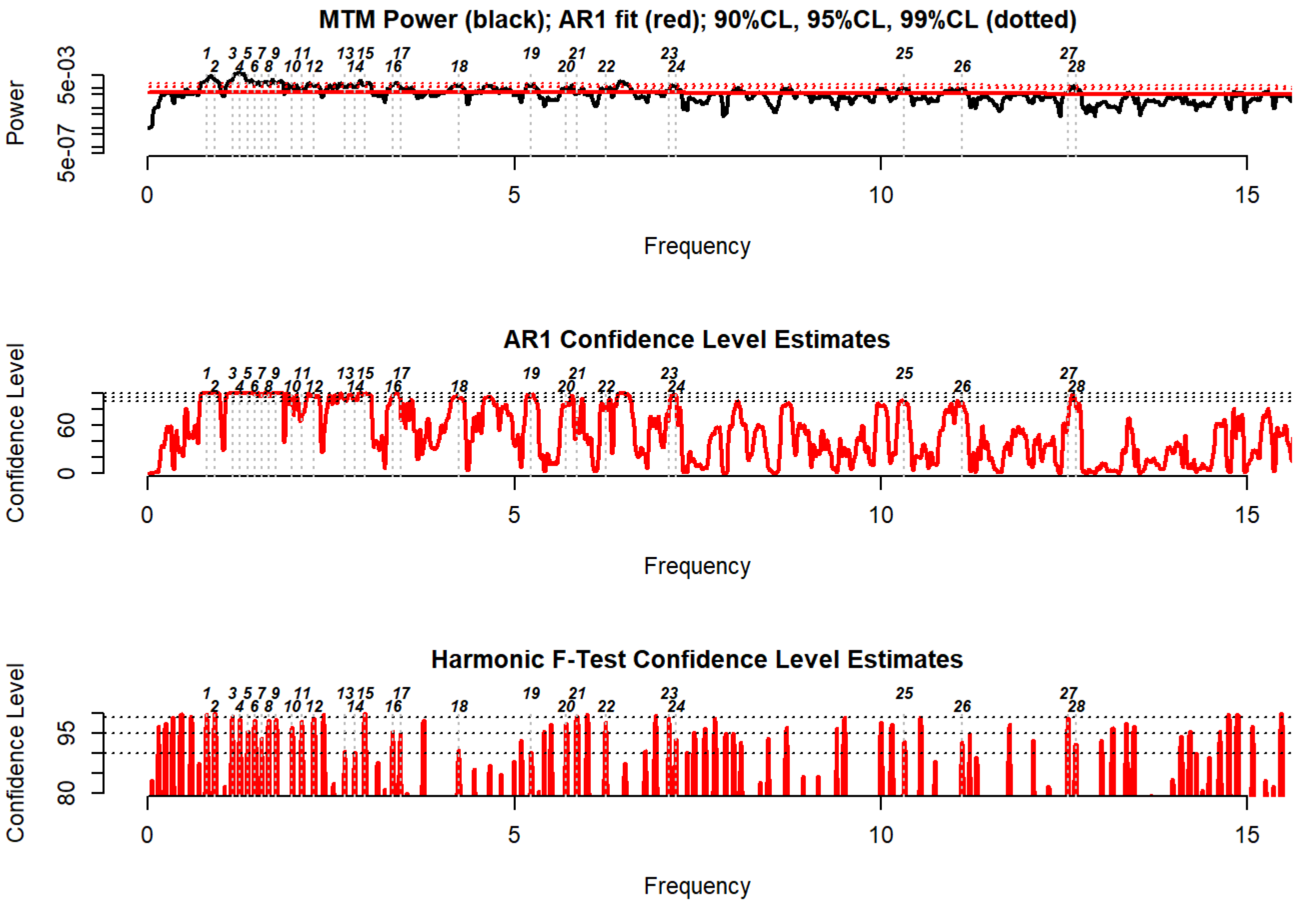
2.2. MTM on the detrended dataset

```
alb_Ti_MTM <- mtm(alb_Ti, xmax=15, siglevel = 0.9, ar1 = T, tbw= 2, output = 1)
```

```
----- PERFORMING Multitaper Spectral Analysis -----
 * Number of data points in stratigraphic series: 4032
 * Stratigraphic series length (space or time): 20.155
 * Sampling interval (space or time): 0.005
 * Will use default setting of 3 DPSS tapers
 * Mean value subtracted= 4.069401e-05
 * Linear trend NOT subtracted
```

```
 * Nyquist frequency: 100
 * Rayleigh frequency: 0.04960317
 * MTM Power spectrum bandwidth resolution (halfwidth): 0.09920635
 * Padded to 20160 points
 * Estimated AR1 coefficient = 0.4427859

 * Searching for significant spectral peaks that satisfy 90 % CL
     requirements outlined in Meyers (2012):
 * Number of significant F-test peaks identified = 94
ID  / Frequency / Period / Harmonic_CL / Rednoise_CL
1   0.7936508   1.26   99.6495   99.9071
2   0.9126984   1.095652   99.90678   99.90939
3   1.150794   0.8689655   99.05213   99.99092
4   1.25   0.8   98.30687   100
5   1.359127   0.7357664   95.50549   99.41661
6   1.458333   0.6857143   98.12654   98.55564
7   1.547619   0.6461538   93.79633   96.96442
8   1.646825   0.6072289   98.12533   97.42249
9   1.746032   0.5727273   98.30366   99.24096
10   1.964286   0.5090909   96.34805   93.20886
11   2.093254   0.4777251   97.98995   68.89833
12   2.261905   0.4421053   98.62524   96.54462
13   2.678571   0.3733333   90.55385   91.9462
14   2.81746   0.3549296   90.19723   92.8981
15   2.956349   0.338255   99.80865   98.932
16   3.333333   0.3   95.41094   97.09887
17   3.44246   0.2904899   94.96645   78.86869
18   4.236111   0.2360656   90.58225   95.06536
19   5.228175   0.1912713   90.09819   97.21911
20   5.704365   0.1753043   97.37723   87.29627
21   5.853175   0.1708475   99.11158   69.01658
22   6.240079   0.1602544   97.67422   84.33962
23   7.103175   0.1407821   98.72186   65.90099
24   7.202381   0.138843   93.3723   96.0572
25   10.31746   0.09692308   92.89927   86.07821
26   11.10119   0.09008043   92.65311   88.88133
27   12.5496   0.07968379   98.55134   70.54842
28   12.65873   0.07899687   92.1856   82.09713
29   17.09325   0.05850261   94.11179   68.76633
30   17.8373   0.05606229   90.02154   88.05182
31   25   0.04   97.34224   99.05331
32   28.75   0.03478261   99.3598   82.94557
33   36.37897   0.02748841   93.34558   67.44022
34   36.49802   0.02739875   96.30253   68.38105
35   43.29365   0.02309808   99.42679   86.71654
36   44.6627   0.02239005   91.43392   93.59203
37   50.90278   0.01964529   94.31732   88.98035
38   53.5119   0.01868743   95.83561   91.34791
39   54.4246   0.01837404   93.35017   99.19354
40   56.4881   0.01770285   97.75355   89.75403
41   57.39087   0.01742437   90.87208   57.797
42   57.60913   0.01735836   94.16682   73.16123
43   57.95635   0.01725436   98.8438   87.94543
44   58.11508   0.01720724   97.76266   96.49958
45   58.22421   0.01717499   96.77038   79.02898
46   59.31548   0.01685901   92.31666   83.12247
47   59.51389   0.0168028   92.95351   82.93598
48   60.66468   0.01648406   95.20807   97.90035
```

49	61.06151	0.01637693	97.25952	59.65102
50	61.21032	0.01633712	96.41152	70.29164
51	61.33929	0.01630277	99.90038	91.56283
52	61.43849	0.01627644	97.2732	92.98992
53	64.62302	0.01547436	92.18034	95.99514
54	65.87302	0.01518072	94.95728	60.97955
55	67.86706	0.01473469	91.5305	98.91116
56	67.98611	0.01470889	96.37001	91.48216
57	70.82341	0.01411962	92.50066	93.04393
58	71.00198	0.01408411	95.82738	79.77178
59	73.15476	0.01366965	92.5475	73.40234
60	74.89087	0.01335276	99.11115	94.81942
61	75.77381	0.01319717	98.99135	97.25962
62	77.07341	0.01297464	97.1098	73.18008
63	78.65079	0.01271443	93.09069	96.18004
64	79.89087	0.01251707	98.51331	88.16902
65	80.17857	0.01247216	96.89047	83.7865
66	80.60516	0.01240615	96.57814	85.30011
67	80.77381	0.01238025	94.01293	80.79683
68	81.875	0.01221374	94.37741	64.65222
69	81.99405	0.01219601	97.83026	62.50613
70	82.2123	0.01216363	99.64703	73.589
71	82.33135	0.01214604	91.42229	87.60278
72	82.61905	0.01210375	94.18218	99.46475
73	83.80952	0.01193182	92.76434	98.51632
74	84.59325	0.01182127	94.4466	96.81177
75	85.5754	0.0116856	96.13613	57.87317
76	86.8254	0.01151737	93.10284	98.94794
77	87.14286	0.01147541	94.39533	85.17613
78	87.29167	0.01145585	95.06977	72.27986
79	87.48016	0.01143116	93.37054	62.7484
80	88.10516	0.01135007	97.95976	99.80612
81	89.33532	0.01119378	91.8167	95.82547
82	91.25992	0.01095771	99.14693	81.4381
83	91.51786	0.01092683	99.20682	98.60804
84	91.72619	0.01090201	99.51717	94.34934
85	93.03571	0.01074856	99.57157	86.42848
86	93.64087	0.0106791	92.99197	96.78454
87	93.95833	0.01064302	94.83938	98.07256
88	94.09722	0.01062731	94.58366	95.04817
89	94.40476	0.01059269	90.77981	78.9516
90	95.13889	0.01051095	93.32958	94.27396
91	95.50595	0.01047055	90.64873	96.05761
92	97.66865	0.0102387	97.14153	71.41045
93	98.90873	0.01011033	90.6295	58.61966
94	99.00794	0.0101002	90.26207	79.29464

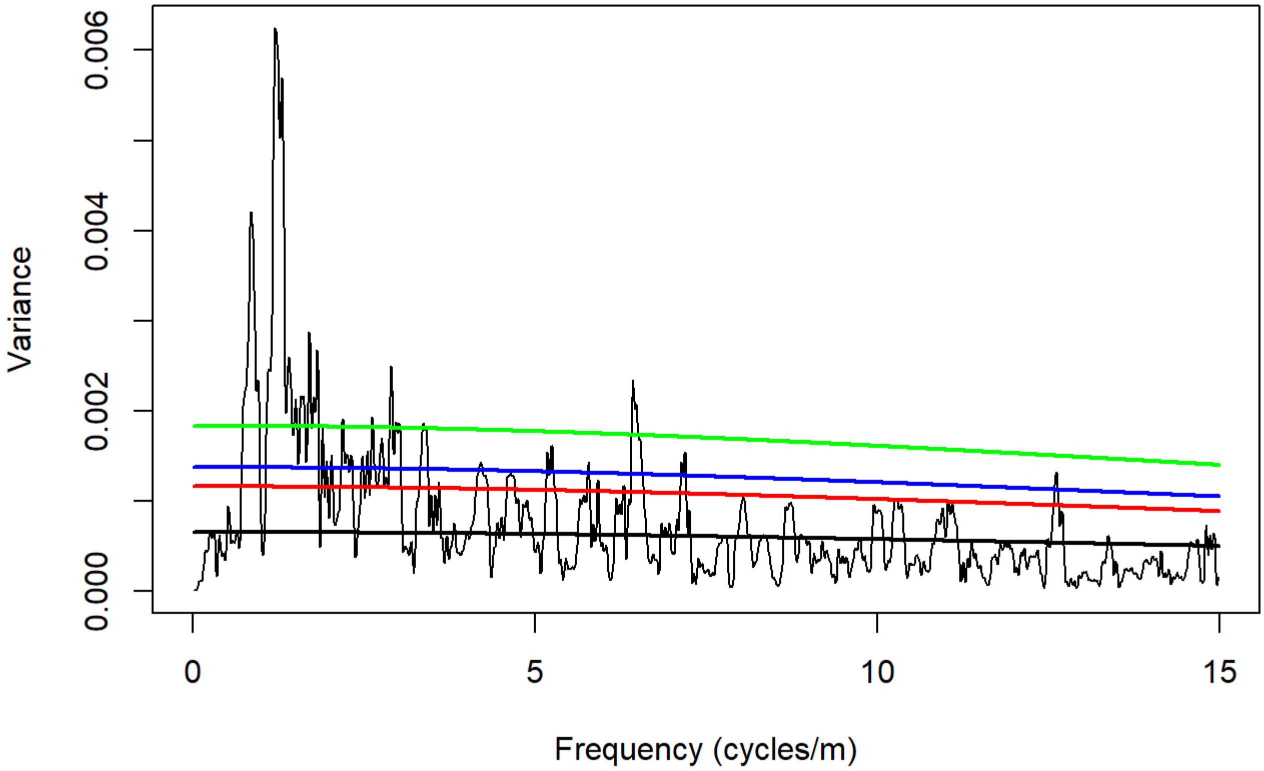



```
alb_Ti_MTM <- iso(dat=alb_Ti_MTM, xmin=0, xmax=15, genplot=F)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 10079
 * Number of columns= 8
 * Minimum= 0.009920635 , Maximum= 99.99008
 * Isolating data between 0 and 15
 * Number of data points following culling= 1511
```

```
plot(alb_Ti_MTM$Frequency,
     alb_Ti_MTM$Power,
     type = 'l',
     xlab = "Frequency (cycles/m)",
     ylab = "Variance",
     )

lines(alb_Ti_MTM$Frequency,
      alb_Ti_MTM$AR1_fit,
      type = 'l',
      col = 'black',
      lwd = 2
      )

lines(alb_Ti_MTM$Frequency,
      alb_Ti_MTM$AR1_90_power,
      type = 'l',
      col = 'red',
      lwd = 2
      )
```

```
lines(alb_Ti_MTM$Frequency,
      alb_Ti_MTM$AR1_95_power,
      type = 'l',
      col = 'blue',
      lwd = 2
      )

lines(alb_Ti_MTM$Frequency,
      alb_Ti_MTM$AR1_99_power,
      type = 'l',
      col = 'green',
      lwd = 2
      )
```



The 2 pi-MTM on the detrended data is performed to show the range of cyclicities in the detrended signal. Allowing to visually identify > 90 % CL periodicities.

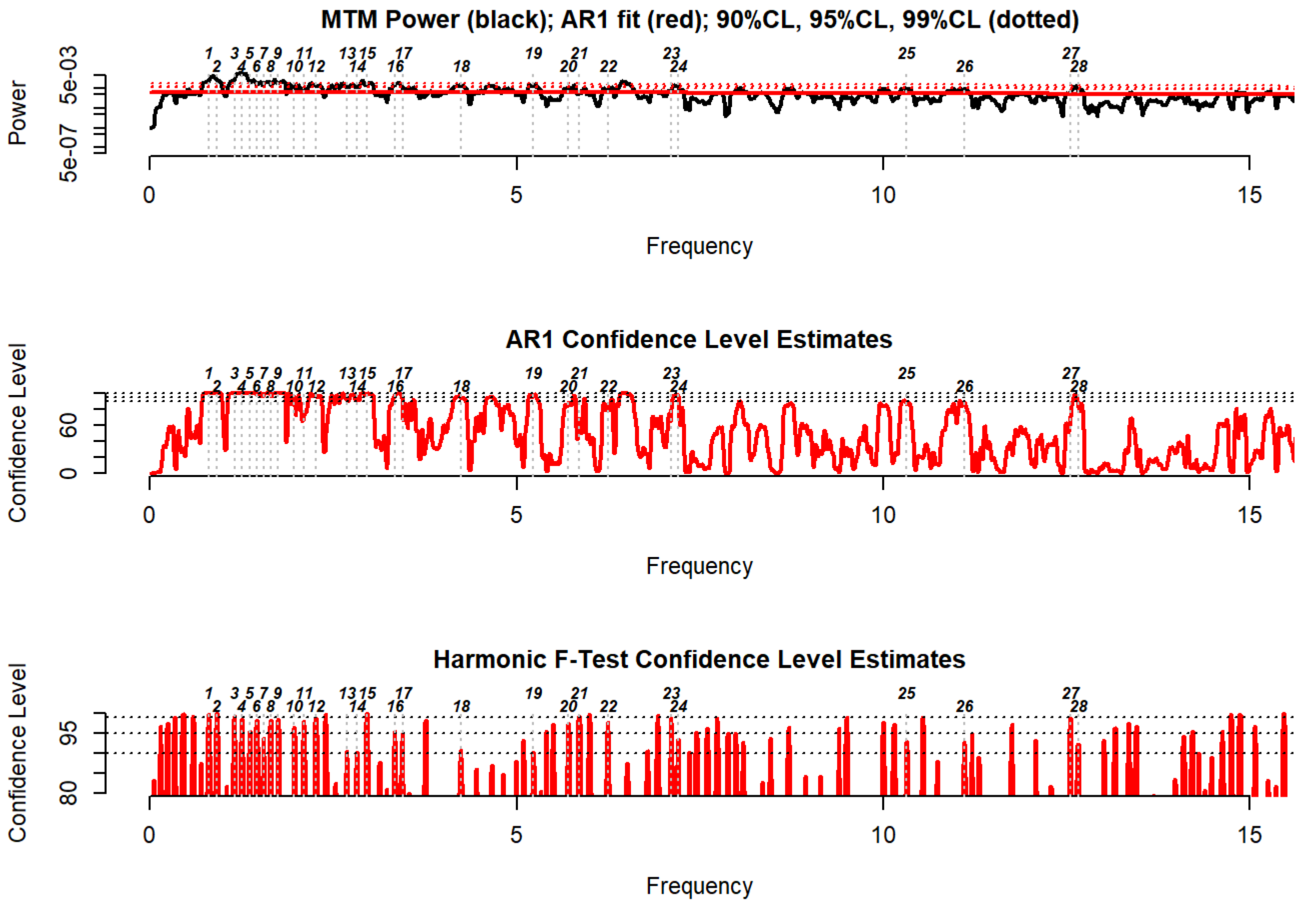
2.3. Identification and extraction of the >90% CL periodicities

```
alb_Ti_MTM<-mtm(alb_Ti, xmax=15, siglevel = 0.9, ar1 = T, tbw= 2, output = 2)
```

```
----- PERFORMING Multitaper Spectral Analysis -----
 * Number of data points in stratigraphic series: 4032
 * Stratigraphic series length (space or time): 20.155
 * Sampling interval (space or time): 0.005
 * Will use default setting of 3 DPSS tapers
 * Mean value subtracted= 4.069401e-05
 * Linear trend NOT subtracted
```

```
 * Nyquist frequency: 100
 * Rayleigh frequency: 0.04960317
 * MTM Power spectrum bandwidth resolution (halfwidth): 0.09920635
 * Padded to 20160 points
 * Estimated AR1 coefficient = 0.4427859

 * Searching for significant spectral peaks that satisfy 90 % CL
    requirements outlined in Meyers (2012):
 * Number of significant F-test peaks identified = 94
ID  / Frequency / Period / Harmonic_CL / Rednoise_CL
1   0.7936508   1.26   99.6495   99.9071
2   0.9126984   1.095652   99.90678   99.90939
3   1.150794   0.8689655   99.05213   99.99092
4   1.25   0.8   98.30687   100
5   1.359127   0.7357664   95.50549   99.41661
6   1.458333   0.6857143   98.12654   98.55564
7   1.547619   0.6461538   93.79633   96.96442
8   1.646825   0.6072289   98.12533   97.42249
9   1.746032   0.5727273   98.30366   99.24096
10   1.964286   0.5090909   96.34805   93.20886
11   2.093254   0.4777251   97.98995   68.89833
12   2.261905   0.4421053   98.62524   96.54462
13   2.678571   0.3733333   90.55385   91.9462
14   2.81746   0.3549296   90.19723   92.8981
15   2.956349   0.338255   99.80865   98.932
16   3.333333   0.3   95.41094   97.09887
17   3.44246   0.2904899   94.96645   78.86869
18   4.236111   0.2360656   90.58225   95.06536
19   5.228175   0.1912713   90.09819   97.21911
20   5.704365   0.1753043   97.37723   87.29627
21   5.853175   0.1708475   99.11158   69.01658
22   6.240079   0.1602544   97.67422   84.33962
23   7.103175   0.1407821   98.72186   65.90099
24   7.202381   0.138843   93.3723   96.0572
25   10.31746   0.09692308   92.89927   86.07821
26   11.10119   0.09008043   92.65311   88.88133
27   12.5496   0.07968379   98.55134   70.54842
28   12.65873   0.07899687   92.1856   82.09713
29   17.09325   0.05850261   94.11179   68.76633
30   17.8373   0.05606229   90.02154   88.05182
31   25   0.04   97.34224   99.05331
32   28.75   0.03478261   99.3598   82.94557
33   36.37897   0.02748841   93.34558   67.44022
34   36.49802   0.02739875   96.30253   68.38105
35   43.29365   0.02309808   99.42679   86.71654
36   44.6627   0.02239005   91.43392   93.59203
37   50.90278   0.01964529   94.31732   88.98035
38   53.5119   0.01868743   95.83561   91.34791
39   54.4246   0.01837404   93.35017   99.19354
40   56.4881   0.01770285   97.75355   89.75403
41   57.39087   0.01742437   90.87208   57.797
42   57.60913   0.01735836   94.16682   73.16123
43   57.95635   0.01725436   98.8438   87.94543
44   58.11508   0.01720724   97.76266   96.49958
45   58.22421   0.01717499   96.77038   79.02898
46   59.31548   0.01685901   92.31666   83.12247
47   59.51389   0.0168028   92.95351   82.93598
48   60.66468   0.01648406   95.20807   97.90035
```

49	61.06151	0.01637693	97.25952	59.65102
50	61.21032	0.01633712	96.41152	70.29164
51	61.33929	0.01630277	99.90038	91.56283
52	61.43849	0.01627644	97.2732	92.98992
53	64.62302	0.01547436	92.18034	95.99514
54	65.87302	0.01518072	94.95728	60.97955
55	67.86706	0.01473469	91.5305	98.91116
56	67.98611	0.01470889	96.37001	91.48216
57	70.82341	0.01411962	92.50066	93.04393
58	71.00198	0.01408411	95.82738	79.77178
59	73.15476	0.01366965	92.5475	73.40234
60	74.89087	0.01335276	99.11115	94.81942
61	75.77381	0.01319717	98.99135	97.25962
62	77.07341	0.01297464	97.1098	73.18008
63	78.65079	0.01271443	93.09069	96.18004
64	79.89087	0.01251707	98.51331	88.16902
65	80.17857	0.01247216	96.89047	83.7865
66	80.60516	0.01240615	96.57814	85.30011
67	80.77381	0.01238025	94.01293	80.79683
68	81.875	0.01221374	94.37741	64.65222
69	81.99405	0.01219601	97.83026	62.50613
70	82.2123	0.01216363	99.64703	73.589
71	82.33135	0.01214604	91.42229	87.60278
72	82.61905	0.01210375	94.18218	99.46475
73	83.80952	0.01193182	92.76434	98.51632
74	84.59325	0.01182127	94.4466	96.81177
75	85.5754	0.0116856	96.13613	57.87317
76	86.8254	0.01151737	93.10284	98.94794
77	87.14286	0.01147541	94.39533	85.17613
78	87.29167	0.01145585	95.06977	72.27986
79	87.48016	0.01143116	93.37054	62.7484
80	88.10516	0.01135007	97.95976	99.80612
81	89.33532	0.01119378	91.8167	95.82547
82	91.25992	0.01095771	99.14693	81.4381
83	91.51786	0.01092683	99.20682	98.60804
84	91.72619	0.01090201	99.51717	94.34934
85	93.03571	0.01074856	99.57157	86.42848
86	93.64087	0.0106791	92.99197	96.78454
87	93.95833	0.01064302	94.83938	98.07256
88	94.09722	0.01062731	94.58366	95.04817
89	94.40476	0.01059269	90.77981	78.9516
90	95.13889	0.01051095	93.32958	94.27396
91	95.50595	0.01047055	90.64873	96.05761
92	97.66865	0.0102387	97.14153	71.41045
93	98.90873	0.01011033	90.6295	58.61966
94	99.00794	0.0101002	90.26207	79.29464




```
alb_Ti_MTM <- iso(dat=alb_Ti_MTM, xmin=0, xmax=15, genplot=F)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 94
 * Number of columns= 1
 * Minimum= 0.7936508 , Maximum= 99.00794
 * Isolating data between 0 and 15
 * Number of data points following culling= 28
```

```
write.csv(alb_Ti_MTM,"alb_Ti_sigfreq_MTM_rsp0.005_det0.20_Zscore_ACL.csv")
```

Step 3: Ratio of frequencies

3.1. Ratio of the significant frequencies extracted from the MTM (in Excel)

The comparison between the ratios of the observed >90% CL and the theoretical ratio of the Milankovitch cycles is conducted in a separate Excel file. See Supplementary Materials 6 for more details.

Based on Zhao et al (2022b) paper, the 405 kyr cycle should be recorded between 1.75 and 2.25 m but nothing is visible in the Ti data (but is is observable within the other detrital elements). However, all the other frequency bands observed by Zhao et al (2022b), and corresponding to Milankovitch periodicities are identify in the Ti data.

In addition, a significant peak is located around 0.85 m where the 173-kyr long obliquity (Inclination metronome) should be identified and this explains why we focus our study on the 173 kyr metronome.

The duration of target cycles are recalculated from the literature (Laskar et al (2004); Laskar (2020); Wu et al (2024)).

Step 4: EHA and CWT

4.1. Evolutive Harmonic Analysis (EHA)

```
eha(alb_Ti,
    tbw=2,
    fmin=0.01,
    fmax=15,
    step=0.005,
    win=6,
    demean=T,
    detrend=T,
    siglevel=0.90,
    sigID=F,
    ydir=1,
    output=0,
    pl=1,
    palette=1,
    centerZero=T,
    ncolors=100,
    genplot=4,
    verbose=T
    )
```

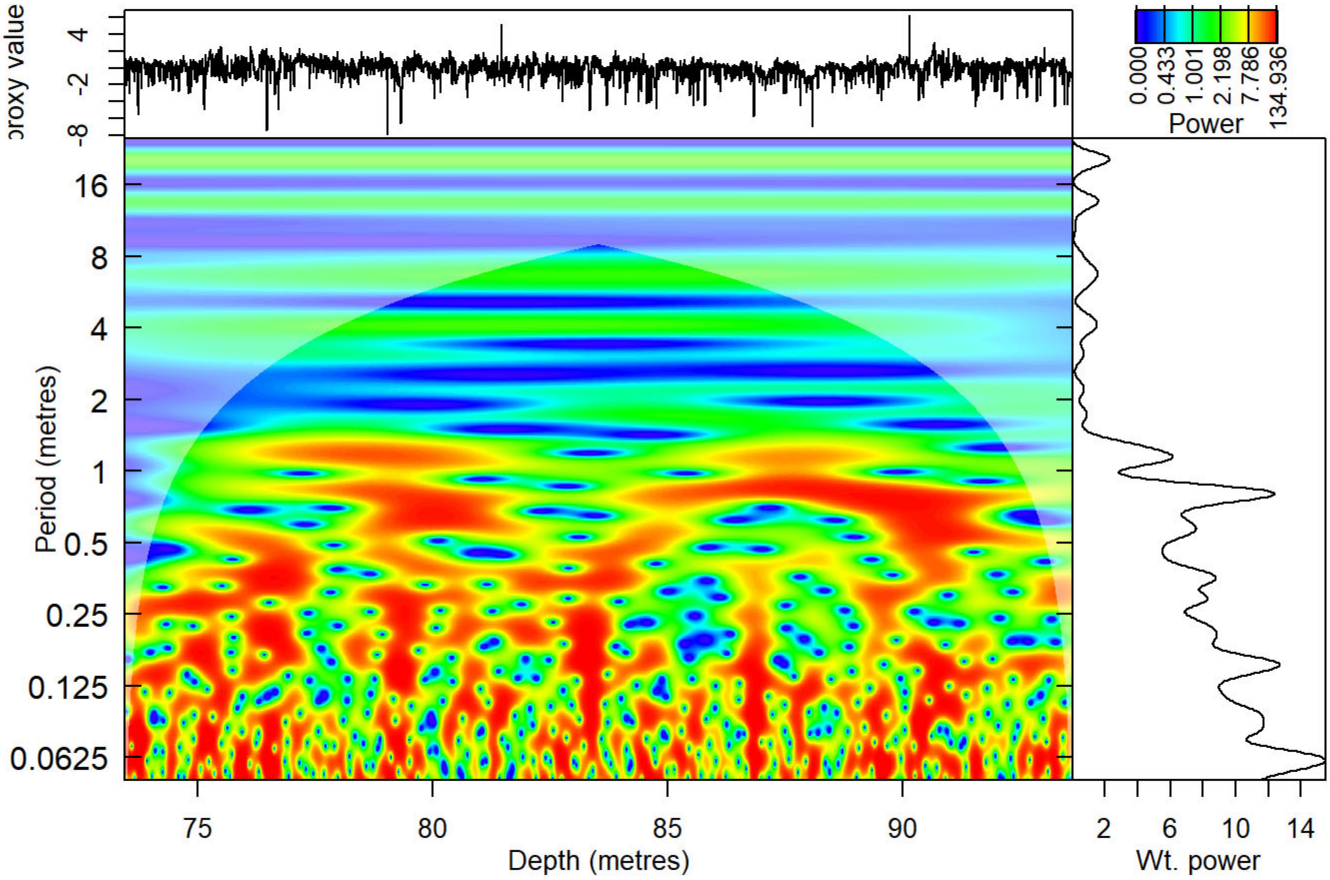
```
----- PERFORMING EVOLUTIVE HARMONIC ANALYSIS -----
* Number of data points in stratigraphic series: 4032
* Stratigraphic series length (space or time): 20.155
* Sampling interval (space or time): 0.005
* Number of data points per window: 1201
* Moving window size (space or time): 6
* Window step points: 1
* Window step (space or time): 0.005
* Number of windows: 2832
* Mean value for each window will be subtracted
* Linear trend for each window will be subtracted
* Nyquist frequency: 100
* Rayleigh frequency: 0.1665279
* MTM Power spectrum bandwidth resolution (halfwidth): 0.3330558
* Will use 3 DPSS tapers
* Padded to 4096 points
```

The EHA is performed on the Ti detrended series and confirms the presence of recurrent periodicities along the ACL as suggested by the > 90 % CL frequencies observed in the MTM

4.2. WaverideR (non-detrended data)

4.2.1. Continuous Wavelet Transform (CWT)

```
alb_Ti_wt <- analyze_wavelet(alb_Ti_ndet, dj = 1/100,
                             lowerPeriod = 0.05,
                             upperPeriod = 25,
                             verbose = FALSE,
                             omega_nr = 10
                             )

plot_wavelet(wavelet = alb_Ti_wt,
             lowerPeriod = NULL,
             upperPeriod = NULL,
             n.levels = 100,
             palette_name = "rainbow",
             color_brewer = "grDevices",
             useRaster = TRUE,
             periodlab = "Period (metres)",
             x_lab = "Depth (metres)",
             keep_editable = FALSE,
             dev_new = F,
             add_lines = NULL,
             add_points = NULL,
             add_abline_h = NULL,
             add_abline_v = NULL,
             add_MTM_peaks = FALSE,
             add_data = TRUE,
             add_avg = TRUE,
             add_MTM = FALSE,
             demean_mtm = TRUE,
             detrend_mtm = TRUE,
             padfac_mtm = 5,
             tbw_mtm = 3,
             plot_horizontal = TRUE
             )
```



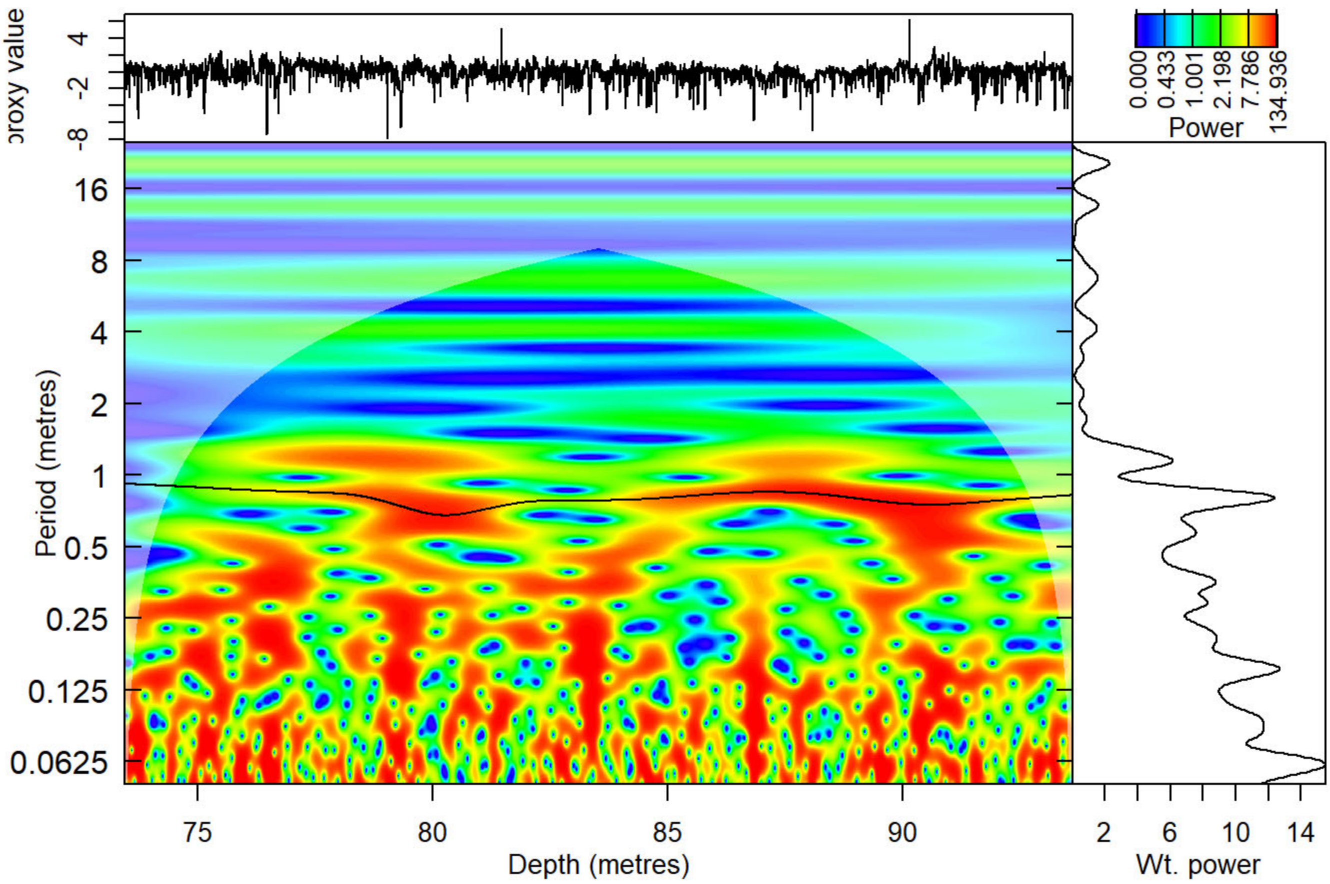
The Continuous Wavelet Transfrom (CWT) is performed on the Ti non-detrended series and exhibits similar results as the EHA analysis with a lot of power between 0.7-1m

4.2.2. Tracking (in depth domain) of the 173 kyr cycle

The powerful 0.7-1m (supposed to correspond to the 173 kyr cycle) is tracked along the ACL

```
#Tracking the wavelet (remove the "#" in front of the 3 next command lines)

#alb_Ti_track <- track_period_wavelet(astro_cycle = 173,
#                                    wavelet = alb_Ti_wt,
#                                     n.levels = 100,
#                                     periodlab = "Period (metres)",
#                                     x_lab = "depth (metres)",
#                                     palette_name = "rainbow",
#                                     color_brewer = "grDevices",
#                                     plot_horizontal = TRUE
#                                     )

#alb_Ti_track_comp <- completed_series(wavelet = alb_Ti_wt,
#                                      tracked_curve = alb_Ti_track,
#                                      period_up = 1,
#                                      period_down = 0.75,
#                                      extrapolate = TRUE,
#                                      genplot = FALSE,
#                                      keep_editable = FALSE
#                                      )

#alb_Ti_track_comp <- loess_auto(alb_Ti_track_comp)

#write.csv(alb_Ti_track_comp,"alb_Ti_track.csv")
```

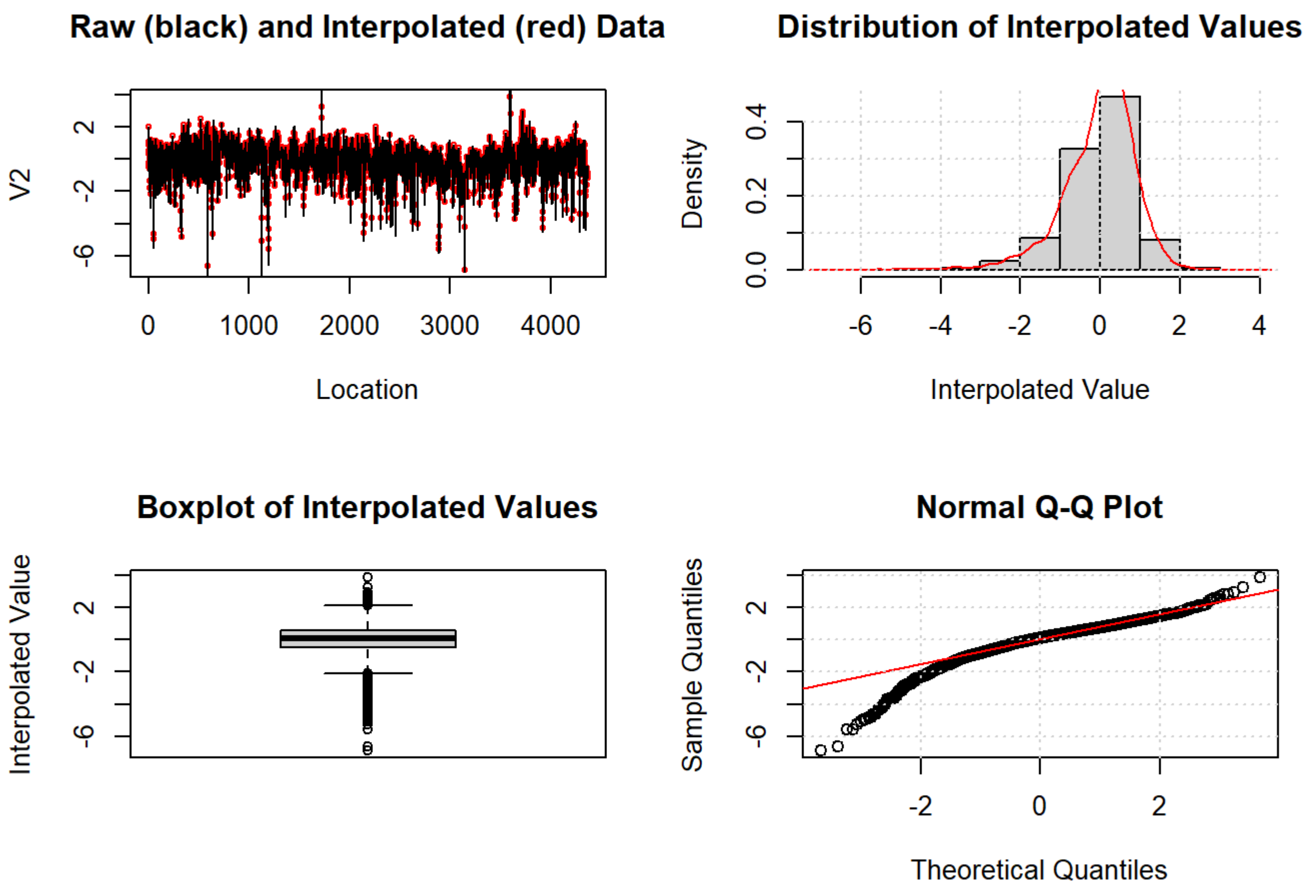
```r
# Loading the tracked curve
alb_Ti_track_comp <- read.csv("alb_Ti_track.csv")
alb_Ti_track_comp <- alb_Ti_track_comp[,c(2,3)]


plot_wavelet(wavelet = alb_Ti_wt,
             lowerPeriod = NULL,
             upperPeriod = NULL,
             n.levels = 100,
             palette_name = "rainbow",
             color_brewer = "grDevices",
             useRaster = TRUE,
             periodlab = "Period (metres)",
             x_lab = "Depth (metres)",
             keep_editable = FALSE,
             dev_new = F,
             add_lines = cbind(alb_Ti_track_comp[,1],alb_Ti_track_comp[,2]),
             add_points = NULL,
             add_abline_h = NULL,
             add_abline_v = NULL,
             add_MTM_peaks = FALSE,
             add_data = TRUE,
             add_avg = TRUE,
             add_MTM = FALSE,
             demean_mtm = TRUE,
             detrend_mtm = TRUE,
             padfac_mtm = 5,
             tbw_mtm = 3,
             plot_horizontal = TRUE
             )
```



4.2.3. Depth to time domain convertion using the tracked cycle

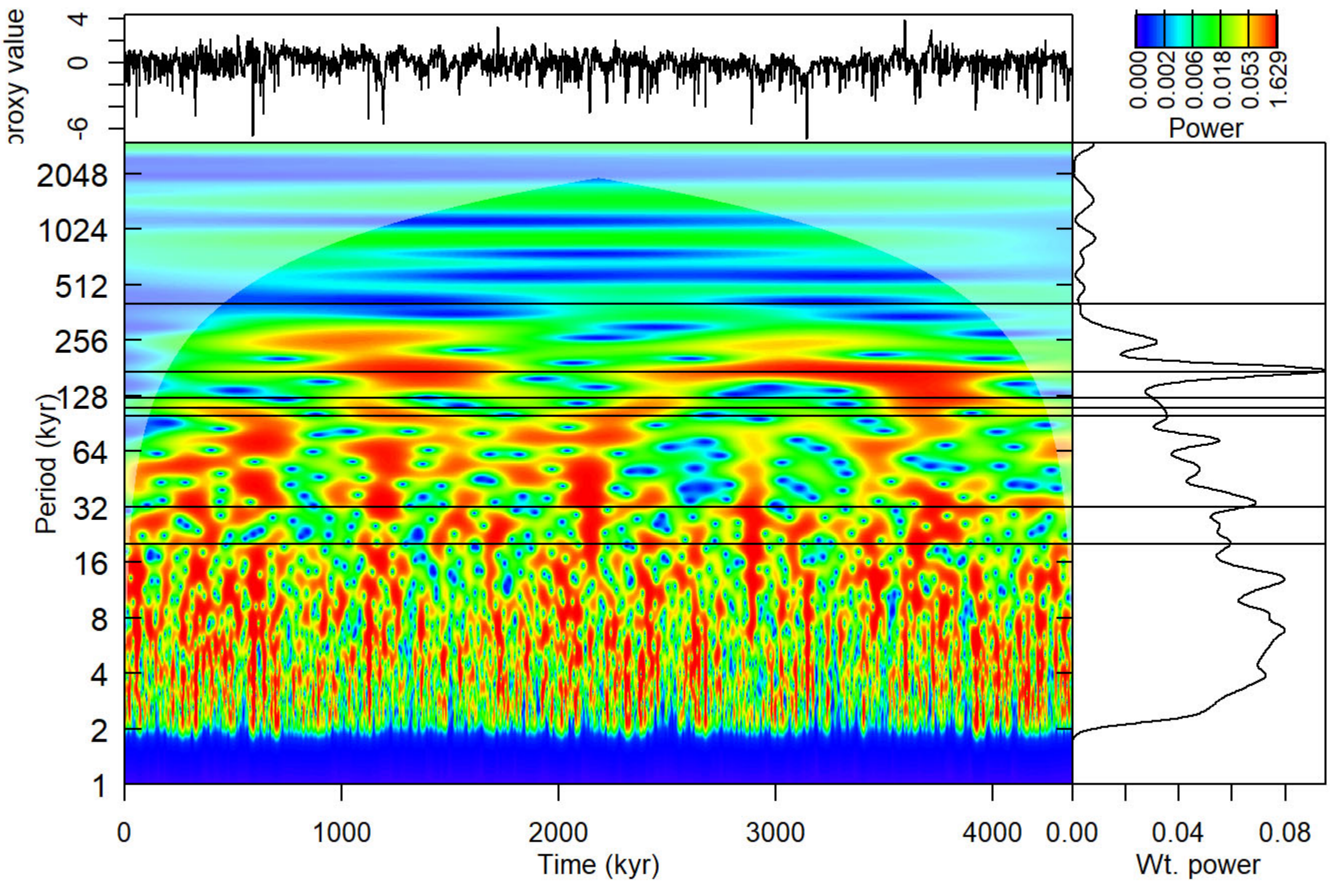
```
alb_Ti_time <- curve2tune(data = alb_Ti_ndet,
                          tracked_cycle_curve = alb_Ti_track_comp,
                          tracked_cycle_period = 173,
                          genplot = FALSE,
                          keep_editable = FALSE
                          )

alb_Ti_time <- linterp(alb_Ti_time)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * Determining median sampling interval for series
 * Will interpolate to median sampling interval of 1.082284
 * New number of samples= 4038
```




```
alb_Ti_time_wt <- analyze_wavelet(alb_Ti_time,
                                  dj = 1/100,
                                  lowerPeriod = 1,
                                  upperPeriod = 3000,
                                  verbose = FALSE,
                                  omega_nr = 10
                                  )

plot_wavelet(wavelet = alb_Ti_time_wt,
             lowerPeriod = NULL,
             upperPeriod = NULL,
```

```
n.levels = 100,
palette_name = "rainbow",
color_brewer = "grDevices",
useRaster = TRUE,
periodlab = "Period (kyr)",
x_lab = "Time (kyr)",
keep_editable = FALSE,
dev_new = F,
add_lines = NULL,
add_points = NULL,
add_abline_h = c(20,32,100,110,125,173,405),
add_abline_v = NULL,
add_MTM_peaks = FALSE,
add_data = TRUE,
add_avg = TRUE,
add_MTM = FALSE,
demean_mtm = TRUE,
detrend_mtm = TRUE,
padfac_mtm = 5,
tbw_mtm = 3,
plot_horizontal = TRUE
)
```



The CWT performed in time domain shows a lot of power and/or prominent peaks in the Milankovitch bands (precession: ~20 kyr, obliquity: ~32 kyr, short eccentricity: ~100-125 kyr and 173 kyr) in line with the expectations from the literature.

Step 5: Average Spectral Misfit (ASM)

```
freq <- c(1.151,1.458,1.548,1.647,1.746,1.964,2.093,5.228,5.704,5.853,
          6.240,7.103,7.202,10.317,11.101,12.55,12.659)

target <- c(1/405,1/173,1/131.3,1/123.9,1/99.2,1/94.9,1/38.8,1/32.1,
            1/31.6,1/31.3,1/30.8, 1/24.4,1/20.2,1/19.8,1/19.3,1/16.8,1/16.7)

rayleigh <- 0.1

nyquist <- 15
```

```
asm(freq,
    target,
    fper=NULL,
    rayleigh,
    nyquist,
    sedmin=0.05,
    sedmax=5,
    numsed=500,
    linLog=1,
    iter=100000,
    output=F,
    genplot=T
    )
```

```
----- PERFORMING AVERAGE SPECTRAL MISFIT ANALYSIS -----

**** WARNING: No uncertainty assigned to astronomical target frequencies.


 * Analysis complete:
    Optimal Sedimentation Rate (cm/ka) at = 0.4931261
    Ho-SL (%) = 9.634
      or p-value = 0.09634
    ASM (cycles/ka) = 0.001008439
    Number of Astronomical Terms Fit = 17
```

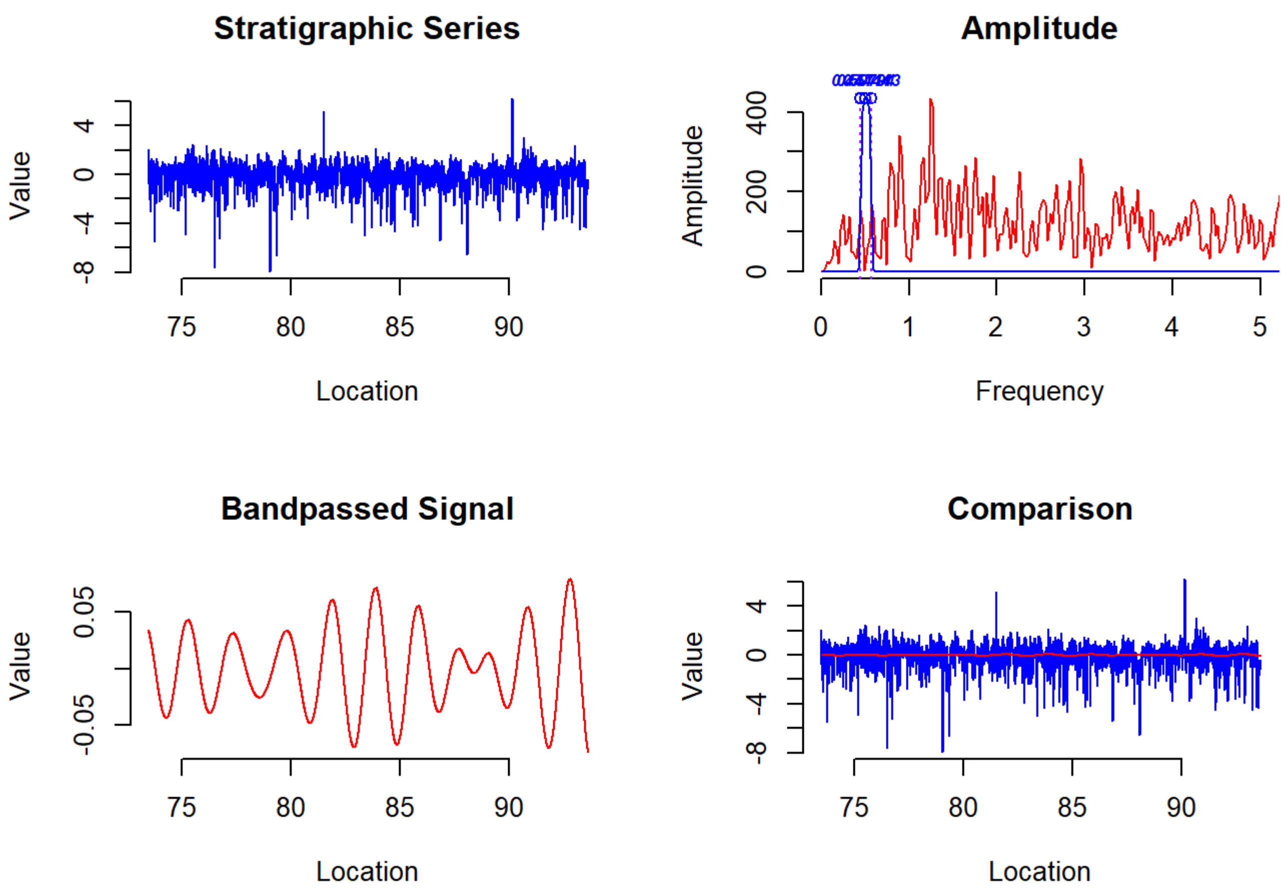
The ASM analysis is performed confronting the > 90 % CL frequencies from the MTM analysis with the theroretical duration of Milankovitch cycles.

The ASM results in a sedimentation rate of 0.493 cm/ka, consistent with the 0.4-0.6 cm/kyr expectation for Blatica during the Cambrian.

Step 6: Milankovitch bands filters in depth domain

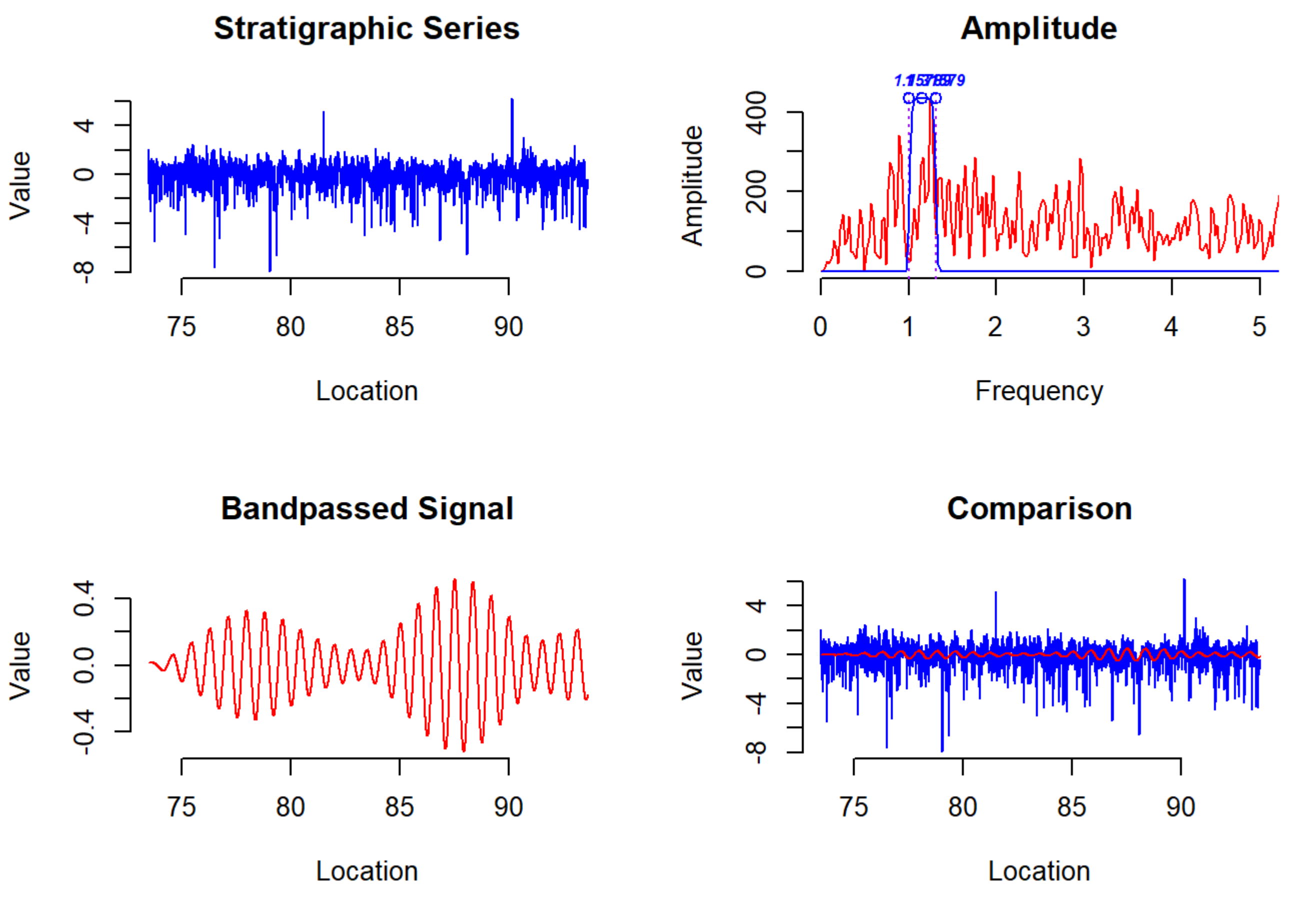
```
#405 kyr cycle (1.75-2.25 m)
alb_Ti_405 <- taner(alb_Ti, xmax=5, fhigh=1/1.75, flow=1/2.25, demean = T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= 4.069401e-05
```



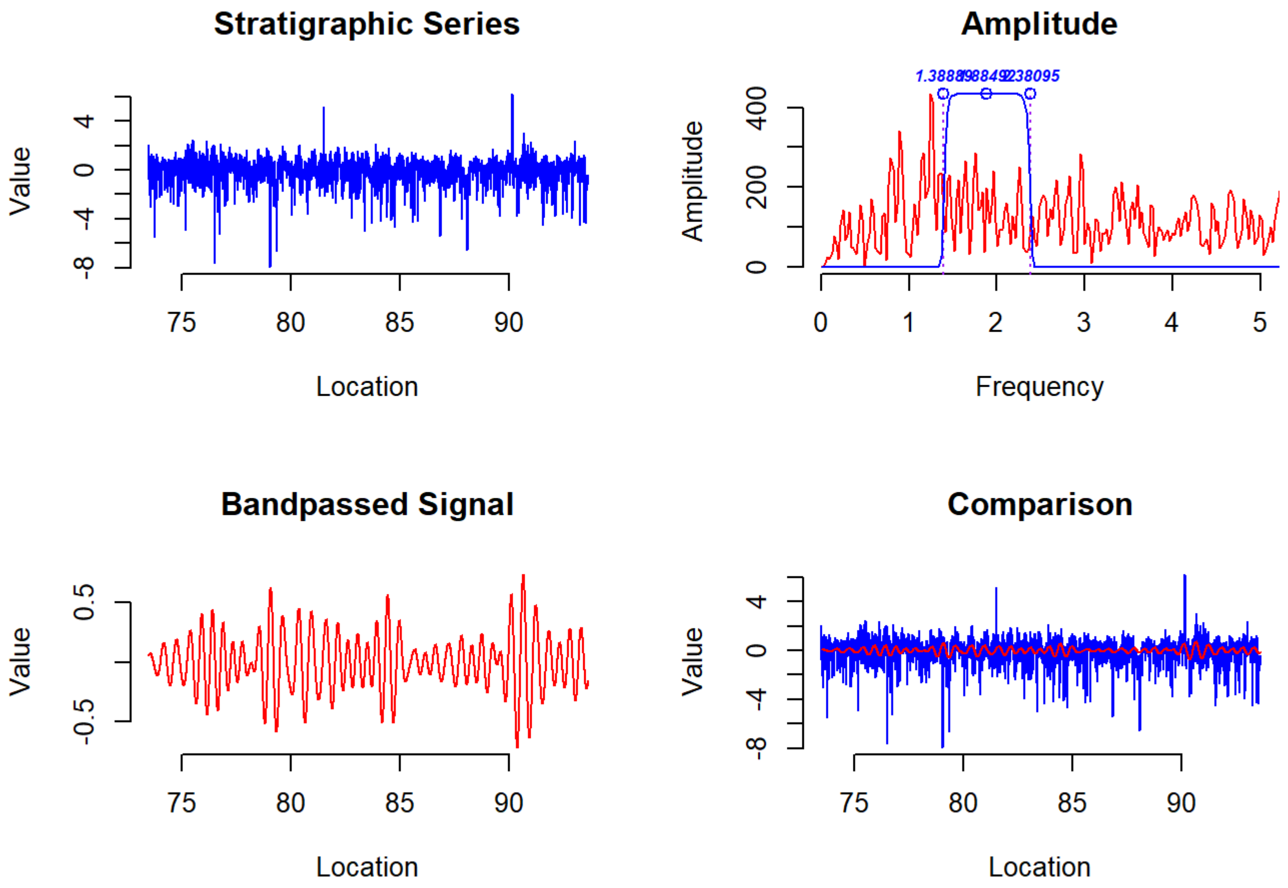

```
#173 kyr cycle (0.76-1 m)
alb_Ti_173 <- taner(alb_Ti,xmax=5, fhigh=1/0.76, flow=1, demean = T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= 4.069401e-05
```



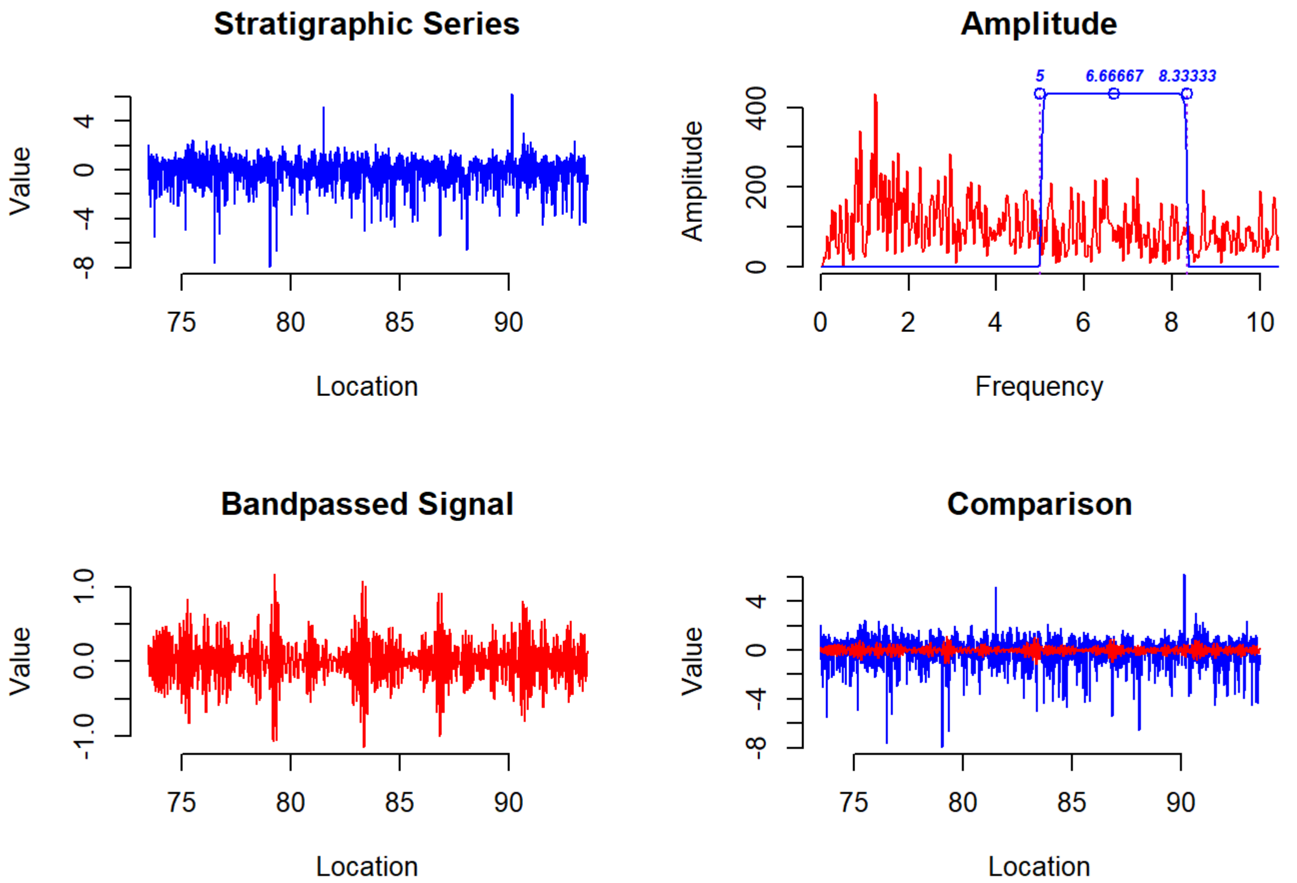

```r
#short eccentricity band (0.42-0.72 m)
alb_Ti_100 <- taner(alb_Ti, xmax=5, fhigh=1/0.42, flow=1/0.72, demean = T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= 4.069401e-05
```



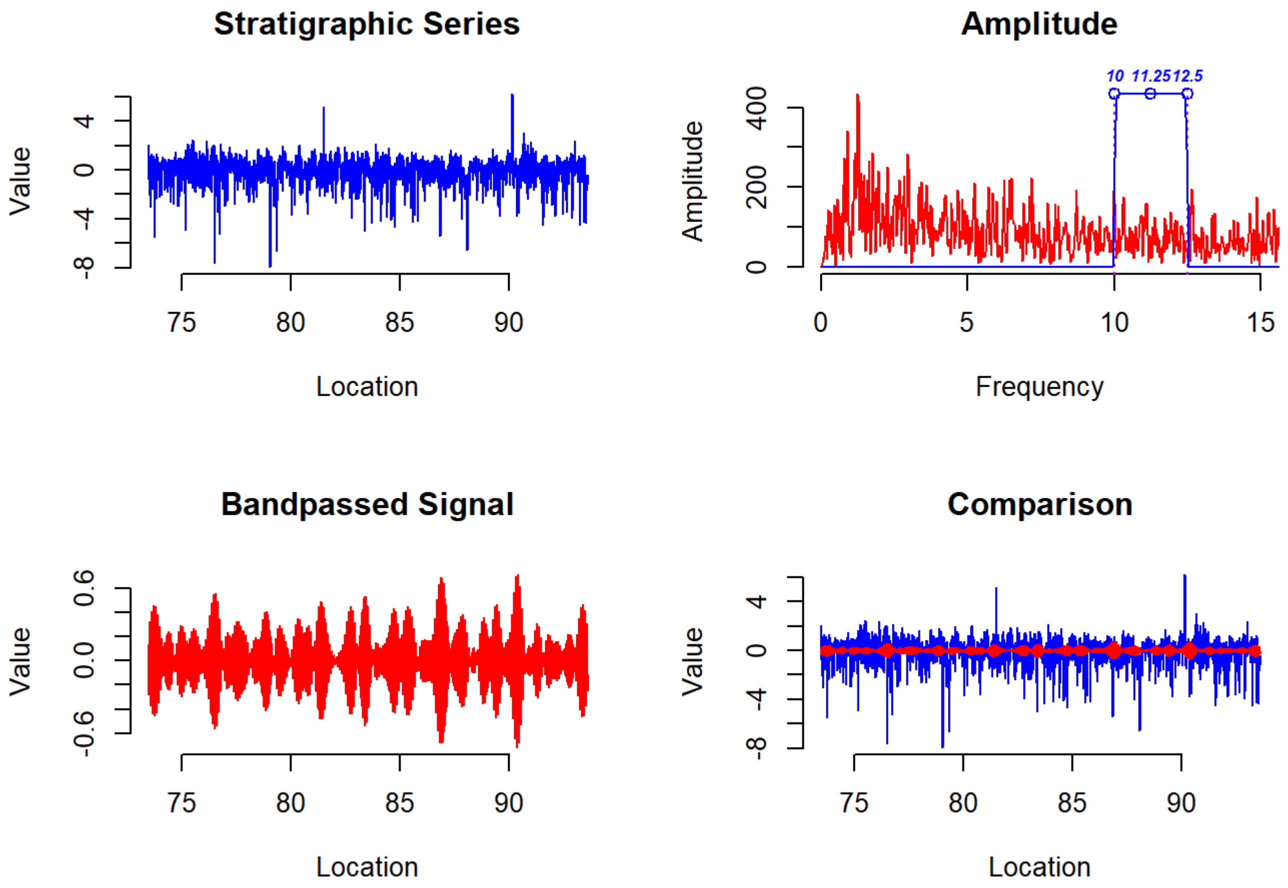

```r
#obliquity band (0.12-0.2 m)
alb_Ti_31 <- taner(alb_Ti, xmax=10, fhigh=1/0.12, flow=1/0.2, demean=T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= 4.069401e-05
```




```
#precession band (0.08-0.1 m)
alb_Ti_20 <- taner(alb_Ti, xmax=15, fhigh=1/0.08, flow=1/0.1, demean=T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= 4.069401e-05
```



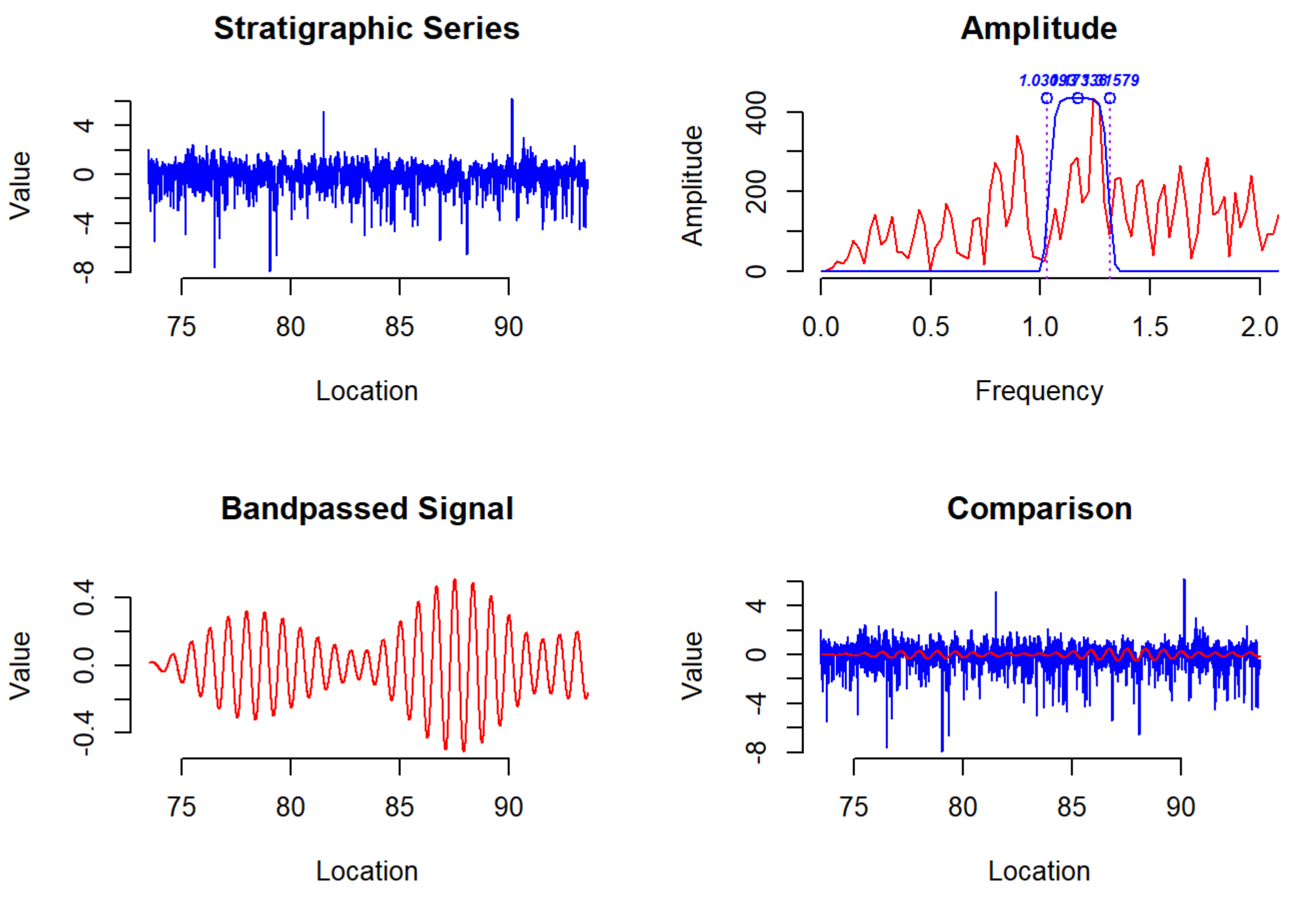
The filtering of the Milankovitch bands in depth domain allows to see the imprint of the astronomical cycles on the Ti sedimentary record.

Step 7: Tuning of the Ti series

7.1. Filtering of the 0.76-0.97 m band

```
Ti_173R <- taner(alb_Ti, xmax=2, fhigh=1/0.97, flow=1/0.76, demean=T)
```

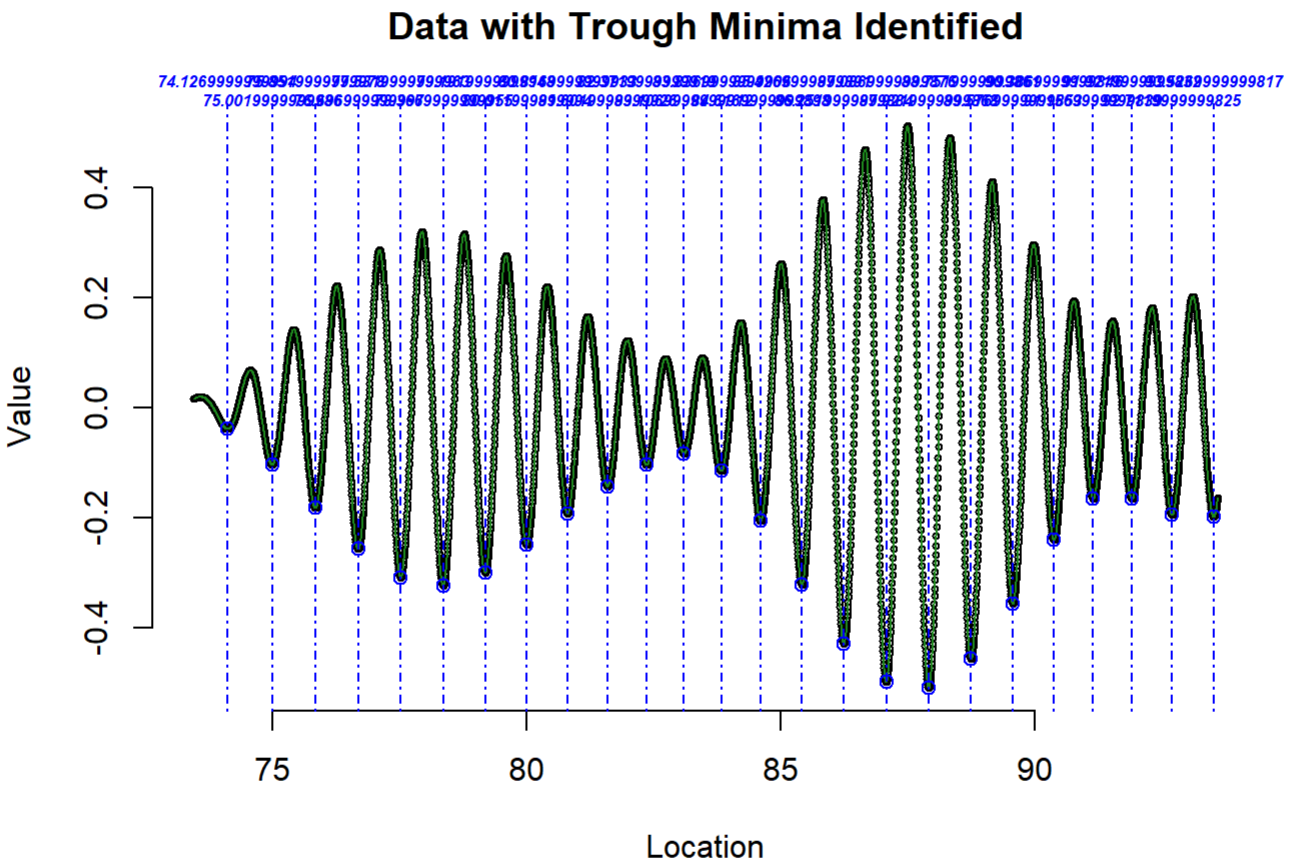
```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= 4.069401e-05
```



7.2. Identification of the trough of the filtered signal

```
Ti_173_min <- trough(Ti_173R, level = 200, genplot = T)
```

```
----- FINDING MINIMA OF TROUGHS, FILTERING AT THRESHOLD VALUE -----
 * Number of data points= 4032
 * Number of columns= 2
 * Identifying minima of troughs
 * Number of troughs identified= 25
 * Filtering troughs at threshold of 200
 * Number of troughs <= 200 : 25
```




```
Ti_173_min <- Ti_173_min[,c(2,3)]

#write.csv(Ti_173_min,"Ti_173_rsp0.005_minTan_0.76-0.97m.csv")
```

7.3. Trough = multiple of 173 kyr cycle

Once the ".csv" file is created, go into it and for each location, add a multiple of 173 for the trough value as follows:

Location Trough_Value

74.101; 173

74.961; 346

75.813; 519

76.661; 692

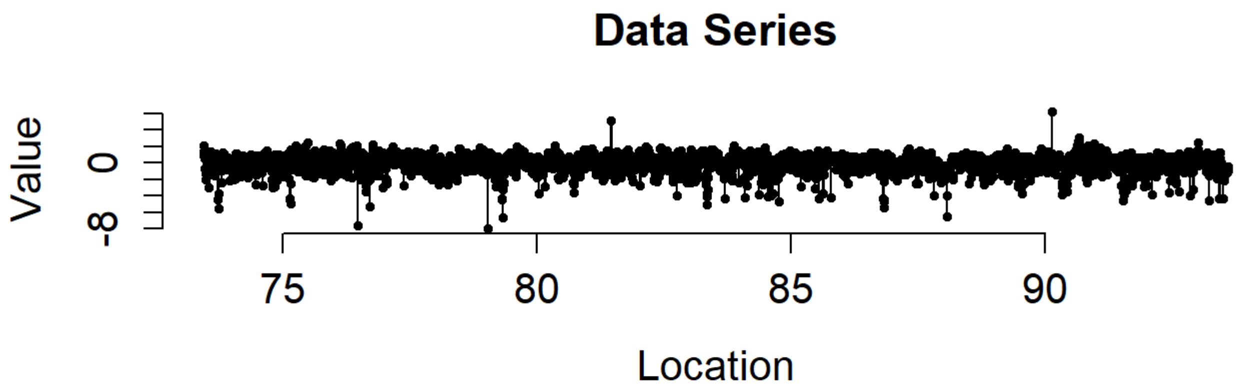
…; …

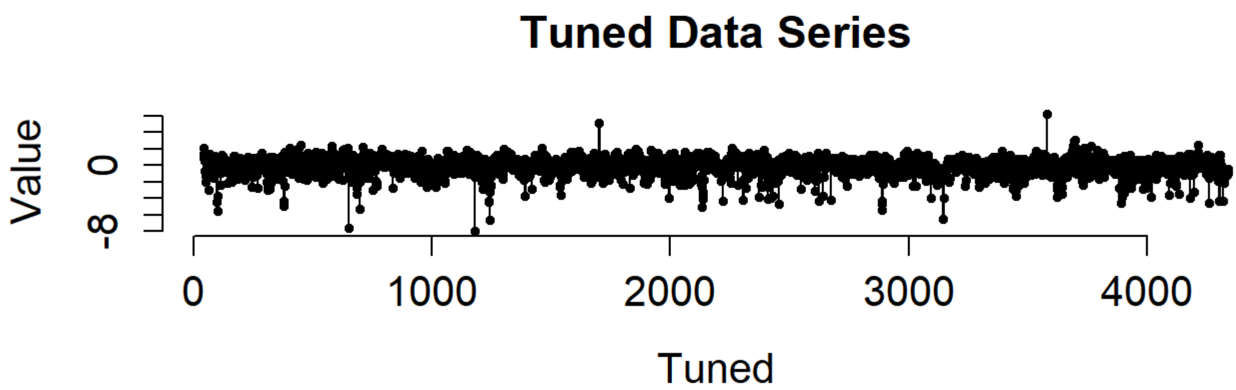
93.543; 4325

7.4. Tuning of the 5mm spaced Ti detrended dataset

```
Ti_173_min <- read.csv("Ti_173_rsp0.005_minTan_0.76-0.97m.csv", sep=";")

Ti_173_tuned <- tune(alb_Ti, Ti_173_min, extrapolate=T, genplot=T, check=T, verbose=T)
```

```
----- TUNING STRATIGRAPHIC SERIES -----
 * Number of data points= 4032
 * Number of time control points= 25
 * Sorting datasets into ensure increasing order, removing empty entries

 * Mean sampling interval= 1.067338
 * Median sampling interval= 1.054878
 * Maximum sampling interval= 1.184932
 * Minimum sampling interval= 0.9885714
```



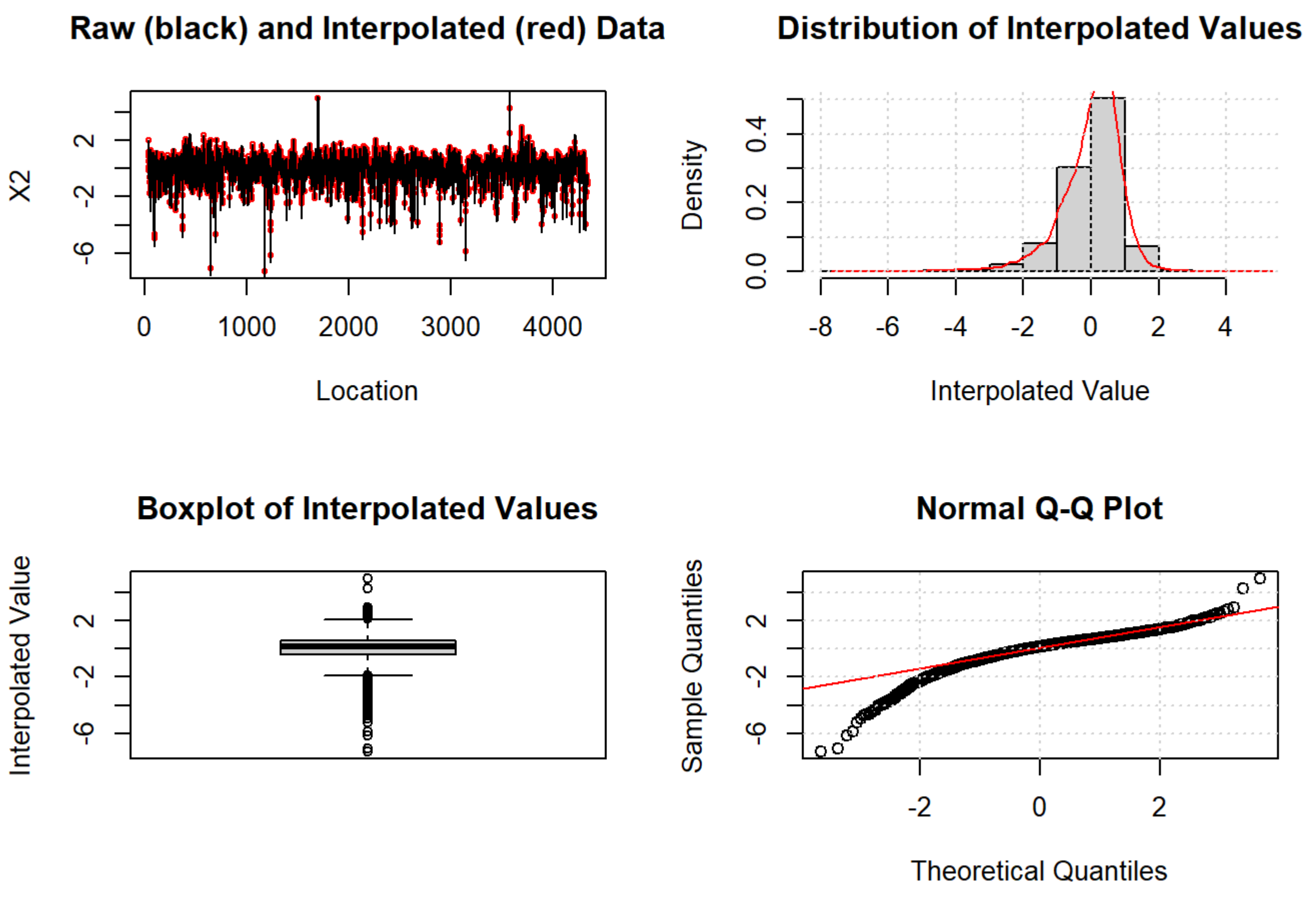


7.5. Evenly spaced dataset in time domain

Interpolation of the tuned dataset every 1.067338 kyr (mean sampling interval) to have an evenly space tune dataset

```
alb_Ti_time <- linterp(Ti_173_tuned, dt=1.067338, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * New number of samples= 4031
```



Step 8: MTM and EHA in time domain

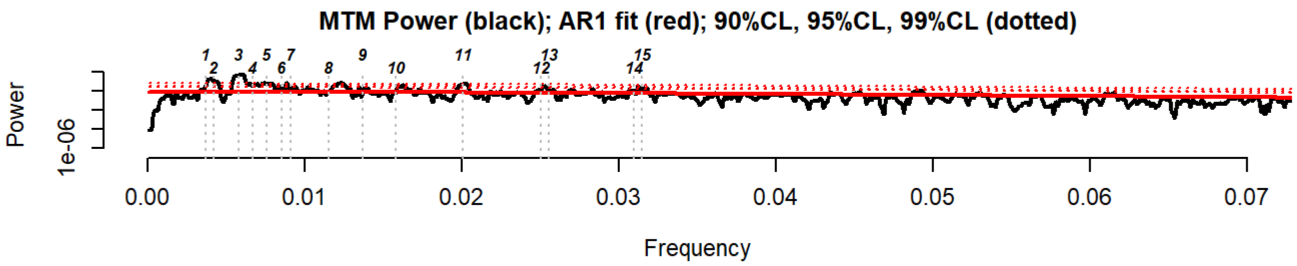
8.1. MTM in time domain

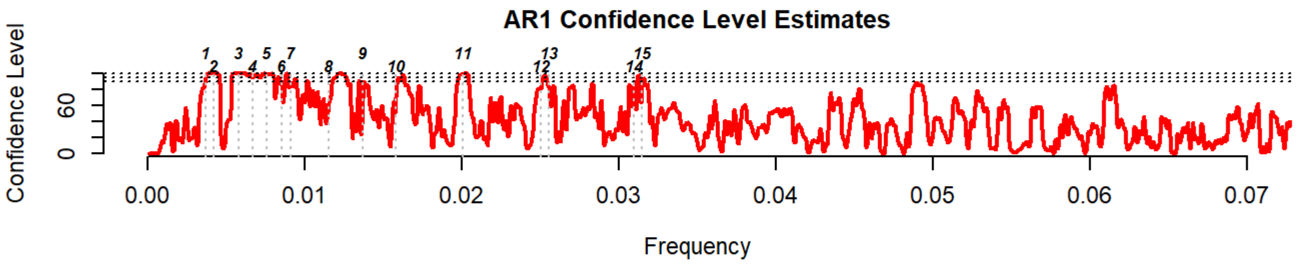
```
alb_Ti_time_MTM<-mtm(alb_Ti_time, xmax=0.07, siglevel = 0.9, ar1 = T, tbw= 2, output = 1)
```

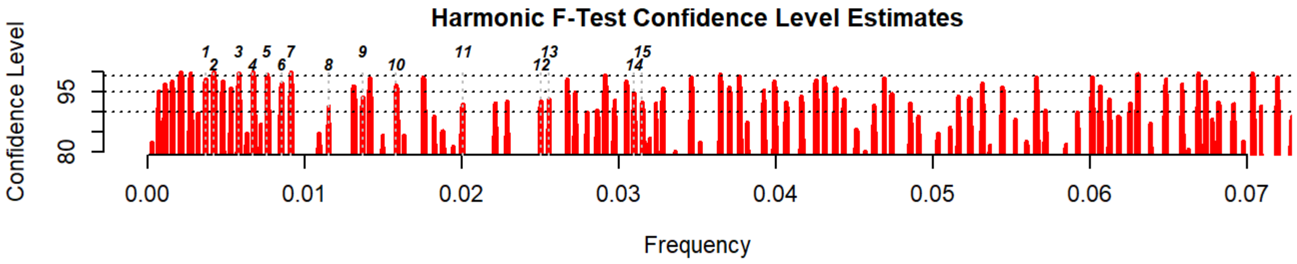
```
----- PERFORMING Multitaper Spectral Analysis -----
 * Number of data points in stratigraphic series: 4031
 * Stratigraphic series length (space or time): 4301.372
 * Sampling interval (space or time): 1.067338
 * Will use default setting of 3 DPSS tapers
 * Mean value subtracted= 0.0002517748
 * Linear trend NOT subtracted
 * Nyquist frequency: 0.4684552
 * Rayleigh frequency: 0.0002324263
 * MTM Power spectrum bandwidth resolution (halfwidth): 0.0004648526
 * Padded to 20156 points
 * Estimated AR1 coefficient = 0.6212844

 * Searching for significant spectral peaks that satisfy 90 % CL
     requirements outlined in Meyers (2012):
 * Number of significant F-test peaks identified = 92
ID  / Frequency / Period / Harmonic_CL / Rednoise_CL
1   0.003672153   272.3198   98.11969   94.30495
2   0.004183465   239.0363   99.9596   99.94852
3   0.005763886   173.4941   99.59287   100
```

4	0.006693545	149.3977	99.93526	94.85659
5	0.007576721	131.9832	99.38519	98.51764
6	0.00850638	117.5588	97.05777	84.83089
7	0.009110658	109.7616	99.83016	88.81513
8	0.01148129	87.09824	91.49029	60.62901
9	0.01366599	73.17437	93.73957	69.35043
10	0.0158042	63.27431	96.79027	70.85455
11	0.02003415	49.91477	91.8715	99.14432
12	0.02500783	39.98748	92.75957	81.17411
13	0.02551914	39.18627	93.30452	82.46565
14	0.03091116	32.35077	94.76663	81.53078
15	0.03146896	31.77735	92.44902	89.46365
16	0.07888157	12.67723	98.24804	81.27618
17	0.08311151	12.03203	99.41217	93.76132
18	0.08520325	11.73664	99.78533	78.37017
19	0.0924081	10.82156	98.55063	97.42502
20	0.1046331	9.557203	99.35061	72.60485
21	0.1083518	9.2292	98.04082	59.37082
22	0.1189499	8.406903	93.34178	95.41128
23	0.1204373	8.303074	90.56264	88.05812
24	0.1385657	7.216795	98.05109	97.67991
25	0.1396348	7.16154	90.55456	86.19492
26	0.1450733	6.893068	92.72452	92.61329
27	0.1464678	6.82744	93.29638	82.1956
28	0.1504653	6.64605	94.22877	72.70561
29	0.1521852	6.570942	96.01006	87.28064
30	0.1688726	5.921625	94.73928	59.53296
31	0.1694304	5.90213	98.06945	75.66421
32	0.1751478	5.709465	99.53258	73.8443
33	0.1756126	5.694353	92.28933	86.49587
34	0.1777043	5.627325	95.84424	91.07312
35	0.1787734	5.593673	98.74848	96.1525
36	0.1841654	5.4299	95.13835	93.33122
37	0.1899758	5.263828	92.77685	94.60851
38	0.1930437	5.180175	98.45542	77.28544
39	0.1984357	5.039415	92.93684	76.75734
40	0.199133	5.02177	96.27157	79.9269
41	0.2035488	4.912826	97.12894	91.63699
42	0.2126595	4.702353	95.2339	97.48242
43	0.2133567	4.686986	99.82262	79.82971
44	0.2140075	4.672733	98.66001	95.50713
45	0.2169824	4.608669	99.91905	83.88459
46	0.218191	4.583141	98.57328	96.36083
47	0.2366447	4.225744	95.4402	83.09314
48	0.2404563	4.15876	97.94883	89.73545
49	0.2438496	4.100889	90.44932	89.0816
50	0.2458483	4.067549	98.96937	65.27153
51	0.2491021	4.014418	97.02854	88.59115
52	0.2545871	3.927929	97.9532	96.12543
53	0.2637443	3.791552	91.03357	83.59602
54	0.2665332	3.751877	95.18007	61.42055
55	0.2670445	3.744694	94.39814	81.11712
56	0.2676953	3.73559	98.92259	69.35863
57	0.2682066	3.728469	91.48261	90.09225
58	0.2702984	3.699616	94.62618	94.21628
59	0.2719717	3.676853	97.87828	82.45936
60	0.2763876	3.618107	99.5166	97.56497
61	0.2775032	3.603562	99.72265	80.50463

62	0.2790371	3.583752	97.50418	83.856
63	0.2865209	3.490147	98.47766	87.8011
64	0.2881943	3.469881	90.22236	90.43317
65	0.2933539	3.408852	99.06799	84.75965
66	0.2948878	3.39112	90.61869	90.75301
67	0.295771	3.380994	99.87185	88.54789
68	0.29856	3.349411	96.87521	79.55894
69	0.301256	3.319436	93.67934	98.21133
70	0.3028829	3.301606	93.53422	82.58865
71	0.3036266	3.293519	95.67298	82.83303
72	0.3043239	3.285973	99.44436	97.6364
73	0.3049281	3.279461	96.0226	79.69787
74	0.3101807	3.223927	97.95119	96.23019
75	0.3262173	3.065441	97.45783	81.97655
76	0.3330503	3.002549	92.79158	99.85386
77	0.3377451	2.960813	99.22818	75.69901
78	0.3433231	2.912708	93.21386	89.50133
79	0.3459726	2.890402	94.27931	88.59534
80	0.3467628	2.883816	91.75708	77.67877
81	0.3510857	2.848307	98.04238	91.04519
82	0.3755357	2.662862	91.87629	57.88583
83	0.4113276	2.431152	99.71812	89.88467
84	0.4196481	2.382949	94.69839	85.34974
85	0.4240639	2.358135	98.08403	97.02254
86	0.4422853	2.260984	98.02701	77.99548
87	0.4428895	2.257899	96.66744	82.09898
88	0.4442375	2.251048	94.98735	77.30791
89	0.4534877	2.205132	92.15221	64.84901
90	0.453999	2.202648	95.81803	85.82515
91	0.460832	2.169988	91.3433	86.07989
92	0.4617151	2.165838	93.16843	87.15591



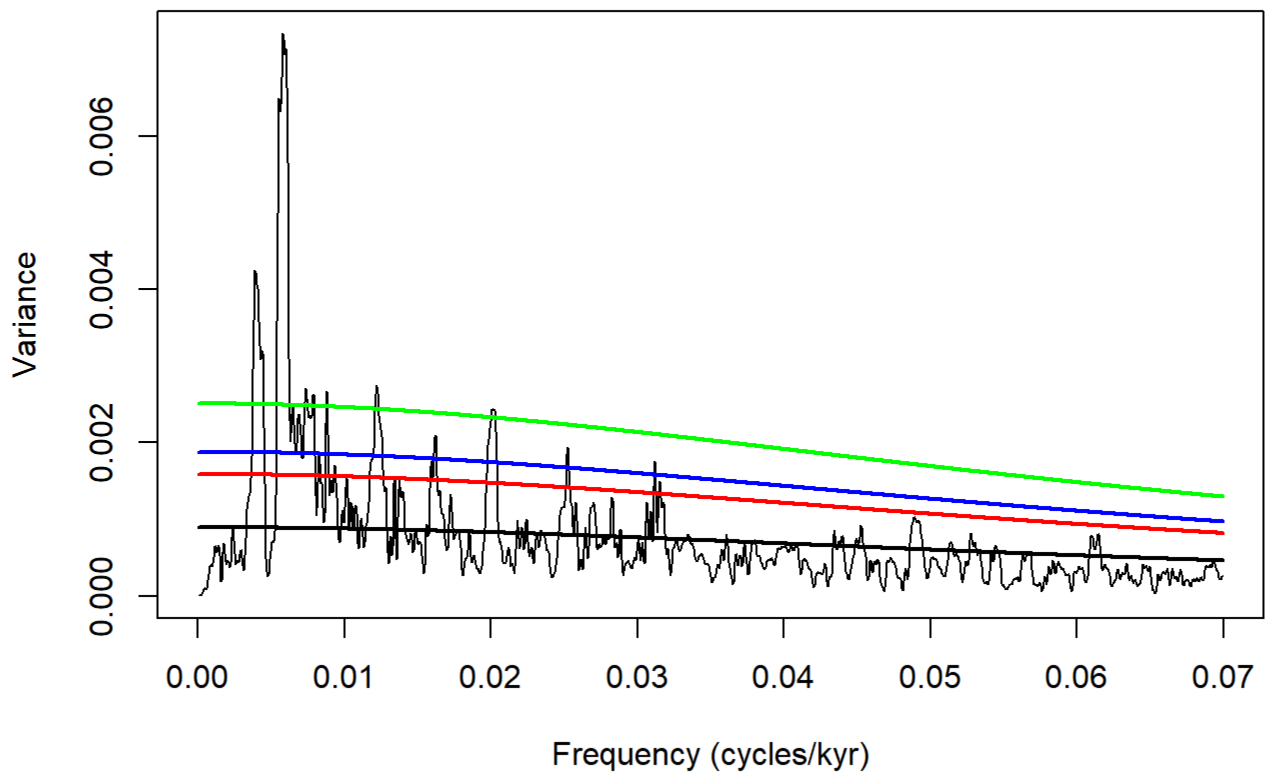




```
alb_Ti_time_MTM <- iso(dat=alb_Ti_time_MTM,xmin=0,xmax=0.07, genplot=F)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 10077
 * Number of columns= 8
 * Minimum= 4.648295e-05 , Maximum= 0.4684087
 * Isolating data between 0 and 0.07
 * Number of data points following culling= 1505
```

```
plot(alb_Ti_time_MTM$Frequency,
     alb_Ti_time_MTM$Power,
     type = 'l',
     xlab = "Frequency (cycles/kyr)",
     ylab = "Variance"
     )

lines(alb_Ti_time_MTM$Frequency,
      alb_Ti_time_MTM$AR1_fit,
      type = 'l',
      col = 'black',
      lwd = 2
      )

lines(alb_Ti_time_MTM$Frequency,
      alb_Ti_time_MTM$AR1_90_power,
      type = 'l',
      col = 'red',
      lwd = 2
      )

lines(alb_Ti_time_MTM$Frequency,
      alb_Ti_time_MTM$AR1_95_power,
      type = 'l',
      col = 'blue',
      lwd = 2
      )

lines(alb_Ti_time_MTM$Frequency,
      alb_Ti_time_MTM$AR1_99_power,
      type = 'l',
      col = 'green',
      lwd = 2
      )
```



The 2 pi-MTM on the tuned dataset shows the range of cyclicities in the signal in time domain. Allowing to visually identify > 90 % CL periodicities.

8.2. EHA in time domain

```
alb_Ti_time_EHA<- eha(alb_Ti_time,
                      tbw=2,
                      fmin=0.001,
                      fmax=0.07,
                      step=1,
                      win=1100,
                      demean=T,
                      detrend=T,
                      siglevel=0.90,
                      sigID=F,
                      ydir=1,
                      output=1,
                      pl=1,
                      palette=1,
                      centerZero=T,
                      ncolors=200,
                      genplot=4,
                      verbose=T
                      )
```

```
----- PERFORMING EVOLUTIVE HARMONIC ANALYSIS -----
* Number of data points in stratigraphic series: 4031
* Stratigraphic series length (space or time): 4301.372
* Sampling interval (space or time): 1.067338
```

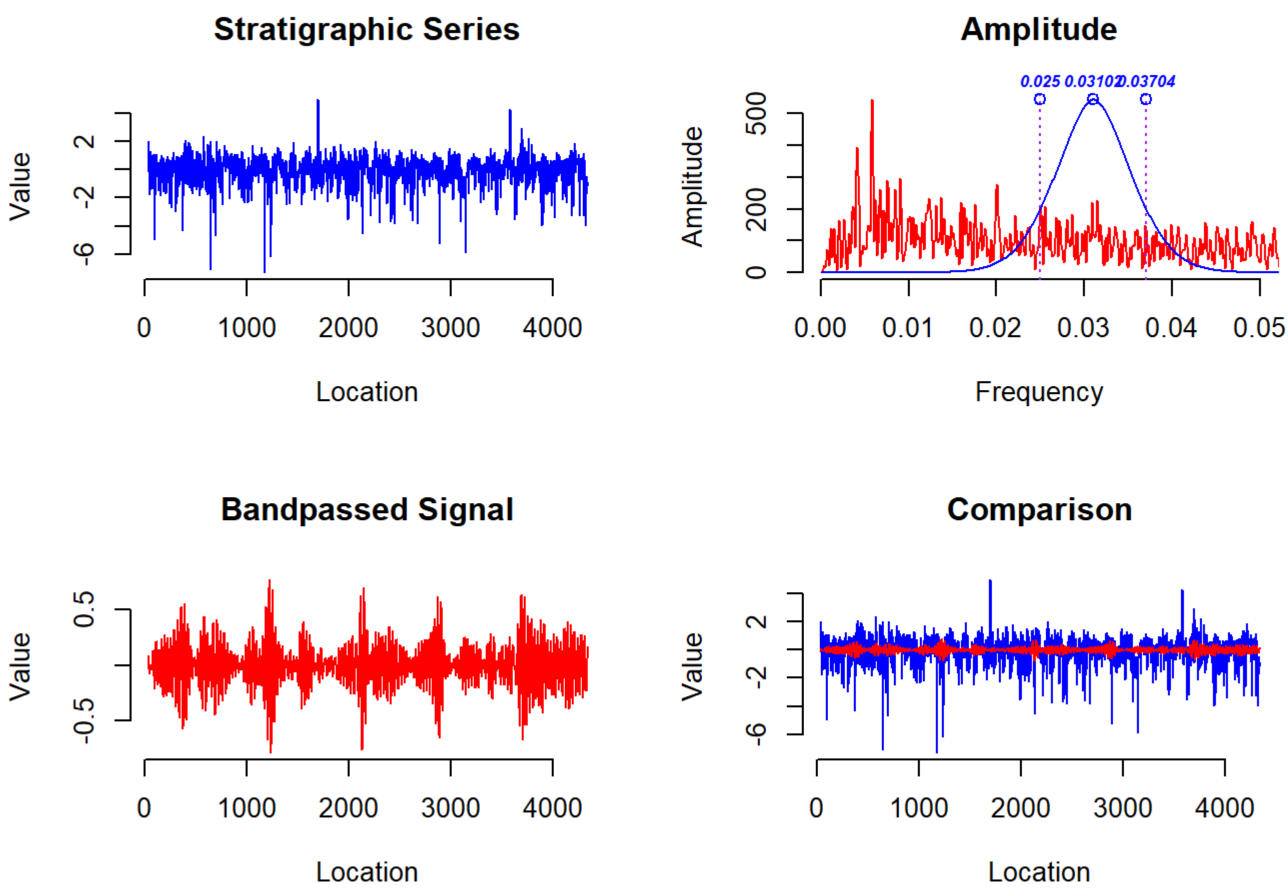
```
 * Number of data points per window: 1031
 * Moving window size (space or time): 1099.358
 * Window step points: 1
 * Window step (space or time): 1.067338
 * Number of windows: 3001
 * Mean value for each window will be subtracted
 * Linear trend for each window will be subtracted
 * Nyquist frequency: 0.4684552
 * Rayleigh frequency: 0.0009087394
 * MTM Power spectrum bandwidth resolution (halfwidth): 0.001817479
 * Will use 3 DPSS tapers
 * Padded to 4096 points
```

The EHA is performed on the Ti tuned series and confirms the presence of recurrent periodicities in the Milankovitch bands along the ACL as suggested by the > 90 % CL frequencies observed in the 2 pi-MTM

Step 9: Hilbert transform analysis between obliquity and the 173 kyr cycle

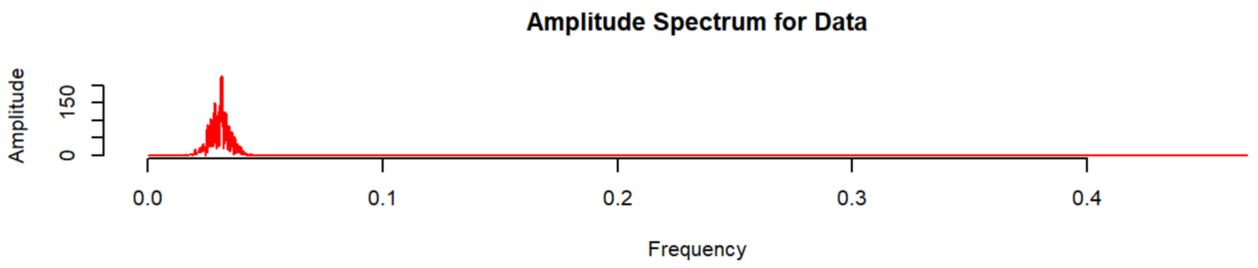
```
#Filter out the obliquity cycle
alb_Ti_time_obl <- taner(alb_Ti_time, xmax=1/20, fhigh=1/27, flow=1/40)
```

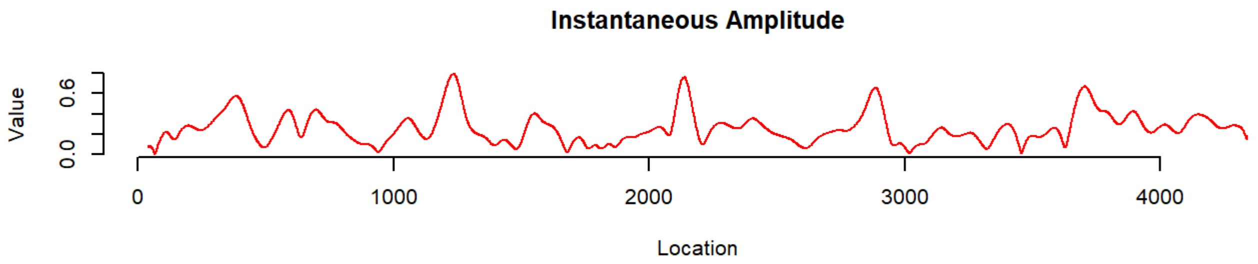
```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4031
 * Sample interval= 1.067338
 * Mean value removed= 0.0002517748
```

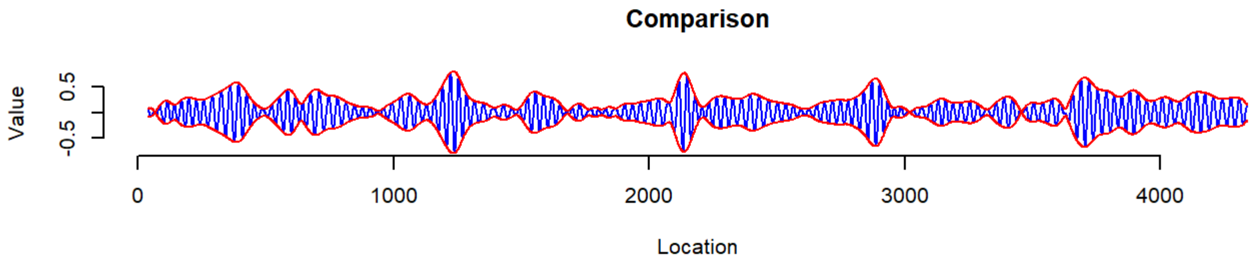


```
#Do the Hilbert transform to extract the amplitude
alb_Ti_time_obl_hilbert <- hilbert(alb_Ti_time_obl)
```

```
----- PERFORMING HILBERT TRANSFORM ON STRATIGRAPHIC SERIES -----
 * Number of data points= 4031
 * Sample interval= 1.067338
 * Mean value removed= 0.0001213115
```

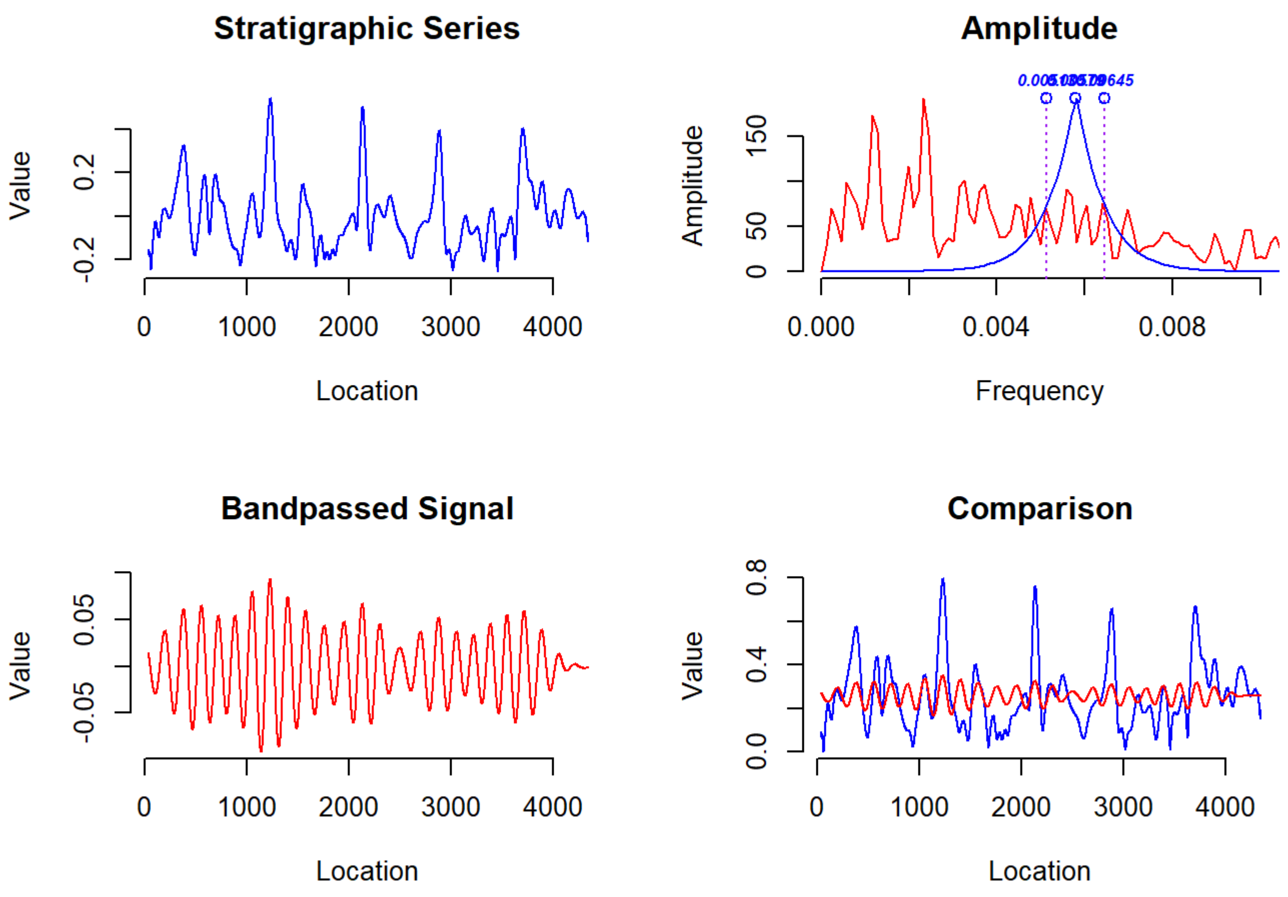






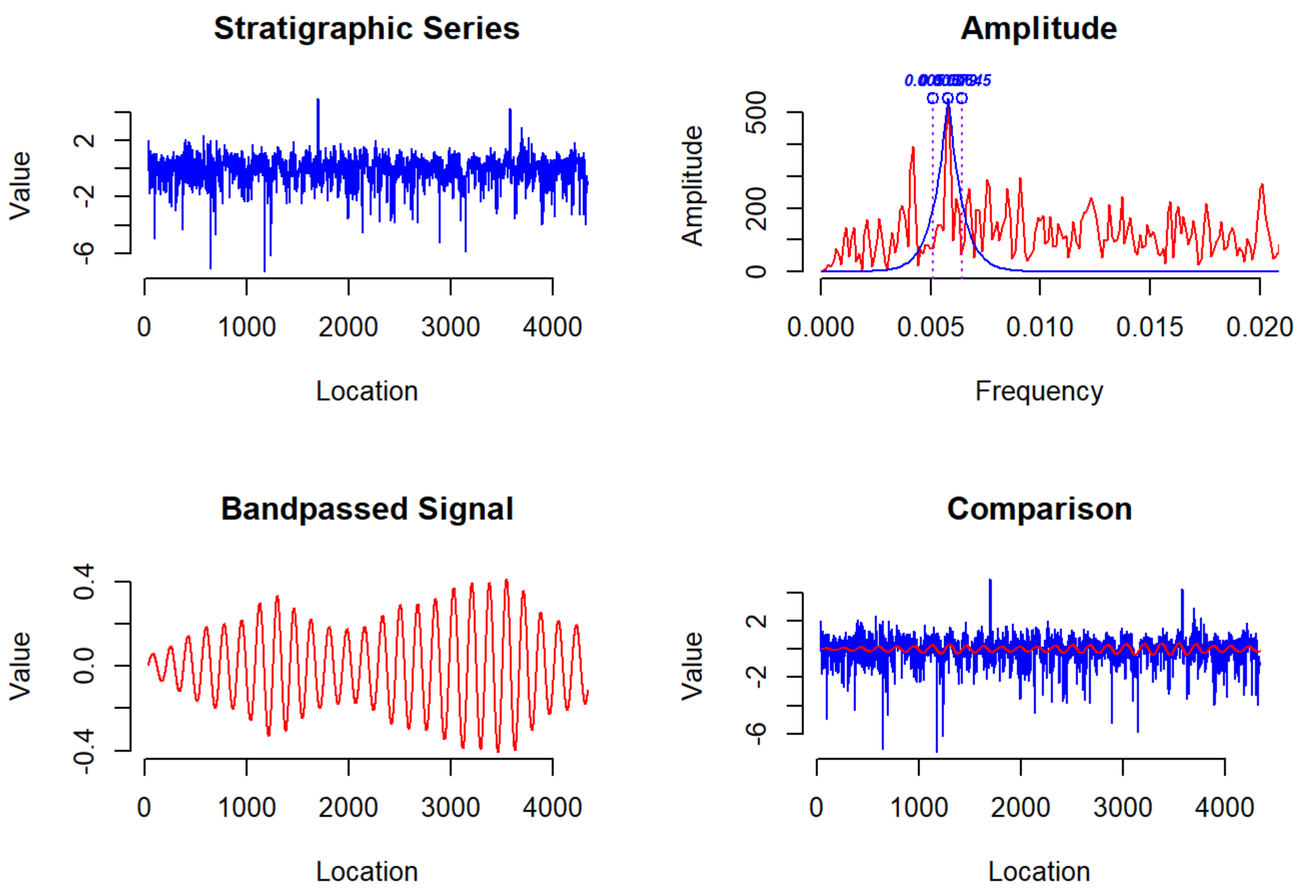

```
#Filter out the 173 kyr cycle from the amplitude modulation of the obliquity cycle
alb_Ti_time_obl_hilbert_173 <-taner(alb_Ti_time_obl_hilbert,
                                    xmax=1/100,
                                    fhigh=1/195,
                                    flow=1/155,
                                    detrend=TRUE
                                    )
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4031
 * Sample interval= 1.067338
 * Mean value removed= 0.2578766
 * Linear trend removed. m= 5.15436e-06 b= -0.01128923
```

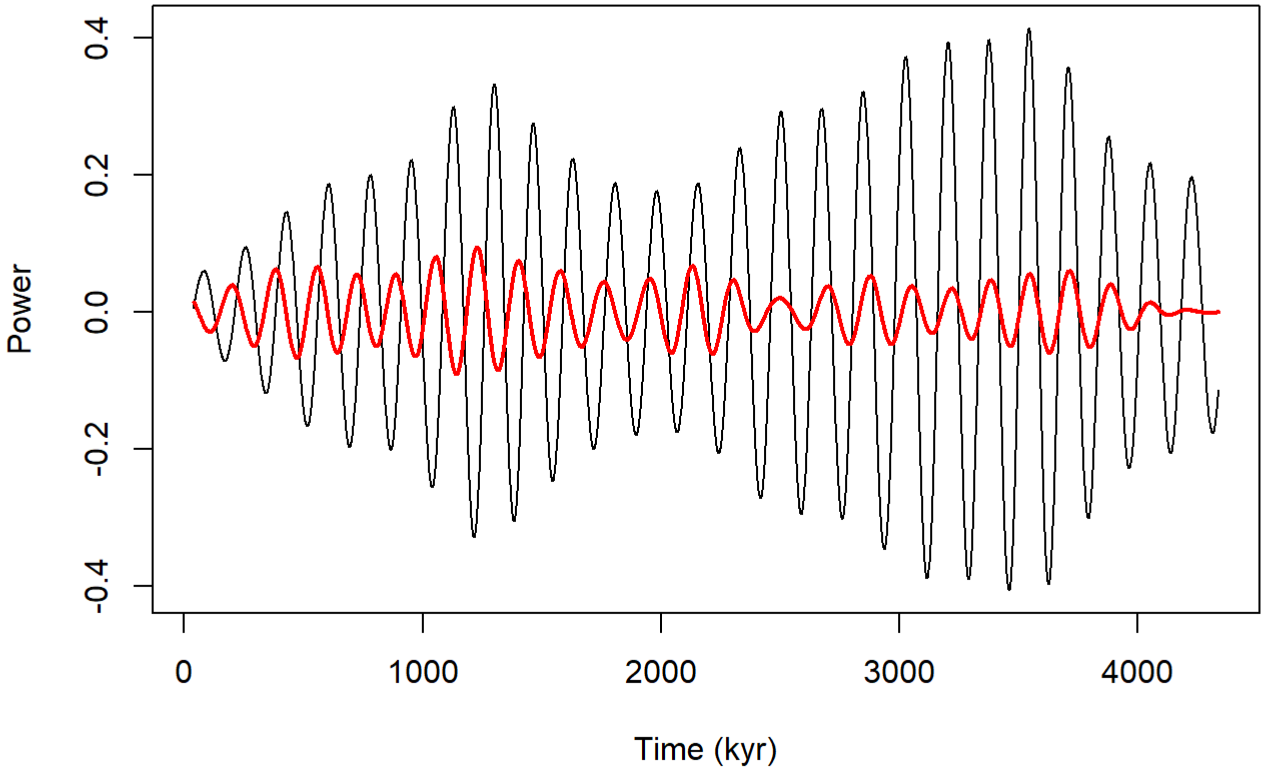



```r
#Filter out the 173 kyr obliquity cycle directly from the proxy record
alb_Ti_time_173 <- taner(alb_Ti_time,
                         xmax=1/50,
                         fhigh=1/195,
                         flow=1/155,
                         demean=T
                         )
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4031
 * Sample interval= 1.067338
 * Mean value removed= 0.0002517748
```




```
#Plot the 173 kyr obliquity cycle extracted from the amplitude modulation of the
#obliquity cycle vs the 173 kyr obliquity cycle directly extracted from the proxy
#record.

plot(alb_Ti_time_173[,1],
     alb_Ti_time_173[,2]-mean(alb_Ti_time_173[,2]),
     type="l",
     xlab ="Time (kyr)",
     ylab = "Power"
     )

lines(alb_Ti_time_obl_hilbert_173[,1],
      alb_Ti_time_obl_hilbert_173[,2]-mean(alb_Ti_time_obl_hilbert_173[,2]),
      col="red",
      lwd=2
      )
```



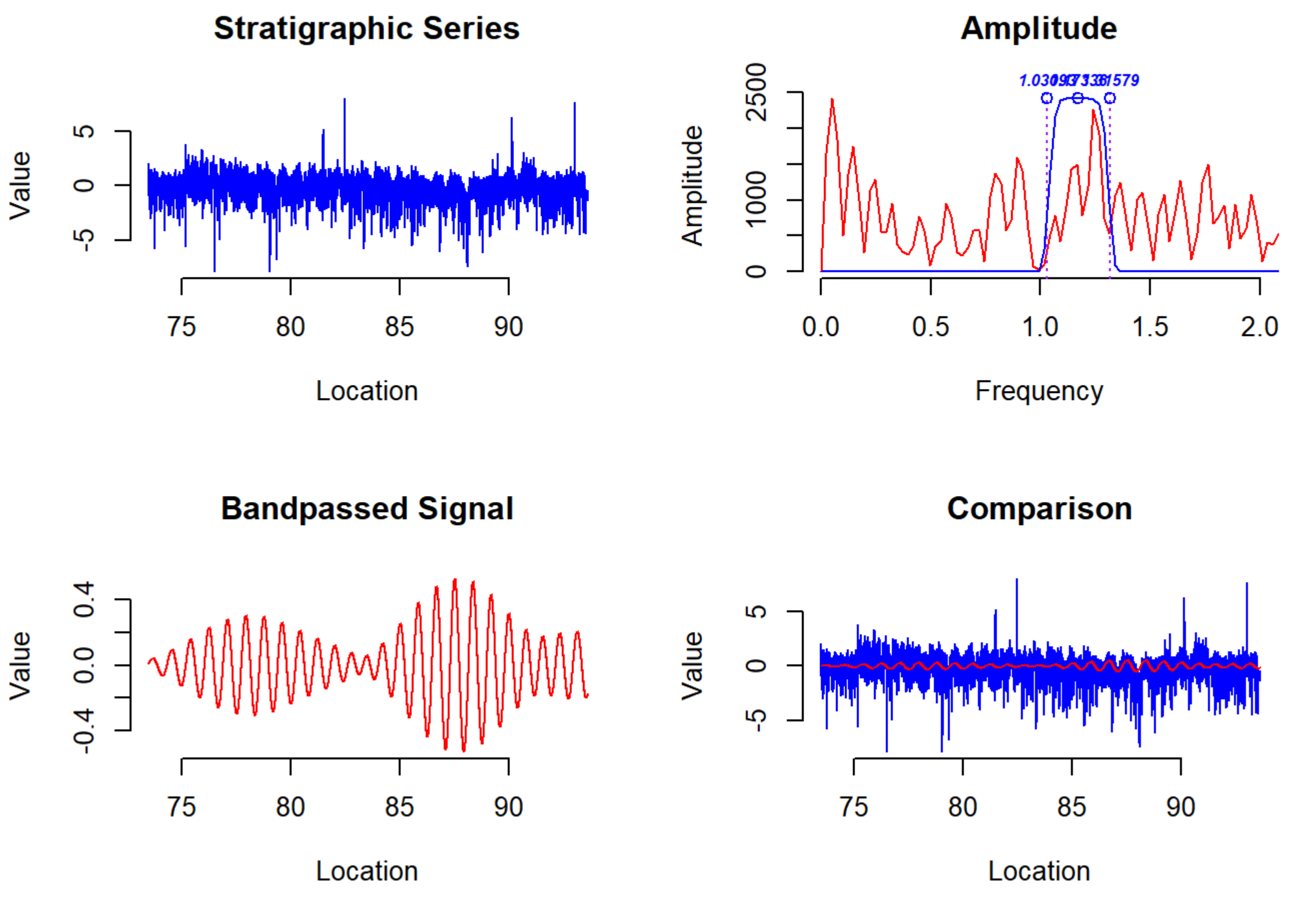
Step 10: Hilbert transform analysis between the 173 kyr and the 1.2 Myr cycles

10.1. Tuning of the 1mm non-detrended Ti series

Same tuning procedure as for step 7 but on the non resampled and non detrended Ti dataset

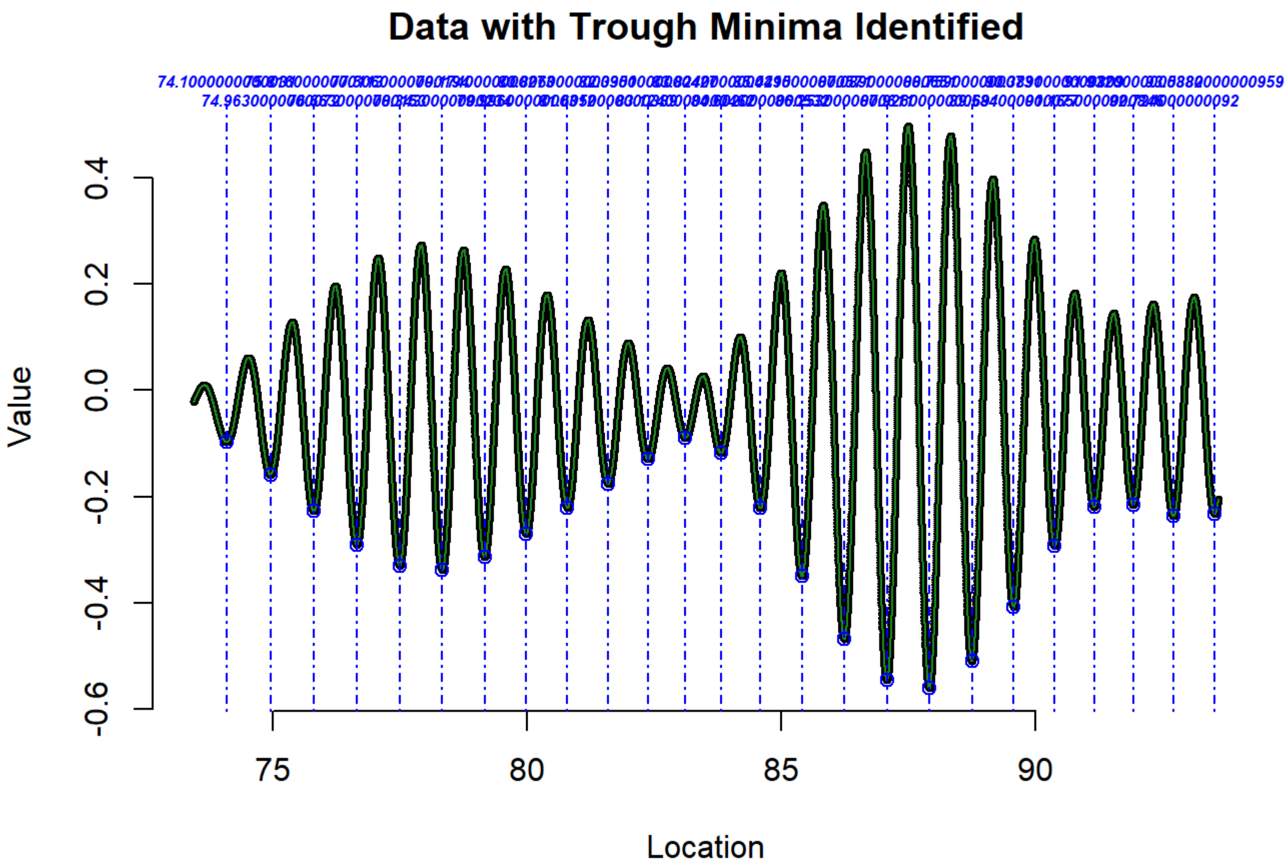
```
#tuning of the non detrended 1mm Ti series
Ti_1mm_173R <- taner(alb_Ti_1mm, xmax=2, fhigh=1/0.97, flow=1/0.76, demean=T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 20158
 * Sample interval= 0.001
 * Mean value removed= -0.03216273
```



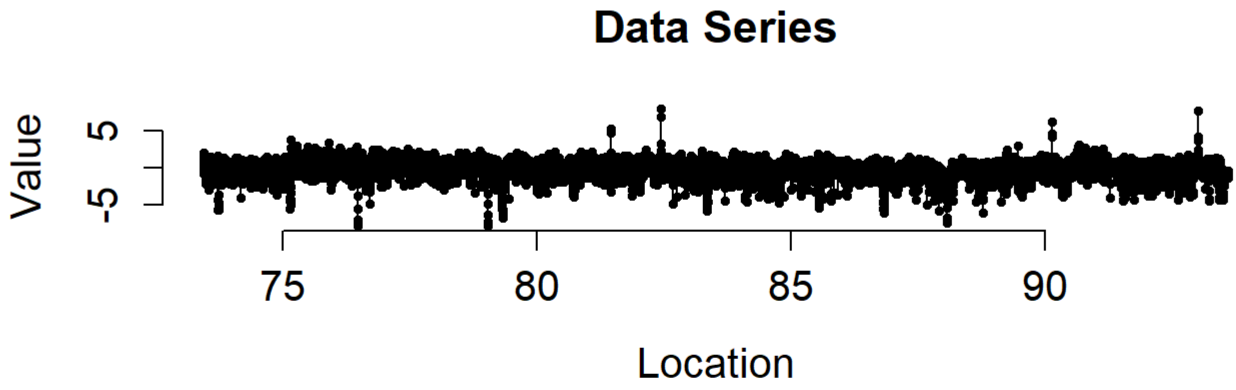

```
Ti_1mm_173_min <- trough(Ti_1mm_173R, level = 200, genplot = T)
```

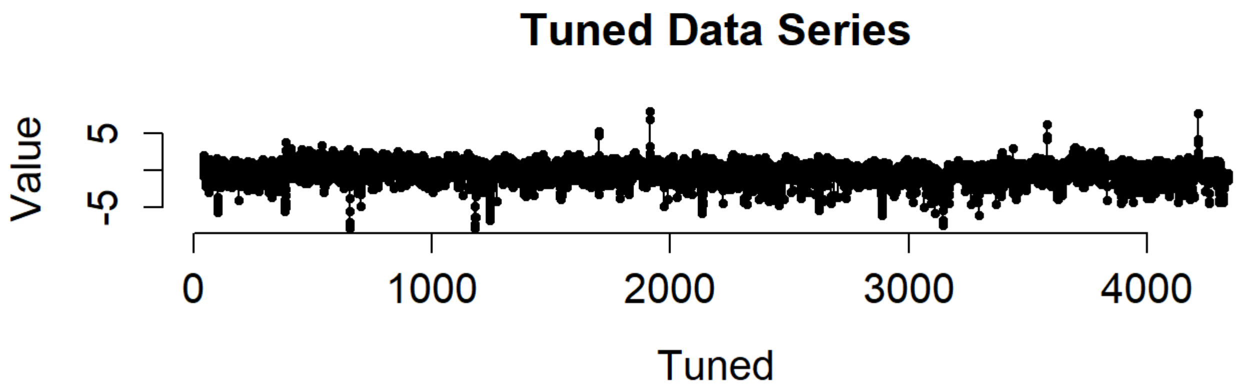
```
----- FINDING MINIMA OF TROUGHS, FILTERING AT THRESHOLD VALUE -----
 * Number of data points= 20158
 * Number of columns= 2
 * Identifying minima of troughs
 * Number of troughs identified= 25
 * Filtering troughs at threshold of 200
 * Number of troughs <= 200 : 25
```




```r
Ti_1mm_173_min <- Ti_1mm_173_min[,c(2,3)]

#write.csv(Ti_1mm_173_min,"Ti_1mm_173_minTan_0.76-0.97m.csv")

#Before continuing, go to the .csv file and for each location, add a multiple of
#173 for the trough value as explain in step 7.3.

Ti_1mm_173_min <- read.csv("Ti_1mm_173_minTan_0.76-0.97m.csv", sep=";")

Ti_1mm_173_tuned <- tune(alb_Ti_1mm,
                         Ti_1mm_173_min,
                         extrapolate=T,
                         genplot=T,
                         check=T,
                         verbose=T
                         )
```

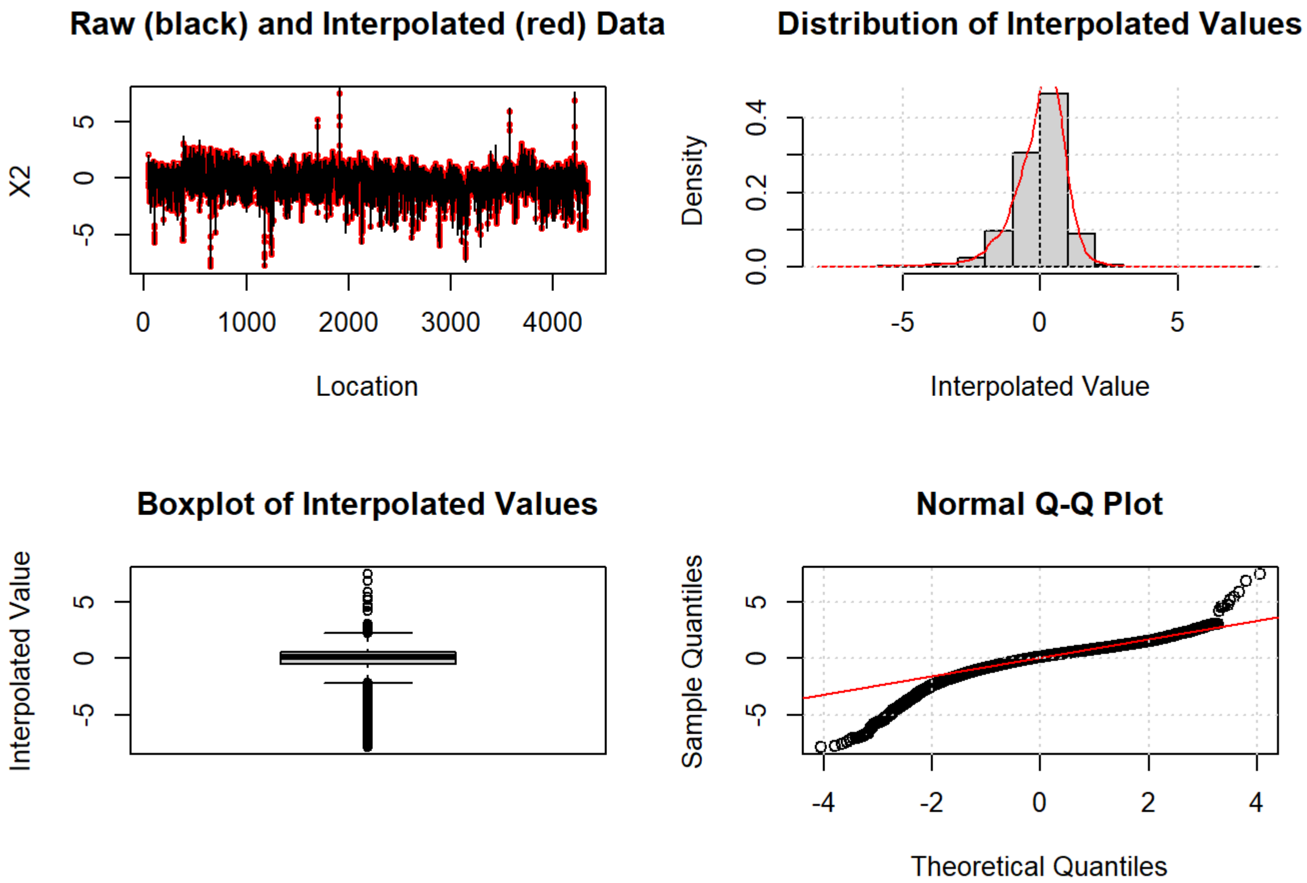
```
----- TUNING STRATIGRAPHIC SERIES -----
 * Number of data points= 20158
 * Number of time control points= 25
 * Sorting datasets into ensure increasing order, removing empty entries

 * Mean sampling interval= 0.2131761
 * Median sampling interval= 0.2104623
 * Maximum sampling interval= 0.2471429
 * Minimum sampling interval= 0.2004635
```






```
#Interpolation every 0.2131761 kyr (= mean saling rate)
alb_Ti_1mm_time <- linterp(Ti_1mm_173_tuned, dt=0.2131761, genplot=T)
```

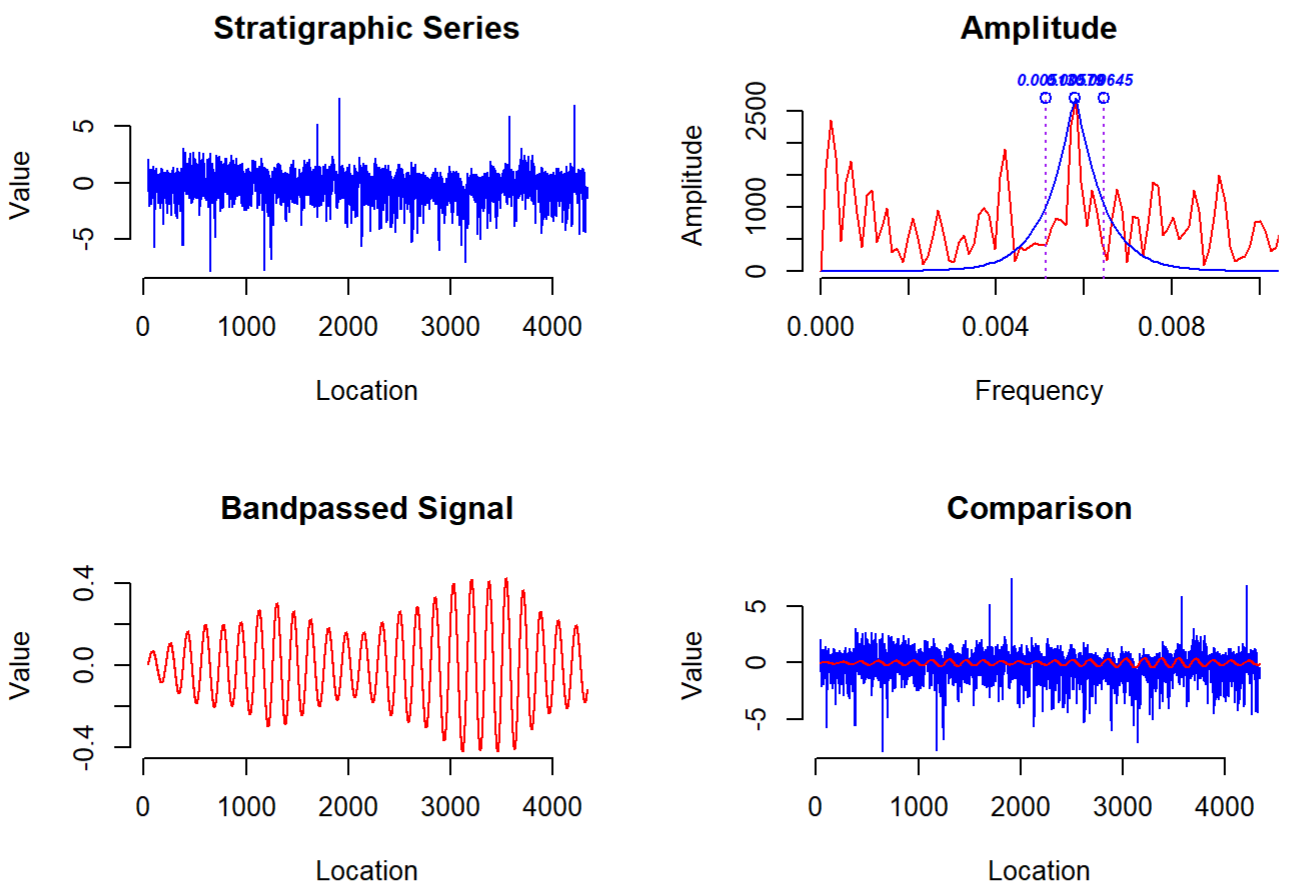
```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 20158
 * New number of samples= 20157
```



10.2. Hilbert analysis

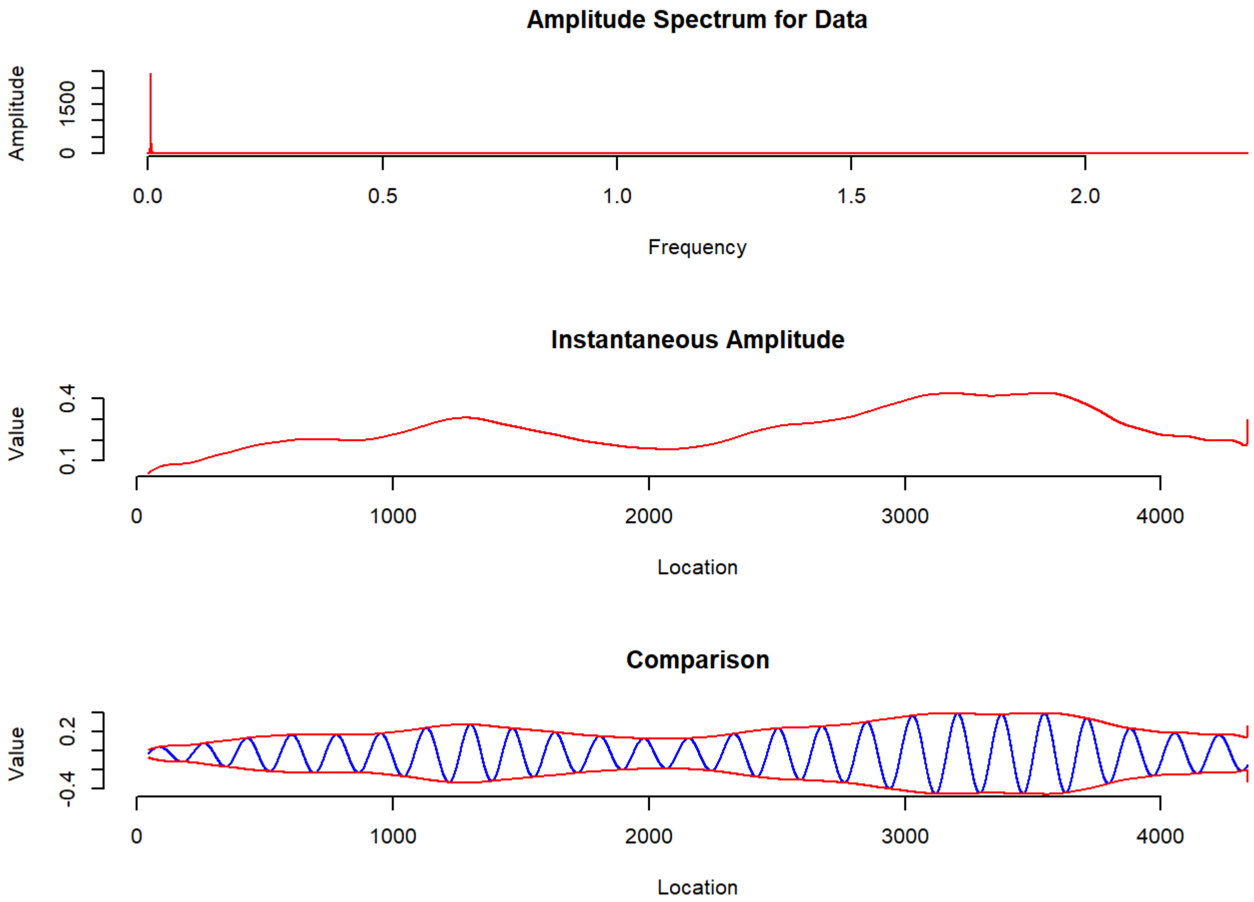
```
#Filter out the 173 kyr long obliquity cycle
alb_Ti_1mm_time_173 <- taner(alb_Ti_1mm_time, xmax=1/100, fhigh=1/155, flow=1/195)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 20157
 * Sample interval= 0.2131761
 * Mean value removed= -0.03228278
```



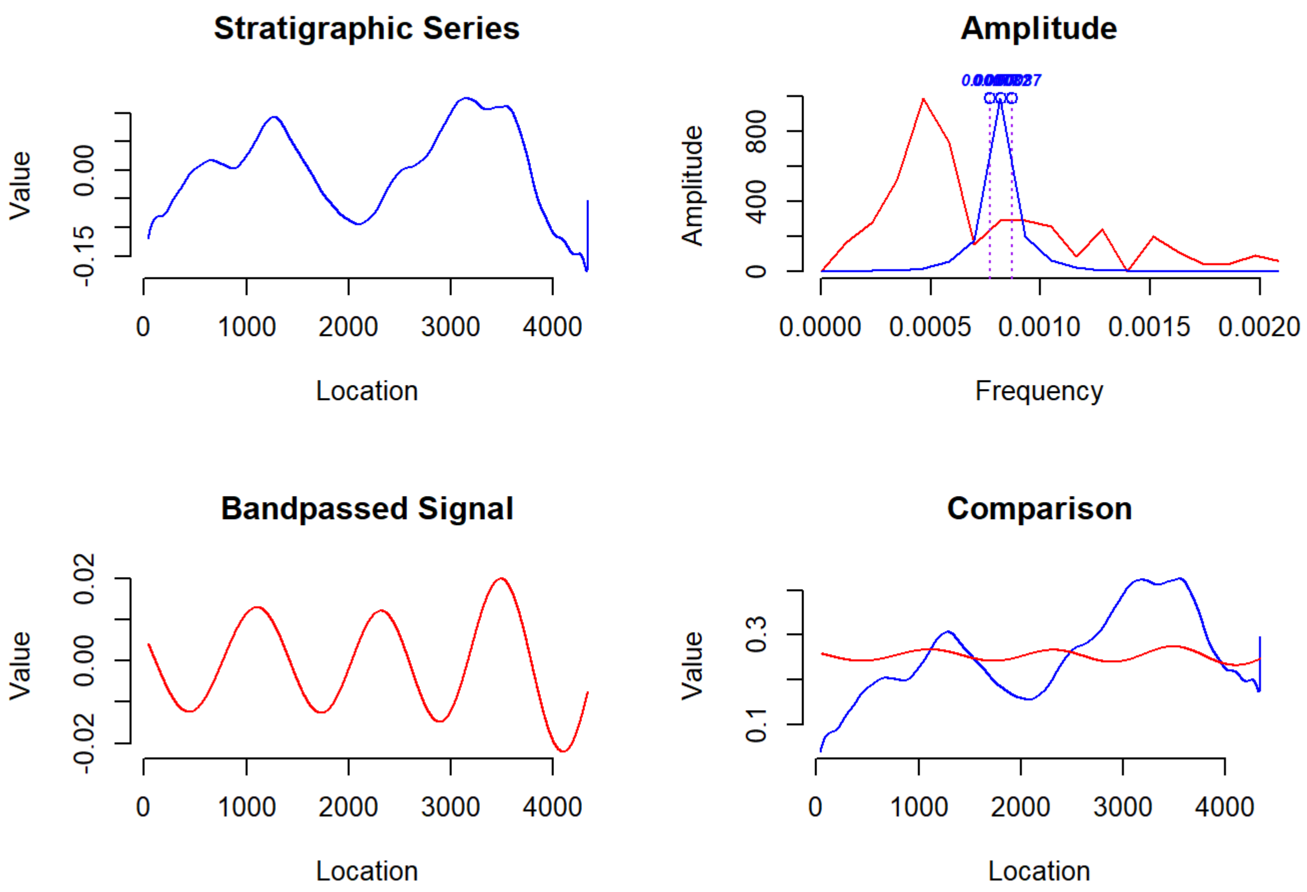

```r
#Do the Hilbert transform to extract the amplitude
alb_Ti_1mm_time_173_hilbert <- hilbert(alb_Ti_1mm_time_173)
```

```
----- PERFORMING HILBERT TRANSFORM ON STRATIGRAPHIC SERIES -----
 * Number of data points= 20157
 * Sample interval= 0.2131761
 * Mean value removed= -0.03265143
```



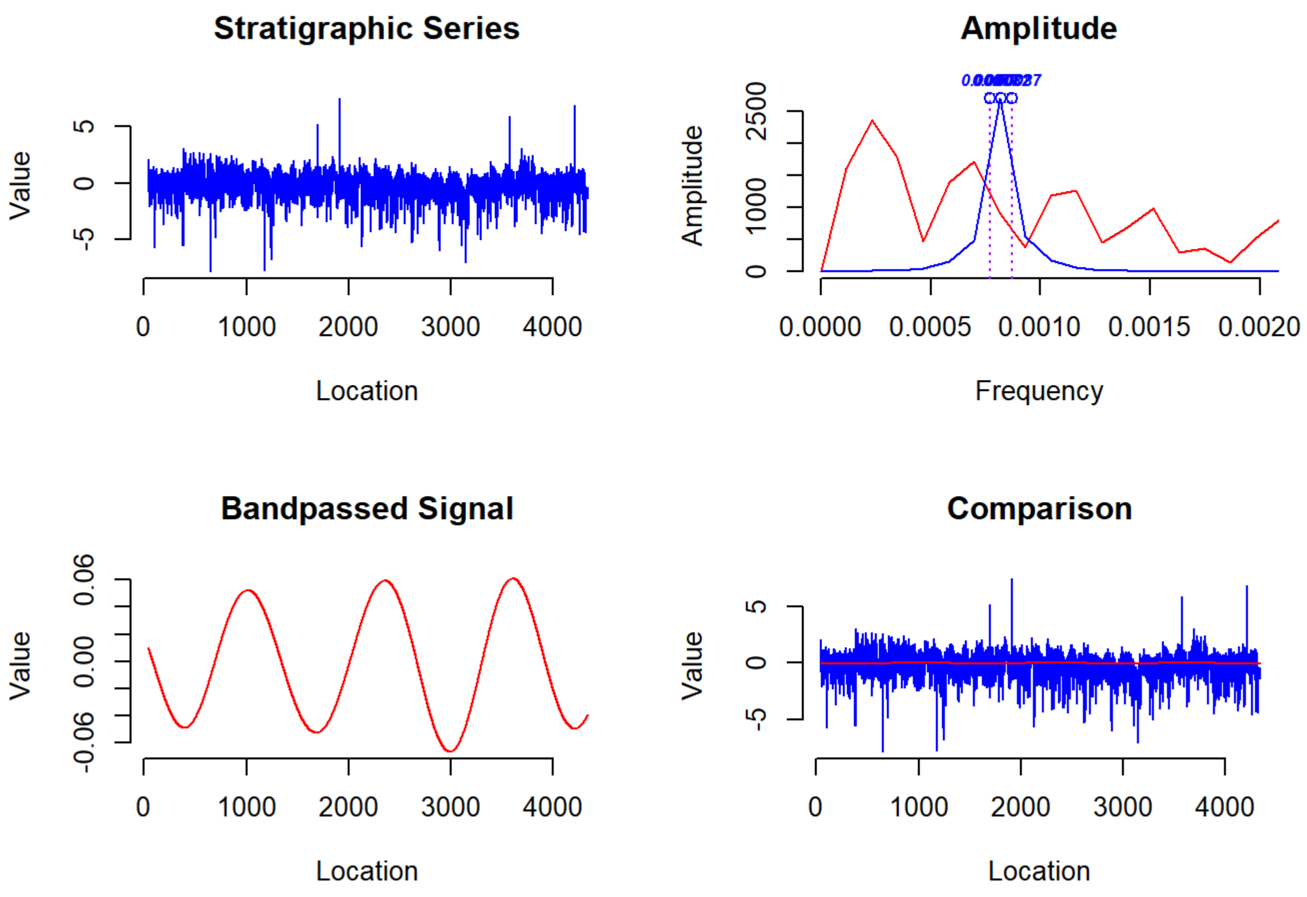

```
#Filter out the 1.2 Myr cycle from the amplitude modulation of the 173 kyr cycle
alb_Ti_1mm_time_173_hilbert_1300 <- taner(alb_Ti_1mm_time_173_hilbert,
                                          xmax=1/500,
                                          fhigh=1/1300,
                                          flow=1/1150,
                                          detrend=T
                                          )
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 20157
 * Sample interval= 0.2131761
 * Mean value removed= 0.2545402
 * Linear trend removed. m= 4.437838e-05 b= -0.09725471
```

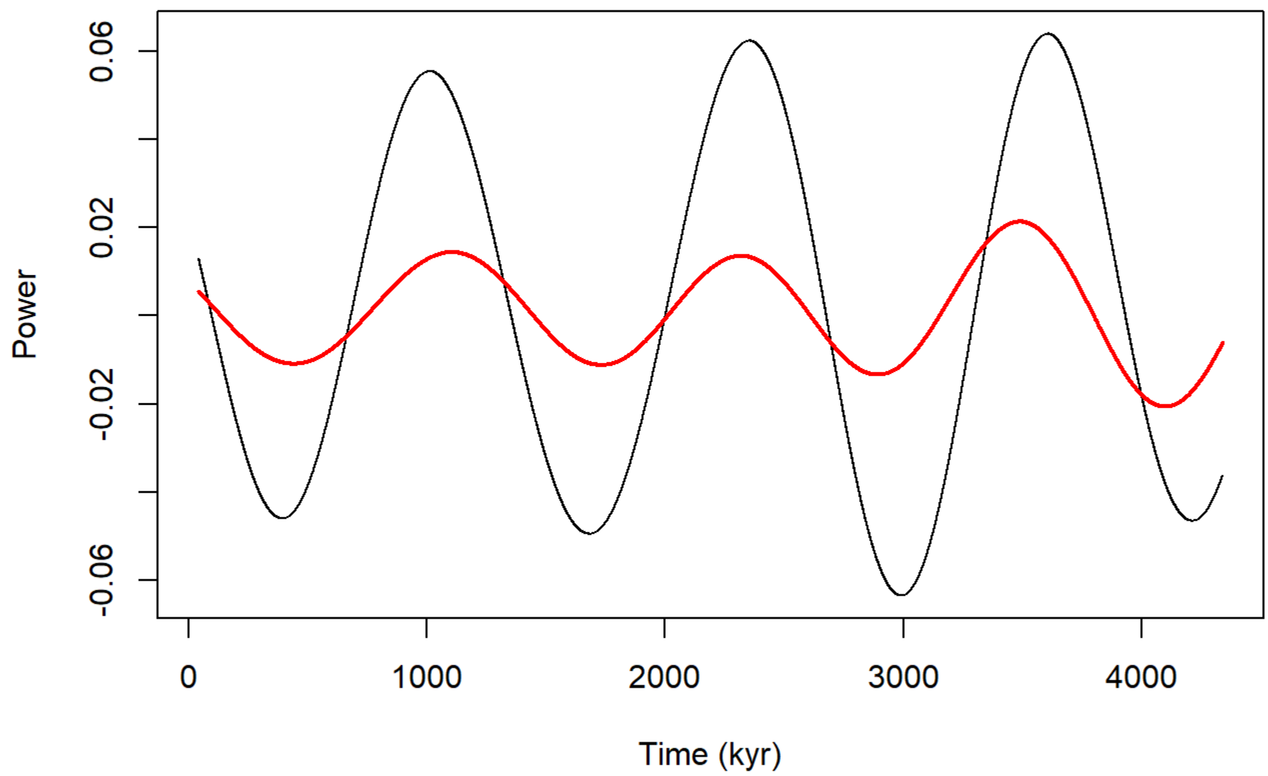



```
#Filter out the 1.2 Myr obliquity cycle directly from the proxy record
alb_Ti_1mm_time_1300 <- taner(alb_Ti_1mm_time,
                              xmax=1/500,
                              fhigh=1/1300,
                              flow=1/1150,
                              demean=T
                              )
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 20157
 * Sample interval= 0.2131761
 * Mean value removed= -0.03228278
```




```r
#Plot the 1.2 Myr obliquity cycle extracted from the amplitude modulation of the
#173 kyr long obliquity cycle vs the 1.2 Myr obliquity cycle directly extracted
#from the proxy record.

plot(alb_Ti_1mm_time_1300[,1],
     alb_Ti_1mm_time_1300[,2]-mean(alb_Ti_1mm_time_1300[,2]),
     type="l",
     xlab = "Time (kyr)",
     ylab = "Power")

lines(alb_Ti_1mm_time_173_hilbert_1300[,1],
      alb_Ti_1mm_time_173_hilbert_1300[,2]-mean(alb_Ti_1mm_time_173_hilbert_1300[,2]),
      col="red",
      lwd=2
      )
```



Step 11: Age-depth model and sedimentation rate based on 4 proxy comparison

11.1. Age-Depth model (bandpass filtering)

11.1.1. Minimal_tuning function

```
minimal_tuning <- function (data = NULL, pts = 5, cycle = 173, tune_opt = "max",
                            output = 0, genplot = FALSE, keep_editable = FALSE)
{
  astro_mindetect <- as.data.frame(data)
  astro_mindetect$min <- 0
  for (i in pts:(nrow(data) - pts)) {
    if ((data[i, 2] - data[(i + pts), 2] < 0) & (data[i,
                                                      2] - data[(i - (pts - 1)), 2] < 0)) {
      astro_mindetect[i, 3] <- 1
    }
  }
  astro_mindetect_error_corr <- astro_mindetect
  astro_mindetect_error_corr <- astro_mindetect_error_corr[astro_mindetect_error_corr$min ==
                                                             1, ]
  astro_maxdetect <- as.data.frame(data)
  astro_maxdetect$max <- 0
  for (i in pts:(nrow(data) - pts)) {
    if ((data[i, 2] - data[(i + pts), 2] > 0) & (data[i,
                                                      2] - data[(i - (pts - 1)), 2] > 0)) {
```

```
      astro_maxdetect[i, 3] <- 1
    }
  }
  astro_maxdetect_error_corr <- astro_maxdetect
  astro_maxdetect_error_corr <- astro_maxdetect_error_corr[astro_maxdetect_error_corr$max ==
                                                            1, ]
  max <- astro_maxdetect_error_corr
  colnames(max) <- c("A", "B", "C")
  min <- astro_mindetect_error_corr
  colnames(min) <- c("A", "B", "C")
  min[, 3] <- -1
  peaks <- rbind(max, min)
  peaks <- peaks[order(peaks[, 1]), ]
  i <- 1
  res_rownr <- nrow(peaks)
  while (i < res_rownr) {
    if ((i < res_rownr) & (peaks[i, 3] == peaks[(i + 1),
                                                 3])) {
      if ((i < res_rownr) & (peaks[i, 3] == 1 & peaks[(i +
                                                         1), 3] == 1) & (peaks[i, 2] > peaks[(i + 1
                                                                                                  2])) {
        peaks[(i + 1), ] <- NA
        peaks <- na.omit(peaks)
        res_rownr <- res_rownr - 1
      }
      if ((i < res_rownr) & (peaks[i, 3] == 1 & peaks[(i +
                                                         1), 3] == 1) & (peaks[i, 2] < peaks[(i + 1
                                                                                                  2])) {
        peaks[i, ] <- NA
        peaks <- na.omit(peaks)
        res_rownr <- res_rownr - 1
      }
      if ((i < res_rownr) & (peaks[i, 3] == -1 & peaks[(i +
                                                          1), 3] == -1) & (peaks[i, 2] < peaks[(i +
                                                                                                    2]))
        peaks[(i + 1), ] <- NA
        peaks <- na.omit(peaks)
        res_rownr <- res_rownr - 1
      }
      if ((i < res_rownr) & (peaks[i, 3] == -1 & peaks[(i +
                                                          1), 3] == -1) & (peaks[i, 2] > peaks[(i +
                                                                                                    2]))
        peaks[i, ] <- NA
        peaks <- na.omit(peaks)
        res_rownr <- res_rownr - 1
      }
    }
    if ((peaks[i, 3] != peaks[(i + 1), 3]) | is.na(peaks[i,
                                                         3] != peaks[(i + 1), 3])) {
      i <- i + 1
    }
  }
  if (tune_opt == "min") {
    peaks_min <- peaks[peaks[, 3] < 0, ]
    dist <- peaks_min[2:(nrow(peaks_min)), ] - peaks_min[1:(nrow(peaks_min) -
                                                              1), ]
    sed_rate <- (dist[, 1] * 100)/cycle
    sed_rate <- cbind(sed_rate, peaks_min[1:(nrow(peaks_min) -
```

```
                                           1), 1], peaks_min[2:(nrow(peaks_min)), 1])
  }
  if (tune_opt == "max") {
    peaks_min <- peaks[peaks[, 3] > 0, ]
    dist <- peaks_min[2:(nrow(peaks_min)), ] - peaks_min[1:(nrow(peaks_min) -
                                                      1), ]
    sed_rate <- (dist[, 1] * 100)/cycle
    sed_rate <- cbind(sed_rate, peaks_min[1:(nrow(peaks_min) -
                                           1), 1], peaks_min[2:(nrow(peaks_min)), 1])
  }
  if (tune_opt == "minmax") {
    peaks_min <- peaks
    dist <- peaks_min[2:(nrow(peaks_min)), ] - peaks_min[1:(nrow(peaks_min) -
                                                      1), ]
    sed_rate <- (dist[, 1] * 100)/(cycle/2)
    sed_rate <- cbind(sed_rate, peaks_min[1:(nrow(peaks_min) -
                                           1), 1], peaks_min[2:(nrow(peaks_min)), 1])
  }
  top <- c(sed_rate[1, 1], data[1, 1], sed_rate[1, 2])
  bot <- c(sed_rate[nrow(sed_rate), 1], sed_rate[nrow(sed_rate),
                                             3], data[nrow(data), 1])
  sed_rate <- rbind(top, sed_rate, bot)
  data[, 3] <- NA
  p <- 1
  for (i in 1:nrow(data)) {
    if (data[i, 1] < sed_rate[p, 2]) {
      data[i, 3] <- sed_rate[p, 1]
    }
    if (data[i, 1] == sed_rate[p, 2] & p + 1 <= nrow(sed_rate)) {
      data[i, 3] <- (sed_rate[p, 1] + sed_rate[(p + 1),
                                           1])/2
    }
    if (p > nrow(sed_rate)) {
      p <- nrow(sed_rate)
    }
    if (p == nrow(sed_rate)) {
      data[i, 3] <- sed_rate[nrow(sed_rate), 1]
    }
    if (data[i, 1] > sed_rate[p, 2]) {
      data[i, 3] <- sed_rate[p, 1]
    }
    if (data[i, 1] == sed_rate[p, 3] & p + 1 <= nrow(sed_rate)) {
      p <- p + 1
    }
  }
  tracked_cycle_curve <- data[, c(1, 3)]
  sedrates <- data.frame(tracked_cycle_curve)
  dat <- as.matrix(tracked_cycle_curve)
  dat <- na.omit(dat)
  dat <- dat[order(dat[, 1], na.last = NA, decreasing = F),
  ]
  npts <- length(dat[, 1])
  start <- dat[1, 1]
  end <- dat[length(dat[, 1]), 1]
  x1 <- dat[1:(npts - 1), 1]
  x2 <- dat[2:(npts), 1]
  dx = x2 - x1
  dt = median(dx)
```

```
  xout <- seq(start, end, by = dt)
  npts <- length(xout)
  interp <- approx(dat[, 1], dat[, 2], xout, method = "linear",
                   n = npts)
  sedrates <- as.data.frame(interp)
  npts <- length(sedrates[, 1])
  sedrates[1] = sedrates[1] * 100
  sedrates[2] = 1/sedrates[2]
  dx = sedrates[2, 1] - sedrates[1, 1]
  midptx = (sedrates[2:npts, 1] + sedrates[1:(npts - 1), 1])/2
  slope = (sedrates[2:npts, 2] - sedrates[1:(npts - 1), 2])/dx
  yint = sedrates[2:npts, 2] - (slope * sedrates[2:npts, 1])
  midpty = (slope * midptx) + yint
  hsum = cumsum(midpty * dx)
  hsum = append(0, hsum)
  out = data.frame(cbind(sedrates[, 1]/100, hsum))
  data[, 4] <- out[, 2]
  colnames(data) <- c("depth", "proxy", "cm/kyr", "time")
  if (output == 0) {
    data <- data
    if (genplot == TRUE) {
      if (keep_editable == FALSE) {
        oldpar <- par(no.readonly = TRUE)
        on.exit(par(oldpar))
      }
      layout.matrix <- matrix(c(1, 2, 3, 4), nrow = 4,
                              ncol = 1)
      graphics::layout(mat = layout.matrix, heights = c(1),
                       widths = c(1))
      par(mar = c(4, 4, 1, 1))
      plot(x = data[, 1], y = data[, 2], type = "l", main = "Data depth domain",
           xlab = "meters", ylab = "proxy")
      plot(x = data[, 1], y = data[, 3], type = "l", xlab = "meters",
           ylab = "cm/kyr (ka)", main = "sedimentation rate plot")
      plot(data[, 1], data[, 4], type = "l", xlab = "meters",
           ylab = "Time (ka)", main = "Data time domain")
      plot(data[, 4], data[, 2], type = "l", xlab = "time (ka)",
           ylab = "proxy", main = "Data time domain")
    }
  }
  if (output == 1) {
    data <- data[, c(1, 3)]
    if (genplot == TRUE) {
      if (keep_editable == FALSE) {
        oldpar <- par(no.readonly = TRUE)
        on.exit(par(oldpar))
      }
      layout.matrix <- matrix(c(1), nrow = 1, ncol = 1)
      graphics::layout(mat = layout.matrix, heights = c(1),
                       widths = c(1))
      par(mar = c(4, 4, 1, 1))
      plot(x = data[, 1], y = data[, 2], type = "l", xlab = "meters",
           ylab = "cm/kyr (ka)", main = "sedimentation rate plot")
    }
  }
  if (output == 2) {
    data <- data[, c(1, 4)]
    if (genplot == TRUE) {
```

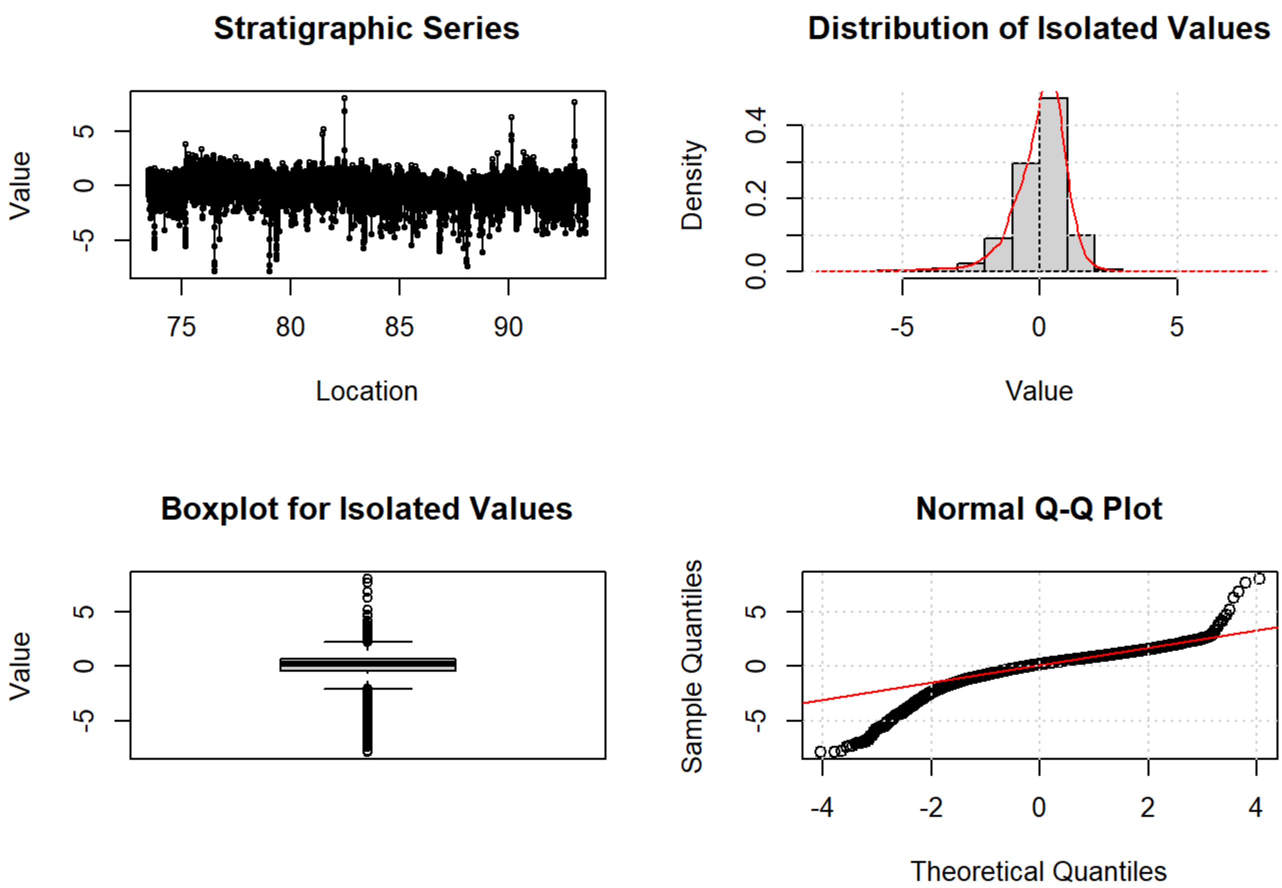
```
        if (keep_editable == FALSE) {
          oldpar <- par(no.readonly = TRUE)
          on.exit(par(oldpar))
        }
        layout.matrix <- matrix(c(1), nrow = 1, ncol = 1)
        graphics::layout(mat = layout.matrix, heights = c(1),
                         widths = c(1))
        par(mar = c(4, 4, 1, 1))
        plot(data[, 1], data[, 2], type = "l", xlab = "meters",
             ylab = "Time (ka)", main = "Data time domain")
      }
    }
    return(data)
  }
```

11.1.2. Taner filtering of the detrital elements in depth domain

11.1.2.1. Titanium

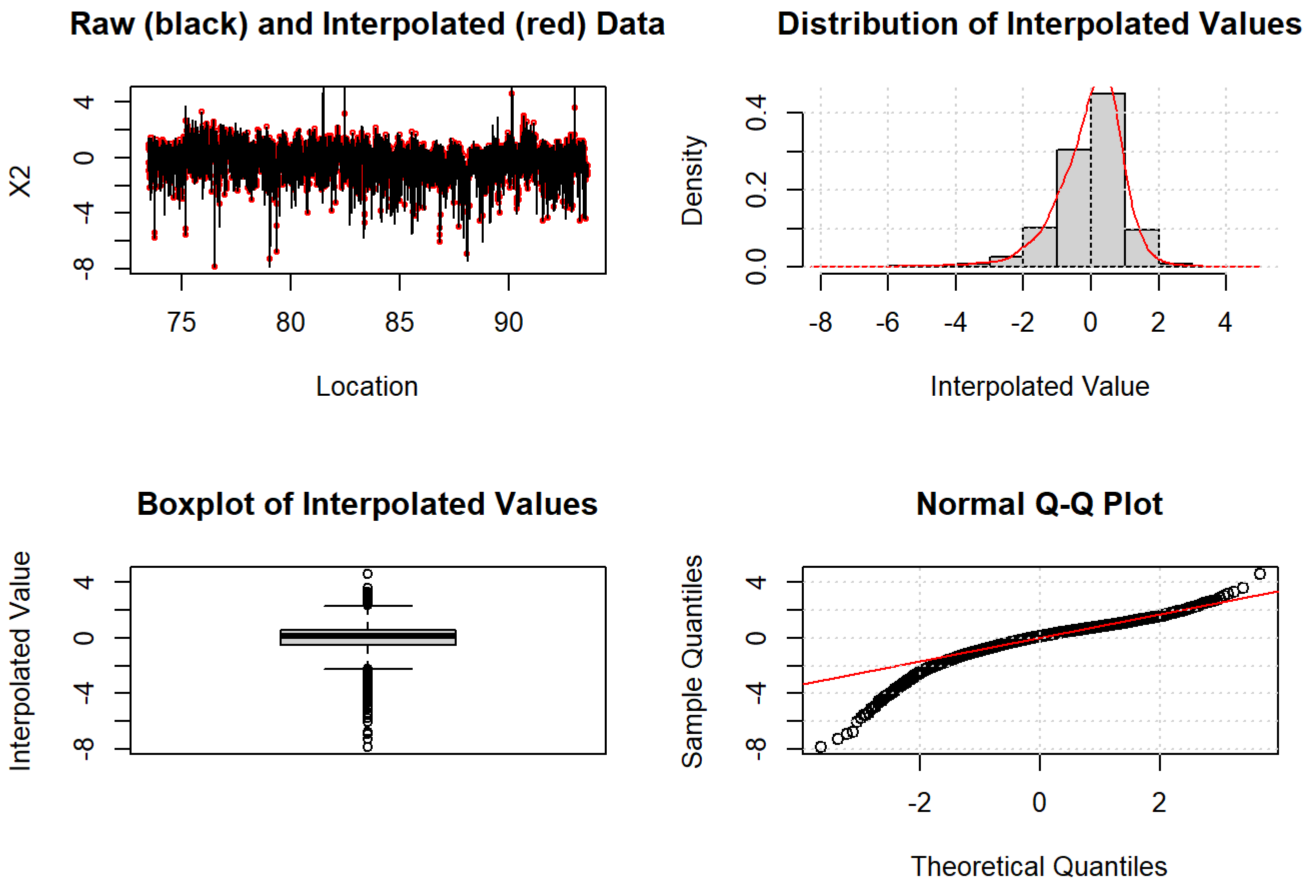
```
alb_Ti <- cbind(Alb$DepthAdj,Alb$Ti)
alb_Ti <- na.omit(alb_Ti)
alb_Ti[!is.finite(alb_Ti)] <- NA
alb_Ti <- na.omit(alb_Ti)
alb_Ti <- iso(dat=alb_Ti, xmin=73.453, xmax=93.609)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30577
 * Number of columns= 2
 * Minimum= 62.111 , Maximum= 93.61
 * Isolating data between 73.453 and 93.609
 * Number of data points following culling= 19310
```



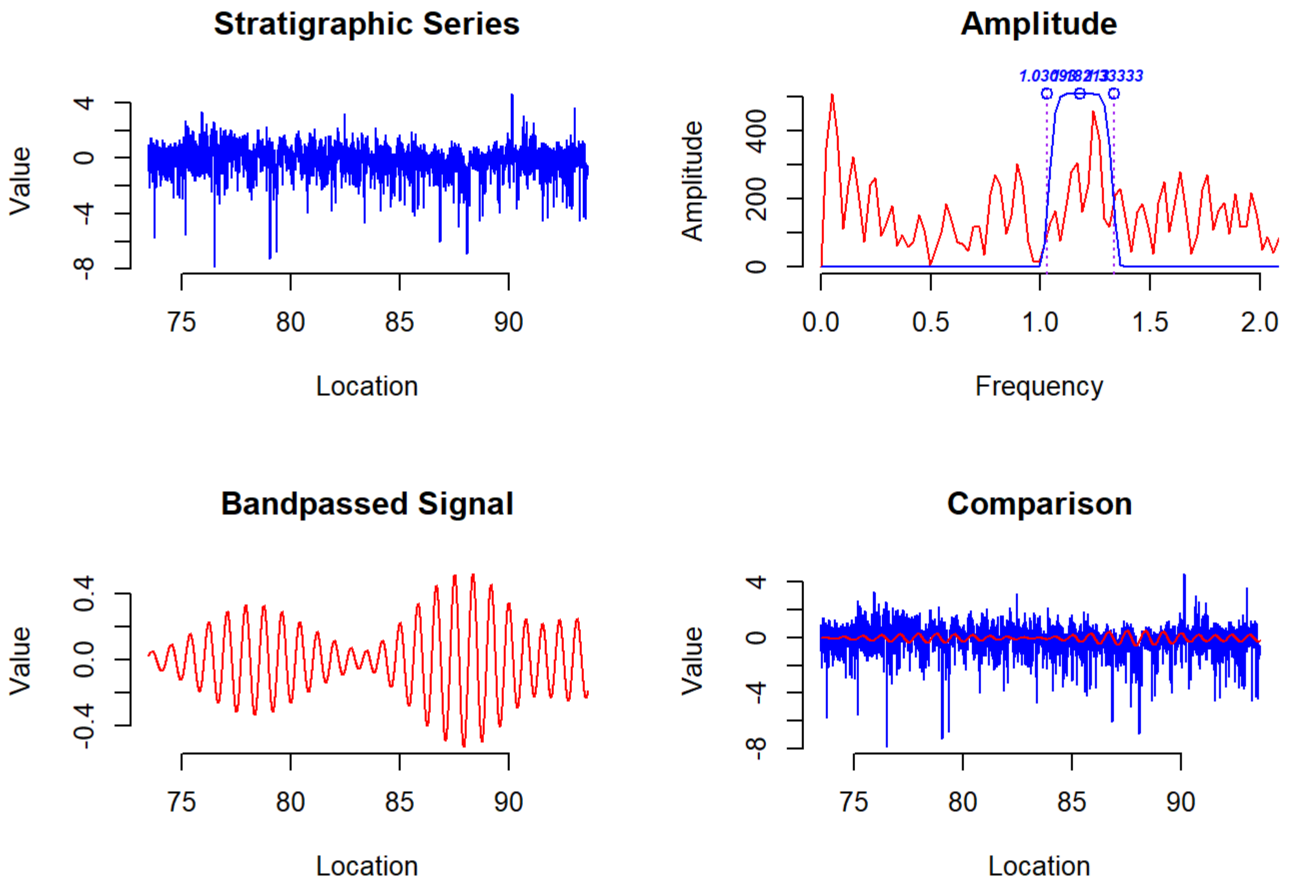

```
alb_Ti <- linterp(alb_Ti, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 19310
 * New number of samples= 4032
```

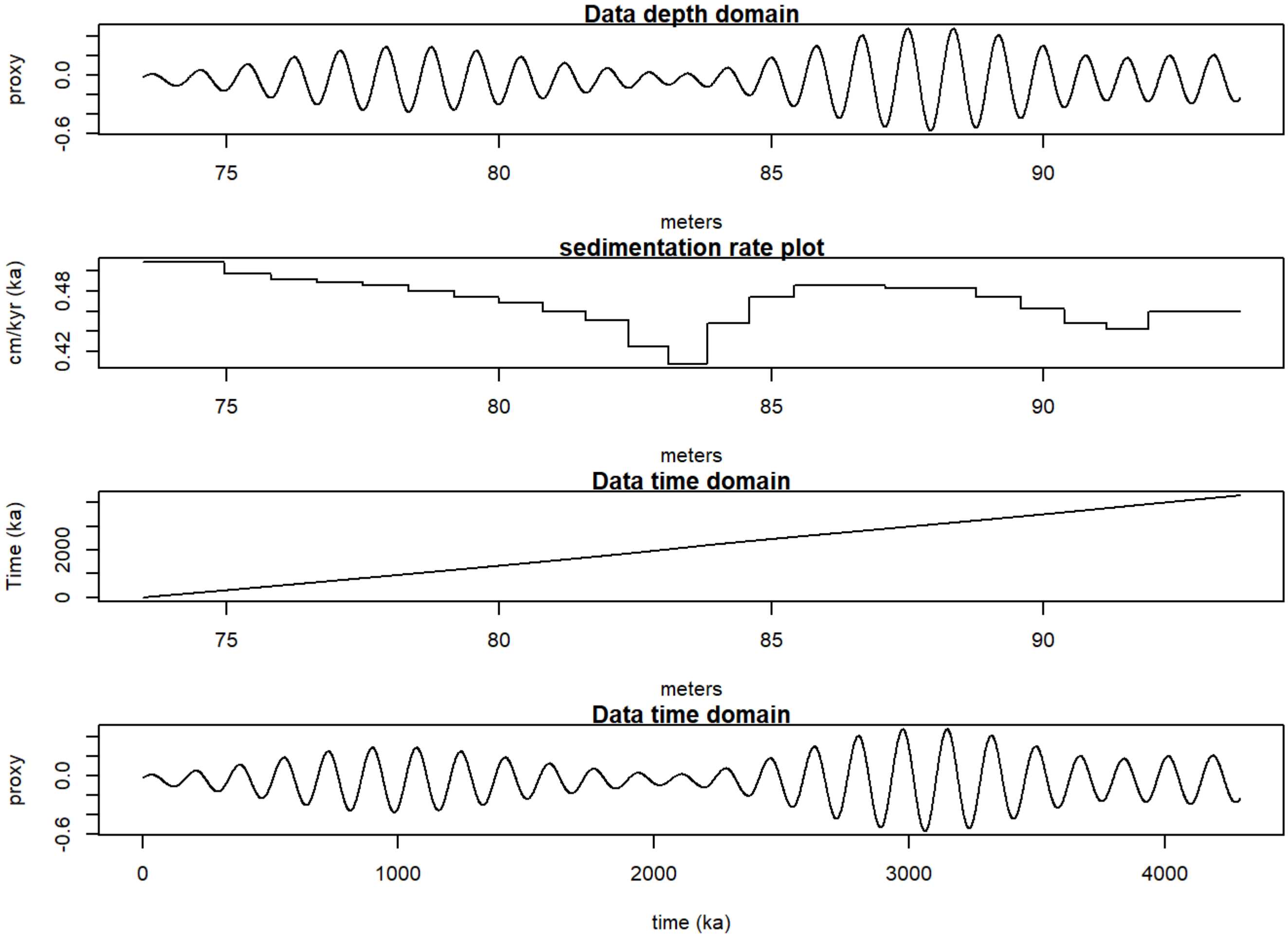



```
Ti_173R <- taner(alb_Ti,xmax=2,fhigh=1/0.97,flow=1/0.75,demean=TRUE)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= -0.04021631
```




```
Ti_173R_min_tun <-    minimal_tuning(data = Ti_173R,
                               pts = 20,
                               cycle = 173,
                               tune_opt = "min",
                               output = 0,
                               genplot = TRUE,
                               keep_editable = FALSE
                               )
```

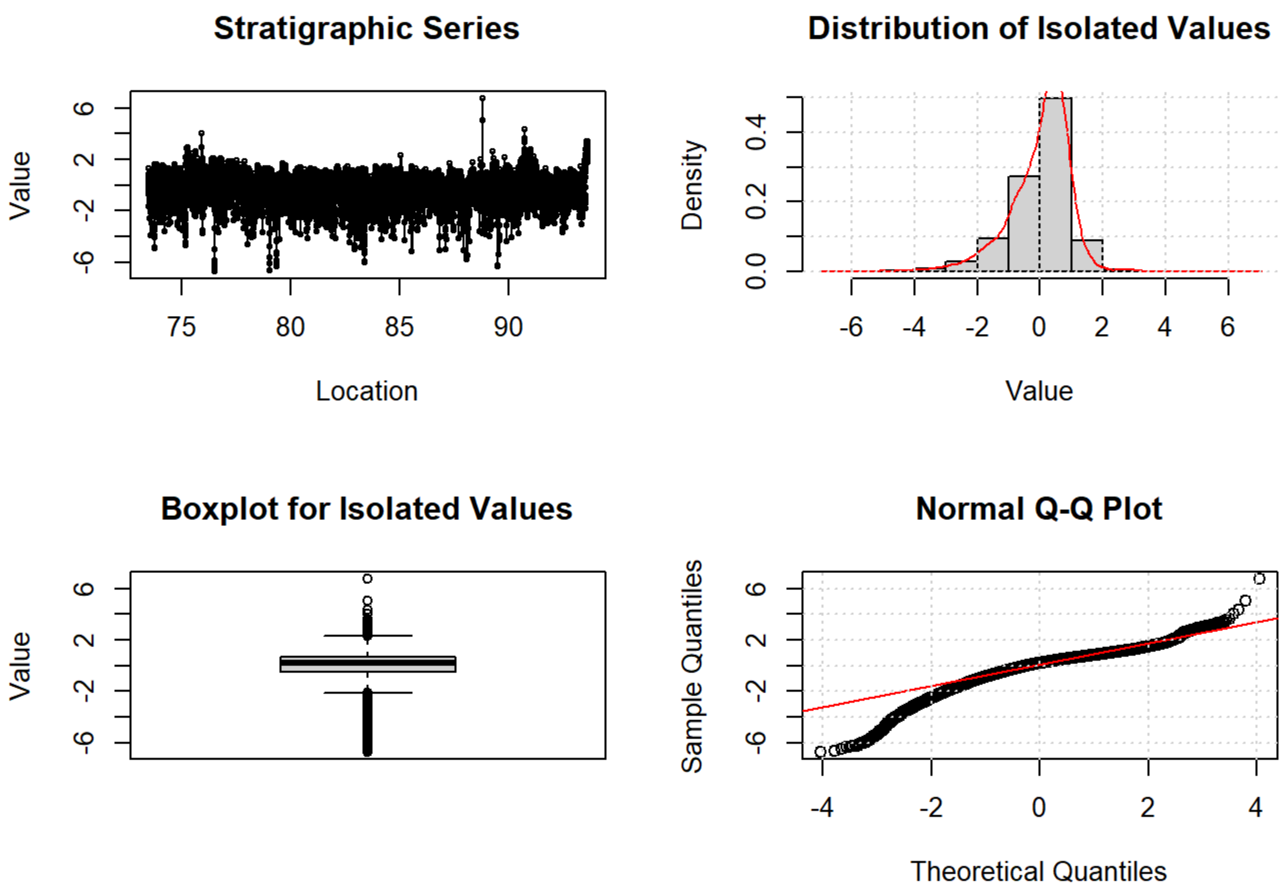



```
colnames(Ti_173R_min_tun)<-c("Ti Depth","Ti","Ti SR","Ti time")
```

11.1.2.2. Silicon

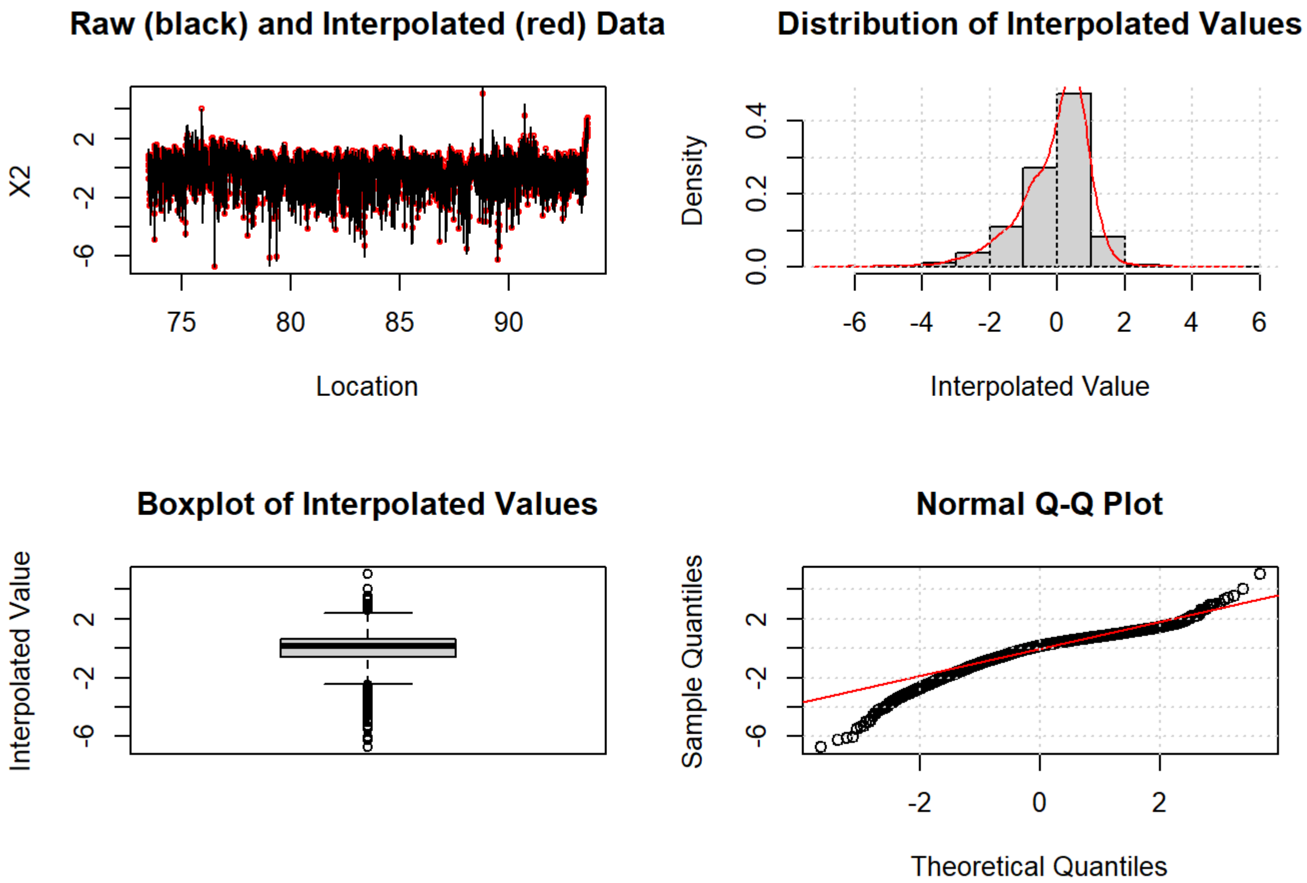
```
alb_Si <- cbind(Alb$DepthAdj,Alb$Si)
alb_Si <- na.omit(alb_Si)
alb_Si[!is.finite(alb_Si)] <- NA
alb_Si <- na.omit(alb_Si)
alb_Si <- iso(dat=alb_Si, xmin=73.453, xmax=93.609)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30577
 * Number of columns= 2
 * Minimum= 62.111 , Maximum= 93.61
 * Isolating data between 73.453 and 93.609
 * Number of data points following culling= 19310
```



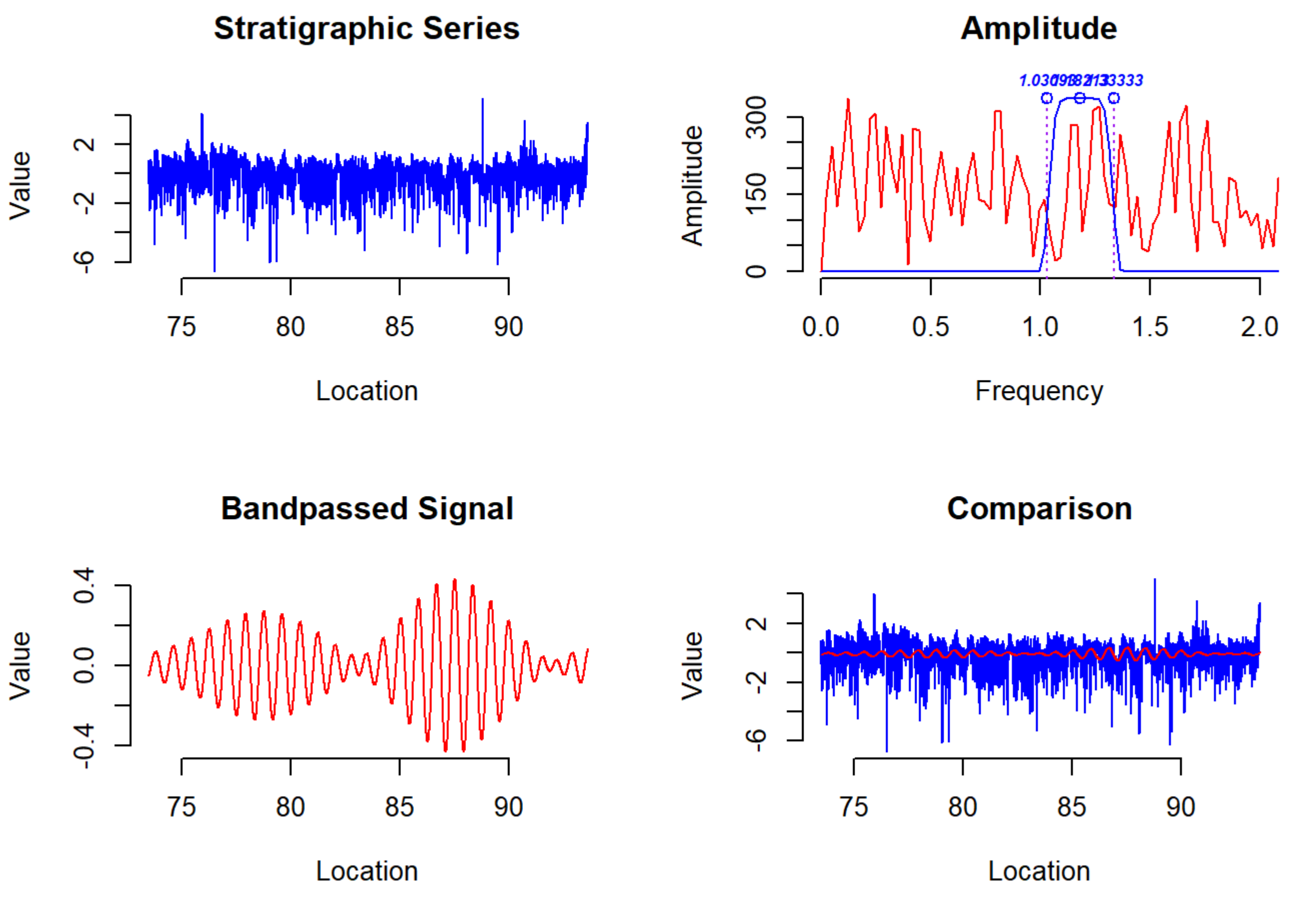

```r
alb_Si <- linterp(alb_Si, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 19310
 * New number of samples= 4032
```

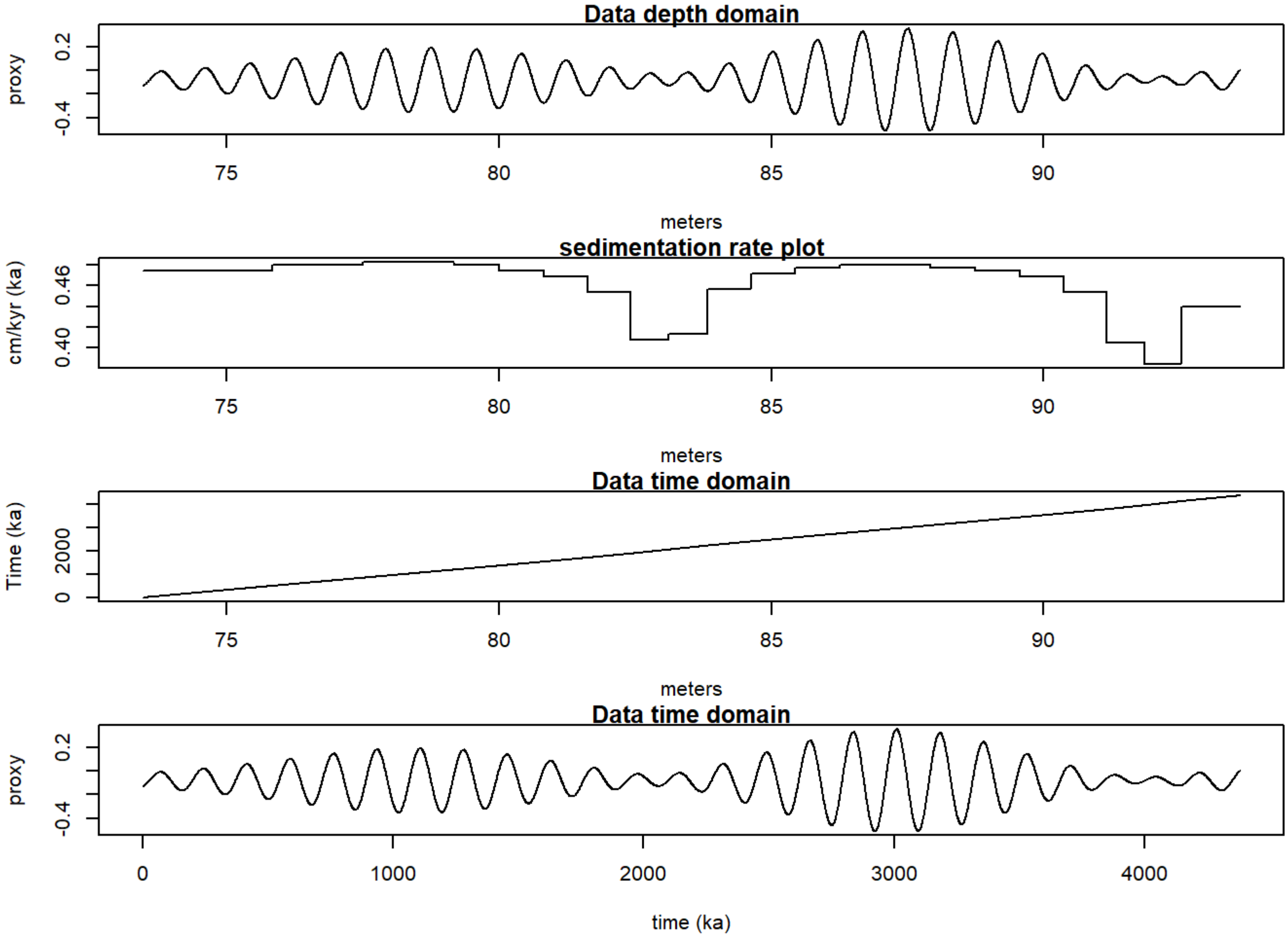



```
Si_173R <- taner(alb_Si,xmax=2,fhigh=1/0.97,flow=1/0.75,demean=TRUE)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= -0.0791156
```




```
Si_173R_min_tun <-    minimal_tuning(data = Si_173R,
                              pts = 20,
                              cycle = 173,
                              tune_opt = "min",
                              output = 0,
                              genplot = TRUE,
                              keep_editable = FALSE
                              )
```

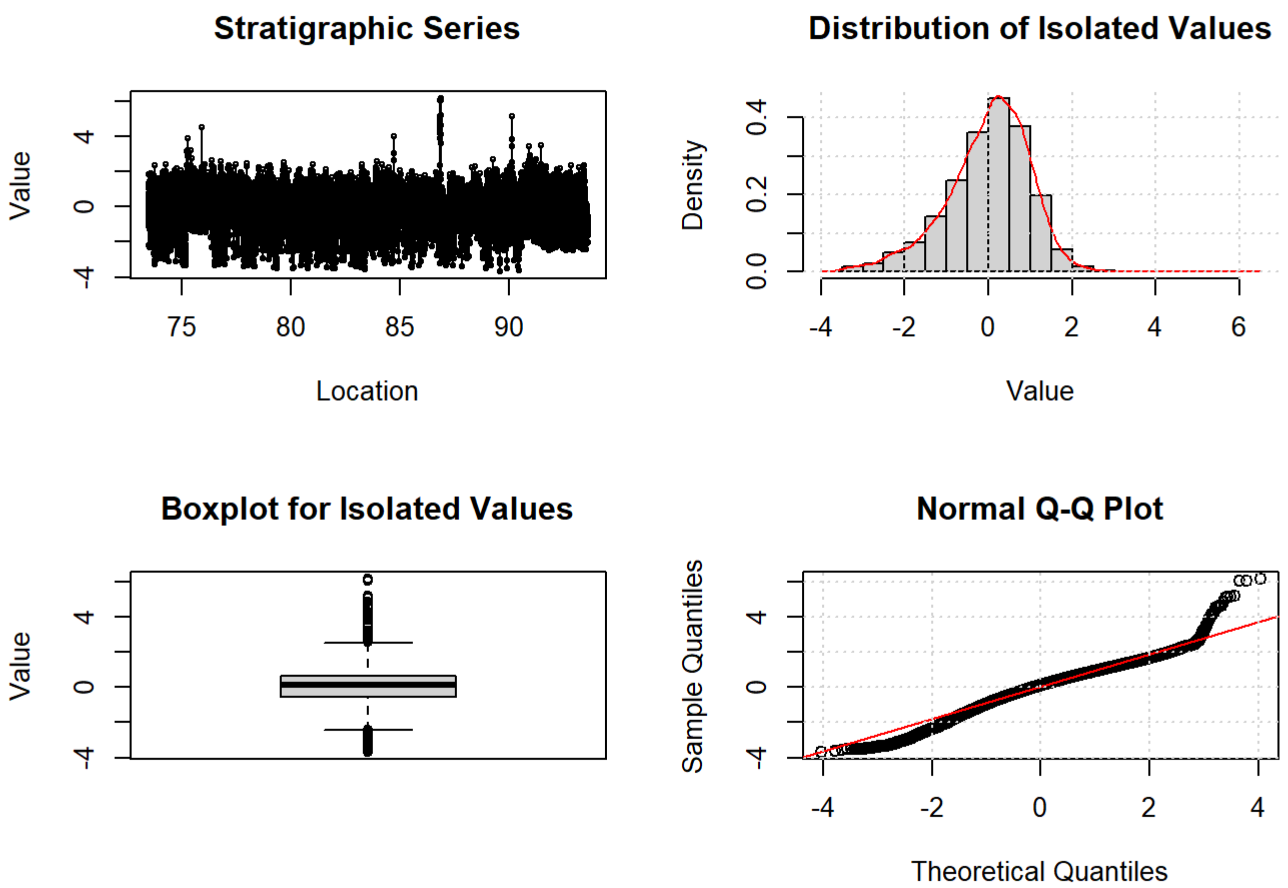



```
colnames(Si_173R_min_tun)<-c("Si Depth","Si","Si SR","Si time")
```

11.1.2.3. Aluminium

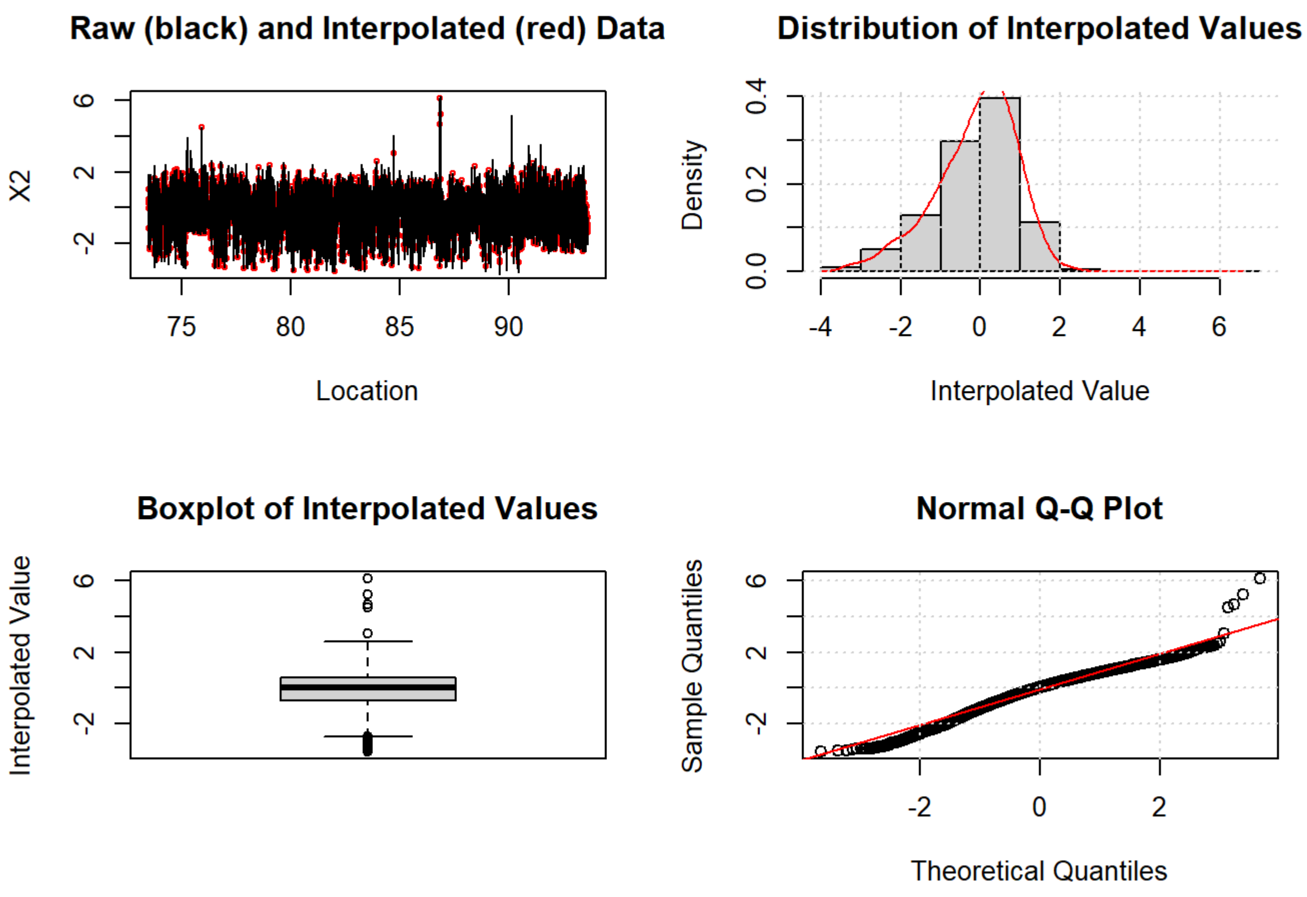
```
alb_Al <- cbind(Alb$DepthAdj,Alb$Al)
alb_Al <- na.omit(alb_Al)
alb_Al[!is.finite(alb_Al)] <- NA
alb_Al <- na.omit(alb_Al)
alb_Al <- iso(dat=alb_Al, xmin=73.453, xmax=93.609)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30062
 * Number of columns= 2
 * Minimum= 62.111 , Maximum= 93.609
 * Isolating data between 73.453 and 93.609
 * Number of data points following culling= 18796
```



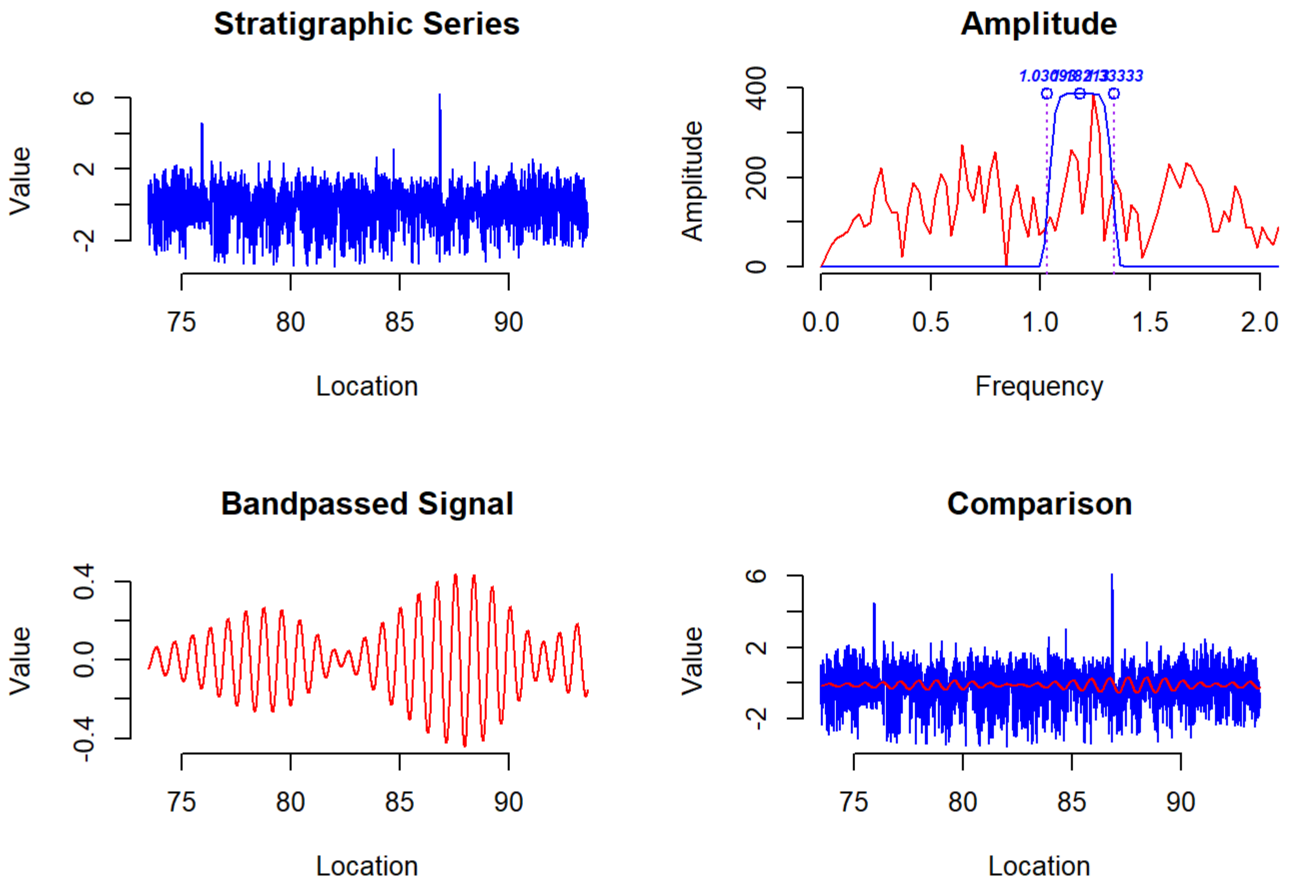

```
alb_Al <- linterp(alb_Al, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 18796
 * New number of samples= 4032
```

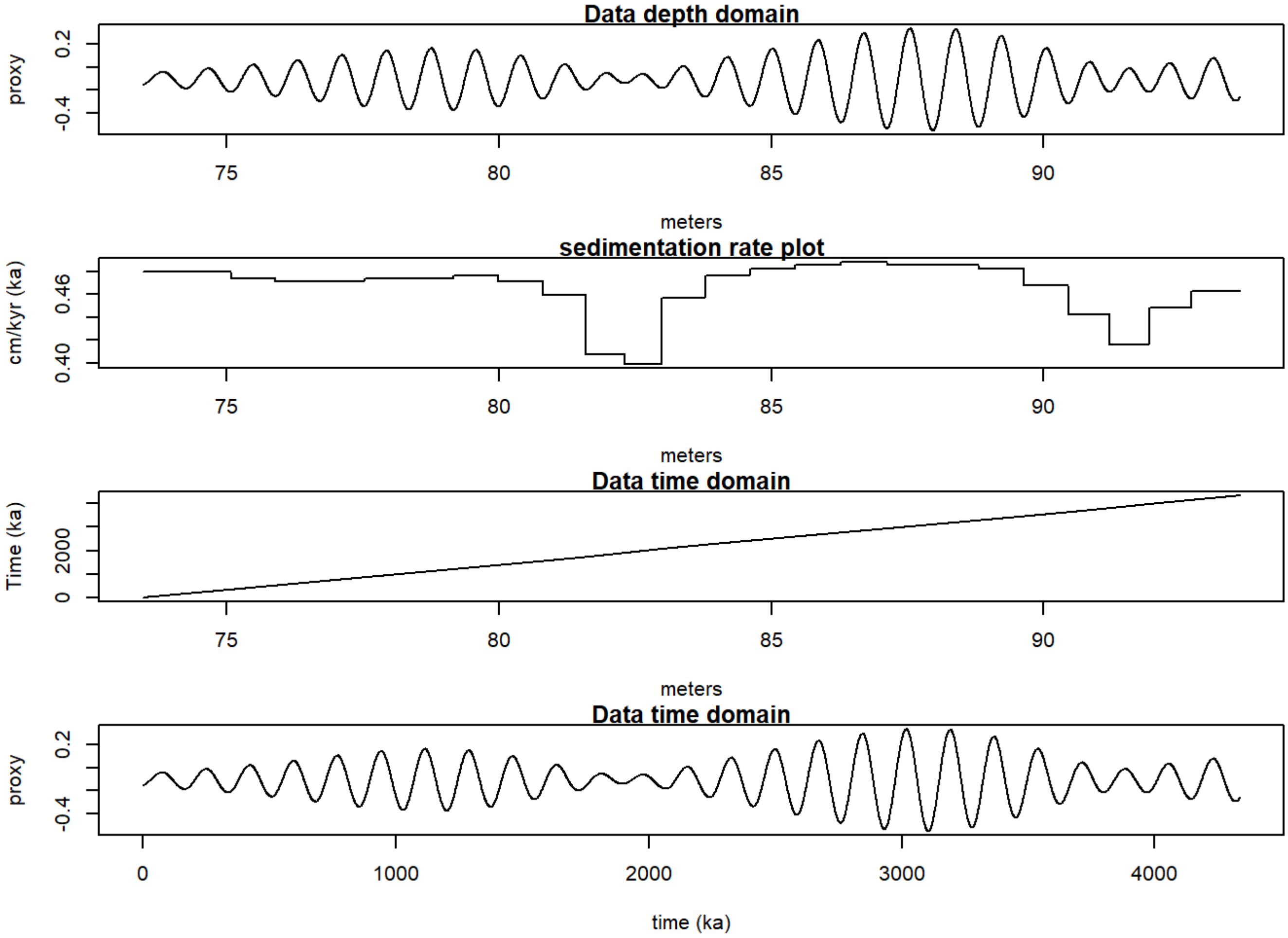



```
Al_173R <- taner(alb_Al,xmax=2,fhigh=1/0.97,flow=1/0.75,demean=TRUE)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= -0.1067612
```




```
Al_173R_min_tun <-    minimal_tuning(data = Al_173R,
                              pts = 20,
                              cycle = 173,
                              tune_opt = "min",
                              output = 0,
                              genplot = TRUE,
                              keep_editable = FALSE
                              )
```

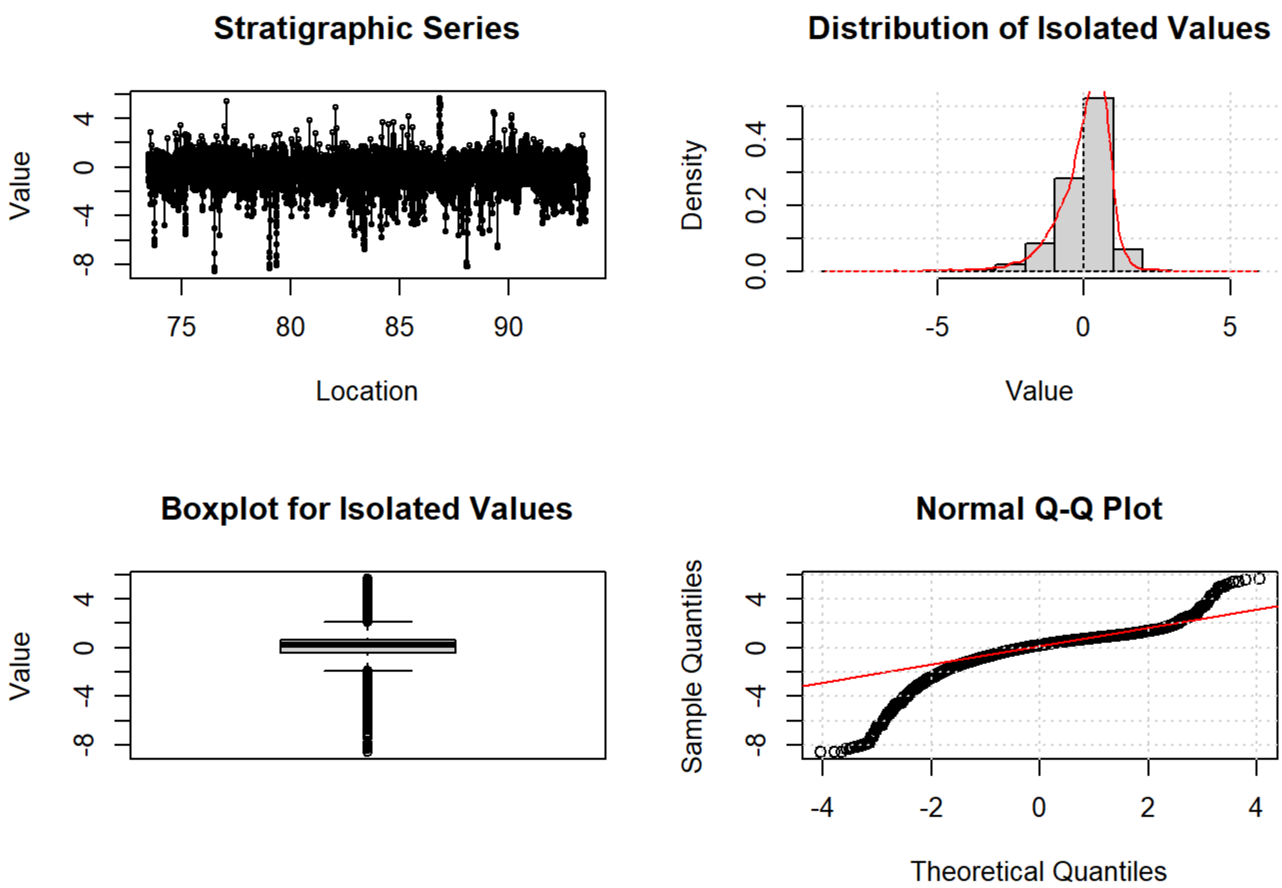



```
colnames(Al_173R_min_tun)<-c("Al Depth","Al","Al SR","Al time")
```

11.1.2.4. Potassium

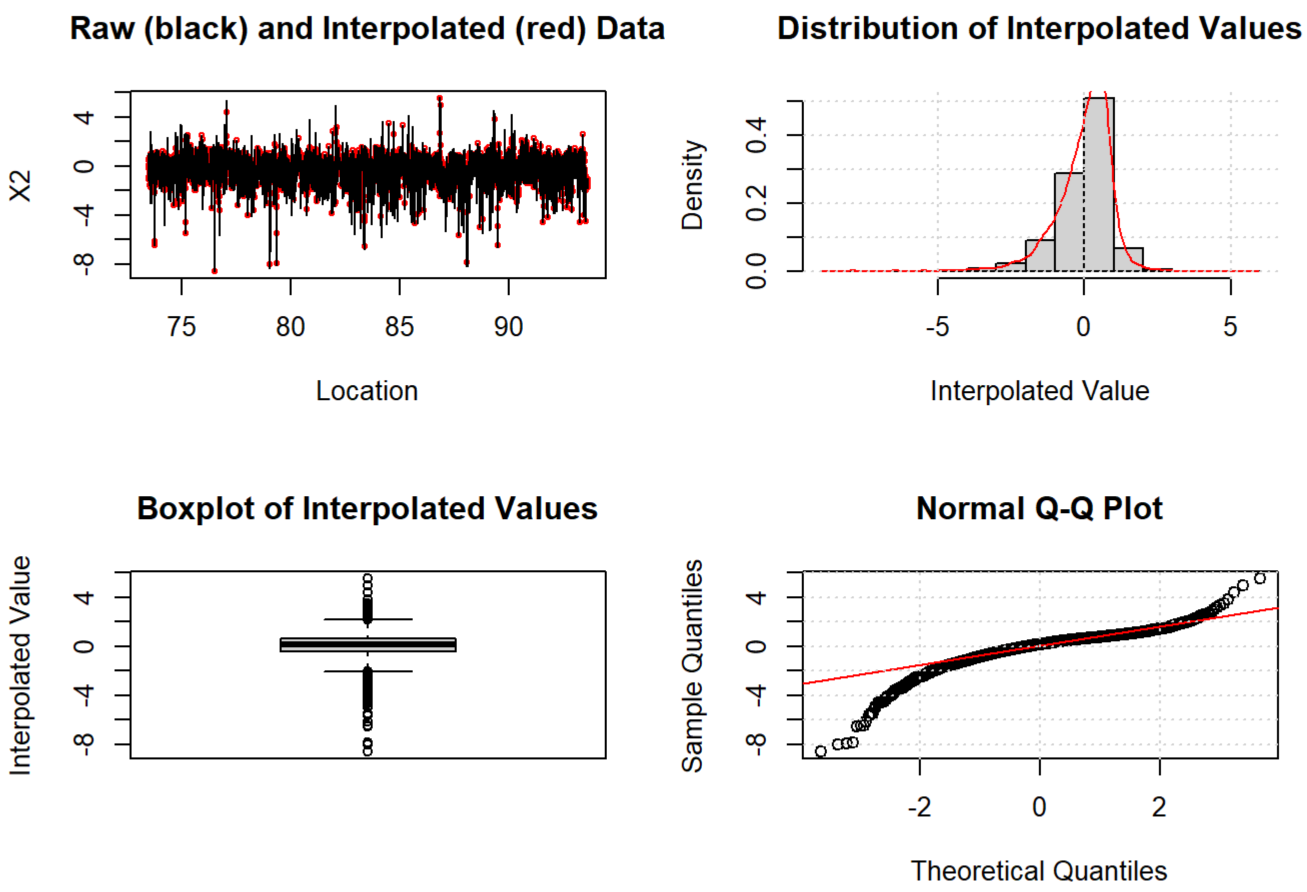
```
alb_K <- cbind(Alb$DepthAdj,Alb$K)
alb_K <- na.omit(alb_K)
alb_K[!is.finite(alb_K)] <- NA
alb_K <- na.omit(alb_K)
alb_K <- iso(dat=alb_K, xmin=73.453, xmax=93.609)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 19311
 * Number of columns= 2
 * Minimum= 73.453 , Maximum= 93.61
 * Isolating data between 73.453 and 93.609
 * Number of data points following culling= 19310
```



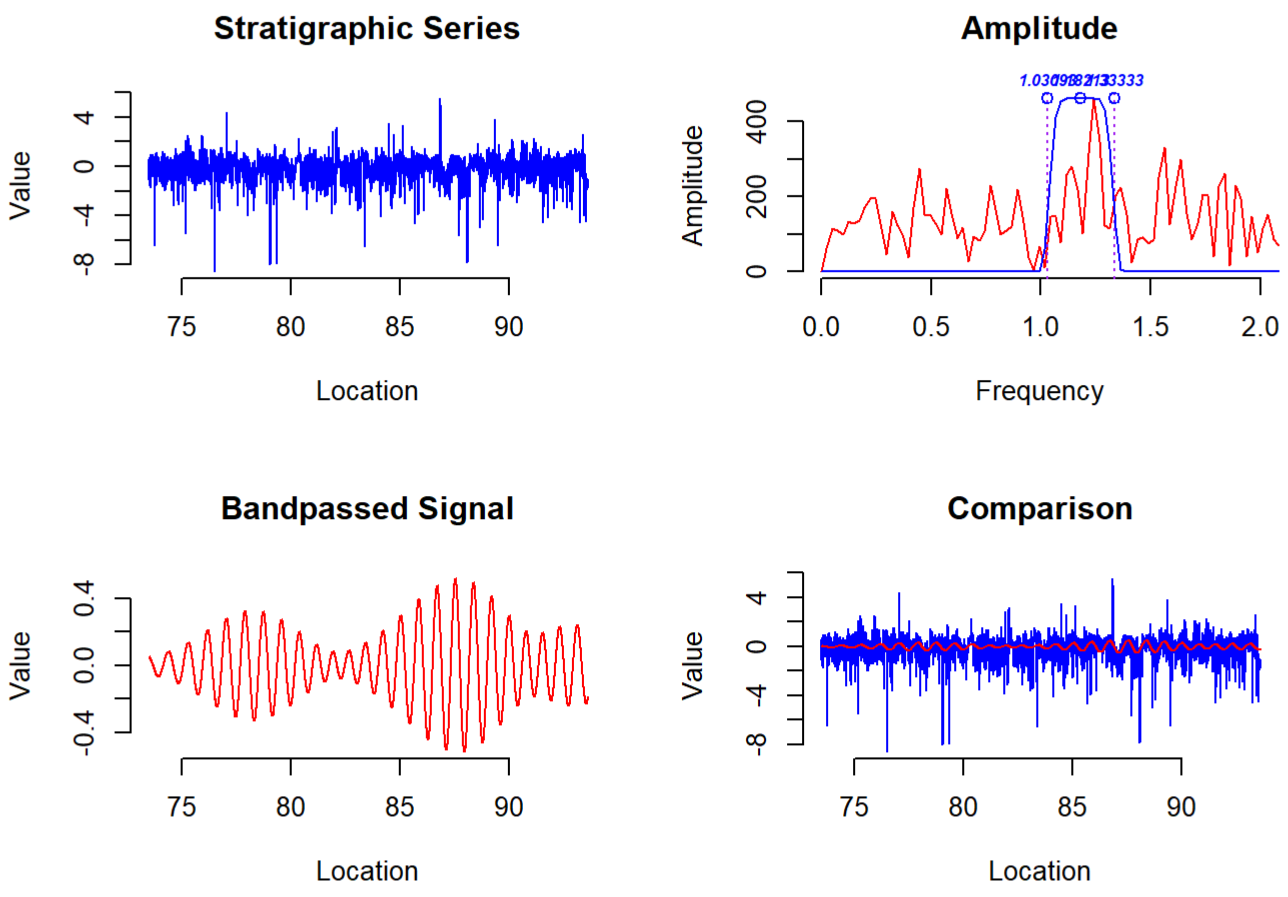

```
alb_K <- linterp(alb_K, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 19310
 * New number of samples= 4032
```

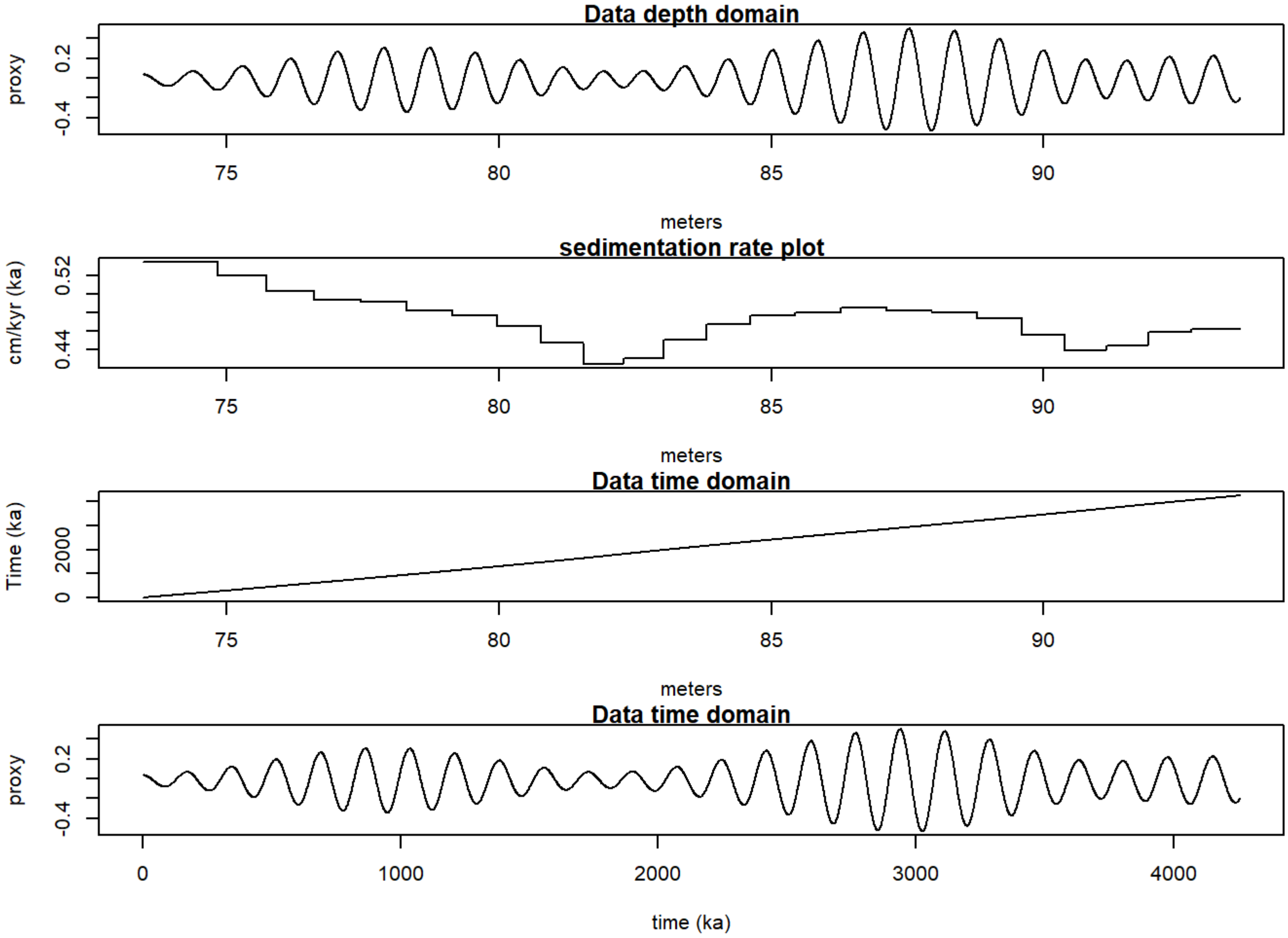



```
K_173R <- taner(alb_K,xmax=2,fhigh=1/0.97,flow=1/0.75,demean=TRUE)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= -0.01677853
```




```
K_173R_min_tun <-    minimal_tuning(data = K_173R,
                           pts = 20,
                           cycle = 173,
                           tune_opt = "min",
                           output = 0,
                           genplot = TRUE,
                           keep_editable = FALSE
                           )
```

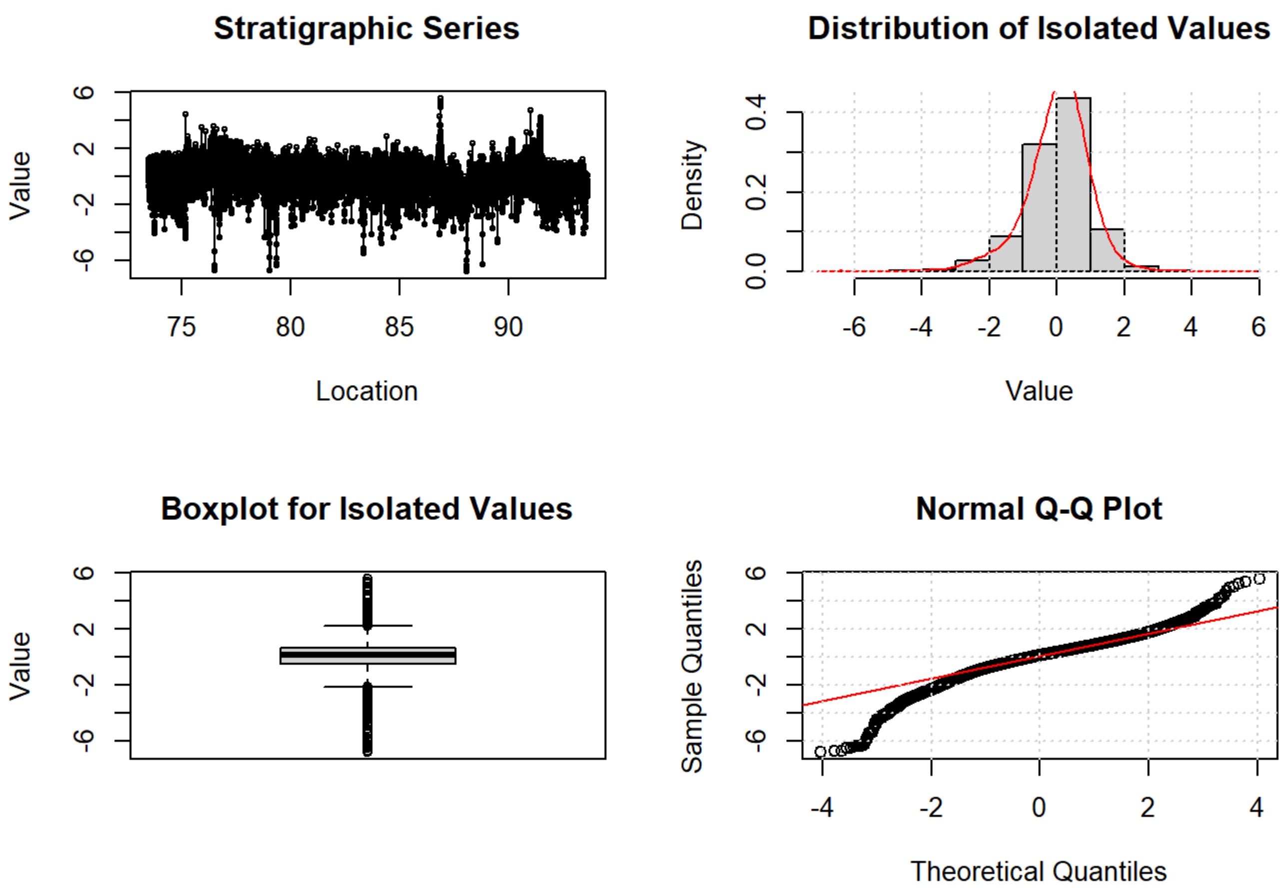



```
colnames(K_173R_min_tun)<-c("K Depth","K","K SR","K time")
```

11.1.2.5. Zirconium

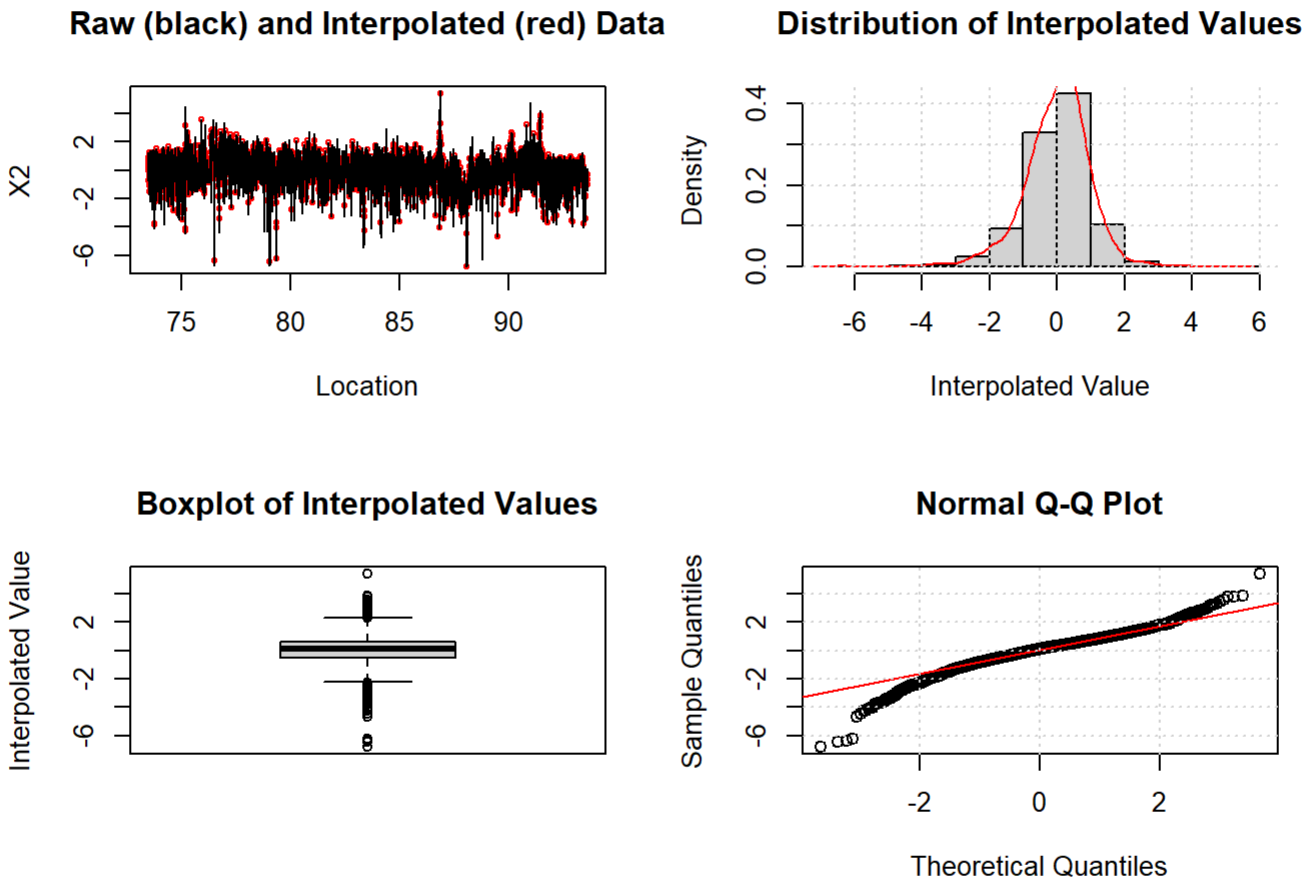
```
alb_Zr <- cbind(Alb$DepthAdj,Alb$Zr)
alb_Zr <- na.omit(alb_Zr)
alb_Zr[!is.finite(alb_Zr)] <- NA
alb_Zr <- na.omit(alb_Zr)
alb_Zr <- iso(dat=alb_Zr, xmin=73.453, xmax=93.609)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 18653
 * Number of columns= 2
 * Minimum= 73.453 , Maximum= 93.609
 * Isolating data between 73.453 and 93.609
 * Number of data points following culling= 18653
```



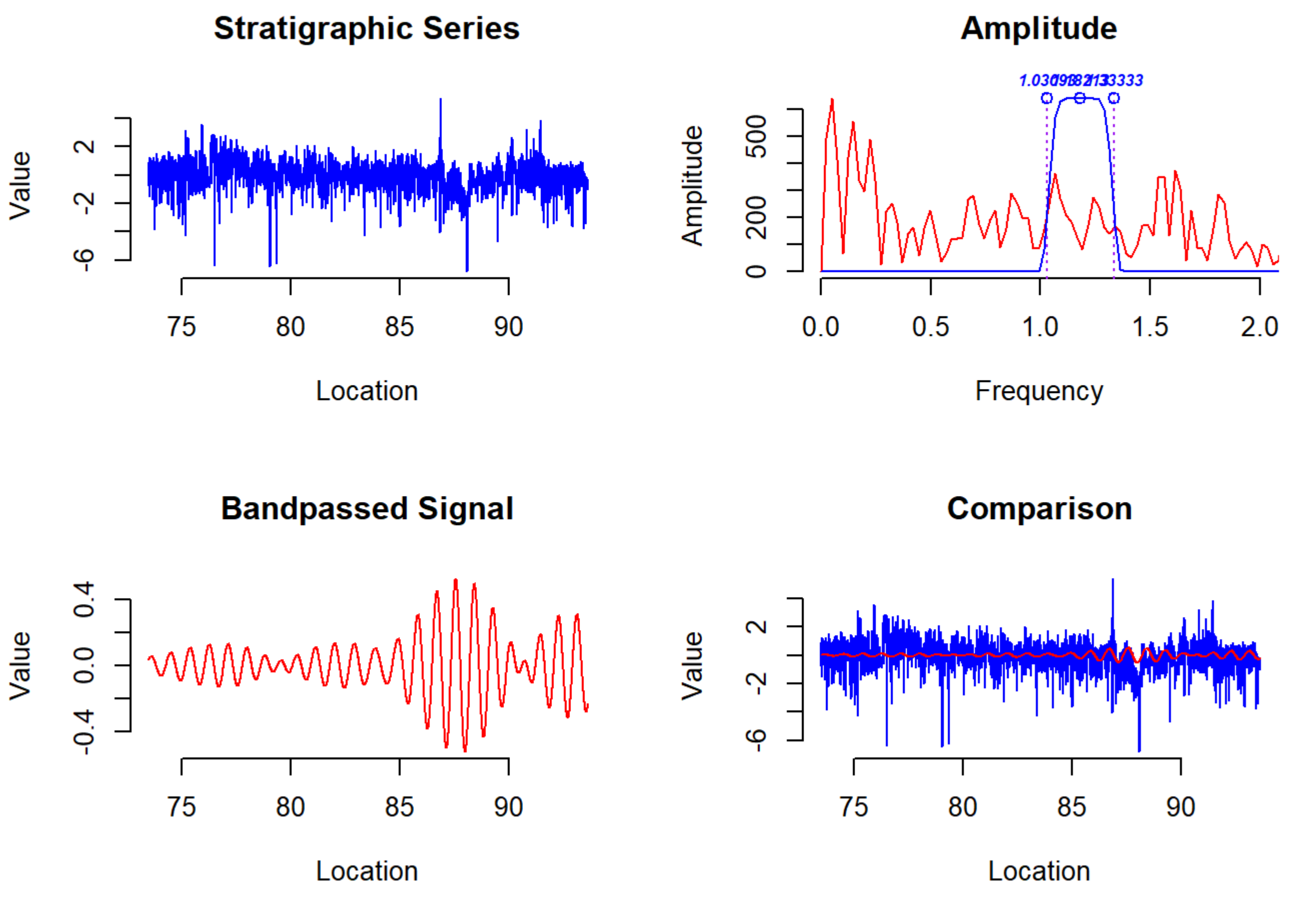

```r
alb_Zr <- linterp(alb_Zr, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 18653
 * New number of samples= 4032
```

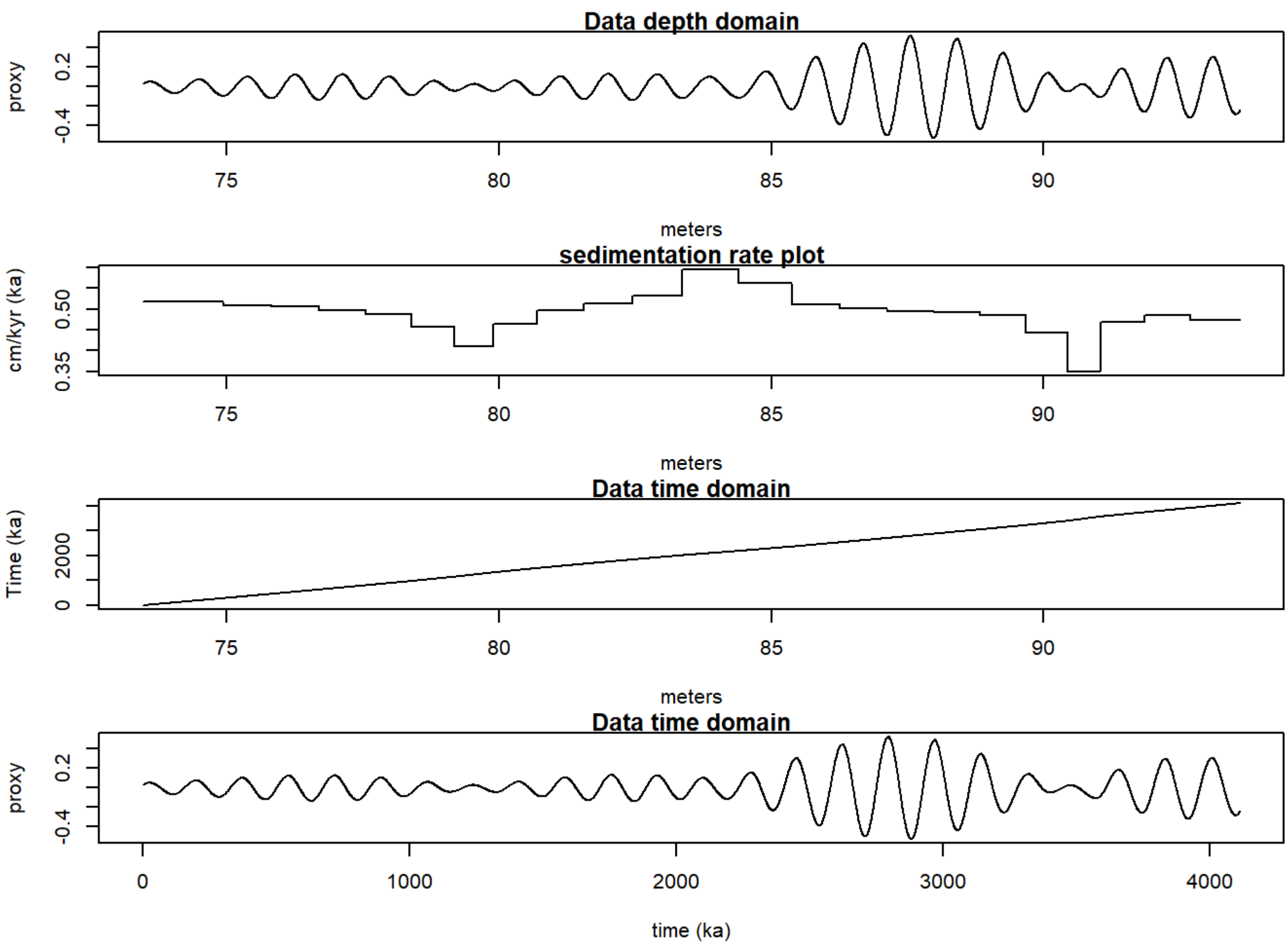



```
Zr_173R <- taner(alb_Zr,xmax=2,fhigh=1/0.97,flow=1/0.75,demean=TRUE)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 4032
 * Sample interval= 0.005
 * Mean value removed= -0.004319494
```




```
Zr_173R_min_tun <-    minimal_tuning(data = Zr_173R,pts = 20,cycle = 173,
tune_opt = "min",output = 0,genplot = TRUE,keep_editable = FALSE)
```




```
colnames(Zr_173R_min_tun)<-c("Zr Depth","Zr","Zr SR","Zr time")
```

11.1.3. File containing the filtering of all the detrital element

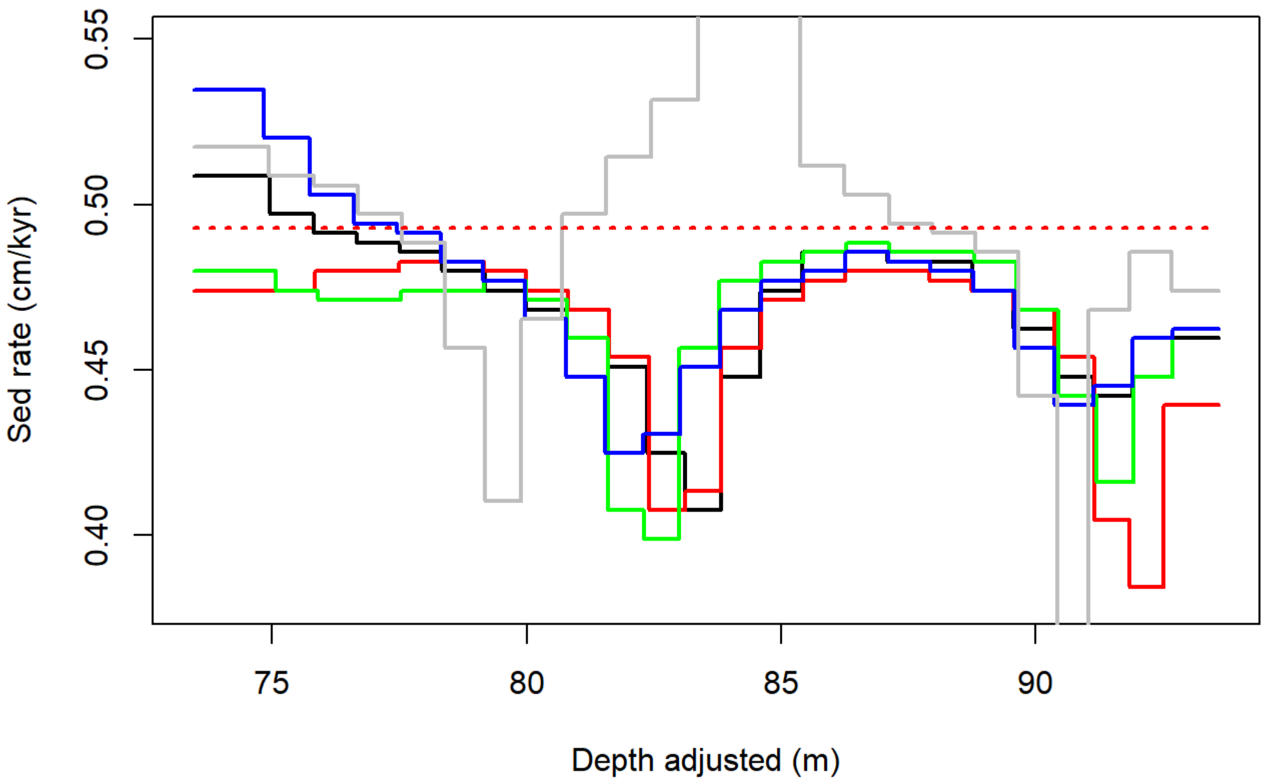
```
#All detrital
Det_173_min_tun <- cbind(Ti_173R_min_tun,
                         Si_173R_min_tun,
                         Al_173R_min_tun,
                         K_173R_min_tun,
                         Zr_173R_min_tun
                         )

head((Det_173_min_tun))
```

```
  Ti Depth          Ti     Ti SR   Ti time Si Depth         Si     Si SR
1   73.453 -0.01918895 0.5086705 0.0000000   73.453 -0.1302751 0.4739884
2   73.458 -0.01773397 0.5086705 0.9829545   73.458 -0.1289772 0.4739884
3   73.463 -0.01629626 0.5086705 1.9659091   73.463 -0.1275983 0.4739884
4   73.468 -0.01487777 0.5086705 2.9488636   73.468 -0.1261400 0.4739884
5   73.473 -0.01348043 0.5086705 3.9318182   73.473 -0.1246042 0.4739884
6   73.478 -0.01210616 0.5086705 4.9147727   73.478 -0.1229929 0.4739884
   Si time Al Depth         Al     Al SR  Al time K Depth          K      K SR
1 0.000000   73.453 -0.1533187 0.4797688 0.000000  73.453 0.03580243 0.5346821
2 1.054878   73.458 -0.1524303 0.4797688 1.042169  73.458 0.03562798 0.5346821
3 2.109756   73.463 -0.1514751 0.4797688 2.084337  73.463 0.03539204 0.5346821
4 3.164634   73.468 -0.1504541 0.4797688 3.126506  73.468 0.03509460 0.5346821
5 4.219512   73.473 -0.1493681 0.4797688 4.168675  73.473 0.03473567 0.5346821
6 5.274390   73.478 -0.1482183 0.4797688 5.210843  73.478 0.03431536 0.5346821
     K time Zr Depth         Zr    Zr SR   Zr time
1 0.0000000   73.453 0.02894888 0.517341 0.0000000
2 0.9351351   73.458 0.03032727 0.517341 0.9664804
3 1.8702703   73.463 0.03166989 0.517341 1.9329609
4 2.8054054   73.468 0.03297492 0.517341 2.8994413
5 3.7405405   73.473 0.03424055 0.517341 3.8659218
6 4.6756757   73.478 0.03546501 0.517341 4.8324022
```

11.1.4. Sedimentation rate

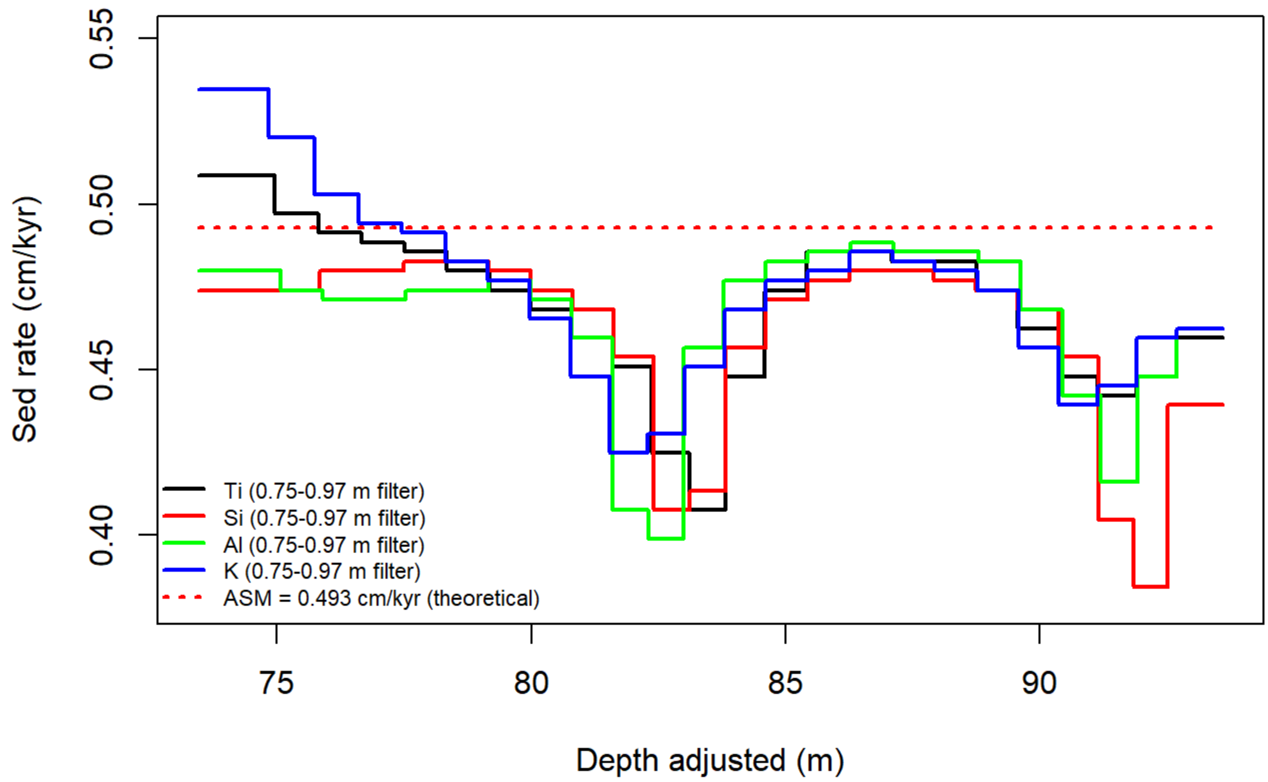
```
plot(Det_173_min_tun[,1],
     Det_173_min_tun[,3],
     type="l",
     xlab = "Depth adjusted (m)",
     ylab = "Sed rate (cm/kyr)",
     ylim=c(0.38,0.55),
     lwd = 2
     )

lines(Det_173_min_tun[,1],
      Det_173_min_tun[,7],
      col="red",
      lwd=2
      )

lines(Det_173_min_tun[,1],
      Det_173_min_tun[,11],
      col="green",
      lwd=2
      )
```

```
lines(Det_173_min_tun[,1],
      Det_173_min_tun[,15],
      col="blue",
      lwd=2
      )

lines(Det_173_min_tun[,1],
      Det_173_min_tun[,19],
      col="grey",
      lwd=2
      )

lines(Det_173_min_tun[,1],
      Det_173_min_tun[,19]-Det_173_min_tun[,19]+0.493,
      col="red",
      lwd=2,
      lty=3
      )
```




```
#Zr sedimentation rate is significantly different compared to the other detrital
#element and will not be used.

  plot(Det_173_min_tun[,1],
       Det_173_min_tun[,3],
       type="l",
       xlab = "Depth adjusted (m)",
       ylab = "Sed rate (cm/kyr)",
       ylim=c(0.38,0.55),
       lwd = 2
       )
```

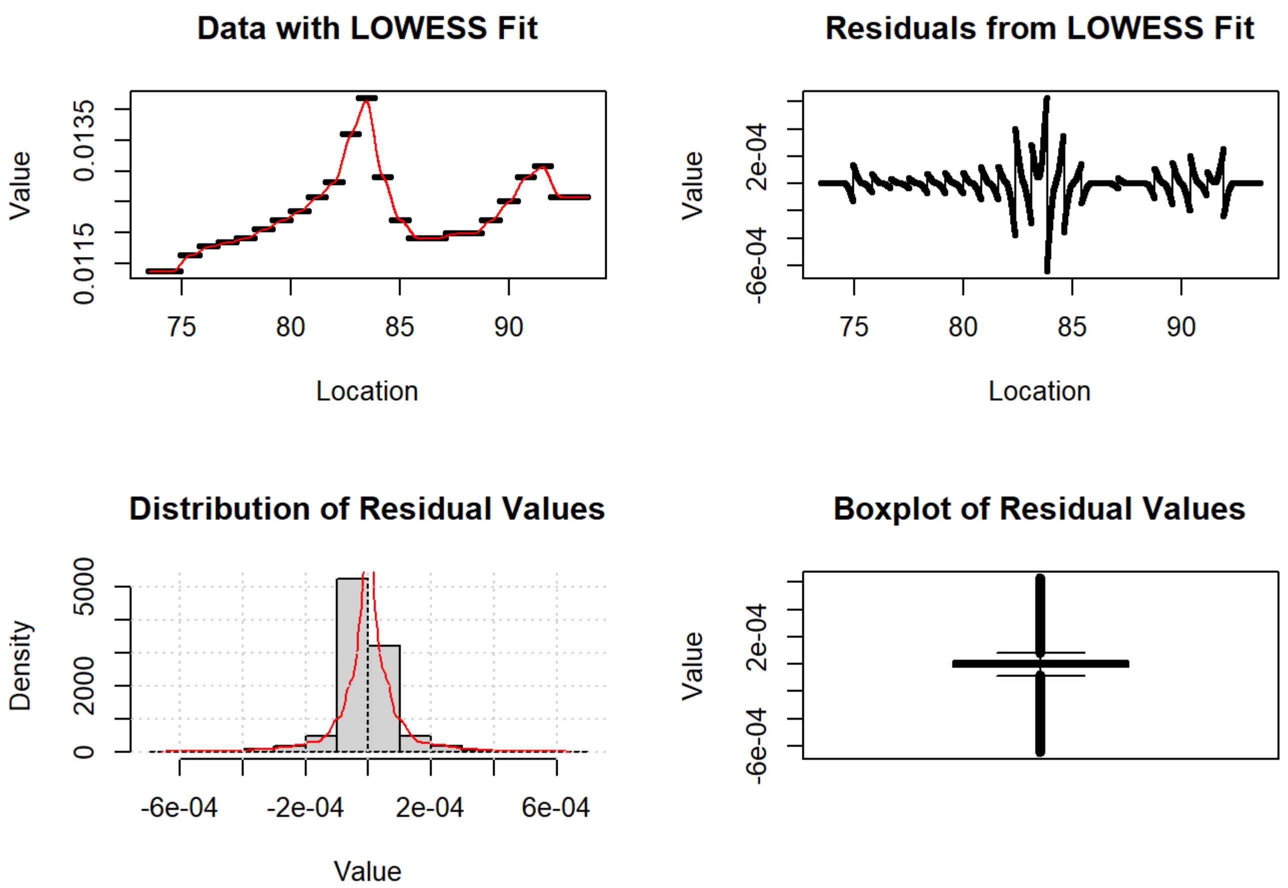
```
lines(Det_173_min_tun[,1],
      Det_173_min_tun[,7],
      col="red",
      lwd=2
      )

lines(Det_173_min_tun[,1],
      Det_173_min_tun[,11],
      col="green",
      lwd=2
      )

lines(Det_173_min_tun[,1],
      Det_173_min_tun[,15],
      col="blue",
      lwd=2
      )

lines(Det_173_min_tun[,1],
      Det_173_min_tun[,19]-Det_173_min_tun[,19]+0.493,
      col="red",
      lwd=2,
      lty=3
      )

legend("bottomleft",
       legend = c("Ti (0.75-0.97 m filter)",
                  "Si (0.75-0.97 m filter)",
                  "Al (0.75-0.97 m filter)",
                  "K (0.75-0.97 m filter)",
                  "ASM = 0.493 cm/kyr (theoretical)"),
       col = c("black", "red", "green", "blue", "red"),
       lty = c(1, 1, 1, 1,3),
       lwd = c(2, 2, 2, 2,2),
       pch = c(NA, NA, NA, NA,NA),
       pt.cex = 2,
       bty = "n",         # No box around legend
       cex = 0.7)
```



11.1.5. Mean and standard deviation calculation

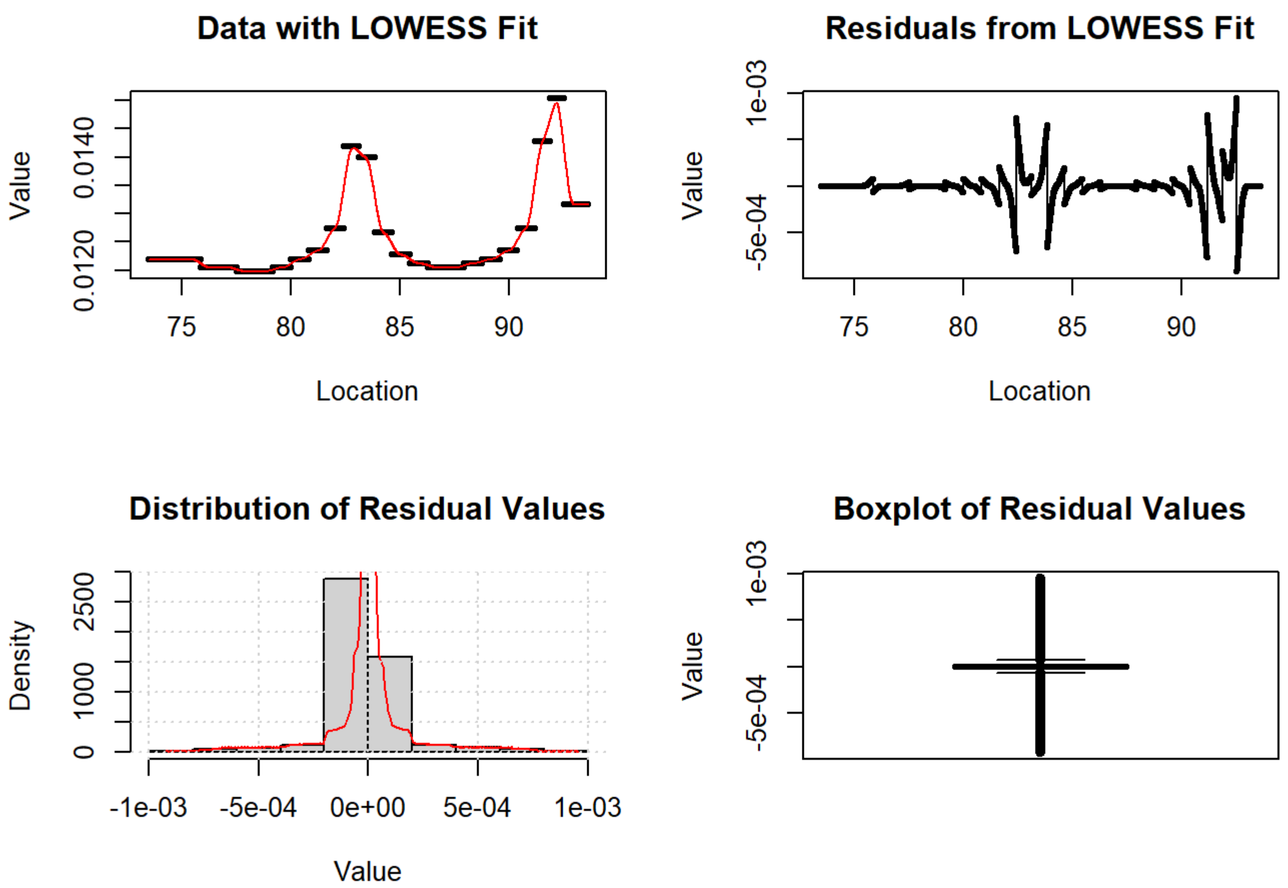
```
#Smoothing the sed rate and turning it into frequency to calculate the mean and the
#standard deviation of the age model
  Ti_173_freq<-noLow(cbind(Det_173_min_tun[,c(1)],1/(Det_173_min_tun[,c(3)]*173)),
                     0.05,
                     output = 2
                     )
```

```
----- REMOVING LOWESS SMOOTHER FROM STRATIGRAPHIC SERIES -----
Call:
loess(formula = (dat[, 2]) ~ dat[, 1], span = smooth, degree = 1)

Number of Observations: 4032
Equivalent Number of Parameters: 31.09
Residual Standard Error: 9.956e-05
Trace of smoother matrix: 36.89  (exact)

Control settings:
  span     :  0.05
  degree   :  1
  family   :  gaussian
  surface  :  interpolate     cell = 0.2
  normalize:  TRUE
 parametric:  FALSE
drop.square:  FALSE
```



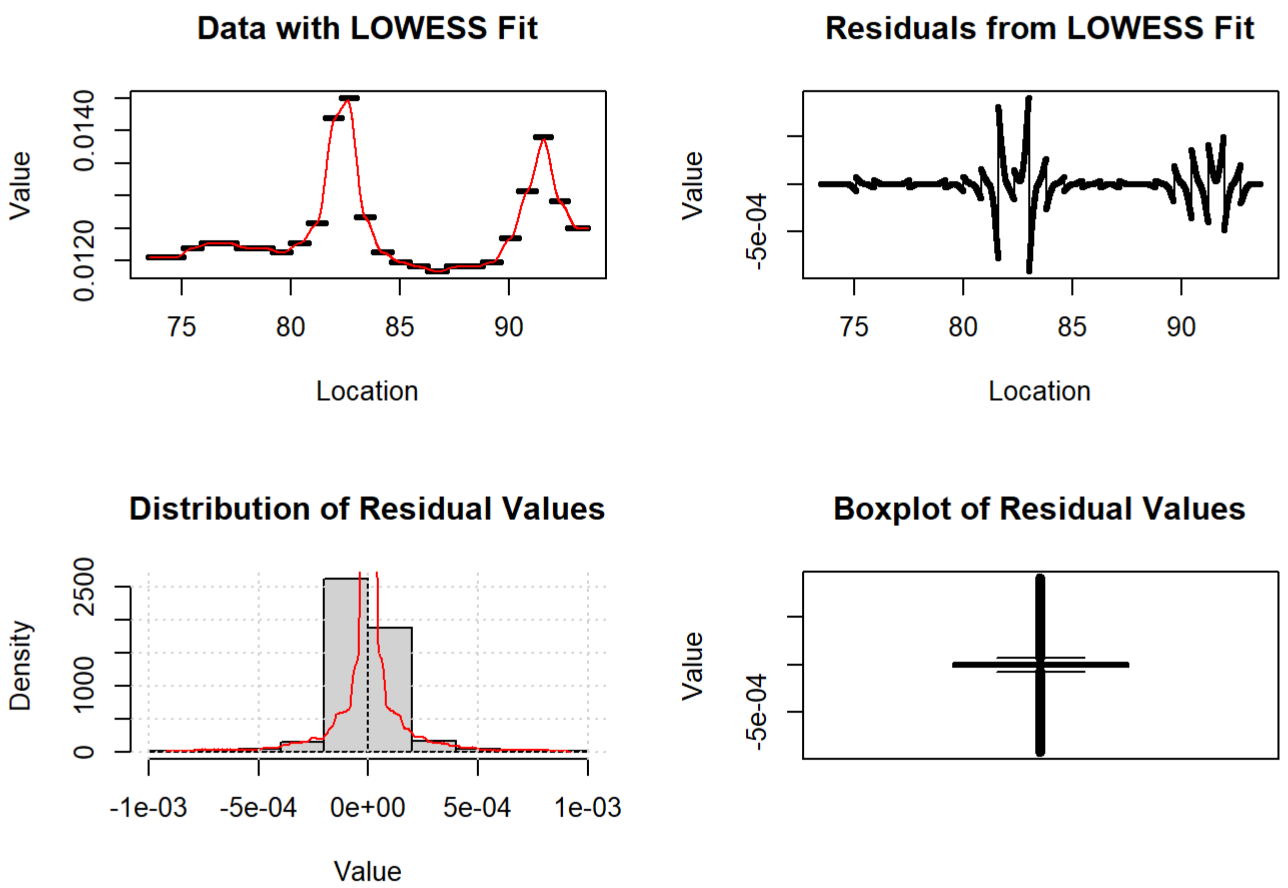

```r
Si_173_freq<-noLow(cbind(Det_173_min_tun[,c(1)],1/(Det_173_min_tun[,c(7)]*173)),
                   0.05,
                   output = 2
                   )
```

```
----- REMOVING LOWESS SMOOTHER FROM STRATIGRAPHIC SERIES -----
Call:
loess(formula = (dat[, 2]) ~ dat[, 1], span = smooth, degree = 1)

Number of Observations: 4032
Equivalent Number of Parameters: 31.09
Residual Standard Error: 0.0001639
Trace of smoother matrix: 36.89  (exact)

Control settings:
  span     :  0.05
  degree   :  1
  family   :  gaussian
  surface  :  interpolate     cell = 0.2
  normalize:  TRUE
 parametric:  FALSE
drop.square:  FALSE
```



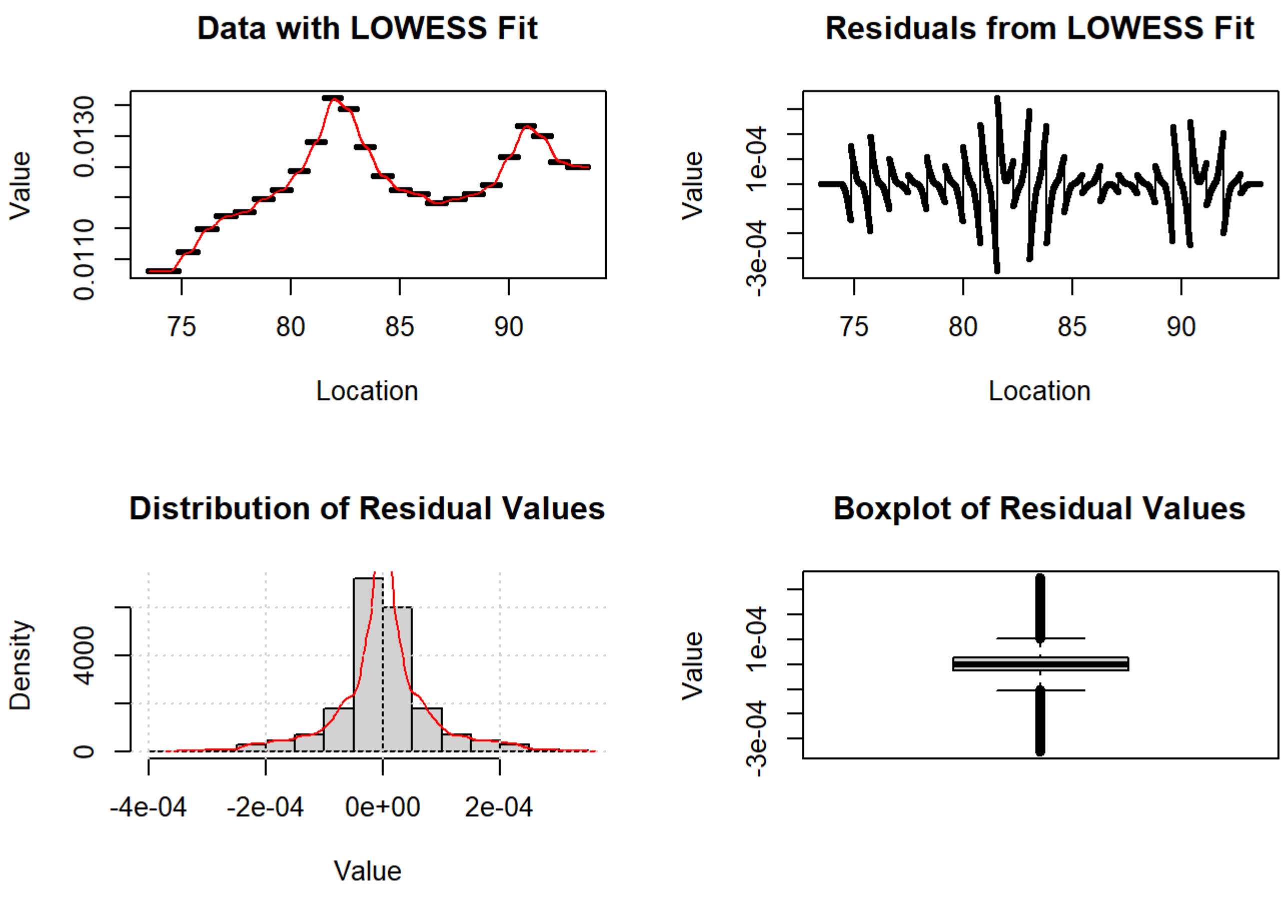

```r
Al_173_freq<-noLow(cbind(Det_173_min_tun[,c(1)],1/(Det_173_min_tun[,c(11)]*173)),
                  0.05,
                  output = 2
                  )
```

```
----- REMOVING LOWESS SMOOTHER FROM STRATIGRAPHIC SERIES -----
Call:
loess(formula = (dat[, 2]) ~ dat[, 1], span = smooth, degree = 1)

Number of Observations: 4032
Equivalent Number of Parameters: 31.09
Residual Standard Error: 0.0001489
Trace of smoother matrix: 36.89  (exact)

Control settings:
  span     :  0.05
  degree   :  1
  family   :  gaussian
  surface  :  interpolate     cell = 0.2
  normalize:  TRUE
 parametric:  FALSE
drop.square:  FALSE
```




```
K_173_freq<-noLow(cbind(Det_173_min_tun[,c(1)],1/(Det_173_min_tun[,c(15)]*173)),
                   0.05,
                   output = 2
                   )
```

```
----- REMOVING LOWESS SMOOTHER FROM STRATIGRAPHIC SERIES -----
Call:
loess(formula = (dat[, 2]) ~ dat[, 1], span = smooth, degree = 1)

Number of Observations: 4032
Equivalent Number of Parameters: 31.09
Residual Standard Error: 7.944e-05
Trace of smoother matrix: 36.89  (exact)

Control settings:
  span     :  0.05
  degree   :  1
  family   :  gaussian
  surface  :  interpolate      cell = 0.2
  normalize:  TRUE
 parametric:  FALSE
drop.square:  FALSE
```

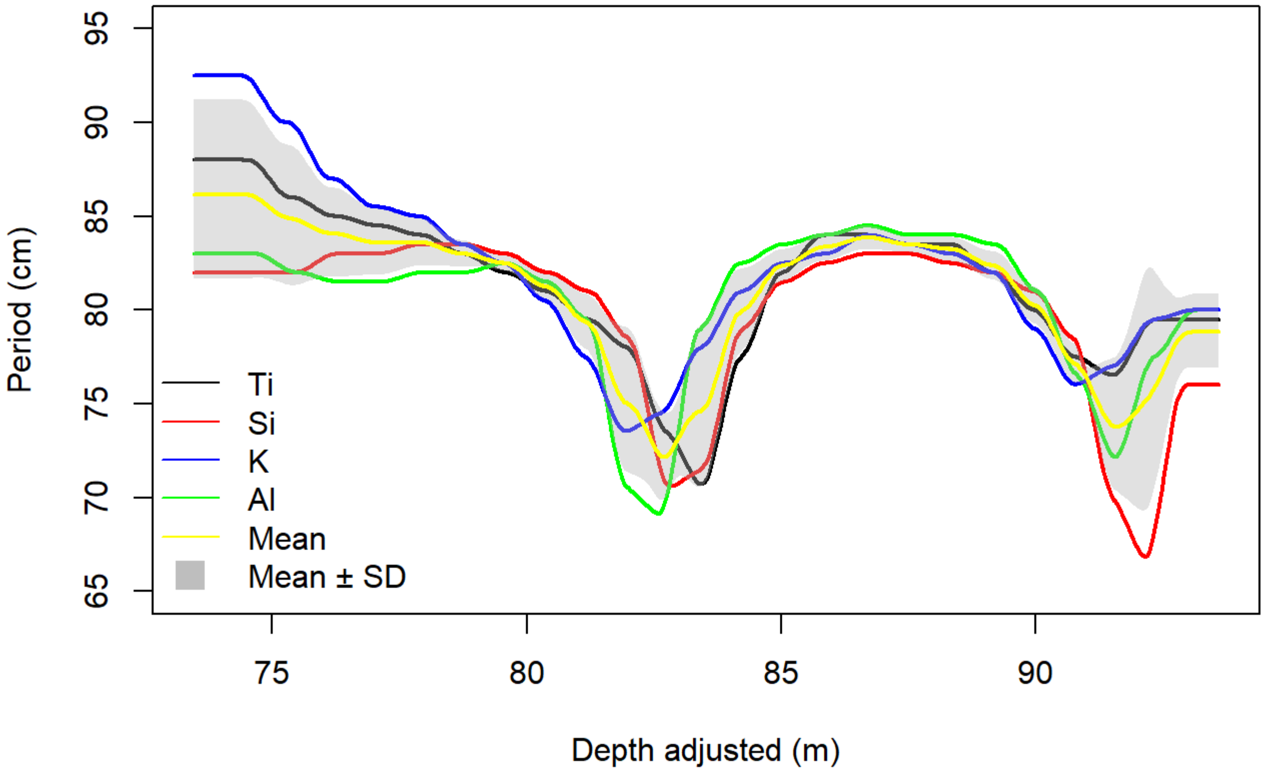



```
Det_173_freq <- cbind(Det_173_min_tun[,1],
                      Ti_173_freq[,2],
                      Si_173_freq[,2],
                      Al_173_freq[,2],
                      K_173_freq[,2]
                      )

head(Det_173_freq)
```

```
       [,1]       [,2]       [,3]       [,4]       [,5]
[1,] 73.453 0.01136364 0.01219512 0.01204819 0.01081081
[2,] 73.458 0.01136364 0.01219512 0.01204819 0.01081081
[3,] 73.463 0.01136364 0.01219512 0.01204819 0.01081081
[4,] 73.468 0.01136364 0.01219512 0.01204819 0.01081081
[5,] 73.473 0.01136364 0.01219512 0.01204819 0.01081081
[6,] 73.478 0.01136364 0.01219512 0.01204819 0.01081081
```

```
Det_173_freq<-as.data.frame(Det_173_freq)
Det_173_freq$mean<-rowMeans(Det_173_freq[,c(2:5)], na.rm = FALSE)

library(matrixStats)
Det_173_freq$sds<-rowSds(as.matrix(Det_173_freq[,c(2:5)]), na.rm = FALSE)
colnames(Det_173_freq)<- cbind("Depth",
                               "Ti freq",
                               "Si freq",
                               "Al freq",
                               "K freq",
                               "mean",
                               "sds"
                               )
```

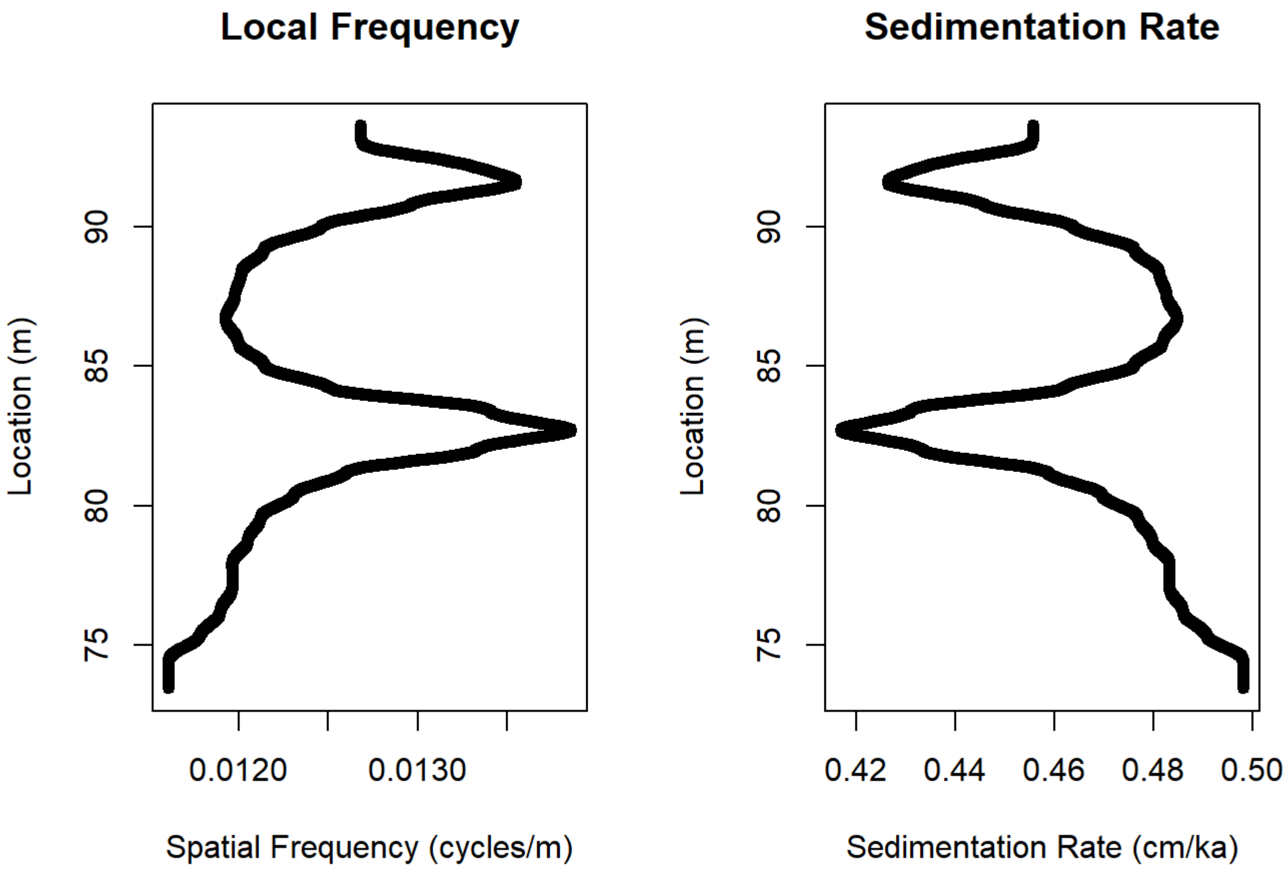
```r
plot(Det_173_freq[,1],
     1/(Det_173_freq[,2]),
     type="l",
     col="black",
     lwd= 2,
     xlab = "Depth adjusted (m)",
     ylab = "Period (cm)",
     ylim = c(65,95)
     )

lines(Det_173_freq[,1],
      1/(Det_173_freq[,3]),
      col="red",
      lwd=2
      )

lines(Det_173_freq[,1],
      1/(Det_173_freq[,4]),
      col="green",
      lwd=2
      )

lines(Det_173_freq[,1],
      1/(Det_173_freq[,5]),
      col="blue",
      lwd=2
      )

#Graphical visualisation of the uncertaineties
depth<-Det_173_freq[,1]
curve_mean <- Det_173_freq[,6]
curve_sd <- Det_173_freq[,7]

# Add polygon for mean ± SD
polygon(c(depth, rev(depth)),
        1/c(curve_mean + curve_sd, rev(curve_mean - curve_sd)),
        col = rgb(0.7, 0.7, 0.7, 0.4), border = NA)

# Optionally overlay mean line
lines(depth, 1/curve_mean, col = "yellow", lwd = 2)
legend("bottomleft",
       legend = c("Ti", "Si", "K", "Al", "Mean", "Mean ± SD"),
       col = c("black", "red", "blue", "green","yellow", rgb(0.7, 0.7, 0.7, 0.8)),
       lty = c(1, 1, 1, 1, 1,NA),
       lwd = c(1, 1, 1, 1, 1,NA),
       pch = c(NA, NA, NA, NA,NA, 15),
       pt.cex = 2,
       bty = "n",         # No box around legend
       cex = 1)         # Larger legend text
```



11.1.6. Building of the Age model

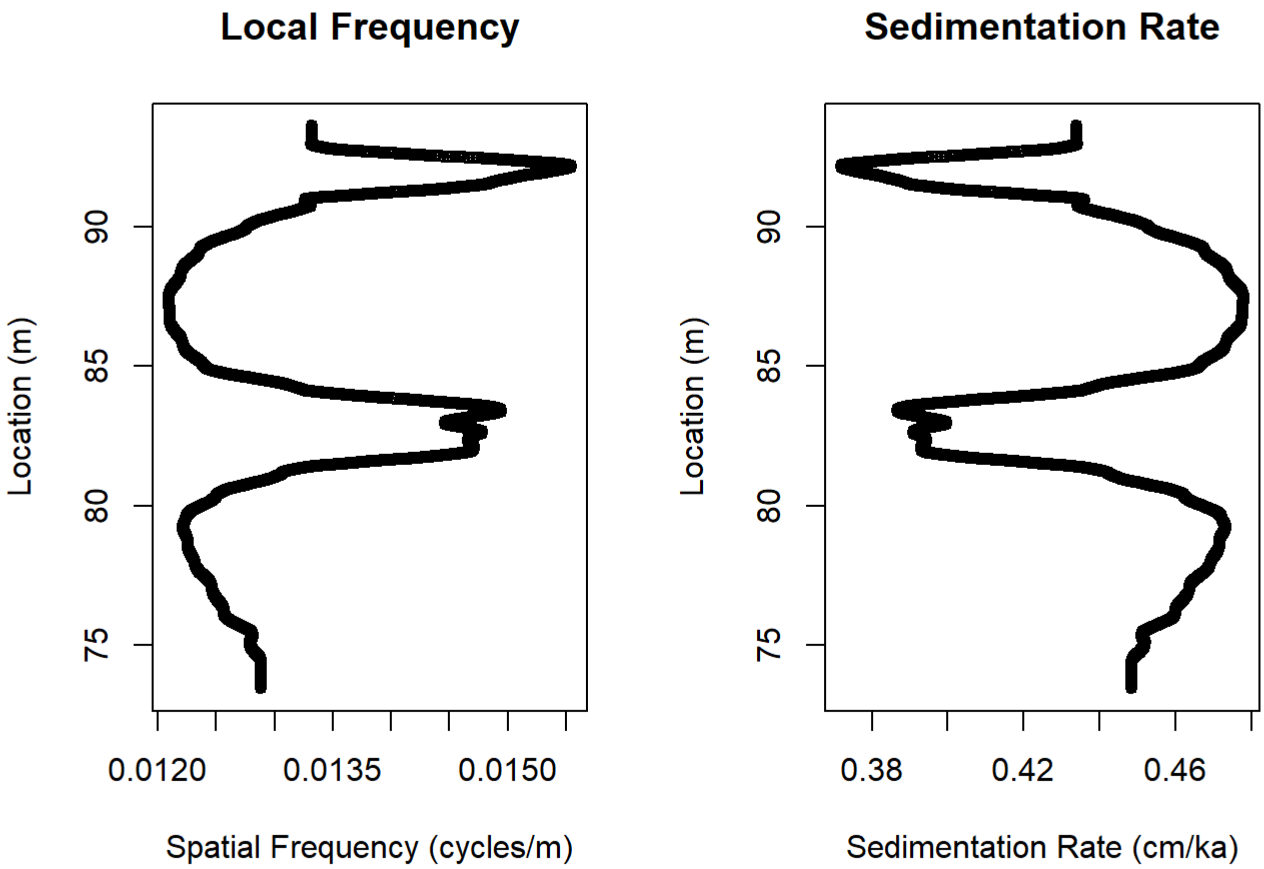
```
#Calculating the minimal, mean and maximal sed rates
mean_sed<-freq2sedrate(cbind(Det_173_freq[,1],
                             (Det_173_freq[,6])),
                       period=17300
                       )
```

```
----- CONVERTING RECORD OF SPATIAL FREQUENCY TO SEDIMENTATION RATE CURVE-----

 * Sorting into increasing depth/height order.
     Will remove empty entries.
 * Number of control points = 4032
```



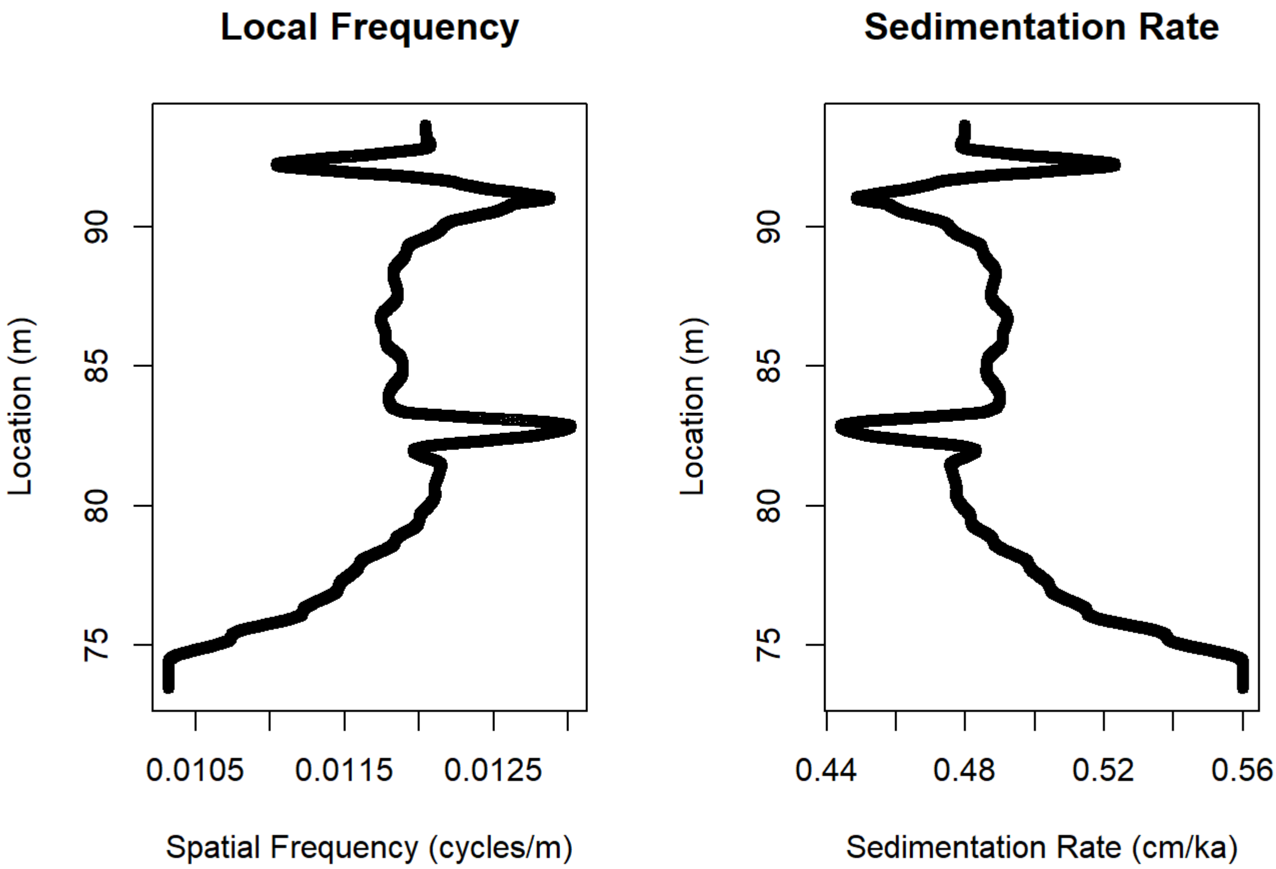

```
max_sed<-freq2sedrate(cbind(Det_173_freq[,1],
                            (Det_173_freq[,6]+2*Det_173_freq[,7])),
                      period=17300
                      )
```

```
----- CONVERTING RECORD OF SPATIAL FREQUENCY TO SEDIMENTATION RATE CURVE-----

 * Sorting into increasing depth/height order.
     Will remove empty entries.
 * Number of control points = 4032
```



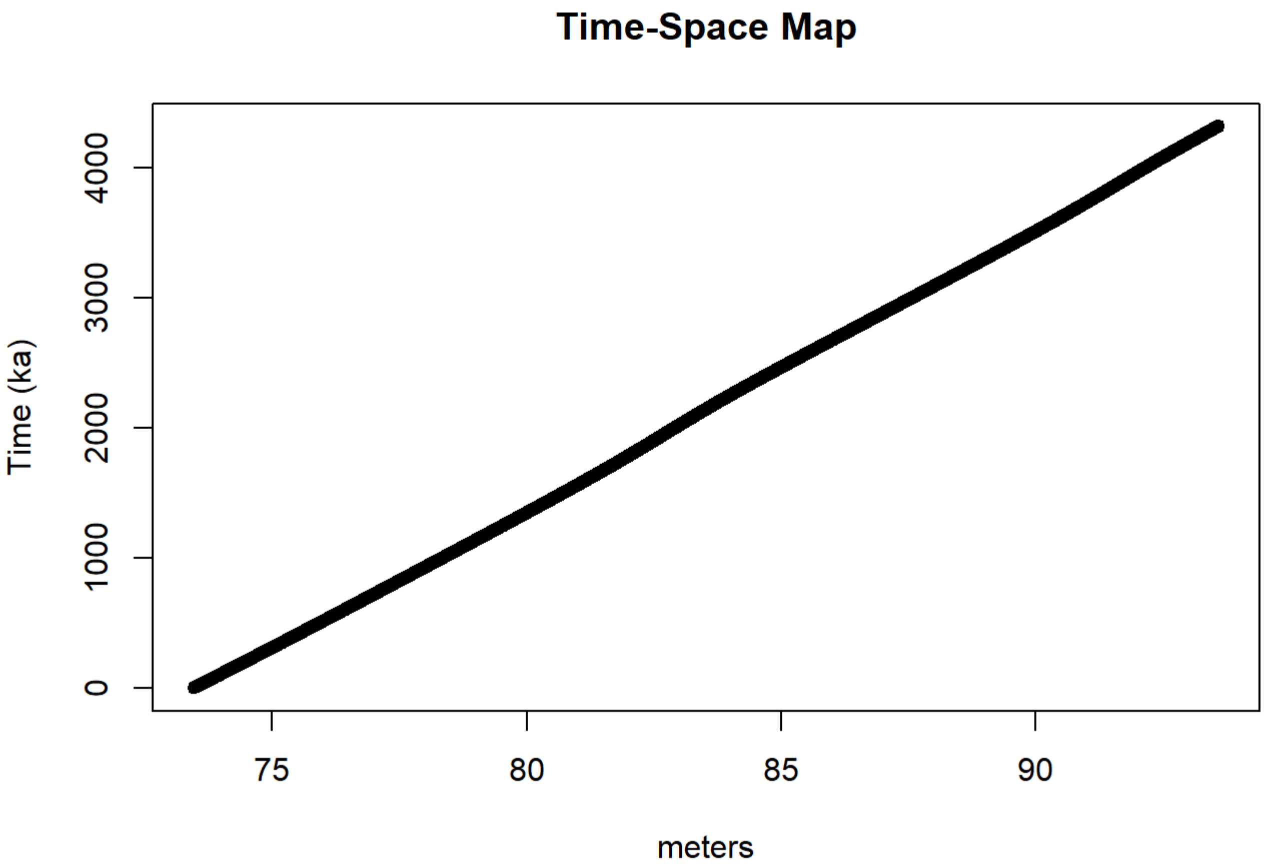

```
min_sed<-freq2sedrate(cbind(Det_173_freq[,1],
                            (Det_173_freq[,6]-2*Det_173_freq[,7])),
                      period=17300
                      )
```

```
----- CONVERTING RECORD OF SPATIAL FREQUENCY TO SEDIMENTATION RATE CURVE-----

 * Sorting into increasing depth/height order.
     Will remove empty entries.
 * Number of control points = 4032
```



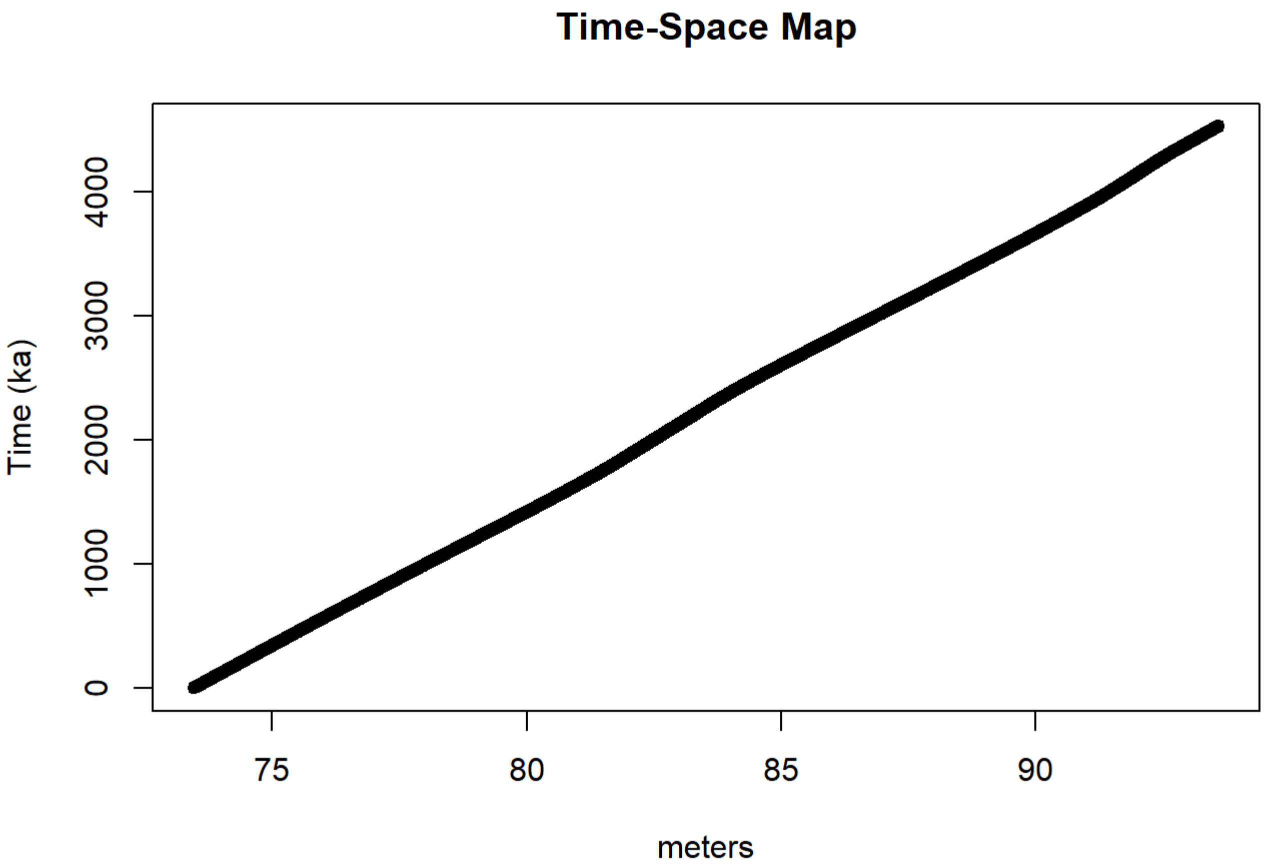

```
#Sed rate to time and creation fo the Age Model
Mean_AgeModel<-sedrate2time(mean_sed)
```

```
----- INTEGRATING SEDIMENTATION RATE CURVE-----

 * Sorting sedrates into increasing depth/height order.
     Will remove empty entries.
 * Number of sedimentation rates= 4032
```



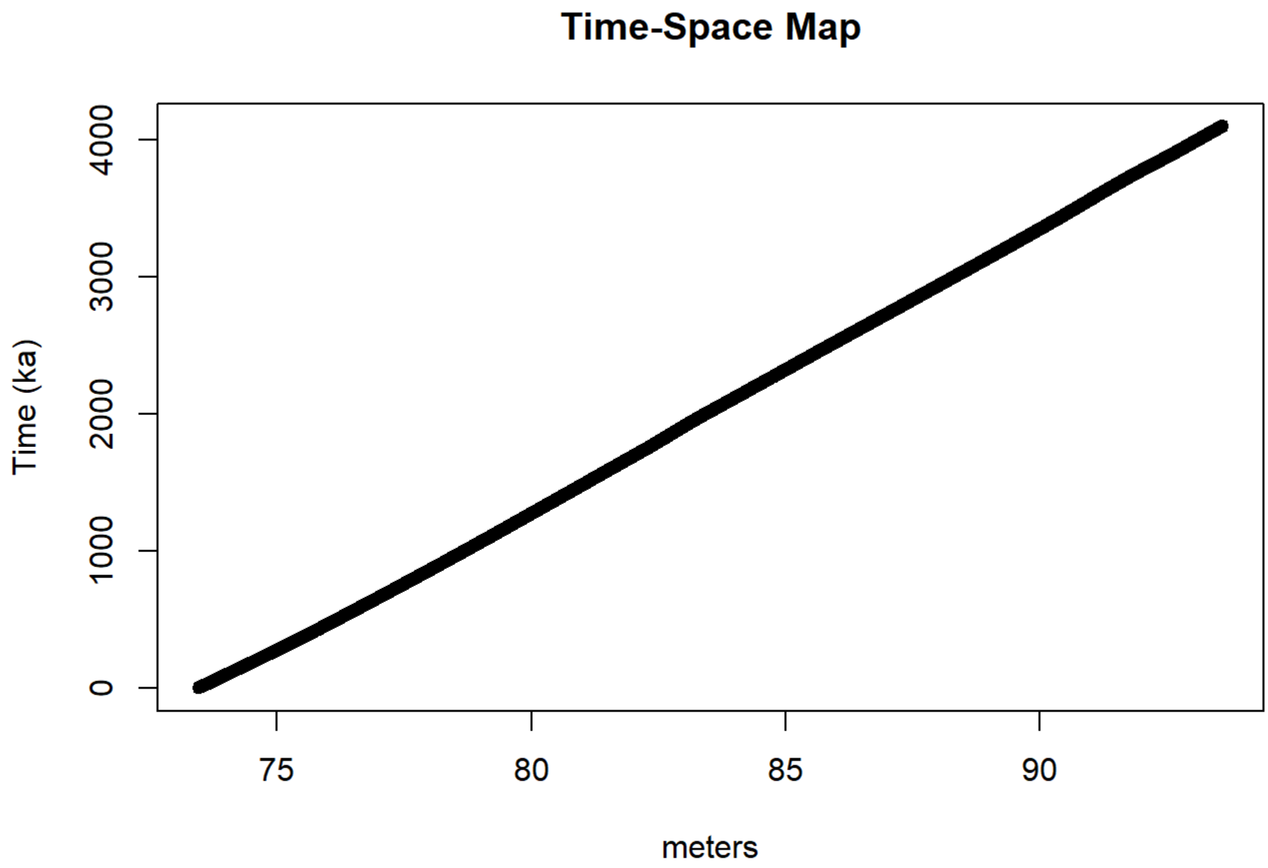

```
Max_AgeModel<-sedrate2time(max_sed)
```

```
----- INTEGRATING SEDIMENTATION RATE CURVE-----

 * Sorting sedrates into increasing depth/height order.
     Will remove empty entries.
 * Number of sedimentation rates= 4032
```

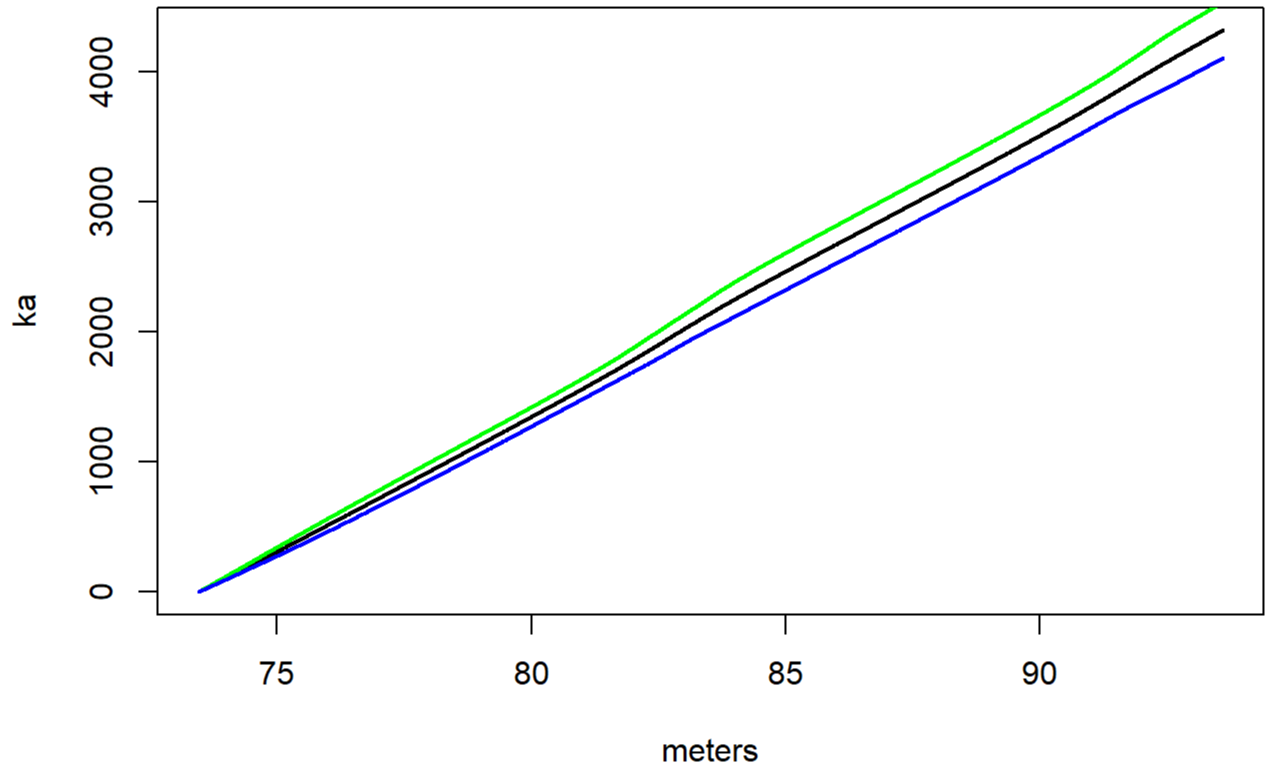



```
Min_AgeModel<-sedrate2time(min_sed)
```

```
----- INTEGRATING SEDIMENTATION RATE CURVE-----

 * Sorting sedrates into increasing depth/height order.
     Will remove empty entries.
 * Number of sedimentation rates= 4032
```

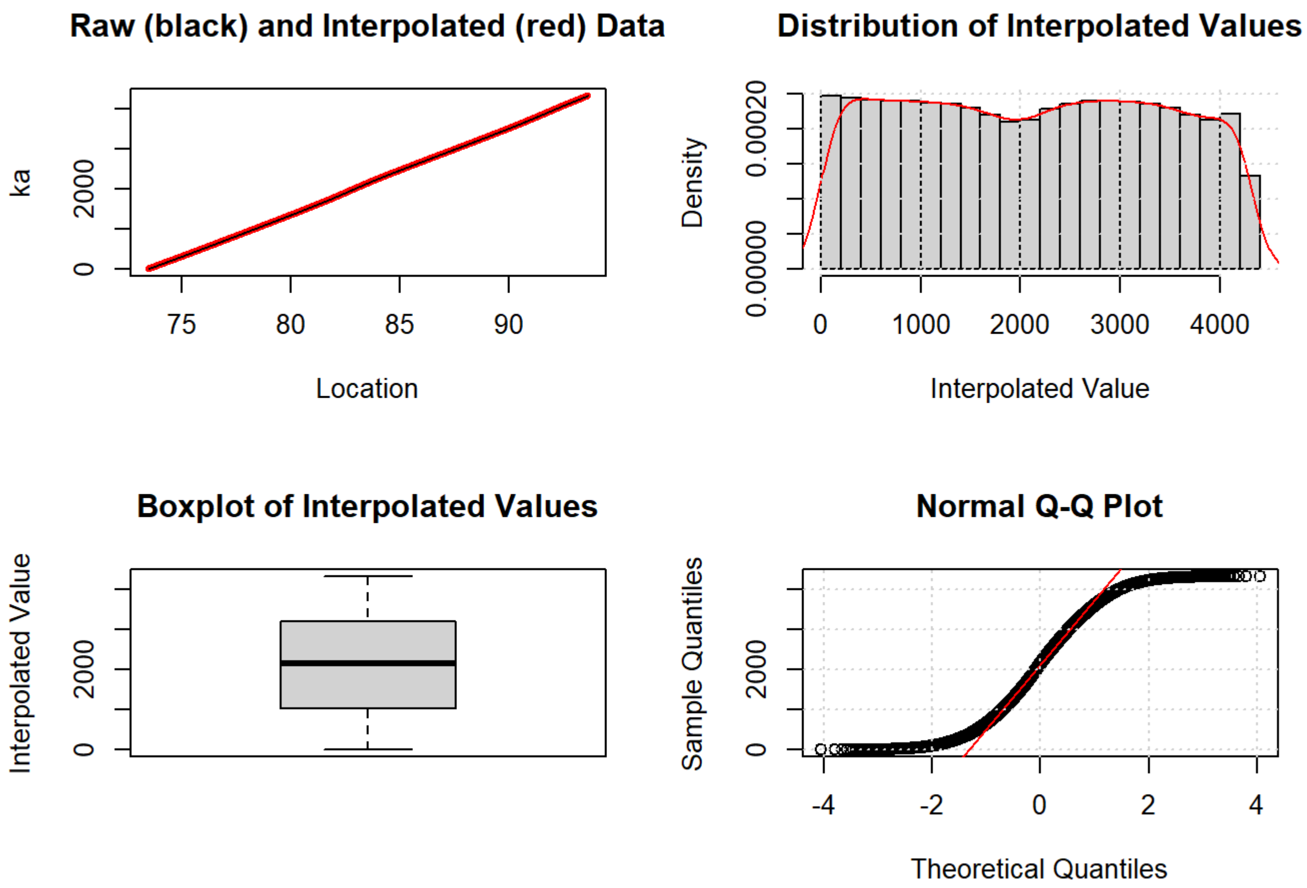



```
plot(Mean_AgeModel,type="l", lwd=2)
lines(Max_AgeModel,col="green",lwd=2)
lines(Min_AgeModel,col="blue",lwd=2)
```



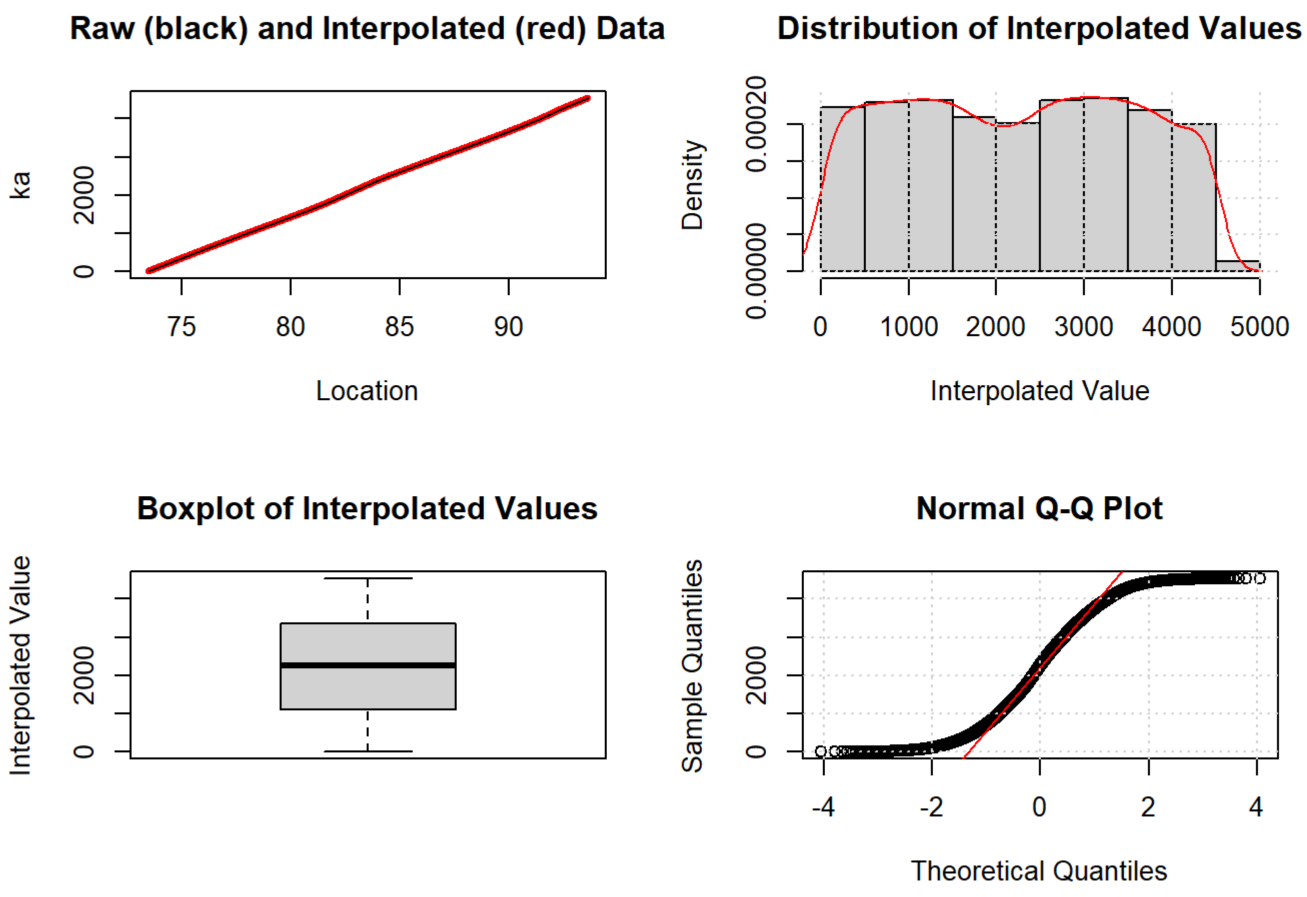
```
Age_Model <- cbind(Mean_AgeModel,Max_AgeModel[,2],Min_AgeModel[,2])
colnames(Age_Model)<- cbind("Adjusted depth (m)",
                            "Mean age (ka)",
                            "Max age (ka)",
                            "Min age (ka)"
                            )
#Interpolation of the Age-Model every 1 mm to have an age-depth correlation for
#the entire Ti dataset with the original sampling step of 1mm
Mean_Age_Model_1mm <- linterp(Mean_AgeModel, dt=0.001, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * New number of samples= 20155
```



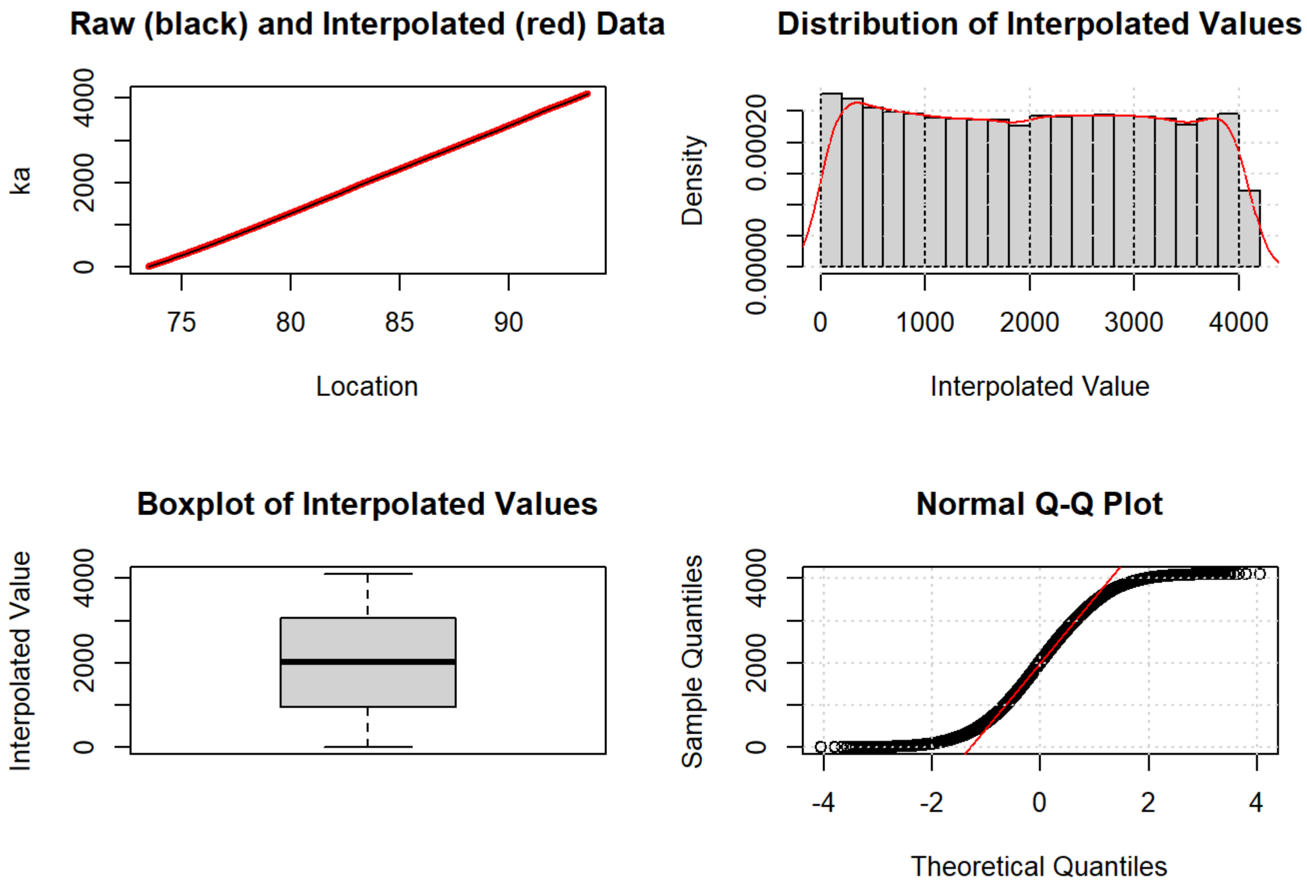

```
Max_Age_Model_1mm <- linterp(Max_AgeModel, dt=0.001, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * New number of samples= 20155
```




```
Min_Age_Model_1mm <- linterp(Min_AgeModel, dt=0.001, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * New number of samples= 20155
```




```
  Age_Model_1mm <- cbind(Mean_Age_Model_1mm,Max_Age_Model_1mm[,2],Min_Age_Model_1mm[,2])
  colnames(Age_Model)<- cbind("Adjusted depth (m)",
                              "Mean age (ka)",
                              "Max age (ka)",
                              "Min age (ka)"
                              )
  #Saving of the age models as .csv files
#  write.csv(Age_Model,"AgeModel_rsp5mm_filter0.75-0.97m.csv")
#  write.csv(Age_Model_1mm,"AgeModel_rsp1mm_filter0.75-0.97m.csv")
```

11.2. Age-Depth model (Wavelet tracking; preferred)

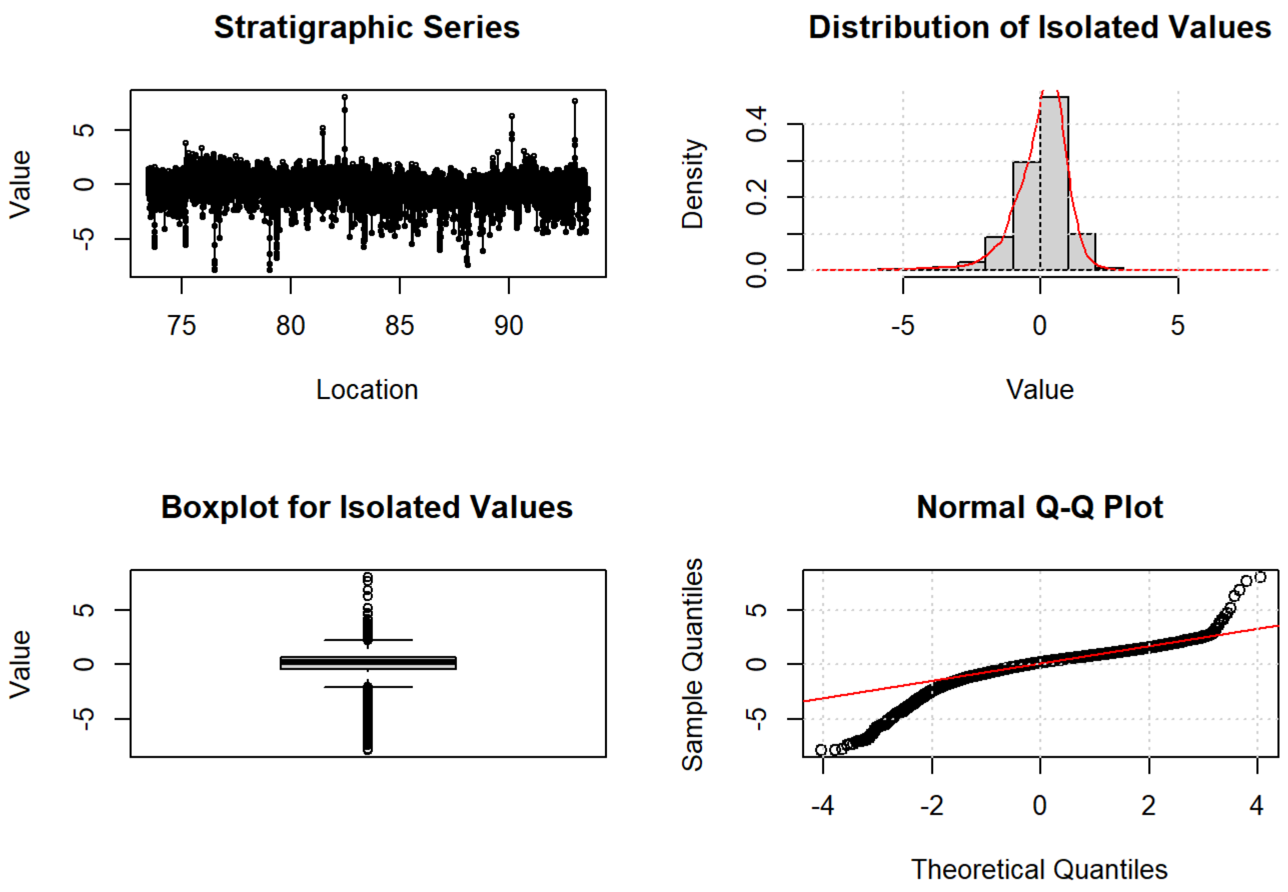
11.2.1. Tracking of the 173 kyr for Ti, Al, Si and K

As shown in the time series analysis (MTM, EHA and CWT), the 173 kyr cycle is comprise between 0.75 and 0.9 m. To avoid overpass this range when tracking the Wavelet, especially with periodicities lower than 0.74 m, that could be linked to the short eccentricity (100-135 kyr) band, we used a lowpass filtering of the tracked Wavelet in accordance with the general trend observed in the CWT.

11.2.1.1. Titanium

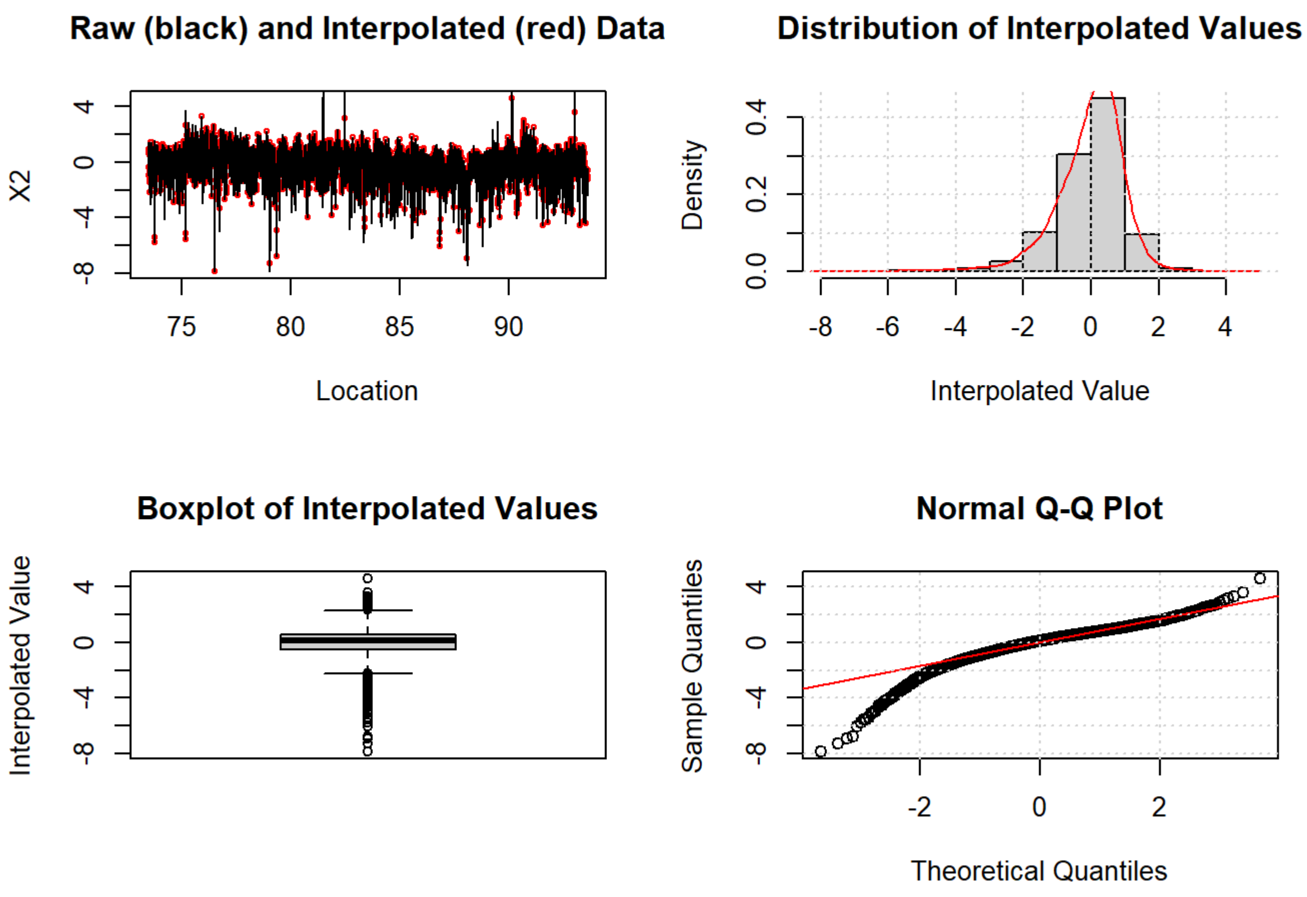
```
    alb_Ti <- cbind(Alb$DepthAdj,Alb$Ti)
    alb_Ti <- na.omit(alb_Ti)
    alb_Ti[!is.finite(alb_Ti)] <- NA
    alb_Ti <- na.omit(alb_Ti)
    alb_Ti <- iso(dat=alb_Ti, xmin=73.453, xmax=100)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30577
 * Number of columns= 2
 * Minimum= 62.111 , Maximum= 93.61
 * Isolating data between 73.453 and 100
 * Number of data points following culling= 19311
```



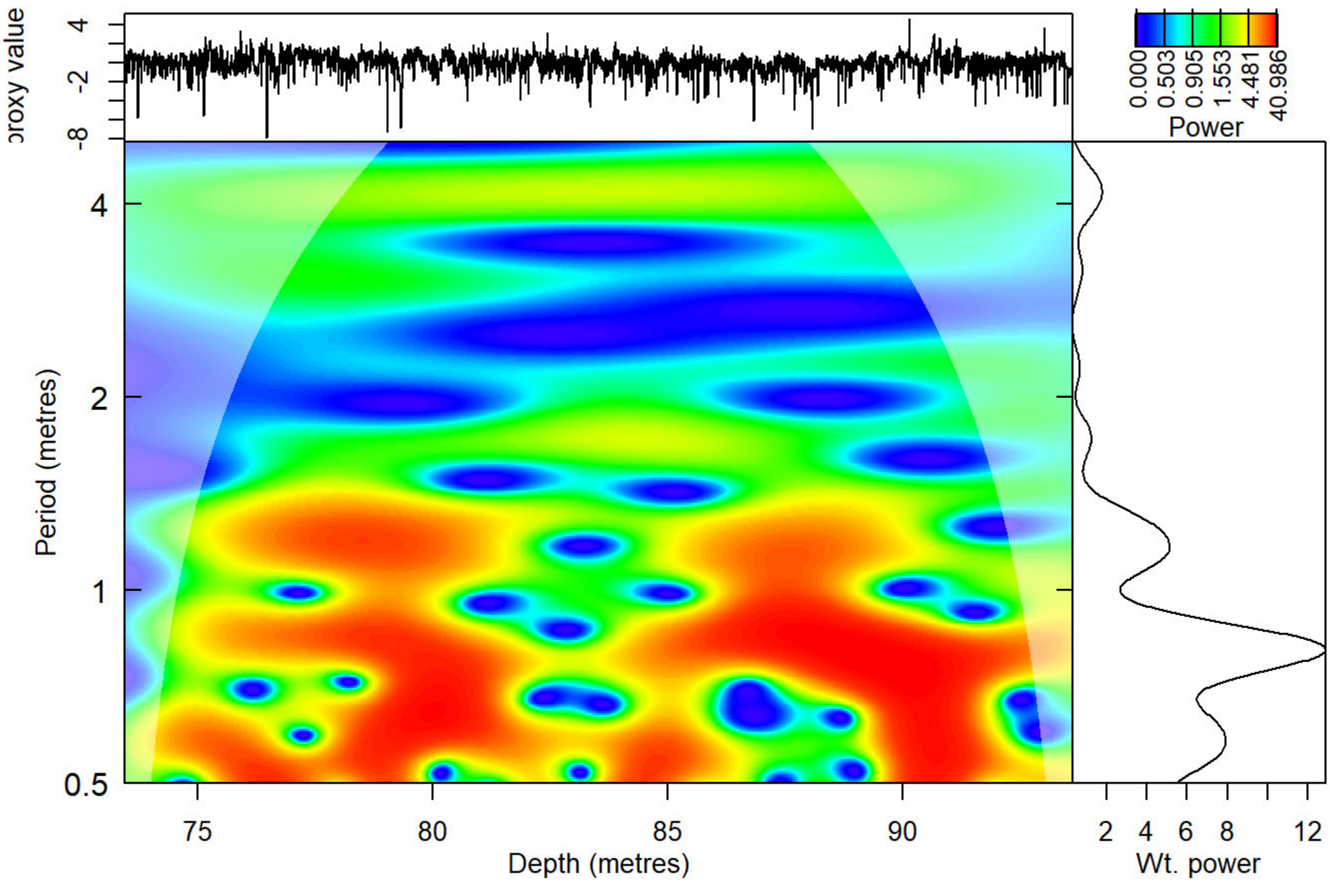

```
alb_Ti_ndet <-  linterp(alb_Ti, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 19311
 * New number of samples= 4032
```



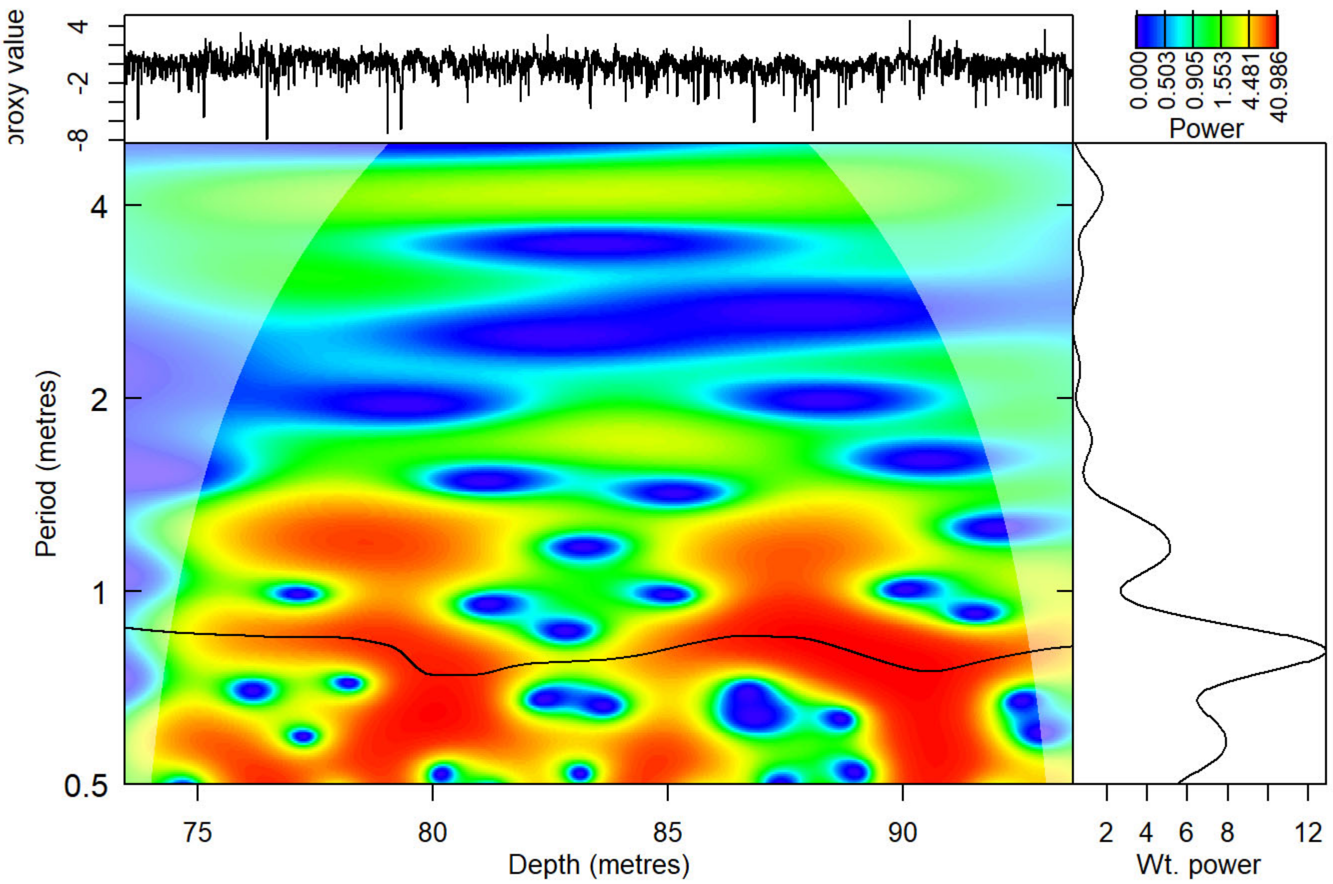

```
#Waverider
alb_Ti_wt <- analyze_wavelet(alb_Ti_ndet,
                             dj = 1/100,
                             lowerPeriod = 0.5,
                             upperPeriod = 5,
                             verbose = FALSE,
                             omega_nr = 10
                             )

plot_wavelet(wavelet = alb_Ti_wt,
             lowerPeriod = NULL,
             upperPeriod = NULL,
             n.levels = 100,
             palette_name = "rainbow",
             color_brewer = "grDevices",
             useRaster = TRUE,
             periodlab = "Period (metres)",
             x_lab = "Depth (metres)",
             keep_editable = FALSE,
             dev_new = F,
             add_lines = NULL,
             add_points = NULL,
             add_abline_h = NULL,
             add_abline_v = NULL,
             add_MTM_peaks = FALSE,
             add_data = TRUE,
             add_avg = TRUE,
             add_MTM = FALSE,
             demean_mtm = TRUE,
             detrend_mtm = TRUE,
             padfac_mtm = 5,
```

```
             tbw_mtm = 3,
             plot_horizontal = TRUE
             )
```




```
   #track the period (m) of the 173 kyr cycle
#    alb_Ti_track_WR <- track_period_wavelet(astro_cycle = 173,
#                                            wavelet = alb_Ti_wt,
#                                            n.levels = 100,
#                                            periodlab = "Period (metres)",
#                                            x_lab = "depth (metres)",
#                                            palette_name = "rainbow",
#                                            color_brewer = "grDevices",
#                                            plot_horizontal = TRUE
#                                            )

#   alb_Ti_track_WR_comp <- completed_series(wavelet = alb_Ti_wt,
#                                            tracked_curve = alb_Ti_track_WR,
#                                            period_up = 1,
#                                            period_down = 0.70,
#                                            extrapolate = TRUE,
#                                            genplot = FALSE,
#                                            keep_editable = FALSE
#                                            )

#    alb_Ti_track_WR_comp[alb_Ti_track_WR_comp[,2]<0.74,2]<-0.74

#    alb_Ti_track_WR_comp <- loess_auto(alb_Ti_track_WR_comp)

#    write.csv(alb_Ti_track_WR_comp,"alb_Ti_track_WR.csv")

# Loading the tracked curve
```

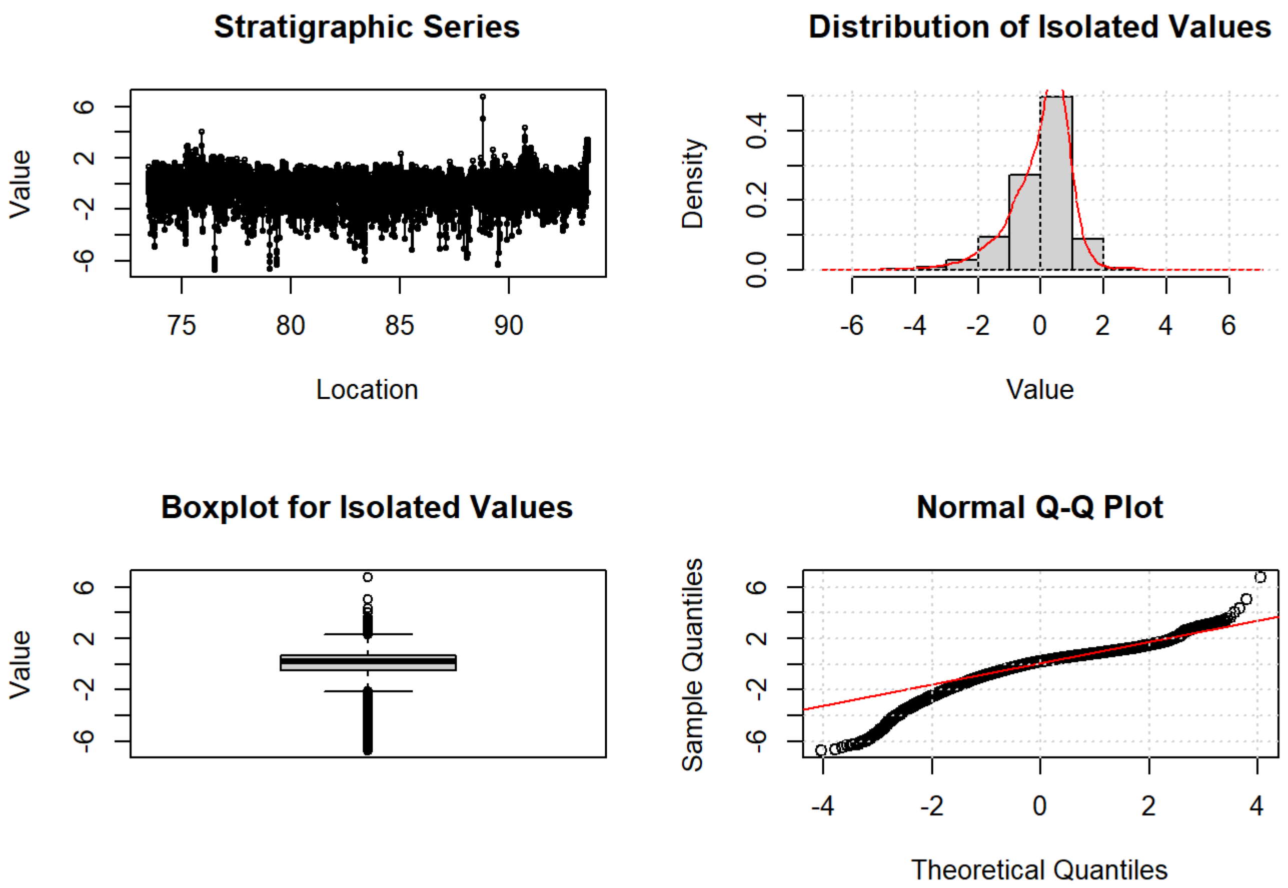
```
alb_Ti_track_WR_comp <- read.csv("alb_Ti_track_WR.csv")
alb_Ti_track_WR_comp <- alb_Ti_track_WR_comp[,c(2,3)]


plot_wavelet(wavelet = alb_Ti_wt,
             lowerPeriod = NULL,
             upperPeriod = NULL,
             n.levels = 100,
             palette_name = "rainbow",
             color_brewer = "grDevices",
             useRaster = TRUE,
             periodlab = "Period (metres)",
             x_lab = "Depth (metres)",
             keep_editable = FALSE,
             dev_new = F,
             add_lines = cbind(alb_Ti_track_WR_comp[,1],
                               alb_Ti_track_WR_comp[,2]),
             add_points = NULL,
             add_abline_h = NULL,
             add_abline_v = NULL,
             add_MTM_peaks = FALSE,
             add_data = TRUE,
             add_avg = TRUE,
             add_MTM = FALSE,
             demean_mtm = TRUE,
             detrend_mtm = TRUE,
             padfac_mtm = 5,
             tbw_mtm = 3,
             plot_horizontal = TRUE
             )
```



11.2.1.2. Silicon

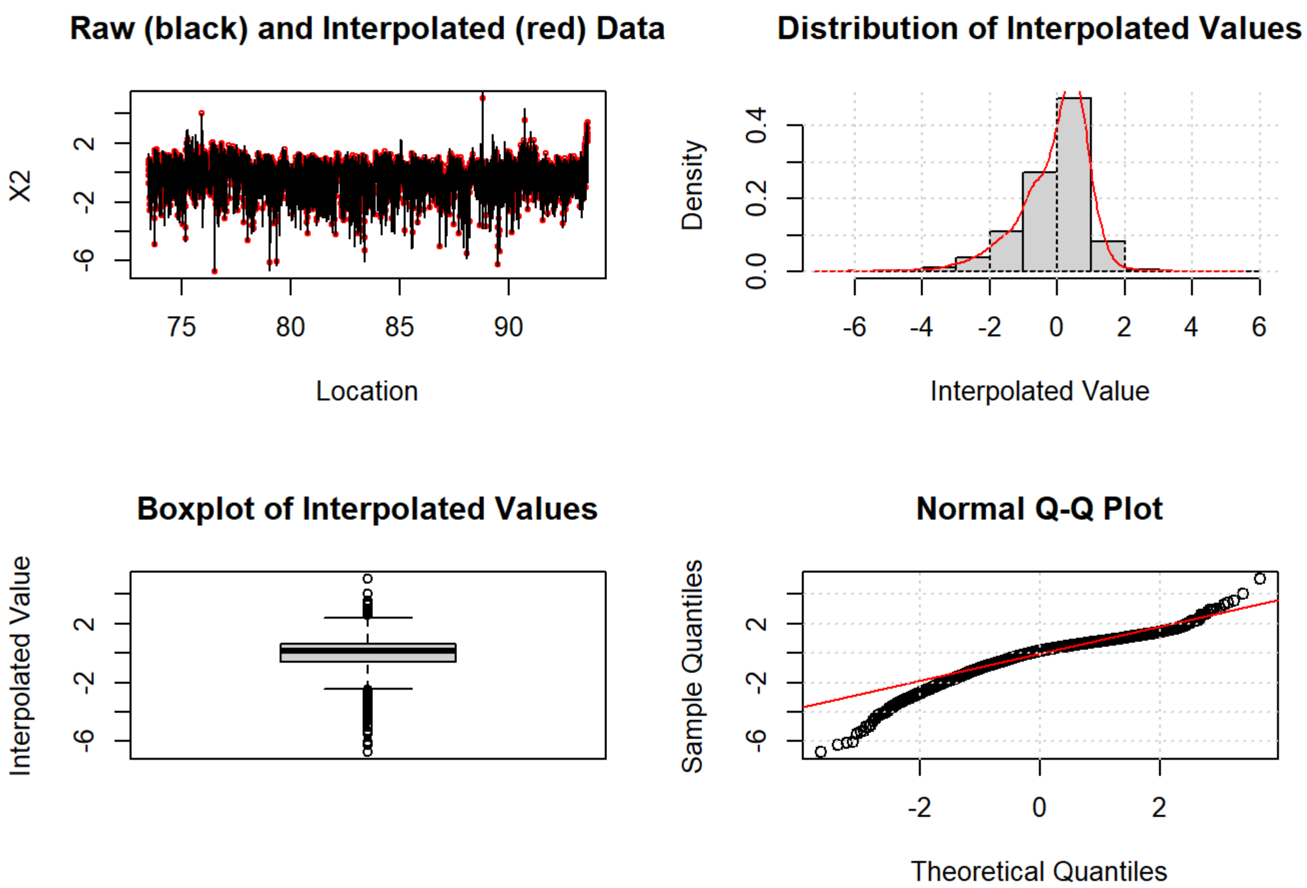
```
alb_Si <- cbind(Alb$DepthAdj,Alb$Si)
  alb_Si <- na.omit(alb_Si)
  alb_Si[!is.finite(alb_Si)] <- NA
  alb_Si <- na.omit(alb_Si)
  alb_Si <- iso(dat=alb_Si, xmin=73.453, xmax=100)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30577
 * Number of columns= 2
 * Minimum= 62.111 , Maximum= 93.61
 * Isolating data between 73.453 and 100
 * Number of data points following culling= 19311
```



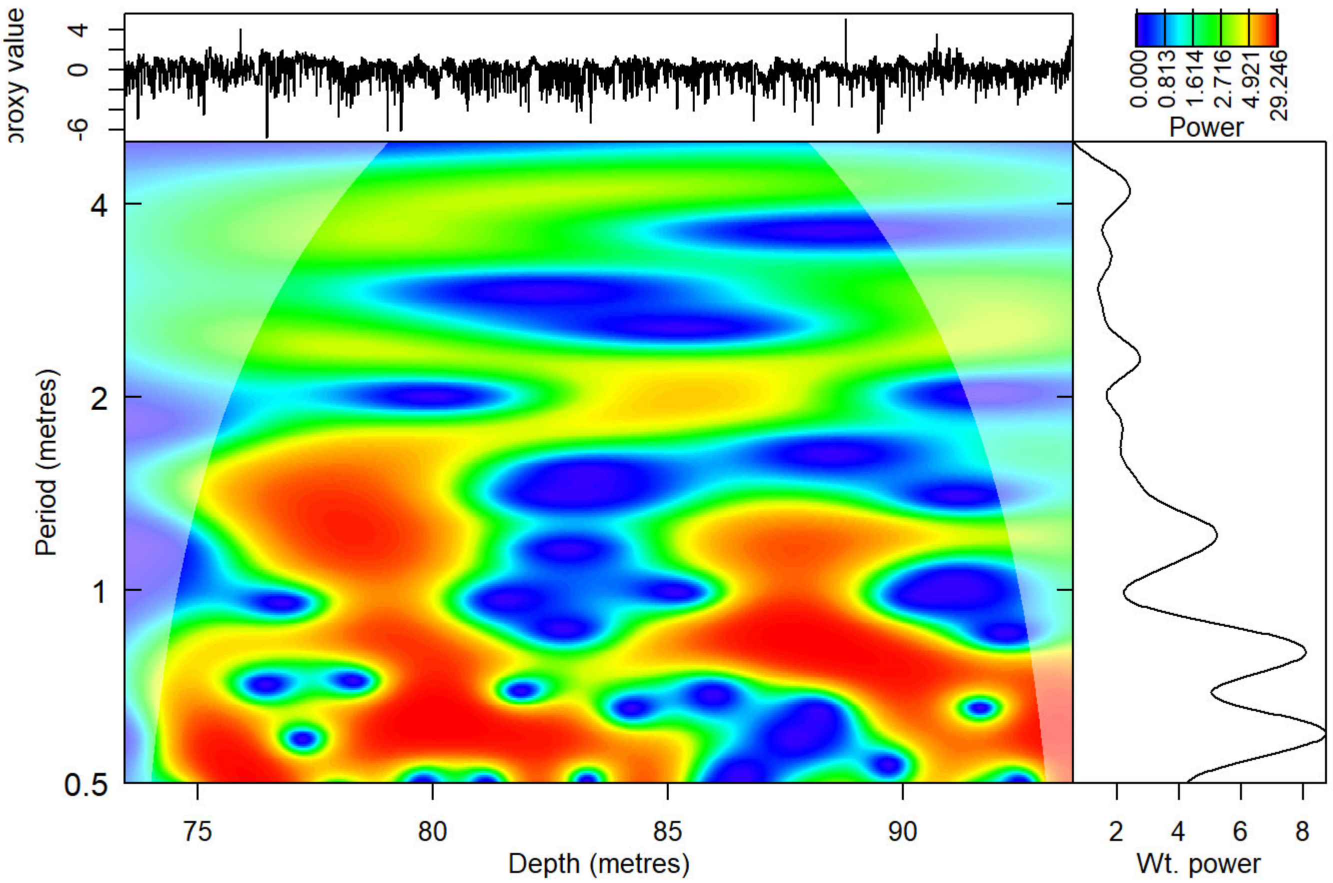

```
  alb_Si_ndet <-  linterp(alb_Si, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 19311
 * New number of samples= 4032
```



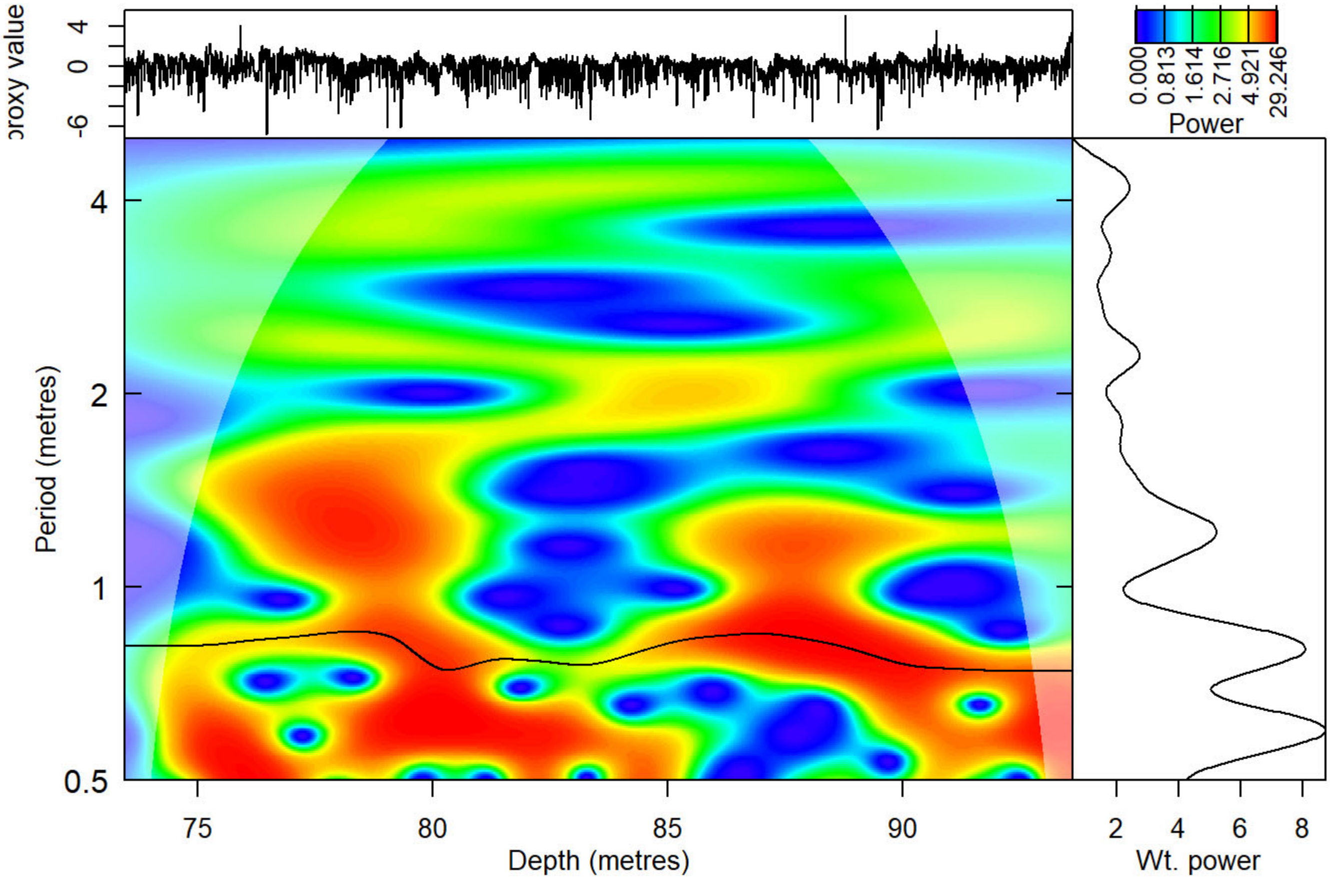

```
#Waverider
alb_Si_wt <- analyze_wavelet(alb_Si_ndet,
                             dj = 1/100,
                             lowerPeriod = 0.5,
                             upperPeriod = 5,
                             verbose = FALSE,
                             omega_nr = 10
                             )

plot_wavelet(wavelet = alb_Si_wt,
             lowerPeriod = NULL,
             upperPeriod = NULL,
             n.levels = 100,
             palette_name = "rainbow",
             color_brewer = "grDevices",
             useRaster = TRUE,
             periodlab = "Period (metres)",
             x_lab = "Depth (metres)",
             keep_editable = FALSE,
             dev_new = F,
             add_lines = NULL,
             add_points = NULL,
             add_abline_h = NULL,
             add_abline_v = NULL,
             add_MTM_peaks = FALSE,
             add_data = TRUE,
             add_avg = TRUE,
             add_MTM = FALSE,
             demean_mtm = TRUE,
             detrend_mtm = TRUE,
             padfac_mtm = 5,
```

```
            tbw_mtm = 3,
            plot_horizontal = TRUE
            )
```




```
    #track the period (m) of the 173 kyr cycle
#    alb_Si_track_WR <- track_period_wavelet(astro_cycle = 173,
#                                         wavelet = alb_Si_wt,
#                                         n.levels = 100,
#                                         periodlab = "Period (metres)",
#                                         x_lab = "depth (metres)",
#                                         palette_name = "rainbow",
#                                         color_brewer = "grDevices",
#                                         plot_horizontal = TRUE
#                                         )

#   alb_Si_track_WR_comp <- completed_series(wavelet = alb_Si_wt,
#                                         tracked_curve = alb_Si_track_WR,
#                                         period_up = 1,
#                                         period_down = 0.70,
#                                         extrapolate = TRUE,
#                                         genplot = FALSE,
#                                         keep_editable = FALSE
#                                         )

#    alb_Si_track_WR_comp[alb_Si_track_WR_comp[,2]<0.74,2]<-0.74

  #To keep a similar trend in the Si data in the 73-80 m interval, when tracking,
  #we deliberately went for a higher band (above 0.9 m) and we implemented a
  #highpass filter for all the values above 0.86m to keep a similar trend between
  #Si and the other detrital elements
```

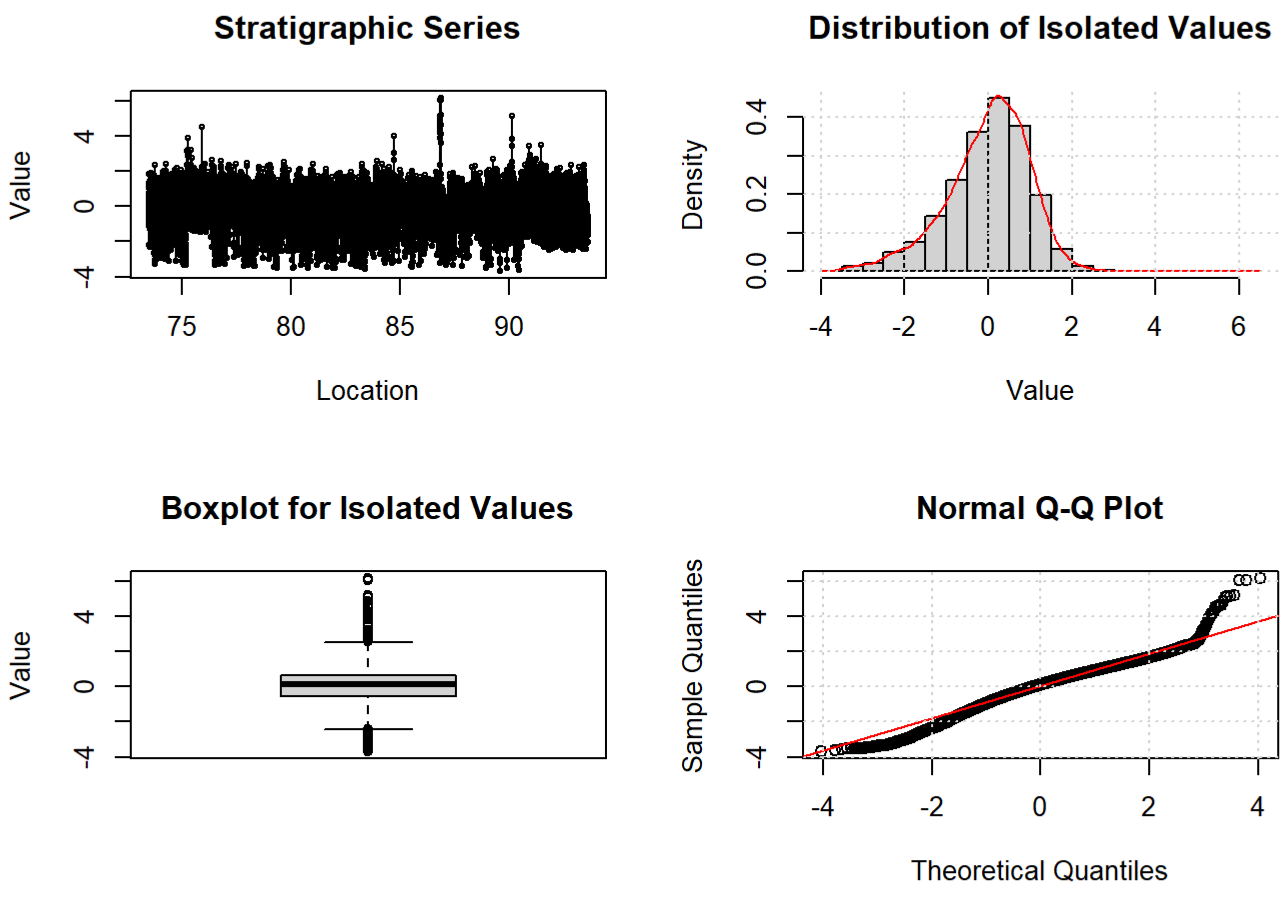
```r
#     alb_Si_track_WR_comp[alb_Si_track_WR_comp[,2]>0.86,2]<-0.81

#     alb_Si_track_WR_comp <- loess_auto(alb_Si_track_WR_comp)

#     write.csv(alb_Si_track_WR_comp,"alb_Si_track_WR.csv")


# Loading the tracked curve
    alb_Si_track_WR_comp <- read.csv("alb_Si_track_WR.csv")
    alb_Si_track_WR_comp <- alb_Si_track_WR_comp[,c(2,3)]

    plot_wavelet(wavelet = alb_Si_wt,
                 lowerPeriod = NULL,
                 upperPeriod = NULL,
                 n.levels = 100,
                 palette_name = "rainbow",
                 color_brewer = "grDevices",
                 useRaster = TRUE,
                 periodlab = "Period (metres)",
                 x_lab = "Depth (metres)",
                 keep_editable = FALSE,
                 dev_new = F,
                 add_lines = cbind(alb_Si_track_WR_comp[,1],
                                   alb_Si_track_WR_comp[,2]),
                 add_points = NULL,
                 add_abline_h = NULL,
                 add_abline_v = NULL,
                 add_MTM_peaks = FALSE,
                 add_data = TRUE,
                 add_avg = TRUE,
                 add_MTM = FALSE,
                 demean_mtm = TRUE,
                 detrend_mtm = TRUE,
                 padfac_mtm = 5,
                 tbw_mtm = 3,
                 plot_horizontal = TRUE
                 )
```



11.2.1.3. Aluminium

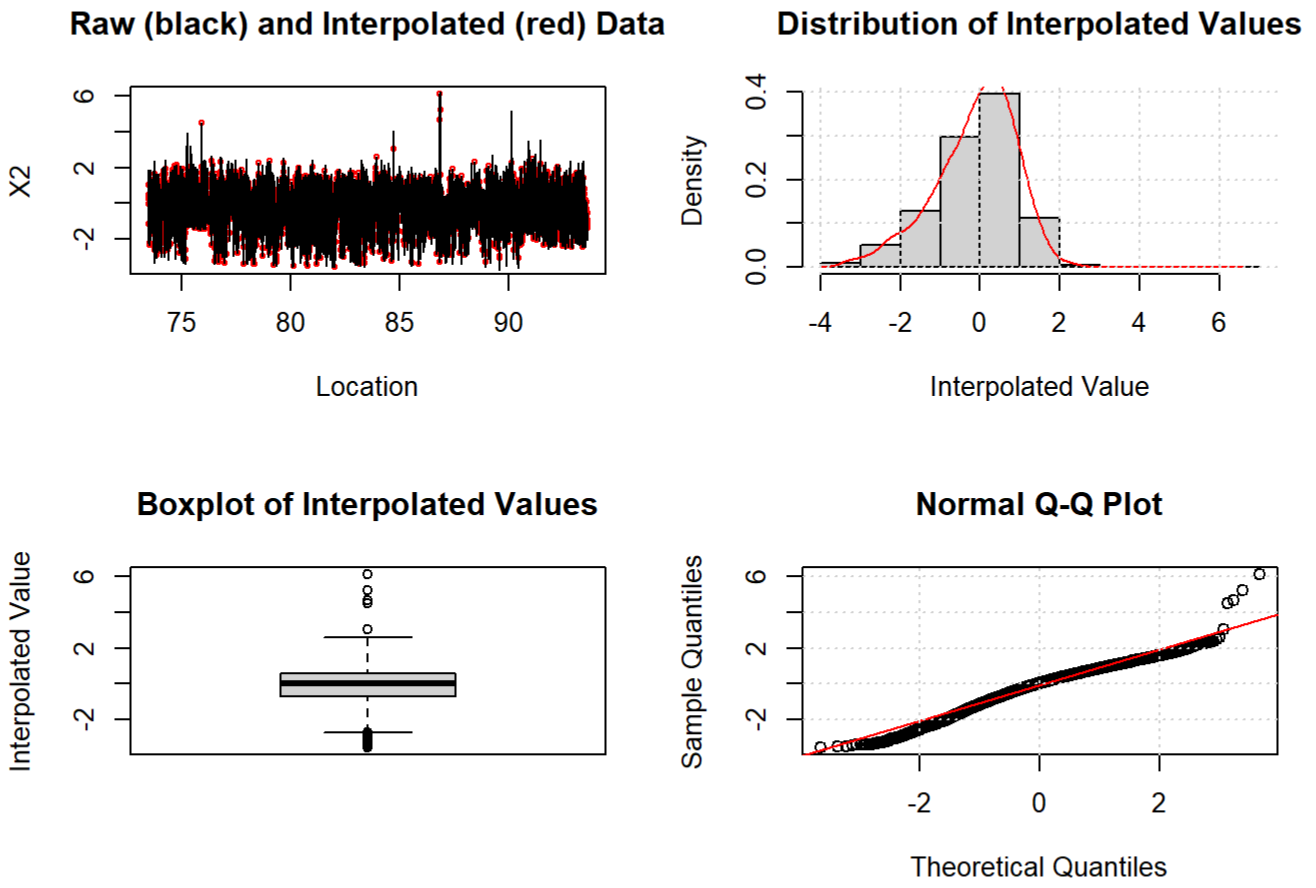
```
alb_Al <- cbind(Alb$DepthAdj,Alb$Al)
alb_Al <- na.omit(alb_Al)
alb_Al[!is.finite(alb_Al)] <- NA
alb_Al <- na.omit(alb_Al)
alb_Al <- iso(dat=alb_Al, xmin=73.453, xmax=100)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30062
 * Number of columns= 2
 * Minimum= 62.111 , Maximum= 93.609
 * Isolating data between 73.453 and 100
 * Number of data points following culling= 18796
```



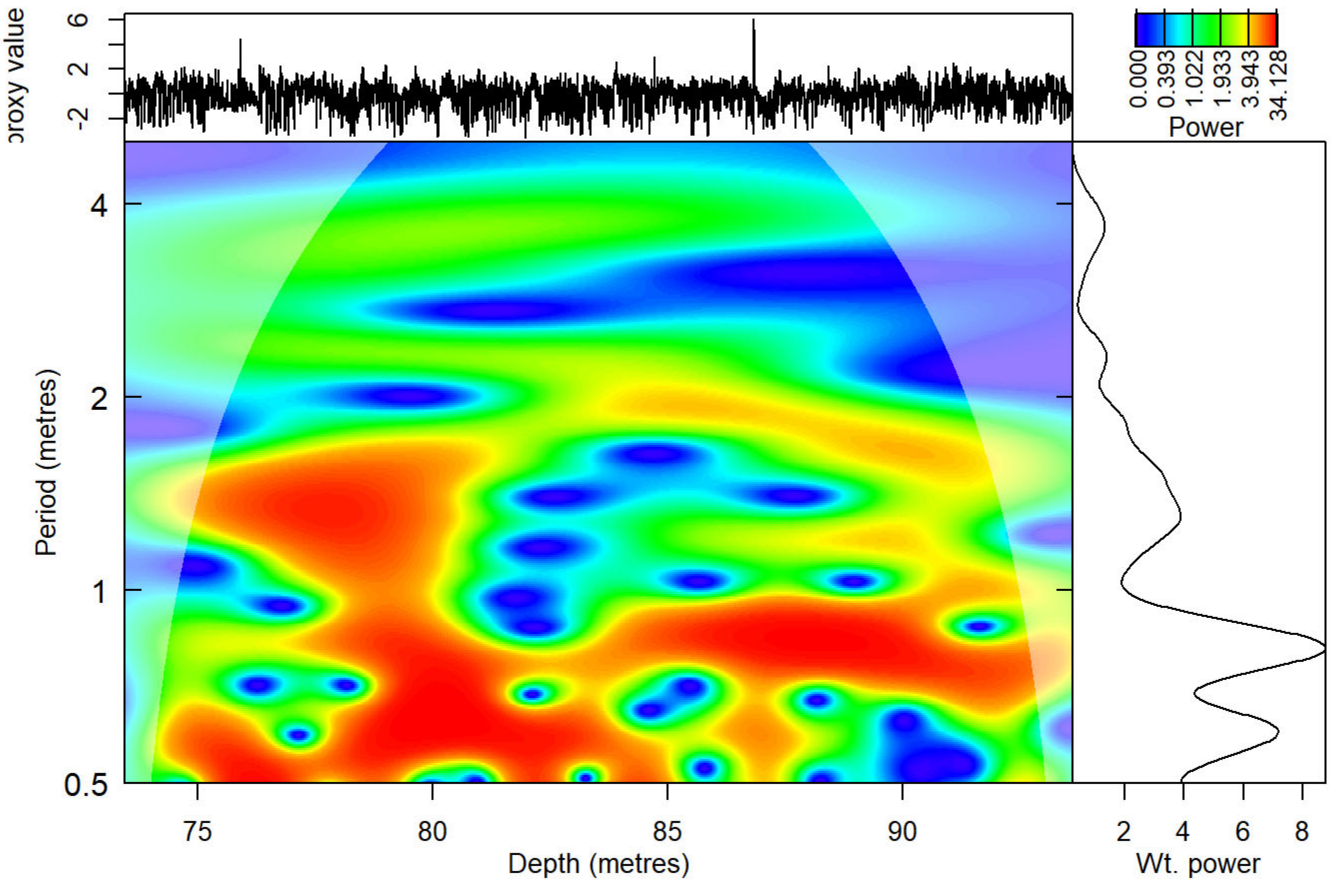

```
alb_Al_ndet <-  linterp(alb_Al, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 18796
 * New number of samples= 4032
```



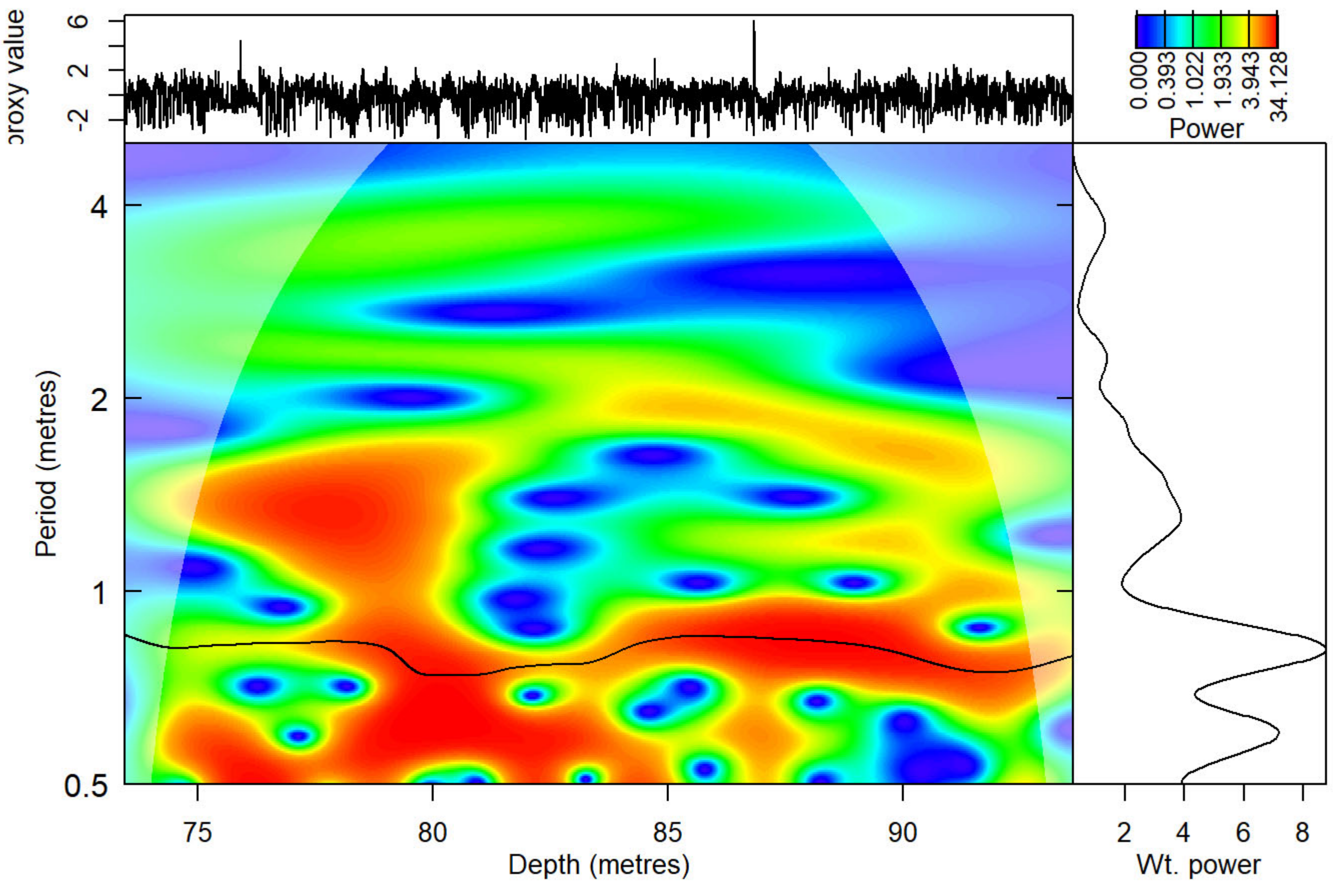

```
#Waverider
alb_Al_wt <- analyze_wavelet(alb_Al_ndet,
                             dj = 1/100,
                             lowerPeriod = 0.5,
                             upperPeriod = 5,
                             verbose = FALSE,
                             omega_nr = 10
                             )

plot_wavelet(wavelet = alb_Al_wt,
             lowerPeriod = NULL,
             upperPeriod = NULL,
             n.levels = 100,
             palette_name = "rainbow",
             color_brewer = "grDevices",
             useRaster = TRUE,
             periodlab = "Period (metres)",
             x_lab = "Depth (metres)",
             keep_editable = FALSE,
             dev_new = F,
             add_lines = NULL,
             add_points = NULL,
             add_abline_h = NULL,
             add_abline_v = NULL,
             add_MTM_peaks = FALSE,
             add_data = TRUE,
             add_avg = TRUE,
             add_MTM = FALSE,
             demean_mtm = TRUE,
             detrend_mtm = TRUE,
             padfac_mtm = 5,
```

```
              tbw_mtm = 3,
              plot_horizontal = TRUE
              )
```




```
   #track the period (m) of the 173 kyr cycle
#  alb_Al_track_WR <- track_period_wavelet(astro_cycle = 173,
#                                         wavelet = alb_Al_wt,
#                                         n.levels = 100,
#                                         periodlab = "Period (metres)",
#                                         x_lab = "depth (metres)",
#                                         palette_name = "rainbow",
#                                         color_brewer = "grDevices",
#                                         plot_horizontal = TRUE
#                                         )

#  alb_Al_track_WR_comp <- completed_series(wavelet = alb_Al_wt,
#                                          tracked_curve = alb_Al_track_WR,
#                                          period_up = 1,
#                                          period_down = 0.70,
#                                          extrapolate = TRUE,
#                                          genplot = FALSE,
#                                          keep_editable = FALSE
#                                          )

#    alb_Al_track_WR_comp[alb_Al_track_WR_comp[,2]<0.74,2]<-0.74

#    alb_Al_track_WR_comp <- loess_auto(alb_Al_track_WR_comp)

#    write.csv(alb_Al_track_WR_comp,"alb_Al_track_WR.csv")
```

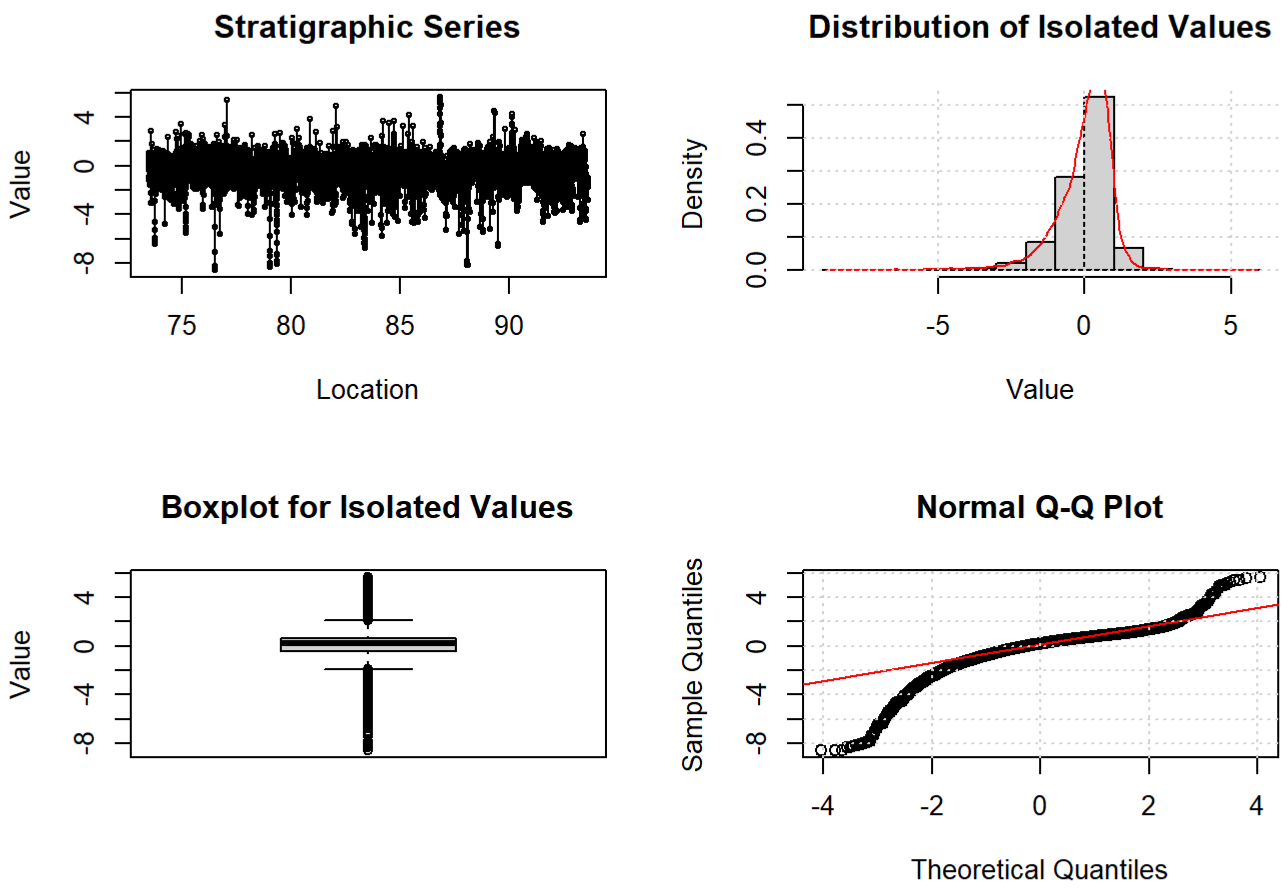
```r
# Loading the tracked curve
    alb_Al_track_WR_comp <- read.csv("alb_Al_track_WR.csv")
    alb_Al_track_WR_comp <- alb_Al_track_WR_comp[,c(2,3)]

    plot_wavelet(wavelet = alb_Al_wt,
                 lowerPeriod = NULL,
                 upperPeriod = NULL,
                 n.levels = 100,
                 palette_name = "rainbow",
                 color_brewer = "grDevices",
                 useRaster = TRUE,
                 periodlab = "Period (metres)",
                 x_lab = "Depth (metres)",
                 keep_editable = FALSE,
                 dev_new = F,
                 add_lines = cbind(alb_Al_track_WR_comp[,1],
                                   alb_Al_track_WR_comp[,2]),
                 add_points = NULL,
                 add_abline_h = NULL,
                 add_abline_v = NULL,
                 add_MTM_peaks = FALSE,
                 add_data = TRUE,
                 add_avg = TRUE,
                 add_MTM = FALSE,
                 demean_mtm = TRUE,
                 detrend_mtm = TRUE,
                 padfac_mtm = 5,
                 tbw_mtm = 3,
                 plot_horizontal = TRUE
                 )
```



11.2.1.4. Potassium

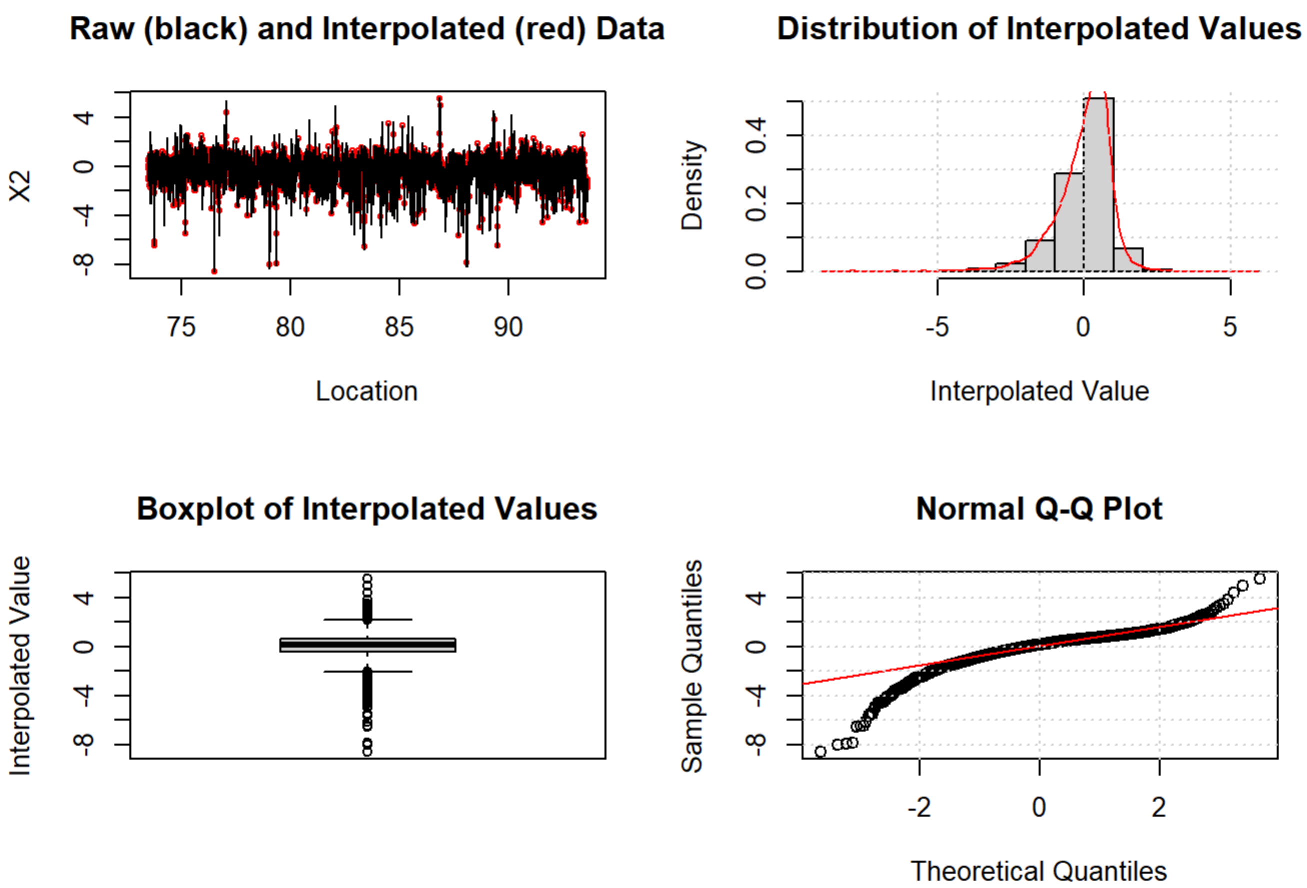
```
alb_K <- cbind(Alb$DepthAdj,Alb$K)
alb_K <- na.omit(alb_K)
alb_K[!is.finite(alb_K)] <- NA
alb_K <- na.omit(alb_K)
alb_K <- iso(dat=alb_K, xmin=73.453, xmax=100)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 19311
 * Number of columns= 2
 * Minimum= 73.453 , Maximum= 93.61
 * Isolating data between 73.453 and 100
 * Number of data points following culling= 19311
```



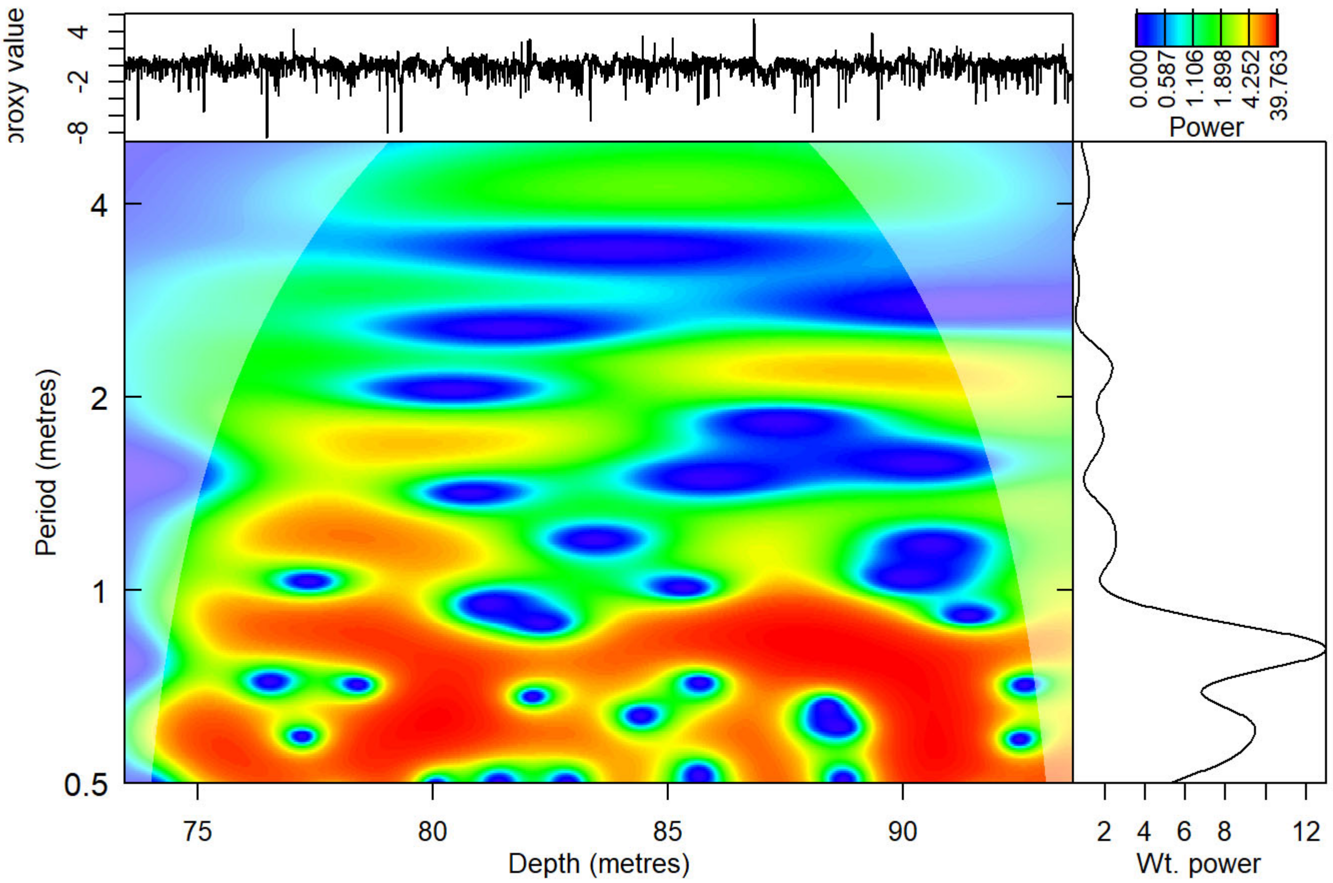

```
alb_K_ndet <-  linterp(alb_K, dt=0.005, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 19311
 * New number of samples= 4032
```



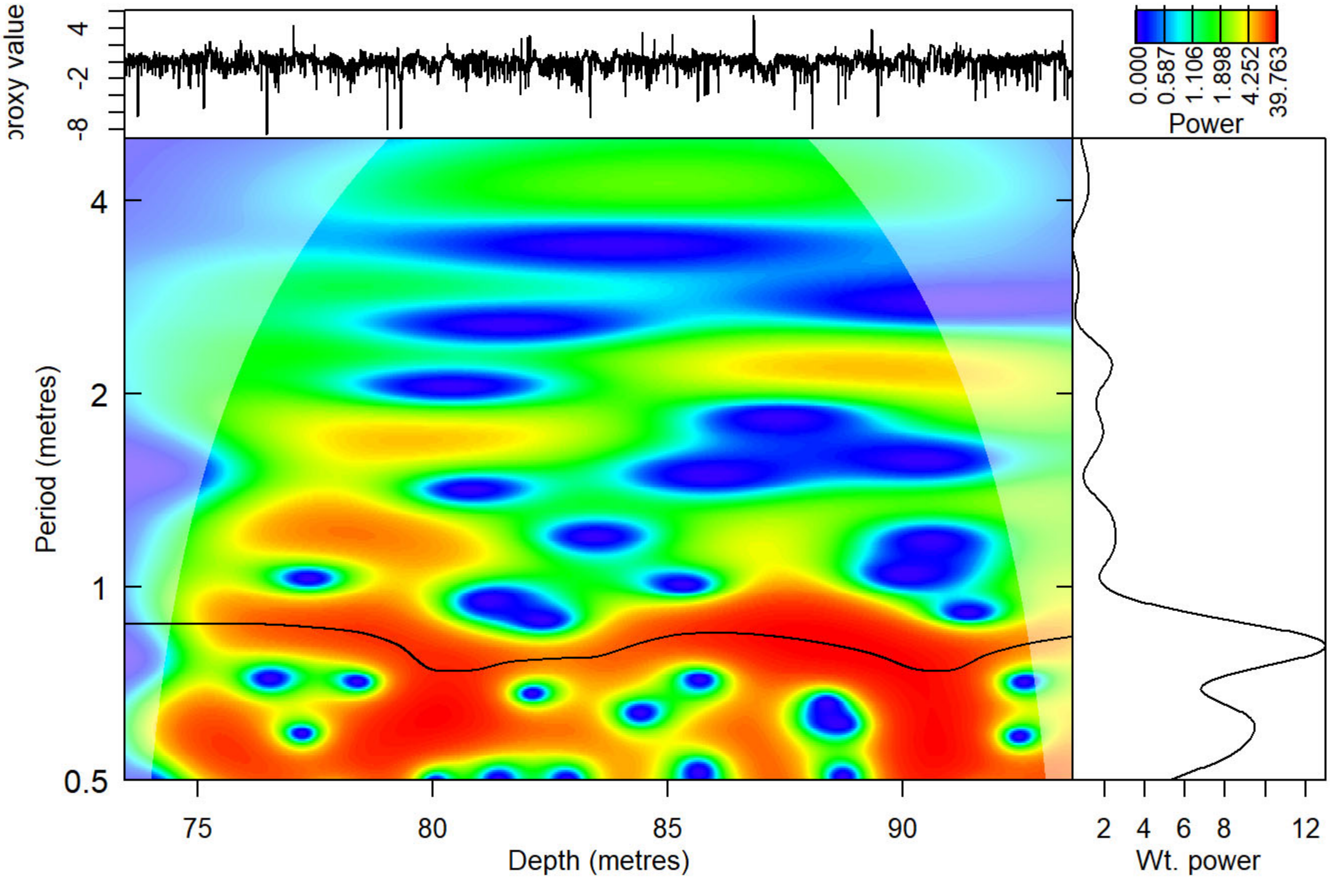

```
#Waverider
alb_K_wt <- analyze_wavelet(alb_K_ndet,
                            dj = 1/100,
                            lowerPeriod = 0.5,
                            upperPeriod = 5,
                            verbose = FALSE,
                            omega_nr = 10
                            )

plot_wavelet(wavelet = alb_K_wt,
             lowerPeriod = NULL,
             upperPeriod = NULL,
             n.levels = 100,
             palette_name = "rainbow",
             color_brewer = "grDevices",
             useRaster = TRUE,
             periodlab = "Period (metres)",
             x_lab = "Depth (metres)",
             keep_editable = FALSE,
             dev_new = F,
             add_lines = NULL,
             add_points = NULL,
             add_abline_h = NULL,
             add_abline_v = NULL,
             add_MTM_peaks = FALSE,
             add_data = TRUE,
             add_avg = TRUE,
             add_MTM = FALSE,
             demean_mtm = TRUE,
             detrend_mtm = TRUE,
             padfac_mtm = 5,
```

```
             tbw_mtm = 3,
             plot_horizontal = TRUE
             )
```




```
    #track the period (m) of the 173 kyr cycle
#alb_K_track_WR <- track_period_wavelet(astro_cycle = 173,
#                                        wavelet = alb_K_wt,
#                                        n.levels = 100,
#                                        periodlab = "Period (metres)",
#                                        x_lab = "depth (metres)",
#                                        palette_name = "rainbow",
#                                        color_brewer = "grDevices",
#                                        plot_horizontal = TRUE
#                                        )

#   alb_K_track_WR_comp <- completed_series(wavelet = alb_K_wt,
#                                            tracked_curve = alb_K_track_WR,
#                                            period_up = 1,
#                                            period_down = 0.70,
#                                            extrapolate = TRUE,
#                                            genplot = FALSE,
#                                            keep_editable = FALSE
#                                            )

#    alb_K_track_WR_comp[alb_K_track_WR_comp[,2]<0.74,2]<-0.74

    #To keep a similar trend in the K data in the 73-80 m interval, when tracking,
    #we implemented a highpass filter for all the values above 0.875m to keep a
    #similar trend between K and the other detrital elements

#     alb_K_track_WR_comp[alb_K_track_WR_comp[,2]>0.875,2]<-0.875
```

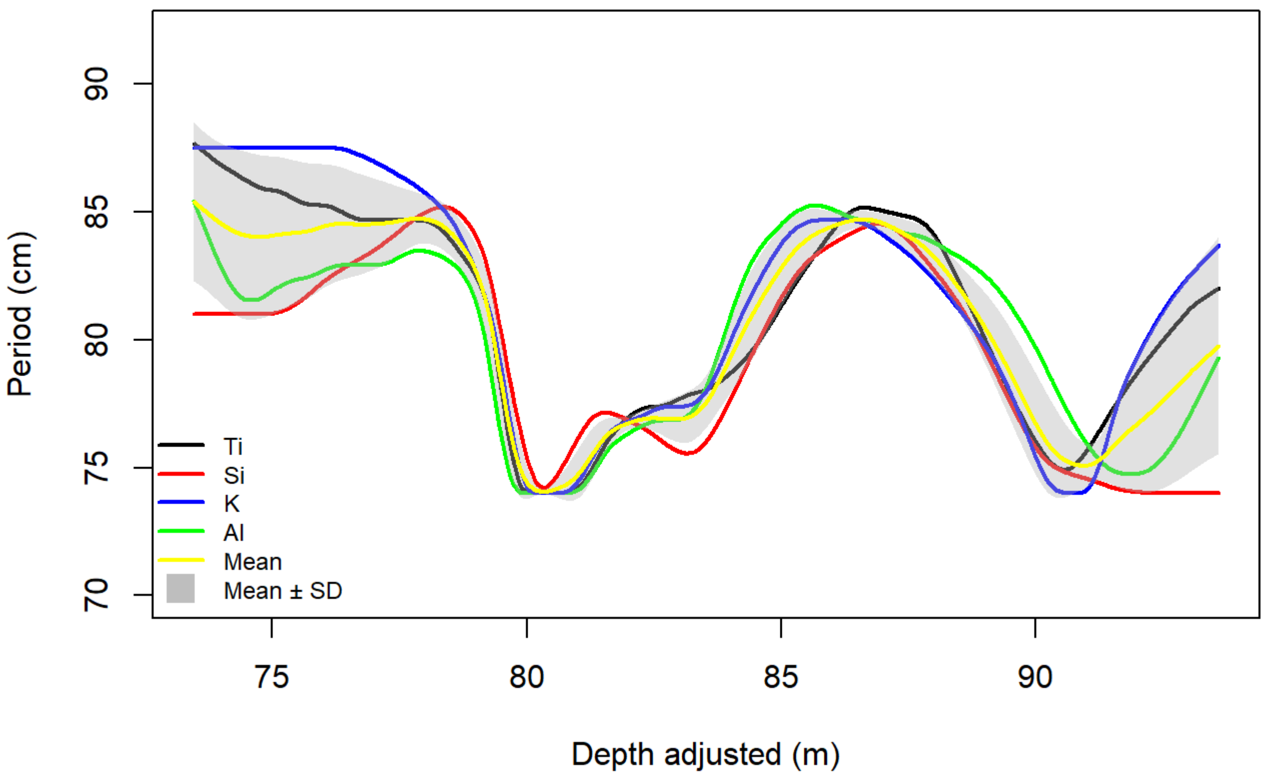
```r
#     alb_K_track_WR_comp <- loess_auto(alb_K_track_WR_comp)

#     write.csv(alb_K_track_WR_comp,"alb_K_track_WR.csv")


# Loading the tracked curve
    alb_K_track_WR_comp <- read.csv("alb_K_track_WR.csv")
    alb_K_track_WR_comp <- alb_K_track_WR_comp[,c(2,3)]

    plot_wavelet(wavelet = alb_K_wt,
                 lowerPeriod = NULL,
                 upperPeriod = NULL,
                 n.levels = 100,
                 palette_name = "rainbow",
                 color_brewer = "grDevices",
                 useRaster = TRUE,
                 periodlab = "Period (metres)",
                 x_lab = "Depth (metres)",
                 keep_editable = FALSE,
                 dev_new = F,
                 add_lines = cbind(alb_K_track_WR_comp[,1],
                                   alb_K_track_WR_comp[,2]),
                 add_points = NULL,
                 add_abline_h = NULL,
                 add_abline_v = NULL,
                 add_MTM_peaks = FALSE,
                 add_data = TRUE,
                 add_avg = TRUE,
                 add_MTM = FALSE,
                 demean_mtm = TRUE,
                 detrend_mtm = TRUE,
                 padfac_mtm = 5,
                 tbw_mtm = 3,
                 plot_horizontal = TRUE
                 )
```



11.2.1.5. Depth model resulting from the 173 kyr cycle tracking of the 4 detrital elements

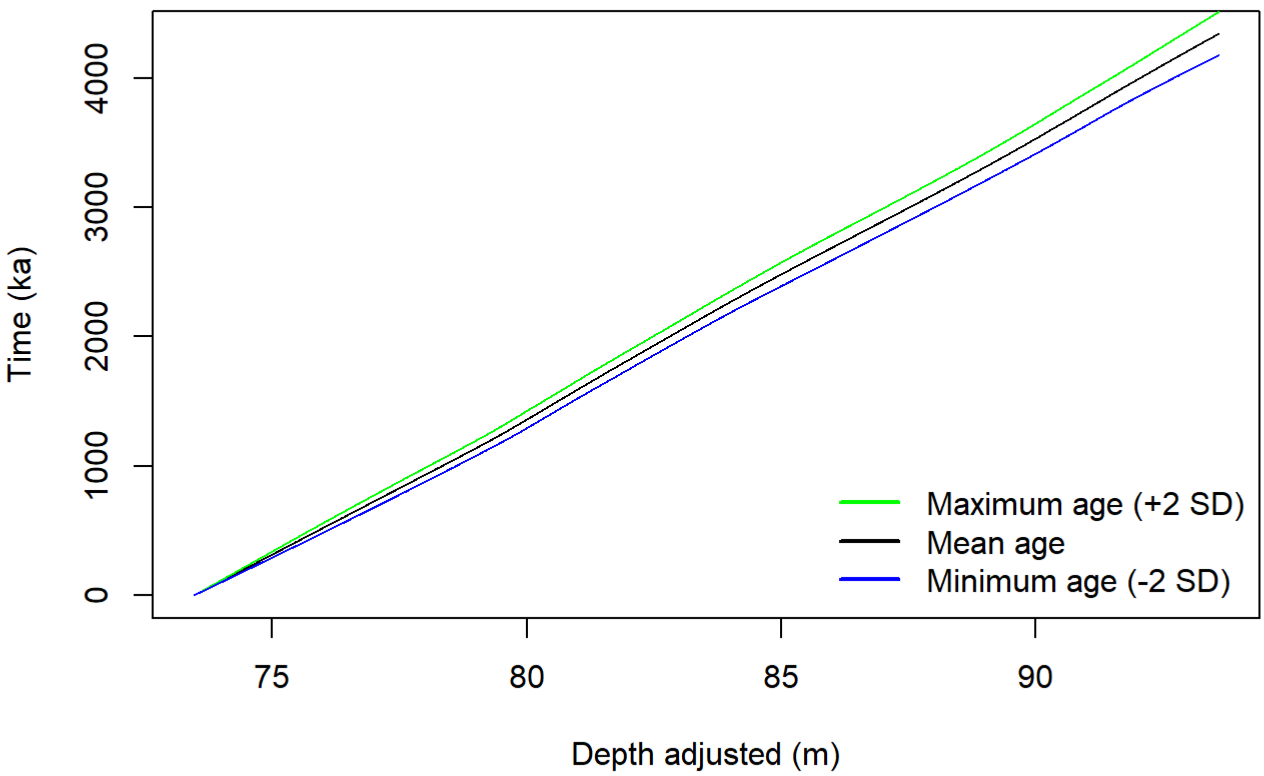
```
alb_Ti_track_comp1 <- read.csv("alb_Ti_track_WR.csv")
alb_Si_track_comp1 <- read.csv("alb_Si_track_WR.csv")
alb_Al_track_comp1 <- read.csv("alb_Al_track_WR.csv")
alb_K_track_comp1 <- read.csv("alb_K_track_WR.csv")

plot(alb_Ti_track_comp1[,2],
     100*(alb_Ti_track_comp1[,3]),
     type="l",col="black",
     lwd= 2,
     xlab = "Depth adjusted (m)",
     ylab = "Period (cm)",
     ylim = c(70,92)
     )

lines(alb_Si_track_comp1[,2],
      100*(alb_Si_track_comp1[,3]),
      col="red",
      lwd=2
      )

lines(alb_Al_track_comp1[,2],
      100*(alb_Al_track_comp1[,3]),
      col="green",
      lwd=2
      )

lines(alb_K_track_comp1[,2],
      100*(alb_K_track_comp1[,3]),
```

```
      col="blue",
      lwd=2
      )

track_comp_1 <- cbind(alb_Ti_track_comp1[,3],
                      alb_Si_track_comp1[,3],
                      alb_Al_track_comp1[,3],
                      alb_K_track_comp1[,3]
                      )

depth<-alb_Ti_track_comp1[,2]
curve_mean <- rowMeans(100*(track_comp_1))
curve_sd <-  rowSds(100*(track_comp_1))

  # Add polygon for mean ± SD
polygon(c(depth, rev(depth)),
        c(curve_mean + curve_sd, rev(curve_mean - curve_sd)),
        col = rgb(0.7, 0.7, 0.7, 0.4), border = NA)

  # Optionally overlay mean line
lines(depth, curve_mean, col = "yellow", lwd = 2)

legend("bottomleft",
       legend = c("Ti", "Si", "K", "Al", "Mean", "Mean ± SD"),
       col = c("black", "red", "blue", "green","yellow", rgb(0.7, 0.7, 0.7, 0.8)),
       lty = c(1, 1, 1, 1, 1,NA),
       lwd = c(2, 2, 2, 2, 2,NA),
       pch = c(NA, NA, NA, NA,NA, 15),
       pt.cex = 2,
       bty = "n",         # No box around legend
       cex = 0.75)         # Larger legend text
```



11.2.2. Age model

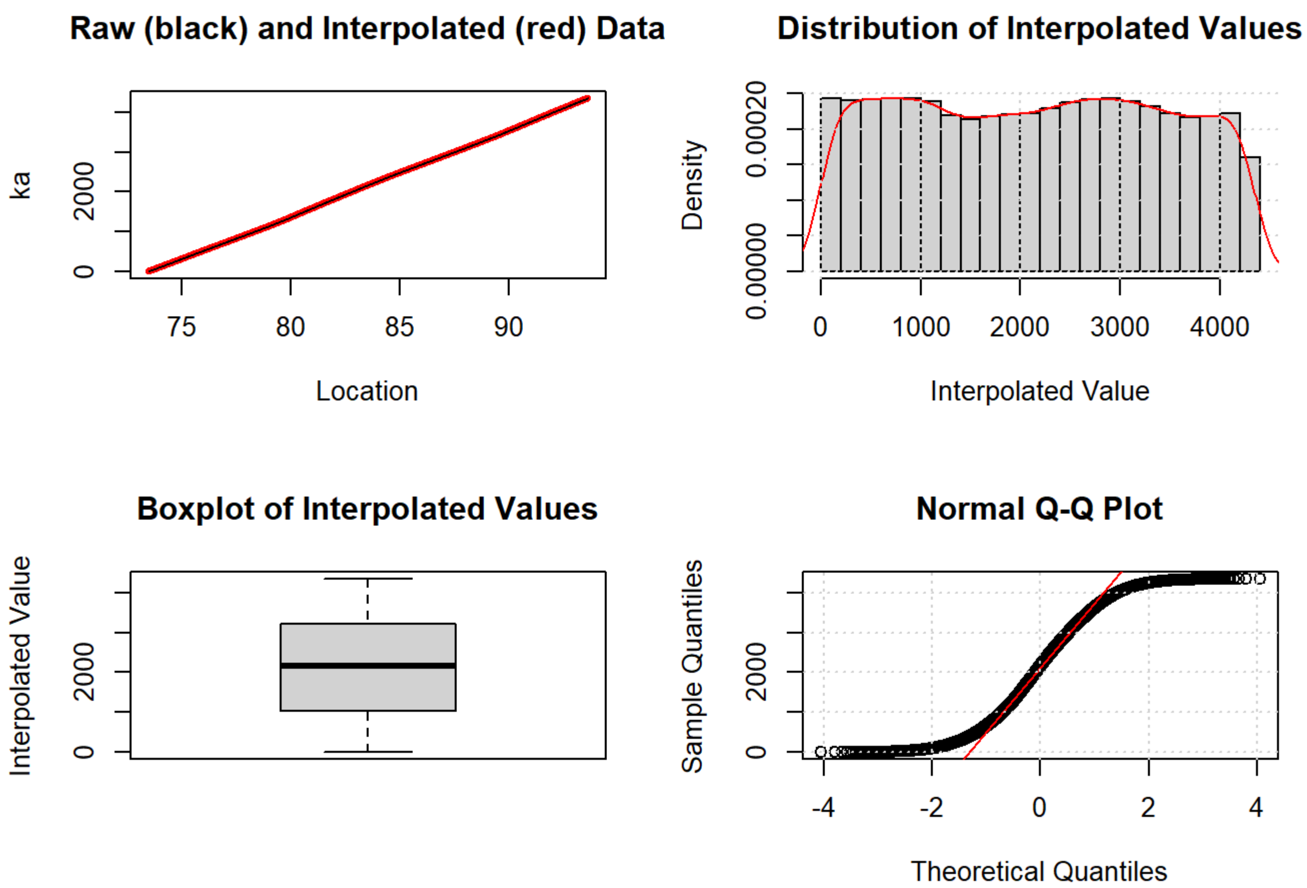
```
#Age model
track_comp_1_mean <- rowMeans(1/track_comp_1)

track_comp_1_sds <- rowSds(1/track_comp_1)

track_comp_1_plus_2Sd <- cbind(alb_Ti_track_comp1[,2],
                               1/(track_comp_1_mean+(2*track_comp_1_sds)))

track_comp_1_min_2Sd <- cbind(alb_Ti_track_comp1[,2],
                              1/(track_comp_1_mean-(2*track_comp_1_sds)))

track_comp_1_mean <- cbind(alb_Ti_track_comp1[,2],1/track_comp_1_mean)

time_track_plus_2Sd <- curve2time(track_comp_1_plus_2Sd,tracked_cycle_period = 173)

time_track_min_2Sd <- curve2time(track_comp_1_min_2Sd,tracked_cycle_period = 173)

time_mean <- curve2time(track_comp_1_mean,tracked_cycle_period = 173)

Mean_AgeModel_WR<-time_mean
Max_AgeModel_WR<-time_track_plus_2Sd
Min_AgeModel_WR<-time_track_min_2Sd

plot(Mean_AgeModel_WR,type="l", xlab="Depth adjusted (m)", ylab="Time (ka)")
lines(Max_AgeModel_WR,col="green")
lines(Min_AgeModel_WR,col="blue")

 legend("bottomright",
       legend = c("Maximum age (+2 SD)","Mean age", "Minimum age (-2 SD)"),
       col = c("green","black","blue"),
       lty = c(1, 1, 1),
       lwd = c(2, 2, 2),
       pch = c(NA, NA, NA),
       pt.cex = 2,
       bty = "n",          # No box around legend
       cex = 1)          # Larger legend text
```




```
Age_Model_WR <- cbind(Mean_AgeModel_WR,Max_AgeModel_WR[,2],Min_AgeModel_WR[,2])
colnames(Age_Model_WR)<- cbind("Adjusted depth (m)",
                               "Mean age (ka)",
                               "Max age (ka)",
                               "Min age (ka)"
                               )
```

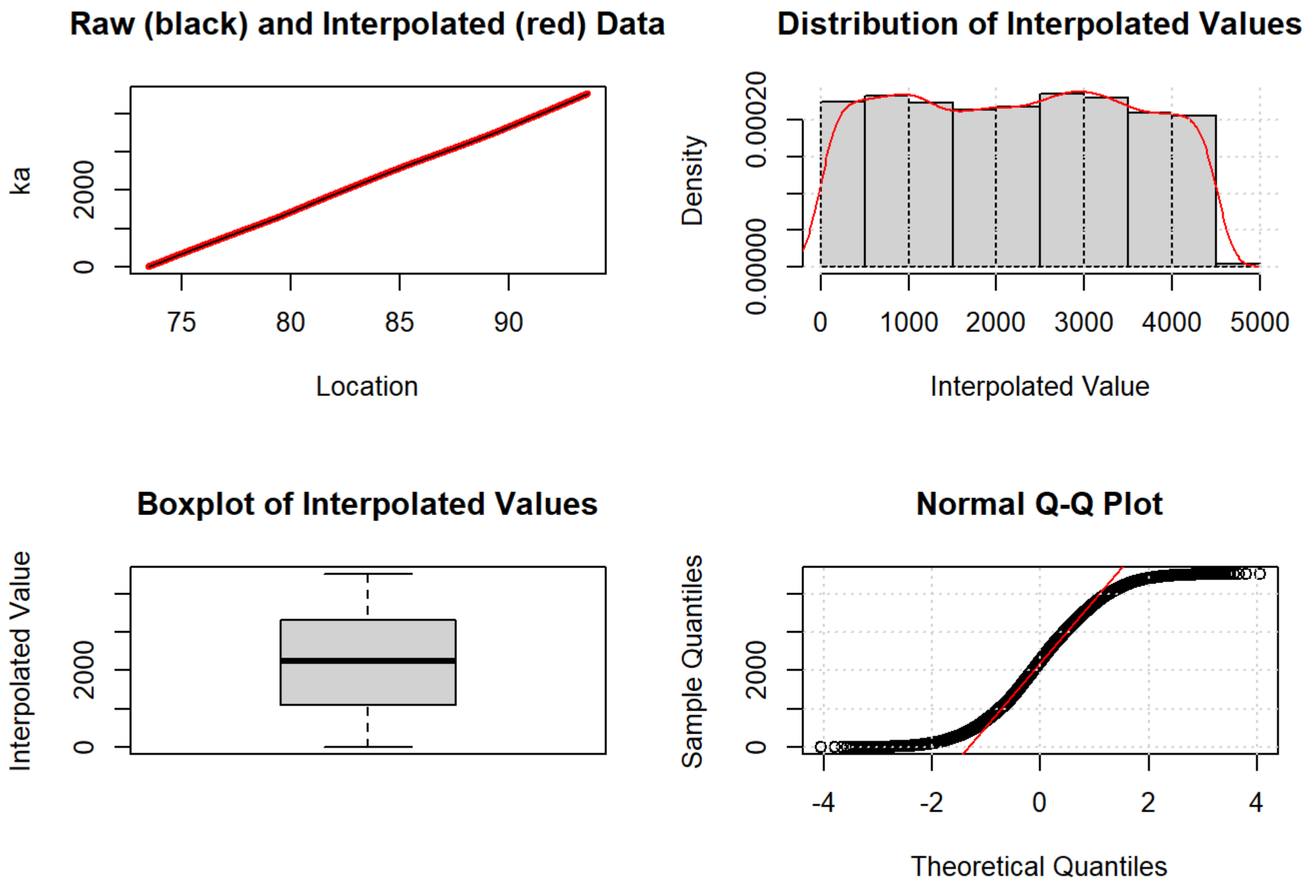
```
#Interpolation every 1mm of the Age-depth model to have a direct comparison
#between the age model and the original sampling rate of 1mm
Mean_Age_Model_WR_1mm <- linterp(Mean_AgeModel_WR, dt=0.001, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * New number of samples= 20155
```



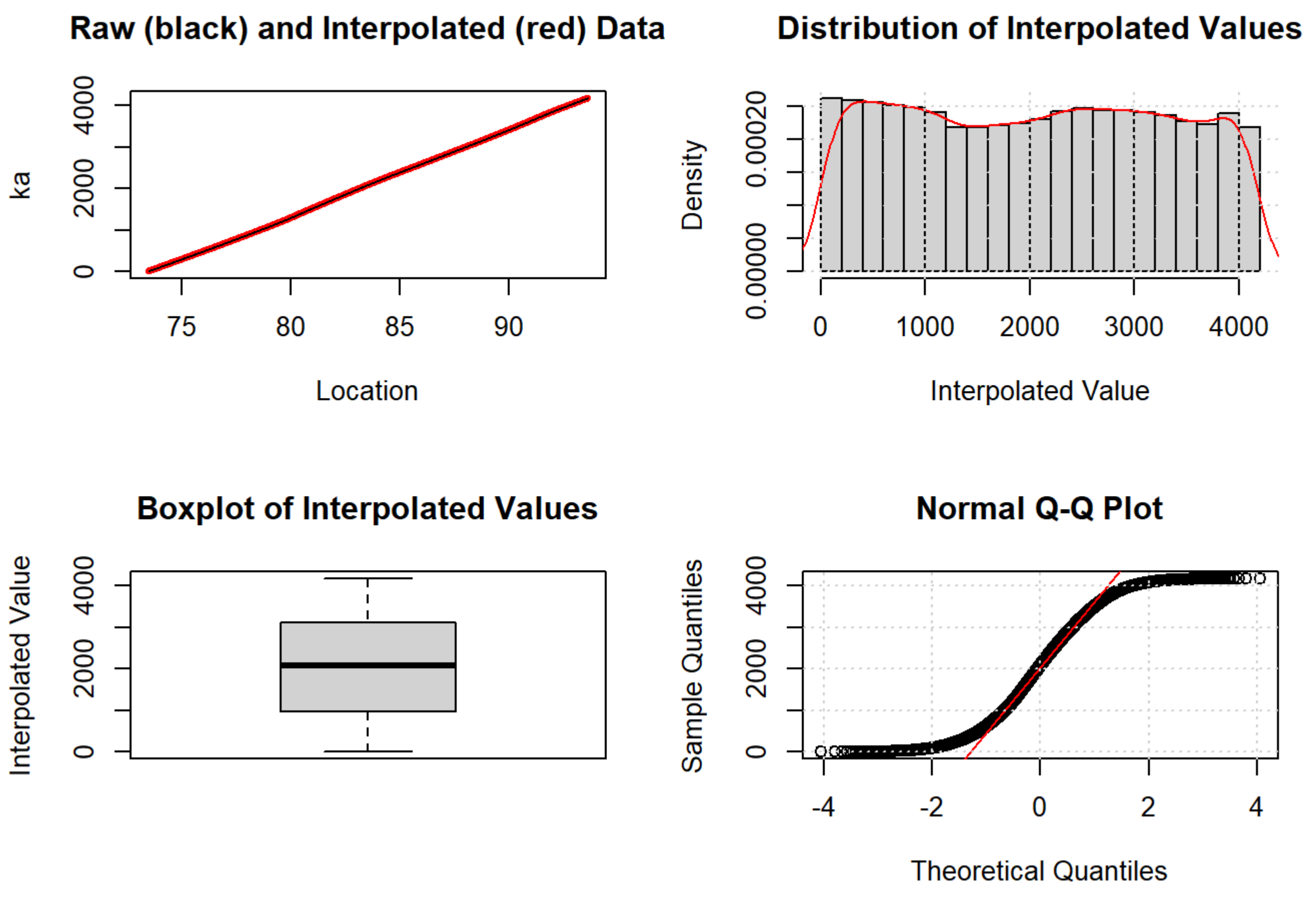

```
Max_Age_Model_WR_1mm <- linterp(Max_AgeModel_WR, dt=0.001, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * New number of samples= 20155
```




```
Min_Age_Model_WR_1mm <- linterp(Min_AgeModel_WR, dt=0.001, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 4032
 * New number of samples= 20155
```

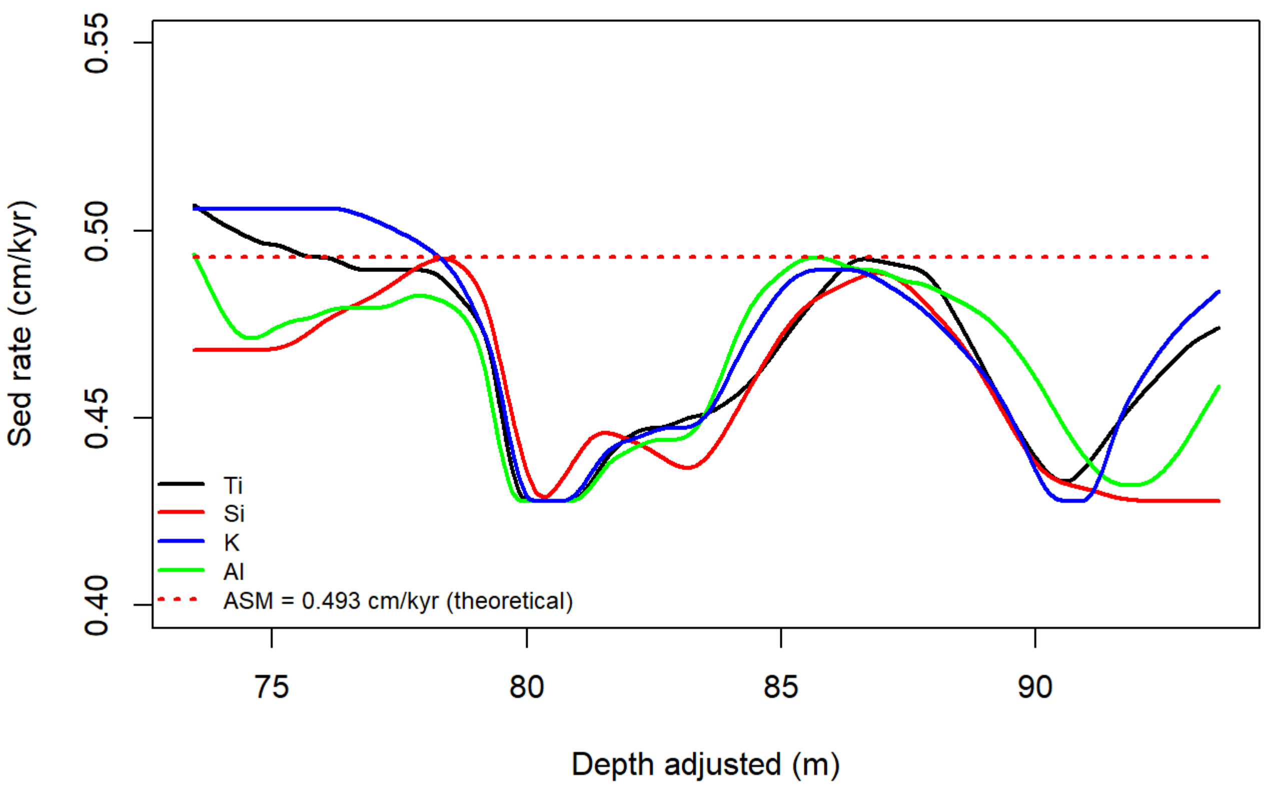



```
  Age_Model_WR_1mm <- cbind(Mean_Age_Model_WR_1mm,
                            Max_Age_Model_WR_1mm[,2],
                            Min_Age_Model_WR_1mm[,2]
                            )

  colnames(Age_Model_WR)<- cbind("Adjusted depth (m)",
                                 "Mean age (ka)",
                                 "Max age (ka)",
                                 "Min age (ka)"
                                 )

  #Saving of the age model as .csv files
#  write.csv(Age_Model_WR,"AgeModel_WR_rsp5mm.csv")
#  write.csv(Age_Model_WR_1mm,"AgeModel_WR_rsp1mm.csv")
```

11.2.3. Sedimentation rate

```
  plot(alb_Ti_track_comp1[,2],
       (100*(alb_Ti_track_comp1[,3]))/173,
       type="l",
       col="black",
       lwd= 2,
       xlab = "Depth adjusted (m)",
       ylab = "Sed rate (cm/kyr)",
       ylim = c(0.4,0.55)
       )

  lines(alb_Si_track_comp1[,2],
        (100*(alb_Si_track_comp1[,3]))/173,
        col="red",
```

```
       lwd=2
       )

lines(alb_Al_track_comp1[,2],
       (100*(alb_Al_track_comp1[,3]))/173,
       col="green",
       lwd=2
       )

lines(alb_K_track_comp1[,2],
       (100*(alb_K_track_comp1[,3]))/173,
       col="blue",
       lwd=2
       )

lines(alb_K_track_comp1[,2],
       (alb_K_track_comp1[,3])-(alb_K_track_comp1[,3])+0.493,
       col="red",
       lwd=2,
       lty=3
       )

legend("bottomleft",
        legend = c("Ti", "Si", "K", "Al", "ASM = 0.493 cm/kyr (theoretical)" ),
        col = c("black", "red", "blue", "green","red"),
        lty = c(1, 1, 1, 1, 3),
        lwd = c(2, 2, 2, 2, 2),
        pch = c(NA, NA, NA, NA),
        pt.cex = 2,
        bty = "n",          # No box around legend
        cex = 0.75)          # Larger legend text
```



Step 12: Astronomical Time Scale

This step is performed in Microsoft Excel. The ATS is presented in Supplementary Materials 6.

The built age-model data are set along the composite ACL-ACU core at the corresponding adjusted depth (from 73.452 to 93.609 m).

The data from 73.452 to 73.72 are overlapping with the one of Zhao et al (2022b).

From 62.111 m to 73.72 m the absolute age of Zhao et al (2022b) are used. The absolute age of 499.9115 ± 0.9 Ma located at 73.72 m is used to anchor both ACU and ACL in time domain.

From 73.721 to 93.609 m, the time data used are from our newly built age-model.

Step 13: Milankovitch filters of the 1 kyr resampled Miaolingian composite dataset

13.1. Creation of a ".csv" file

This step is conducted in Microsoft Excel.

The created file contains the Adjusted depth, the Time in kyr and the Ti Z-score values as follows:

AdjDepth; Time; Ti

62.111; 497083.4; 1.57549322

62.112; 497083.6; 1.10323208

62.113; 497083.7; 0.63097093

...; ...; ...

93.609; 504154.084; -0.5940352

93.610; 504154.296; -2.3646753

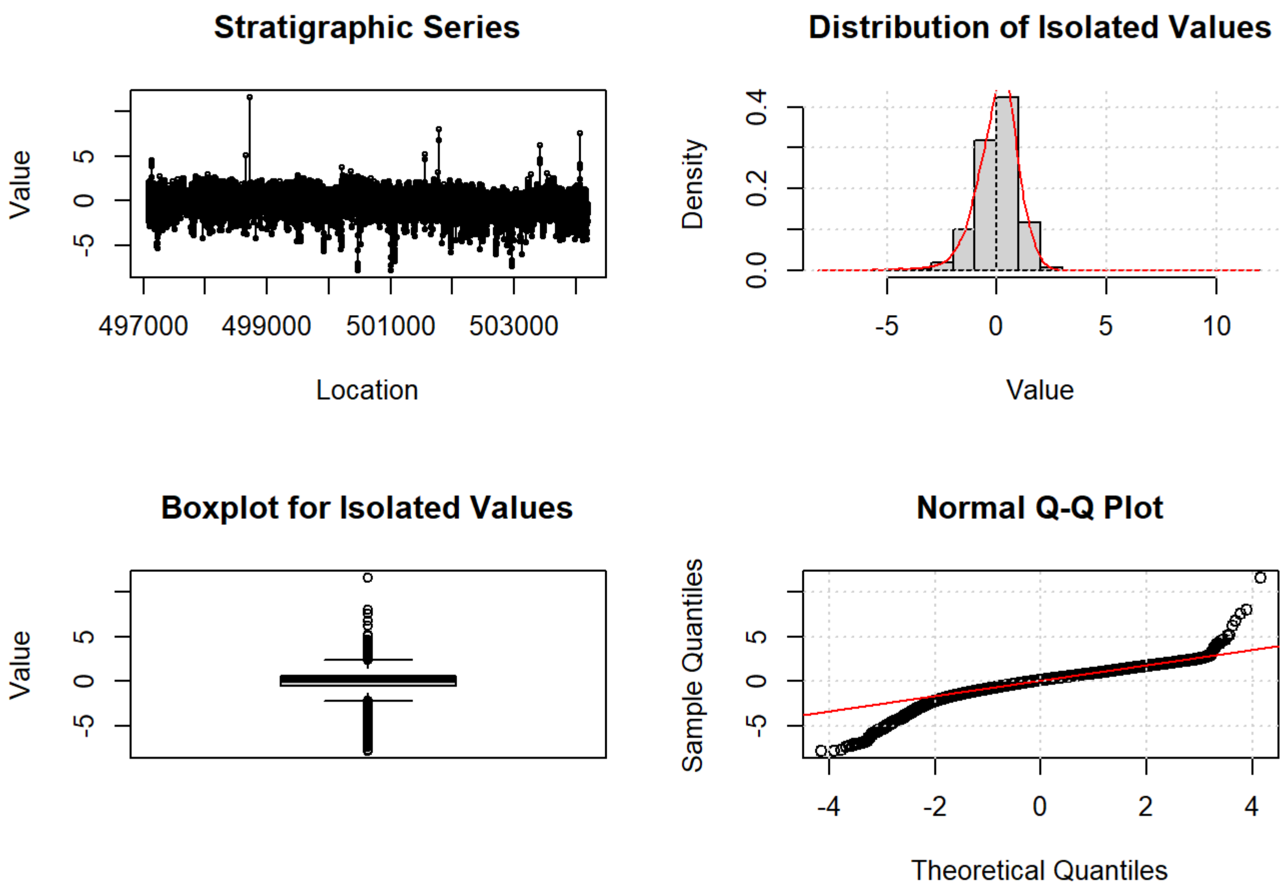
I called this file alb_Ti_Mia_WR.csv as this includes all the Ti data for the entire Miaolingian Epoch recorded in the core tuned using the WaverideR age-depth model.

13.2. Reading of the file in R and resampling every 1 kyr of the time interval

```
alb_Ti_Mia <- read.csv("alb_Ti_Mia_WR.csv",sep=";")
alb_Ti_Mia <- cbind(alb_Ti_Mia$Time,alb_Ti_Mia$Ti)
alb_Ti_Mia <- na.omit(alb_Ti_Mia)
alb_Ti_Mia[!is.finite(alb_Ti_Mia)] <- NA
alb_Ti_Mia <- na.omit(alb_Ti_Mia)
```

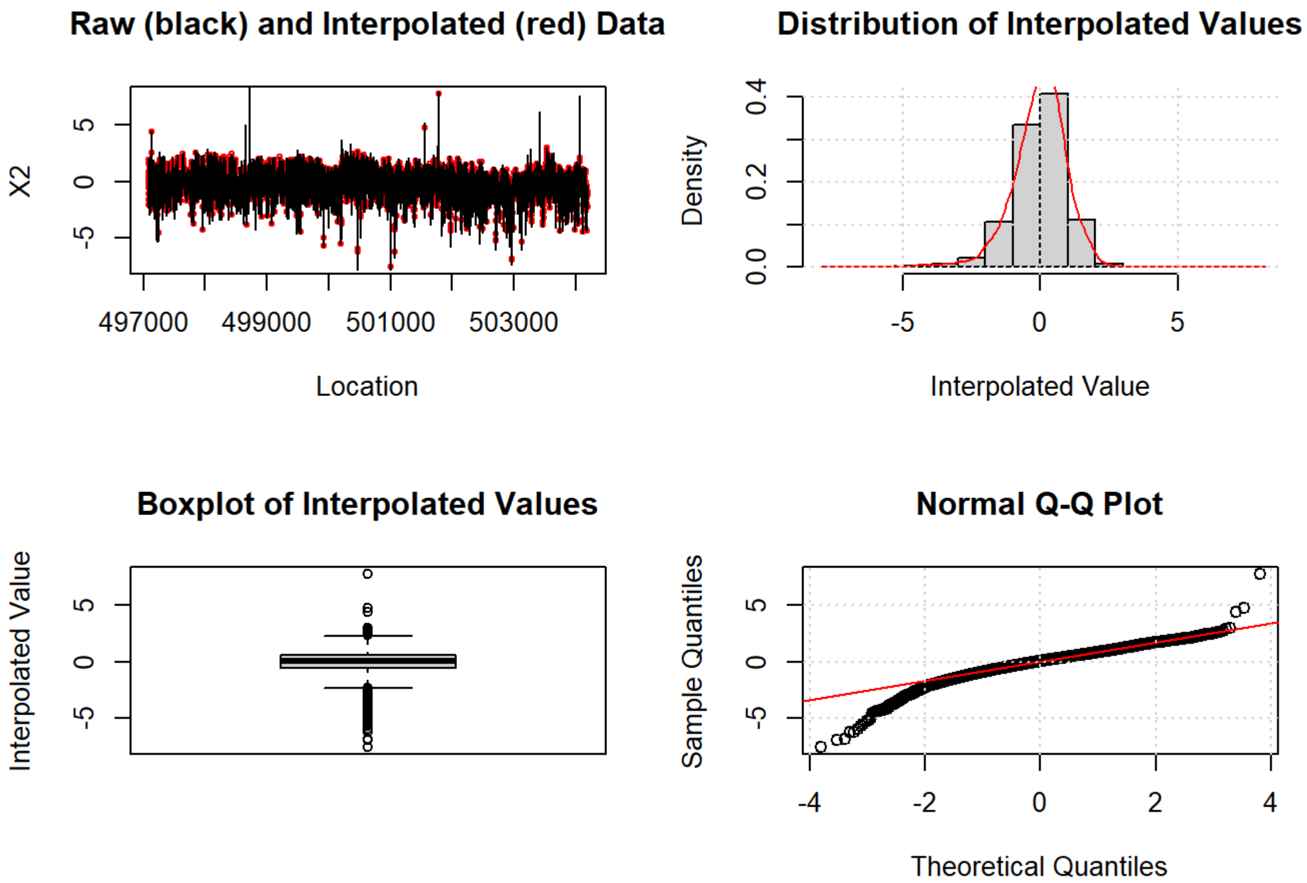
```
MIA<- iso(dat=alb_Ti_Mia, xmin=497000, xmax=505000)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30577
 * Number of columns= 2
 * Minimum= 497083.4 , Maximum= 504197.4
 * Isolating data between 497000 and 505000
 * Number of data points following culling= 30577
```



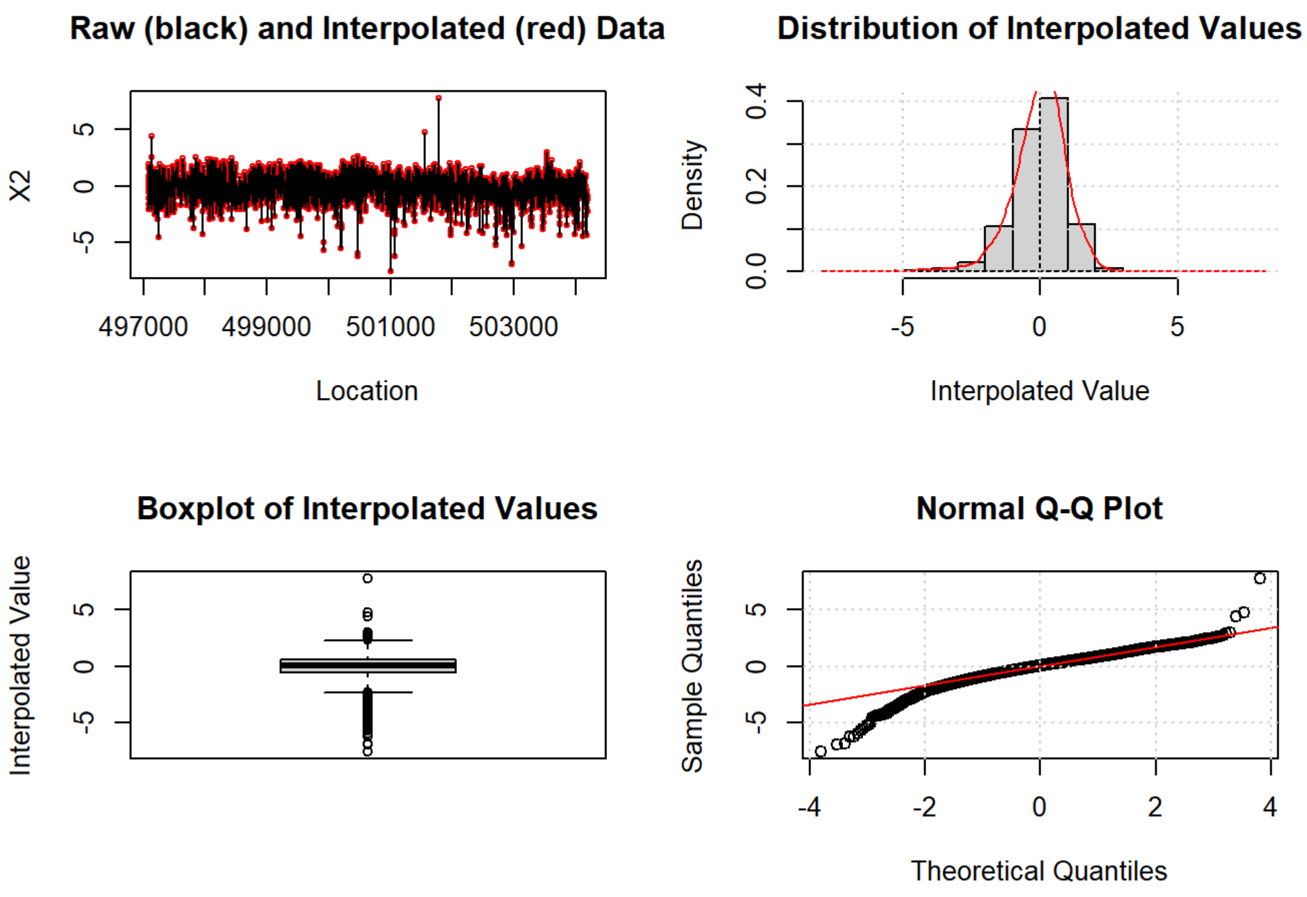

```
MIA <- linterp(MIA,dt=1, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 30577
 * New number of samples= 7115
```




```r
MIA_Ti_tuned <- linterp(MIA, genplot=T)
```

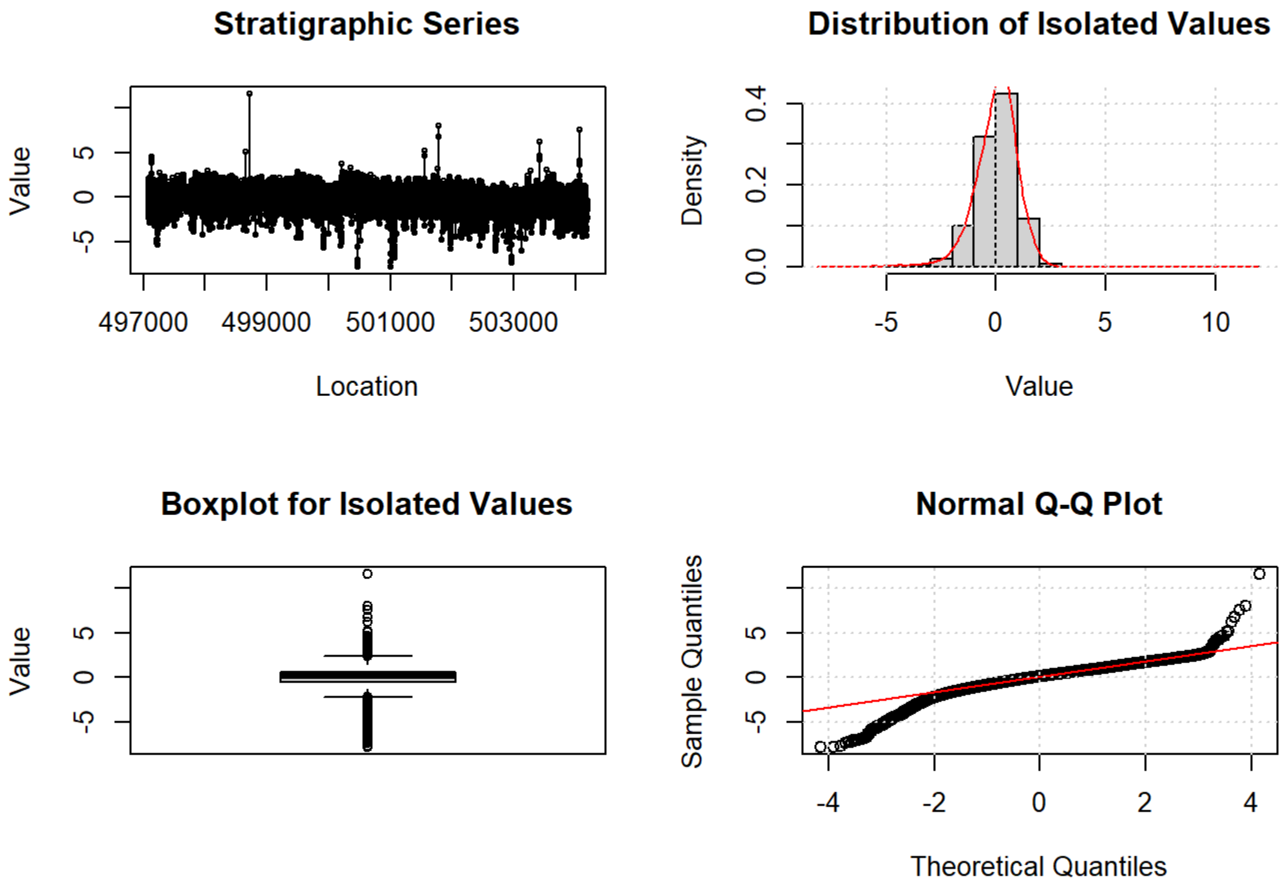
```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 7115
 * Determining median sampling interval for series
 * Will interpolate to median sampling interval of 1
 * New number of samples= 7115
```



13.3. Resampling every 1 kyr and Milankovitch filters

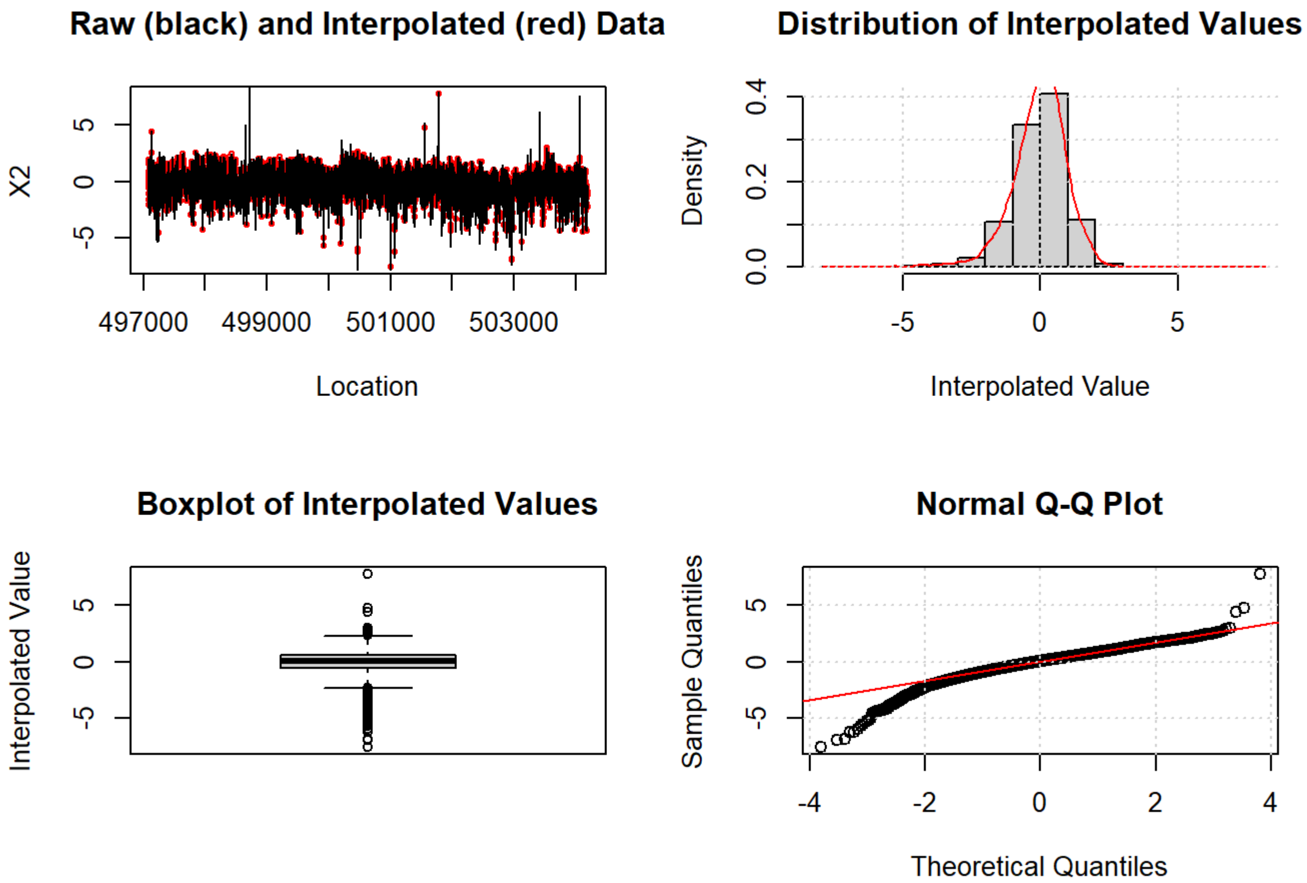
```
#Resampling every 1 kyr
MIA<- iso(dat=alb_Ti_Mia, xmin=497000, xmax=505000)
```

```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30577
 * Number of columns= 2
 * Minimum= 497083.4 , Maximum= 504197.4
 * Isolating data between 497000 and 505000
 * Number of data points following culling= 30577
```



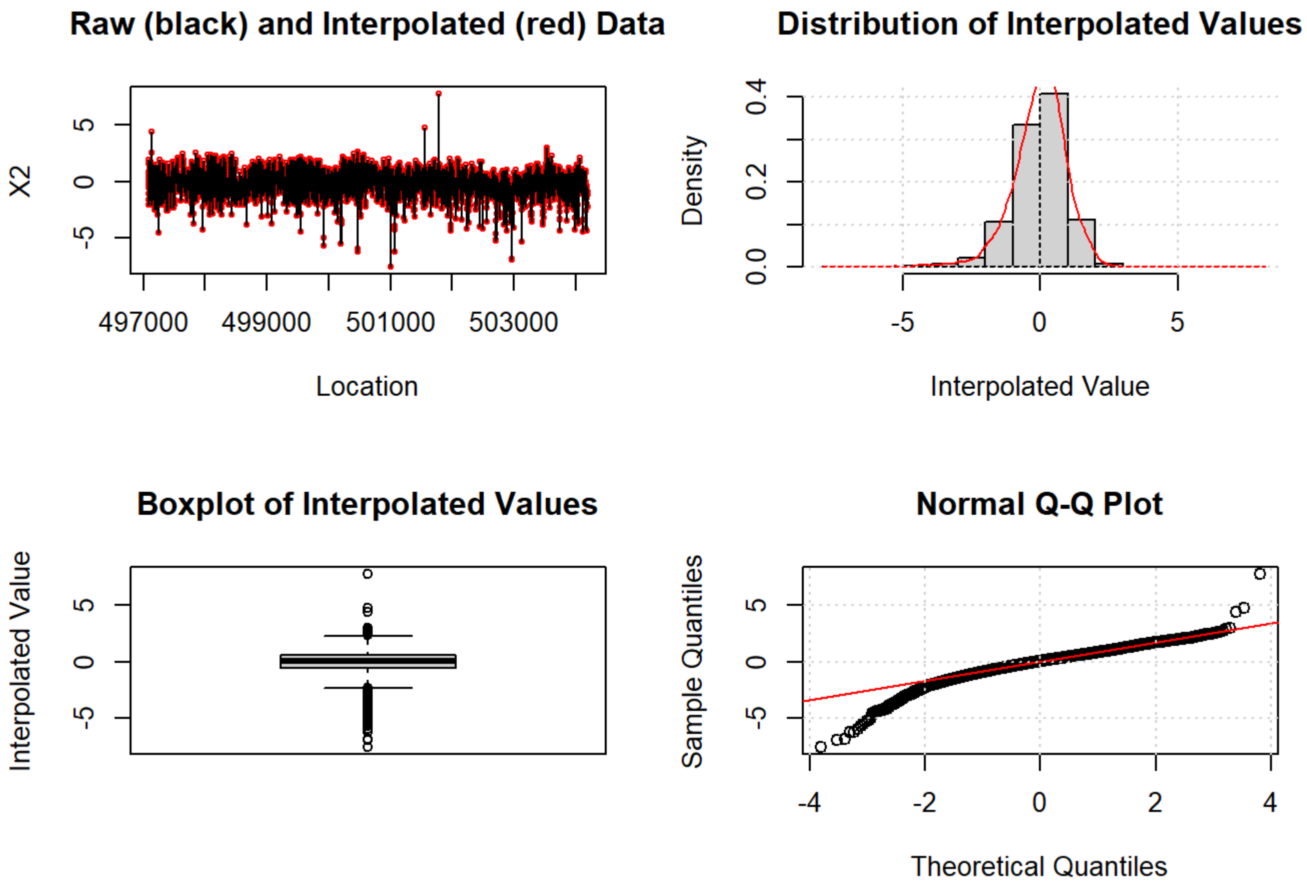

```
MIA <- linterp(MIA,dt=1, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 30577
 * New number of samples= 7115
```



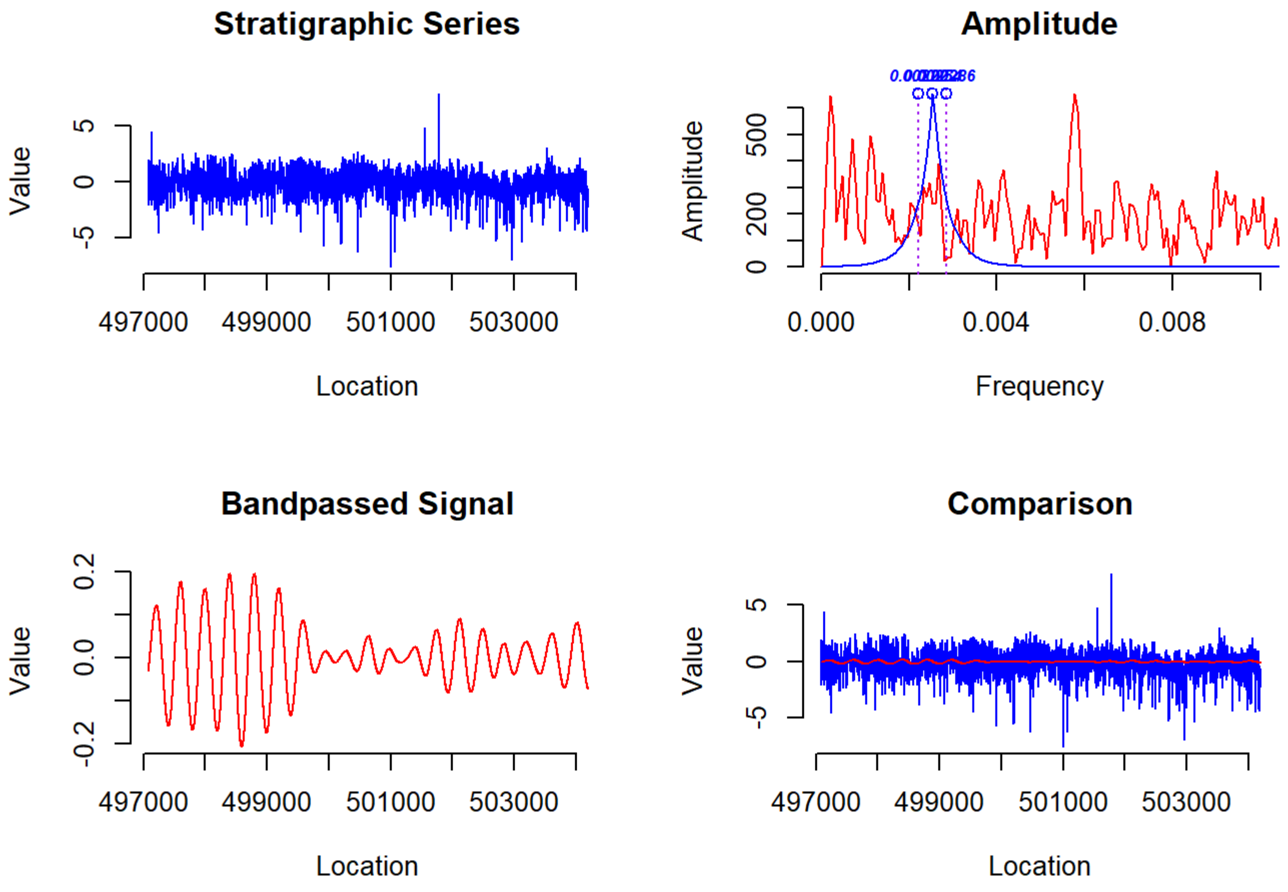

```
MIA_Ti_tuned <- linterp(MIA, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 7115
 * Determining median sampling interval for series
 * Will interpolate to median sampling interval of 1
 * New number of samples= 7115
```



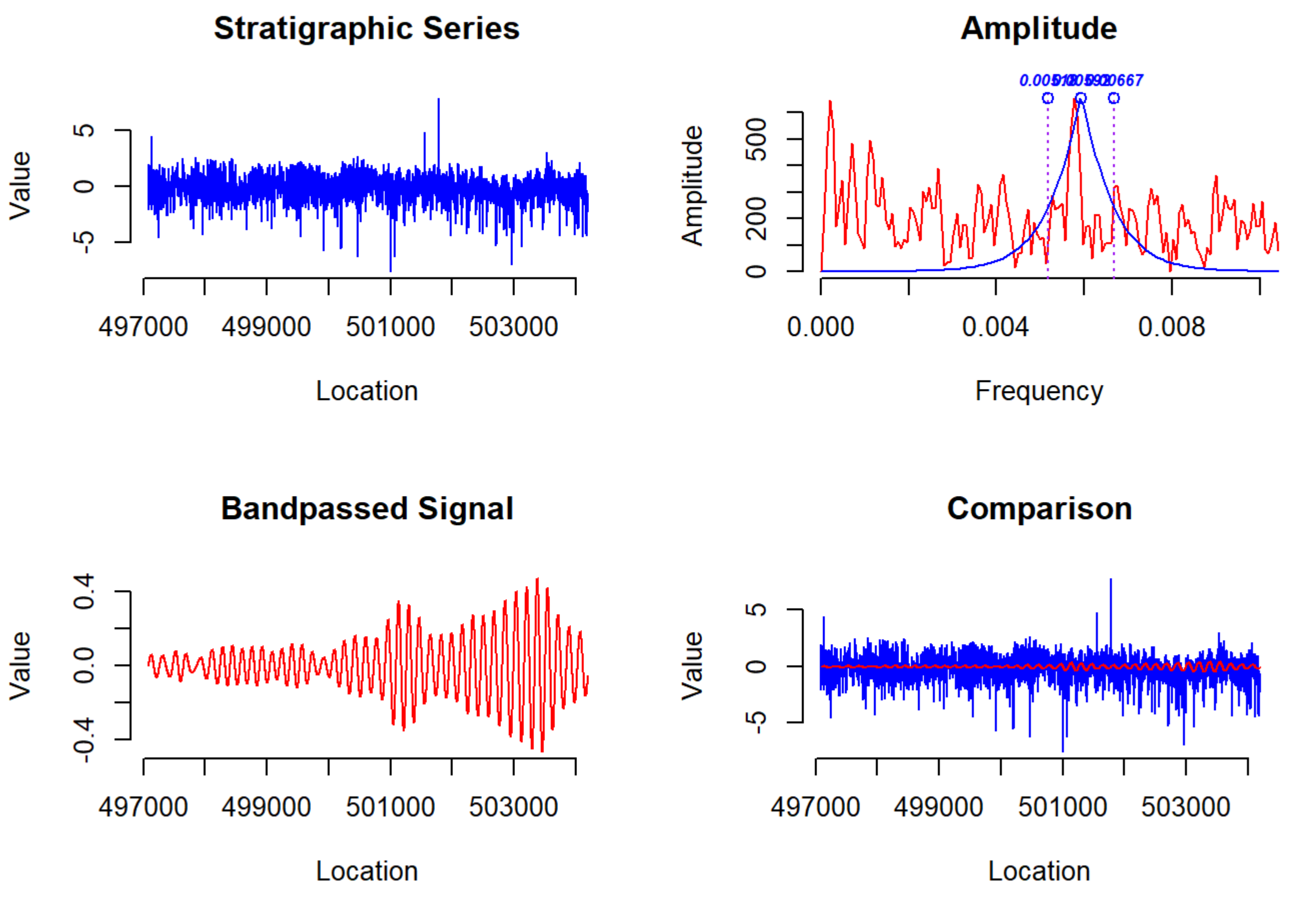

```
#Filter out the long eccentricity cycle
MIA_Ti_405 <- taner(MIA_Ti_tuned,xmax=0.01, fhigh=1/450, flow=1/350, demean = T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 7115
 * Sample interval= 1
 * Mean value removed= -0.03173093
```



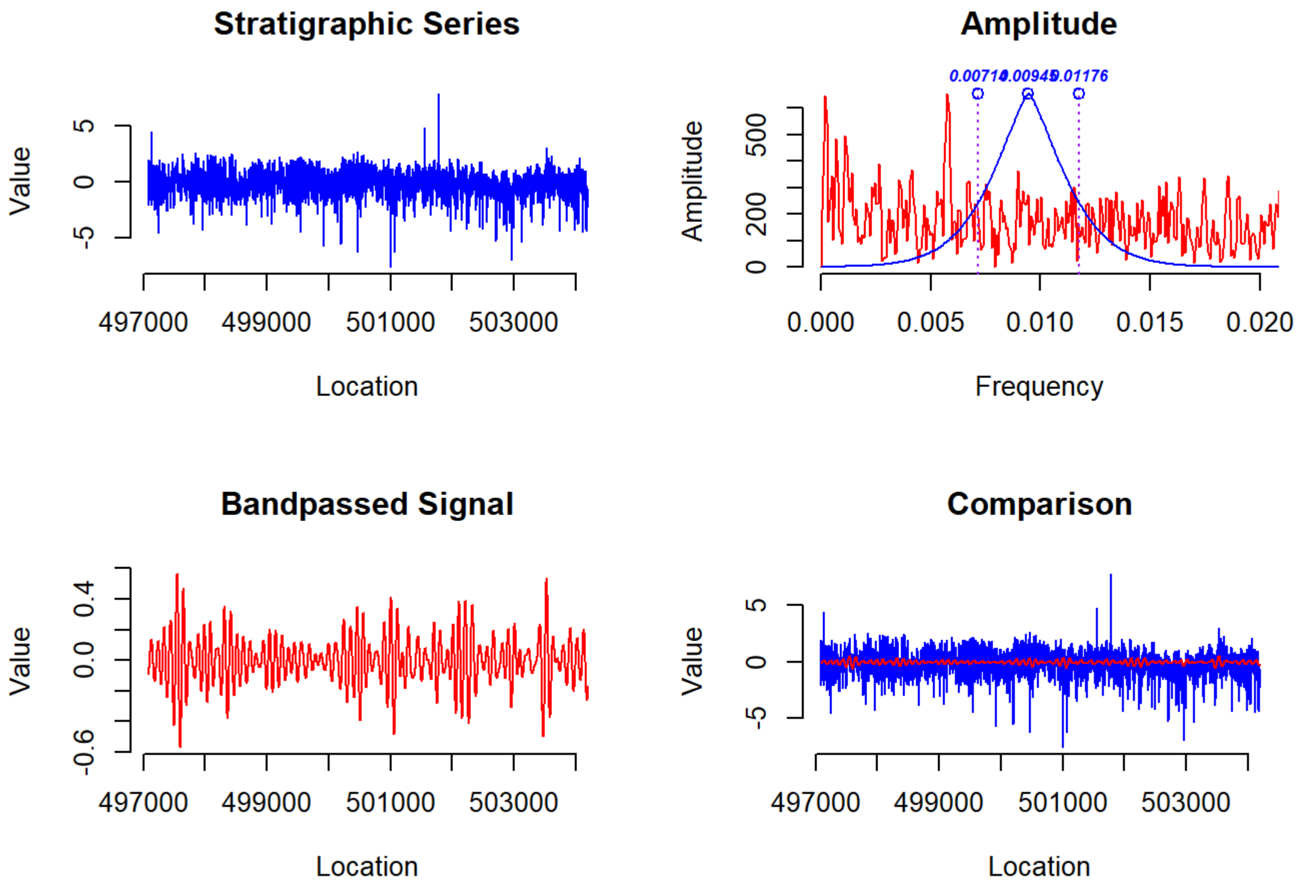

```
#Filter out the 173-kyr obliquity cycle
MIA_Ti_173 <- taner(MIA_Ti_tuned, xmax=0.01, fhigh=1/193, flow=1/150, demean=T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 7115
 * Sample interval= 1
 * Mean value removed= -0.03173093
```



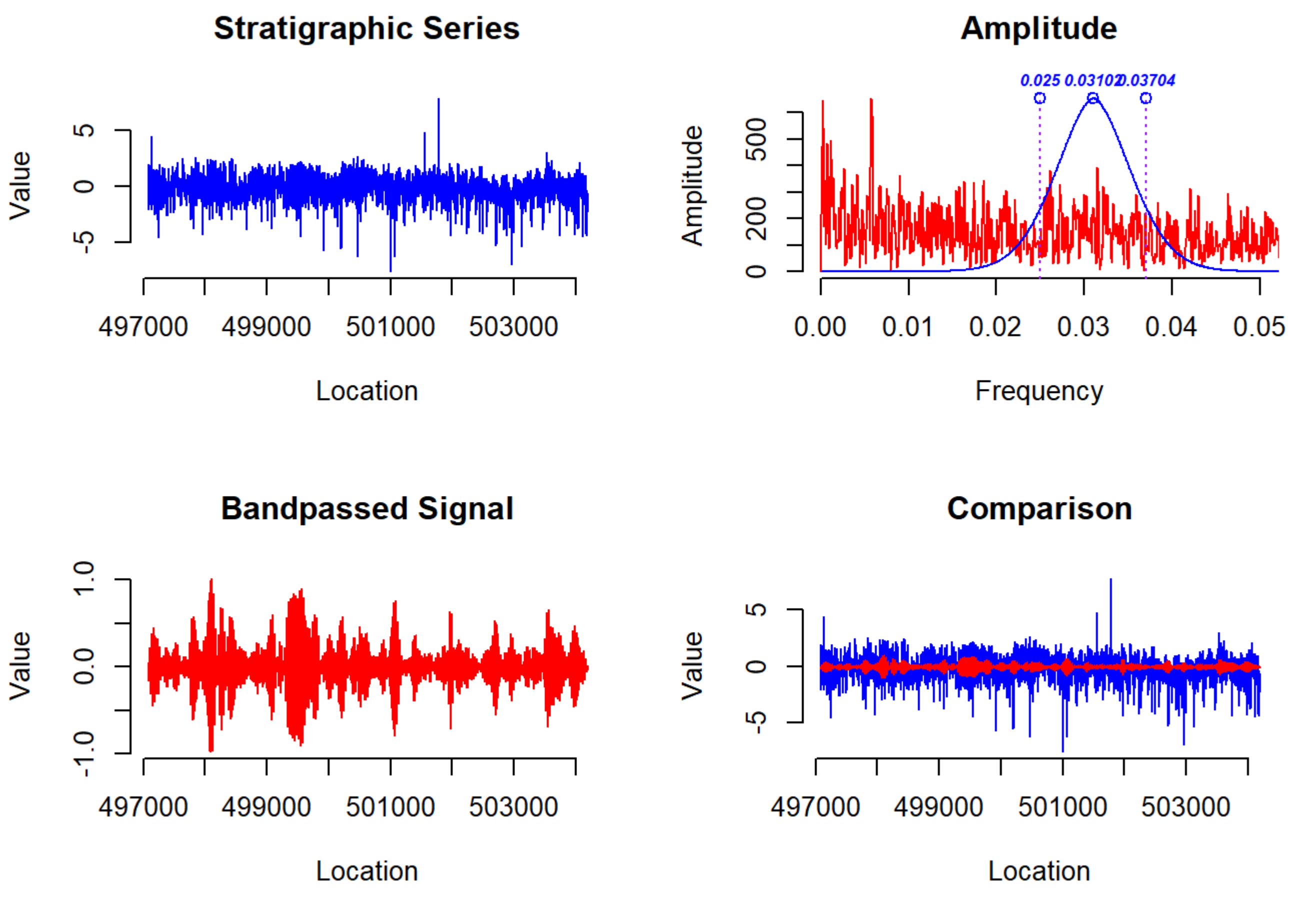

```r
#Filter out the short eccentricity cycle
MIA_Ti_100 <- taner(MIA_Ti_tuned, xmax=0.02, fhigh=1/85, flow=1/140, demean = T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 7115
 * Sample interval= 1
 * Mean value removed= -0.03173093
```



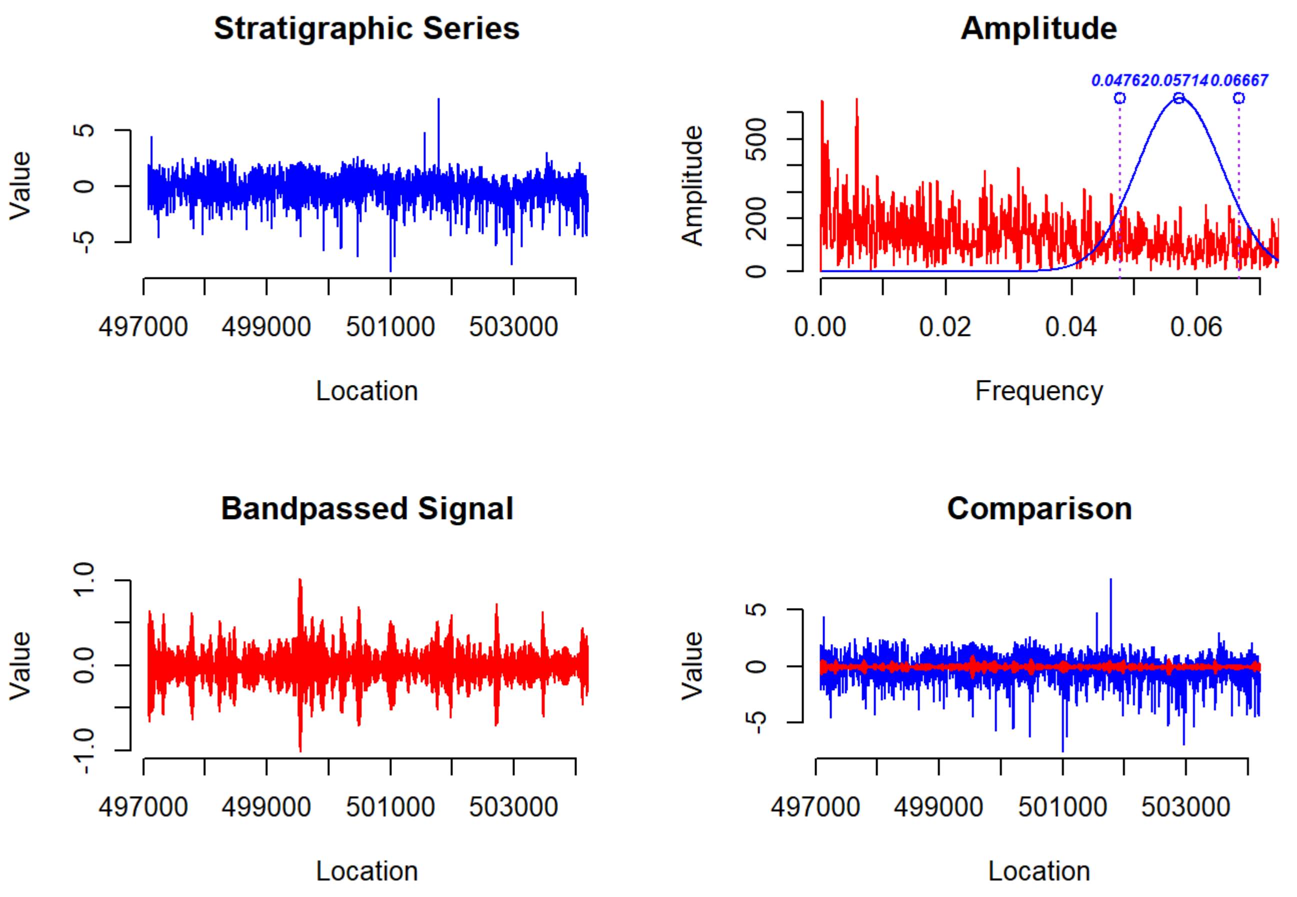

```
#Filter out the obliquity cycle
MIA_Ti_31 <- taner(MIA_Ti_tuned, xmax=0.05, fhigh=1/27, flow=1/40, demean=T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 7115
 * Sample interval= 1
 * Mean value removed= -0.03173093
```




```r
#Filter out the precession cycle
MIA_Ti_20 <- taner(MIA_Ti_tuned,xmax=0.07, fhigh=1/15, flow=1/21, demean=T)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 7115
 * Sample interval= 1
 * Mean value removed= -0.03173093
```




```
#Saving of the filtered Milankovitch periodicities
#write.csv(MIA_Ti_tuned,"MIA_WR_rsp_1kyr.csv")
#write.csv(MIA_Ti_405,"MIA_WR_405_rsp_1kyr.csv")
#write.csv(MIA_Ti_173,"MIA_WR_173_rsp_1kyr.csv")
#write.csv(MIA_Ti_100,"MIA_WR_100_rsp_1kyr.csv")
#write.csv(MIA_Ti_31,"MIA_WR_31_rsp_1kyr.csv")
#write.csv(MIA_Ti_20,"MIA_WR_20_rsp_1kyr.csv")
```

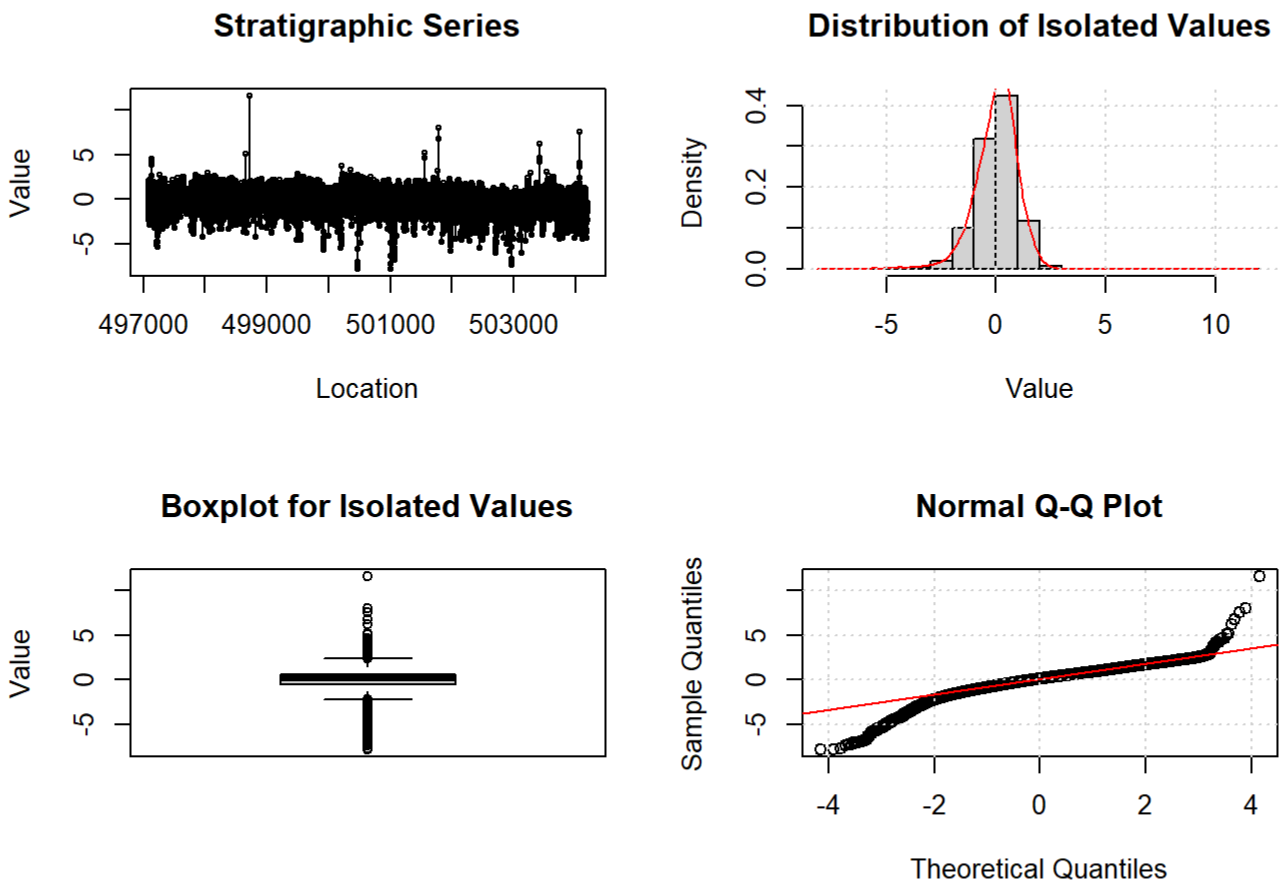
Step 14: Lag-1 autcorrelation of the Miaolingian Series

14.1. Resampling of the dataset every 5 kyr

```
alb_Ti_Mia <- read.csv("alb_Ti_Mia_WR.csv",sep=";")
alb_Ti_Mia <- cbind(alb_Ti_Mia$Time,alb_Ti_Mia$Ti)
alb_Ti_Mia <- na.omit(alb_Ti_Mia)
alb_Ti_Mia[!is.finite(alb_Ti_Mia)] <- NA
alb_Ti_Mia <- na.omit(alb_Ti_Mia)

MIA<- iso(dat=alb_Ti_Mia, xmin=497000, xmax=505000)
```

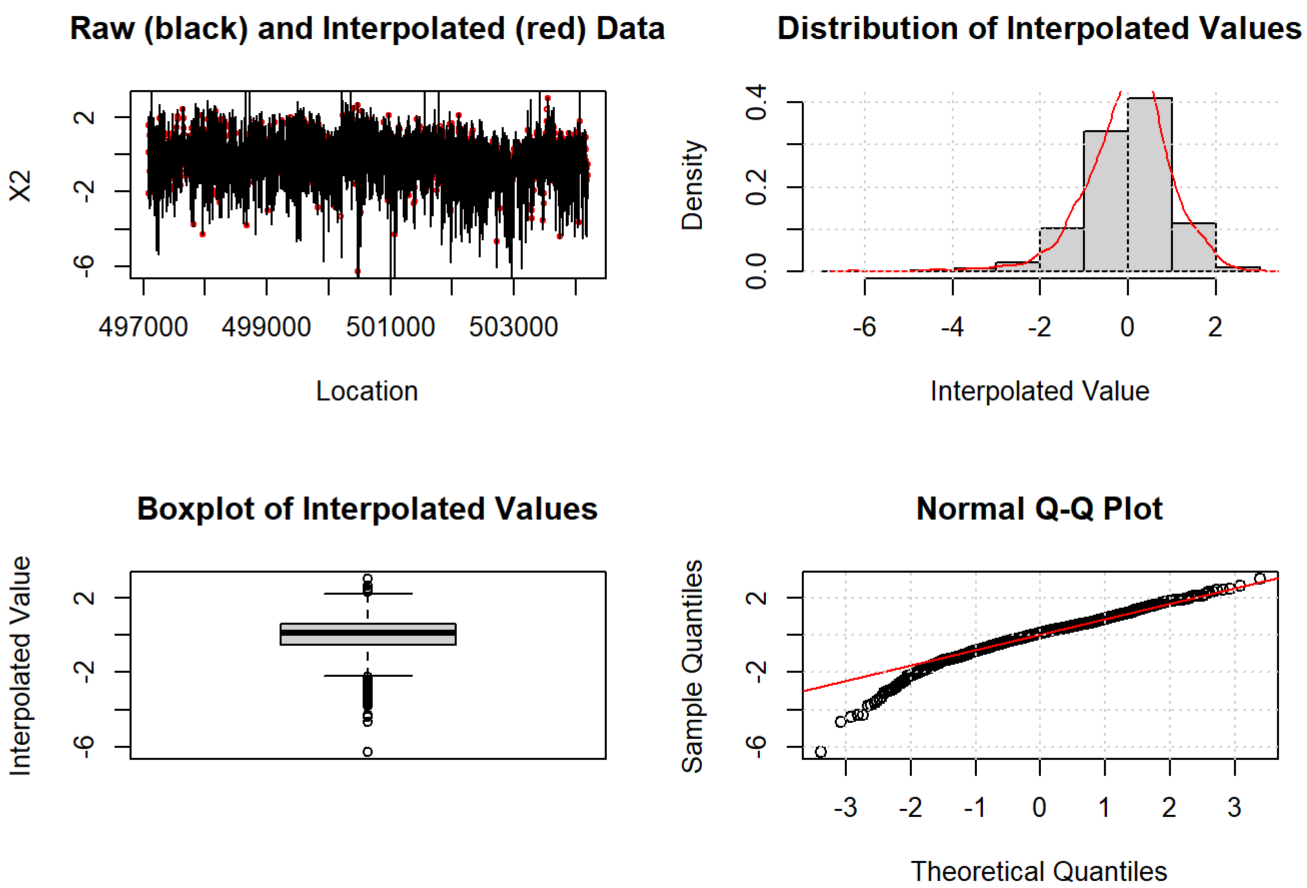
```
----- ISOLATE STRATIGRAPHIC DATA BY LOCATION -----
 * Number of data points= 30577
 * Number of columns= 2
 * Minimum= 497083.4 , Maximum= 504197.4
```

```
 * Isolating data between 497000 and 505000
 * Number of data points following culling= 30577
```



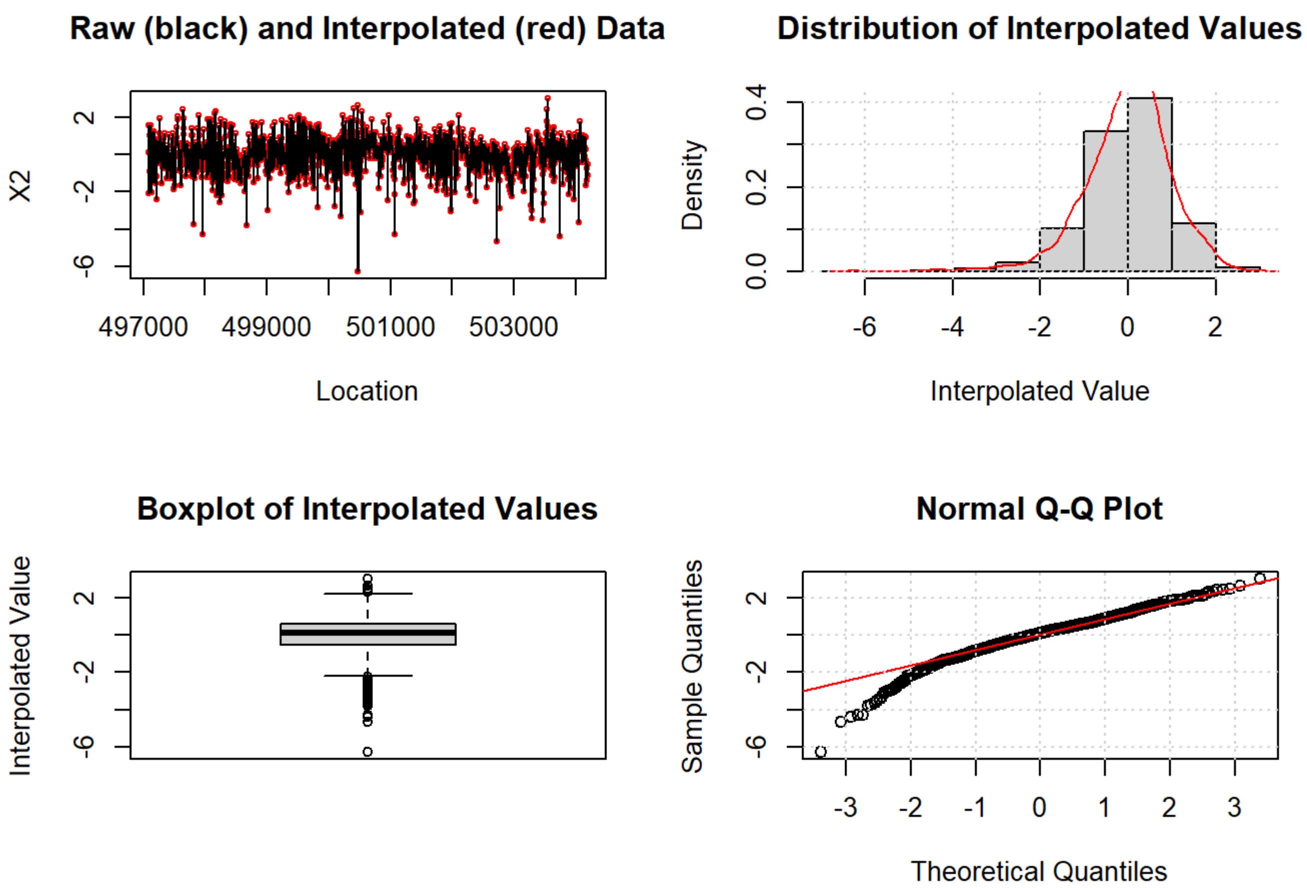

```r
MIA <- linterp(MIA,dt=5, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 30577
 * New number of samples= 1423
```




```
MIA_Ti_tuned <- linterp(MIA, genplot=T)
```

```
----- APPLYING PIECEWISE-LINEAR INTERPOLATION TO STRATIGRAPHIC SERIES -----

 * Number of samples= 1423
 * Determining median sampling interval for series
 * Will interpolate to median sampling interval of 5
 * New number of samples= 1423
```



14.2. Lag-1 autocorrelation

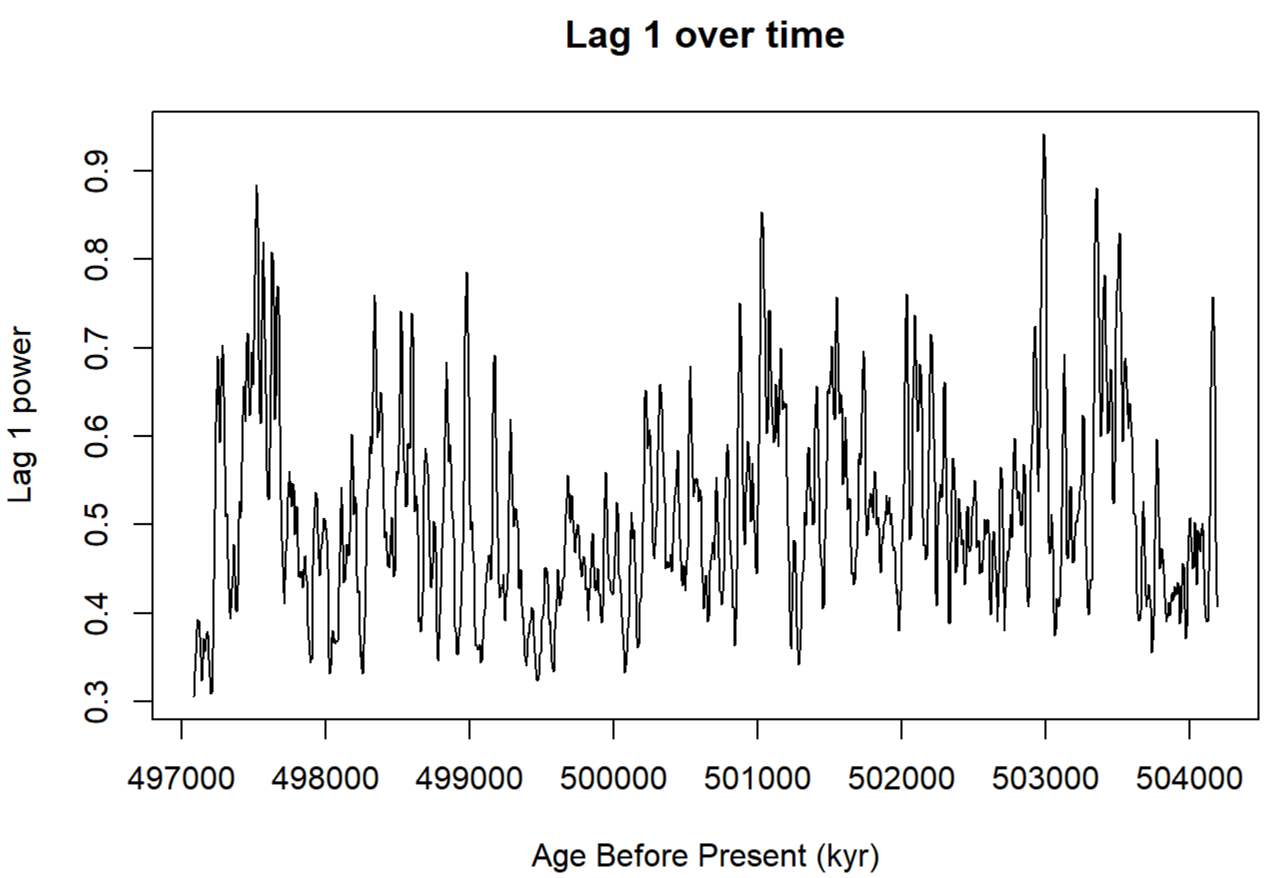
Lag-1 window set from 20 to 90 kyr to avoid the 5-20 kyr high frequency noise and limit to 90 kyr that correspond to the lower boundary of the short eccentricity band

```
win_min <- 20
win_max <- 90
n_sim <- 100
dat <- data.frame(MIA_Ti_tuned)
dt2 <- dat[2, 1] - dat[1, 1]
dat <- dat[order(dat[, 1], na.last = NA, decreasing = F), ]
npts <- length(dat[, 1])
start <- dat[1, 1]
end <- dat[length(dat[, 1]), 1]
x1 <- dat[1:(npts - 1), 1]
x2 <- dat[2:(npts), 1]
dx = x2 - x1
dt = mean(dx)
sdt = sd(dx)
xout <- seq(start, end, by = dt)
npts <- length(xout)
interp <- approx(dat[, 1], dat[, 2], xout, method = "linear", n = npts)
d <- as.data.frame(interp)
mat_sim <- matrix(data = NA,
                  nrow = nrow(d),
                  ncol = n_sim)


xout_vals <- d[, 1]
i <- 1
```

```
npts <- length(xout_vals)
new_sampling_rate <- NULL

fit <- for(i in 1:n_sim){

  if (sdt == 0) {
    new_sampling_rate <- runif(n=1, min = dt, max = win_min)}
  else if ((dt - (2 * sdt)) > 0) {
    new_sampling_rate <- truncnorm::rtruncnorm(
      n = 1,
      a = dt - 2 * sdt,
      b = dt + (2 * sdt),
      mean = dt,
      sd = sdt
    )}else {
      new_sampling_rate <- truncnorm::rtruncnorm(
        n = 1,
        a = dt / 2,
        b = dt + (2 * sdt),
        mean = dt,
        sd = sdt
      )
    }




  win_size <- stats::runif(n = 1,
                           min = min(c(win_min, win_max)),
                           max = max(c(win_min, win_max)))


  dt_new <- new_sampling_rate

  xout_new <- seq(from = start, to = end, by = dt_new)

  npts_new <- length(xout_new)

  interp_new <- approx(dat[, 1],
                       dat[, 2],
                       xout_new,
                       method = "linear",
                       n = npts
                       )

  d_new <- as.data.frame(interp_new)
  d_new[, 3] <- NA
  for (k in 1:nrow(d_new)) {
    row_nr_1 <- DescTools::Closest(d_new[, 1],
                                   d_new[k, 1] - (win_size / 2),
                                   which = TRUE)
    row_nr_2 <- DescTools::Closest(d_new[, 1],
                                   d_new[k, 1] + (win_size / 2),
                                   which = TRUE)
    data_sel <- d_new[row_nr_1[1]:row_nr_2[1], ]
    corr <- acf(data_sel[, 2], plot = F)
    a <- as.numeric(unlist(corr[1])[1])
    d_new[k, 3] <- a
```

```
  }
  yleft_comp <- d_new[1, 3]
  yright_com <- d_new[nrow(d_new), 3]
  app <- approx(
    d_new[, 1],
    d_new[, 3],
    xout_vals,
    method = "linear",
    n = npts,
    yleft = yleft_comp,
    yright = yright_com
  )
  app_res <- cbind(app$y)
  app_res_norm <- (app_res - min(app_res, na.rm = TRUE)) /
    (max(app_res, na.rm = TRUE) - min(app_res, na.rm = TRUE))
  mat_sim[,i] <- app_res_norm
}

mat_sim_mean <- rowMeans(mat_sim)
mat_sim_sd <- rowSds(mat_sim)
results <- cbind(xout_vals, mat_sim_mean, mat_sim_sd)

lag_1 <- results
```

```
plot(lag_1,
     type = "l",
     main = "Lag 1 over time",
     xlab = "Age Before Present (kyr)",
     ylab = "Lag 1 power"
     )
```

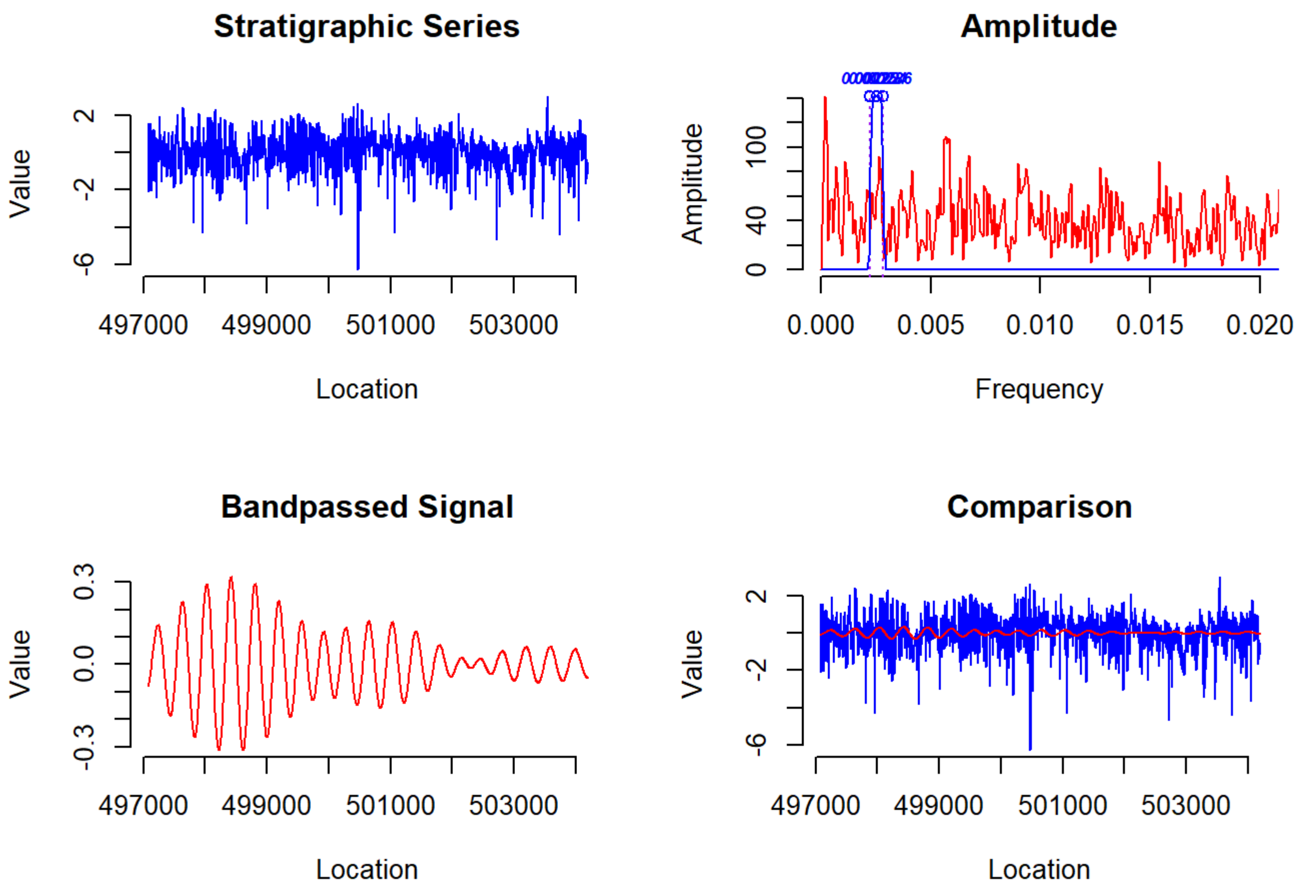


```
#    write.csv(lag_1,"lag1-rsp5kyr-window20-90kyr.csv")
```

14.3. Filtering of the Milankovitch cycles and comparison with lag-1 results

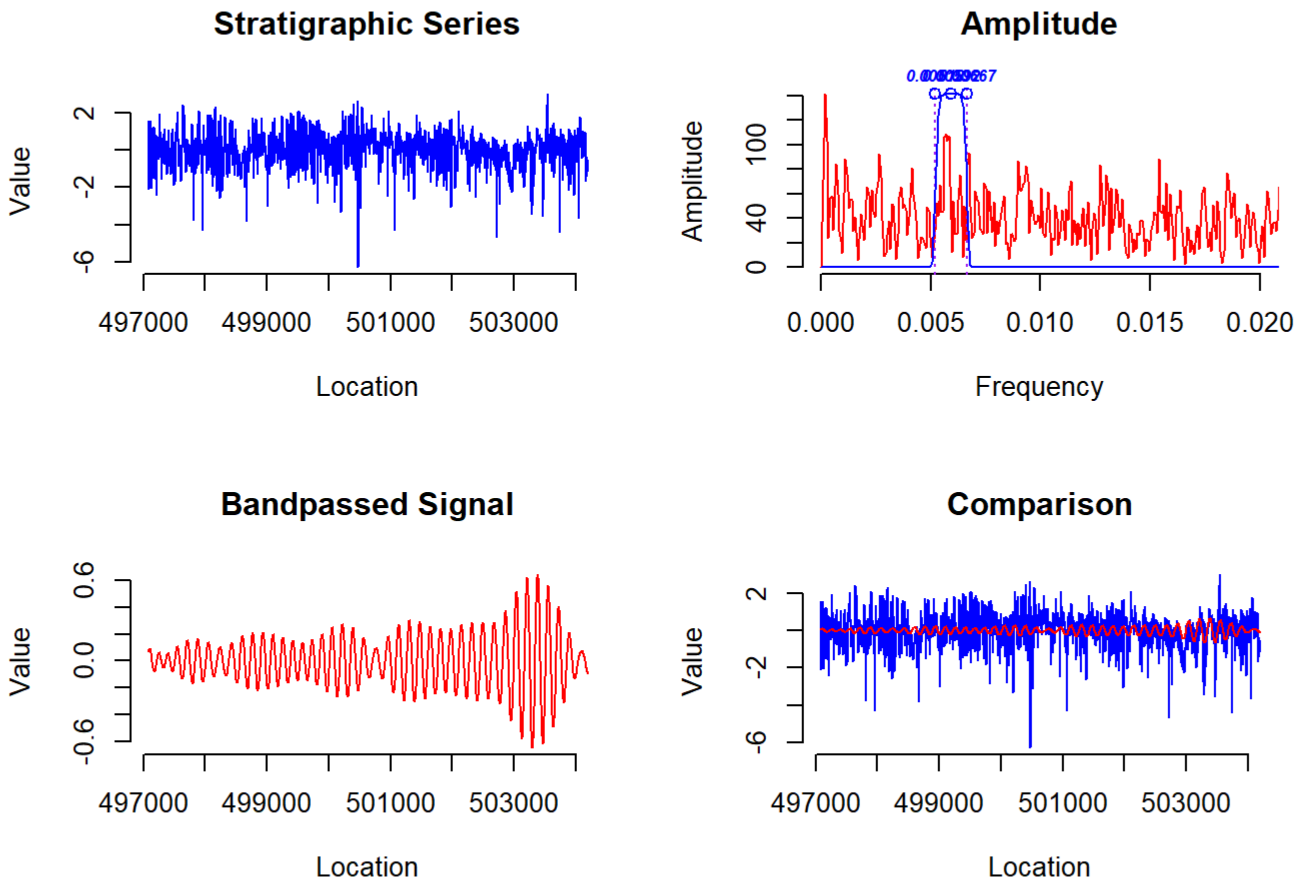
```
MIA_Ti__405 <- taner(MIA_Ti_tuned[,c(1,2)],flow=1/350,fhigh=1/450,roll=10^20,xmax=1/50)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= -0.00624567
```



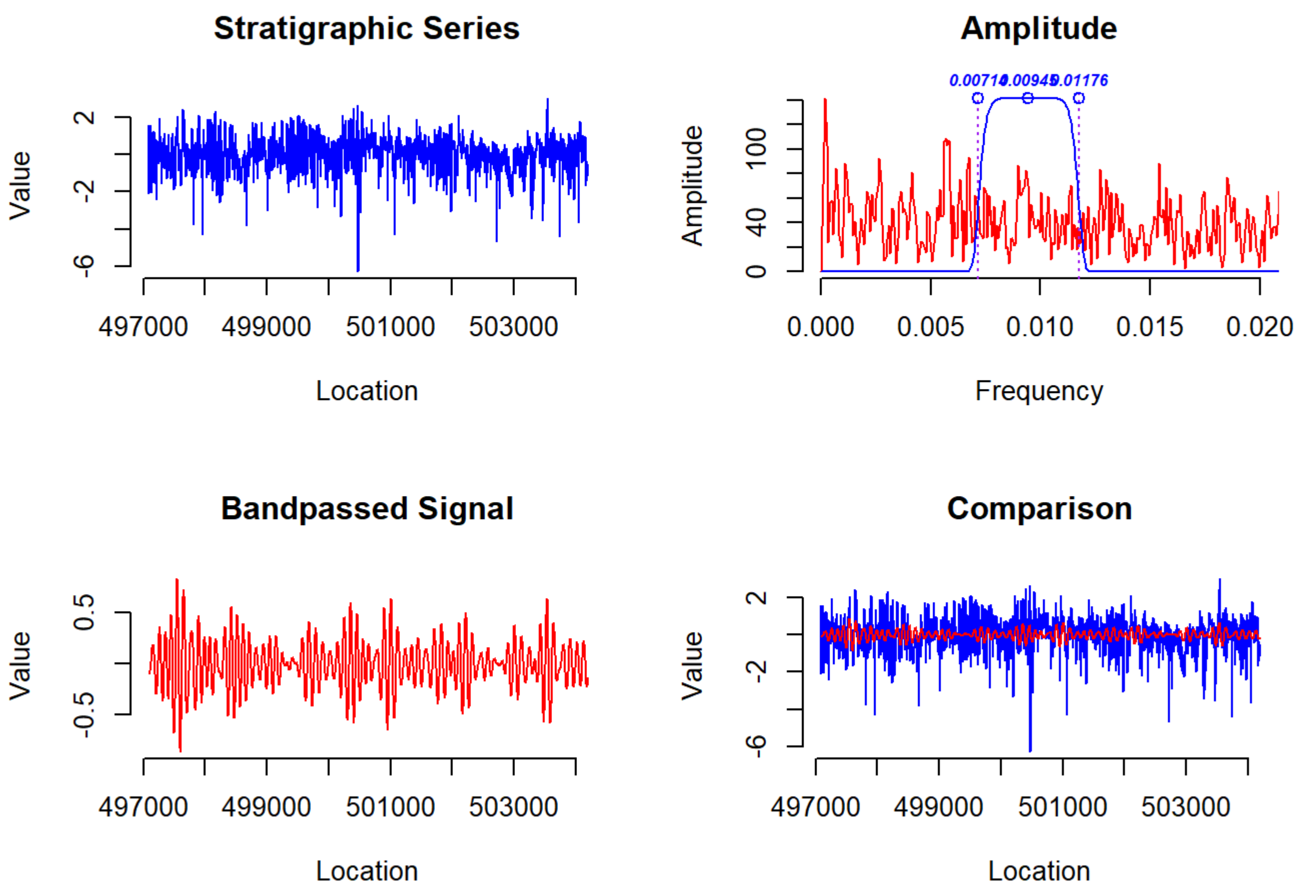

```
MIA_Ti__173<- taner(MIA_Ti_tuned[,c(1,2)],flow=1/150,fhigh=1/193,roll=10^20,xmax=1/50)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= -0.00624567
```



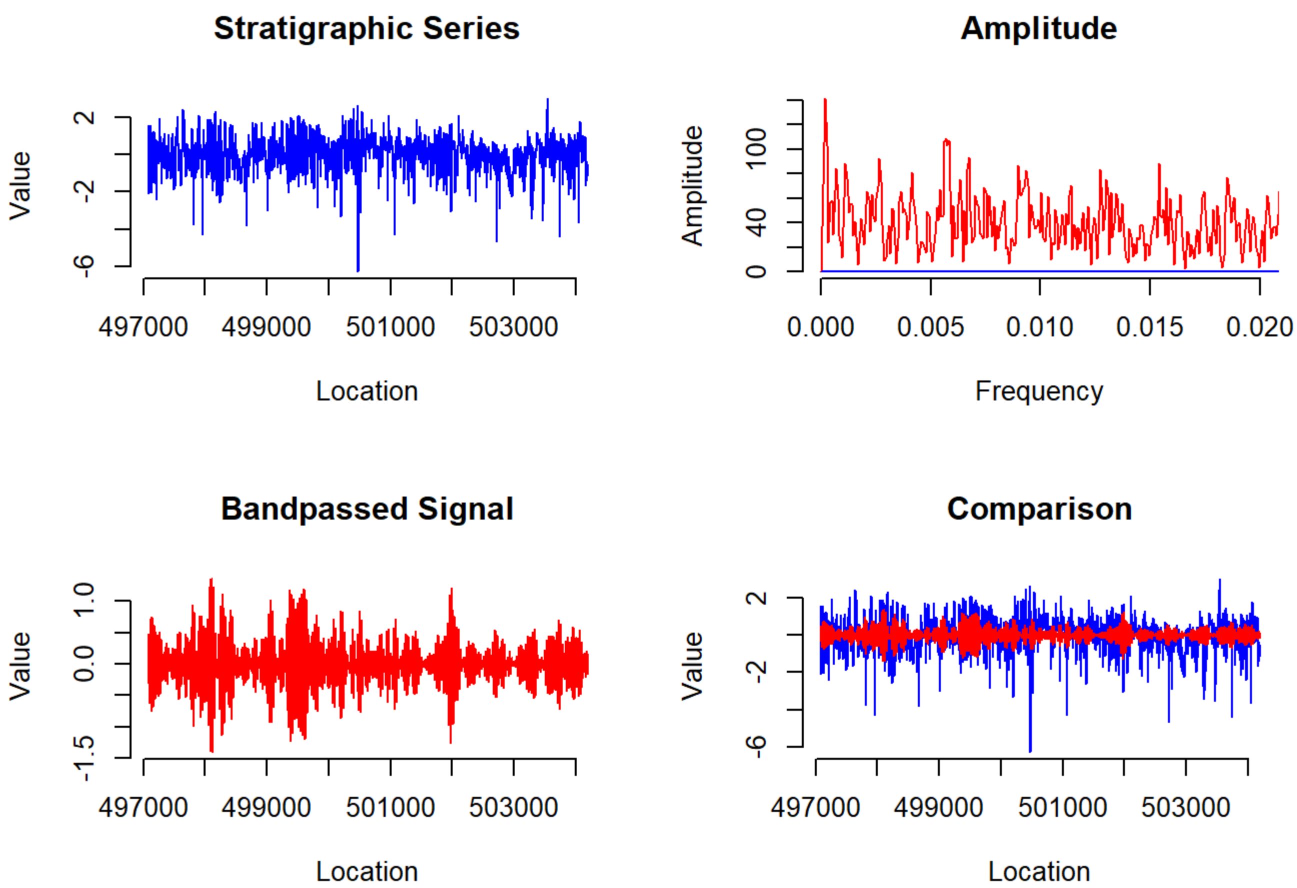

```
MIA_Ti__100<- taner(MIA_Ti_tuned[,c(1,2)],flow=1/140,fhigh=1/85,roll=10^20,xmax=1/50)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= -0.00624567
```



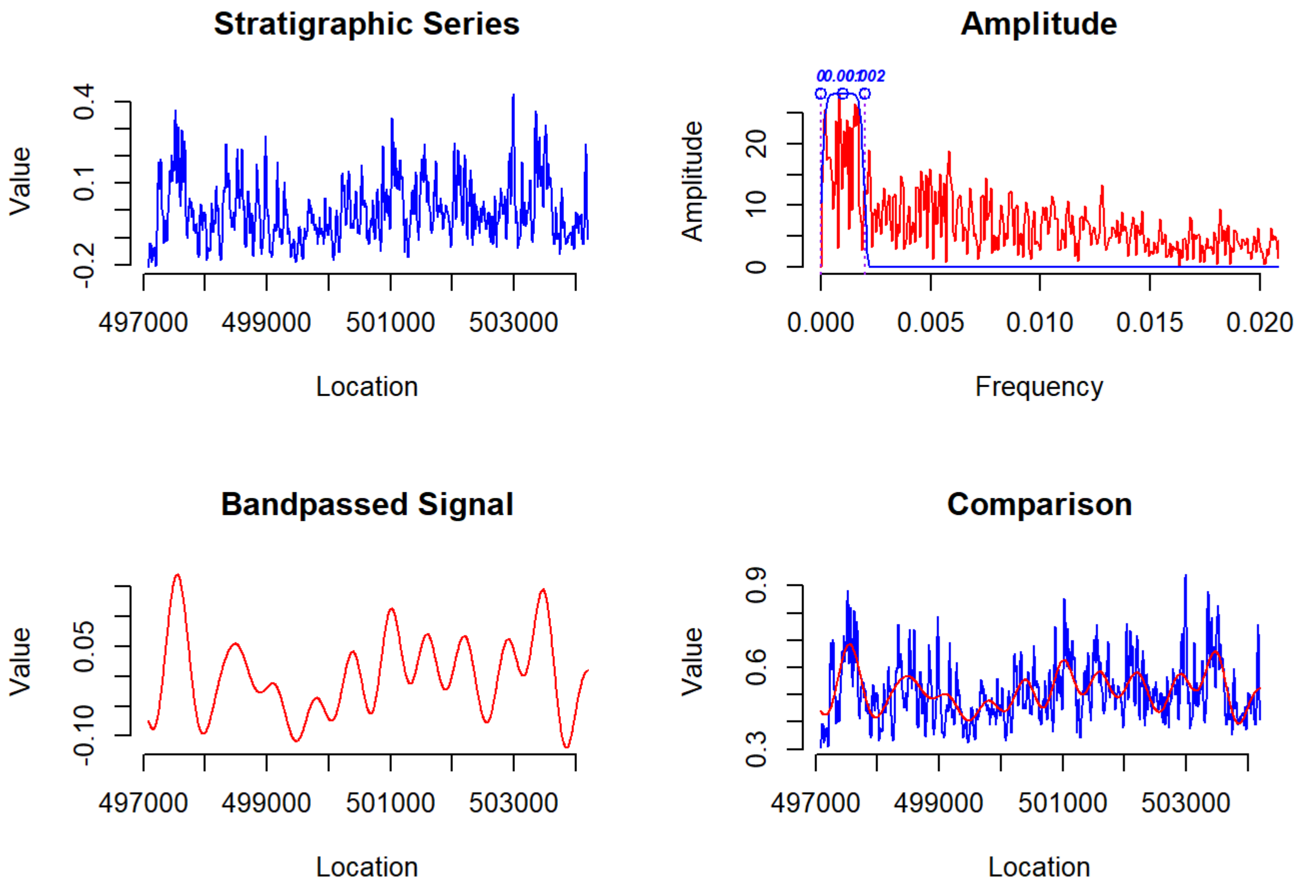

```
MIA_Ti__31 <- taner(MIA_Ti_tuned[,c(1,2)],flow=1/27,fhigh=1/40,roll=10^20,xmax=1/50)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= -0.00624567
```



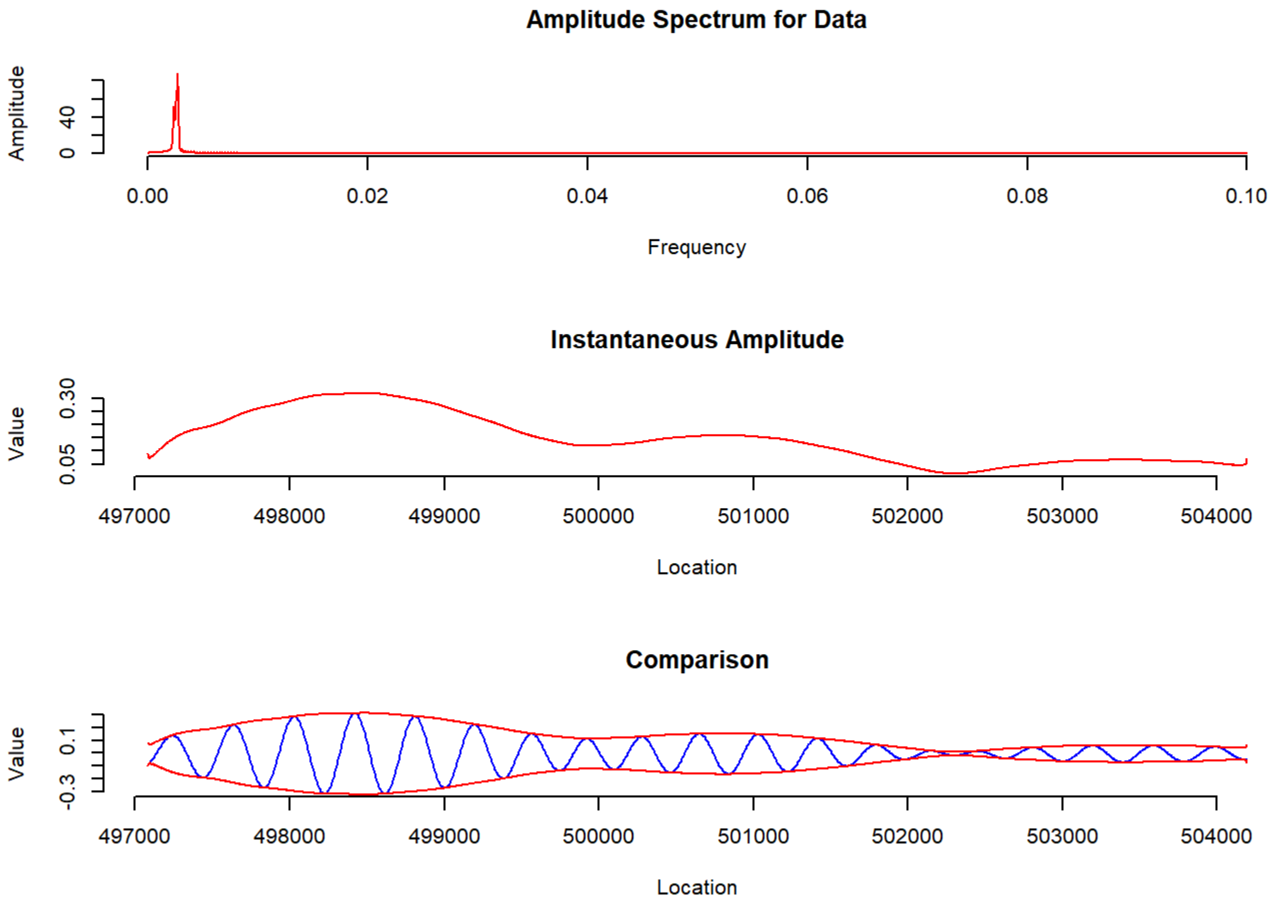

```
lag_1_background<- taner(lag_1[,c(1,2)],flow=1/500,fhigh=0,roll=10^20,xmax=1/50)
```

```
----- TANER BANDPASS FILTERING STRATIGRAPHIC SERIES-----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= 0.5138215
```



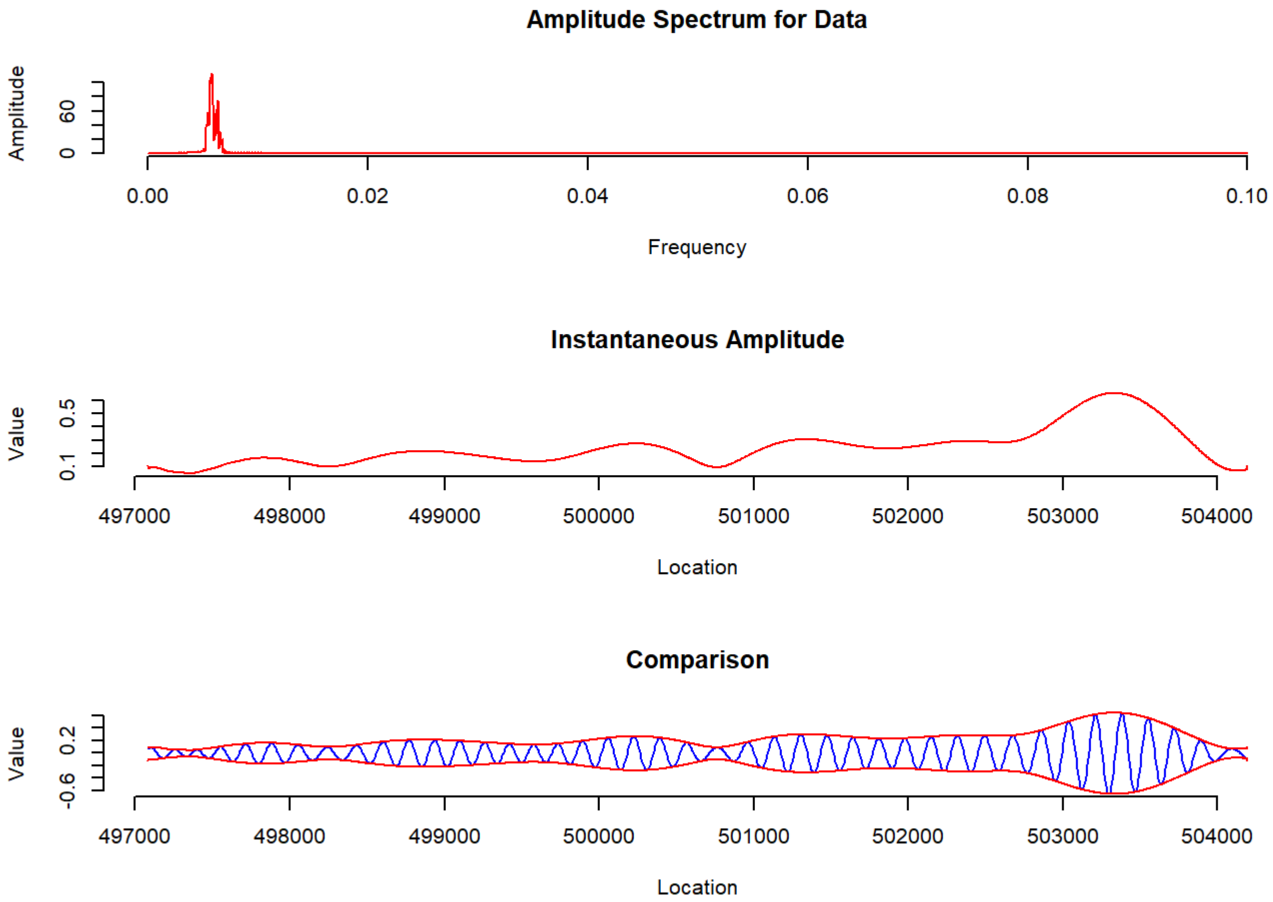

```
MIA_Ti__405_hilbert <- hilbert(MIA_Ti__405)
```

```
----- PERFORMING HILBERT TRANSFORM ON STRATIGRAPHIC SERIES -----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= -0.005499469
```



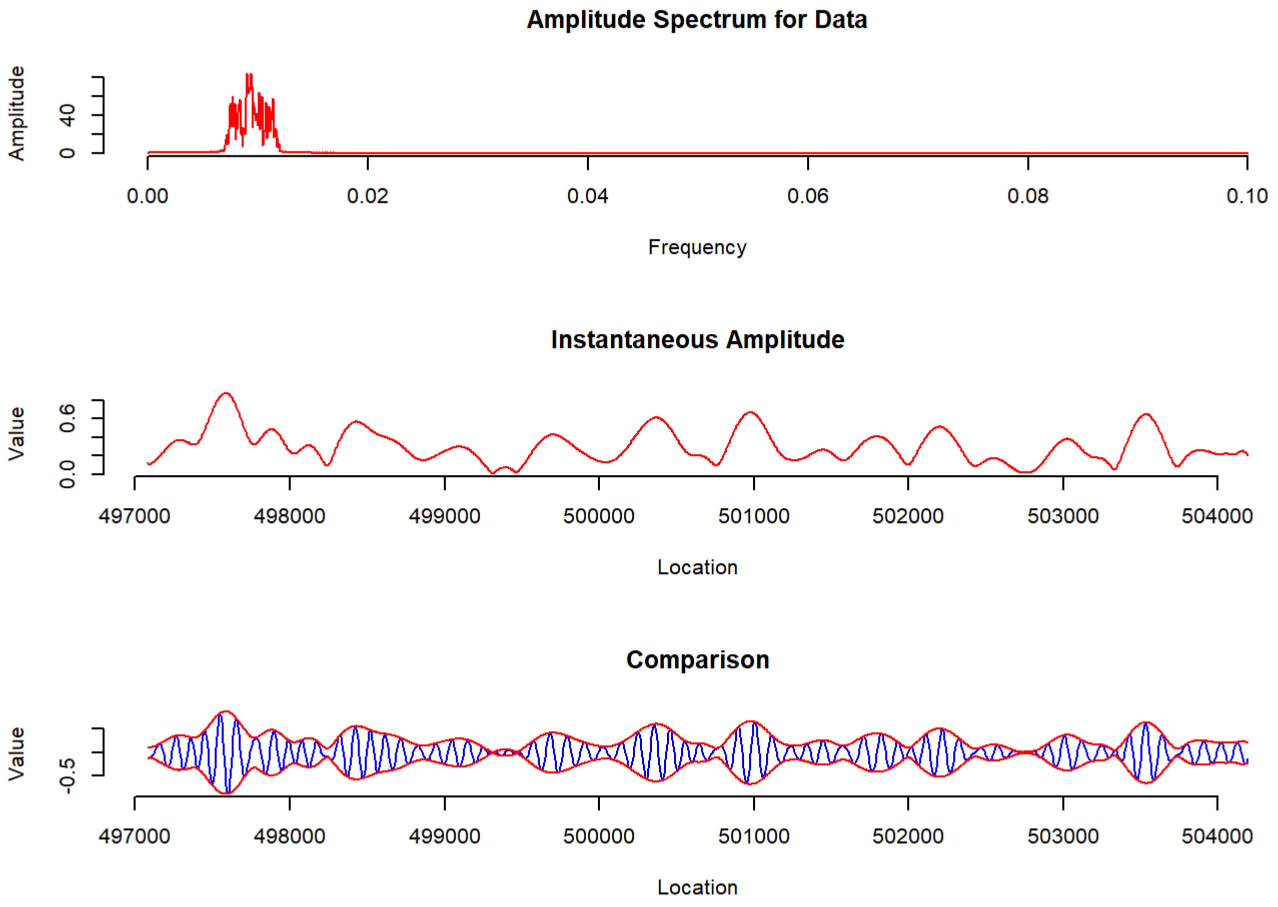

```
MIA_Ti__173_hilbert <- hilbert(MIA_Ti__173)
```

```
----- PERFORMING HILBERT TRANSFORM ON STRATIGRAPHIC SERIES -----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= -0.005971174
```



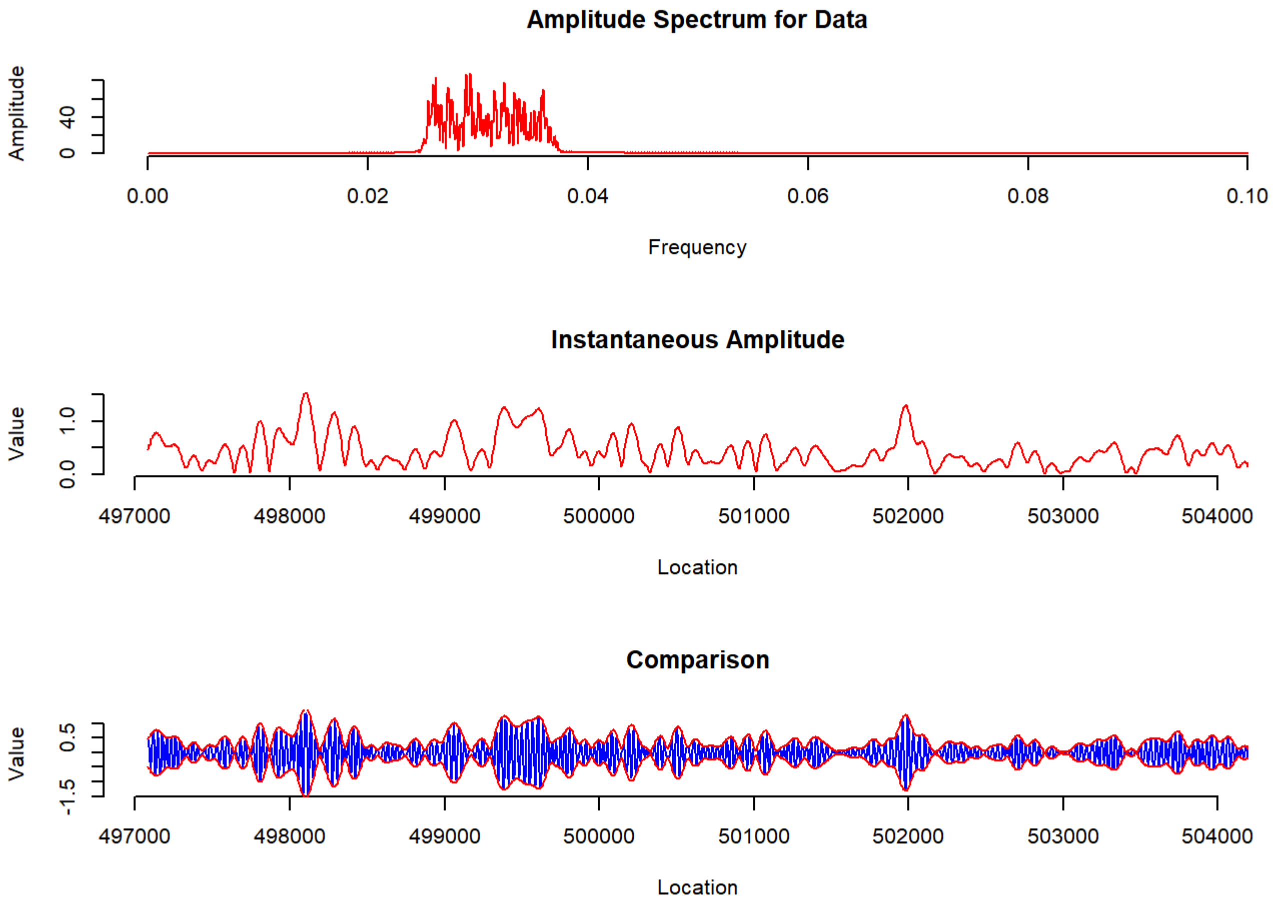

```
MIA_Ti__100_hilbert <- hilbert(MIA_Ti__100)
```

```
----- PERFORMING HILBERT TRANSFORM ON STRATIGRAPHIC SERIES -----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= -0.006772776
```




```
MIA_Ti__31_hilbert <- hilbert(MIA_Ti__31)
```

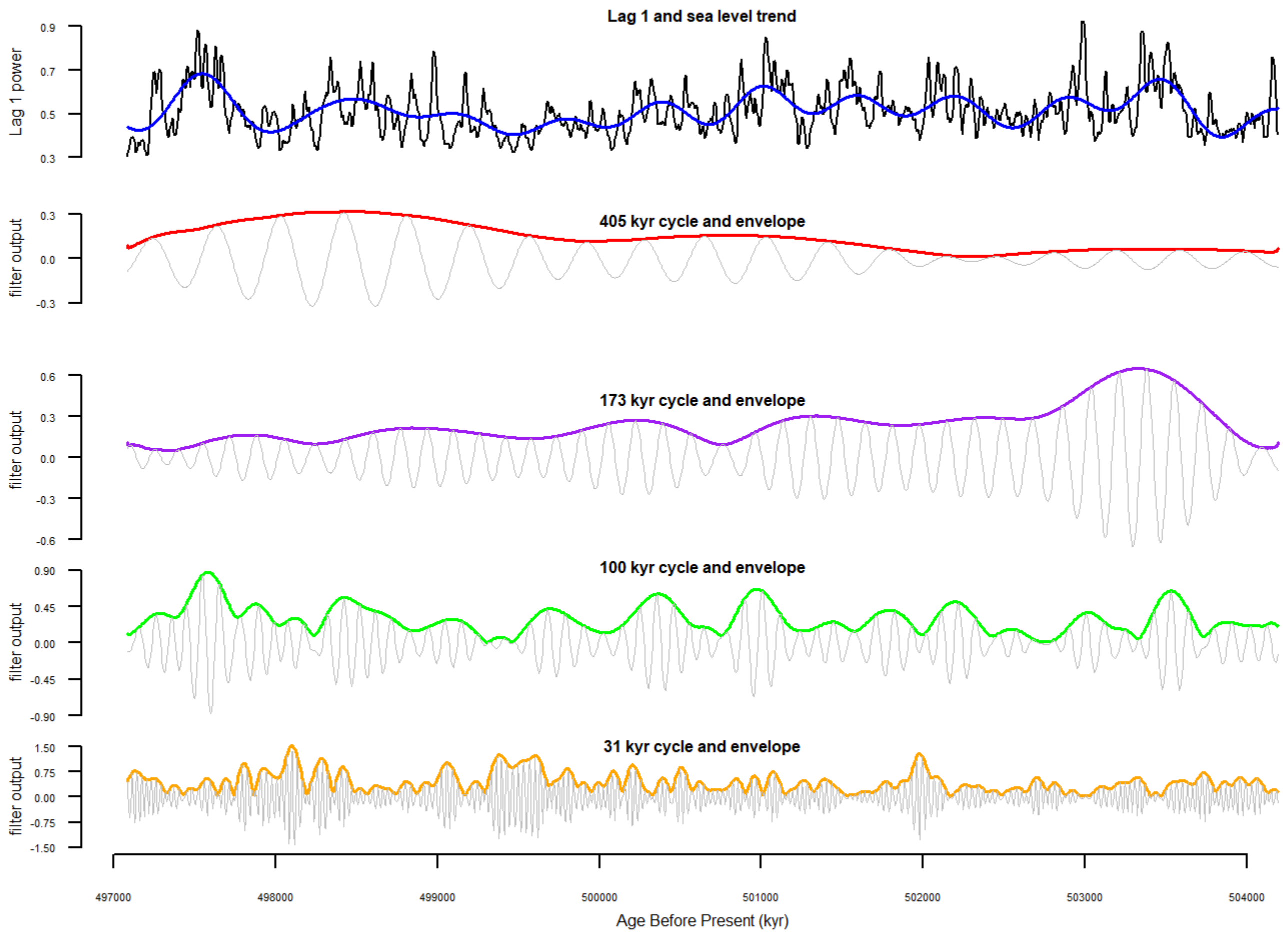
```
----- PERFORMING HILBERT TRANSFORM ON STRATIGRAPHIC SERIES -----
 * Number of data points= 1423
 * Sample interval= 5
 * Mean value removed= -0.006150106
```




```
  #Creation of a matrix to display the lag 1 results and the Milankovitch filters
  #in one single figure
    layout.matrix <- matrix(c(1,2,3,4,5), nrow = 5, ncol = 1)
    graphics::layout(mat = layout.matrix,
heights = c(1), widths = c(1))

  #Lag 1 results
    par(mar = c(0,3,2,1))

    plot(lag_1[,c(1,2)],
         type="l",
         ylab="",
         xlab = "",
         ylim=c(0.3,0.9),
         bty = "n",
         yaxt = "n",
         xaxt = "n"
         )

    axis(2, seq(from = 0.3, to = 0.9, by = 0.2), cex.axis = 0.5, las = 1)

    title(ylab="Lag 1 power", line=2.2, cex.lab=0.75)

    title(main ="Lag 1 and sea level trend", line=0, cex.main=0.75)

    lines(lag_1_background[,1],(lag_1_background[,2]),col="blue", lwd=1.5)


    # 405 kyr cycle and envelope
    par(mar = c(0,3,0,1))
```

```
plot(MIA_Ti__405_hilbert[,1],
     (MIA_Ti__405_hilbert[,2]),
     type = "l",
     col="red",
     lwd=1.5,
     ylim = c(-0.6,0.6),
     xlab = "",
     ylab = "",
     xaxt ="n",
     yaxt = "n",
     bty = "n"
     )

lines(MIA_Ti__405[,1],(MIA_Ti__405[,2]),col="grey", lwd=0.5)

axis(2, seq(from = -0.3, to = 0.3, by = 0.3), cex.axis = 0.5, las=1)

title(ylab="filter output", line=2.2, cex.lab=0.75)

title(main ="405 kyr cycle and envelope", line=-2.5, cex.main=0.75)

#173 kyr cycle and envelope
 par(mar = c(0,3,0,1))

 plot(MIA_Ti__173_hilbert[,1],
      (MIA_Ti__173_hilbert[,2]),
      col="purple",
      lwd=1.5,
      type = "l",
      ylab = "",
      xlab = "",
      yaxt ="n",
      xaxt = "n",
      bty = "n",
      ylim = c(-0.6,0.7)
      )

lines(MIA_Ti__173[,1],
      (MIA_Ti__173[,2]-mean(MIA_Ti__173[,2])),
      col="grey",
      lwd=0.5
      )

axis(2, seq(from = -0.6, to = 0.6, by = 0.3), cex.axis = 0.5, las=1)

title(ylab="filter output", line=2.2, cex.lab=0.75)

title(main ="173 kyr cycle and envelope", line=-2, cex.main=0.75)

#100 kyr cycle and envelope
 par(mar = c(0,3,0,1))

plot(MIA_Ti__100_hilbert[,1],
     (MIA_Ti__100_hilbert[,2]),
     col="green",
     lwd=1.5,
     type = "l",
     ylim = c(-1.1,1.1),
```

```
      bty = "n",
      ylab ="",
      xlab = "",
      yaxt = "n",
      xaxt = "n"
      )

lines(MIA_Ti__100[,1],(MIA_Ti__100[,2]),col="grey", lwd=0.5)

axis(2, seq(from = -0.9, to = 0.9, by = 0.45), cex.axis = 0.5, las=1)

title(ylab="filter output", line=2.2, cex.lab=0.75)

title(main ="100 kyr cycle and envelope", line=-1, cex.main=0.75)

#31 kyr cycle and envelope
 par(mar = c(3,3,0,1))

plot(MIA_Ti__31_hilbert[,1],
      (MIA_Ti__31_hilbert[,2]),
      col="orange",
      lwd=1.5,
      type = "l",
      ylim = c(-1.6,1.6),
      bty = "n",
      ylab ="",
      xlab ="",
      yaxt = "n",
      xaxt = "n"
      )

lines(MIA_Ti__31[,1],(MIA_Ti__31[,2]),col="grey", lwd=0.5)

axis(2, seq(from = -1.5, to = 1.5, by = 0.75), cex.axis = 0.5, las=1)

title(ylab="filter output", line=2.2, cex.lab=0.75)

axis(1, seq(from = 497000, to = 504000, by = 1000), cex.axis = 0.5)

title(xlab="Age Before Present (kyr)", line=2, cex.lab=0.75)

title(main ="31 kyr cycle and envelope", line=-0.5, cex.main=0.75)
```




```
    #Saving the lag-1 results and Milankovitch filters
#    write.csv(lag_1_background,"Lag1_20-90window_background_0-1over500kyr.csv")
#    write.csv(MIA_Ti__405_hilbert,"MIA_TI_rsp_5kyr_405kyr_hilbert.csv")
#    write.csv(MIA_Ti__173_hilbert,"MIA_TI_rsp_5kyr_173kyr_hilbert.csv")
#    write.csv(MIA_Ti__100_hilbert,"MIA_TI_rsp_5kyr_100kyr_hilbert.csv")
#    write.csv(MIA_Ti__31_hilbert,"MIA_TI_rsp_5kyr_31kyr_hilbert.csv")
```