Cyclic degassing of Erebus volcano, Antarctica

Tehnuka Ilanko[1*], Clive Oppenheimer[1], Alain Burgisser[2], Philip Kyle[3]

[1]Department of Geography, Cambridge University, Downing Place, Cambridge CB2 3EN, UK

[2]ISTerre, Université de Savoie – CNRS, Chambéry, Savoie, France

[3]Department of Earth & Environmental Science, New Mexico Institute of Mining & Technology, Socorro, NM87801, USA

[*]Corresponding author. Email: ti235@cam.ac.uk

Online resource 2: Wavelet power spectra

Wavelet transforms are an increasingly popular method for analysing periodicity in time series data. Similar to a Fourier transform analysis, a wavelet transform involves finding the coefficients that fit a known wavelet function to the measured data. A Fourier analysis decomposes the signal into components that fit a continuous sine wave, and thus assumes that the periodicity of the signal does not change over time (i.e. it is stationary). For non-stationary data, Fourier analysis over the entire time series cannot identify *when* changes in periodicity occur. A short-time (or windowed) Fourier transform, analysing the signal along smaller time windows within the data, provides some time resolution. The window size determines the balance between time resolution and frequency resolution. A small window will be highly localised in time, but have a poorer frequency resolution.

A wavelet analysis operates on a similar principle but uses a wavelet function, which has a finite time span, to provide a more balanced time-frequency resolution. The chosen 'mother wavelet' function should have an amplitude that sums to zero. A family of wavelets can be generated by scaling and shifting the mother wavelet. Here, we have used a Morlet wavelet function, following Oppenheimer et al. (2009) and Grinsted et al. (2004).

The MATLAB codes used for calculating the cross-correlation and coherence are from Grinsted et al. (2004), following Torrence & Compo (1998) and Torrence & Webster (1999). Here, we outline the pre-processing applied to our data, and associated limitations.

Regions with short-lived high power over a wide period range may, in some cases, arise from (<3 min) data gaps where fitting errors were high. This results in apparent periodicities at high frequencies. Adapting the filtering procedure to avoid these gaps would require including retrievals that were not well fit to the measured spectra, and which also cause periodicity at high frequencies. A comparison of wavelets generated with and without filtering and resampling (Fig. B1) showed that it does affect wavelet results, particularly at high frequencies, but that the structures at lower frequencies highlighted persist. We therefore do not consider the high frequency perturbations further in this study.

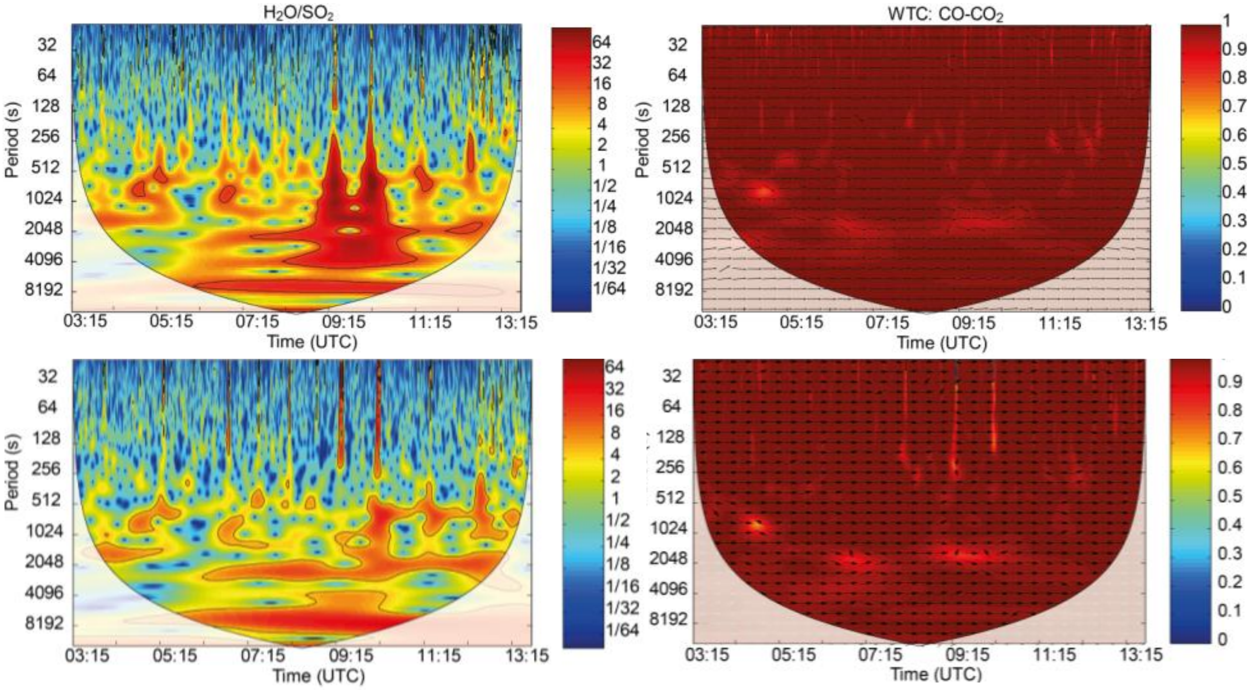

Figure B1. Comparison of wavelet ratio periodograms (H_2O/SO_2) and coherence (CO-CO2) plots generated including (top) and excluding (bottom) FTIR retrievals with 'goodness of fit' errors greater than 5% (CO, CO_2, H_2O, SO_2, HCl) and 10% (OCS, HF).

The published code also assumes the data are uniformly spaced in time. Since the sampling rates may not be even, and filtering for high error leaves gaps in the data, here they have been resampled using a Fourier transform. The Fourier coefficients of the data are found and used to regenerate a dataset at uniform intervals. Unlike a linear or polynomial interpolation, the Fourier method does not place greater weighting on the data points immediately nearest to an interpolated point. Using a Fourier interpolation therefore reduces a bias towards high frequency changes. While it may require greater computational time than other interpolation methods, the difference is negligible for the data sizes dealt with here.

We note also that some caution is required in interpreting certain types of broadband features in the periodograms. Rapid and short-lived perturbations, such as from puffs of gas during passive degassing, or gas released by explosions, may result in effects similar to those at the edge of the dataset, where a cone of influence is marked. This is demonstrated in Figure B2, where a wavelet power spectrum has been computed for an impulse function in a dataset of identical length and sampling rate to that presented here. The delta-like function will appear to have infinite periodicities, and thus the significant area in its periodogram will cover longer times at long periods, resulting in false broadband periodicities. Although filtering by goodness of fit of the column amount retrievals should remove some such data, not all sudden increases in degassing yield poor retrievals, and interpolation may recreate some of this effect.

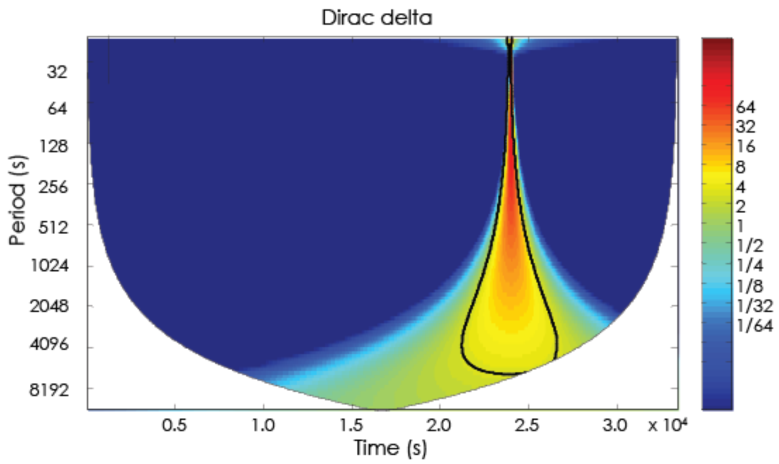

Figure B2. Wavelet periodogram calculated for a time-delayed Dirac delta. Colour scale shows wavelet power normalised by variance. White area represents area outside cone of influence. Note the shape of the high significance area, which resembles that at the edges of the periodogram where the time series ends

As the alternative is to include retrieved gas amounts that have a poor fit to the measured spectra, and as the features highlighted in the periodograms and coherence plots are present in both filtered and unfiltered versions, we have considered the filtering and interpolation acceptable.

Finally, Grinsted et al. (2004) suggest that these analyses produce more reliable and significant results if the input data have a normally distributed power density function. The Erebus gas data (after being filtered as described above) are closer to a log-normal than a normal distribution. However, the periodograms generated from taking the logarithms are sufficiently similar to those from the data themselves that it was not considered necessary to process the data further.