Electronic Supplementary Material (ESI) for Journal of Analytical Atomic Spectrometry.

Electronic Supplementary Information

Here we carry out two different experiments, "uniformity of multiple time scale" and "autocorrelation function", to test the temporal dependence of our observed RFCE changes. Both methods have been used in spatial and temporal analyses in astrophysics.[1,2] In sight of these two experiments, we discuss the evidence of the significant changes of the RFCEs of H1, H2, and H3 and no significant changes of the RFCEs of L1 or L2.

Uniformity of Multiple Time Scales

Given a n-length time sequence $s_1, s_2, ..., s_n$, let $\overline{s}_b$ denote the mean value of the data in the bth bin, where bins are separated in fixed time scales. These b mean values have the mean value of $\overline{\overline{s_b}}$. Note that $\overline{\overline{s_b}}$ is also the mean value $\overline{s}$ of the original time sequence s_i. Then we compute the standard deviation δ of the b bin mean values, weighted by the number of data points (w) in each bin, as

$$\delta = \sqrt{\frac{\sum_{i=1}^{b} w_i}{(\sum_{i=1}^{b} w_i)^2 - \sum_{i=1}^{b} w_i^2} \sum_{i=1}^{b} w_i(\overline{s_i} - \overline{s})^2}. \quad (1)$$

The δ value describes the dispersion of the b bin mean values when a fixed bin width is given. We then estimate the standard deviation of δ using a bootstrapping method. Our procedure is as follows: for each data point in the signal sequence, we have an estimate of s_i and an uncertainty σ_i (standard error). In each bootstrap trial, we generate a random realization of the signal sequence by drawing a set of random values for each data point from their Gaussian distributions with mean s_i and standard deviation σ_i. We then compute the dispersion of the bin mean values δ for this random realization. We repeat this procedure 1,000 times, thereby deriving a sample of 1,000 values for δ. We take the mean and standard deviation of these 1,000 realizations as our central value $\langle\delta\rangle$ and 1σ uncertainty σ_δ. Here, the angle brackets $\langle\cdot\rangle$ denote averaging over the realizations. To compare with, we also generate an artificial noise array, i.e., a random time sequence with normal distribution (mean = 0, standard deviation = σ_i) at each time point, and apply the same bootstrapping method to compute $\langle\delta\rangle$ and σ_δ as described above. At a given bin width (i.e., time scale), if the δ value of the signal sequence significantly deviates (at 1σ level here) from that of the zero-averaged noise sequence, the signal sequence is detected to have intrinsic temporal variabilities distinguishable from the noise sequence.

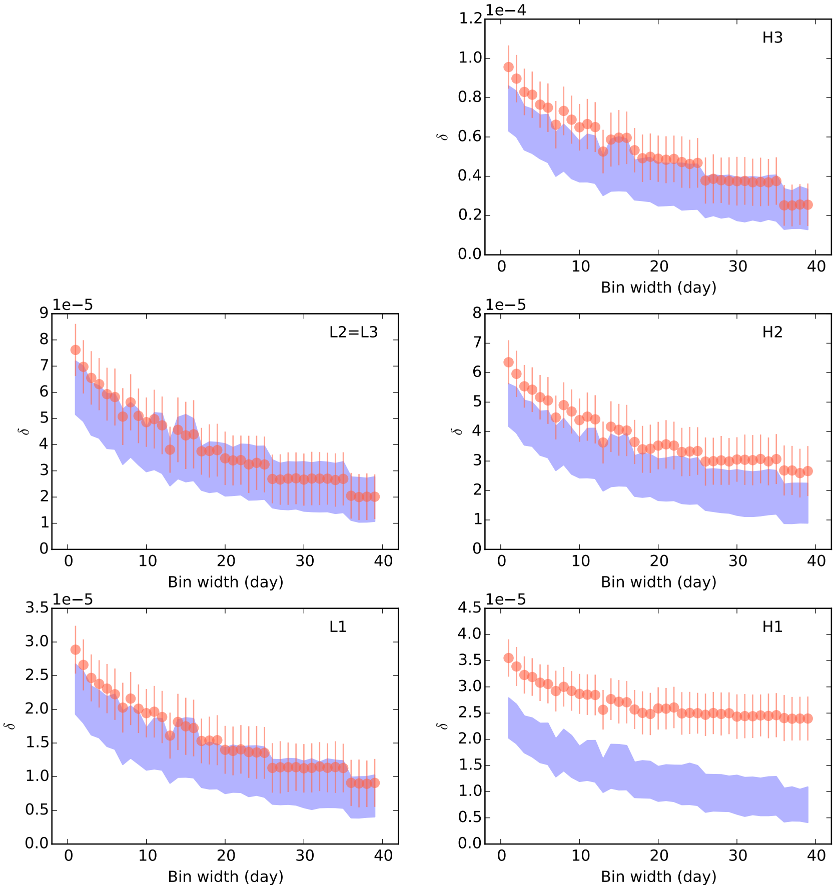

Figure 1: Relation between the dispersion of bin mean values (δ) and bin width (time scale). Red dots and error bars are δ values of the signal sequences (i.e., RFCE changes) and their 1σ errors. Blue bands are the 1σ ranges of δ of zero-averaged noise sequences.

We illustrate the relation between δ and bin width (time scale) for both the signal sequences (i.e., RFCE changes of the Faraday cups) and the generated noise sequences in Figure 1. It clearly shows that H1 has the strongest trend of varying RFCEs, and that the signal points of H2 are all above the 1σ band of the noise, while H3 only shows small-scale variabilities. In contrast, the δ values of L1 and L2 are overwhelmed by the blue noise bands in general, implying that their RFCEs do not show significant changes and are uniform of both small and large time scales.

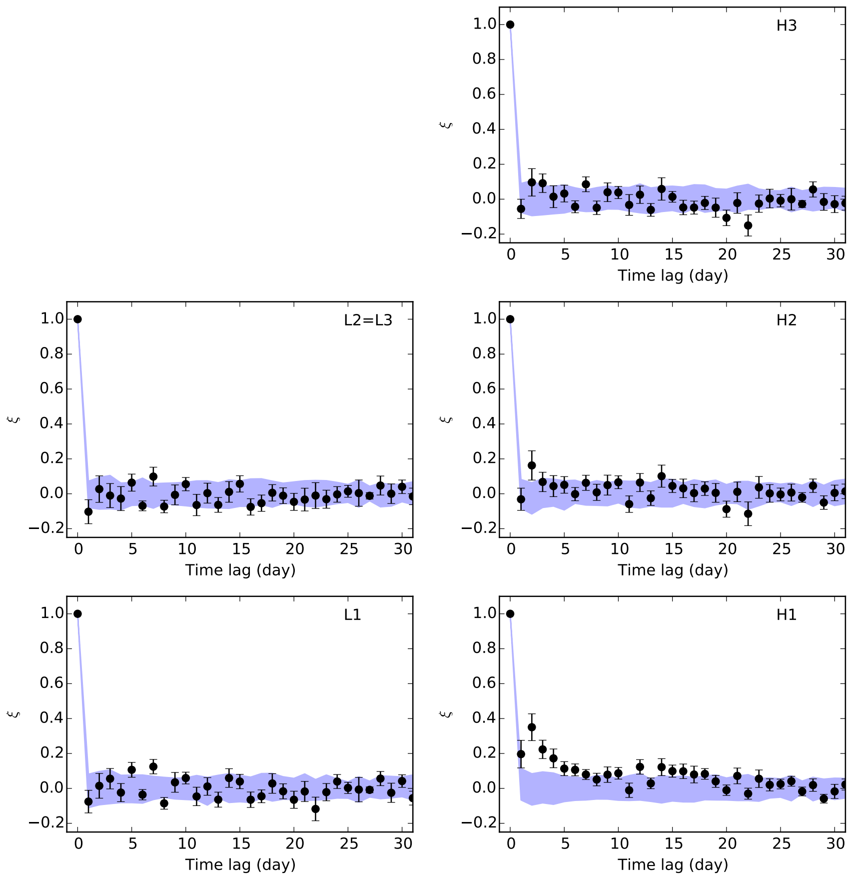

Figure 2: Relation between the autocorrelation function (ξ) of time sequences and time lag. Black dots and error bars are ξ values of the signal sequences (i.e., RFCE changes) and their 1σ errors. Blue bands are the 1σ ranges of ξ of zero-averaged noise sequences.

Autocorrelation Function

Autocorrelation function is another method to describe the intrinsic variability of a time sequence, defined as

$$\xi(k) = \frac{\sum_{i=1}^{n-k}(s_i - \overline{s})(s_{i+k} - \overline{s})}{\sum_{i=1}^{n}(s_i - \overline{s})^2}. \quad (2)$$

The autocorrelation function of a time sequence reflects the correlation of all pairs of data points with a given time lag k, i.e., its periodicity (for detailed discussion, see this webpage). Even if our time sequence is not periodical, non-zero autocorrelation function can reveal some fine-structure correlations, which is an indication of intrinsic temporal variability. In practice, we apply the same bootstrapping method as described above to calculate $\langle\xi\rangle$ and σ_ξ values of the original signal sequences and artificially generated noise sequences.

We illustrate the relation between ξ and time lag for both signal and noise sequences in Figure 2. Only H1 and H2 show significant correlations (i.e., temporal variabilities) at small time lags ($k < 5$ days), while all the others act similarly like noise.

References

1. K. Kreckel et al., *MNRAS*, 2020, **499**, 193-209.
2. S. Kozłowski, *ApJ*, 2016, **826**, 118-134.

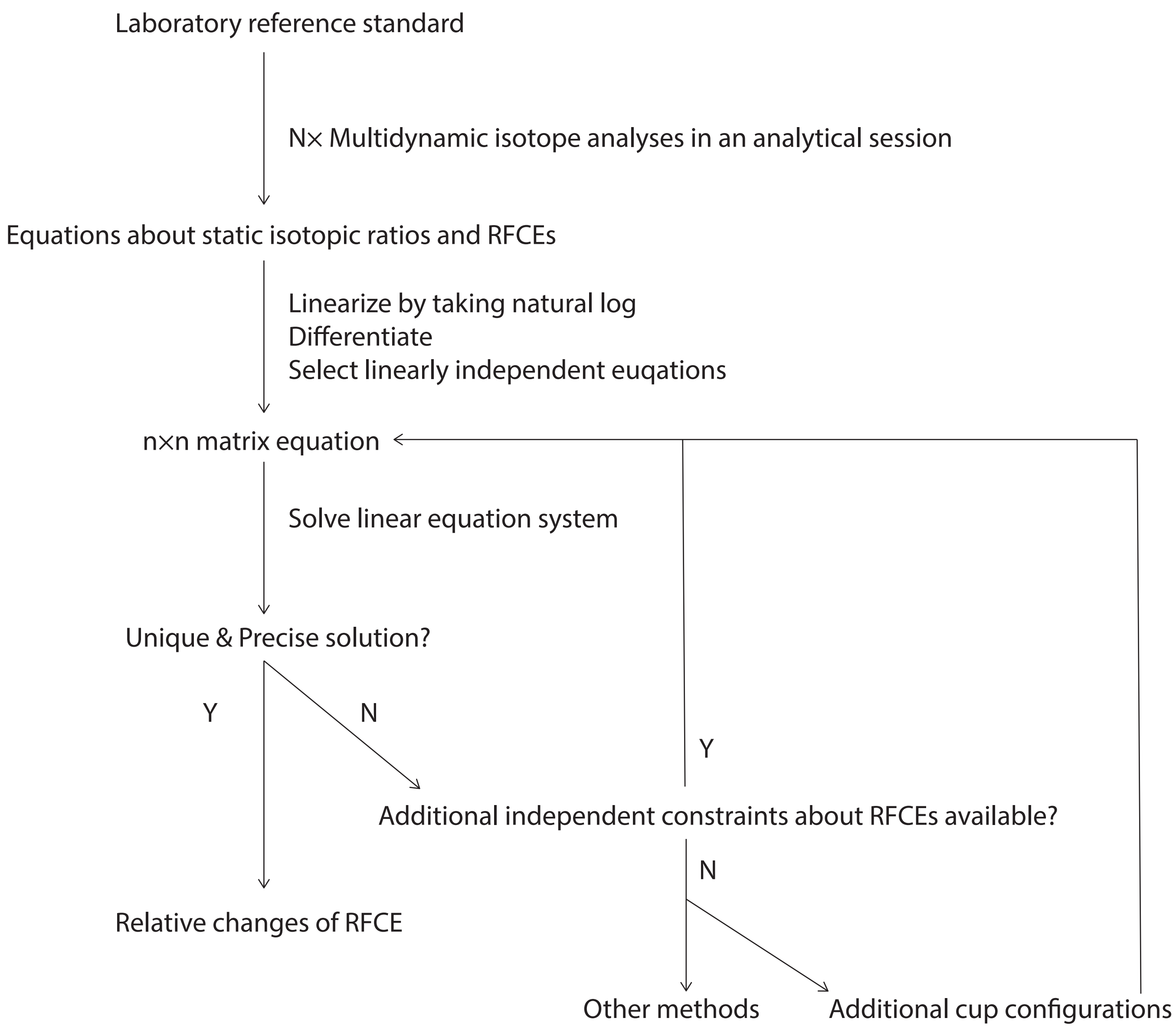

Figure 3. Flow chart of the calculation method used in this study (described in section 4 and 5.2 in the main text).