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Solar irradiance: from multiple observations to a single composite

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Abstract. We review recent developments in combining solar irradiance datasets from different instruments to obtain one single composite, which is the key to understanding how irradiance varies on decadal timescales and beyond.

Keywords. Solar irradiance, Solar variability

1. Context

The solar electromagnetic spectrum and its evolution in time are paramount for understanding solar variability and for quantifying its impact on Earth's climate. Several instruments have been monitoring the total radiative output of the Sun (TSI, or total solar irradiance) and the spectrally-resolved solar irradiance (SSI, or spectral solar irradiance) since the 1970's. These observations have deeply impacted our perception of how the Sun varies in time (Ermolli *et al.* 2013, Solanki *et al.* 2013). Today there is a growing demand for understanding solar variability on timescales of decades and beyond. This is considerably longer than the lifetime of an individual instrument. Such an objective can be met only by doing data fusion, i.e. by carefully stitching together the different data sets to make one single and homogeneous composite.

2. Fragmented observations

Both the SSI and the TSI have been monitored by multiple missions. However, as Figure 1 shows, the observations are highly fragmented in time and in spectral coverage, which considerably complicates making a composite record. We are facing two practical problems here. First, as shown by Figure 1, there are frequent periods during which specific spectral bands are not observed. Such voids can be filled only by having recourse to SSI models. Conversely, there are also periods when several instruments are observing simultaneously. One then has to make the best use of all available datasets, which often differ in spectral resolution, temporal resolution, stability, etc.

Different approaches have been developed for merging simultaneous observations. There is a long history of applying such methods to combine observations of the sunspot number. This problem has recently received considerable interest because of the impact the choice of the method may have on estimates of the long-term solar variability (Clette *et al.* 2014).

One common composite-creation method is the backbone method, which relies on a small subset of overlapping time series ("backbones") that offer the longest duration of observations. Daisy-chaining is a method that consists of stitching together records

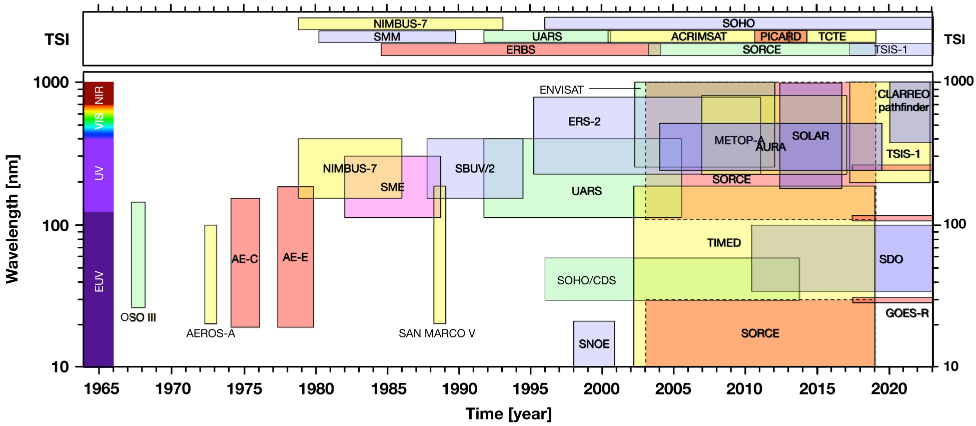

Figure 1. Overview of the main satellite missions that have been making SSI or TSI observations. The quality and resolution are highly mission-dependent.

by comparing them during an overlap period when there are at least two observers. Daisy-chaining has also been used for making solar irradiance composites, such as the intensity of the Lyman-α line (Woods *et al.* 2000), the MgII index (Viereck *et al.* 2004) and the TSI (Fröhlich 2006). In all these reconstructions, at each time step the data from one single instrument are selected, generally the "best" one. DeLand & Cebula (2008) were the first to use daisy-chaining with SSI data and came up with a composite of the UV flux between 120 and 400 nm. Because relative errors tend to be considerably larger in the SSI than in the TSI for the MgII index, the transition from one instrument to another tends to produce discontinuities that hamper the analysis of long-term variations.

A different attempt for combining SSI records was used by Haberreiter *et al.* (2017), who decided instead to combine all existing observations by weighted averaging. In addition they bypassed the daisy-chaining by doing a more global merging. The same approach has been applied to the TSI by Dudok de Wit *et al.* (2017).

3. Making the composite

Although the backbone and the daisy-chain methods are appreciated for their conceptual simplicity, they fail to meet some of the important standards of transparent and reproducible science. First, by selecting one instrument only out of several (and discarding the others) one throws away precious information. Second, the selection of the backbone or the preferred instrument is often based on subjective evaluation. In the absence of quantitative criteria for determining which observations are of the best quality, it becomes difficult to assess the uncertainty of the end product and update the latter when new data become available.

To overcome these shortcomings we developed a new statistical framework that exploits all available information and explicitly states what the assumptions are. Its main ingredient is the notion of uncertainty: each observation comes with a data-driven uncertainty that quantifies its quality. This uncertainty then allows us to assign different weights to the observations when combining them for building a composite. The Bayesian framework is ideally suited for this (Gelman *et al.* 2013). However, while we are still working on a fully Bayesian method, at this stage we consider a simpler maximum likelihood approach.

The main steps of the method are (see Dudok de Wit *et al.* 2017 for details):

(a) Determine the uncertainty of the observations by applying the same estimator to all records. This is crucial for allowing them to be meaningfully compared. Although some

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data sets include uncertainties, these values often cannot be compared because they rely on different assumptions.

(b) Decompose the observations and their uncertainties into different timescales (e.g. by using a wavelet decomposition) because their properties are timescale dependent. In general the uncertainty on short timescales (called precision) is better understood than that on long timescales (called stability).

(c) Merge the different observations by doing a weighted average, scale-by-scale, using their uncertainty to weight them. Finally, the composite is obtained by recombining all timescales. The uncertainty of the composite is obtained by error propagation.

This approach has been successfully applied so far to the determination of the new TSI composite, which is presently undergoing validation tests and TSI-community endorsement before we propose it as the new official TSI composite.

4. Significance of results

Our new approach for making composites by data fusion raises several methodological questions, such as the importance of distinguishing the statistical problem (What is the best way of assembling the observations to obtain a composite?) from the scientific one (What prior information may I use to correct the original data sets?).

Interestingly, we often find the uncertainties of SSI and TSI records to behave as pink noise, with a $1/f$ scaling of their power spectral density. Such a scaling is a hallmark of non-stationarity. It also means that the uncertainty of the difference between the SSI (or TSI) taken at two different dates depends on the time interval, unlike what would happen with white noise. Consequently, the popular notion of stability as a time-invariant rate is not appropriate and should be replaced by a scale-dependent uncertainty.

Finally, thanks to the possibility of estimating uncertainties at different timescales and propagating them to the end product, for the first time we are able to obtain realistic and time-dependent values of uncertainty of the composite. For the TSI, the standard deviation of the uncertainty ranges from 0.4 W/m^2 in the 1980's to less than 0.1 W/m^2 after 2000, with the improvement largely being due to newer instruments having lower noise. (Note that these are *relative* uncertainties, not *absolute* scale uncertainties.) These values may seem small, but they imply that differences between TSI levels observed during different solar minima are barely or not statistically significant. In particular, they warn us against the risk of over-interpreting weak trends.

References

Clette, F., Svalgaard, L., Vaquero, J. M., & Cliver, E. W. 2014, *SSR*, 186, 35

DeLand, M. T., & Cebula, R. P. 2008, *JGR*, 113, 11103

Dudok de Wit, T., Kopp, G., Fröhlich, C., & Schöll, M. 2017, *GRL*, 44, 1196

Ermolli, I., Matthes, K., Dudok de Wit, T. *et al.* 2013, *ACP*, 13, 3945

Fröhlich, C. 2006, *SSR*, 125, 53

Gelman, A., Carlin, J. B., Stern, H. S., Rubin, D. B., & Dunson, D. B. 2013, *Bayesian Data Analysis* (London: Chapman & Hall)

Haberreiter, M., Schöll, M., Dudok de Wit, T., *et al.* 2017, *JGR*, 122, 5910

Solanki, S. K., Krivova, N. A., & Haigh, J. D. 2013, *ARAA*, 51, 311

Viereck, R. A., Floyd, L. E., Crane, P. C. *et al.* 2004, *Space Weather*, 2, S10005

Woods, T. N., Tobiska, W. K., Rottman, G. J., & Worden, J. R. 2000, *JGR*, 105, 27195