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**An introduction to factor analysis for radio frequency interference (RFI) detection on
satellite observations**

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ABSTRACT

A novel radio frequency interference (RFI) detection method is introduced for satellite-borne passive microwave radiometer observations. The method is based on factor analysis, in which, variability among observed, correlated variables are described in terms of *factors*. In this article, the method is applied to the TRMM/TMI and Aqua/AMSR-E satellite measurements over land surface to detect the RFI signals, respectively, in 10 GHz and 6 GHz channels. The RFI detection results are compared with other traditional methods, such as, spectral difference method and principal component analysis (PCA) method. It has been found that the newly proposed method is able to detect RFI signals in the C and X-band radiometer channels as effective as the conventional PCA method.

Keywords: radio-frequency interference (RFI); TRMM Microwave Imager (TMI); Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E); passive microwave radiometry; land surface retrieval; identification algorithm;

1. INTRODUCTION

The Radio Frequency Interference (RFI) on satellite observations is known as the disturbance of electromagnetic radiation that interrupts the natural radiometric measurements by the satellite sensors. In other words, the natural thermal emission of the earth is obscured by active microwave sensors. The RFI poses a serious problem in satellite measurements, particularly at lower frequency bands, as they are mostly the un-protected bands in the microwave region (Johnson *et al.* 2006; Piepmeier *et al.* 2008; Misra *et al.* 2009; Adams *et al.* 2010). Currently, many microwave sensors are operated in unprotected bands, in order to facilitate specific geophysical retrieval. If the RFI signals are not adequately detected or removed from the satellite measurements, they can introduce significant errors in the retrieval process (Leroux *et al.* 2013). It is therefore necessary to reject the RFI signals prior to applying the retrieval algorithms on satellite measurements.

In the context of passive microwave (PMW) remote sensing, the existence of RFI errors are noted on those satellite sensors, having lower frequency channels, for instance, the SSM/I, WindSat, TMI, AMSR-E, and recently launched AMSR2 measurements. Generally speaking, the RFI locations are persistent in time and populated in urban areas (Li *et al.* 2004; Chaurasia *et al.* 2012). Therefore, a pre-processed RFI map may help to detect and remove the stationary RFI scenes, to a limited extent. Njoku *et al.* (2005) have provided a global survey of RFI contamination for 6.9 and 10.7 GHz frequencies. Nevertheless, simple RFI map is not able to detect all RFI signals, especially the signals that are not stationary and originating from new RFI sources.

As the RFI is becoming an increasingly serious hindrance in PMW remote sensing research and applications, there have recently been some progresses made to detect the RFI contamination. Primarily, many studies have found a good promise in detecting strong RFI contaminated scenes by employing simple spectral difference method (Li *et al.* 2004; Ellingson and Johnson 2006; Wu and

Weng 2011). A variation of the spectral difference method incorporating the means and standard deviations of the spectral indices has also been found effective (Njoku *et al.* 2005). Truesdale (2013) has developed a probability distribution method for computing the likelihood of brightness temperature measurements containing RFI signals. Lacava *et al.* (2013) have implemented a multi-temporal robust satellite techniques approach to identify the RFI signals. In addition, the uses of principal component analysis (PCA) indices have allowed even more accurately detecting the RFI signals (Li *et al.* 2006; Zou *et al.* 2012; Zhao *et al.* 2013).

In this paper, we propose and introduce a novel RFI detection technique that adapts the spectral difference method with factor analysis (FA) implementation. At this stage, the method is applied to the TMI and AMSR-E datasets over land surface. The method is comprehensively compared with other traditional RFI detection techniques, including, spectral difference method, PCA, and normalized PCA.

This paper is organized as follows. Section 2 provides a brief description of the datasets used. The factor analysis based RFI detection technique is introduced in Section 3. The execution of the factor analysis technique along with the results obtained from some other traditional RFI detection techniques are presented in Section 4. Section 5 offers a summary of the work.

2. DATA

The principal datasets used in this work are the TMI calibrated and AMSR-E resampled brightness temperature data.

The TMI onboard the TRMM satellite is based on the design of the Special Sensor Microwave/Imager (SSM/I). It is a multi-channel, dual polarized, conical scanning passive

microwave radiometer that measures the intensity of radiation at five separate frequencies: 10.7, 19.4, 21.3, 37, 85.5 GHz. Its swath width is 760 km on the surface. In order to maintain the consistency in measurements, two external calibration targets (one cold, one hot) are used. Spatial resolutions of the measurements vary based on the channel frequencies. Low frequency channel, that is 10.65 GHz channel, has a resolution of 63 x 37 km. By contrast, the higher-frequency channels have smaller footprint sizes (e.g. 7 x 5 km for 85.5 GHz). In depth description of the TMI instrument is described in Simpson *et al.* (1996), Islam *et al.* (2012), Islam *et al.* (2014a), and Islam *et al.* (2014b). In this article, the datasets are obtained from the Level 1B product files (1B11), available at NASA Goddard DAAC.

On the other hand, the Advanced Microwave Scanning Radiometer for EOS (AMSR-E) is a conically scanning passive microwave radiometer system that measures brightness temperatures at six frequencies starting from a C-band frequency at 6 GHz (6-89 GHz). The instrument has dual polarization capability, which leverages to separate horizontally and vertically polarized measurements at each frequency. The observations of cosmic background radiation and an on-board warm target are used to facilitate the necessary calibration of the measurements. Spatial resolution of the individual channel measurements differs from 5.4 km at 89.0 GHz to 56 km at 6.9 GHz. A comprehensive description of the AMSR-E instrument is given in Kawanishi *et al.* (2003). In this work, the brightness temperatures data are taken from AMSR-E Level-2A (AE_L2A) Global Swath Spatially-Resampled Brightness Temperatures product, obtained from NSIDC DAAC in Boulder, Colorado. That means footprint sizes for all twelve channels are spatially consistent.

3. THE RFI DETECTION METHODS

Traditionally, spectral difference method has been acknowledged as a good way to detect RFI pixels over land surface. The fundamental perception of the spectral difference method is based on the

physical phenomenon of surface emissivity with respect to frequencies. Naturally, higher frequency channels those are sensitive to land surface should have higher brightness temperature measurements than the lower frequency channels for the same polarizations:

$$TB_{Higher} - TB_{Lower} > 0 \quad (1)$$

where, TB_{Higher} and TB_{Lower} can be 6 GHz (10 GHz) and 10 GHz (18 GHz), respectively. This is mainly due to the fact that dielectric constant of water over land surface varies with respect to frequencies, and as such, the resulting surface emissivity increases with respect to frequencies. Nevertheless, if a particular frequency is contaminated by RFI signals, a reversed spectral gradient is seen as:

$$TB_{Lower} - TB_{Higher} > 0 \quad (2)$$

By using this simple spectral measurement difference (spectral index) in a given polarization, one can identify for possible RFI contamination. Previously, Yang *et al.* (2011) have mentioned that 5 K is a good threshold to detect RFI signals, based on a microwave land surface emissivity model over various land types at 10 GHz.

Due to natural radiation measured by radiometer channels, a good correlation exists between the channel measurements. Nonetheless, the spectral difference method does not account for this natural correlation between the channels in identifying RFI signals. Therefore, the spectral difference method has been incorporated with principal component analysis (PCA) by several authors, and noted as very effective for RFI detection.

Mathematically, let data matrix X to be constructed from RFI indices derived from satellite brightness temperature observations and centered so that each column has mean zero. Then, based on the singular value decomposition,

$$X = UDV^T \quad (3)$$

where, U and V are orthonormal, and D is diagonal with non-negative and decreasing values. The covariance matrix is then constructed from the data matrix X :

$$S = n^{-1} X^T X = n^{-1} VDU^T UDV^T = n^{-1} VD^2 V^T \quad (4)$$

Note that PCA is based on linear combinations of X that are uncorrelated and are of high variance. On the other hand, factor analysis looks for linear combination of variables known as factors. Theoretically, the factor analysis model for $k < p$ common factors is:

$$x = \mu + \Lambda f + u \quad (5)$$

where, f is uncorrelated having unit variance, u has unknown diagonal covariance matrix Ψ , and f and u are taken to be uncorrelated.

In fact, factor analysis can be written as a model for the covariance matrix Σ of the data:

$$S = LL^T + \Upsilon \quad (6)$$

This decomposition with $p \times k$ matrix Λ introduces a k factor model. The decomposition is scale independent, therefore, this can be considered as a model of the correlations of the data matrix.

Since, PCA also seeks a linear space like Λf to explain the data, the covariance matrix is defined as:

$$S = LL^T + \Xi \quad (7)$$

where, Ξ is the error matrix, which is not diagonal. Therefore,

$$\Sigma - \Psi = \Lambda\Lambda^T \quad (8)$$

where, $\Lambda = p \times k$.

Note that the data matrix X is comprised of RFI indices, and the RFI indices vector is prepared as a function of spectral difference signatures. For instance, for the TMI imager, a vector of five component RFI indices can be written as:

$$R_{indices} = \begin{pmatrix} TB10V - TB19V \\ TB10H - TB19H \\ TB19V - TB21V \\ TB21V - TB37V \\ TB19H - TB37H \end{pmatrix} \quad (9)$$

Besides, normalized RFI indices can be used as follows:

$$R_{indices} = \begin{pmatrix} \frac{TB10V - TB19V - \mu}{\sigma} \\ \frac{TB10H - TB19H - \mu}{\sigma} \\ \frac{TB19V - TB21V - \mu}{\sigma} \\ \frac{TB21V - TB37V - \mu}{\sigma} \\ \frac{TB19H - TB37H - \mu}{\sigma} \end{pmatrix} \quad (10)$$

where, μ and σ are the mean and standard deviation of the five RFI indices, respectively.

4. RESULTS AND EXECUTION

In this article, we will be investigating the RFI detection by five different techniques: spectral difference method, PCA method, normalized PCA (N-PCA) method, FA method, and normalized FA (N-Factor) method. Note that, for the normalized methods (N-PCA and N-Factor), the normalized RFI indices are used as inputs. It is also worth mentioning that scattering effects originating from snow and ice can also lower the brightness temperatures at higher frequency channels than lower frequency channels. This could result into false RFI signals. Therefore, in this work, only satellite measurements from summer period are investigated. Further, primary RFI signals are originated

from land-based sources, such as transmitters used by active commercial services. Therefore, the investigation is restricted to land surface only.

For the sake of clarity, we show the averaged spectral difference map for 10 GHz vertical polarization channel (TB10V – TB19V) for a day in Figure 1, from TRMM/TMI. It can be seen that, in some places, the brightness temperatures at low frequency channels are considerably higher than the measurements at high frequency channels (positive spectral difference). Such positive spectral difference signatures show an indication of possible RFI contamination. The difference can be as high as 10 K in some areas. The RFI contamination is more pronounced in Mexico and parts of South America, and in Western Asia.

The spectral difference signatures can further be explained through scatter plots between 10 GHz and 19 GHz channels, with the same polarization (Figure 2). The scatter plots are constructed from two different domain of interest on 1st August 2013 TMI data. The data points shown in the top panels are from the South America region, whereas, the data points given in the bottom panels are from the Western Asia region. The positive spectral differences with 5 K threshold are denoted as red and rest other points are denoted as black. Assuming 5 K as a threshold, a linear correlation exists in RFI free data points. By contrast, more than 50 K positive differences are seen at 10 GHz channel than the 19 GHz channel, implying RFI signals. Therefore, certainly, the use of spectral difference signatures as RFI indices in the PCA and FA methods would further help to detect the RFI signatures. Nevertheless, it is important to be remembered that weak RFI signals are difficult to distinguish from spectral difference signatures, due to natural geophysical variability in the measurements.

Figure 3 presents the spatial distribution of RFI detection by five different techniques. This particular example is constructed from five-day TRMM/TMI data, over the Mexico. The averaged values for the spectral difference index for vertically polarized 10 GHz band are shown. Corresponding PCA, N-PCA, Factor and N-Factor indices are also included. Higher the index score, higher the RFI contamination will be. Apparently, the RFI distributions by different methods are very similar, the figure shows. More importantly, it is encouraging to see that the newly developed RFI detection technique by the factor analysis can detect very similar to those detected by the PCA method. Such performance is evident for both factor analysis and normalized factor analysis methods.

Another example of RFI identification is shown in Figure 4 for one day averaged TMI data. The plots exhibit the RFI contaminated signals over Western part of the Asia on 1st April 2013. Again, the RFI detection by the factor analysis methods (Factor and N-Factor) is in close agreement with the PCA method (PCA and N-PCA).

Nevertheless, selecting a threshold to remove RFI signals for different techniques is quite arbitrary. Generally, a threshold of 5 as PCA index, 1 as N-PCA index, and 0.5 as Factor and N-Factor index agree well with each other in screening the RFI signals from satellite measurements. Figure 5 demonstrates the efficiency of the RFI removals by different detection techniques with the above thresholds, but for the same example, as shown in Figure 4. The thresholds used here are chosen by subjective examination. One can clearly see that factor analysis method is efficient enough to detect and screen the RFI signals. In other words, both PCA and FA methods agree reasonably well with each other in excluding the RFI signals.

Another way to examine the performance of the RFI detection is through observing the channel correlations. Naturally, microwave signals produced from different channels are highly correlated with each other. On the contrary, RFI signals are not due to natural variation of microwave radiation, rather they introduce from external targets. Therefore, in the presence of RFI signals in a given channel, the correlations of that channel to other channels will be significantly lower. As such, we construct the multi-channel correlations on RFI-contaminated and RFI-free scenes in Figure 6. This figure is constructed from multiple summer day observations separating into RFI-free and RFI-contaminated pixels, as detected by the factor analysis method. Left panel displays the correlations in RFI-free pixels and right panel displays the correlations in RFI-contaminated pixels. It can be seen that channel correlations in RFI-contaminated pixels are smaller than the RFI-free pixels.

It is worth mentioning that only one narrow band is allocated in the 10.6-10.7 GHz range to passive sensing. That is why, some RFI signals have been noted in the TMI's lowest frequency channel at 10.65 GHz (X-band). On the other hand, in the 6.7-7.1 GHz, no bandwidth is allocated to passive sensing. Therefore, more RFI contamination is expected in the AMSR-E 6.9 GHz channel (C-band). Figure 7 demonstrates the RFI signals at 6.9 GHz for vertical polarization as found by the five methods, but applied to one AMSR-E orbital pass data onboard Aqua satellite. Significant RFI signals are seen in this orbital pass. Similar to the results shown for TMI data, it is evident that the factor analysis method successfully detects the RFI signals in 6 GHz channel. One can confirm that the factor analysis method is equally effective as of the well-known PCA method. This is true for both normalized and un-normalized RFI indices.

It is important to outline that, in general, 6 GHz channel is avoided in certain geophysical retrieval algorithm (e.g. soil moisture) due to significant RFI contamination in this band. As such, with the

help of the RFI detection techniques, and by employing certain index thresholds, one can reject the possible RFI contaminated signals, prior to use the 6 GHz channel in their retrieval algorithms. This will eventually improve the geophysical retrieval, as a whole, at least on those areas, where RFI contamination is minimal.

5. CONCLUSIONS

The microwave information over land at low frequency channels is mainly used to obtain important surface properties such as soil moisture, skin temperature, and vegetation information (Gupta *et al.* 2013; Srivastava *et al.* 2013a; Srivastava *et al.* 2013b; Srivastava *et al.* 2013c). This information is extremely important for not only satellite data assimilation studies, but also for geophysical retrievals and product monitoring purpose. Furthermore, many applications are directly impacted by the geophysical products, thus satellite measurements, including the applications in hydrology, ecology, climate change, and in weather forecasting. Given the importance, it is crucial to detect and remove unwanted RFI signals from the satellite measurements.

In this communication, we present a novel RFI detection algorithm with factor analysis implementation. The method takes the advantage of channel correlations as well as the spectral differences between lower and higher frequency channels. The method is applied to X-band channels of TRMM/TMI and C-band channels of Aqua/AMSR-E satellite observations. The method is compared with some other traditional methods available in the literature, including, spectral difference method and PCA method. Similar to the traditional methods, the factor analysis method yield indices, and as such, the users can decide a subjective threshold to discard the RFI signals in the satellitetmi measurements. Based on the analysis, it is reasonable to conclude that the proposed factor analysis based RFI detection technique is an effective method at detecting the RFI signals in 6 GHz and 10 GHz channels. [At the same time, due to lack of independent validation datasets, the RFI](#)

detection models are difficult to validate. As such, the RFI detection uncertainties associated with the PCA based method itself should also to be kept in mind, while interpreting the results.

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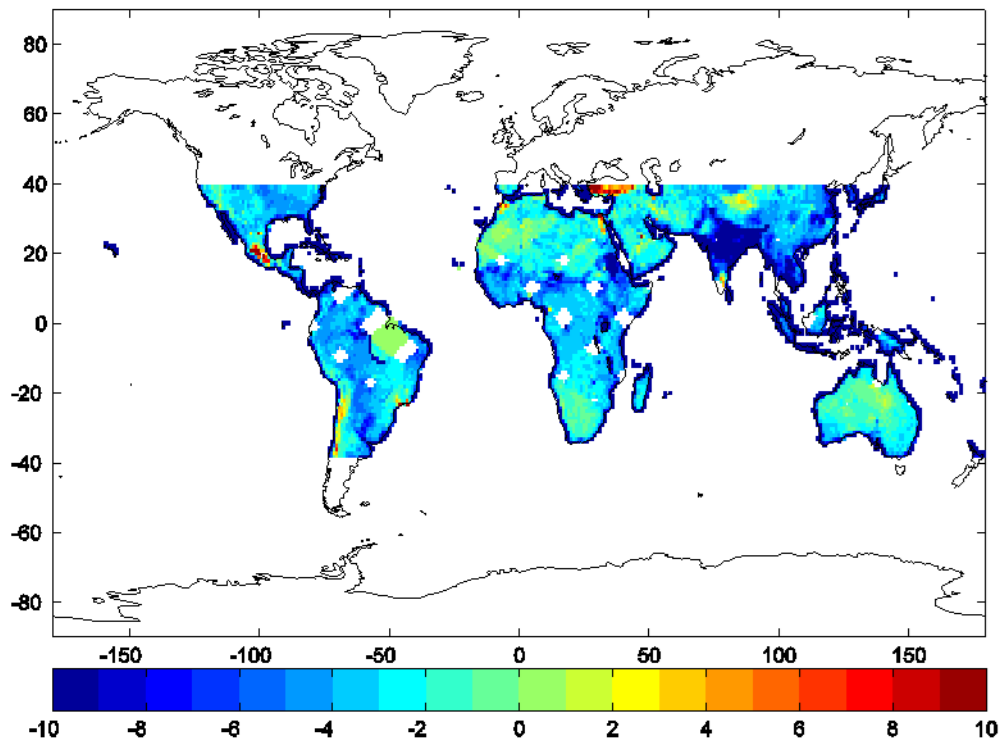


Figure 1: An example illustrating the differences in brightness temperatures between vertically polarized 10.65 and 19.35 GHz channels ($TB_{10V} - TB_{19V}$). The map is constructed from one day ascending and descending TRMM/TMI orbital samples on 1st August 2013.

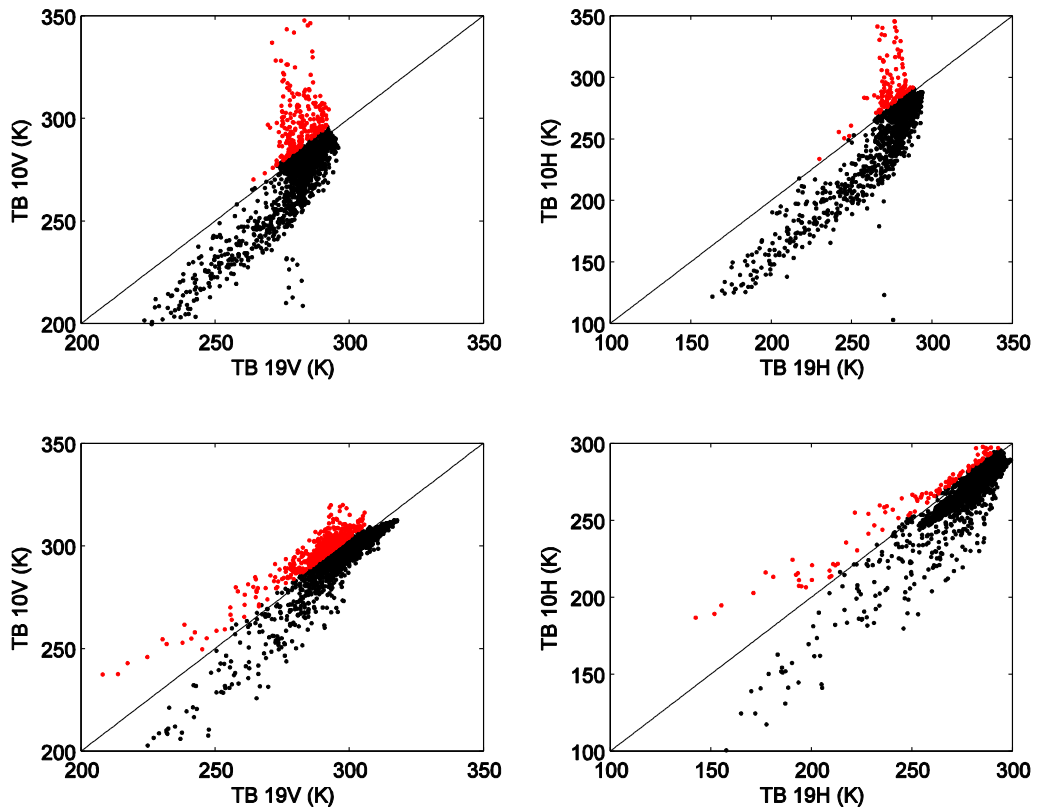


Figure 2: Scatter plots between 19 GHz and 10 GHz in vertical polarization (left) and horizontal polarization (right) channels from TRMM/TMI. Top panels are constructed from an example domain over South America and bottom panels are constructed from an example domain over X on 1st August 2013. Data points with $TB_{10V} - TB_{19V} \geq 5$ K are indicated in red and $TB_{10V} - TB_{19V} < 5$ K are indicated in black.

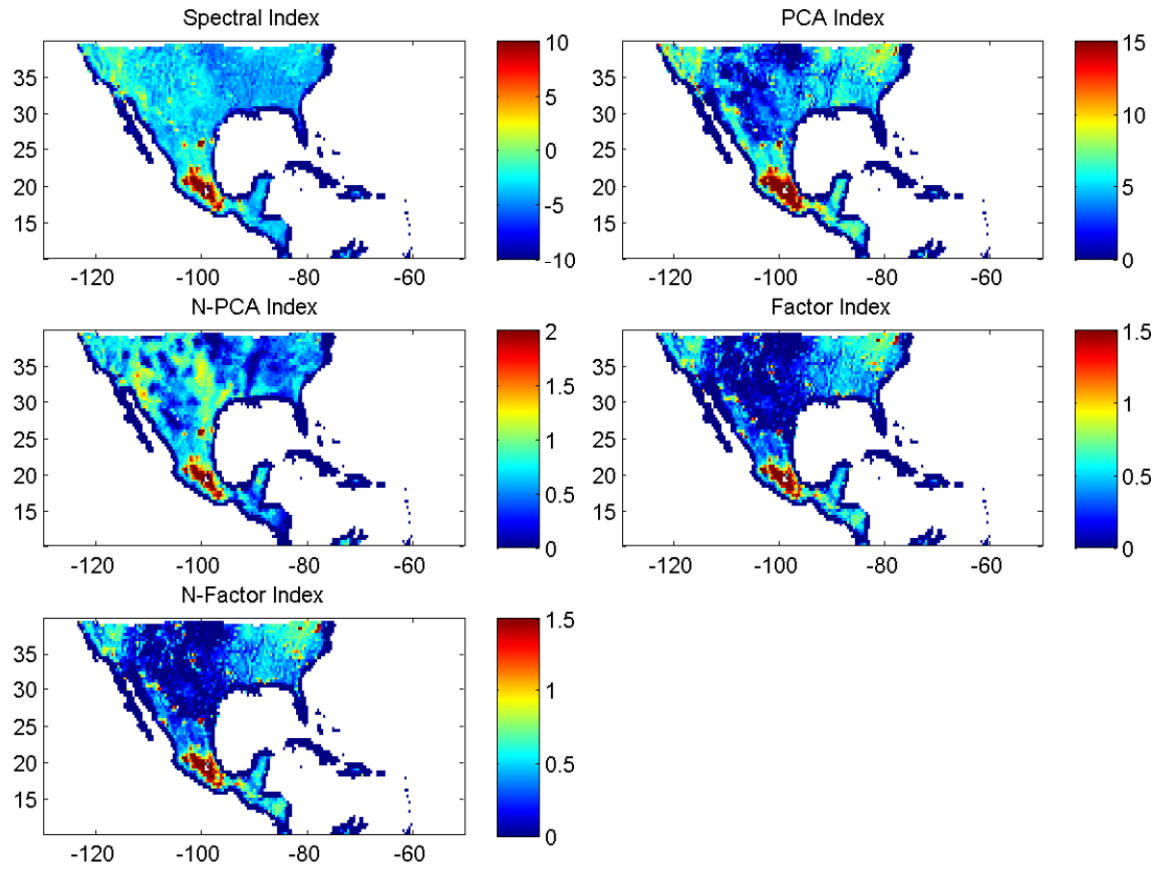


Figure 3: Spatial distribution of the RFI detection indices at 10 GHz for vertical polarization by five different RFI detection methods over South America. Data are averaged from five day TMI orbital samples.

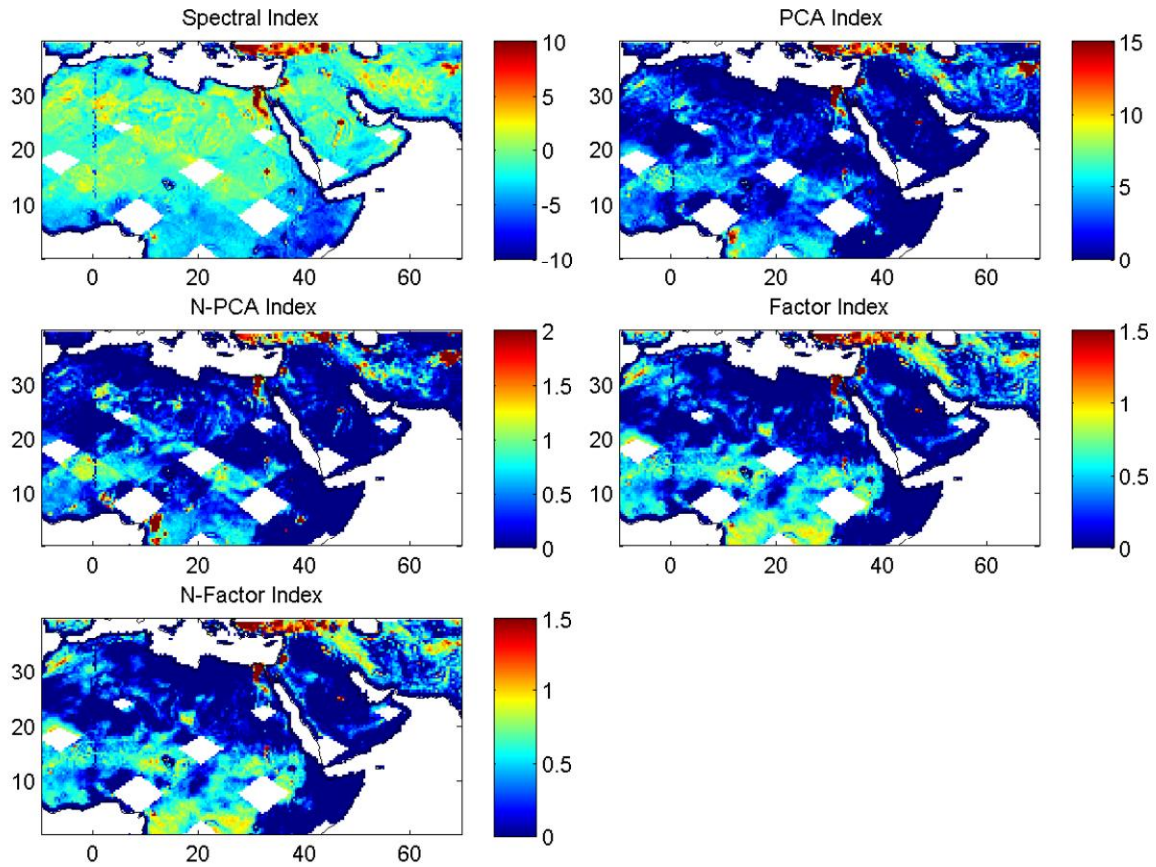


Figure 4: Spatial distribution of the RFI detection indices at 10 GHz for vertical polarization by five different RFI detection methods over Western Asia. Data are averaged from one day TMI orbital samples (1st April 2013).

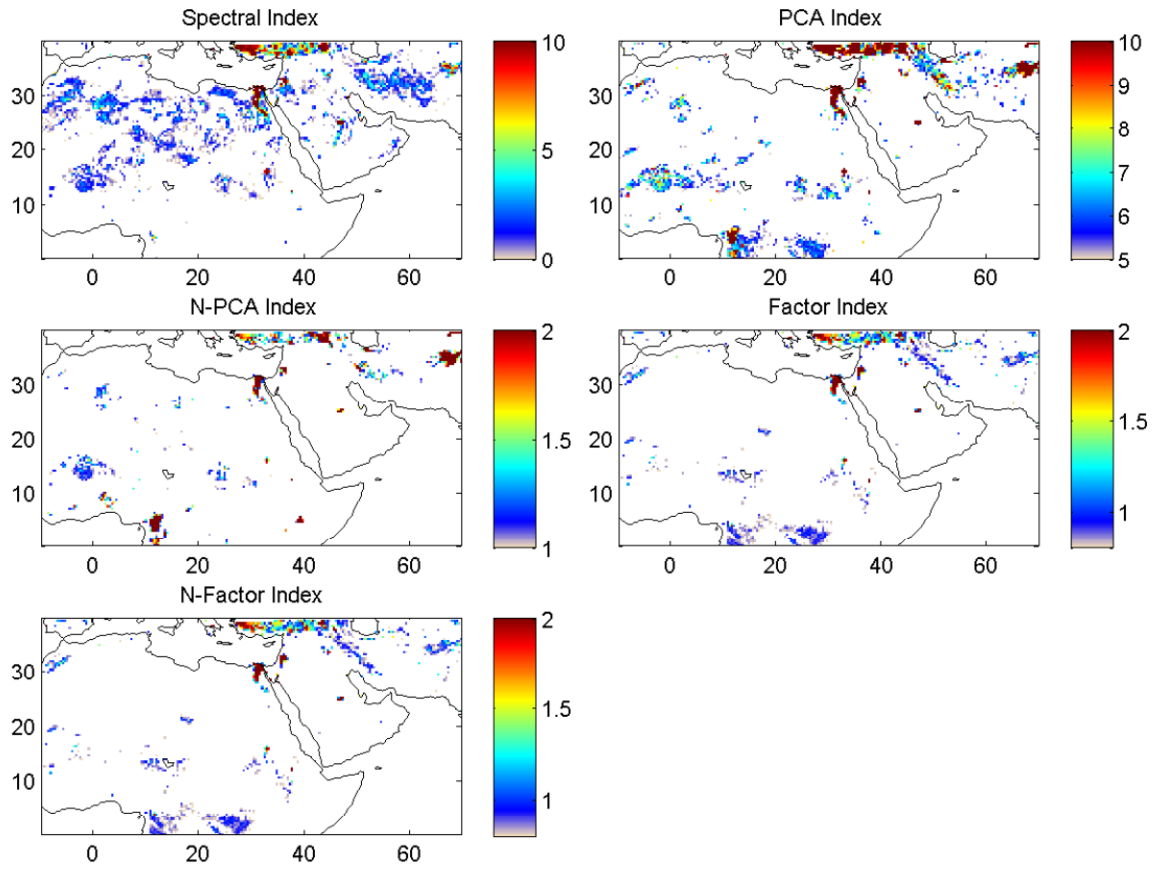


Figure 5: Same as Figure 4, but after excluding the RFI signals with applying index thresholds.

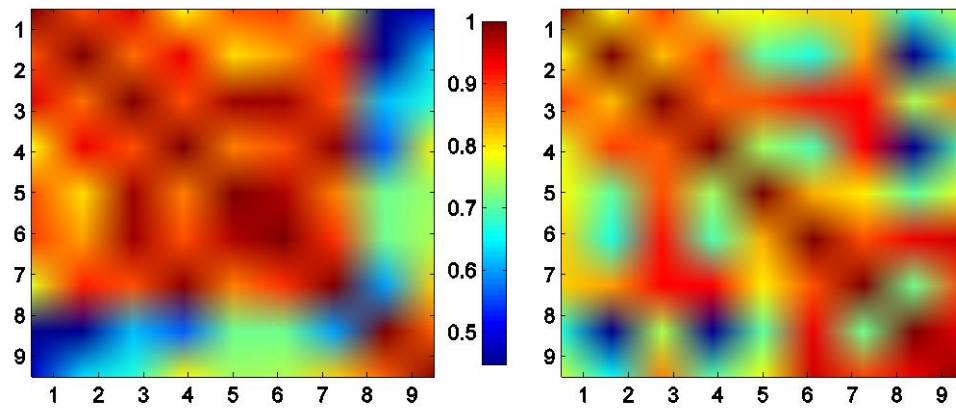


Figure 6: Correlation matrix of the TMI channels from RFI free (left) and RFI contaminated (right) scenes.

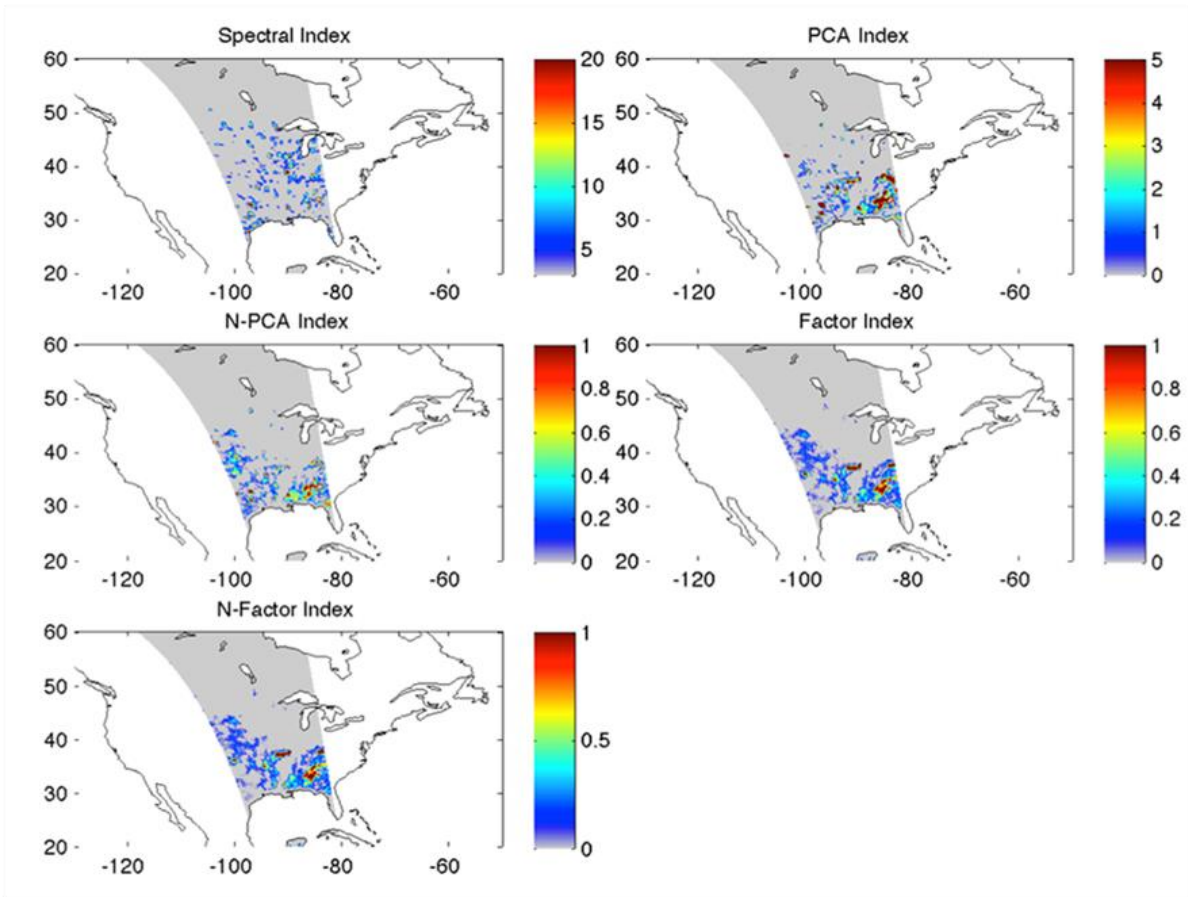


Figure 7: Spatial distribution of the RFI detection indices at 6 GHz for vertical polarization by five different RFI detection methods over Western Asia. Data are averaged from one day AMSR-E orbital samples.