

Generating Pseudo-Realistic Infrared Observations for Observing System Simulation Experiments

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ABSTRACT Observing System Simulation Experiments (OSSEs) are essential for evaluating and designing remote sensing systems using synthetic observations. A key aspect of OSSEs is tuning observation errors, typically by comparing data assimilation (DA) statistics from real and synthetic observations. However, during instrument design, only limited specifications, such as channels' frequency and spectral response functions, are available. This paper presents a method for generating pseudo-realistic infrared observations for proposed instruments using high-resolution measurements from the Infrared Atmospheric Sounding Interferometer (IASI) as a reference. The approach involves converting IASI measurements into infrared spectra using the Fast Fourier Transform (FFT) and inverse FFT (iFFT), then deriving channel-specific radiances for new instruments by convolving sensor response functions. Validation using IASI and AIRS simulations shows a mean difference below 0.1 K and a standard deviation under 0.5 K when comparing Fourier-derived AIRS brightness temperatures with those from a radiative transfer model. The accuracy of these conversions is confirmed by reconstructing IASI brightness temperatures via FFT, yielding negligible differences. An example of how these pseudo-observations can be used in OSSE experiments is presented, and the results are discussed.

INDEX TERMS IASI, AIRS, Fourier Transform, Infrared Instruments, Satellite Observations, OSSE

I. INTRODUCTION

OBSERVING System Simulation Experiments (OSSEs) are data assimilation experiments in which synthetic observations are used in place of real observations to assess the impact of proposed observing systems on numerical weather forecasts [1]–[3]. OSSEs are used to evaluate the performance of remote sensing systems and to develop new observation strategies [4]. A critical aspect of OSSEs is the tuning of simulated observation errors to ensure that synthetic observations realistically represent real measurements. However, when designing a new instrument, only a limited set of specifications is available, and no actual observations exist to support data assimilation experiments with real data. Therefore, generating pseudo-realistic observations that accurately reflect expected instrument performance is essential for robust OSSE studies.

In the context of data assimilation, observation error encompasses random errors arising from instrument noise, forward

model inaccuracies, and representativeness errors, for example, those caused by interpolating model fields to the observation locations. Because it is often difficult to disentangle these error sources, observation errors in the OSSE framework are typically evaluated as a whole by comparing estimates from data assimilation experiments using real observations with those using synthetic (or simulated) observations. The systematic component of observation error is referred to as observation bias, which may result from instrument calibration issues, forward model deficiencies, or biases in the model state used to simulate observations. Observation bias is generally addressed through variational bias correction techniques. Thus, while we refer to these as *observation errors* and *biases*, they do not necessarily originate solely from observations, as it is not straightforward to isolate contributing sources.

Infrared remote sensing is an essential tool for studying atmospheric temperature and moisture, which are critical

variables for weather forecasting and climate research. Instruments such as the Infrared Atmospheric Sounding Interferometer (IASI), the Atmospheric Infrared Sounder (AIRS), and the Cross-track Infrared Sounder (CrIS) provide high-resolution measurements of infrared radiation, which are used to infer atmospheric properties. High-resolution instruments can provide more detailed information on atmospheric temperature and moisture, which can subsequently improve weather forecasting [5]–[7]. They can also provide more accurate measurements of trace gases such as ozone, carbon monoxide, and methane, which are important for understanding atmospheric chemistry and air quality. High-resolution instruments can also be used to detect atmospheric phenomena such as clouds, aerosols, and volcanic ash, which can have significant impacts on weather and climate.

The Midwave Infrared Sounding of Temperature and Humidity in a Constellation for Winds (MISTiC) concept aims to enhance atmospheric motion vector (AMV) retrievals using a SmallSat constellation. The MISTiC instrument measures radiances across 590 spectral bands (1750–2450 cm^{-1}), capturing water vapor and CO_2 absorption features critical for temperature and moisture profiling. Operating in a sun-synchronous orbit at 705 km, its constellation design enables global coverage with a 3-hour refresh rate. By ensuring full ground overlap between instruments, MISTiC improves temporal sampling for AMV derivation, overcoming traditional limitations of polar-orbiting sensors [2], [8].

The accuracy of OSSEs depends on the accuracy of the observation errors that are used in the data assimilation experiments. Converting measurements from high-resolution instruments to lower-resolution instruments can help to determine observation errors more accurately for proposed instruments, which improves the accuracy of OSSEs [9]. This paper presents a methodology for generating pseudo-real infrared observations for proposed infrared instruments based on existing measurements from IASI. IASI includes 8461 spectral channels that can be used through the Fourier and inverse Fourier transform to derive infrared spectra that can then be used to generate synthetic observations for the proposed instruments.

This paper is organized in four sections. Section II explains the infrared instruments and their corresponding measurements used in the study, Section III discusses the basics of Fourier transform interferometry, the results are discussed in Section IV, and the last section, Section V, provides a summary of the work.

II. DATA AND INSTRUMENTS

IASI is a key instrument onboard the Metop series of satellites operated by EUMETSAT. IASI is a Fourier transform spectrometer that measures the infrared radiation emitted by the Earth's atmosphere to provide valuable information about atmospheric composition and temperature. IASI covers a spectral range from 645 cm^{-1} to 2760 cm^{-1} , with a sampling resolution of 0.25 cm^{-1} . IASI has 8461 channels partitioned into three bands of 645 cm^{-1} to 1210 cm^{-1} , 1210 cm^{-1} to

2000 cm^{-1} , and 2000 cm^{-1} to 2760 cm^{-1} [10], [11]. The high spectral resolution of IASI enables it to retrieve information on a wide range of atmospheric parameters, including temperature and humidity profiles, trace gas concentrations, cloud properties, and surface properties. IASI data also play a crucial role in improving numerical weather forecasts [10], [12].

The Atmospheric Infrared Sounder (AIRS) aboard NASA's Aqua satellite is a high-resolution infrared spectrometer designed for atmospheric sounding. It features 2,378 spectral channels spanning the wavenumber range of 650–2,675 cm^{-1} . These channels are grouped into three spectral bands: Band 1 (650–1,095 cm^{-1}), Band 2 (1,210–1,610 cm^{-1}), and Band 3 (2,180–2,675 cm^{-1}). The instrument's spectral resolution varies across this range, with a nominal resolving power of approximately 1,200, resulting in spectral resolutions of about 0.54 cm^{-1} at the lowest wavenumbers and approximately 2.23 cm^{-1} at the highest wavenumbers [13], [14].

The IASI and AIRS data utilized in this study, for the evaluation of the Fourier transform methodology, were generated using the Community Radiative Transfer Model [15] and a subset of profiles obtained from the ECMWF reanalysis [13]. Hereafter, we refer to these CRTM simulated brightness temperatures as the reference IASI/AIRS observations. It is also feasible to use collocated AIRS and IASI measurements; however, users should be aware of the temporal and spatial discrepancies between the collocated measurements.

III. FOURIER TRANSFORM INTERFEROMETRY

Interferometers are widely used in infrared spectroscopy to measure the interference pattern between two light beams. The interferogram obtained from an interferometer contains valuable spectral information. However, to obtain a traditional spectrum, we need to convert the interferogram to the frequency domain. This can be achieved using the Fast Fourier Transform (FFT) and the inverse Fast Fourier Transform (iFFT). In this section, we discuss the step-by-step process of converting interferometer measurements to a spectrometer using FFT and iFFT.

A. FOURIER TRANSFORM

The primary measurements of the interferometers are discrete power measurements. Let's consider x to be the difference in the optical path of the two rays traveling through the interferometer; x is also equivalent to the time element (t) in a Fourier transform. Let $I(t)$ represent the discrete point measurements of our interferogram, resulting in a set of N data points $I(x)$. The spectrum $R(\sigma)$, as a function of wavenumber σ , can be computed from the interferogram using the Fourier transform as follows [16]:

$$R(\sigma) = \int_{-\infty}^{\infty} I(x) e^{-2\pi i \sigma x} dx \quad (1)$$

The spectrum $R(\sigma)$ can be converted back to the spatial-domain signal $I(x)$ or time-domain signal $I(t)$ using the

inverse Fourier transform:

$$I(x) = \int_{-\infty}^{\infty} R(\sigma) e^{2\pi i \sigma x} d\sigma \quad (2)$$

The readers are referred to [17] and [18] for more information on Fourier and inverse Fourier transforms.

According to the Nyquist theorem, the optical path sampling interval (Δx) and the spectral sampling interval ($\Delta\sigma$) in the interferogram and spectral domains should meet the following conditions [16]:

$$\Delta\sigma = \frac{1}{2x_{\max}} \quad (3)$$

$$\Delta x = \frac{1}{2(\sigma_2 - \sigma_1)} \quad (4)$$

Here, $x_{\max}$ denotes the maximum optical path difference, while σ_1 and σ_2 define the minimum and maximum wavenumbers in the spectral bandwidth, respectively. For example, in the case of the IASI instrument, $x_{\max}$ is 2 cm, and the spectral range spans from $\sigma_1 = 645 \text{ cm}^{-1}$ to $\sigma_2 = 2760 \text{ cm}^{-1}$, resulting in a spectral sampling interval of $\Delta\sigma = 0.25 \text{ cm}^{-1}$ and a spatial sampling interval of $\Delta x \approx 2.23 \times 10^{-4} \text{ cm}$ [16], [19].

Reducing $x_{\max}$ leads to coarser spectral resolution. For instance, truncating the interferogram to $x_{\max} = 1.0 \text{ cm}$ results in a spectral resolution of approximately 0.5 cm^{-1} in the reconstructed spectrum.

B. APODIZATION FUNCTIONS

Before performing the FFT, it is a common practice to apply a windowing function to the time-domain measurements. The windowing function helps reduce spectral leakage and artifacts that can arise due to the finite length of the measured signal. Two commonly used windowing functions are the Hamming and Gaussian windows.

1) Hamming Window

The Hamming window is defined by the following equation:

$$W_H(n) = 0.54 - 0.46 \cos\left(\frac{2\pi n}{N-1}\right) \quad (5)$$

where n is the index of the data point and N is the total number of data points. The Hamming window tapers the signal smoothly towards the ends, reducing the impact of spectral leakage.

To apply the Hamming window to the measured signal $f(n)$, we multiply each data point by the corresponding value of the Hamming window:

$$f_{\text{hamming}}(n) = f(n) \cdot W_H(n) \quad (6)$$

2) Gaussian Window

The Gaussian window is defined as:

$$W_G(n) = e^{-\frac{(n-(N-1)/2)^2}{2\Omega^2}} \quad (7)$$

where Ω controls the width of the Gaussian window. The Gaussian window provides better frequency resolution at the expense of increased spectral sidelobes. Similar to the Hamming window, we apply the Gaussian window to the measured signal $f(n)$ by element-wise multiplication:

$$f_{\text{gaussian}}(n) = f(n) \cdot W_G(n) \quad (8)$$

C. CHANNEL-SPECIFIC RADIANCES

The sensor response function (SRF) is used to integrate the infrared spectra to compute channel specific radiances. Let R_λ denote the radiance as a function of wavelength λ , and $SRF_i(\lambda)$ represent the sensor response function for channel i . Channel-specific radiances, denoted as R_i , can be computed by integrating the product of radiance and the sensor response function over the spectral range of channel i :

$$R_i = \frac{\int_{\lambda_{\min,i}}^{\lambda_{\max,i}} R_\lambda \cdot SRF_i(\lambda) d\lambda}{\int_{\lambda_{\min,i}}^{\lambda_{\max,i}} SRF_i(\lambda) d\lambda} \quad (9)$$

where $\lambda_{\min,i}$ and $\lambda_{\max,i}$ represent the minimum and maximum wavelengths, respectively, for channel i [9].

By performing the integration, we obtain channel-specific radiances R_i , which are weighted measurements that capture the contribution of the radiance at each wavelength within the spectral range of the channel. This computation is repeated for each channel of interest, utilizing the corresponding sensor response function, to obtain a set of channel-specific radiances.

IV. RESULTS

A. IASI TO IR SPECTRA

While the process of deconvolution of IASI radiances to the corresponding infrared spectrum follows similar steps as converting time domain measurements to spectral measurements, the only pre-processing step required is to interpolate the IASI channel radiances to ensure a high-resolution spectrum is formed before the iFFT conversion. To compute infrared spectra from IASI radiances, the initial step involves the application of a filter. This filter serves to taper and eliminate radiances that fall outside of the desired frequency range [9]. Figure 1 illustrates an example of this process, where the tapering extends 5 cm^{-1} beyond the frequency grid.

In order to utilize the FFT algorithm, it is necessary to have a signal that spans from zero to the maximum required frequency. Hence, the second step involves padding the given IASI spectra with zeros. This padding serves to extend the spectra from the minimum IASI frequency to zero, as well as from the IASI maximum frequency to the desired $V_{\max}$. Figure 2 demonstrates this process, providing an illustration of a typical IASI spectra with the added zero-padding.

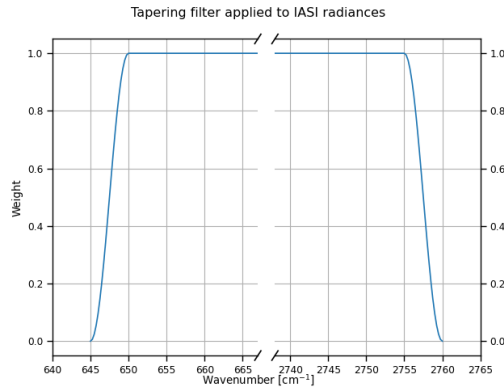


FIGURE 1. Illustration of the filter applied to the IASI radiances to taper and eliminate radiances outside the desired frequency range.

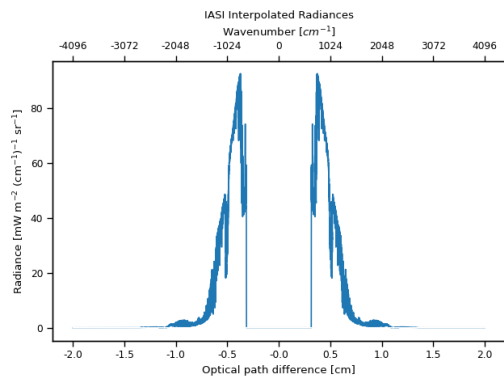


FIGURE 2. Example of IASI spectra with zero-padding applied to extend the spectra from the minimum IASI frequency to zero and from the IASI maximum frequency to the desired $V_{\max}$.

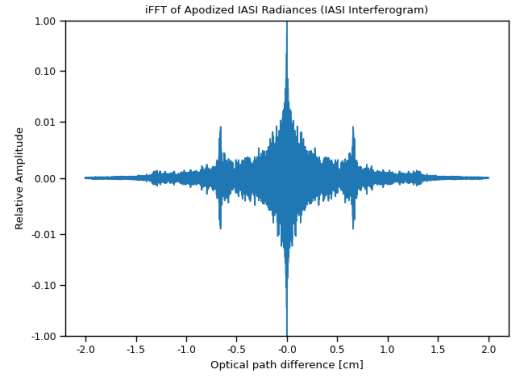


FIGURE 3. Interferogram obtained by applying the inverse Fourier transform to the extended IASI spectra. The time-domain signal is apodized with the IASI apodization function.

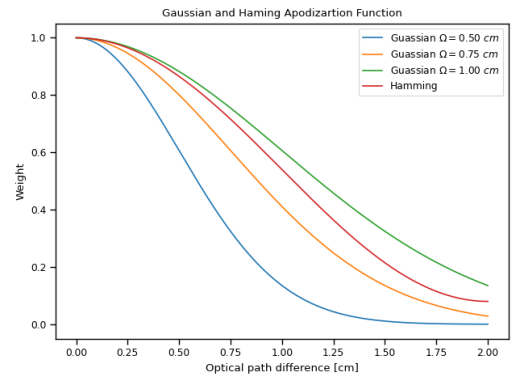


FIGURE 4. Comparison of the Gaussian and Hamming apodization functions commonly used in Fourier transform interferometry.

After padding the spectra, the next step involves converting the extended spectra into an interferogram by applying the inverse Fourier transform. The resulting interferogram represents the signal in the time domain and is illustrated in Figure 3. It is important to note that this time-domain signal remains apodized with the IASI apodization function, accounting for the smoothing and tapering effects applied during the data processing.

Gaussian and Hamming are commonly utilized apodization functions in Fourier transform interferometry. Figure 4 provides a visual comparison between these two functions, illustrating their distinctive characteristics. The Gaussian function's impact on the output signal heavily relies on the standard deviation, where a larger value tends to result in a smoother signal. In this paper, a standard deviation of 0.75 cm is chosen for the Gaussian apodization, which is consistently used throughout, however Figure 4 also includes the graphs for standard deviations of 0.50 cm and 1.00 cm for comparison.

Moving forward, the signal obtained in the previous step is divided by the windowing function to eliminate the apodization effect. This division operation yields an unapodized time-domain signal, which is presented in Figure 5.

The unapodized time-domain signal can be transformed into an infrared spectrum by employing the Fourier transform. The resulting infrared signal is plotted alongside the input IASI signal, as shown in Figure 6. As depicted, the infrared signal exhibits larger variations compared to the IASI signal. This discrepancy arises due to the smoothing effect induced by the apodization function applied to the IASI signal. Consequently, the IASI signal appears smoother in comparison to the infrared signal.

B. IR SPECTRA TO AIRS

Once the infrared spectra are computed, computing channel-specific radiances for a spectrometer like AIRS only requires convolving the IR spectra with the sensor response function, as discussed in Section III-C. For this purpose, both measured channel response functions and hypothetical response functions close to the expected channel response functions are utilized.

Figure 7 shows two common channel response functions employed for the AIRS spectrometer: Gaussian and measured sensor response functions. Additionally, a hypothetical triangular response function, used in previous studies for the MISTiC instrument, is also included (see [2]). These response

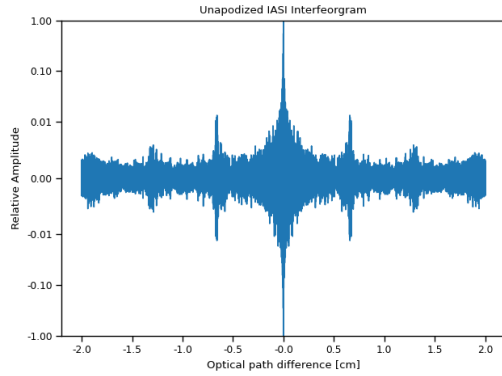


FIGURE 5. Unapodized time-domain signal obtained by dividing the apodized time-domain signal by the windowing function.

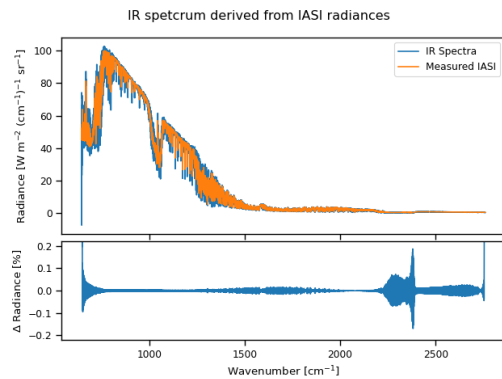


FIGURE 6. Comparison between the computed infrared spectrum and the input IASI signal. The infrared spectrum exhibits larger variations due to the apodization effect.

functions describe the sensitivity of the spectrometer across different channels.

To evaluate the performance of the sensor response functions, the corresponding AIRS brightness temperatures are computed using the IR spectra derived from IASI radiances. Figure 8 displays the results, where the top panel presents the CRTM simulated AIRS brightness temperatures, and the bottom panel illustrates the differences between the RT simulations and the brightness temperatures computed using the Fourier transform of IASI radiances.

The errors introduced by RT modeling in simulating AIRS and IASI radiances are likely comparable and tend to cancel out when comparing the AIRS radiances simulated using CRTM with those derived using the Fourier transform of the CRTM simulated IASI radiances. Moreover, we applied the same SRFs both in simulating AIRS/IASI radiances using CRTM and during the Fourier transform conversions. Consequently, the differences shown in Figure 8 predominantly stem from the Fourier transform conversions and associated assumptions. Nonetheless, the disparities between the RT simulated and Fourier-based AIRS Tb's are generally less than 0.05 K when real AIRS SRFs are utilized.

The differences between RT simulated AIRS Tb's using

real AIRS SRFs and those derived using Fourier transform of IASI radiances can reach up to 2 K for certain channels when Gaussian or triangular response functions are employed for the AIRS instrument during the Fourier transform. These findings underscore the significance of utilizing proper sensor response functions for the calibration or RT modelling of IR instruments.

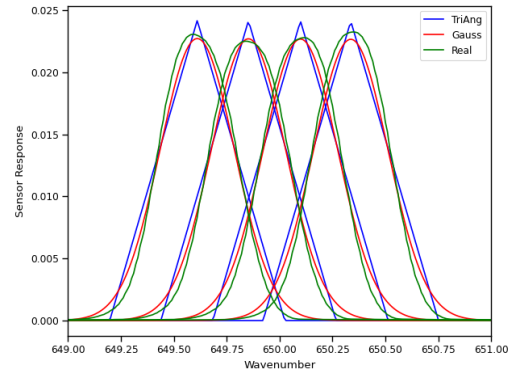


FIGURE 7. Common channel response functions used for the AIRS spectrometer: Gaussian, measured sensor response functions, and a hypothetical triangular response function.

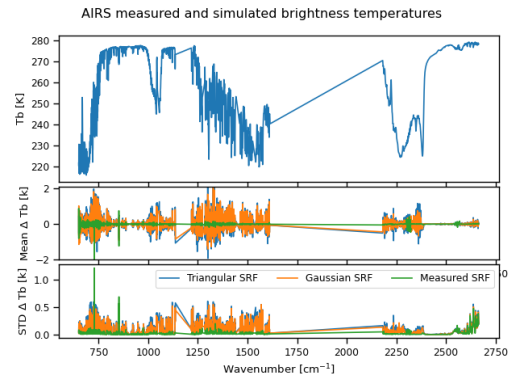


FIGURE 8. AIRS brightness temperatures computed using IR spectra derived from IASI radiances and different sensor response functions. The top panel shows the CRTM simulated AIRS brightness temperatures, while the bottom panels show the mean and standard deviation of the differences between the CRTM simulations and brightness temperatures computed using the Fourier transform of IASI radiances.

C. IR SPECTRA TO IASI

The comparison begins with the IR spectra. To convert these spectra into IASI channel radiances, we first need to transform them from the frequency domain to a time-domain signal. This transformation is accomplished using the inverse Fourier transform. Once the IR spectra are transformed into the time domain, they will be convolved with the IASI apodization function and then converted back into the frequency domain, as described in Section III.

Figure 9 depicts the results of the Fourier transform conversion of the IASI brightness temperatures. The top panel displays the original IASI brightness temperatures simulated

using CRTM. The middle panel illustrates the mean differences between CRTM simulated and Fourier transform-based brightness temperatures. The bottom panel shows the standard deviation of the differences between the two sets of brightness temperatures. Overall, the channel-specific mean difference between the two set of brightness temperatures is less than 0.01 K for most channels but can reach up to 0.05 K for some channels. The standard deviation of differences is less than 0.01 K for most channels, but can reach up to 0.05 K for some channels. Additionally, the bottom panel of Figure 6 shows the differences between the CRTM simulated IASI radiances and those calculated using the Fourier transform of the IR spectra. The differences are generally less than 0.01 % for most channels, but can reach up to 0.1 % for some channels.

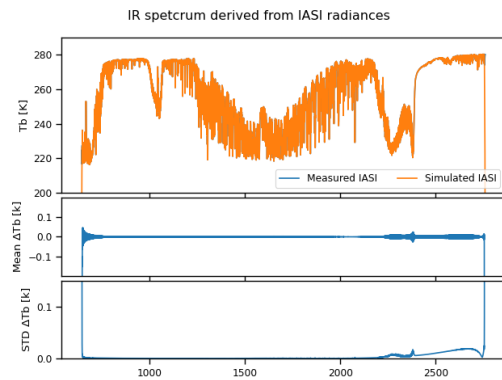


FIGURE 9. Comparison between the IASI measured brightness temperatures (input) and the IASI simulated brightness temperatures. The bottom panel shows the difference between the measured and simulated brightness temperatures.

D. APPLICATION IN OSSE

We employed the proposed technique to develop a set of observations for MISTiC and evaluate these observations within the Global Modeling and Assimilation Office (GMAO) OSSE framework [2]. The OSSE framework employs the Goddard Earth Observing System (GEOS-5, [20]) 7 km Nature Run [21], [22] as the basis for the simulated observations and for verification of analysis and forecast skills. Simulated observations were generated [23] for data types ingested quasi-operationally during 2015, including Advanced Microwave Sounding Unit (AMSU-A), IASI, AIRS, Advanced Technology Microwave Sounder (ATMS), Microwave Humidity Sounder (MHS), Cross-track Infrared Sounder (CrIS), High-resolution Infra Red Sounder / 4. (HIRS4), rawinsondes, aircraft, atmospheric motion vectors (AMVs), Global Navigation Satellite System - Radio Occultation (GNSS-RO), and surface data types. The Gridpoint Statistical Interpolation (GSI, [24]) data assimilation system and GEOS 25 km forward model with 72 vertical levels were used to assimilate the simulated observations and generate forecasts. This framework has been extensively calibrated and validated to ensure accurate representation of real world observation impacts [3],

[25].

Figure 10 illustrates the original IASI radiances, along with the derived infrared spectra, and the MISTiC radiances computed using a triangular sensor response function. The broader sensor response function for MISTiC results in a smoothing of the MISTiC radiances when compared to both the original IASI and the derived infrared spectra.

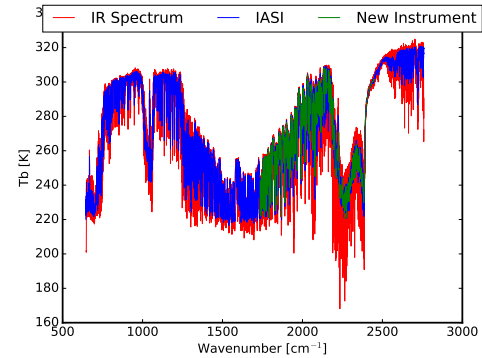


FIGURE 10. Original IASI radiances along with the IR spectra derived from the radiances through Fourier transform and also the radiances averaged using the MISTiC passbands.

Figure 11 presents an example of pseudo-real MISTiC observations derived from IASI radiances, compared to simulations from the CRTM and the background provided by the GEOS model. A high degree of consistency is observed in the water vapor channels (e.g., Channel 1839.15 cm^{-1}), which peak in the mid-troposphere. This consistency arises because these channels are largely insensitive to surface emissivity, as their weighting functions typically peak well above the ground. Additionally, cloud-contaminated observations have been excluded. As a result, there is strong agreement between the simulations and observations, consistent with the behavior of other hyperspectral infrared instruments in data assimilation systems.

In contrast, the channel operating at 2359.77 cm^{-1} is primarily sensitive to stratospheric temperature. Due to the absence of non-LTE corrections during daytime, a noticeable discrepancy exists between simulated and observed values, particularly between day and night observations.

The mean differences between IASI-derived and simulated values for all MISTiC channels are shown in Figure 12. As noted in [2], not all channels are assimilated into the system due to significant discrepancies between observed and simulated values. These differences stem from surface emissivity issues, forward modeling challenges, and limitations in the NWP model's ability to provide reliable inputs for accurate simulation of certain channels.

Correlated observation errors are another important factor in the assimilation of hyperspectral infrared radiances. Figure 13 presents an example of the observation error correlation matrix for the MISTiC instrument, calculated using the differences between the observations and the model forecast (OMF). These correlations are typically estimated from the

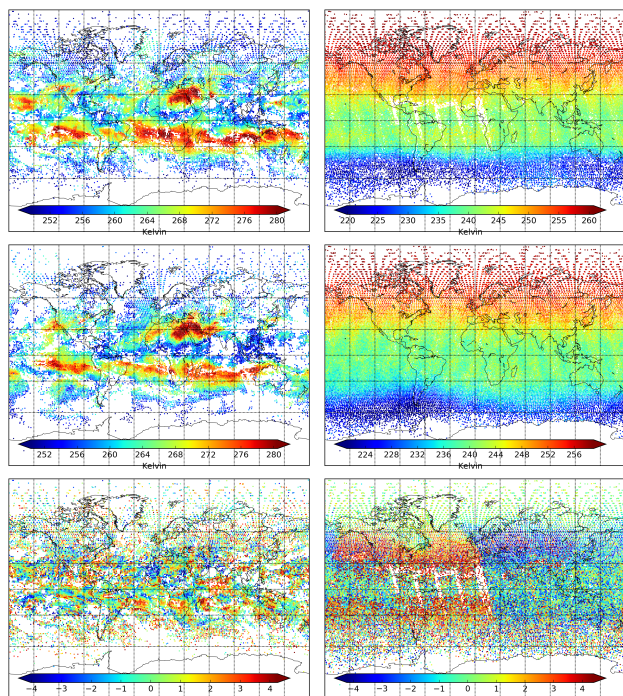


FIGURE 11. MISTiC pseudo-observations derived from IASI radiances versus CRTM-simulated brightness temperatures using the GEOS background. The left panels correspond to Channel 102 at 1839.15 cm^{-1} , while the right panels represent Channel 520 at 2359.77 cm^{-1} . From top to bottom, the panels display MISTiC pseudo-real observations, CRTM-simulated observations, and their differences.

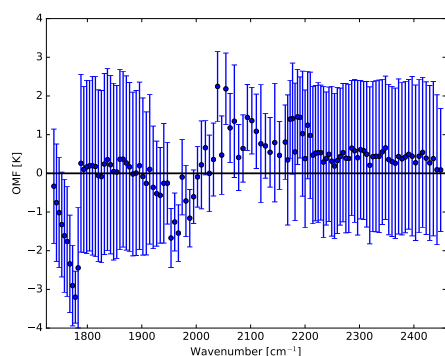


FIGURE 12. Observed minus CRTM simulated brightness temperatures for different MISTiC channels.

observation error statistics derived from data assimilation systems using real observations. Correlated errors may arise from spatial or spectral correlations in the model fields (e.g., temperature or water vapor) or from the measurements themselves. However, since current methodologies do not allow for a clear separation of these two sources, we refer to the total correlated error as *correlated observation error*.

In the OSSE framework, the simulated observations tend to have deficient error stemming from the insufficient error in each of these categories. Because the observation error is crucial to the optimal use and weighting of observations by the data assimilation system, it is important that the simulated

observations have realistic levels of observation error.

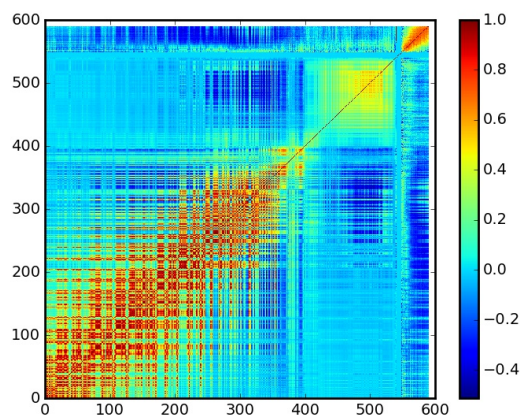


FIGURE 13. Correlated observation error derived from the GEOS GSI statistics for all MISTiC channels.

An OSSE experiment was performed to evaluate the impact of MISTiC observations on NWP forecast skill. Observations for an orbiting MISTiC platform were simulated with local time of ascending node at 0130 UTC. The experiment period was 01 July to 31 August of the second year of the Nature Run, with forecasts performed once daily initialized at 0000 UTC. Two cases are run, a Control case in which only data types used in 2015 are assimilated, and an experiment case in which the MISTiC platform is assimilated in addition to the Control observing network.

Figure 14 demonstrates the impact of simulated MISTiC radiance observations in comparison to other infrared and microwave radiance data types. The observation impacts are estimated using a linearized, or adjoint, version of the numerical weather prediction model to calculate the contribution of each observation in reducing the forecast error at 24 hr of a global total wet energy diagnostic. The MISTiC instrument performs with slightly greater impact than the CrIS platform.

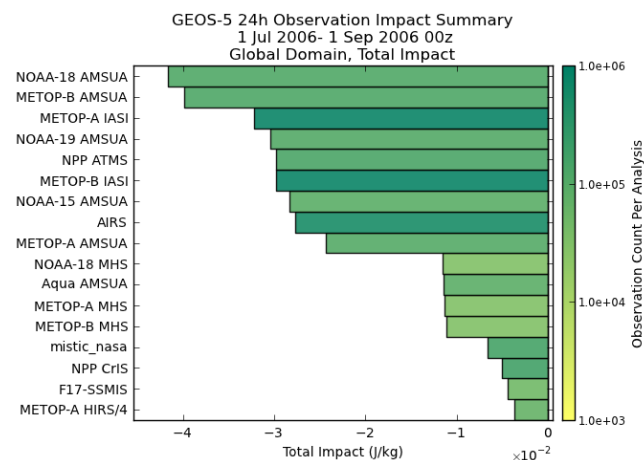


FIGURE 14. Forecast Sensitivity Observation Impact (FSOI) estimates of radiative observation impacts on 24 hr forecast error. Negative values indicate a beneficial reduction of forecast error. Bar color indicates total number of ingested observations per forecast cycle. The MISTiC platform is listed as MISTiC_nasa.

V. CONCLUSION

In conclusion, this paper presents a novel method for generating pseudo-realistic infrared observations, which is essential for evaluating proposed infrared instruments in the absence of real-world observational data. By leveraging high-resolution measurements from the Infrared Atmospheric Sounding Interferometer (IASI) and utilizing the Fast Fourier Transform (FFT) and inverse FFT, we demonstrate a robust technique for transforming IASI data into channel-specific radiances for other infrared instruments. The validation results, comparing simulated brightness temperatures from IASI and AIRS, reveal minimal differences, affirming the effectiveness and accuracy of this approach. Additionally, the sensitivity of the method to sensor response functions highlights the importance of selecting appropriate response functions for accurate simulation. Additionally, we demonstrate the application of pseudo-real observations in an OSSE framework, highlighting the impact of observations from MISTiC, a proposed constellation of hyperspectral infrared sounders.

This work provides a valuable tool for the design of future infrared instruments, especially when limited real-world data are available, and offers a new avenue for enhancing the fidelity of Observing System Simulation Experiments (OSSEs) in remote sensing applications.

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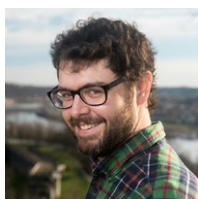


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