Understanding Spectro-Temporal Signature Variability of Unresolved Resident Space Objects using a Simulation Model

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ABSTRACT

Ground-based hyperspectral imagers provide the capability of measuring the spectral signature of an unresolved resident space object (URSO) as a function of time during an observation period (or spectro-temporal signature). Understanding signature dependency on URSO properties can be used to develop information extraction algorithms for object identification, and to infer, classify, predict and diagnose its condition and health. Given the limited availability of URSO spectro-temporal data, ground-based remote sensing observations can be complemented by physics-based simulation models and laboratory data to support design, development, implementation and validation of signature exploitation algorithms. This is particularly important when training machine-learning models that require large amounts of data.

This paper presents results of a simulation study using the Digital Imaging and Remote Sensing Image Generation (DIRSIG™) model to look at changes in the ground-based measured spectral radiance for an unresolved satellite to material composition and satellite orientation. To simplify the simulation study, a uniform illumination source and uniform atmospheric transmissivity (100%) is used. That facilitates direct comparison of simulated ground-based spectral radiance curves with actual materials spectral signatures. We will add solar illumination and realistic atmospheric conditions at future stages of the work. The simulation study uses the satellite bus CAD model for a DirecTV-10 satellite (Boeing 702 bus) and assumes that the exterior of the payload module, the antennas and the solar panel are covered by a single material. Simulations conducted show spectral signatures as a function of time, for changes in the composition of the solar panels, and changes in satellite orientation with respect to the imaging plane. Simulation results show how spectral signatures change as a function of these parameters. In particular, the significant effect of the solar panels in the ground –based spectral radiance which is the largest external component of the satellite bus.

These types of controlled computational experiments help us develop knowledge and understanding of the dependency of spectro-temporal signatures on different parameters. Furthermore, we can use this model to generate simulated data sets that can complement ground-based observations for training of machine learning models.

1. INTRODUCTION

Advancing Space Domain Awareness (SDA) to provide tactical, predictive, and intelligence information on resident space objects (RSO) will rely on successfully extracting information from ground-based remote sensing assets. Radar and optical remote sensing systems are the primary assets for ground-based observations [1]. Radar is primarily used for targets in LEO while optical assets are used for observations at higher orbits.

The spatially unresolved RSO (URSO) problem arises because optical remote sensing assets cannot spatially resolve RSO that are far away (e.g. GEO) or that are small (e.g. nanosatellites). Furthermore, the low cost of small aperture COTS telescopes is motivating their use for observation of LEO satellites with high spatial diversity even though they cannot spatially resolve them [2, 3, 4].

Standard astronomical measurements such as photometry, spectroscopy, and polarimetry have been used since the beginning of the space age to characterize a satellite's optical signature [5]. Signature variability is due to the superposition of object shape, attitude, motion, and material composition under a specific viewing and illumination geometry [6]. Hyperspectral and polarization remote sensing systems [7, 8] and the geographical diversity provided by assets such as the USAFA Falcon Telescope Network [9] or OWL-Net [4] are bringing enormous amounts of data that can provide further insights into aspects of URSO that were previously inaccessible. Accurate signature interpretation may allow us to perceive, predict, comprehend, and react appropriately to changing situations in the space domain.

Hyperspectral sensors allow extraction of URSO information from the spectral and temporal (spectro-temporal) variability of measured spectra providing a quantitative approach for their characterization. Even though the URSO cannot be spatially resolved, many of its properties can be extracted from the spectro-temporal information.

Recent studies show promise for leveraging machine-learning (ML) techniques to infer satellite properties such as operational status [10], orbital regime [11], and shape [12] from light curves. These ML models exhibit strong performance when trained and tested on simulated data from simple simulation models. However, ML models trained on this simulated data have significant reduction (up to 33% in accuracy) when applied to real observations [11, 12]. High-fidelity physics-based models for spectro-temporal signature generation can yield significant improvements in ML model performance, and lead to predictable false-alarm rates in certain observer-illuminator geometries [13, 14]. Simulated datasets are key for training of ML models for SDA as availability of real data is rather limited.

The Digital Imaging and Remote Sensing Image Generation (DIRSIG^{TM}) model produces synthetic imagery using a suite of physics-based radiation propagation modules. DIRSIG^{TM} can simulate images taken from different sensors with variation in collection geometry, spectral response, solar elevation and angle, atmospheric models, target, and background. DIRSIG^{TM} has been applied to RSO and URSO simulation scenarios in [15] and has been shown to be a valuable tool for generating synthetic data for training of deep convolutional networks for satellite or aerial image analysis as shown in [16].

In order to interpret ground-based spectro-temporal signatures to solve information extraction problems in RSO remote sensing, we need to understand their dependency on operational conditions including the geographic location and angular resolution of the telescope, observation geometry, satellite attitude and orbital characteristics, materials in the surface of the RSO, atmospheric conditions among other variables. We can develop this knowledge by using physics-based simulation models.

This paper presents results of a simulation study using the Digital Imaging and Remote Sensing Image Generation (DIRSIG™) model to look at changes in the ground-based measured spectral radiance for an unresolved satellite to material composition and satellite orientation. To simplify the simulation study, a uniform illumination source and uniform atmospheric transmissivity (100%) is used. That facilitates direct comparison of simulated ground-based spectral radiance curves with actual materials spectral signatures. We will add solar illumination and realistic atmospheric conditions at future stages of the work. The simulation study uses the satellite bus CAD model for a DirecTV-10 satellite (Boeing 702 bus) and assumes that the exterior of the payload module, the antennas and the solar panel are covered by a single material. Simulations conducted show spectral signatures as a function of time, for changes in the composition of the solar panels, and changes in satellite orientation with respect to the imaging plane. Simulation results show how spectral signatures change as a function of these parameters. In particular, the significant effect of the solar panels which is the largest external component of the satellite bus.

Physics-based models helps us conduct controlled computational experiments to help us develop knowledge and understanding of the dependency of spectro-temporal signatures on different parameters. Furthermore, we can use these models to generate simulated data sets that can complement ground-based observations for training of machine learning models.

The paper is organized as follows. Section 2 provides a brief overview of DIRSIG^{TM}. Section 3 provides a brief description of the simulation workflow and the ancillary data and resources needed to implement the simulation experiment using the DIRSIG^{TM} model. Results are presented followed by discussion in Sections 4 and 5 respectively.

2. DIRSIG^{TM} MODEL

Access to URSO remote sensing data that provides a rich collection of scenarios is a challenge. Physics-based simulation tools can generate rich data sets complementing telescope observations. Rochester Institute of Technology (RIT) has developed and maintains a state-of-the-art image simulation software tool called Digital Imaging and Remote Sensing Image Generation (DIRSIG™) model, which is a physics-driven synthetic image generation model [17] developed by the RIT Digital Imaging and Remote Sensing Laboratory over the course of 30 years. The model can produce passive multidimensional optical imagery (single-band, multi-spectral, polarimetric, or hyperspectral) from the visible through the thermal infrared region of the electromagnetic spectrum. The tool has the capability to simulate images of a wide variety of resolved and non-resolved space objects across the electromagnetic spectrum, ranging from UV to thermal infrared. DIRSIG™ can incorporate material bidirectional reflectance distribution function (BRDF) and emissivity from laboratory measurements, existing materials databases (such as the AFRL Satellite Assessment Center (SatAC) and Non-Conventional Exploitation Factors (NEF) databases), or based on first-principles for simple materials. The space object motion and articulation are described using a two-line element (TLE) set from either an externally generated lookup table of values (i.e., generated using Systems ToolKit (STK) [18]) or internally using the Simplified General Perturbations Version 4 (SGP4) orbit model [19] to predict the satellite position during the period of observation. Due to the hierarchical nature of the geometry descriptions, the user can specify a time varying articulation of specific space object components such as solar panels that track the sun. With this flexibility, it is straightforward to accurately model the signatures of complex object articulations that describe things such as rotating solar panels for maximum power transfer, a tumbling rocket body or the deployment of the payload fairing shells during a launch sequence. Early application DIRSIG^{TM} for SDA is described in [20, 15].

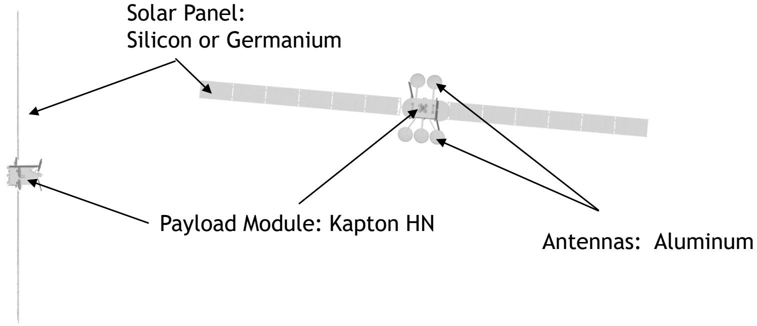
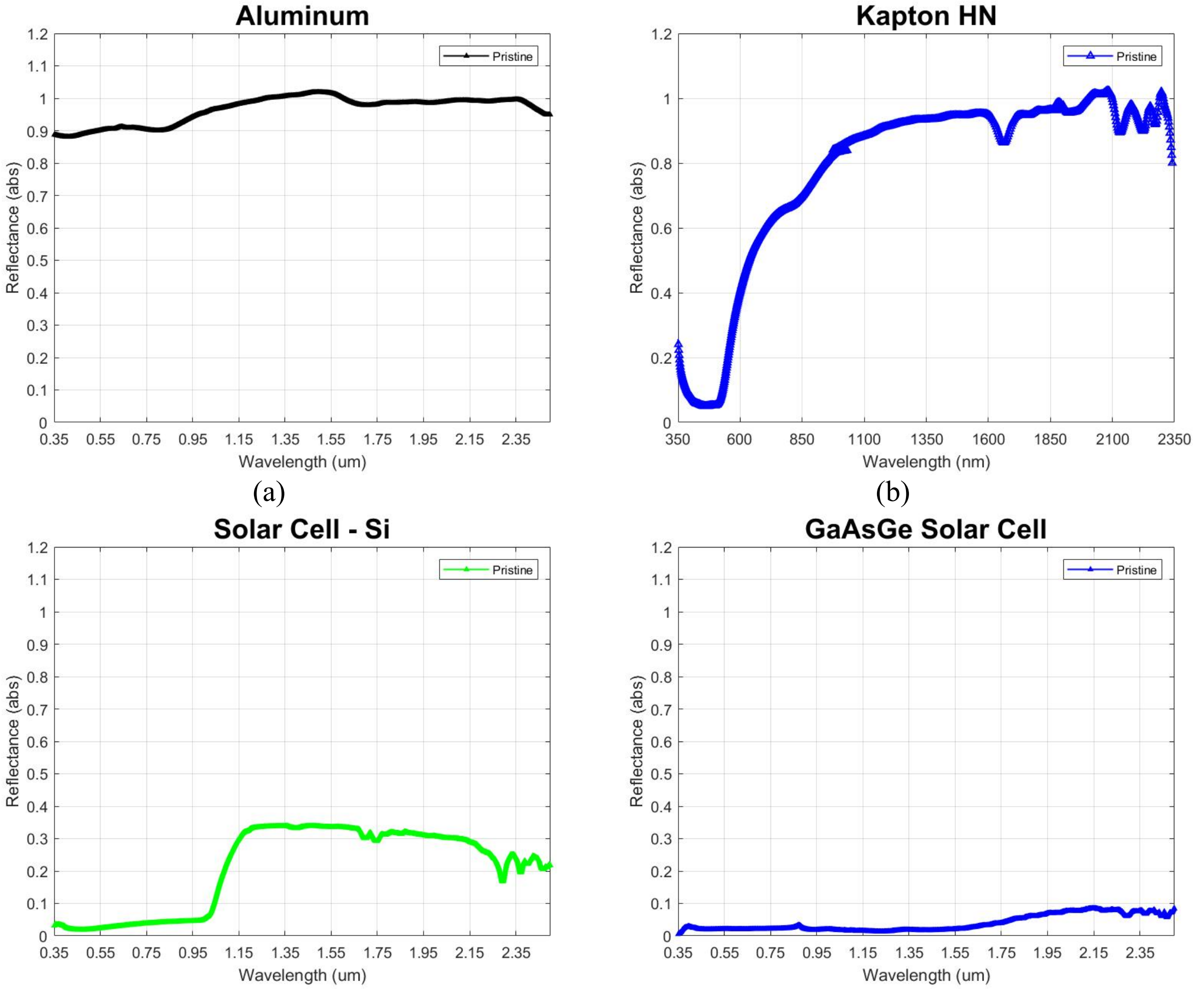


Figure 1: CAD model for a DirecTV-10 satellite (Boeing 702 bus) used in the simulation study.

3. SIMULATING GROUND-BASED HYPERSPECTRAL OBSERVATIONS

The DIRSIG™ model is used to simulate changes in the ground-based measured spectral radiance for an unresolved satellite to material composition and satellite orientation. The main components of a simulation consist of (1) a 3D CAD model for the satellite; (2) spectral reflectance signatures for the materials in the surface of the spacecraft; (3) the location of the observer (telescope) via geographic Coordinate System (GCS) and of the satellite via its Two-Line Element (TLE); and (4) atmospheric conditions.

The simulation study uses the satellite bus CAD model for a DirecTV-10 satellite (Boeing 702 bus) and assumes that the exterior of the payload module, the antennas and the solar panel are covered by one material each, as shown in Figure 1. The payload module is covered with Kapton HN, antennas by aluminum, and solar panels by either silicon or germanium. We assume that the observer location coincides with that of the USAFA-16 Falcon Telescope in Colorado Springs, at a latitude of 39^{o} N and longitude of -105^{o} W and that the satellite is in GEO orbit. More realistic conditions are considered for future stages of the work and are needed to generate data for training of machine learning models.



(a) (b)

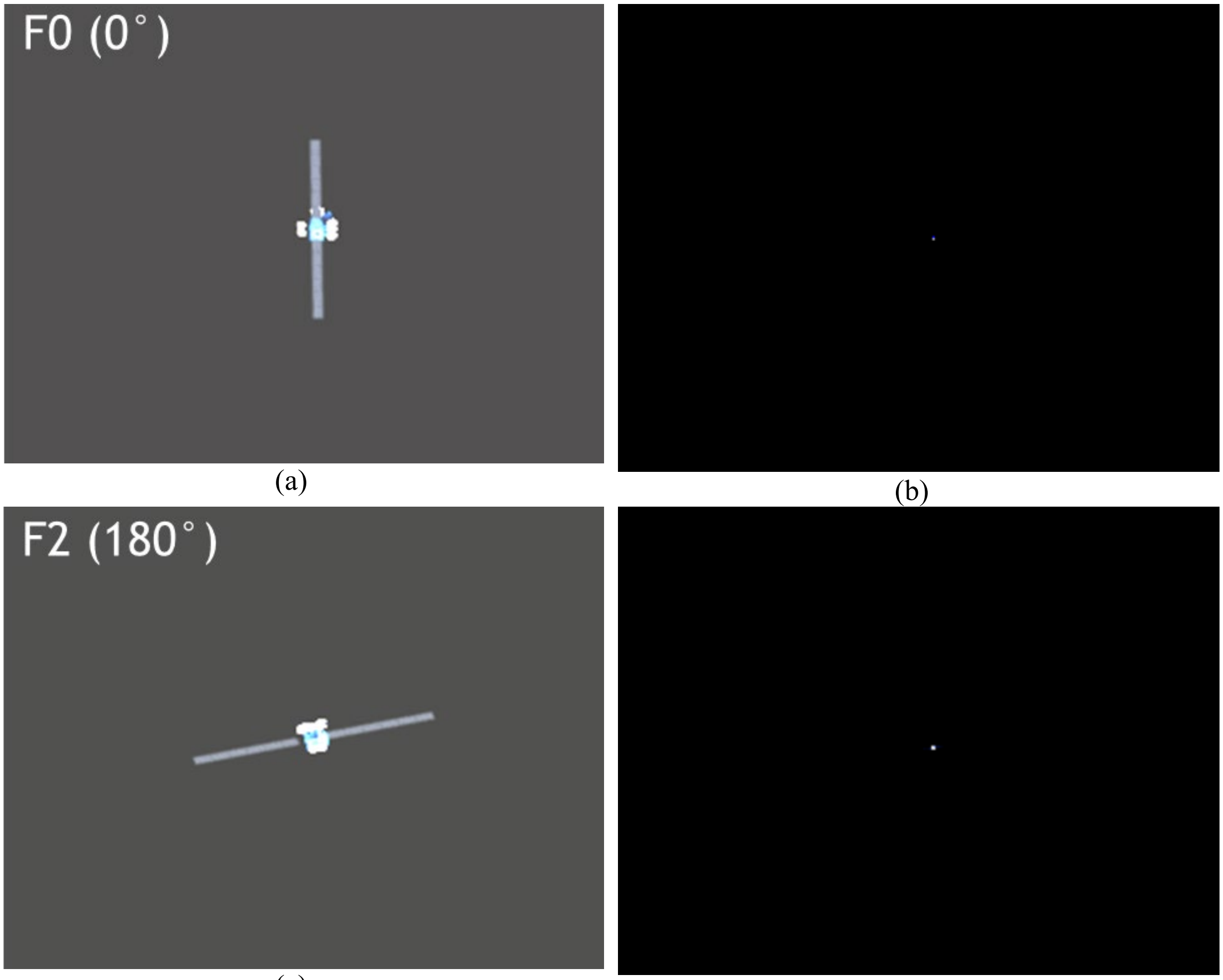
(c) (d)

Figure 2: Spectral signatures of materials used in the simulation: (a) Aluminum, (b) Kapton HN, (c) silicon solar cell, and (d) germanium solar cell.

The DIRSIG™ model allows the user to define an imaging platform based on the simulation needs. In this study, an imaging focal plane array of 320×240 with a pixel size of 0.5×0.5 µm was simulated. Hyperspectral observations were simulated in the 0.37-2.5 nm spectral range with 1 nm spectral resolution. The imaging platform was set to track the satellite between 4:00-7:00 UTC with an image integration time of 8 ms. We assume in the simulations that the satellite orientation is constant. The same view of the satellite is facing the observer all the time. The simulation is run for the two satellite orientations shown in Figure

3 .The instantaneous field of view (IFOV) is determined by the focal length of the optical system. To simulate unresolved imagery, the focal length of the imaging platform is set to 5 mm.

The DIRSIG™ radiometry solver computes the incident spectral radiance at the sensor focal plane array in W cm^{-2} µm^{-1}sr^{-1}. To simplify the simulation study, a uniform illumination source and uniform atmospheric transmissivity (100%) is used. That facilitates interpretation of the results as direct comparison of simulated ground-based spectral radiance curves with actual materials' spectral signatures is possible. More details on how to set up the simulation workflow are provided in [21, 22].



(a) (b)

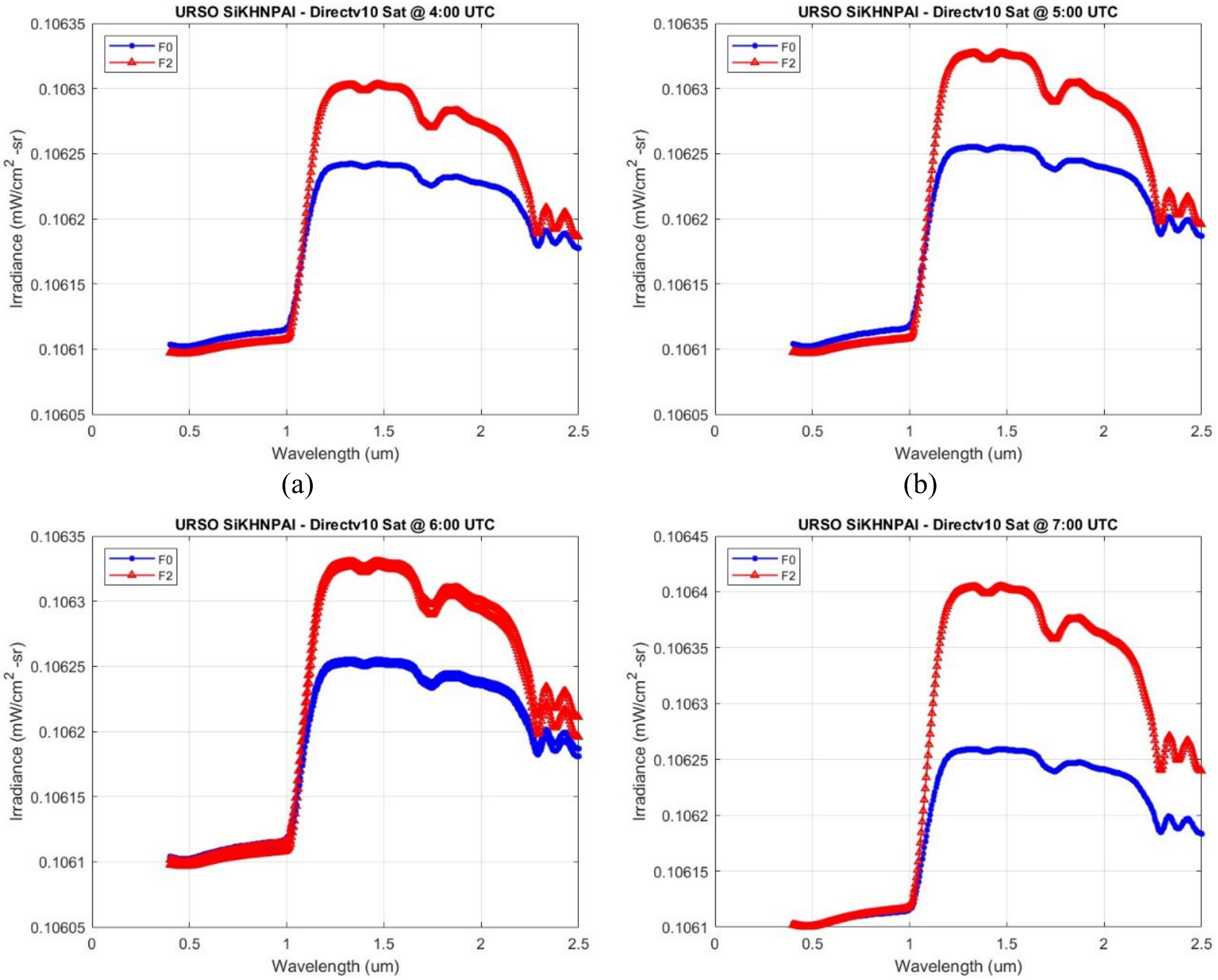
(c) (d)

Figure 3: Simulation results were conducted with the satellite at two different orientations in the imaging plane: Euler angle of 0^o (a) resolved image and (b) unresolved image; and Euler angle of 180^o (c) resolved image and (d) unresolved image.

4. RESULTS

Simulated spectral radiances in mW cm^{-2} µm^{-1}sr^{-1} are shown in Figure 4 and Figure 5. The figures show snapshots of the ground-based spectral radiance from 4:00 to 7:00 UTC. In both simulations cases, the payload body is covered by Kapton HN and the antenna by aluminum. Figure 4 shows the results for silicon solar panels and Figure 5 for germanium solar panels. The panels are the largest component of the satellite bus and its dominance of the mixed spectral signature for the unresolved simulation is clear. Note that the silicon spectral reflectance signature transition from very low reflectance (below 5%) to over 30%

reflectance at around 1μm. We can see that transition edge in the simulated spectral radiance for silicon. Germanium has a low reflectance (below 10%) for the entire spectral range with a slight reflectance increase around 1.75μm as shown in Figure 2(d). The spectral signature for the germanium solar panel in shown in Figure 6 at a different scale from that in Figure 2(d). The shape correspondence between the spectral radiance responses in Figure 5 and Figure 6 and that of the solar panels is clear.



(a) (b) (c) (d)

Figure 4: Simulation results for the silicon solar cell: (a) 4:00 UTC, (b) 5:00 UTC, (c) 6:00 UTC, and (d) 7:00 UTC.

The differences in reflectance between the solar panels is also evident when looking at the magnitudes of the spectral radiances where in the simulations for the silicon panels it ranges from 0.1061 mW cm^{-2} μm^{-1}sr^{-1} to 0.10645 mW cm^{-2} μm^{-1}sr^{-1}while for the germanium panels it ranges from 0.1061 mW cm^{-2} μm^{-1}sr^{-1} to 0.10619 mW cm^{-2} μm^{-1}sr^{-1}. The spectral signature for aluminum is relatively flat between 90-100% over the entire spectral range and for Kapton HN is high 80-100% after 1μm and has a very broad absorption feature between 0.35μm and 1μm. They seem not to be significant contributors to the spectral radiances in Figure 4 and Figure 5.

5. DISCUSSION AND CONCLUSIONS

Preliminary results presented in this paper show the potential of using a physics-based simulation model such as DIRSIG^{TM} to generate simulated ground-based observations that could potentially be used to understand URSO signatures and to complement to telescope observations for the development, testing and validation of machine learning models for remote sensing image exploitation for SDA. Clearly challenges remain to properly tune the simulation model to closely reproduce telescope observations and to their eventual use to extrapolate to cases not included in the observational data.

Spectral radiance changes due to changes in solar panels' materials and in satellite orientation are clearly observed in the simulated signatures. Furthermore, the dominance of the solar panels in the overall radiance signature is clear as they are the largest component of the satellite bus. Using a uniform illumination source and uniform atmospheric transmissivity (100%) helped us understand the spectral mixing interactions in remote sensing of a URSO. Direct comparison of simulated ground-based spectral radiance curves with actual materials spectral signatures allow us to easily determine the effects of different materials in the simulated spectral radiance. Clearly, we need to add realistic solar illumination and atmospheric conditions at future stages of the work for training of machine learning models based on simulated data.

6. ACKNOWLEDGEMENTS

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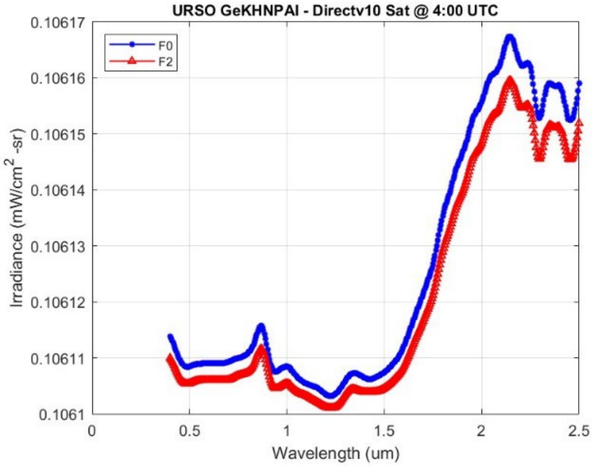
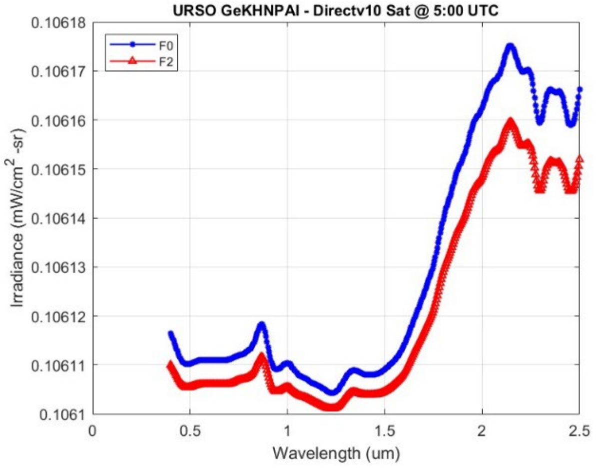


(a)



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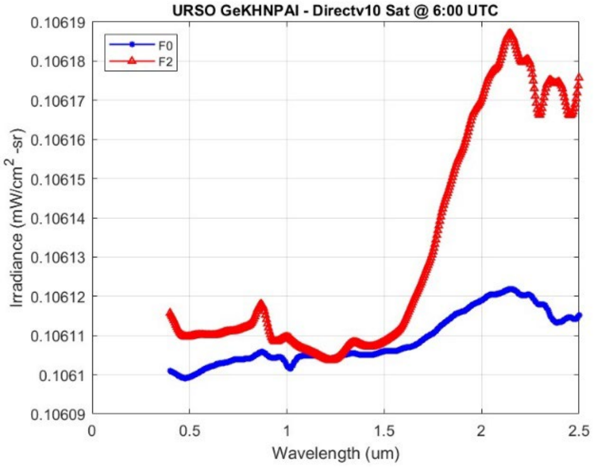
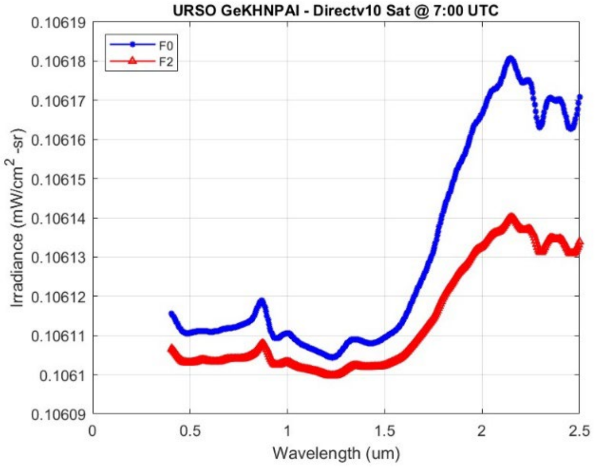


(c)



(d)

Figure 5: Simulation results for the germanium solar cell: (a) 4:00 UTC, (b) 5:00 UTC, (c) 6:00 UTC, and (d) 7:00 UTC.

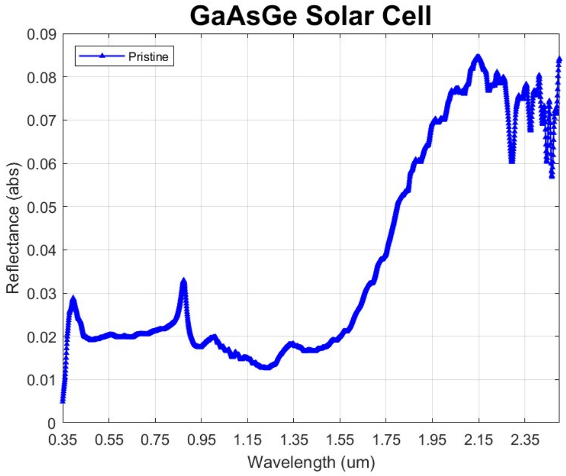


Figure 6: Spectral signature for the germanium solar panel at a different scale from Figure 2.

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