Electromagnetic Environment Simulation: Addressing Operational Training Gaps In Space

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ABSTRACT

As the space domain becomes more contested, Space Force Guardians face critical training gaps in electromagnetic environment simulation that need to be addressed. There is currently a lack of tools that enable personnel to accurately simulate radar platforms in realistic scenarios and assess the effects of both intentional and unintentional signal disruption on space-based sensors. These limitations hinder training effectiveness and degrade operational readiness in important Space Force exercises such as Space Flag.

This paper addresses these shortfalls by demonstrating how physics-based Modeling & Simulation (M&S) capabilities can help Guardians prepare for modern space threats and environments. By leveraging high-fidelity, site-specific radio frequency (RF) simulation environments, users are able to construct training scenarios including Synthetic Aperture Radar (SAR), and advanced ground-based interference configurations.

We will present examples of how these capabilities can enhance readiness in both educational settings and in exercises. These applications illustrate how Guardians can reduce reliance on physical assets, save training time, and improve mission planning outcomes. In this paper, we will also cover the technical foundation that supports this M&S capability.

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INTRODUCTION

As the battle for space superiority continues to evolve, the U.S. must find tools and technologies to help prepare for novel threats. These evolving threats make physics-based modeling and simulation (M&S) capabilities essential tools. Realistic simulation environments enable thorough assessments of how electromagnetic signals behave when they interact with terrain, atmospheric conditions, and both intentional and unintentional interference. To maximize effectiveness, these simulated environments should include accurate degradation effects as well as objects and clutter return signatures for specific scenarios.

Technical limitations introduced by current M&S tools leave key capability gaps in space operations mission planning and training. SAR operations require understanding of complex imaging and interference that cannot be adequately represented with low fidelity models. Analysis of electromagnetic interference (EMI) effectiveness on satellites requires accurate propagation modeling that accounts for antenna patterns, platform dynamics, and terrain-specific effects across orbital regimes from LEO to GEO. When using accurate models, Guardians can gain the ability to plan and practice strategies without the costs of using live assets or restricted range access. However, using insufficient models can be wasteful, and at worst detrimental, to a mission's success.

Advanced training tools can be used to support important exercises such as Space Flag. High-fidelity simulation tools transform these exercises by replacing white card notifications with real observable effects. Instead of receiving a card abstracting the effects of EMI, operators can now see actual degraded SAR imagery for example, and understand the impact on their ISR capabilities. The shift from notional declarations to measurable effects ensures training exercises challenge operators with threats that behave similar to the challenges they will encounter in contested environments.

Beyond exercises, the utility of high-fidelity simulation environments extends to formal instruction and education, such as qualification training. M&S tools allow users to generate radar scenarios that reinforce EMS signal propagation theory and concepts. Students can explore how terrain, geometry, and waveform characteristics affect the received radar platform return, building intuition that is difficult to develop through traditional pedagogical material alone.

The scope of this paper primarily focuses on electromagnetic propagation and radar, excluding kinetic threats and optical sensor modeling. All examples shown in this paper use unclassified parameters and notional effects to demonstrate capability.

TECHNICAL FOUNDATION: FROM STATISTICAL APPROXIMATIONS TO PHYSICS-BASED MODELING

As the need for higher fidelity electromagnetic simulation has expanded, so too have the methods for generating synthetic radar data. Historically, RF M&S for radar applications has relied heavily on statistical approximations, particularly in the modeling of ground clutter returns. While effective for early algorithm development and coarse analysis, these traditional models often fall short in operational realism.

Traditional Covariance-Based Statistical Model

For a long time, the dominant approach to radar clutter modeling treated returns from the environment as random vectors governed by a statistical distribution, typically defined through a space-time covariance matrix (Ward, 1994). These covariance-based models were built on the assumption that clutter behaved as colored noise, where spatial and temporal dependencies could be captured statistically.

The mathematical foundation of this approach represents clutter returns from a given iso-range ring as:

$$\mathbf{x_c} = \sum_{\mathbf{i=1}}^{\mathbf{N_c}} \boldsymbol{\gamma}_\mathbf{i} \mathbf{v_i} \qquad (1)$$

where x_c is the total clutter return vector containing all spatial channels and temporal pulses, $\mathrm{N_c}$ is the number of clutter patches within the iso-range ring of interest, γ_i represents random complex reflectivity coefficients that capture the scattering strength from each clutter patch, and v_i denotes steering vectors that encode the spatial and temporal phase shifts based on the geometry between the radar and the i-th clutter patch. Essentially, this equation states that the total clutter is the sum of contributions from all individual clutter patches, each with its own random amplitude and deterministic phase relationship.

Under the assumption of independent scatterers, the clutter covariance matrix becomes:

$$\mathbf{E}\{\,\mathbf{x_c}\,\mathbf{x_c^H}\,\} \;=\; \sum_{\mathbf{i=1}}^{\mathbf{N_c}} \boldsymbol{G_i}\,\boldsymbol{v_i}\,\boldsymbol{v_j^H} \qquad (2)$$

where $\mathrm{E}\{\;\cdot\;\}$ denotes statistical expectation, $(\cdot)^{\mathrm{H}}$ represents the Hermitian transpose, and $\mathrm{G_i} \;=\; \mathrm{E}[|\gamma_\mathrm{i}|^2]$ which is the second moment of the random reflectivity coefficient γ_i, and represents the average power from the i-th clutter patch. This covariance matrix captures how much power comes from each direction within the range ring and how correlated the returns are across different spatial channels and pulses. Traditional STAP (space-time adaptive processing) algorithms use estimates of this covariance matrix to design filters that suppress clutter while preserving targets.

However, such models inherently abstract away the physical structure of the environment. They do not account for physical features like buildings, hills, or shorelines that define landscapes in the real world. These limitations become particularly problematic for applications requiring site-specific fidelity such as SAR, and cognitive radar where the waveform is adapted based on the environment. This has led to the adoption of terrain-specific, physics-based simulation frameworks, which model RF interactions using impulse responses derived from terrain geometry, material properties, and propagation physics.

The Stochastic Transfer Function Model

In order to accurately capture terrain-specific propagation effects and generate signal dependent clutter returns, we can use what is known as a stochastic transfer function model instead. This type of model describes radar returns as the outputs of a convolution between the transmitted waveform and a site-specific Green's function impulse response. These impulse responses, or Green's functions, capture how electromagnetic energy scatters in a complex scene, accounting for linear nature of the interactions described by Maxwell's equations. Terrain elevation and material-dependent reflectivity can be incorporated in the impulse response using public data sources like digital terrain elevation models (DTED) and land cover databases, or data from classified sources as well. Conceptually, a covariance model answers the question "What's the average energy pattern from clutter like in this area?" while a stochastic transfer function answers, "What would actually happen if I transmit this waveform to illuminate this exact environment with this terrain, platform geometry, and radar trajectory?".

The stochastic transfer function model represents radar measurements through a linear system framework (Guerci et al., 2016):

$$\mathbf{Y(\boldsymbol{\omega})} \;=\; \mathbf{H_c(\boldsymbol{\omega})\,S(\boldsymbol{\omega})} \;+\; \mathbf{H_t(\boldsymbol{\omega})\,S(\boldsymbol{\omega})} \;+\; \mathbf{N(\boldsymbol{\omega})} \qquad (3)$$

where ω is angular frequency, $H_c(\omega)$ and $H_t(\omega)$ denote frequency-domain transfer functions for clutter and target channels respectively, $S(\omega)$ represents the transmitted waveform spectrum, and $N(\omega)$ captures additive noise. The multiplication in frequency domain corresponds to convolution in time domain, meaning each channel "filters" the transmitted signal according to its physical characteristics. $H_c(\omega)$ encodes all the phase delays and amplitude changes from every terrain patch, building, and environmental feature in the scene. This formulation decouples the channel impulse response from the transmitted waveform, enabling evaluation of different radar configurations and waveforms using the same underlying environmental model (Gogineni et al., 2022). Ultimately, this produces an output dependent on the input signal, which accurately models pulse-to-pulse phase coherency necessary for simulating SAR.

To construct a site-specific channel impulse response, simulation tools might use a patch-based summation approach or a path tracing method. In patch-based models, the environment is discretized into thousands or millions of surface elements, each contributing to the overall radar return based on variables such as material composition, surface orientation, and visibility to the radar. On the other hand, path-tracing methods simulate energy propagation through continuous 3D geometry, capturing multipath effects, occlusions, and scattering behavior by tracing the interactions of electromagnetic energy with terrain and other objects. Equally valid; both approaches incorporate terrain-dependent backscatter characteristics that vary with environment characteristics and radar parameters.

IMPLEMENTATION UTILIZING GPU ACCELERATION

The challenge of solving for stochastic transfer function models lies in calculating millions of scattering interactions in a usable time window; as the size and resolution of the scene increases, so does the computational load. This has driven the adoption of GPU acceleration that exploits the parallel nature of scattering calculations. Whether computing contributions from individual patch elements or tracing energy along multiple bounce paths, the work can be mapped to thousands of concurrent GPU threads, transitioning a theoretical model into a capability that is able to be used in real time applications. As it is not the focal point of the paper, the following is a high-level discussion about how the path tracing method can be implemented on a GPU to support a radar simulation use case. For more detail, the references (Visina et al., 2021) and (Visina et al., 2022) describe this process with less abstraction.

GPU Acceleration

Ray tracing is a rendering technique that models visible light propagation by simulating the paths of rays cast through a scene and evaluating their intersections with geometric surfaces. This is primarily performed for computer graphics and accounts for effects like shadows, reflections, and opacity. Ray tracing was originally developed for optical rendering, but it can be adapted to support electromagnetic propagation modeling for radar simulation. For optical sensors, ray tracing is used to simulate visible light interactions with surfaces to produce images based on radiance and intensity from a specific viewpoint. To simulate radar systems, similar geometric effects apply, but the sensor operates in the RF domain, and returns are understood using only range and amplitude and pulse to pulse signal coherence. Unlike optical sensors that passively capture reflected light as 2D intensity images, radar systems actively transmit signals and measure the complex amplitude and phase of returns as a function of time delay (range). As a result, applying GPU-based rendering techniques to radar simulation requires substantial modifications to the underlying technology. Radar simulation requires additional physical quantities to be computed per fragment to maintain a coherent model, such as slant range and radar reflectivity, the latter of which must be defined in terms of radar cross section (RCS), which varies with polarization, aspect angle, and material. The ability to compute these attributes is not available in a native ray tracing pipeline and must be explicitly calculated using custom shader code. When computed correctly, the per-fragment range and reflectivity values are then accumulated into azimuth-range bins, which mimic the structure of radar receiver buffers, enabling the synthesis of raw I&Q data.

Performance Optimization for Real-Time Use

Performance optimization targets the rapid turnaround times required for tactical planning and training. When operators analyze EMI effectiveness or evaluate collection strategies, simulation latency directly impacts their ability to explore decision outcomes. Wide area radar scenes of approximately 1,000 square kilometers at 1-meter resolution can be rendered in real-time when leveraging GPU accelerated techniques like ray tracing. In this context, real-time refers to the ability of the simulation to generate radar returns fast enough to keep pace with dynamic scenario updates such as changes in platform motion or beam direction. This ensures that outputs remain synchronized with user inputs or other simulation environments, supporting live interaction during mission rehearsal. This level of performance, enabled by hardware RT cores specifically designed for ray-triangle intersection acceleration, enables users to evaluate multiple tactical alternatives within a single planning session. Operators can quickly modify signal interference and observe SAR degradation or adjust radar platform parameters to explore radar collection tradeoffs and how to optimize performance for specific mission requirements. The transition from hours-long batch processing to real-time interaction fundamentally changes the learning dynamic, enabling active exploration rather than passive observation of pre-computed results.

APPLICATIONS AND TRAINING VIGNETTES

Space Force operations in contested electromagnetic environments require an in-depth understanding of both space-based sensor capabilities and challenges. Physics-based M&S tools address critical training gaps identified by operational units and enable personnel to visualize and experiment with complex radar environments to directly support mission success. This section of the paper identifies examples of how M&S capability can be used to assist Space Force Guardians in training exercises and in education. The examples in this section are created using an M&S tool which is built on ISL's RFView, an M&S capability based on stochastic transfer function models of radar environments.

SAR and SAR Interference

Space-based SAR is both a crucial capability and vulnerability in modern space operations. Satellite SAR sensors can threaten to reveal information about operations, and space assets face growing threats both in orbit and from the ground. M&S tools enable Space Force personnel to understand both sides of this EMS contest, developing expertise in utilizing SAR capabilities while defending against adversary surveillance. The next few examples focused on SAR and SAR interference demonstrate how users may freely alter parameters, configure EMI effects, and generate SAR imagery, to understand how SAR operates and plan for training exercises. Configurable simulation parameters not shown in the examples include detailed antenna characteristics (beamwidth, polarization, gain, boresight, etc.), radar system parameters (pulse repetition frequency, center frequency, transmit power, pulse width, etc.), platform kinematics, and weather effect toggles (clouds and fog) among others.

Understanding SAR

SAR image quality depends on numerous interdependent factors that operators should understand to effectively employ SAR and defend against it. The fundamental relationships between system parameters and performance have direct operational implications. Figure 1 demonstrates how a longer aperture achieves higher resolution for a specific SAR configuration. The ability to simulate, and therefore visualize this concept, aids in understanding that longer collection times improve resolution, though it may also increase vulnerability to signal disruption. Similarly, bandwidth limitations directly affect target discrimination capabilities, with higher bandwidths allowing separation of closely spaced objects that would otherwise merge into indistinguishable returns. These fundamentals are important to understand to analyze what a sensor would be able to see given a few known parameters.

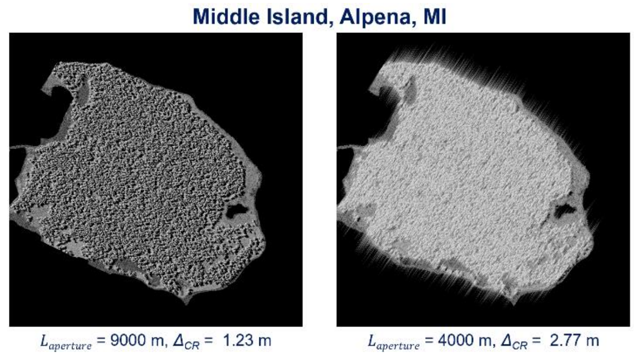

Figure 1: Simulated SAR Image Demonstrating Varying Aperture Lengths (RFView)

Geometric Effects

A fundamental distinction between SAR and optical imagery lies in the way they collect and resolve data. Optical sensors capture light reflected off the Earth's surface in straight lines from above, producing images based on ground range (i.e., horizontal distance across the terrain). In contrast, SAR measures distances in slant range, the direct line between the radar and the target, which introduces unique geometric distortions such as foreshortening, layover, and shadowing. These distortions differ from what is seen in optical imagery and must be understood for accurate intelligence assessment. SAR image overlay, illustrated in Figure 2, exemplifies how SAR's slant-range geometry differs fundamentally from optical imaging. Tall structures, like the Eiffel Tower, appear to lean away from their shadows, with building tops displaced toward the sensor. This effect affects target mensuration and can cause misidentification if not properly understood.

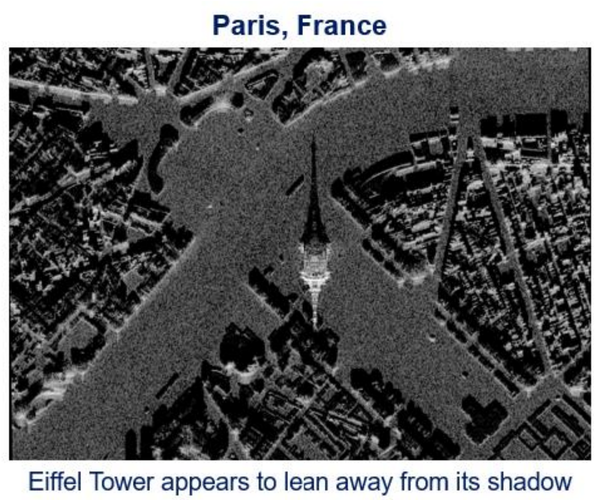

Figure 2: Simulated SAR Image Demonstrating the SAR Overlay Effect (RFView)

SAR Interference

In this section, we'll cover a few examples of how SAR interference can be simulated and explored and why it's relevant to education and training, similar to SAR concepts from the previous section. All effects shown are notional representations for unclassified discussion.

One of the most basic challenges for SAR radar is broadband noise interference, which can attenuate the signal-to-noise ratio required for clear image formation. Figure 3 shows a notional example of how ground-based noise interference can degrade SAR image quality. The uniform noise elevation across the image reduces contrast and obscures targets. Guardians can use this simulation capability combined with SAR generation to observe how intentional interference manifests differently than natural unintentional interference and learn to recognize threat indicators.

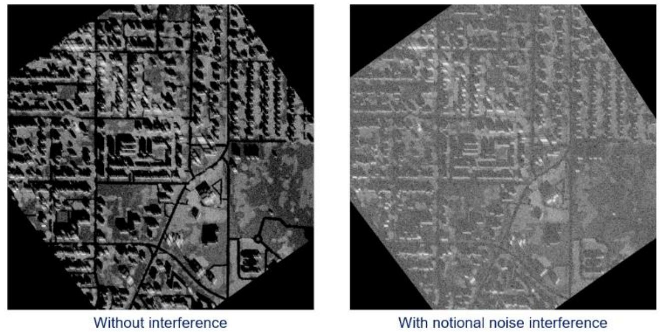

Figure 3: Simulated SAR Image Demonstrating the Effects of Noise Interference (RFView)

Interference Analysis

Electromagnetic interference, or EMI, presents an evolving threat to space-based sensors. Guardians must prepare to face these threats by emulating these effects themselves. As such, they require modeling tools that enable the design and evaluation of ground-based interference. This section of paper presents an example scenario simulating ground-based EMI to support training exercises and improve decision-making.

At the core of this capability is a physics-based calculation of the power received at the satellite, which includes transmit and receive beam patterns, antenna gain, signal propagation loss, and terrain-induced line-of-sight (LOS) blockages. The computed result is an accurate signal-to-noise ratio (SNR) at the receiving platform, which when used with SAR simulation, can be used to predict SAR imagery under realistic environmental conditions. The resulting imagery can be used to assess the visibility of ground targets and the effectiveness of different EMI configurations on satellite radar sensors.

Figure 4 provides a Google Earth overview of a LEO satellite with a radar targeting an area in the Appalachian Mountains and an isotropic source of interference on the ground. The simulation represents a moment in time where the satellite position and inference platform remain stationary, but the radar beam direction of the satellite is dynamic. The satellite sweeps its radar beam across multiple aim points in a 40 km by 40 km grid at 100 m resolution and the power level of the interference at the receiving radar is calculated for each aim position. Due to this configuration, when plotting the interference power level vs aim position like in Figure 5, we get a pattern that closely matches the beam pattern of the satellite. In this case the satellite radar is configured with the following parameters: 1024 horizontal and 128 vertical antenna elements with 0.015 m element spacing and a center frequency of 10 GHz, or a 0.01° azimuth beamwidth, and 0.79° elevation beamwidth, typical for a SAR satellite.

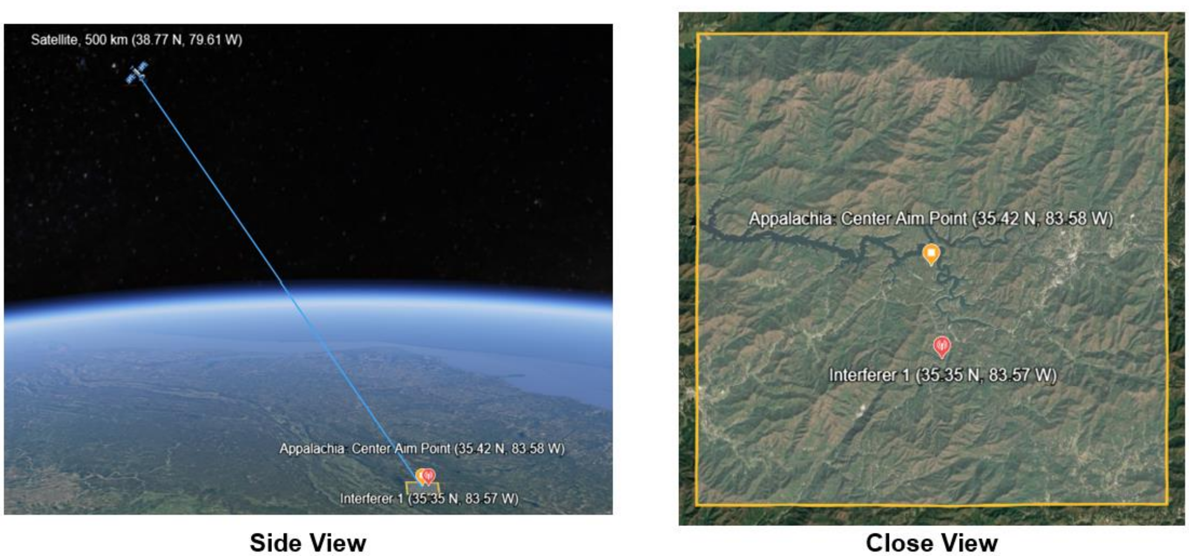

Figure 4: Visual Representation of Satellite and Interferer Scenario

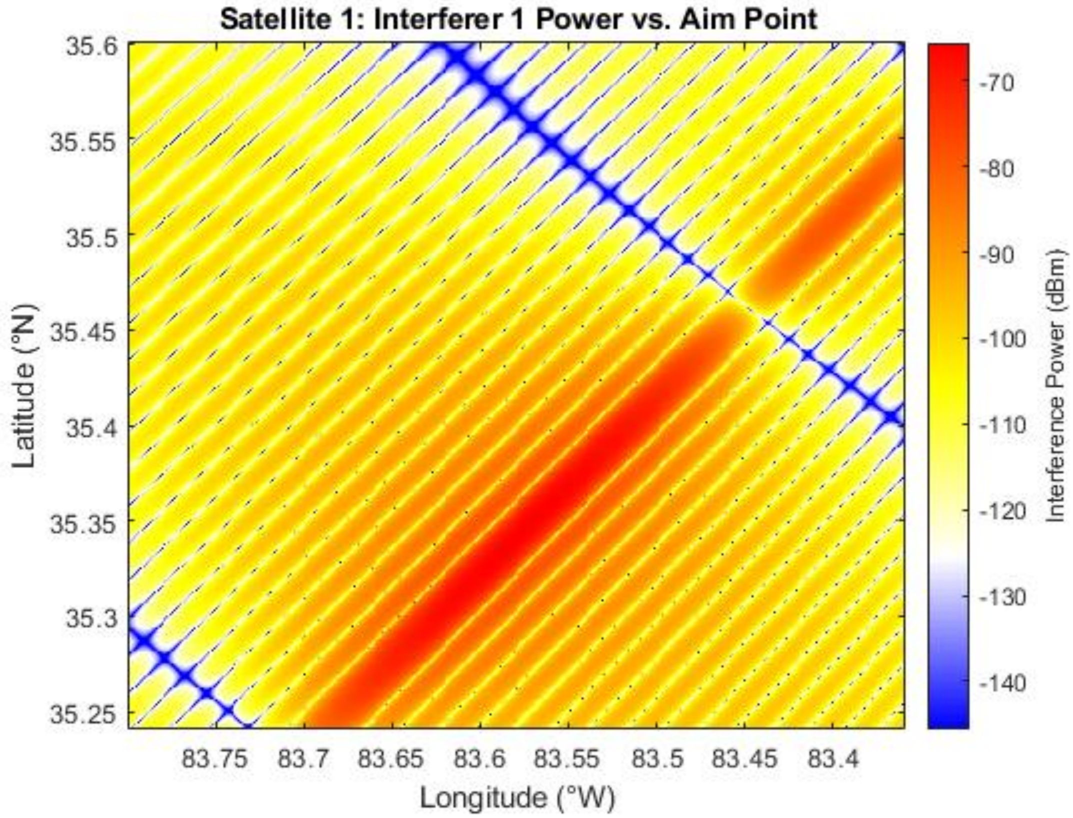

Figure 5: Interference Power Vs Satellite Aim Point (RFView)

Figure 6 displays the satellite interference receive pattern over an optical satellite image of the terrain, allowing the user to attain a better understanding of how the position of the interference relates to the targeted area of the satellite geographically.

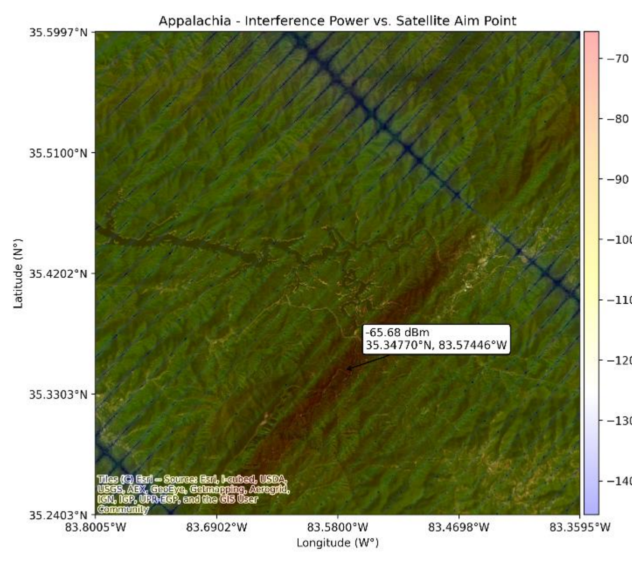

Figure 6: Interference Power at Satellite Overlaid on Terrain (RFView)

Applications for Training and Education

The capabilities covered in this section are expected to support Space Force training objectives beginning in late 2025 and early 2026. In addition to being used in education, the tools show promise for enhancing exercises where participants will be able to create realistic environments for one another, enhancing readiness across Space Force. Units who are tasked with replicating operational challenges will particularly benefit from the ability to design effective threats for these exercises. With the capability shown in this section, users of the tool can configure and simulate interference and then use the SAR image generation to know exactly how effective the sensor would be able to operate in that scenario.

EMS environment simulation also offers significant potential to improve Space Force education, though the integration into formal curricula remains in early stages. An interactive visualization of electromagnetic propagation can help make abstract concepts tangible for those learning about radar principles. For example, students can configure platforms in a simulated environment and observe how signals interact with between platforms and the terrain, to understand how changes in system parameters affect performance. Hands-on exploration builds intuition that traditional classroom material struggles to convey, which in turn accelerates the development of radar expertise.

FUTURE DEVELOPMENT

In using an impulse response to represent a channel model, the M&S software capability can be scaled to hardware-in-the-loop (HWIL) testing by leveraging transceiver cards and FPGA technology to perform a real-time convolution between input signals and the simulated channel impulse response.

Figure 9 showcases a HWIL system using a PXIe-1092 chassis hosting PXIe-5785 transceiver cards. A system under test (SUT) would connect to the transceiver card directly through its RF coaxial output through an RF front end that includes mixers for RF to IF frequency conversion and variable attenuators for dynamic range adjustment. This configuration enables the SUT to transmit and receive returns convolved with channel models that mimic what it would experience in the field. As an example, an engineer may use this technology to evaluate electronic protection algorithm performance against realistic EMI within controlled laboratory environments.

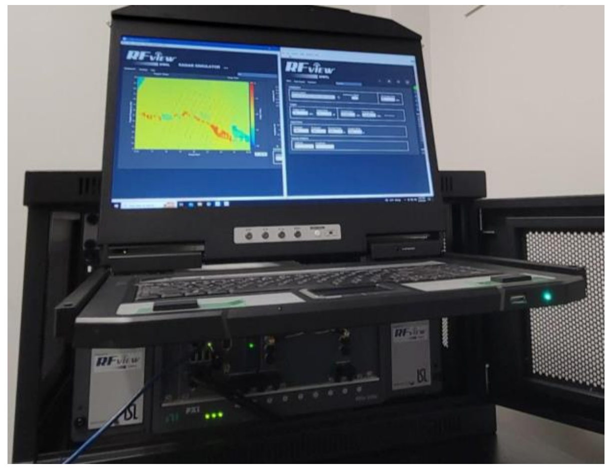

Figure 7: Hardware-In-The-Loop System (ISL)

Other improvements to developing M&S tools should include integration with classified databases so that users can perform mission-specific analysis using real threat parameters and high-resolution terrain data. Also, the incorporation of cognitive algorithms for platforms in the simulated environment could help in algorithm development as well as in preparing operators for systems using artificial intelligence.

CONCLUSION

The transition from statistical covariance models to stochastic transfer function models solves fundamental limitations posed by previous methods used for radar simulation. Unlike statistical approaches that treat clutter as random noise, stochastic transfer functions model the physics of how radar signals interact with terrain, buildings, and other objects, providing the fidelity needed to simulate all radar modes, especially SAR. When implemented via GPU-accelerated rasterization and ray tracing, theoretical models can be transformed into mission viable training and education tools used for SAR image generation and interference modeling.

The SAR and SAR interference capability demonstrated in this paper directly address training gaps identified by Space Force personnel. Through a graphical user interface that allows the manipulation of various platform parameters in a simulated radar environment, users are able to develop an understanding of how SAR systems operate and potentially where vulnerabilities exist. Also in this paper, an example covering interference configuration analysis was used to demonstrate how simulated scenarios can help reveal how platform location and antenna configurations affect other platforms in a complex environment. These capabilities will prove valuable as Guardians prepare for exercises in late 2025 and early 2026.

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