Operational space weather forecasts to support satellite operations

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1. ABSTRACT

The paper presents the UK operational deployment of the Advanced Ensemble Networked Assimilation System (AENeAS; [1]) at the UK Met Office, aimed at enhancing Space Situational Awareness (SSA) and Space Domain Awareness (SDA) in Low Earth Orbit (LEO). AENeAS, a physics-based data assimilation model, integrates diverse data sources – including electron density profiles, total electron content (TEC) measurements, radio occultation data, and derived neutral densities – to accurately predict satellite trajectories and mitigate collision risks. This capability is vital due to the increasing congestion in LEO, posing significant threats to the safety and longevity of space-based assets.

The operational implementation of AENeAS provides satellite operators with real-time thermospheric nowcasts and actionable forecasts, with uncertainties, crucial for collision avoidance decisions. Moreover, the model's validation, using independent data sources like the Swarm and CHAMP satellites, demonstrates its superior performance over other models in offering more accurate neutral density estimates. This advancement underscores AENeAS's significant contribution to the SSA/SDA community, highlighting its role in creating a safer, more reliable, and sustainable operational environment for satellite technologies amid growing space congestion. The integration of novel thermospheric observations and the provision of critical atmospheric data make AENeAS a pivotal tool for the future of space operations management.

2. INTRODUCTION

The proliferation of satellite technology has brought about a significant evolution in how we communicate, navigate, and monitor our planet. However, the growing number of objects in Low Earth Orbit (LEO) introduces a heightened risk of collisions, which could lead to substantial disruptions of the space-based infrastructure that underpins many aspects of contemporary life. Addressing this challenge requires advanced predictive tools capable of accurately modeling the complex dynamics of the upper atmosphere, particularly within the ionosphere and thermosphere. The Advanced Ensemble Networked Assimilation System (AENeAS) is a critical innovation in this arena. By integrating first-principles models with real-time observations using a sophisticated variant of the ensemble Kalman filter, the Local Ensemble Transform Kalman Filter (LETKF), AENeAS offers a cutting-edge approach to forecasting atmospheric conditions. This capability is vital for satellite operators who require precise orbit determination and effective strategies for collision avoidance.

AENeAS has been implemented and is now operational at the UK Met Office Space Weather Operations Centre (MOSWOC) under the Space Weather Instrumentation, Measurement, Modelling, and Risk (SWIMMR) initiative. Launched in 2020, SWIMMR represents a significant step forward in enhancing the UK's capacity to predict and mitigate the impacts of space weather. As the UK moves toward a future with an increased reliance on space-based assets, ensuring the protection of both terrestrial and orbital technological infrastructures is of paramount importance. Supported by the UK Research and Innovation's Strategic Priorities Fund, SWIMMR aligns closely with national research goals, fostering interdisciplinary collaboration to address the multifaceted challenges posed by space weather phenomena.

3. BACKGROUND

Modeling the upper atmosphere, particularly the thermosphere, is essential for understanding the forces acting on satellites and debris in LEO. There are three primary categories of models used for this purpose: empirical models, physics-based models, and data assimilation models.

Empirical models, which often incorporate machine learning techniques, typically offer lower spatial and temporal resolution [2]. Examples of such models include: NRLMSIS-2.0 [3], DTM2020 [4], JB2008 [5], and HASDM-ML [6]. These models are frequently employed in operational settings due to their simplicity and computational efficiency, despite their limitations in accuracy and resolution.

Physics-based models, in contrast, are grounded in the fundamental equations governing the physical processes within the thermosphere, often in conjunction with the ionosphere. These models are driven by initial and boundary conditions, as well as proxies for solar and geomagnetic activity. Examples include: CTIPe [7], TIE-GCM [8], [9], WAM [10], GITM [11], WACCM-X [12], and GAIA [13]. These models provide a more detailed and dynamic understanding of the thermosphere, enabling predictions that reflect real-time solar and geomagnetic influences.

Data assimilation models combine observational data with either empirical or physics-based models to improve prediction accuracy. For example, HASDM [14] incorporates data assimilation into an empirical framework, while AENeAS [1] integrates it into a physics-based context. Fig. 1 showcases model outputs of neutral density at an altitude of 250 km, illustrating the thermosphere's response to the geomagnetic storm on March 17, 2013. Physics-based models, in particular, are adept at capturing the dynamic response of the thermosphere to solar and geomagnetic activity.

Although empirical models are widely used in operational orbit prediction and space traffic management, there is a growing shift toward the use of physics-based models in these applications. For instance, the US Space Weather Prediction Centre (SWPC) employs the WAM model, and the UK Met Office uses AENeAS to support advanced orbit prediction capabilities. These physics-based models offer the advantage of providing a consistent data framework that can be applied to multiple objects in orbit, improving computational efficiency when predicting the orbits of thousands of satellites and debris. The ability of physics-based models to forecast thermospheric conditions is crucial for accurate satellite and debris tracking. However, these models often exhibit biases and may underperform relative to empirical models, a limitation that data assimilation techniques, such as those used in AENeAS, are designed to mitigate. The challenges and benefits of using physics-based models for supporting LEO satellite operations, as well as a number of solutions to overcome the challenges, are described in [15].

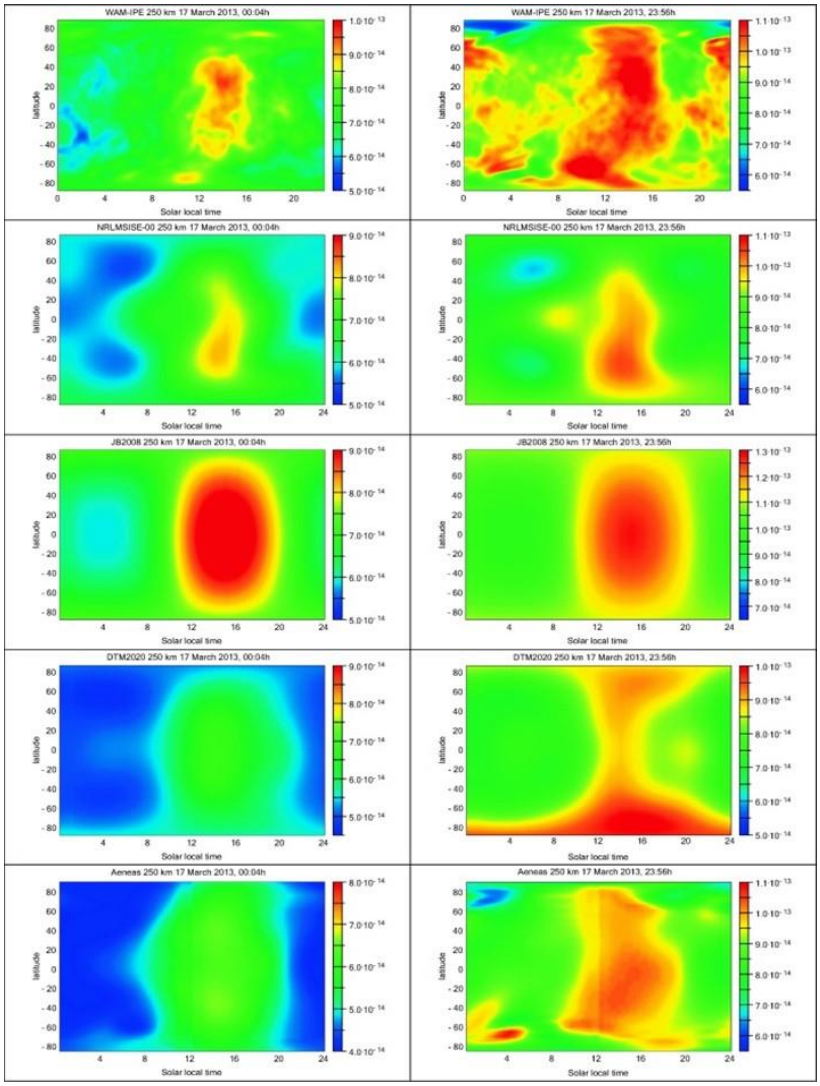

Fig. 1. Model density maps at 250 km just before (left frames) and at the height of the 13 March 2013 minor storm (right frames), from [2].

4. METHODOLOGY

4.1 AENeAS

AENeAS represents a fusion of observational data with a background physics model using an advanced variant of the ensemble Kalman filter (EnKF) [16]. The EnKF is part of the broader family of Kalman filters, which operate by iteratively predicting and correcting system states. Unlike the standard Kalman filter, the EnKF utilizes an ensemble of forecasts to approximate error covariance, thereby avoiding the direct computation of these covariances. The EnKF process involves three main steps:

1. Initialization: An ensemble of state estimates, reflecting the uncertainty in initial conditions, is generated.
2. Forecasting: The ensemble members are advanced forward in time using the physics model.
3. Analysis: When new observational data becomes available, the ensemble is updated through a weighted average based on the Kalman Gain, integrating the observations to refine the forecast.

While the Kalman filter is optimal under specific assumptions – such as Gaussian distributions, linearity, and no biases – the EnKF is more flexible, allowing for non-linear and non-Gaussian processes. AENeAS uses the Local Ensemble Transform Kalman Filter (LETKF) [17], which introduces localization to manage the spurious correlations that can occur due to the limited size of practical ensembles. LETKF operates by transforming the ensemble into observation space within localized regions, reducing computational complexity and improving the accuracy of the model.

The LETKF offers several key advantages:

- Efficiency: By breaking down the global analysis problem into smaller, localized problems, the LETKF can solve these independently and in parallel, significantly improving computational efficiency.
- Reduced Spurious Correlations: Localization ensures that only relevant, nearby observations influence the state update, reducing the impact of distant, uncorrelated data points.
- Scalability: The LETKF is well-suited to high-dimensional systems, as it avoids the need to store or manipulate full covariance matrices, making it scalable to large-scale problems.

Mathematically, the LETKF computes the analysis increment for each ensemble member as a linear combination of the ensemble perturbations, with weights optimized to minimize analysis error variance based on local observations.

4.2 Drag Force Modelling

Accurate modelling of thermospheric density is essential for predicting drag forces on satellites and debris in LEO. The drag force (F_d) acting on an object is given by:

$$F_d = \frac{1}{2} C_d \rho v^2 A,$$

where C_d is the drag coefficient, ρ is the thermospheric density, v the relative velocity of the object, and A is the cross-sectional area perpendicular to the velocity vector.

The thermosphere's density varies significantly with solar and geomagnetic activity, leading to fluctuations that complicate the estimation of drag forces. Accurate drag modeling is crucial for several reasons:

- Orbital Decay Prediction: Errors in density estimates can lead to inaccuracies in predicting how quickly a satellite's orbit will decay due to drag.
- Collision Avoidance: Precise drag force calculations are necessary to improve the accuracy of orbital trajectory predictions, which are critical for collision avoidance strategies.
- Fuel Optimization: Satellites equipped with propulsion systems must adjust their orbits periodically. Improved density models can help optimize fuel usage by reducing the need for frequent corrections.

5. APPLICATION OF AENeAS

AENeAS has a broad range of applications that are vital for maintaining the safe and efficient operation of satellites in LEO. By providing highly accurate predictions of atmospheric densities, AENeAS enables satellite operators to make better-informed decisions regarding orbital adjustments, leading to enhanced collision avoidance, fuel savings, and extended satellite lifespans.

The collision probability between two orbiting objects is determined by analyzing their conjunction data points, where their orbits come closest together. This analysis relies on the relative position and velocity vectors of the objects, as well as the positional uncertainties (errors) in various directions. The probability of collision (P_c) is calculated using:

$$P_c = \exp\left(-\frac{1}{2}\left[d^T (Cov_1 + Cov_2)^{-1} d\right]\right),$$

where d is the "miss distance vector" representing the closest approach between the two objects, and Cov_i for $i = 1{,}2$ are the covariance matrices describing the positional uncertainties of the objects.

Improving the specification of thermospheric conditions with AENeAS reduces positional uncertainties, leading to more accurate predictions of P_c. This accuracy enables satellite operators to make more informed decisions, potentially reducing the frequency of unnecessary orbital maneuvers.

6. HANDLING NON-GAUSSIAN UNCERTAINTIES

In the realm of satellite operations, accurately estimating the probability of collisions between objects in Low Earth Orbit (LEO) is a critical concern. Traditionally, this estimation process has relied on the assumption that the underlying thermospheric density distributions, critical to calculating drag forces, are Gaussian. While Gaussian distributions offer mathematical simplicity and ease of implementation, they do not always capture the complex realities of the thermosphere, particularly during periods of heightened solar or geomagnetic activity. Non-Gaussian probability distribution functions (PDFs) present a more flexible and realistic approach, allowing for the representation of statistical features such as heavy tails, skewness, and multimodality, which are often observed in thermospheric data. By utilizing non-Gaussian PDFs, satellite operators can achieve more accurate estimations of collision probabilities, leading to improved decision-making and enhanced safety in space operations.

6.1 Limitations of Gaussian Assumptions

The Gaussian distribution, often assumed in traditional models, is characterized by its symmetrical bell curve, which is defined entirely by its mean and variance. This assumption implies that extreme values (outliers) are rare and that the distribution of data points is symmetrically centered around the mean. In the context of thermospheric density and drag forces, these assumptions may not hold true, especially under the influence of dynamic space weather conditions. For instance, during geomagnetic storms or periods of high solar activity, the thermosphere can exhibit significant deviations from a normal distribution, including skewed distributions where one side of the mean contains more extreme values than the other, or distributions with heavy tails that indicate a higher likelihood of extreme events.

Relying on Gaussian assumptions can therefore lead to underestimation or overestimation of satellite collision probabilities. For example, if the thermospheric density distribution has a heavy tail, a Gaussian model might underestimate the likelihood of encountering high-density regions, which could result in inaccurate predictions of drag forces and, consequently, collision risks. Similarly, skewed distributions can lead to biased estimations of satellite positions, affecting the accuracy of conjunction analyses used to predict close approaches between objects in orbit.

6.2 Advantages of Non-Gaussian PDFs

Non-Gaussian PDFs offer a more accurate and flexible framework for modeling the uncertainties associated with thermospheric density and drag forces. These PDFs can accommodate the statistical nuances of real-world data, leading to more precise estimations of collision probabilities. Specifically:

- Heavy Tails: Non-Gaussian PDFs can capture the higher probability of extreme events, such as sudden increases in thermospheric density due to solar flares or geomagnetic storms. This capability is particularly important for modeling the drag forces acting on satellites, as it allows for a more realistic estimation of how these forces vary over time. By accurately representing the likelihood of extreme density values, non-Gaussian PDFs reduce the risk of underestimating collision probabilities, which is crucial for avoiding unexpected satellite conjunctions.

- Skewness: The ability to model skewed distributions is another key advantage of non-Gaussian PDFs. In many cases, the distribution of thermospheric density may be asymmetrical, with more frequent occurrences of high or low-density values depending on the space weather conditions. Skewed distributions can lead to more accurate predictions of satellite positions, particularly in scenarios where the traditional Gaussian assumption might cause systematic biases. By better representing the true distribution of density values, non-Gaussian PDFs improve the precision of orbital predictions and collision probability estimates.

- Multimodality: Non-Gaussian PDFs can also model multimodal distributions, where the data exhibits multiple peaks corresponding to different regimes or states of the thermosphere. This is especially relevant during complex space weather events, where the thermosphere might exhibit different behaviors in different regions or at different times. By capturing these multiple modes, non-Gaussian PDFs provide a more comprehensive view of the possible states of the thermosphere, leading to more robust collision probability calculations.

6.3 Practical Implementation in Satellite Operations

Incorporating non-Gaussian PDFs into the estimation of satellite collision probabilities involves using advanced statistical techniques and data assimilation methods that can accurately capture the underlying distribution of thermospheric parameters. One effective approach is the use of ensemble modeling, where multiple simulations are run to generate a range of possible outcomes, each reflecting different initial conditions and uncertainties. The resulting ensemble can then be analyzed to construct a non-Gaussian PDF, which provides a detailed representation of the probability distribution of thermospheric densities.

By integrating non-Gaussian PDFs into the collision probability estimation process, satellite operators can achieve a more nuanced understanding of the risks involved in satellite conjunctions. This improved risk assessment enables operators to make more informed decisions about collision avoidance maneuvers, reducing the likelihood of unnecessary maneuvers and conserving valuable fuel resources. Moreover, the enhanced accuracy in collision probability estimates contributes to the overall safety and sustainability of space operations, as it allows for more precise management of the increasingly crowded space environment.

6.4 Implementation with AENeAS

AENeAS, as an ensemble-based model, offers the capability to estimate these non-Gaussian PDFs directly from its ensemble members. There are several approaches to constructing PDFs from ensemble data:

1. Frequentist Approach: This method involves treating ensemble members as samples from an underlying random process. A PDF is constructed by counting the occurrences of each outcome and representing these counts as a histogram. However, this approach can be sensitive to the choice of bin sizes and boundaries, potentially leading to an unstructured PDF.

2. Kernel Density Estimation (KDE): KDE is a non-parametric method for estimating the PDF of a random variable. It involves placing a kernel function, such as a Gaussian curve, at each data point and summing these kernels to produce a smooth estimate of the PDF. The choice of bandwidth in KDE is crucial; a narrower bandwidth results in more detailed features but risks overfitting, while a broader bandwidth may oversmooth the data.

3. Fitting to a Known Distribution: If the data is believed to follow a specific distribution, such as Gaussian or exponential, the parameters of this distribution can be estimated from the ensemble data. This approach involves selecting an appropriate distribution, fitting it to the data using techniques like maximum likelihood estimation (MLE), and validating the fit using statistical tests. The resulting parameterized distribution provides a mathematical model of the PDF.

Among these various approaches, AENeAS employs Kernel Density Estimation (KDE) to estimate the underlying PDFs of neutral densities. Fig. 2 presents a typical PDF of neutral density derived using KDE, with the ensemble members' raw output depicted as black crosses and the smoothed PDF shown in blue, calculated using Silverman's Rule (a popular heuristic that can be used as a "rule of thumb" to estimate the bandwidth for the KDE).

This means that, using AENeAS as the underlying LEO thermosphere model in satellite prediction applications, we can improve the underlying estimates of collisions probability not only by reducing the error in specifying the neutral density, but also by better understanding the errors and uncertainties.

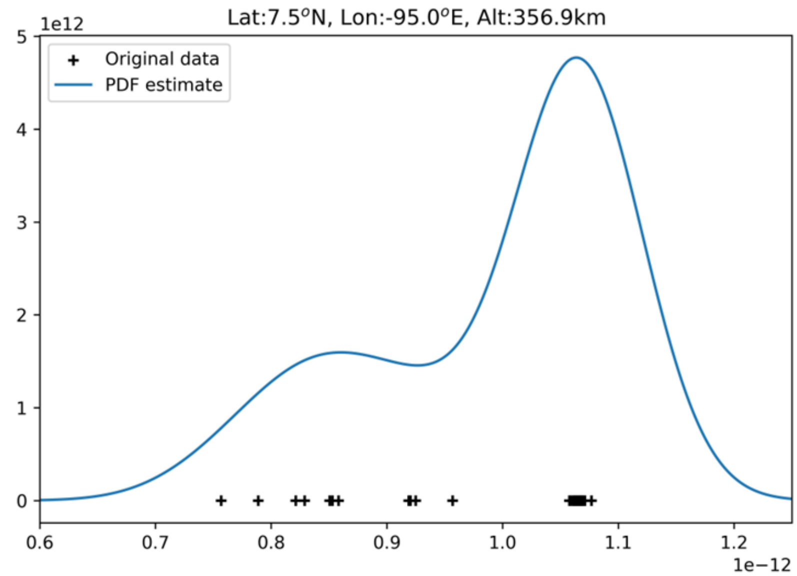

Fig. 2. Estimated PDF of neutral densities at a specific location
(7.5˚N, -95˚E and an altitude of 357 km)

7. CONCLUSIONS

The operational deployment of AENeAS at the UK Met Office represents a significant advancement in the realm of satellite orbit prediction and collision avoidance. AENeAS's integration of sophisticated data assimilation techniques with real-time atmospheric observations marks a substantial improvement in the accuracy of thermospheric models. This enhanced precision is critical for the safety and sustainability of space operations, both in the UK and globally.

Utilizing AENeAS as the foundational LEO thermosphere model in satellite prediction applications allows for a significant enhancement in the estimation of collision probabilities. This improvement is achieved not only by refining the accuracy of neutral density specifications, critical for precise drag force calculations, but also by providing a deeper and more nuanced understanding of the associated errors and uncertainties. By integrating AENeAS, operators can account for the complex variability in thermospheric conditions, leading to more accurate predictions of satellite trajectories and potential collision events. The advanced data assimilation techniques employed by AENeAS enable the model to capture and represent the inherent uncertainties in thermospheric density with greater fidelity. This results in a more comprehensive error analysis, allowing satellite operators to make more informed decisions regarding collision avoidance maneuvers. Ultimately, this leads to a reduction in the likelihood of unnecessary orbital adjustments, optimizing fuel use and extending satellite operational lifespans, while simultaneously ensuring a higher level of safety and reliability in space operations.

8. REFERENCES

[1] S. Elvidge and M. J. Angling, 'Using the local ensemble Transform Kalman Filter for upper atmospheric modelling', *J. Space Weather Space Clim.*, vol. 9, p. A30, 2019, doi: 10.1051/swsc/2019018.

[2] S. Bruinsma *et al.*, 'Thermosphere and Satellite Drag', *Advances in Space Research*, 2023, doi: 10.1016/j.asr.2023.05.011.

[3] J. T. Emmert *et al.*, 'NRLMSIS 2.0: A Whole-Atmosphere Empirical Model of Temperature and Neutral Species Densities', *Earth and Space Science*, vol. 8, no. 3, p. e2020EA001321, 2021, doi: 10.1029/2020EA001321.

[4] S. Bruinsma and C. Boniface, 'The operational and research DTM-2020 thermosphere models', *J. Space Weather Space Clim.*, vol. 11, p. 47, 2021, doi: 10.1051/swsc/2021032.

[5] B. R. Bowman, W. K. Tobiska, F. A. Marcos, C. Y. Huang, C. S. Lin, and W. J. Burke, 'A New Empirical Thermospheric Density Model JB2008 Using New Solar and Geomagnetic Indices', 2008.

[6] R. J. Licata, P. M. Mehta, W. K. Tobiska, and S. Huzurbazar, 'Machine-Learned HASDM Thermospheric Mass Density Model With Uncertainty Quantification', *Space Weather*, vol. 20, no. 4, p. e2021SW002915, 2022, doi: 10.1029/2021SW002915.

[7] M. V. Codrescu *et al.*, 'A real-time run of the Coupled Thermosphere Ionosphere Plasmasphere Electrodynamics (CTIPe) model', *Space Weather*, vol. 10, no. 2, Feb. 2012, doi: 10.1029/2011SW000736.

[8] R. L. Richmond, 'Meteor burst communications, Part1: MBC advances assist C3 objectives', *Mil Elect/Count Meas*, no. August, pp. 68–72, 1982.

[9] L. Qian *et al.*, 'The NCAR TIE-GCM: A Community Model of the Coupled Thermosphere/Ionosphere System', in *Modeling the Ionosphere-Thermosphere System*, J. Huba, R. Schunk, and G. Khazanov, Eds., in Geophysical Monograph Series. , Chichester, UK: John Wiley & Sons, Ltd, 2014, pp. 73–83. doi: 10.1002/9781118704417.ch7.

[10] T.-W. Fang *et al.*, 'Space Weather Environment During the SpaceX Starlink Satellite Loss in February 2022', *Space Weather*, vol. 20, no. 11, p. e2022SW003193, 2022, doi: 10.1029/2022SW003193.

[11] A. J. Ridley, Y. Deng, and G. Toth, 'The Global Ionosphere-Thermosphere Model (GITM)', *Journal of Atmospheric and Solar Terrestrial Physics*, vol. 68, pp. 839–864, 2006.

[12] H.-L. Liu *et al.*, 'Development and Validation of the Whole Atmosphere Community Climate Model With Thermosphere and Ionosphere Extension (WACCM-X 2.0)', *Journal of Advances in Modeling Earth Systems*, vol. 10, no. 2, pp. 381–402, 2018, doi: 10.1002/2017MS001232.

[13] Y. Miyoshi, H. Fujiwara, H. Jin, H. Shinagawa, H. Liu, and K. Terada, 'Model study on the formation of the equatorial mass density anomaly in the thermosphere', *Journal of Geophysical Research: Space Physics*, vol. 116, no. A5, 2011, doi: 10.1029/2010JA016315.

[14] M. F. Storz, B. R. Bowman, J. I. Branson, S. J. Casali, and W. K. Tobiska, 'High accuracy satellite drag model (HASDM)', *Advances in Space Research*, vol. 36, no. 12, pp. 2497–2505, 2005.

[15] M. K. Brown and S. Elvidge, 'Using WACCM-X neutral densities for orbital propagation: Challenges and solutions', *Journal of Space Safety Engineering*, Apr. 2024, doi: 10.1016/j.jsse.2024.04.012.

[16] G. Evensen, *Data Assimilation, the Ensemble Kalman Filter*, 2nd ed. Springer-Verlag Berline Heidelberg, 2009.

[17] B. R. Hunt, E. J. Kostelich, and I. Szunyogh, 'Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter', *Physica D: Nonlinear Phenomena*, vol. 230, no. 1–2, pp. 112–126, Jun. 2007, doi: 10.1016/j.physd.2006.11.008.