Visualizing Space Debris

Team 9: Little Einsteins

Sophie Hollowell, Paige Huynh, Aaron Liu, Tim Phan, Jane Yijun Sun, Ethan Yang

1 Introduction

Space debris encompasses all non-functional, human-made objects orbiting Earth, including rocket remnants, fragments from past collisions, and nonfunctioning satellites. With millions of debris pieces traveling at thousands of kilometers an hour, even small fragments can cause catastrophic collisions. The rise of debris in recent years (the Kessler syndrome) also contributes to concerns surrounding higher collision risk, increased operational costs, and the long-term sustainability of space operations. While large objects can be tracked, the vast majority of smaller debris (1 mm to 10 cm) remains unmonitored, creating substantial uncertainty in evaluating collision risk and driving spacecraft design and mission planning.

As a result, tracking and visualization of space debris becomes an important and challenging problem to tackle. Our goal is to enhance existing debris models and tracking systems through an interactive heatmap visualization, enabling more effective exploration of collision risk and supporting better decision-making for space operations which need to navigate the orbital debris environment.

2 Problem Definition

Space debris can come in various sizes, speeds, altitudes, and orbital paths making it difficult to visualize. Existing visualizations represent debris as deterministic points in a 3D space, leading to performance limitations and poor scalability when rendering the millions of orbital debris objects [19]. Furthermore, point-based representations fail to account for small, untracked debris that still pose significant risks to spacecraft. Other current debris management methods rely on models such as ORDEM and MASTER which estimate debris populations using statistical methods, but those model outputs are not spatially represented.

To address the limitations of existing orbital debris visualizations, our project focuses on developing a probabilistic heatmap visualization of orbital debris density. Instead of modeling individual objects, we estimate spatial concentrations of debris and represent them as continuous risk fields. This approach accounts for computational efficiency needed and provides a clearer, more intuitive representation of high-risk regions in Earth's orbits for stakeholders.

To create this probabilistic heatmap visualization of orbital debris density, we hope to combine the best of both worlds between point based representations and statistical methods like ORDEM. By using the data for point based representations as heat densities and adding in the statistical methods like ORDEM, we gain a more comprehensive and granular heatmap. This accounts for debris of all sizes while providing great scaling as the heatmap doesn't need to animate and render millions of points.

3 Literature Survey

Cascading orbital collisions were first hypothesized by Kessler and Cour-Palais [8] in 1978; since then, the problem has worsened. The latest ESA estimates give the number of untracked fragments from 1 mm to 10 cm at about 129 million [4]. These objects are too small to be reliably detected by ground-based radar and optical systems [11, 13]. Still, even millimeter-size fragments move at such a speed that they could damage or destroy an operational spacecraft [5]. With the debris population increasing through fragmentation events and launch activity [15], it poses a progressively more severe hazard to satellite operators and mission planners.

Since direct tracking does not cover the entire size spectrum, statistical environment models play a leading role in estimating the actual debris flux. For instance, NASA's ORDEM 3.0 [10] uses radar measurements and returned surface impact data to infer the debris flux from LEO to GEO using Bayesian inference. On the other hand, ESA uses Monte Carlo population synthesis for MASTER-2009 [6]. Both models broadly agree in LEO but differ at higher altitudes and in smaller size regimes, as the comparative studies by Krisko et al. [9] and Liu et al. [14] have shown. Underlying both models are fragment distributions from breakup models, such as the NASA Standard Breakup Model described by Johnson et al. [7], to reproduce the populations of objects too small to be directly observed.

From a space operations perspective, conjunction analysis is typically performed on collision probabilities between two objects. Alfano [1] proposes a widely used numerical method for computing collision probability from the covariance ellipsoids of two objects. This method works well when objects are under tracking observation but cannot be extended to the numerous untracked objects. Colombo et al. [3] used a similar concept by considering debris density as a continuous function in space, but their study is in the context of immediate collision effect and debris generation with no visual representation as discussed in this paper. In recent years, several active debris removal (ADR) proposals have been made [12, 19], but to choose objects for removal, a spatial risk assessment is required which is not readily available in existing tools.

The risk is substantial. Colvin et al. [2] have estimated that the annual cost of collision with debris is between 86 and 103 million dollars, and the satellite-based services threatened by debris, such as GPS, weather prediction, and climate monitoring, enable more than 190 billion dollars of global economic activities [16, 18]. Regulators such as the FCC and FAA have begun taking an interest [17], but those responsible for policy and those who operate satellites do not have a tool to easily visualize where debris risk lies. The results from debris environment models such as ORDEM and MASTER are often expressed in statistical tables or plots for different bands of altitude, which are useful for understanding engineering risk but do not provide a spatial sense of where the risk is concentrated.

Our project fills this gap by converting debris flux and density information into an interactive 3D heatmap that allows users to explore the space collision risk profile in different orbit regimes.

4 Proposed Method

The overarching idea for this project is to develop an interactive visualization of orbital debris that represents debris density and collision risk as a continuous spatial field rather than discrete tracked objects. Our approach combines:

- Probabilistic modeling that captures expected debris flux and accounts for small, untracked fragments.
- Real-world satellite debris data that provides known positions of objects > 10 cm.

4.1 Data Sources

We use two data sources for this project:

1. **NASA Orbital Debris Engineering Model (ORDEM):** This is a statistical environment model that estimates the flux (impact rate) of debris particles on spacecraft surfaces over time. The model estimates the debris environment using probabilistic distributions based on high-fidelity datasets, advanced data analysis techniques, and a large set of observational data (both in-situ and ground-based) which covers object size range from 10 μm to 1 m.
2. **CelesTrak & Space-Track:** Provide Two-Line Element (TLE) data describing the orbital parameters of tracked objects (> 10 cm). These datasets allow us to approximate spatial positions over time using orbital propagation models.

4.2 Data Preparation

For the purposes of joint visualization and combined risk, we must first transform the ORDEM outputs and satellite-derived debris observations into a common positional representation of latitude, longitude, and altitude. Rather than explicitly defining a fixed spatial grid, the spatial aggregation and data fusion occur later during the H3 binning stage, where both datasets are mapped into a shared hexagonal spatial framework.

Our main goals with data preparation are 1) mapping observations from multiple sources into a common spatial representation and 2) transforming raw inputs into comparable risk metrics. While both datasets describe data points in the same space, their preprocessing pipelines diverge due to inherent differences in their data structure and intended use.

ORDEM Data Processing: We use Telescope/Radar flux, which provides debris flux as a function of latitude and altitude. To prepare this data, we:

- Ran ORDEM in Telescope/Radar mode for latitudes $\in [-90, 90]$ in bins of 10° with elevation fixed at 90° to remove directional bias and ensure flux is interpreted as a scalar quantity.
- Parsed output files to extract flux values across latitude, altitude, and particle size thresholds.
- Resolved duplicate altitude entries inherent to ORDEM's boundary-based output format.
- Performed Monte Carlo simulation (1,000 iterations) with Gaussian noise at 10% standard deviation proportional to each flux value, estimating mean flux and standard deviation per grid cell to quantify measurement uncertainty.
- Converted cumulative flux thresholds into disjoint size ranges and computed a weighted risk score across particle sizes, emphasizing the increased danger larger debris poses.
- Applied log scaling to reduce skew in the resulting distribution.
- Interpolated across latitudes and longitudes to provide a smoother spatial field and expanded values uniformly across the same longitude (since ORDEM has no longitudinal resolution and assumes uniformity).

Satellite Data Processing: Satellite debris tracking data is based on Two-Line Element (TLE) sets containing orbital parameters, which are converted into spatial positions using orbital propagation. To prepare this data, we:

- Extracted TLE datasets from multiple debris groups on CelesTrak (e.g., FENGYUN-1C).
- Extracted TLE datasets from Space-Track's full catalog to supplement CelesTrak data.
- Dropped any duplicate data between CelesTrak and Space-Track.
- Propagated each TLE to a specific time using the SPG4 (Simplified General Perturbations) algorithm, giving us the data in TEME (True Equator, Mean Equinox) format.
- We converted each TEME coordinate into ITRS (International Terrestrial Reference System) format, allowing us to estimate the latitude, longitude, and altitude of each debris piece.
- Split the dataset into a $80-20$ train-test split for later evaluation.

Each object is treated as a discrete observation of an individual piece of orbital debris; these are then aggregated spatially, serving as high-confidence indicators of regions with elevated orbital congestion. We interpret satellite-derived densities as spatial proxies for higher-risk regions under the assumption that smaller untracked debris is statistically correlated with the spatial distribution of larger objects.

Spatial Representation & Binning: We use the H3 hexagonal indexing system to spatially aggregate debris observations over Earth's orbital environment. This method maps latitude and longitude coordinates into hex cells, allowing us to improve the computational efficiency while maintaining interpretability. Spatial binning is performed across:

- **Latitude/Longitude**: Debris located in similar lat/lon coordinates are binned together in shared hex cells using H3 indexing.
- **Altitude Bands**: To preserve vertical structure, each observation is additionally assigned to one of the following altitude bands:
  - 0-1000 km: Lower LEO
  - 1000-2000 km: Upper LEO
  - 2000-30000 km: MEO
  - 30000+ km: GEO/High Orbit

Since H3 supports only a 2D spatial representation, we incorporate the altitude as part of **composite key**, consisting of the H3 cell ID and altitude band. This method allows us to retain information on the altitude level of data while leveraging efficient H3 spatial clustering for latitude and longitude points.

Mapping points from the two datasets allows us to fuse the data in a common spatial representation.

Combining ORDEM + Satellite Data: The combination of ORDEM-derived risk estimates and satellite-derived debris observations occurs during the H3 binning stage described above. After both datasets have been transformed into a common lat-lon-alt representation, each observation is assigned to a composite spatial bin defined by its H3 cell ID and altitude band.

Within each composite bin, we aggregate the two sources separately:

- **Satellite Orbital Debris Contribution:** The number of propagated debris objects falling within the bin is counted to represent observed orbital congestion.

- **Ordem Flux Contribution:** The modeled debris risk values within the bin are summed to capture the statistical flux-based collision risk.
  - **Important Note:** To ensure these two values are comparable, we introduce a global scaling factor that maps ORDEM flux values onto the same scale as satellite-derived debris counts.
  - The scaling factor α is defined as:

    $$\alpha = \frac{N_{\text{Satellite}}}{\sum F_{\text{ORDEM}}}$$

    where $N_{\text{satellite}}$ is the total number of tracked debris objects and $\sum F_{\text{ORDEM}}$ is the total aggregated ORDEM risk across all spatial bins.
  - This scaling factor converts ORDEM flux values into a comparable representation to debris count, enforcing consistent magnitude scale and ensuring the final combined risk field is not dominated by differences in units or scale.
  - The ORDEM contribution within each bin is multiplied by α prior to combination.

Therefore, the Final Risk within bins is derived from the following:

$$F_{\text{combined}} = \alpha F_{\text{ORDEM}} + N_{\text{Satellite}}$$

where:

- α: The scaling factor for ORDEM Flux.
- F_{ORDEM}: The total ORDEM risk contribution within the hex cell.
- $N_{\text{Satellite}}$: The total count of debris objects within the hex cell.

Normalization: After bin-level risk aggregation, the ORDEM and satellite contributions remain on different raw scales, so to prevent spatial bins with extreme values from dominating, we apply a final min-max normalization step.

For each resolution level, we compute the minimum and maximum combined risk values across all H3 bins and rescale each bin value using:

$$F' = \frac{F - F_{\min}}{F_{\max} - F_{\min}}$$

where F is the aggregated bin risk and $F_{\min}$ and $F_{\max}$ are the minimum and maximum values within that resolution group.

GeoJSON Construction for Visualization: The final normalized risk values are encoded into a GeoJSON format to enable efficient rendering in the web-based visualization. We construct GeoJSONs for every altitude band, and each H3 cell within the bands is converted into a point geometry corresponding to its hexagonal boundary.

Each GeoJSON contains:

- Cell Point Geometry
- Properties for:
  - Hex ID
  - Altitude Band
  - Final Risk
- Tippecanoe Resolution

This structure allows the frontend visualization to render each hexagonal cell as a spatial unit with color scaling mapped directly to the final risk score. The tippecanoe resolution allows for easy association between Hex resolutions to the zoom resolution of the visualization.

4.3 Visualization Approach

Our main goal here is to create a visualization that is more intuitive and computationally efficient without sacrificing accurate information on debris.

After generating the GeoJson representations of H3 cells grouped by altitude bands, we convert these files into **Mapbox Vector Tile (MVT) in Protocolbuffer Binary Format (PBF)** using Tippecanoe, which significantly reduces storage overhead and improves computational efficiency. This data is then stored in an AWS S3 bucket that is served directly to our frontend application.

The frontend retrieves these PBF files, using the resolution/zoom level and tile's x, y, z coordinates as path segments to specify the PBF file to retrieve. Users can filter the altitude band via a dropdown menu, which determines the set of PBF tiles that is loaded. This approach ensures that we only retrieve and process the data relevant to the current zoom level and location, improving our application's performance and scalability.

The actual visualization is implemented with the **DeckGL** library, which is suited for rendering complex, interactive, 3D visualizations from large datasets. Specifically:

- The MVTLayer is used to fetch and decode the PBF file from the S3 bucket
- Each tile is rendered using an H3HexagonLayer, which creates and displays a hexagonal tile
- Risk values are mapped to colors, with lower-risk regions appearing in yellow and higher-risk regions appearing red
- Interactive tooltips are displayed for each hexagonal cell when hovered over, providing more detailed information including the H3 index, normalized risk score, and lat/long coordinates

This application supports both **2D** and **3D** views. The 3D view renders the heatmap on an interactive globe, while the 2D view uses MapLibre as a basemap that we render cells over, allowing users to view risk scores across the entire globe at once. To avoid reinitializing the WebGL context when switching, we toggle CSS visibility rather than remounting the components, preserving each view's pan and zoom state. Users can switch between the two views with a button.

Again, risk values are normalized independently within each altitude band, ensuring a more consistent interpretation of risk values across orbital regimes regardless of differences in absolute debris density.

4.4 Key Innovations

Our approach proposes several key innovations compared to existing visualization methods:

1. **Integration of Tracked and Untracked Debris:** Unlike current approaches that focus solely on visualizing tracked objects, our method incorporates statistical flux estimates from ORDEM to account for smaller, untracked debris, enabling a more holistic representation of the orbital environment.
2. **Unified Data Framework:** We develop a unified framework that combines statistical modeling (ORDEM) with observational satellite data. By mapping sources into a shared spatial grid, we make combining the data sources into a single representation possible.
3. **3D spatial Density Field Representation:** Instead of visualizing individual debris points, we model as a density field, expanding the use cases from object tracking to spatial risk estimation while simultaneously improving the scalability and interpretability of the visualization.
4. **Intuitive Heatmap-Based Visualization:** By presenting debris density in a heatmap format, we support users in easily identifying high-risk regions. This approach improves readability and accessibility compared to point-based visualizations.

5 Evaluation

We evaluated our approach across three dimensions: model accuracy, computational performance, and usability.

5.1 Model Accuracy

We validated our probabilistic heatmap by applying an 80/20 train-test split on satellite data to avoid bias, comparing predicted risk zones against 3,233 held-out test points across 649,758 hex cells. Our model achieved an overall hit rate of 97.5%, with ˜97% coverage across both LEO altitude bands, 94% in MEO (2000–30,000 km), and 98% in GEO (30,000+ km). Additionally, 54% of all debris points fall within the top 20% highest-risk cells, confirming the model concentrates risk where it matters most. Risk scores are heavily right-skewed (median 0.03, mean 0.08), indicating a small number of high-danger hotspots drive the average up.

5.2 Computational Performance

We measured rendering performance across four runs using Chrome DevTools, testing FPS across multiple interaction types. FPS ranged from 3–40 depending on interaction load, with rotation achieving the smoothest performance (up to 40 FPS) and zoom operations showing more variability (3–35 FPS). GPU memory usage remained low at 2.9–8.6 MB across all tests. Average initial load time was 6.16s on Chrome (cold start), 1.27s on Brave, and 0.49s on Safari, with variance driven by browser caching behavior rather than rendering complexity.

5.3 Usability

We conducted a user performance test to evaluate the usability and interpretability of our visualization by comparing it against an existing orbital debris visualization tool.

- Users took an average of 3.09 seconds to analyze debris around the South Pole using our tool, compared to 6.55 seconds with the alternative — 52% faster.
- Users noted that in LEO, debris is more concentrated near the polar regions (expected behavior), while the alternative visualization did not allow easy interpretation of this result.
- Overall, users found our visualization to be cleaner and more intuitive, as the alternative tool was described as laggy and messy, making it difficult to draw conclusions about debris clustering.

6 Conclusions and Discussion

In our project, we combine NASA ORDEM flux statistics and CelesTrak/Space-Track TLE satellite position data using H3 hexagons to provide an interactive and navigable visualization of risk fields. This addresses issues related to current models that cannot properly visualize statistics and probability distributions of satellites along with objects detected through observation and tracking systems. Compared to other methods, our approach combines probability density estimation with 2D/3D heatmaps of the field in real-time. Our statistical model includes approximately 52 million ORDEM flux points and 16,000 tracked space debris, accounting for the 1mm–1m range of particles undetected by the current systems.

Our visualization, which involves H3 binning and risk aggregation, serializing to GeoJSON, vector tile precomputation using Tippecanoe, storing tiles in AWS S3, and GPU accelerated rendering using Deck.gl, achieves efficiency by avoiding costly calculations in real-time. In an evaluation involving 649,758 hexagons, our approach obtained a 97.5% accuracy rate against the holdout test set, where 54

User performance tests were also done where we tested the performance of our tool by comparing it with another existing orbital debris visualization. The results showed that our tool performed 52% better in analyzing the debris around the South Pole, comparing 3.09 seconds vs. 6.55 seconds. The users also noted that the LEO debris is mostly concentrated in polar regions.

Some possible limitations include ORDEM's longitudinal consistency, whereas flux values are uniformly expanded in longitude instead of reflecting the longitudinal variability in debris population density. In addition, our fusion technique is based on the hypothesis that unobserved small debris statistically correlates with the geographical locations of the larger debris objects, which has yet to be tested against benchmarks. Lastly, visualization provides only a snapshot at an arbitrary propagation time, rather than a dynamic view.

In the future, it is clear that there are many options for increasing the dynamism of this visualization. Tracking changes over time and recommending safe altitude ranges people can enter into orbit, and emphasizing the high-risk areas that contribute to the right-skewed distribution of risks associated with debris (with a median of 0.03 and an average of 0.08). In summary, the team was able to provide a verified, easy to use, and scaleable visualization of the orbital debris environment, both 2D and 3D. Everyone on the team made equal contributions during the entire project.

References

[1] Salvatore Alfano. 2005. A Numerical Implementation of Spherical Object Collision Probability. *The Journal of the Astronautical Sciences* 53, 1 (2005), 103–109. https://doi.org/10.2514/1.13281

[2] T. Colvin, J. Karcz, and M. Wusk. 2023. *Cost and Benefit Analysis of Orbital Debris Remediation*. Technical Report. NASA Office of Technology, Policy, and Strategy. https://www.nasa.gov/wp-content/uploads/2023/03/otps_-_cost_and_benefit_analysis_of_orbital_debris_remediation_-_final.pdf

[3] Cristina Duran, Lorenzo Giudici, and Camilla Colombo. 2021. Modelling the whole space debris environment through a spatial density approach. *2021 AAS/AIAA Astrodynamics Specialist Conference* (08 2021). https://www.researchgate.net/publication/376617864_Modelling_the_whole_space_debris_environment_through_a_spatial_density_approach

[4] European Space Agency. 2024. Space Debris by the Numbers. https://www.esa.int/Safety_Security/Space_Debris Accessed 2026-03-01.

[5] Walter Leal Filho, Ismaila Rimi Abubakar, Julian D. Hunt, and Maria Alzira Pimenta Dinis. 2025. Managing Space Debris: Risks, Mitigation measures, and Sustainability Challenges. *Sustainable Futures* 10 (2025), 100849. https://doi.org/10.1016/j.sftr.2025.100849

[6] S. Flegel, J. Gelhaus, and M. Möckel. 2011. The MASTER-2009 Space Debris Environment Model. *Acta Astronautica* 69, 7–8 (2011), 541–550. https://doi.org/10.1016/j.actaastro.2011.04.013

[7] N.L. Johnson, P.H. Krisko, J.-C. Liou, and P.D. Anz-Meador. 2001. NASA's new breakup model of evolve 4.0. *Advances in Space Research* 28 (01 2001), 1377–1384. https://doi.org/10.1016/s0273-1177(01)00423-9

[8] Donald J. Kessler and Burton G. Cour-Palais. 1978. Collision Frequency of Artificial Satellites: The Creation of a Debris Belt. *Journal of Geophysical Research* 83, A6 (1978), 2637–2646.

[9] P.H. Krisko, S. Flegel, M.J. Matney, D.R. Jarkey, and V. Braun. 2015. ORDEM 3.0 and MASTER-2009 modeled debris population comparison. *Acta Astronautica* 113 (2015), 204–211. https://doi.org/10.1016/j.actaastro.2015.03.024

[10] Paula H. Krisko. 2014. The New NASA Orbital Debris Engineering Model ORDEM 3.0. *Acta Astronautica* 104, 1 (2014), 52–62. https://doi.org/10.1016/j.actaastro.2014.02.013

[11] Sharmila Kuthunur. 2024. Ultrasmall Space Junk Can Be an Invisible Satellite Killer. Scientists Are Learning How to Track It. *Scientific American* (2024). https://www.scientificamerican.com/article/ultrasmall-space-junk-can-be-an-invisible-satellite-killer-scientists-are/

[12] J.-C. Liou. 2008. An Active Debris Removal Parametric Study for LEO Environment Remediation. *Advances in Space Research* (2008).

[13] Meiying Liu, Hu Wang, Hongwei Yi, Yaoke Xue, Desheng Wen, Feng Wang, Yang Shen, and Yue Pan. 2022. Space Debris Detection and Positioning Technology Based on Multiple Star Trackers. *Applied Sciences* 12, 7 (2022). https://doi.org/10.3390/app12073593

[14] Yuyan LIU, Runqiang CHI, Baojun PANG, HU Diqi, Wuxiong CAO, and Dongfang WANG. 2024. Space debris environment engineering model 2019: Algorithms improvement and comparison with ORDEM 3.1 and MASTER-8. *Chinese Journal of Aeronautics* 37, 5 (2024), 392–409. https://doi.org/10.1016/j.cja.2023.12.004

[15] Amey Mishra. 2025. Analyzing the Impact of Space Debris and Reviewing Potential Solutions. *American Journal of Student Research* 3, 4 (2025), 247–252. https://doi.org/10.70251/HYJR2348.34247252

[16] OECD. 2024. *The Economics of Space Sustainability*. OECD Publishing, Paris. https://doi.org/10.1787/b2257346-en

[17] J. Runnels. 2023. Protecting Earth and Space Industries from Orbital Debris. *American Business Law Journal* 60, 1 (2023). https://doi.org/10.1111/ablj.12221

[18] Marit Undseth, Claire Jolly, and Mattia Olivari. 2021. The Economics of Space Debris in Perspective. In *Proceedings of the 8th European Conference on Space Debris* (Darmstadt, Germany), T. Flohrer, S. Lemmens, and F. Schmitz (Eds.). ESA Space Debris Office. https://conference.sdo.esoc.esa.int/proceedings/sdc8/paper/12 Paper 12.

[19] K Wormnes, R Le Letty, L Summerer, R Schonenborg, O Dubois-Matra, E Luraschi, A Cropp, H Krag, and J Delaval. 2013. ESA TECHNOLOGIES FOR SPACE DEBRIS REMEDIATION. https://conference.sdo.esoc.esa.int/proceedings/sdc6/paper/116/SDC6-paper116.pdf