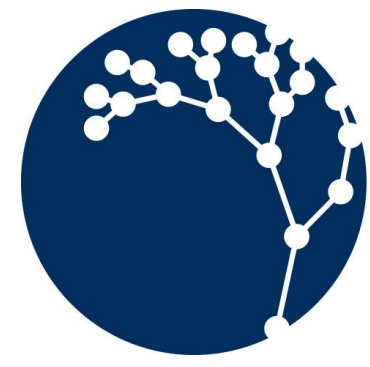




A neural network approach to the ray-tracing in limb scanning observation



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Introduction

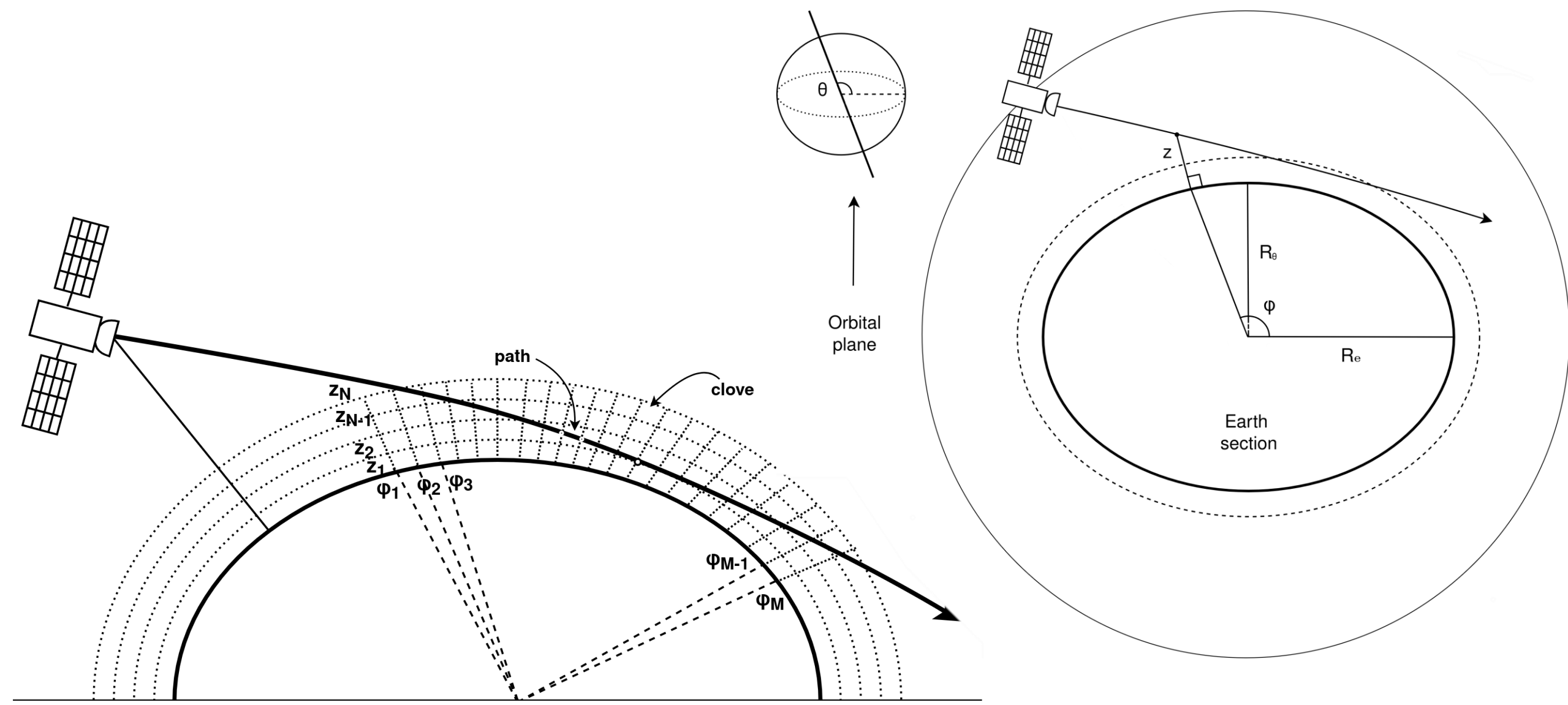
The Importance of Limb Scanning: Limb-scanning instruments are essential for atmospheric research because they are much more sensitive to the middle atmosphere than instruments using nadir-viewing geometry. By observing the atmosphere horizontally along the limb, they provide finer vertical detail in trace gases and temperature profiles.

The Role of Ray Tracing: In limb-scanning atmospheric instruments, ray tracing is fundamental for accurately describing the propagation of the lines of sight (LOS). Due to the vertical gradients of the atmospheric refractive index, these lines do not follow straight paths but instead bend along curved trajectories.

The Problem: Why is a priori pointing difficult? The precise position of the tangent point—the minimum-altitude point along the LOS—depends on the off-nadir angle, the atmospheric state, and the adopted refractivity model. Because the actual atmosphere is only known after the retrieval process, the off-nadir angles must be defined a priori to ensure that the resulting tangent altitudes match the prescribed engineering values.

The Challenge: Can standard models be trusted? Previous studies (e.g., MIPAS) show that using standard homogeneous atmospheres (like US76) can introduce discrepancies of several hundred meters in tangent altitude, particularly in the denser layers of the lower atmosphere.

The Proposed Approach: This work proposes a machine learning approach to achieve a more accurate determination of off-nadir angles by training a Multi-Layer Perceptron (MLP). This method accounts for Earth's eccentricity, satellite positioning, and seasonal atmospheric variability.



Methods

Determination of the Off-Nadir Angles: The off-nadir angles (pointing angles) are defined as the angles between the satellite detectors' direction and the line from the satellite normal to the Earth's surface. These angles are predetermined to ensure that the lines of sight intersect a predefined set of target engineering tangent altitudes. The relationship between off-nadir angles and tangent height is influenced by Earth eccentricity and atmospheric composition.

Standard strategy

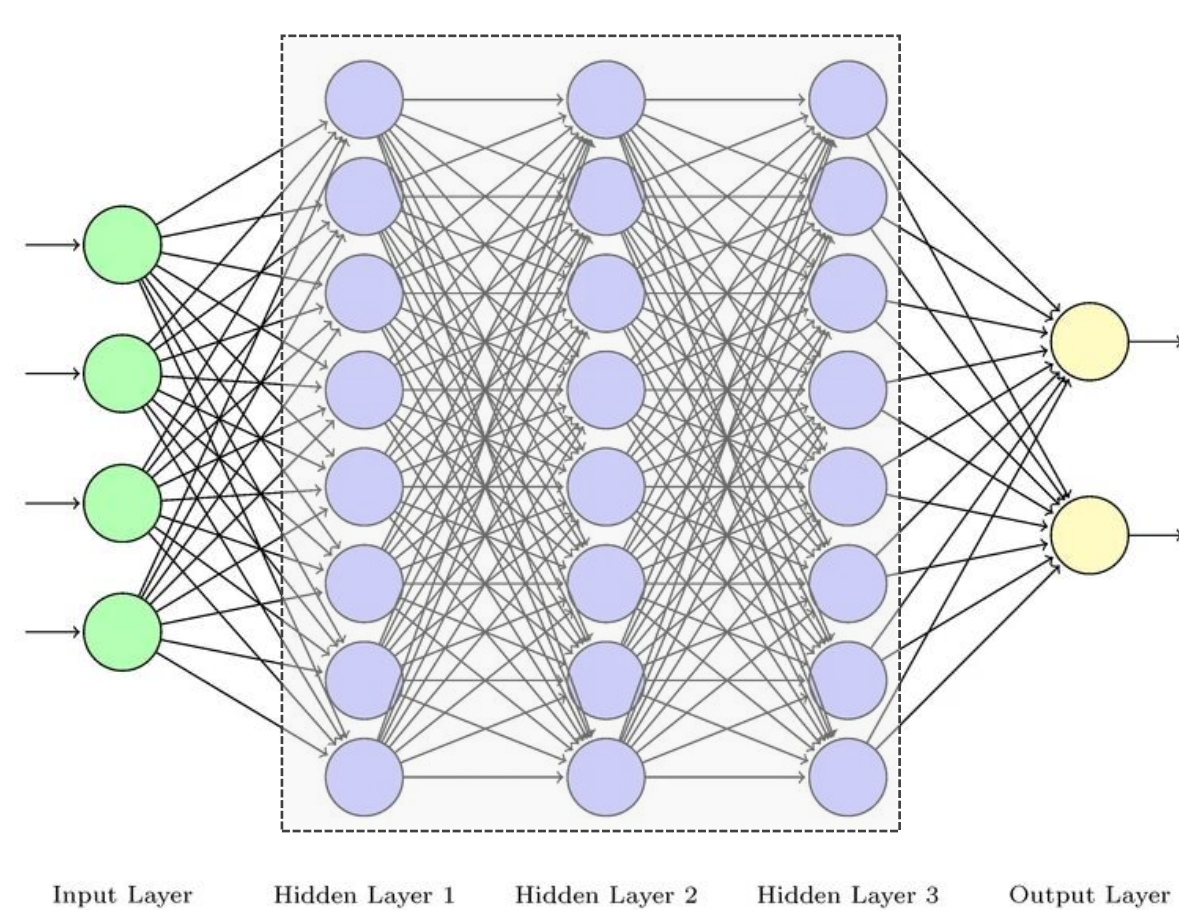
To account for the Earth's shape is adopted the following procedure:

- **Sampling:** A set of m candidate off-nadir angles α_i is sampled from the interval $[61^\circ, 65^\circ]$ to ensure rays remain within the atmosphere.
- **Ray Tracing:** For each satellite acquisition j , lines of sight are traced to obtain candidate tangent altitudes h_{ij} .
- **Interpolation:** A linear spline $s_j(h)$ is built using the nodes (h_{ij}, α_i) .
- **Optimization:** The required angles are obtained by evaluating the spline at the target altitudes $\alpha_{tj} = s_j^{-1}(h)$

To account for the atmosphere composition, we used:

- **Geometric Model:** Computes lines of sight as straight lines, neglecting refractive bending.
- **Standard US76 Model:** A globally uniform model that accounts for refraction.
- **ERA5 reanalysis data:** reference atmosphere treated as "truth" for all comparisons.

MLP Regressor To overcome the limitations of the standard approach, a Multi-Layer Perceptron (MLP) regressor is implemented. This methods simultaneously accounts for orbital geometry, atmospheric refraction, and seasonal variability by learning from the ERA5 reference data.



The proposed model is a Deep Neural Network consisting of three fully connected hidden layers with 256, 128, and 64 neurons, respectively. Non-linearity is introduced via ReLU activation functions. The weights are 8000 optimized using the Adam stochastic gradient descent algorithm with a constant initial learning rate of 10^{-4} , over erations.

Results

Dataset Configuration:

The model is built on a 7-dimensional input vector that integrates temporal data, orbital state, and the tangent altitude require to predict the optimized off-nadir angle.

Input ($X \in \mathbb{R}^7$)	Month, Day Satellite polar angle, Sub-sat. latitude, Sub-sat. longitude Engineering altitude (h_{tj})
Output ($Y \in \mathbb{R}$)	Off-nadir angle (α)

Dataset and Training:

The model is based on a global dataset derived from ERA5 reanalysis:

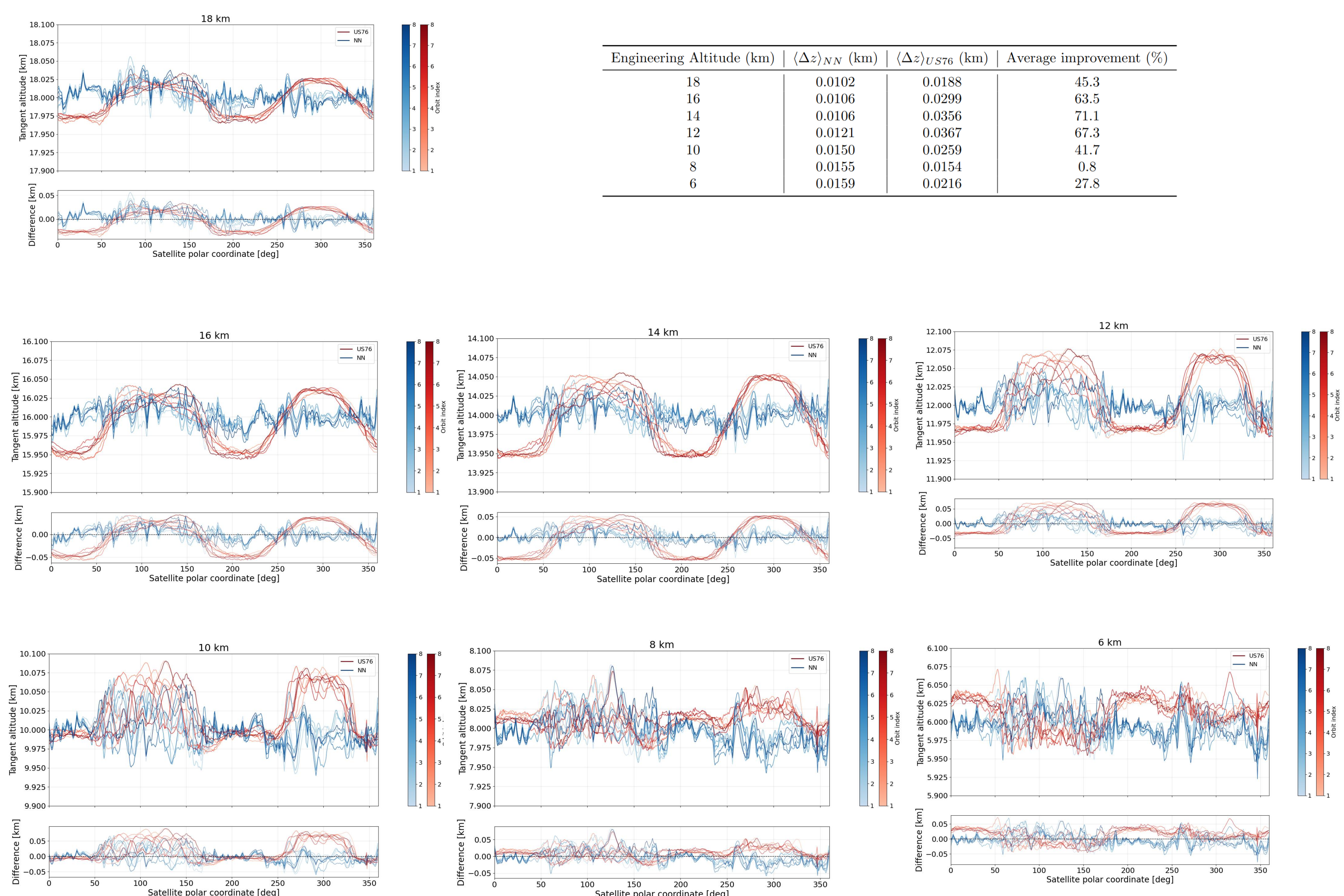
The model was trained on a dataset comprising 29 consecutive orbits, covering diverse latitude bands and seasonal extremes (July and January)

- **TRAINING SET:** Comprised of 29 consecutive orbits covering diverse latitude bands and seasonal extremes (January and July)
- **TEST SET:** A preliminary validation on 8 independent orbits (July).

Vertical Displacement Analysis

The analysis focuses on altitudes below 20 km, where air density and ray curvature are most significant. Accuracy is quantified by measuring the vertical displacement between the true tangent points (ERA5) and those predicted by:

- **STANDARD US76 MODEL:** A globally uniform refractive model (Baseline).
- **NEURAL NETWORK (NN):** The proposed MLP-based neural network.



Results and perspective

- **MISSION CONTEXT:** We used a configuration representative of the proposed CAIRT mission instrument as a case scenario for future instruments, such as the STRIVE mission by NASA.
- **PRELIMINARY VALIDATION:** The current results represent a preliminary assessment of neural network applications in limb-view ray tracing. They demonstrate that the MLP regressor is a robust and effective tool for learning refractive paths and predicting with greater accuracy the off-nadir angles of engineered tangent heights.
- **PERFORMANCE:** Even at this early stage, the neural network shows promising performance, improving by approximately 50% compared to models like US76 by learning seasonal and geometric correlations from ERA5 data.
- **HORIZONTAL DISPLACEMENT INTEGRATION:** Future developments will include the horizontal coordinates of the tangent points within the input of the neural network. By accounting for the full displacement—rather than just vertical adjustments—we expect to further enhance pointing precision.
- **ARCHITECTURAL EXPLORATION:** While the current MLP architecture provides high accuracy, further investigations into alternative deep learning architectures will be conducted to improve generalization and quantify predictive uncertainty.
- **SCIENTIFIC IMPACT:** This study confirms that neural networks are an efficient and viable approach to the ray tracing problem. They offer a more precise alternative that considers multiple factors compared to traditional tracing methods based on globally uniform atmospheric models.

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