

AION: Physics-informed machine learning advances forecasting of high-dimensional ionospheric spatiotemporal states

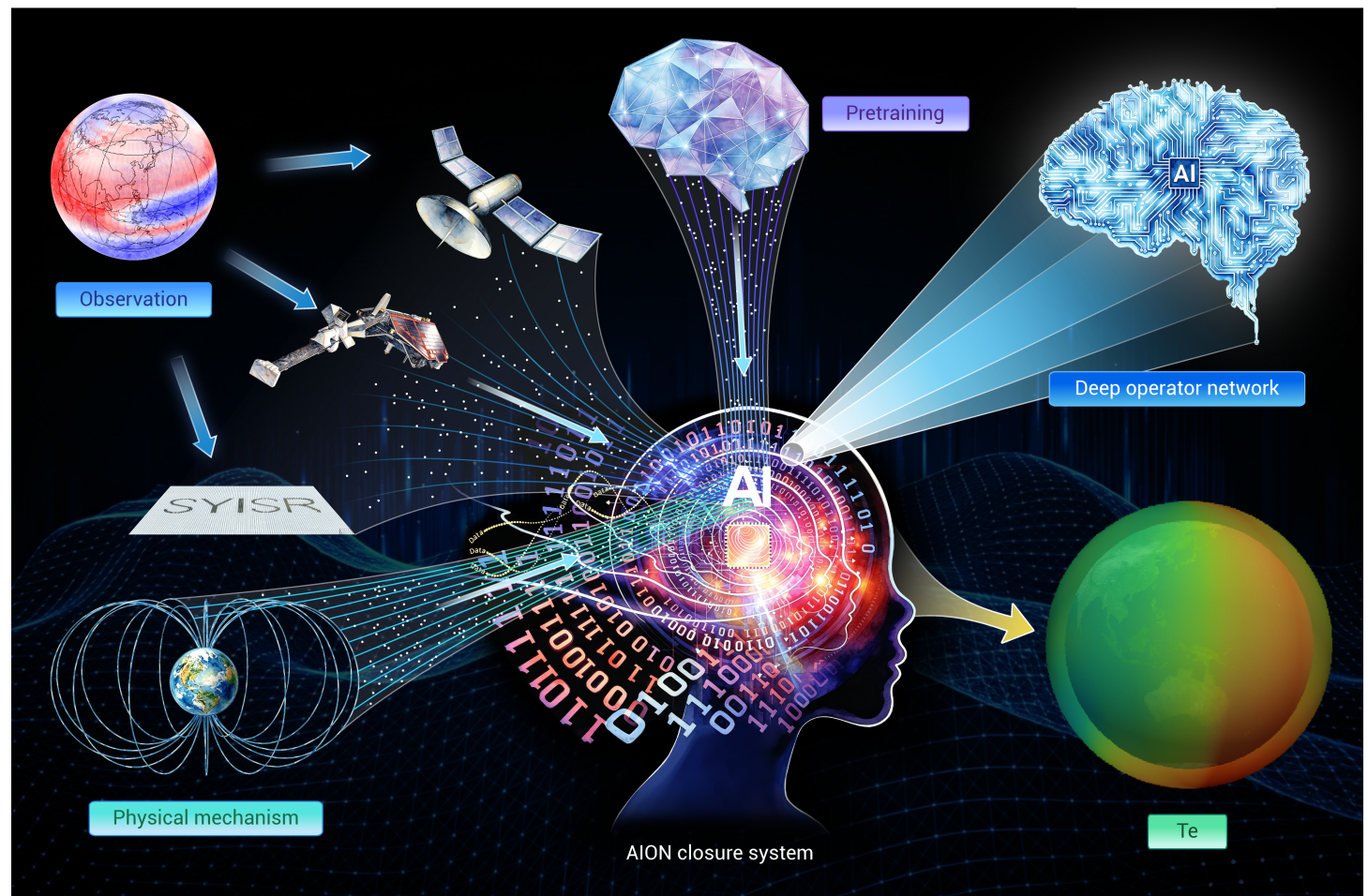
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- We propose AION, an innovation-informatics framework uniting data and physics for ionosphere modeling.
- Built on deep operator network (DeepONet), it learns mappings between drivers and ionospheric states.
- A pretrained closure model encodes plasma transport and heating knowledge within the system.
- This enables electron temperature equation to be embedded directly into the assimilation process.
- AION achieves 54.5% error reduction versus International Reference Ionosphere, benefiting satellite safety.

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Modeling the Earth's ionosphere (50–5000 km) remains a fundamental challenge due to sparse and heterogeneous observations and incomplete physical representations of plasma energy transfer. Existing empirical and physics-based approaches lack a unified mechanism to integrate data-driven learning with first-principles knowledge. We present AION, an innovation-informatics-driven framework that establishes a unified representation of observational data, physical knowledge, and system dynamics for ionospheric modeling. Built upon the deep operator network (DeepONet) architecture, AION learns functional mappings between external drivers and ionospheric states while enforcing physical consistency through differentiable governing equations. A pretrained closure model serves as an explicit representation of plasma transport and heating knowledge, enabling the electron temperature equation to be embedded directly within the assimilation process across varying solar conditions. Across diverse solar activity regimes, AION achieves 24-h electron-temperature forecast errors of 387–413 K, corresponding to a 54.5% improvement over the International Reference Ionosphere, together with a 38.2% enhancement in electron-density prediction. The framework efficiently generates full four-dimensional ionospheric states for complex geometries, demonstrating a scalable and transferable informatics paradigm for data–physics integrated intelligent modeling of complex space environments, with implications for satellite communications, navigation, and spacecraft safety.

INTRODUCTION

The ionosphere—a weakly ionized plasma layer spanning 50 to 5000 km above Earth's surface—serves as a critical interface between the neutral atmosphere and space, shielding the planet from external disturbances while enabling global radio communications.^{1–4} Its dynamics (e.g., ionospheric thermal dynamic) are driven by highly nonlinear interactions with solar irradiance, geomagnetic activity, and neutral atmospheric coupling, governing essential plasma parameters such as electron density and temperature.^{5–7} These processes directly impact communication, navigation, and remote sensing systems, demanding accurate 4D modeling (latitude, longitude, altitude, and time) for space weather forecasting and operational resilience.^{8,9} However, achieving high-fidelity global 4D ionospheric models remains challenging because multiscale transport and strongly anisotropic plasma coupling must be inferred from sparse, heterogeneous observations, and the governing energy balance depends on poorly constrained closure terms for heating and transport.

Previous efforts to model the 4D ionosphere fall into three main approaches. Physics-based models (e.g., SAMI3 and TIE-GCM) solve the coupled continuity, momentum, and energy equations, but depend on uncertain lower-boundary forcing and remain too costly for kilometer-scale runs.^{10–14} Empirical models such as IRI and NeQuick run in milliseconds yet smooth out storm-time extremes.^{15,16} Data-assimilation systems merge models and observations for the highest accuracy.^{17,18} However, faced with today's terabyte-per-day data volumes,^{19–22} data-assimilation systems must contend with heterogeneous or unevenly distributed observations, computational cost, and high dimensionality.²³

Recent advances in machine learning (ML) have demonstrated significant potential in modeling high-dimensional dynamics of complex systems, including atmospheric processes, fluid flows, and plasmas.^{24–33} By learning

nonlinear dynamical operators from data, ML-based methods offer a compelling trade-off between accuracy and computational cost compared to traditional numerical solvers. Notably, neural operator networks excel at approximating mappings between infinite-dimensional function spaces—for example, mapping from initial conditions to partial differential equation (PDE) solutions—enabling domain-invariant predictions beyond fixed-dimensional architectures.^{34,35} These properties make neural operators well suited to real-world systems where adaptive discretizations or transferability is critical.^{36–39}

However, physical uncertainty remains a challenge in both traditional data assimilation and current ML methods. A key issue in modeling ionospheric plasmas is the closure problem: high-order moments (e.g., heat flux, viscosity) cannot be directly inferred from lower-order variables (e.g., density, velocity) and must instead be approximated via closure relations to achieve self-consistent solutions. First-principles approaches (e.g., kinetic theory or fluid approximations) address this problem directly but demand deep physical insight, sophisticated mathematics, and substantial computational resources.^{40–42} Recently, ML has emerged as a promising tool to learn closure relations from data, accelerating the development of reduced order models for complex systems.^{43–46} These studies highlight the potential of machine learning not only for high-precision forecasting, but also for learning the intrinsic closure of ionospheric states, offering a pathway toward efficient and interpretable ionospheric modeling.

While existing machine learning models in atmosphere science have been trained offline, learning parametrization independently of their interaction with dynamics, which can limit their consistency and robustness when coupled to the governing dynamics. Until recently, hybrid models such as NeuralGCM,⁴⁷ machine learning corrects the traditional physical parameterizations of a physical model, which overcome the lack of coupling between machine-learning components and the governing equations. Recently, machine learning has been shown to fully replace the numerical weather prediction (NWP) pipeline, improving both global and local forecasts.⁴⁸ Here, we present AION (Artificial Intelligence for IONosphere), a novel data-driven data-assimilation model of the Earth's ionosphere, that enables high-dimensional generation and forecasting. Compared with existing models, AION is a closure-aware physics-constrained DeepONet framework that assimilate heterogeneous observations with physics-based simulation data. The AION model is capable of generating and forecasting multiple high dimensional ionospheric parameters with high accuracy and low computational cost, that can flexibly accommodate diverse observational geometries and unstructured spatiotemporal sampling.

MATERIALS AND METHODS

Data processing

The datasets used to train AION include physical models and observational measurements, which are listed below:

SAMI3. It is a physics-based numerical model, provides 4D ionospheric parameters via solving a set of electrodynamic and plasma equations. Typically, the system uses dipole coordinate system defined as s (the coordinate along the field line), p (the coordinate orthogonal to the field line), and ϕ (the magnetic longitude). In our dipole-system experiments, the original grid has $(n_s, n_p, n_\phi) = (204, 60, 72)$ points. We then extract the region of interest and downsample it to 2-hour time steps and to every 8th point in s and every 4th point in p and ϕ (i.e. $(1:8:204, 1:4:60, 1:4:72)$). Such settings above

Table 1. Summary of different Ionospheric data sources.

Data source	Introduction	Time resolution	Spatial resolution	Coverage	Parameter	Num. of sensors
SAMI3	Physical numerical model	15 min	Spatially varying	– 45°N – 45°S 180°W – 180°E 70 – 600 km	$N_e, T_e,$ Q_e, K_e	/
COSMIC-2	Radio Occultation (RO)	1 min	Adjacent point spacing: 1–2 km	– 40°N – 40°S 180°W – 180°E 100 – 550 km	N_e	6 LEO satellites
Yunyao	Radio Occultation	1 min	Adjacent point spacing: 1–2 km	– 90°N – 90°S 180°W – 180°E 100 – 550 km	N_e	6 LEO satellites
Sanya ISR	Incoherent Scatter Radar	5.5 min scan cycle	Lat: 8° Lon: 102° Alt: 1 km	8°N – 29°S 102°W – 117°E 90 – 1000 km	N_e, T_e	11 beams
SWARM	ESA earth observation satellites	0.5 s	Lat: 90° Lon: 180° Alt: 3 m	90°N – 90°S 180°W – 180°E 470 – 540 km	N_e, T_e	3 satellites each with 2 Langmuir probes
IRI	International Reference Ionosphere model	1 h	Lat: 5° Lon: 180° Alt: 20 km	90°N – 90°S 180°W – 180°E 90 – 600 km	N_e, T_e	/
CODE	Center for Orbit Determination in Europe	15 min	Lat: 5° Lon: 180°	90°N – 90°S 180°W – 180°E	VTEC	/

cover the longitudes 0° – 360°, the latitudes –45° – +45°, the altitudes 70 – 600 km, and the period May 1 ~ 30, 2024.

COSMIC-2. It consists of six low Earth orbit (LEO) satellites that receive signals from both GPS and GLONASS constellations. The LEO satellites in the COSMIC-2 constellation operate with an orbital inclination of 24°, resulting in electron density profiles that extend up to around 100 km–550 km in altitude and tangent points distributed primarily within ±40° latitude. Electron density (N_e) data in May 2024 have a temporal resolution of 1 minute, with each electron density profile featuring a vertical resolution of approximately 1 to 2 km.⁴⁹

Yunyao. This dataset is provided by Tianjin Yunyao Aerospace Technology Co., Ltd. Similar to COSMIC-2, electron density profile data from ionPfr files are utilized. However, unlike COSMIC-2, the Yunyao LEO satellites operate at an orbital altitude of approximately 500 km, and their tangent points provide broad global coverage from equatorial to polar regions.

Sanya ISR. Experiments conducted use the measurements of electron density and electron temperature over the region of 8°N–29°N and 102°E–117°E with a scan cycle of 5.5 minutes and 0.2° latitude/longitude resolution and 1 km height resolution.

SWARM. It is a constellation of Earth-observing satellites operated by the European Space Agency (ESA), consists of three low Earth orbit satellites equipped with Langmuir probes to provide high-resolution observations of N_e and T_e with a time resolution of 0.5 seconds and spatial resolutions of 0.03° (latitude), 0.05° (longitude), and 3 m (altitude). The orbital altitude is approximately 450–530 km, so the in-situ measurements are also within this altitude range.

The integration of these training datasets and evaluation datasets are summarized in Table 1 ensuring both global coverage and high-resolution temporal-spatial fidelity.

AION Model

In an ideal scenario with sufficient observational data, we aim to construct a nonlinear operator mapping from initial electron density measurement to electron density, temperature, thermal conductivity, and heating in full space, denoted as

$$G: N_e(x, t_0) \mapsto \{N_e(x, t), T_e(x, t), K_e(x, t), Q_e(x, t)\} \quad (1)$$

where $\mathbf{x} \in \mathbb{R}^3$ are the coordinate points defined on the spatial domain Ω , $t \in \mathbb{R}$ are the coordinate points defined on the temporal domain and $t_0 \in t$ are the initial moment time coordinate point. Here, N_e , T_e , K_e , and Q_e are the multi-

dimensional function of the electron density, temperature, thermal conductivity, and heating term, respectively.

We aim to learn an operator G that maps between two infinite-dimensional function spaces, based on a finite set of observed input-output data pairs. Thus, our goal is to develop a parameterized mapping G_θ to approximate $G_\theta \approx G$. Following the work of previous deep operator networks,^{34,35} we extend it into the Earth's dipole coordinates of the ionosphere. Our model consists of three components: the SAMI3 physical model data, partial differential equations, and multiple sources of measurement data, respectively. The first component of the operator for the SAMI3 simulation model F^* is

$$F^*: N_e \mapsto \{N_e, T_e, K_e, Q_e\} \quad (2)$$

where the operator F^* represents the solution mapping of the partial differential equations of the SAMI3 physical model. In this study, the governing partial differential equation PDE set implemented in the SAMI3 model^{10,11} is adopted, thereby F^* can be reduced as

$$F_{PDE}(N_e, T_e, K_e, Q_e) = \frac{\partial T_e}{\partial t} - \frac{2}{3} \frac{1}{N_e k} b_s^2 \frac{\partial}{\partial s} K_e \frac{\partial T_e}{\partial s} - Q_e \quad (3)$$

where F_{PDE} is the physical PDE operator of temperature along the geomagnetic field-aligned direction in the Earth's dipole coordinates, k is the Boltzmann constant, s is the geomagnetic field-aligned direction, and b_s is the metric scale factor.

To further improve the accuracy of these simulation solutions, we introduce an observation operator as

$$F_{Obs}(\tilde{N}_e, \tilde{T}_e) = F_{\theta_1, \tilde{N}_e}(\tilde{N}_e) + F_{\theta_2, \tilde{T}_e}(\tilde{T}_e) \quad (4)$$

where the $\tilde{N}_e$ and $\tilde{T}_e$ denote the observation data, and $F_{\theta_1, \tilde{N}_e}$, $F_{\theta_2, \tilde{T}_e}$ represent the corresponding networks that embedded the observation data into the full operator, parameterized by θ_1 and θ_2 , respectively. Finally, the parameterized mapping operator G_θ could be described as:

$$G_\theta = F_{PDE} + F_{Obs} + \left\{ \begin{matrix} \bigcirc \\ \bigcirc \\ \bigcirc \end{matrix} \right\} \left\{ \begin{matrix} \bigcirc \\ \bigcirc \\ \bigcirc \end{matrix} \right\} \left\{ \begin{matrix} \bigcirc \\ \bigcirc \\ \bigcirc \end{matrix} \right\} \quad (5)$$

where the network in Eq.(5) is introduced to construct an implicit closure for the physical PDE operator F_{PDE} and observation operator F_{Obs} , hereby further eliminating closure errors arising from the approximation of higher-order terms in the model.

Based on the above analysis, we construct a deep operator network-based

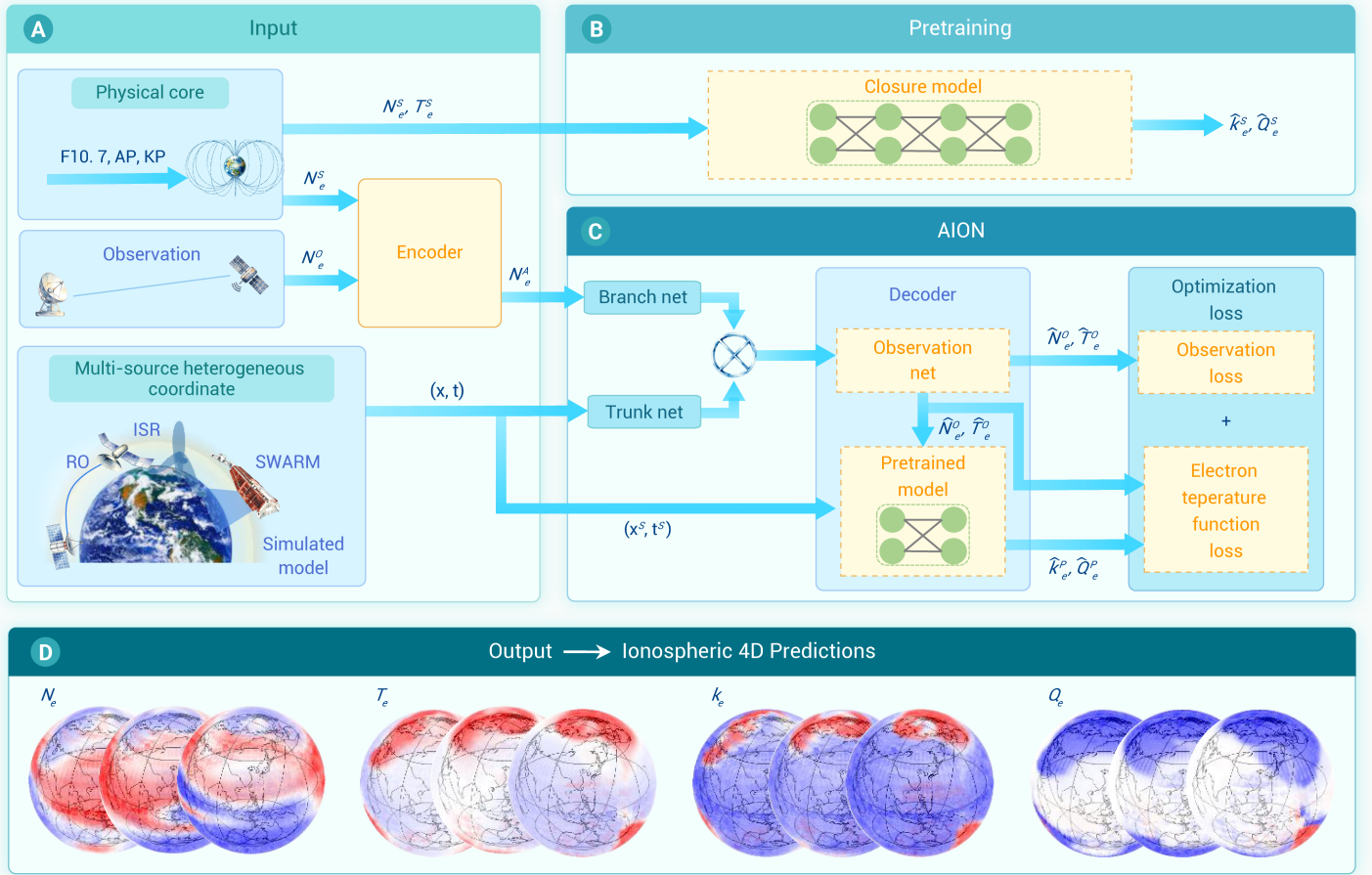


Figure 1. AION framework for 4D ionospheric modeling (A) Input module. Physical electron density N_e^s and observational electron density N_e^o are assimilated by an encoder to provide the initial state N_e^a , while the corresponding output coordinates are specified in multi-source heterogeneous coordinate system. "Heterogeneous" describes the spatiotemporally inconsistent nature of the multi-source sensor data. The text also now clarifies that "Observation data" and "Multi-source heterogeneous data" are used synonymously hereafter to ensure coherence. The system is defined as $\mathbf{x}$ (the three-dimensional spatial coordinate) and t (the temporal coordinate). (B) Pretrained closure model. A closure model is first pretrained to learn the mapping from the electron density N_e^s and temperature T_e^s to the thermal conductivity k_e^s and heating term Q_e^s based on the simulation data. (C) Trained AION module. During AION training, a parallel Branch–Trunk backbone takes the encoded initial state and sampling coordinates, fuses them and feeds a dual-path decoder composed of an observation network and a pretrained network. The observation network predicts the electron density $\hat{N}_e^o$ and temperature $\hat{T}_e^o$. The predictions at observational points are used to compute the observation loss, while those at simulation points are passed to the pretrained network to obtain $\hat{k}_e^o$ and $\hat{Q}_e^o$, thereby enforcing physical consistency through the electron temperature function. (D) Output module. The final outputs are high-resolution 4D fields of key ionospheric parameters.

approximation G_θ with physical constraints as illustrated in ref.¹⁰. To train the model, the important step involves constructing the observational data constraints (electron density data constraint and electron temperature data constraint) and the residual term of the electron temperature equation, which is shown as follows:

$$\begin{aligned} \mathcal{L} = & \omega_{PDE} \sum_{j=1}^{N_j^s} \left\| F_{PDE} \left(\hat{N}_e^o(\mathbf{x}_j^s, t_j^s), \hat{T}_e^o(\mathbf{x}_j^s, t_j^s), \hat{k}_e^o(\mathbf{x}_j^s, t_j^s), \hat{Q}_e^o(\mathbf{x}_j^s, t_j^s) \right) \right\|_2^2 \\ & + \omega_n \sum_i^{(RO, ISR, SWARM)} \sum_{j=1}^{N_j^o} \left\| \hat{N}_e^o(\mathbf{x}_{ij}^o, t_{ij}^o) - \tilde{N}_e(\mathbf{x}_{ij}^o, t_{ij}^o) \right\|_2^2 \\ & + \omega_\tau \sum_i^{(ISR, SWARM)} \sum_{j=1}^{N_j^o} \left\| \hat{T}_e^o(\mathbf{x}_{ij}^o, t_{ij}^o) - \tilde{T}_e(\mathbf{x}_{ij}^o, t_{ij}^o) \right\|_2^2 \end{aligned} \quad (6)$$

where N_j^s and N_j^o are the numbers of sampling points for the j th simulation data from SAMI3 model and observational data from sensors in the spatiotemporal domain, respectively. $\hat{N}_e^o(\mathbf{x}_j^s, t_j^s)$ and $\hat{T}_e^o(\mathbf{x}_j^s, t_j^s)$ are the electron density and temperature in the simulation sampling point $(\mathbf{x}_j^s, t_j^s)$ obtained from the observation network, respectively. $\hat{k}_e^o(\mathbf{x}_j^s, t_j^s)$ and $\hat{Q}_e^o(\mathbf{x}_j^s, t_j^s)$ are the thermal conductivity and heating term obtained from the pretrained closure network, respectively. $\hat{N}_e^o(\mathbf{x}_{ij}^o, t_{ij}^o)$ and $\hat{T}_e^o(\mathbf{x}_{ij}^o, t_{ij}^o)$ are the electron density and temperature in the sampling point of i th measurement sensor obtained from the observation network, respectively. ω_{PDE} , ω_n , and ω_τ are weighting coefficients.

The architecture of the AION model in Figure 1 consists two main components: pretrained closure model and the foundation model. The inputs take two primary components: (1) initial electron density N_e^s , generated by an encoder module, that includes both the simulated electron density N_e^s driven by solar activity indices (F10.7, AP, KP) through a SAMI3-based physical core and the observed density N_e^o ; (2) heterogeneous coordinate information $(\mathbf{x}, t)$ from different sources. For pretraining, the multiple-layer perceptron (MLP) is used to learn the mapping from N_e, T_e to k_e, Q_e based on existing SAMI3 model. This process leverages simulation data to learn the underlined physical mapping for Equation (3) for subsequent AION training, thereby constructing a closure between the observed electron density and temperature.

The foundation model in Figure 1 is constructed based on the DeepONet framework with physical PDE constraints, which includes the branch and trunk networks. The branch network takes the electron density as input, while the trunk network takes the spatiotemporal coordinates. The output of the trunk network is a feature vector—a transformed representation of the input coordinates—which itself carries no explicit physical meaning. Subsequently, the outputs of the branch and trunk networks are coupled and fed into the subsequent decoder module. The decoder module consists of a dual-path design, including both the observation network and the pretrained network. The observation network provides the predicted electron density $\hat{N}_e^o$ and temperature $\hat{T}_e^o$ from observations. These predictions are then divided into two parts: the components at the observational points $(\mathbf{x}^o, t^o)$ are compared with the corresponding measurements to compute the observation loss,

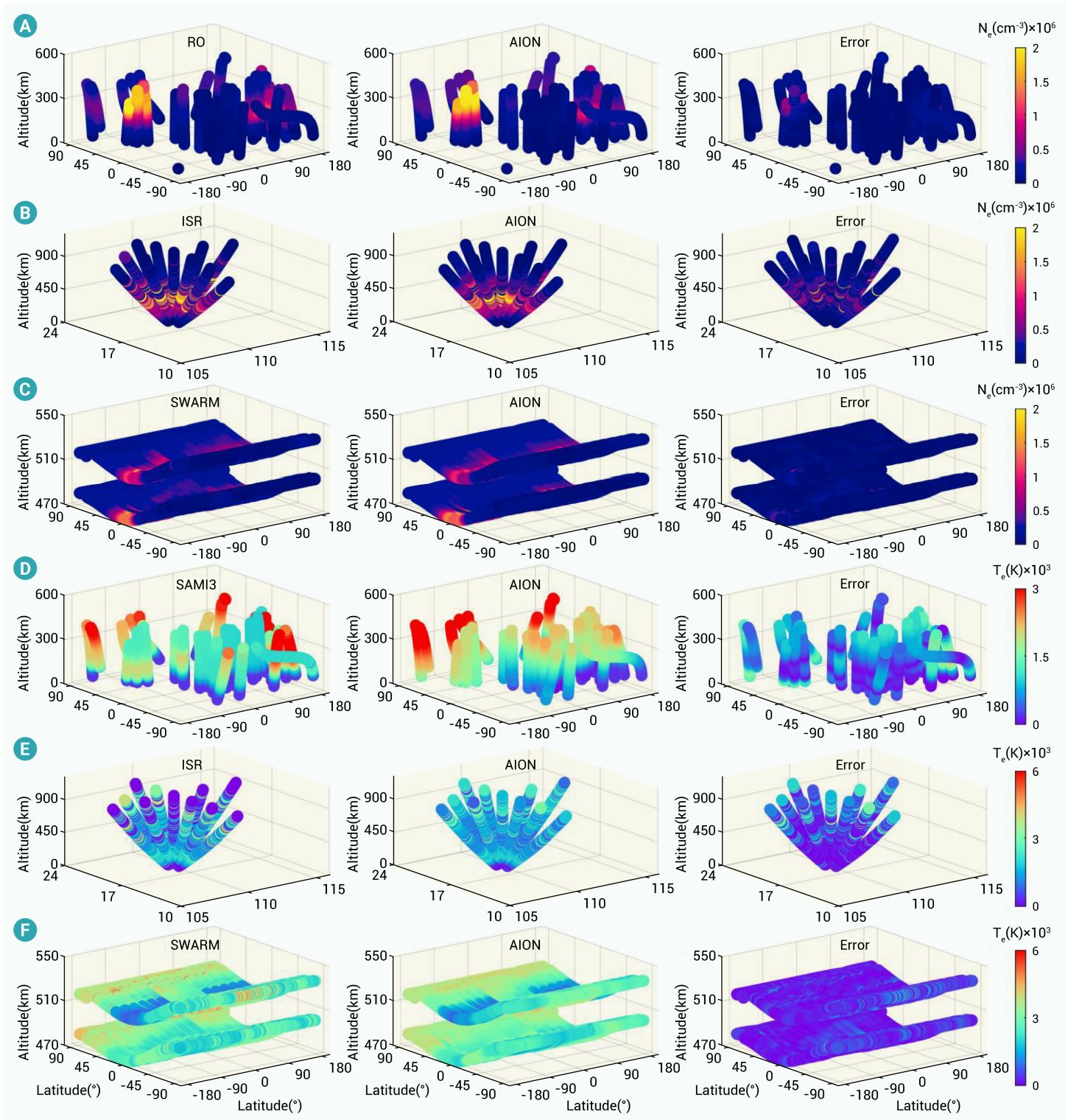


Figure 2. Validation of 24-hour AION-predicted electron density and temperature on 30 May 2024: multi-source observations (left), AION predictions (middle), and errors (right) (A–C) Electron density measurements from RO (0:00–2:00 UT), ISR (24-hour), SWARM (24-hour) and corresponding AION predictions. (D–F) Electron temperature from SAMI3 interpolation (0:00–2:00 UT), ISR measurements (24-hour), SWARM measurements (24-hour) and corresponding AION predictions.

while the components at the simulation points ($\mathbf{x}^s, t^s$) incorporate the observational information as inputs to the pretrained network, yielding the corresponding predictions R_e^p and $\hat{Q}_e^p$. Together, these quantities are used to compute the electron temperature function loss according to Equation. (4), thereby achieving physical closure of the underlying mechanism. Finally, the output provides four-dimensional generation and prediction of critical ionospheric states.

RESULTS

Arbitrary geometry parameter prediction

We validate our framework's ability to reconstruct ionospheric parameters from heterogeneous datasets with varying spatial grids and sensor geometries. For model training, we utilize datasets derived from ionospheric observations spanning 1–28 May 2024, with 29 May reserved for validation and 30 May for testing. The input data are sourced from four types of sensors, including a physics-based simulation model SAMI3, ISR, SWARM satellites,

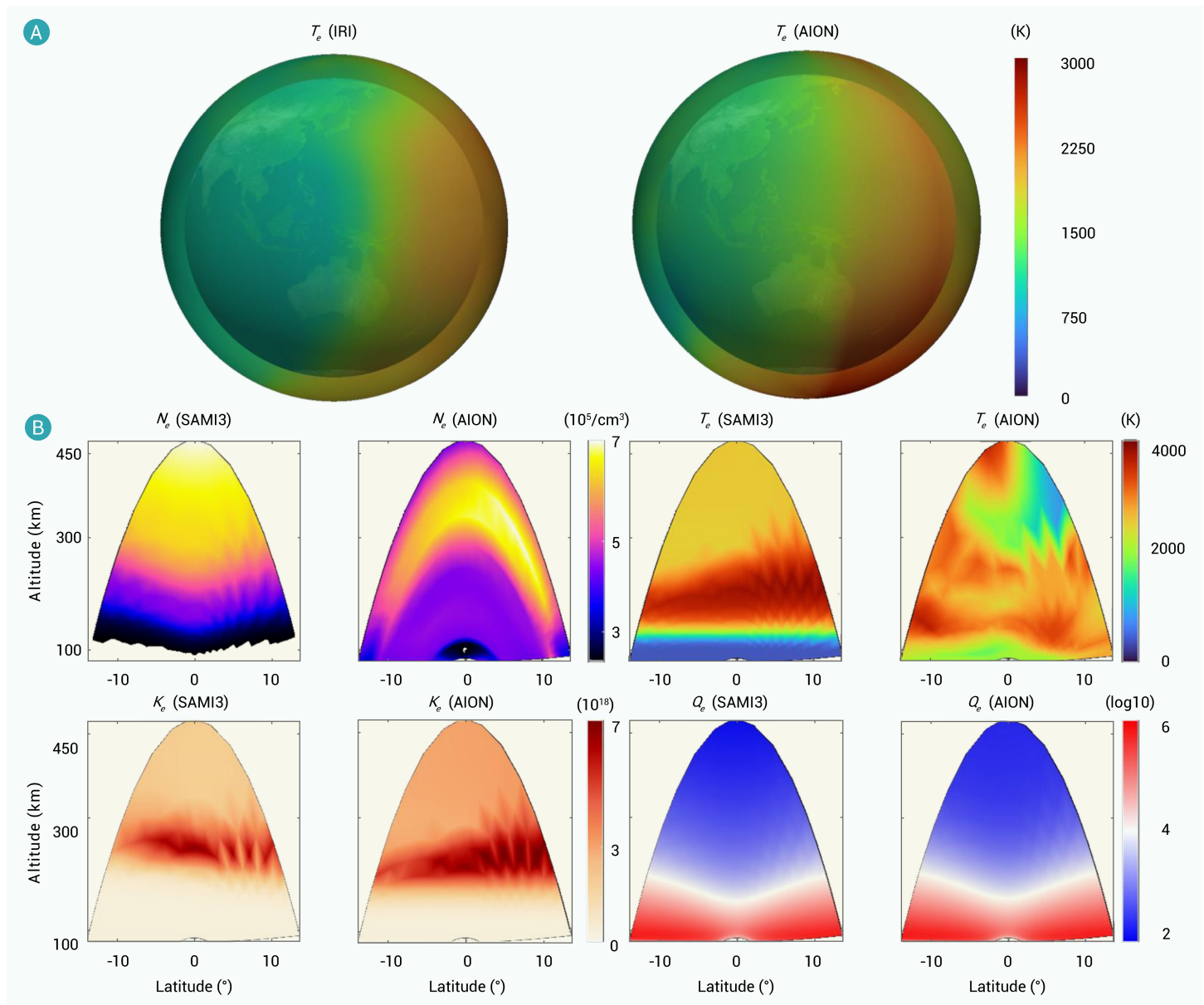


Figure 3. Ionospheric thermal parameters predicted by AION on May 30, 2024 (A) High-resolution global ionospheric electron temperature T_e from the IRI model and AION reconstruction at 20:15 UT. (B) Electron density n_e , electron temperature T_e , thermal conductivity κ_e , and heating term Q_e from the SAMI3 model and AION reconstruction along lon = 300° at 20:00 UT.

and RO measurements explained in Methods. These sensors were selected due to their complementary coverage and the richness of observational data. The chosen time window encompasses a diverse range of ionospheric conditions, including both geomagnetically quiet periods and disturbed intervals under varying geophysical conditions.

Figures 2A–C illustrates performance of our model in predicting global electron density across heterogeneous data geometries on May 30, 2024. Given sparse measurement and initial SAMI3 data at 0:00 UT, May 30, the model predicts the future 24 hour electron density and temperature for typical sensor sampling points. When predictions are generated exclusively at the partial sampling locations of the COSMIC-2 and Yanyao missions (Figure 2A), the model accurately predict fine-scale density structures within the 0:00–2:00 UT interval. Comparable fidelity is observed against ISR measurements at Sanya over a full diurnal cycle (Figure 2B) and SWARM satellite observations (Figure 2C). The errors of the predicted electron density relative to the measurements under different observation geometries are shown in the right column of the figure. The errors are generally small, further confirming the reliability of the AION model in predicting electron density across diverse observation geometries.

Figures 2D–F illustrates the global electron temperature prediction in

heterogeneous data geometries on May 30, 2024. The reconstructions align closely with SAMI3-generated temperatures at collocated RO density locations (Figure 2D), and retain accuracy across ISR (Figure 2E) and SWARM (Figure 2F) measurements. This cross-variable inference capability reflects the model's ability to internalize underlying thermodynamic relationships. By simultaneously reconstructing both N_e and T_e from disparate training sources, the model establishes itself as a unified, physics-consistent representation of the ionosphere. Similarly, AION achieves stable accuracy across diverse observation geometries (maximum errors of $\sim 60,000$ for electron density cm^{-3} and $\sim 4,000$ K for electron temperature), demonstrating stable performance of AION in accurately predicting diverse ionospheric parameters.

These results demonstrate that the model robustly predicts electron density and temperature for various geometry with good spatial coverage. The framework also exhibits good generalization in predicting electron temperature, despite being trained exclusively on regional and sparse observations even without RO data.

High-dimensional ionospheric thermal parameters forecast

Ionospheric thermal parameters cannot be directly measured by most remote sensing instruments and rely on sparse in situ observations or indi-

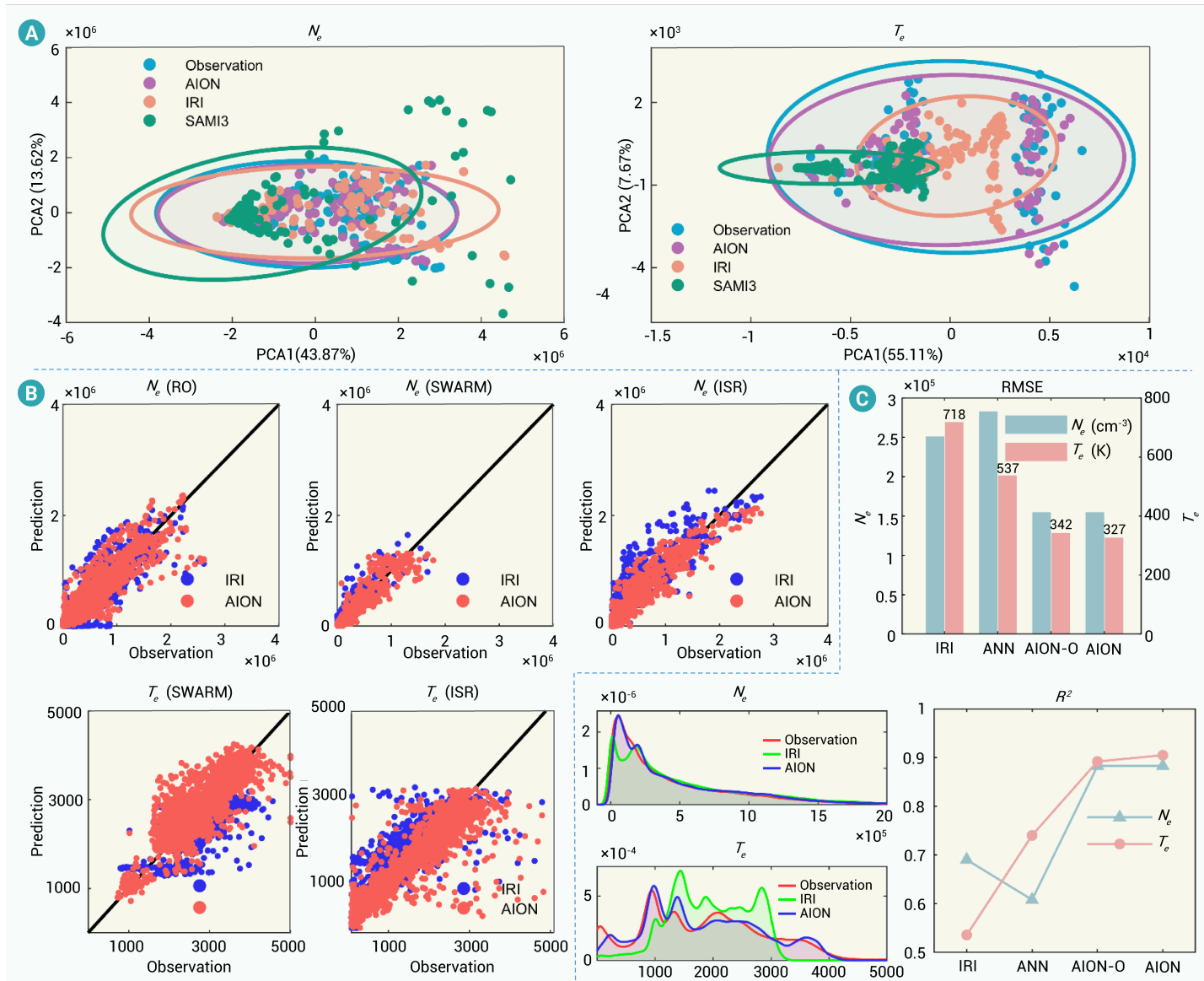


Figure 4. Performance evaluation of AION 24-h forecasts of electron density and temperature on 30 May 2024 (A) PCA comparison of AION-predicted results with models and observations data. Predictions from different models are projected onto the principal component space derived from observational data. Ellipses indicate the confidence regions of each distribution. Axes represent the first two principal components, with the variance explained indicated in parentheses. (B) AION-predicted and IRI-predicted results versus observations from RO, SWARM, and ISR. (C) RMSE comparison of electron density and temperature for IRI, ANN, AION-O, and AION.

rect retrievals, often introducing substantial uncertainty. These quantities exhibit strong variability and model sensitivity, making accurate characterization challenging. Here, we validate AION predictions of ionospheric thermal parameters using statistical models and available measurement data.

Figure 3 presents ionospheric thermal parameters n_e , T_e , κ_e , and Q_e predicted by AION on 30 May 2024 under the combined driving of solar indices and initial electron density. Figure 3A compares the global electron temperature predicted by AION, obtained by assimilating heterogeneous observations, with the benchmark IRI model.¹⁵ AION reproduces the large-scale day–night structure and overall spatial phasing, supporting its ability to capture the dominant global thermal morphology. Figure 3B evaluates latitude–altitude structures of key ionospheric variables against the SAMI3 physics-based simulation, including electron density, electron temperature, thermal conductivity, and heating term. AION recovers the main enhancement region and its vertical gradients across variables while yielding smoother and more spatially coherent fields. Notably, because AION is an assimilation framework rather than a forward model, it is not expected to match SAMI3 pointwise. Instead, by directly constraining the state with observations, AION is designed to reduce model bias and, in principle, provide a closer representation of the real ionosphere, particularly when forcing

uncertainties or parameterization errors are present.

Thus, the model is capable of generating four-dimensional ionospheric thermal parameters generation based on ML. This capability is enabled by assimilating sparse measurements with physical priors from models such as SAMI3, overcoming the limitations of conventional empirical or physics-based frameworks that lack temperature outputs or suffer from inadequate resolution.

DISCUSSION

Evaluation metrics

To evaluate the comprehensive performance of AION, we select root-mean-square errors (RMSE), the coefficient of determination (R^2), and relative error (simplified as error) as evaluation metrics for model performance. RMSE provides an absolute measure of prediction error, emphasizing larger deviations due to its squared error formulation. R^2 quantifies the proportion of variance in the observed data that is explained by the model, serving as an indicator of overall goodness of fit. In contrast, the relative error assesses the prediction accuracy in proportion to the actual values, offering a scale-independent measure particularly useful when comparing across different magnitudes or units. The calculation formulas for three metrics are given as

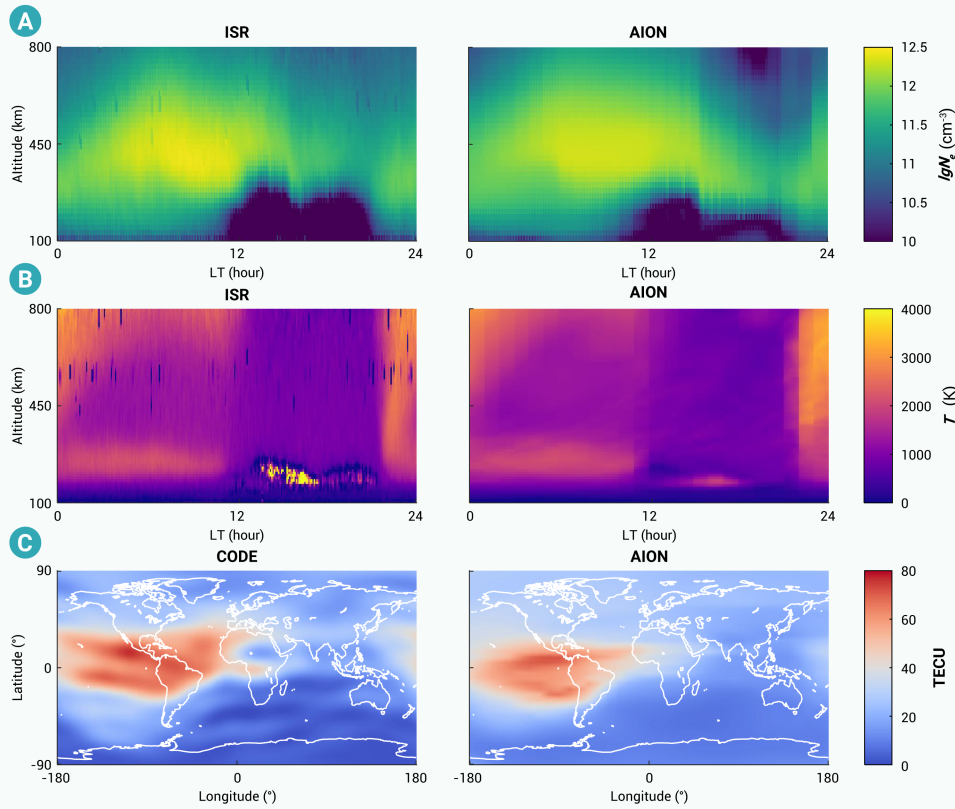


Figure 5. Validation of AION predictions against ISR and CODE on 30 May 2024 (A) Altitude–local time distribution of N_e from ISR (left) and model predictions (right). (B) Altitude–local time distribution of T_e from ISR (left) and predictions (right). (C) Global VTEC at 20:00 UT, with CODE data (left) and model output (right). Latitude spans -90° to 90° and longitude spans -180° to 180° .

ability to generate ionospheric parameters at unobserved locations. The improved distributional agreement stems from the operator network's ability to learn the underlying functional space of ionospheric variables, thereby ensuring the reliability of AION's outputs across diverse regions.

Figure 4B compares AION and IRI predictions with observations at different sensors, showing point-by-point agreement and distributional consistency for N_e and T_e . Scatter plots show that AION follows the 1:1 relationship more closely, with reduced bias and tighter dispersion relative to IRI across RO, SWARM, and ISR. The accompanying marginal distributions further indicate that AION better reproduces the observed population-level statistics, capturing both the central tendency and spread of N_e and T_e .

Figure 4C compares the overall predictive performance of IRI, an ANN-based data

follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y(x_i, t_i) - \hat{y}(x_i, t_i))^2} \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y(x_i, t_i) - \hat{y}(x_i, t_i))^2}{\sum_{i=1}^N (y(x_i, t_i) - \bar{y})^2} \quad (8)$$

$$Error(\%) = \frac{\sqrt{\sum_{i=1}^N (y(x_i, t_i) - \hat{y}(x_i, t_i))^2}}{\sqrt{\sum_{i=1}^N (y(x_i, t_i))^2}} \quad (9)$$

where N denotes the number of total predictions, $y(x_i, t_i)$ is the ground truth at point (x_i, t_i) from measurements or simulation model, $\hat{y}(x_i, t_i)$ is the prediction, and $\bar{y}$ is the mean value of the ground truth.

Model evaluation

In Figure 4, we qualitatively and quantitatively assess the AION predictive performance for 30 May 2024. To assess the prediction performance, we use principal component analysis (PCA) for comparing AION and existing IRI model for benchmark.⁵⁰ We analyze the 24-h forecasts of electron density and temperature at the sampling locations. For 30 May 2024, predictions in the test set are grouped into 24 one-hour lead-time bins. We then perform a PCA-based confidence-region analysis to summarize the high-dimensional variability and quantify uncertainty. Forecasts and observations are separately projected onto the first two principal components (PCA1 and PCA2), and confidence ellipses are constructed in this 2-D space to represent the spread of the projected distributions for each lead time. For N_e , compared to the IRI model, the confidence region of our model providing a more accurate representation of the underlying distribution, with PCA1 and PCA2 account for 57.49% of the total variance. Similarly, for T_e , the confidence region of AION aligns more closely with observation data than the IRI model, capturing a wider range of variability, with PCA1 and PCA2 together explaining 62.78% of the variance. Evaluating the distribution is critical for assessing a model's

assimilation method,⁵¹ AION, and AION-O (AION without the pretrained closure model; i.e., using only the observation network and therefore lacking physics-equation constraints). It shows that AION delivers the strongest overall skill across datasets, with consistently reduced RMSE relative to IRI and the ANN-based assimilation baseline. Quantitatively, AION reduces RMSE by 38.2% (electron density) and 54.5% (electron temperature) relative to IRI, and by 45.2% and 39.1% relative to the ANN-based assimilation baseline, consistently across all satellite and ground measurements. Comparing AION with AION-O further isolates the impact of the pretrained closure model: introducing the closure slightly degrades the N_e accuracy (a modest RMSE increase and R^2 decrease), but yields a clearer improvement for T_e , indicating that the physics-informed constraints primarily benefit the thermal-state reconstruction while imposing a mild trade-off in density fidelity.

Figure 5 shows that AION reproduces ionospheric structures consistently across local profiles and global maps. Along the ISR altitude–local time section, AION closely matches the observed diurnal evolution of log-electron density, capturing the daytime F-region enhancement and nighttime depletion (Figure 5A), with minor smoothing of fine-scale extremes. For electron temperature, AION recovers the dominant vertical gradients and day–night contrast seen by ISR (Figure 5B), while attenuating sporadic localized hot spots. Furthermore, we assess AION using vertical total electron content (VTEC), an electron-density integral that is directly relevant to satellite communication and navigation performance. At the global scale, the AION VTEC map agrees well with the CODE product in its large-scale morphology, including the low-latitude enhancement pattern and longitudinal variability (Figure 5C), highlighting its potential for operational applications in satellite communication and navigation.

Thus, the model is capable of generating four-dimensional electron temperature generation based on ML, particularly with altitudes for given geometry. This capability is enabled by assimilating sparse measurements with physical priors from models such as SAMI3, overcoming the limitations of conventional empirical or physics-based frameworks that lack temperature outputs or suffer from inadequate resolution.

Computation cost

We compared the size and runtime of three ionospheric models—AION, IRI, and SAMI3—that generate datasets or predict ionospheric conditions from

Table 2. Model Parameters and Inference time.

Model	Category	Parameters	Inference time*
AION	AI-based data assimilation model	10.1M	4.4s
SAMI3	Physical numerical model	/	12h
IRI	Empirical model	/	2.7h

* The number of output points for all three models is restricted around 14 million. AION runs on an Nvidia GeForce RTX 3090, while SAMI3 and IRI run on a 16-core Intel(R) Xeon(R) Gold 6226R CPU.

given initial inputs. The inference time does not include model training time, just including using the pretrained AION model to generate the prediction preprocessed states. The total training time for the AION model was 300 minutes, based on 60 epochs at 5 minutes per epoch. AION is built on the TensorFlow framework and is portable to other platforms for deployment. Each model produced electron density for May 30, 2024; IRI and AION used the same set of output coordinates, while SAMI3 was configured to produce a comparable number of points. The results are summarized in Table 2. As shown in Table 2, our model is highly efficient, generating ionospheric parameters over 2000 times faster than traditional models.

CONCLUSION

In summary, we propose AION, a physics-informed, data-driven deep learning framework capable of globally generating and predicting high-dimensional high-resolution ionospheric parameters, covering latitudes (-90° to 90°), longitudes (-180° to 180°), and altitudes (50 km to 600 km). By integrating governing physical equation constraints and priors, our model is capable of generating 4D dynamics of electron density, temperature, thermal conductivity, and heating term at high spatiotemporal resolution. Our study demonstrates that physics-informed machine learning is capable of effectively forecast ionospheric high-dimensional states with good accuracy, high resolution and low computational cost. To the best of our knowledge, AION is the first groundbreaking machine learning framework capable of globally generating and predicting ionospheric parameters, particularly high-fidelity inversion of electron temperature.

AION is distinguished by a closure-aware assimilation design that couples heterogeneous observations. The pretrained closure supplies physically consistent transport and heating terms, enabling the electron temperature equation to be closed and imposed as a differentiable constraint during end-to-end training and forecasting. This physics-informed closure not only stabilizes assimilation under sparse and irregular sampling without explicit data alignment. Incorporating this physics-based constraint strengthens AION's representation of thermodynamic quantities. In addition, the operator-learning architecture endows AION with strong generalization across diverse observation geometries and varying solar forcing conditions.

By assimilating multi-source observations with fundamental physical constraints, our model overcomes key limitations of traditional empirical and assimilation-based approaches. AION is verified under this highly dynamic physical background. Our results demonstrate significant improvements in ionospheric parameter prediction compared to the standard IRI model. The AION model achieves 24-hour forecast with 38.2% reduction in root-mean-square error (RMSE) for electron density, whereas improved by 54.5% for electron temperature. Principal component analysis reveals our model captures 57.49 % and 62.78 % of the total variance in N_e and T_e distributions, respectively, while achieving superior correlation coefficients $R^2 = 0.74 \sim 0.75$ compared to IRI $R^2 = 0.11 \sim 0.25$. Most importantly, the AION model inference speed is fast in seconds without constrained by mesh grid resolution. This demonstrates that hybridizing deep learning with physics-based representations enables more accurate and efficient modeling of complex ionospheric dynamics than purely data-driven or purely physics-based methods alone.

Beyond ionospheric modeling, we introduce a pretrained-closure, physics-constrained paradigm for high-dimensional nonlinear systems with sparse observations and non-closed governing equations. By learning closure terms from physics-based simulations and enforcing them as differentiable constraints during assimilation and forecasting, the approach reduces reliance on dense data while improving stability and interpretability, and is

readily transferable to space weather, climate-process modeling, and plasma transport. Furthermore, future research will be enhanced along two fronts: more extensive data such as high accuracy GNSS observations³⁸ and physical constraints⁵² will be validated across complete seasons and solar cycles. Besides, to address prediction uncertainty and introduce confidence bounds, Bayesian theory will be employed to provide confidence evaluation.

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AUTHOR CONTRIBUTIONS

H. F. conceptualized the research and led the research project. J. M., Y. L., and C. S. built the AION model and conducted numerical experiments. J. M. and Y. L. are the co-first authors. J. M., C. S., and Y. D. offered the data curation. H. F., Y. L., C. S., and Y. D. analyzed the model's prediction results and prepared visualized results. H. F. and Y. J. supervised the work. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ETHICAL STATEMENT AND PATIENT CONSENT

These statements can be used in situations where a study did not involve human or animal participants as well as non-research articles such as reviews: This article does not contain any studies with human or animal participants. There are no human participants in this article and informed consent is not required.

DATA AND CODE AVAILABILITY

Additional data and materials are available online. The SAMI3 model can be requested from <https://ccmc.gsfc.nasa.gov/models/SAMI3~3.22/>. The F10.7, Ap and Kp data are obtained from Helmholtz Centre Potsdam (<https://kp.gfz-potsdam.de/en/data/>). The solar activity data (OMNI) are obtained from Goddard Space Flight Center (GSFC)/Space Physics Data Facility (SPDF) (<https://spdf.gsfc.nasa.gov/pub/data/omni/>). The COSMIC-2 data is publicly available at <https://data.cosmic.ucar.edu/gnss-ro/cosmic2/provisional/spaceWeather/level2>. Yunyao radio occultation dataset is provided by Tianjin Yunyao Aerospace Technology Co., Ltd. Sanya Incoherent Scatter Radar (SYISR) data is accessed through the website at <https://syisr.ac.cn/index>. SWARM data is publicly available at <https://swarm-diss.esa.int/#swarm/Advanced/Plasma>. The relevant code of the IRI-2020 model can be obtained from <https://irimodel.org/>. The CODE VTEC dataset is available at <http://ftp.aiub.unibe.ch/CODE/>. The code implementing AION will be available on the GitHub repository. The model configurations, analysis scripts, and data files used in this study will be made publicly available upon acceptance of this work.