

Article

Development and Validation of a Multi-Source Data-Fused Empirical TEC Model for North America with a Winter Anomaly Correction

Yunhui Wang ¹, Zhenzhen Zhao ^{1,*}, Ting Zhang ², Jianghe Chen ³ and Jiandi Feng ¹

¹ School of Civil Engineering and Spatial Information, Shandong University of Technology, Zibo 255000, China; wangyunhui_0104@163.com (Y.W.); jdfeng@whu.edu.cn (J.F.)

² State Key Laboratory of Precision Geodesy, Innovation Academy for Precision Measurement Science and Technology, CAS, Wuhan 430077, China; zhangting@apm.ac.cn

³ Key Laboratory of Earth and Planetary Physics, Institute of Geology and Geophysics, Chinese Academy of Sciences, Beijing 100029, China; chenjianghe23@mails.ucas.ac.cn

* Correspondence: zzzhao@whu.edu.cn

Abstract

Existing global ionospheric models have limited capability in representing the winter anomaly over North America. This study develops a North American Ionospheric TEC Empirical Model (NAI-TECEM) based on multi-source TEC data fusion. GPS-TEC, CODE-GIM, IRI2020, Jason-TEC, and COSMIC-TEC data from 2010 to 2021 were integrated using 15th-degree and 15th-order spherical harmonic expansion with Helmert variance component estimation. Under geomagnetically quiet conditions, a 19-parameter model was constructed using F10.7p (the average of the daily F10.7 value and its 81-day centered moving average), local time, day of year, geographic latitude, and modified dip latitude to describe diurnal, seasonal, geomagnetic latitude, solar activity, and winter anomaly variations. For internal consistency, parameters were estimated using nonlinear least squares with the Levenberg–Marquardt algorithm, yielding a mean residual of 0.42 TECU and an RMSE of 3.29 TECU. Additional statistical diagnostics and sensitivity analyses confirmed the robustness and stability of the estimated model coefficients. Pearson correlation coefficients between the fitted model and the fused TEC dataset exceed 0.95 at mid-latitude test points and 0.92 at high-latitude test points, indicating strong internal consistency. For external performance, three independent GPS stations (TUKT, IQAL, and NWOT) were used to compare observed TEC, modeled TEC, and reference products, together with a Winter Anomaly Index (WAI) to quantify seasonal anomaly intensity. The model achieved superior agreement with observations compared to IRI2020. Additional sensitivity tests under representative extrapolation and extreme-condition scenarios showed that the modeled TEC remained physically plausible, further supporting the robustness of NAI-TECEM beyond its calibration conditions. Validation for 2022–2024 further confirms that the model accurately reproduces the spatial structure, solar-activity dependence, and WAI-based winter anomaly characteristics over North America.



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Keywords: total electron content (TEC); North American region; winter anomaly; multi-source data fusion; ionospheric empirical model

1. Introduction

The ionosphere is an important component of the near-Earth space environment and directly affects applications such as the Global Navigation Satellite System (GNSS),

high-frequency communication, and space exploration missions [1]. In addition to regular variations, including diurnal, seasonal, and solar-cycle variations, the ionosphere exhibits various anomalous phenomena, such as the winter anomaly (WA), midlatitude summer nighttime anomaly (MSNA), equatorial ionization anomaly (EIA), annual anomaly (AA), and semiannual anomaly (SA). Among these phenomena, the winter anomaly is particularly prominent over the North American region [2].

The winter anomaly refers to the phenomenon that the daytime peak electron density of the F2 layer (NmF2) at mid-latitudes is higher in winter than in summer [3]. Extensive studies have investigated the characteristics and mechanisms of the winter anomaly over North America. Based on GPS-TEC climatological analysis, Ref. [4] demonstrated that the winter anomaly is significant over North America and that TEC variations exhibit clear regional differences. Meanwhile, the mid- and high-latitude ionosphere over North America is strongly affected by the coupling between solar activity and geomagnetic disturbances [5]. Previous studies have shown that ionospheric variations over North America are jointly controlled by multiple factors, and the winter anomaly exhibits pronounced temporal and spatial regional characteristics. The winter anomaly has been observed in both TEC and NmF2, and strong winter anomaly signatures can persist under different solar activity conditions over North America, although they tend to weaken under very high solar activity levels [6]. Investigations of the relationship between the winter anomaly and the semiannual anomaly at mid-latitudes have revealed significant differences between hemispheres and regions, indicating that the formation mechanism of the winter anomaly has strong regional dependence [7]. Furthermore, Ref. [8] reported significant longitudinal differences in mid-latitude TEC over North America, while [9] suggested that the coupling between neutral winds and geomagnetic declination is an important factor contributing to the longitudinal asymmetry of the ionosphere over the Americas. Studies have also shown that the winter anomaly can persist during periods of low solar activity, indicating that its formation and evolution are not solely dependent on high solar activity conditions [10]. Recent research further demonstrated the complexity of the spatial distribution and intensity variations of the winter anomaly [11]. These studies indicate that North America is a typical region for investigating the winter anomaly, which is jointly influenced by solar activity, geomagnetic disturbances, and neutral atmospheric processes, exhibiting strong regional characteristics and complexity in both temporal and spatial domains.

Most existing ionospheric empirical models are developed for global-scale applications and are not specifically optimized for the winter anomaly over North America, limiting their capability to accurately represent regional winter anomaly characteristics [12]. The International Reference Ionosphere (IRI) and NeQuick2 are widely used empirical ionospheric models and have been extensively evaluated against different TEC observations [13]. The global Neustrelitz total electron content model (NTCM-GL) has also been developed for large-scale TEC representation. However, the parameterization of these models is mainly based on global statistical characteristics and does not account for regional anomaly features. Consequently, their capability to reproduce specific regional phenomena, such as the North American winter anomaly, remains limited [14–16]. In addition, although global ionospheric maps (GIMs) provide continuous TEC distributions, their accuracy is affected by the uneven distribution of ground-based GNSS stations. In particular, the sparse observations over oceanic regions of North America reduce the capability of GIM products to represent regional TEC variations and winter anomaly characteristics [17]. Therefore, developing a regional ionospheric empirical model capable of better representing the winter anomaly over North America is of great importance.

The development of an ionospheric empirical model for North America faces two major challenges. First, a single data source is generally insufficient to fully character-

ize the spatiotemporal variations of ionospheric TEC. Ground-based GNSS observations provide high-precision TEC measurements but are limited by the spatial distribution of observation stations, resulting in sparse observations over oceans and remote areas. Compared with individual datasets, the integration of GPS-TEC, Jason-TEC, COSMIC-TEC, and empirical model products can partially compensate for the lack of observations in oceanic regions, improve the spatial continuity and reliability of TEC data, and enhance the capability of empirical models to represent anomalous features [18]. Second, the winter anomaly over North America requires a dedicated parameterization function. Previous studies have mainly focused on the characteristics and influencing factors of the winter anomaly, while relatively few studies have developed specific empirical functions to represent this phenomenon.

To address these challenges, this study integrates five different TEC datasets, including GPS-TEC, CODE-GIM, IRI2020, Jason-TEC, and COSMIC-TEC, to construct a regional TEC dataset for North America. A parameterized function term describing the winter anomaly characteristics is developed and incorporated into a regional TEC empirical model to improve the representation of the North American winter anomaly. The proposed model aims to provide a more accurate description of regional TEC variations and winter anomaly characteristics over North America.

2. Materials and Methods

2.1. Study Area and Data Sources

The study region covers the area from 25°N to 85°N and from 65°W to 140°W. The northern part of the study region extends into the high-latitude ionosphere, where total electron content (TEC) variability is generally more complex than at mid-latitudes. Five TEC datasets, including GPS-TEC, CODE-GIM, IRI2020, Jason-TEC, and COSMIC-TEC, were collected for the period from 1 January 2010 to 31 December 2021 to construct a multi-source fused TEC dataset. The resulting fused TEC product has a spatial resolution of $5^\circ \times 2.5^\circ$ (longitude $\times$ latitude) and a temporal resolution of 1 h.

GPS-TEC observations were obtained from 10 GNSS stations distributed from mid- to high latitudes across North America, providing ground-based constraints on regional TEC variability. The distribution of the stations is shown in Figure 1. CODE-GIM provides continuous gridded TEC background information, whereas IRI2020 supplies empirical-model-based TEC estimates. Jason satellite altimetry data provide supplementary TEC observations over oceanic regions, while COSMIC radio occultation measurements provide electron density profiles and integrated TEC information at complementary spatial locations. These datasets differ in observation technique, spatial coverage, and temporal sampling, and their complementary characteristics provide the basis for constructing a regional multi-source fused TEC dataset over North America.

2.2. Data Preprocessing

2.2.1. Multi-Source TEC Data Preprocessing

Ground-based GPS-TEC data were derived from raw GNSS observations provided by the Crustal Dynamics Data Information System (CDDIS) and processed using the Gopi-TEC software (version 3.5; developed by Gopi Krishna Seemala, Indian Institute of Geomagnetism, Navi Mumbai, India) [19]. Slant total electron content (STEC) was converted to vertical total electron content (VTEC) using:

$$VTEC = [STEC - (DCB_R + DCB_{Si})] \times S(E) \quad (1)$$

$$S(E) = \left\{ 1 - \left(\frac{R_E \times \cos(E)}{R_E + h_{ipp}} \right)^2 \right\}^{\frac{1}{2}} \quad (2)$$

DCB_R and DCB_{Si} denote the differential code biases of the receiver and the i -th observed satellite, respectively; $S(E)$ is the thin-shell mapping function; R_E denotes the Earth radius and is set to 6378 km; E is the satellite elevation angle relative to the receiver; and h_{ipp} denotes the height of the ionospheric pierce point (IPP) [20,21].

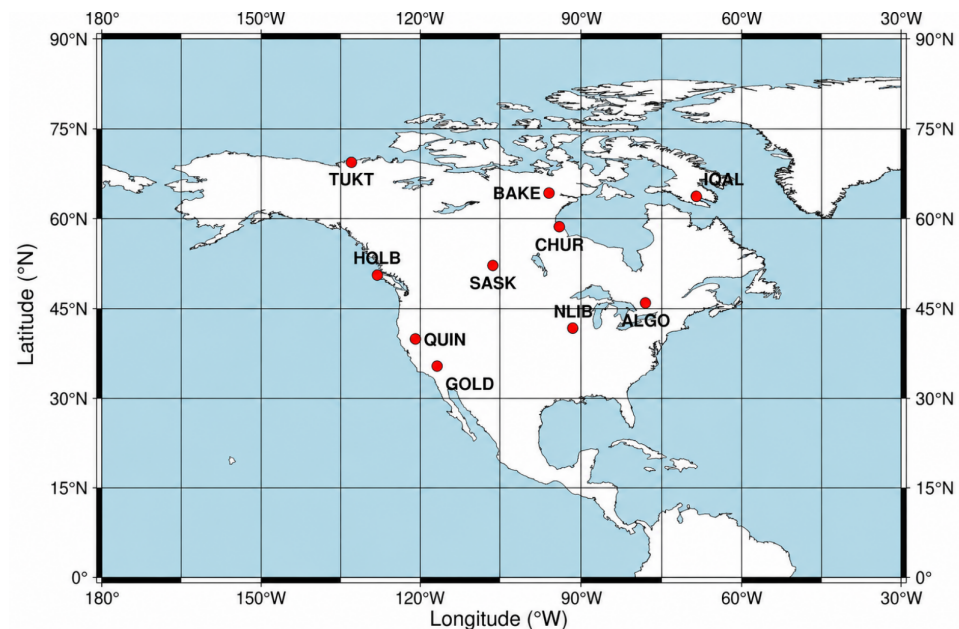


Figure 1. Distribution map of observation stations.

At the beginning of the processing procedure, a satellite elevation cutoff angle of 30° was applied to restrict the ionospheric pierce points to a limited region around the station zenith. Subsequently, within each 1 min window, IPP VTEC observations deviating from the mean by more than one standard deviation were removed in two consecutive screening steps. Finally, the retained high-quality observations within each 1 min window were averaged and subjected to low-pass smoothing. This procedure effectively reduces local spatial differences caused by the different locations of IPPs within the visible satellite coverage, and the remaining errors are negligible compared with the absolute deviations of empirical ionospheric models.

Jason-series satellite altimetry products provided by the Radar Altimeter Database System (RADS) were used to derive ionospheric TEC. First, the smoothed dual-frequency ionospheric correction was extracted from the product, and VTEC was calculated using the Ku-band frequency according to Equation (3):

$$VTEC = -\frac{dR \times f^2}{40.3} \quad (3)$$

where dR represents the dual-frequency ionospheric range correction provided by the Radar Altimeter Database System (RADS) and f is the Ku-band frequency, taken as 13.575 GHz in this study. Negative TEC values were subsequently removed as anomalous observations. The Jason-TEC data were then resampled to a temporal resolution of 10 s, and gross errors were finally removed using the 3σ criterion.

Because the original COSMIC observations are affected by various factors, including instrumental effects, meteorological conditions, and the space environment, the quality of

some electron density profile products is not satisfactory. Therefore, quality control was applied before their use [22]. The retained electron density profiles were integrated using the gradient method to obtain STEC, electron density profiles in the E region are susceptible to disturbances and may contain negative values, while anomalous points may also occur near an altitude of 800 km. Therefore, the integration altitude range was set to 110–750 km.

2.2.2. Solar Activity Parameter

Solar activity is one of the primary drivers of the morphology and variability of the Earth's ionosphere, and variations in solar radiation directly modulate the ionospheric electron density distribution. Therefore, an appropriate representation of solar activity is important for improving the reliability of ionospheric empirical models. Although solar extreme ultraviolet (EUV) radiation is an important parameter for directly characterizing variations in solar activity, long-term continuous EUV observations are relatively limited. Consequently, solar activity proxy indices with clear physical significance and long-term availability are commonly used in practical ionospheric modeling [23].

Among the various solar activity indices, the F10.7 index, corresponding to the solar radio flux at a wavelength of 10.7 cm, has been widely adopted. F10.7 has a long and continuous observational record, good data consistency, and a strong correlation with solar EUV radiation, enabling it to effectively characterize variations in solar activity. Previous studies have shown that F10.7 performs better than the conventional sunspot number in describing ionospheric TEC variations, and it has therefore been widely used in empirical ionospheric modeling.

To further improve the applicability of F10.7 in ionospheric modeling, smoothing is commonly applied to suppress short-term fluctuations and emphasize medium- and long-term variations in solar activity. F10.7a is defined as the 81-day centered moving average of F10.7 and is used to represent the medium-term background level of solar activity. Based on this, an improved index F10.7p can be constructed, defined as the average of F10.7 and F10.7a for the current day [24]. This composite index can not only reflect the current solar radiation intensity but also smooth out the drastic fluctuations caused by sudden activities such as solar flares.

This composite index reflects the current solar radiation intensity while simultaneously smoothing strong short-term fluctuations caused by events such as solar flares. In this study, observations corresponding to $F10.7p > 200$ sfu were excluded to reduce the influence of extremely high solar activity on model stability.

Figure 2 shows the variations in F10.7 and F10.7p from 2010 to 2021. Compared with the original F10.7 index, the F10.7p curve is smoother and effectively suppresses abrupt fluctuations and peaks associated with short-term solar events. Therefore, F10.7p can better represent the medium- and long-term background variation in solar radiation.

2.2.3. Geomagnetic Activity Index

When constructing the North American regional ionospheric empirical model based on multi-source data fusion, the influence of geomagnetic disturbances on the modeling dataset must be appropriately controlled. Strong solar activity can transport energetic particles into the near-Earth space environment through the solar wind and trigger complex magnetosphere–ionosphere–thermosphere coupling processes, eventually causing geomagnetic storms and associated ionospheric storms. These processes can produce strong and complex disturbances in the ionosphere. Therefore, an appropriate geomagnetic index is required to determine the geomagnetic activity level and to select modeling samples under geomagnetically quiet conditions.

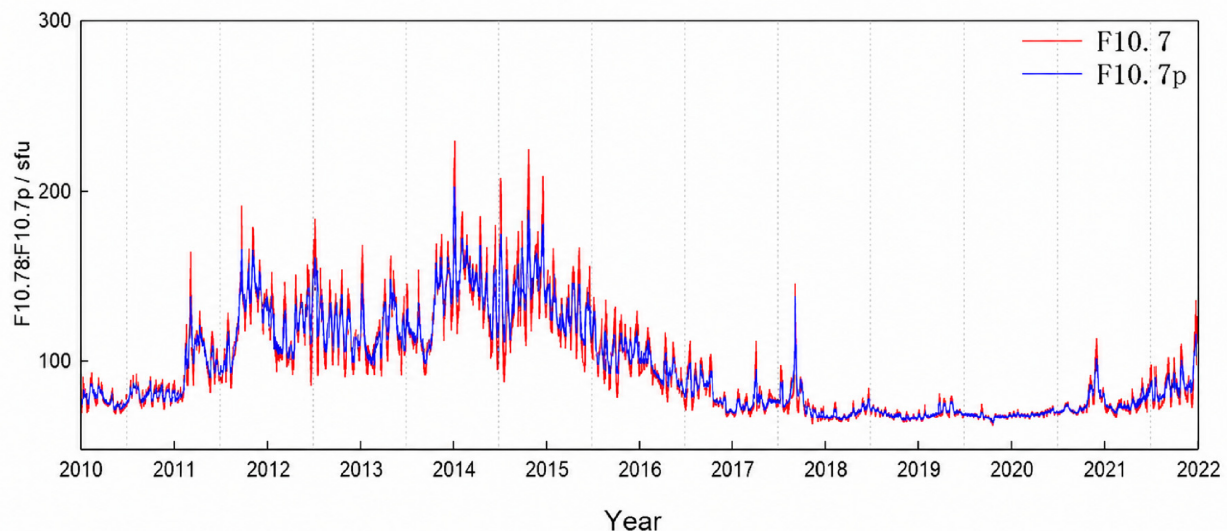


Figure 2. Trend of changes in F10.7 and F10.7p from 2010 to 2021.

Geomagnetic indices characterize geomagnetic activity from different temporal scales and physical perspectives. The planetary geomagnetic K index (Kp) is a global geomagnetic activity index derived statistically from K indices measured at 13 mid-latitude geomagnetic observatories and therefore provides good global representativeness. The planetary geomagnetic Ap index (Ap), which is derived from Kp through a linearized conversion, overcomes the quasi-logarithmic nature of Kp and provides a quantitative representation of the overall level of geomagnetic disturbance during a day. To reduce the influence of geomagnetic disturbances on TEC modeling, TEC data under conditions of $A_p > 30$ nT were excluded during the preprocessing procedure [18]. Although $A_p \leq 20$ nT is often considered a stricter quiet-time condition, $A_p \leq 30$ nT has also been widely adopted in empirical TEC modeling to balance geomagnetic quietness and data availability. Therefore, the developed NAI-TECEM mainly represents TEC variations over North America under quiet to moderately disturbed geomagnetic conditions. It should be noted that Ap was used only for geomagnetic activity screening and was not included as an input parameter of the NAI-TECEM model function; the geomagnetic-latitude variation component of the model was instead represented by the modified dip latitude.

2.3. Multi-Source TEC Fusion

The multi-source TEC fusion was performed over the North American region extending from 25°N to 85°N and from 65°W to 140°W. The resulting fused TEC product has a spatial resolution of $5^\circ \times 2.5^\circ$ and a temporal resolution of 1 h. To provide a unified spatial representation for the different TEC datasets, the spherical harmonic modeling strategy adopted by CODE global ionospheric products was used [25]. TEC was represented using a 15th-degree and 15th-order spherical harmonic expansion as:

$$VTEC = \sum_{n=0}^N \sum_{m=0}^n \tilde{P}_{nm}(\sin\beta) \times \left[\tilde{C}_{nm}\cos(ms) + \tilde{S}_{nm}\sin(ms) \right] \quad (4)$$

$$\tilde{P}_{nm}(\sin\beta) = MC(n, m) \times P_{nm}(\sin\beta) \quad (5)$$

$$MC(n, m) = \sqrt{(n-m)!(2n+1)(2-\delta_{0m})/(n+m)!} \quad (6)$$

$$\delta_{0m} = \begin{cases} 0, & m = 0 \\ 1, & m \neq 0 \end{cases} \quad (7)$$

Here, n and m denote the degree and order of the spherical harmonic functions, respectively; s represents the longitude of the ionospheric pierce point, and β denotes the latitude variable used in the spherical harmonic expansion; The terms ms in the trigonometric functions represent the product of the spherical harmonic order and longitude; N denotes the maximum degree of the spherical harmonic expansion. $\tilde{P}_{nm}(\sin\beta)$ denotes the normalized associated Legendre function of degree n and order m . $\tilde{C}_{nm}$ and $\tilde{S}_{nm}$ are the spherical harmonic coefficients to be estimated.

Because GPS-TEC, CODE-GIM, IRI-TEC, Jason-TEC, and COSMIC-TEC differ in observation technique, spatial distribution, and data characteristics, assigning identical weights to all datasets would not appropriately account for their relative contributions to the fusion. Therefore, Helmert variance component estimation (HVCE) was employed to iteratively determine the relative weights of the different TEC datasets according to their residual characteristics [26]. Considering the computational cost of rigorous variance component estimation, the approximate Helmert formulation was adopted:

$$S\hat{\theta} = W_{\theta} \quad (8)$$

$$\hat{\sigma}_{0_i}^2 = \frac{V_i^T P V_i}{n_i} \quad (9)$$

$$\hat{P}_i = \frac{c}{\hat{\sigma}_{0_i}^2 P_i^{-1}} \quad (10)$$

where V_i is the residual vector of the i -th observation group, P_i is the corresponding weight matrix, n_i represents the number of observations, and $\hat{\sigma}_{0_i}^2$ denotes the estimated unit-weight variance component. S represents the coefficient matrix, $\hat{\theta}$ denotes the estimated parameter vector, W_{θ} represents the observation vector, c is a constant factor, and $\hat{P}_i$ denotes the updated weight matrix.

The iterative HVCE procedure was implemented as follows. First, the observations were divided into five groups according to their data sources: CODE-GIM, IRI-TEC, GPS-TEC, Jason-TEC, and COSMIC-TEC. Their initial a priori weights were set to 2, 0.5, 4, 4, and 4, respectively, yielding the initial weight matrices $P_1, P_2, \dots, P_5$. Second, an initial weighted adjustment was performed using these weights. Third, the unit-weight variance of each observation group was estimated using Equation (9), and the corresponding weights were updated according to Equation (10). Finally, the weighted adjustment, variance-component estimation, and weight updating were repeated until the estimated unit-weight variances became stable and the ratios among the unit-weight variances of the different datasets approached unity.

The fusion procedure covered the full daily interval from 00:00 to 23:00 with a temporal resolution of 1 h. Because Jason-TEC and COSMIC-TEC observations are relatively sparse in both time and space, valid observations within ± 1 h of each target epoch were also included in the fusion. Spatially, Jason-TEC and COSMIC-TEC observations were not interpolated onto the regular grid prior to fusion. Instead, their actual geographic coordinates were directly used to construct the spherical harmonic observation equations. After estimating the spherical harmonic coefficients, TEC values were evaluated on the regular grid to generate the Fusion-TEC dataset with a spatial resolution of $5^\circ \times 2.5^\circ$ and a temporal resolution of 1 h.

2.4. Development of NAI-TECEM

2.4.1. Overall Model Structure

Based on the multi-source fused TEC dataset (Fusion-TEC) over North America during 2010–2021, a North American Ionospheric TEC Empirical Model (NAI-TECEM) was

developed. During model construction, the Ap index was used to select samples under geomagnetically quiet conditions, while the effects of solar activity, local time, seasonal variation, and spatial location on TEC were taken into account [27]. It should be emphasized that the Ap index was used only for sample screening and was not included as an input parameter of the model function. The spatial variation of TEC with geomagnetic latitude was represented using the modified dip latitude.

NAI-TECEM consists of five components describing diurnal variation, seasonal variation, geomagnetic-latitude variation, solar activity response, and the winter anomaly. The overall model is expressed as Equation (11):

$$NAI-TECEM = F_1 \times F_2 \times F_3 \times F_4 \times F_5 \quad (11)$$

The multiplicative form is adopted because F_1 – F_5 represent different modulation factors associated with physical variations rather than independent TEC components. Each factor modifies the TEC value according to a specific physical effect, including diurnal variation, seasonal variation, latitude dependence, solar activity, and winter anomaly. Therefore, the multiplication form enables the combined effects of different physical factors to be considered simultaneously.

2.4.2. Diurnal Variation Component

Ionospheric TEC exhibits a pronounced diurnal variation. To describe its periodic dependence on local time, a fourth-order harmonic function was employed to construct the diurnal variation component. A solar elevation angle modulation term was additionally introduced to account for the influence of changes in solar position and solar radiation on TEC. The diurnal component is expressed in Equations (12)–(14):

$$F_1 = 1 + D_C \sin(h) \quad (12)$$

$$D_C = \sum_{i=1}^4 c_{i+4} \times \cos\left(\frac{2\pi i \times LT}{24} + c_i\right) \quad (13)$$

$$\sin(h) = \sin\varphi \sin\delta + \cos\varphi \cos\delta \cos(V_{LT}) \quad (14)$$

Here, h is the solar elevation angle, which is determined by the geographic latitude φ , solar declination δ , and solar hour angle V_{LT} ; φ denotes the geographic latitude; δ denotes the solar declination determined by the day of year (DOY); V_{LT} is the solar hour angle determined from local time (LT); and c_i denotes the model coefficients to be estimated, where $c_1 - c_4$ represent the phase coefficients of the four harmonic terms and $c_5 - c_8$ represent their corresponding amplitudes. In Equation (13), D_C is constructed using a fourth-order harmonic function of local time (LT) to describe the diurnal variation of TEC. The four harmonic components characterize TEC variations at different temporal scales within a day, while their amplitudes and phases are determined by the model coefficients. Equation (14) describes the solar-illumination geometry through the solar elevation angle, which depends on geographic latitude, solar declination, and solar hour angle. Therefore, the diurnal component combines the LT-dependent harmonic variation with the modulation of solar illumination. The fourth-order harmonic function was adopted because it provides sufficient flexibility to describe the complex diurnal variation of TEC at different temporal scales within a day, while avoiding excessive model complexity and unnecessary parameters.

2.4.3. Seasonal Variation Component

In this study, owing to the periodic nature of the DOY-dependent variation, a fourth-order harmonic combination based on the day of year (DOY) was used to characterize the seasonal variation of TEC, as expressed in Equation (15):

$$F_2 = 1 + \sum_{j=1}^4 c_{j+8} \times \cos\left(\frac{2\pi j \times \text{DOY}}{365.25} + c_{j+12}\right) \quad (15)$$

This component describes the periodic seasonal behavior of TEC, including both annual and semiannual variations.

2.4.4. Geomagnetic-Latitude Variation Component

Because the ionospheric electron density distribution is closely related to the geomagnetic field configuration, TEC exhibits pronounced spatial variations with geomagnetic latitude. In this study, the modified dip latitude (modip) was used to represent the spatial variation of TEC with geomagnetic latitude, as expressed in Equation (16):

$$F_3 = 1 + c_{17} \times \cos(\varphi_m) \quad (16)$$

$$\tan \varphi_m = \frac{I}{\sqrt{\cos \varphi}} \quad (17)$$

Here, φ_m denotes the modip, which is used as a geomagnetic latitude parameter. It is calculated from the magnetic inclination I and geographic latitude φ , as given in Equation (17). In this study, the magnetic inclination I was obtained from IGRF13 at an altitude of 350 km. This variable describes the spatial dependence of TEC on geomagnetic latitude and does not represent variations in geomagnetic activity.

The cosine function in Equation (16) is introduced as an empirical geomagnetic-latitude modulation function rather than a projection correction factor. Although $\sec(\varphi_m)$ or functions are commonly used in geometric mapping or projection-related formulations, such expressions are not applicable to the present model because Equation (16) aims to represent the climatological spatial variation of TEC with geomagnetic latitude. The cosine dependence provides a smooth decreasing variation toward higher geomagnetic latitudes and is therefore adopted to characterize the large-scale latitude dependence of TEC in the study region. It should also be noted that this term is not intended to represent the equatorial trough, which is associated with low-latitude plasma redistribution processes. Instead, it describes the empirical dependence of regional TEC on geomagnetic latitude in the mid- and high-latitude domain.

2.4.5. Solar Activity Component

Solar activity is an important driver of ionospheric TEC variability. In this study, F10.7p was adopted as a proxy for solar activity, and a linear response function was constructed to describe the response of TEC to variations in solar activity, as expressed in Equation (18):

$$F_4 = 1 + c_{18} \times F_{10.7p} \quad (18)$$

Here, $F_{10.7p}$ denotes the smoothed solar activity index defined in Section 2.2.2, and the corresponding model coefficient characterizes the response of TEC to changes in solar activity level.

2.4.6. Winter Anomaly Component

To represent the anomalous enhancement of wintertime TEC over the mid- and high-latitude regions of North America, a dedicated winter anomaly correction component was

introduced into the empirical model. Although the seasonal component accounts for the regular annual and semiannual variations with DOY, it does not explicitly represent the anomalous wintertime enhancement of TEC. This winter anomaly component simultaneously accounts for the seasonal concentration, latitudinal dependence, and solar-activity response of the winter anomaly. Its mathematical expression is given in Equation (19):

$$F_5 = 1 + c_{19} \frac{F_{10.7p}}{\bar{F}_{10.7p}} \cos \left[2\pi \frac{\text{DOY} - 355}{365.25} \right] \exp \left[-0.02(|\phi| - 40)^2 \right] \quad (19)$$

Here, $\bar{F}_{10.7p}$ denotes a single mean value of the daily F10.7p index calculated over all valid modeling days during 2010–2021 after applying the data-screening criteria; DOY denotes the day of year; DOY = 355 corresponds approximately to the period around the Northern Hemisphere winter solstice and is used as the center of the seasonal modulation function; 40°N is used as the central latitude of the winter anomaly latitudinal modulation function over North America, while the coefficient 0.02 controls the latitude attenuation rate and was determined during the empirical model construction; and c_{19} denotes the winter anomaly intensity coefficient, which is constrained to be greater than zero.

Unlike F_4 , which describes the overall solar-cycle dependence of TEC, F_5 represents the solar-activity-dependent modulation of winter anomaly intensity. The normalized solar activity factor $\frac{F_{10.7p}}{\bar{F}_{10.7p}}$ is therefore introduced to describe the relative response of winter anomaly strength under different solar activity conditions. The coefficient c_{19} is estimated from observations rather than fixed to unity because the solar activity sensitivity of winter anomaly may differ from that of the background TEC response.

To further evaluate the robustness of the proposed model under extreme conditions, a sensitivity test was conducted by setting $F_{10.7p} = 200$ sfu and maximizing the winter anomaly contribution (DOY = 355). The maximum simulated TEC value under this combined condition was 49.493 TECU. This value only occurred under the simultaneous enhancement of multiple model components and does not indicate unrealistic amplification, demonstrating the physical stability of the proposed model under extreme solar activity conditions.

Through the combined effects of the seasonal and latitudinal modulation factors, this component enhances the capability of the model to represent the wintertime TEC enhancement and its spatial variation over the mid-latitude region of North America, while allowing the winter anomaly correction to vary with solar activity.

2.5. Parameter Estimation and Evaluation Metrics

NAI-TECEM is a nonlinear empirical model containing 19 coefficients to be estimated. The model parameters were determined using the Marquardt nonlinear least-squares algorithm by minimizing the sum of squared residuals between the TEC values calculated by NAI-TECEM and the Fusion-TEC dataset. The objective function is given in Equation (20).

$$\operatorname{argmin} \sum_{i=1}^K \left[\text{TEC}_{(\text{obs}, i)} - \text{NAI} - \text{TECEM}(c_1, c_2 \dots c_{19}; x_i) \right]^2 \quad (20)$$

Here, K denotes the number of TEC datasets involved in the fusion process, which is equal to 5 in this study. x_i includes the solar activity index $F_{10.7p}$, day of year (DOY), local time (LT), modified dip latitude, and geographic latitude. The initial values of the 19 model coefficients were set as $\beta_0 = 1_{19 \times 1}$, and the optimized model coefficients together with their 95% confidence intervals were subsequently obtained.

To evaluate the internal consistency between the model and the modeling dataset, the mean residual, standard deviation (STD), and root mean square error (RMSE) were used to characterize the model fitting errors. In addition, Pearson correlation coefficients

between NAI-TECEM and Fusion-TEC were calculated at two representative mid-latitude grid points and two high-latitude grid points to evaluate the capability of the model to reproduce temporal TEC variations at different latitudes.

3. Results

3.1. Multi-Source TEC Fusion Results

Figure 3 shows the weights determined for the five TEC data sources using Helmert variance component estimation. Clear differences can be observed among the different datasets. COSMIC-TEC had the highest mean weight of 12.19, followed by GPS-TEC with a mean weight of 11.23. The mean weight of Jason-TEC was 5.37, while those of CODE-GIM and IRI-TEC were 3.42 and 2.46, respectively.

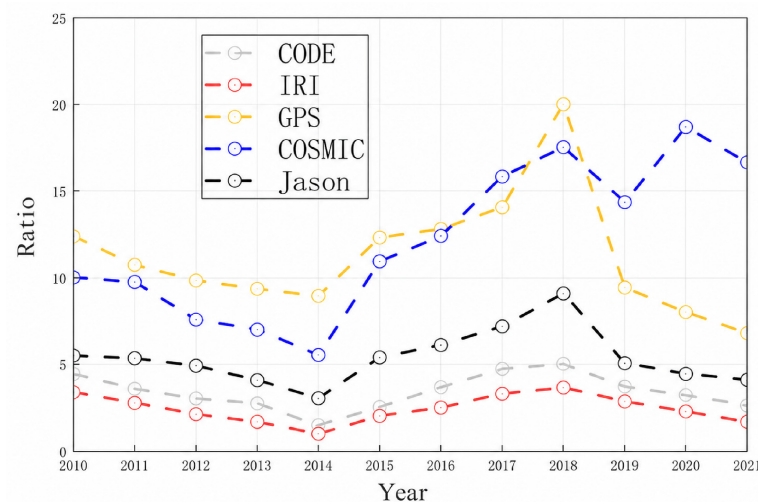


Figure 3. Weights of different TEC data sources.

Under the adopted HVCE-based fusion scheme, a larger relative weight corresponds to a smaller estimated variance component derived from the residuals of that data source. Therefore, the relatively high weights assigned to COSMIC-TEC and GPS-TEC indicate smaller residual variance within the present spherical-harmonic fusion framework. These weights represent relative statistical contributions to the fusion and should not be interpreted as direct measures of the intrinsic accuracy of the different observation techniques. Jason-TEC had a lower relative weight than COSMIC-TEC and GPS-TEC but provided complementary observations over oceanic regions and areas with sparse ground-based GNSS stations. CODE-GIM and IRI-TEC had relatively lower weights but provided continuous background TEC information in regions with limited observations.

It is also noted that the weights of all TEC datasets show relatively lower values around 2014. This period corresponds to the maximum phase of solar cycle 24, during which enhanced solar activity may lead to stronger ionospheric variability and larger residual variance among different TEC products. According to the HVCE principle, the increase in estimated variance components results in lower relative weights. Therefore, the lower weights in 2014 reflect the reduced consistency among multi-source TEC datasets during this period.

3.2. Internal Consistency Validation

3.2.1. Model Fitting and Residual Analysis

The 19 parameters of NAI-TECEM were estimated using the Marquardt nonlinear least-squares algorithm. The estimated model coefficients and their corresponding 95% confidence intervals are listed in Table 1. These parameters are associated with the diurnal,

seasonal, geomagnetic-latitude, solar-activity, and winter-anomaly components of the model and jointly characterize the major TEC variations over North America.

Table 1. Estimated coefficients of NAI-TECEM and their 95% confidence intervals.

Coefficient	Estimate	95% Confidence Interval
c1	0.949 94	$\pm 0.000\ 474$
c2	0.237 47	$\pm 0.003\ 312$
c3	0.840 85	$\pm 0.006\ 635$
c4	−0.060 67	$\pm 0.034\ 947$
c5	1.530 06	$\pm 0.000\ 427$
c6	−0.119 94	$\pm 0.000\ 402$
c7	−6.812 53	$\pm 0.000\ 402$
c8	−0.011 16	$\pm 0.000\ 401$
c9	0.414 32	$\pm 0.001\ 932$
c10	−6.974 71	$\pm 0.001\ 817$
c11	2.484 98	$\pm 0.005\ 324$
c12	−25.664 31	$\pm 0.016\ 526$
c13	−0.127 25	$\pm 0.000\ 236$
c14	−0.131 39	$\pm 0.000\ 241$
c15	0.044 74	$\pm 0.000\ 239$
c16	0.013 83	$\pm 0.000\ 231$
c17	0.244 35	$\pm 0.015\ 235$
c18	0.004 24	$\pm 0.000\ 207$
c19	5.076 42	$\pm 0.005\ 116$

To evaluate the internal consistency between NAI-TECEM and the Fusion-TEC modeling dataset, the model fitting residuals were statistically analyzed. Figure 4 shows the histogram of the NAI-TECEM residuals, while Table 2 summarizes the proportions of residuals within different intervals. As shown in Figure 4, the residuals exhibit an approximately normal distribution and are mainly concentrated within relatively small error ranges. The mean residual is 0.42 TECU, with a standard deviation (STD) of 3.26 TECU and a root mean square error (RMSE) of 3.29 TECU.

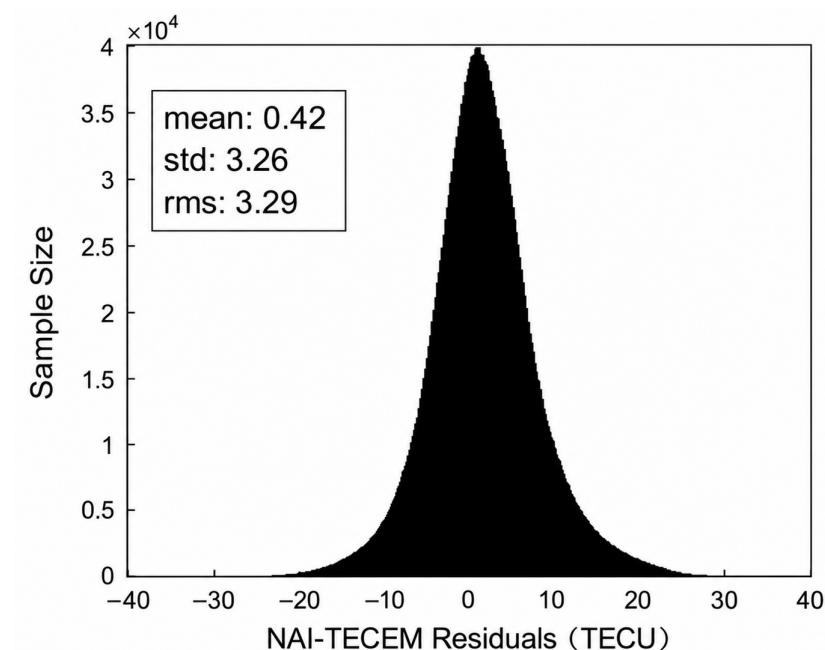


Figure 4. Histogram of NAI-TECEM residuals.

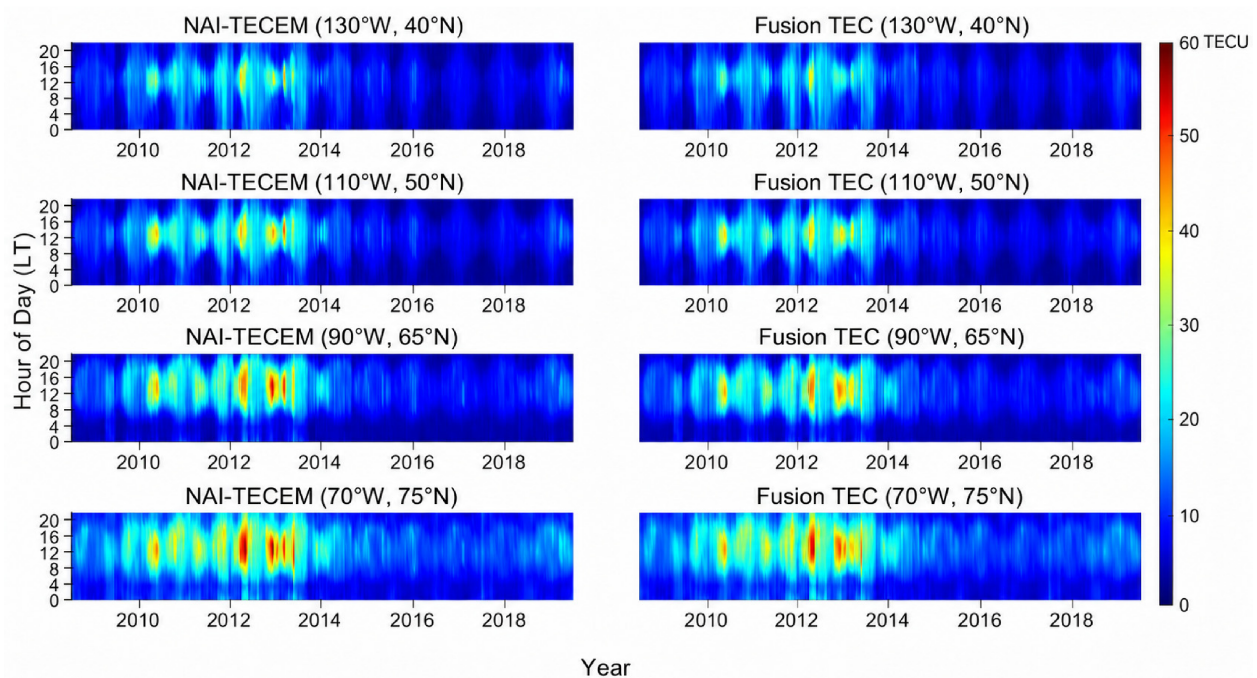
Table 2. Statistical distribution of NAI-TECEM residuals.

Residual Range (TECU)	Percentage
−10–10	87.03%
−20–20	98.74%
−30–30	99.93%

Further statistical analysis shows that 87.03% of the residuals fall within −10 to 10 TECU, 98.74% fall within −20 to 20 TECU, and 99.93% fall within −30 to 30 TECU. These results indicate good internal consistency between NAI-TECEM and the Fusion-TEC modeling dataset.

3.2.2. Validation at Representative Grid Points

To further evaluate the internal consistency of NAI-TECEM with the Fusion-TEC modeling dataset at different latitudes, two representative mid-latitude grid points (130°W, 40°N and 110°W, 50°N) and two representative high-latitude grid points (90°W, 65°N and 70°W, 75°N) were selected. Within the modeling period, TEC time series at the four grid points were calculated using both NAI-TECEM and Fusion-TEC from January 2010 to December 2021 with a sampling interval of 10 days. Figure 5 presents the TEC time-series comparisons between NAI-TECEM and Fusion-TEC at the four representative grid points, while Figure 6 shows their correlation scatter plots.

**Figure 5.** Internal consistency validation of NAI-TECEM at representative mid- and high-latitude grid points during 2010–2021.

As shown in Figure 5, at the two mid-latitude grid points, the TEC variations calculated by NAI-TECEM are generally consistent with those of Fusion-TEC, and the model reproduces the overall TEC variations under different years and solar activity levels. At the two high-latitude grid points, the fitting results exhibit somewhat greater dispersion; nevertheless, NAI-TECEM still captures the overall temporal variations of Fusion-TEC.

Figure 6 further shows the Pearson correlations between NAI-TECEM and Fusion-TEC. At the two mid-latitude test points, the Pearson correlation coefficients are higher than 0.95, indicating a strong linear correlation between the model and Fusion-TEC. At

the two high-latitude test points, the correlation coefficients remain above 0.92. Although slightly lower than those at the mid-latitude test points, the reduced agreement is consistent with the greater complexity of ionospheric variability at high latitudes.

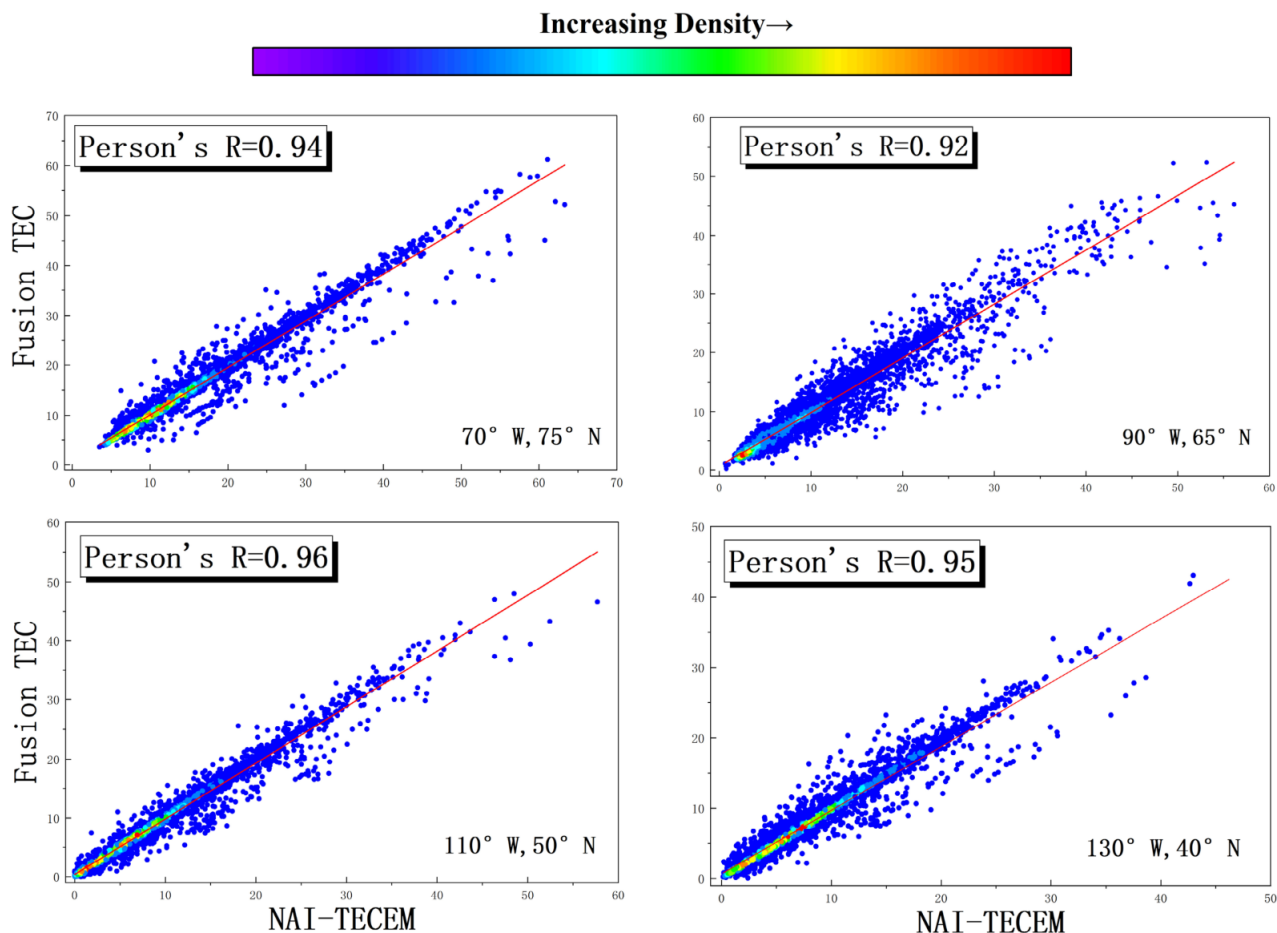


Figure 6. Correlation scatter plots between NAI-TECEM and Fusion-TEC during 2010–2021.

Overall, the time-series and correlation analyses demonstrate good internal consistency between NAI-TECEM and the Fusion-TEC modeling dataset at both mid- and high-latitude grid points. The fitting performance is slightly weaker at high latitudes than at mid-latitudes, reflecting the greater complexity of ionospheric variability in high-latitude regions.

3.3. Predictive Performance Evaluation

3.3.1. Station-Based Predictive Performance Evaluation

To further evaluate the capability of NAI-TECEM to reproduce actual GPS-TEC observations and its regional applicability, GPS-TEC observations around the winter solstice at the TUKT, IQAL, and NWOT stations were used as references and compared with the corresponding NAI-TECEM and IRI2020 results. MOD-TEC represents the TEC values calculated by the proposed NAI-TECEM model. TUKT and IQAL were included in the construction of the Fusion-TEC dataset, whereas NWOT (105.591°W, 40.055°N) was not involved in the multi-source TEC fusion and therefore provides an independent spatial validation of the model.

Figures 7 and 8 present comparisons among NAI-TECEM, IRI2020, and GPS-TEC observations at the TUKT and IQAL stations around the winter solstice during 2010–2021. Overall, both models reproduce the main diurnal and interannual variations of TEC to

some extent; however, clear differences are observed in curve shape, daytime peak intensity, peak occurrence time, and variation amplitude under different solar activity levels.

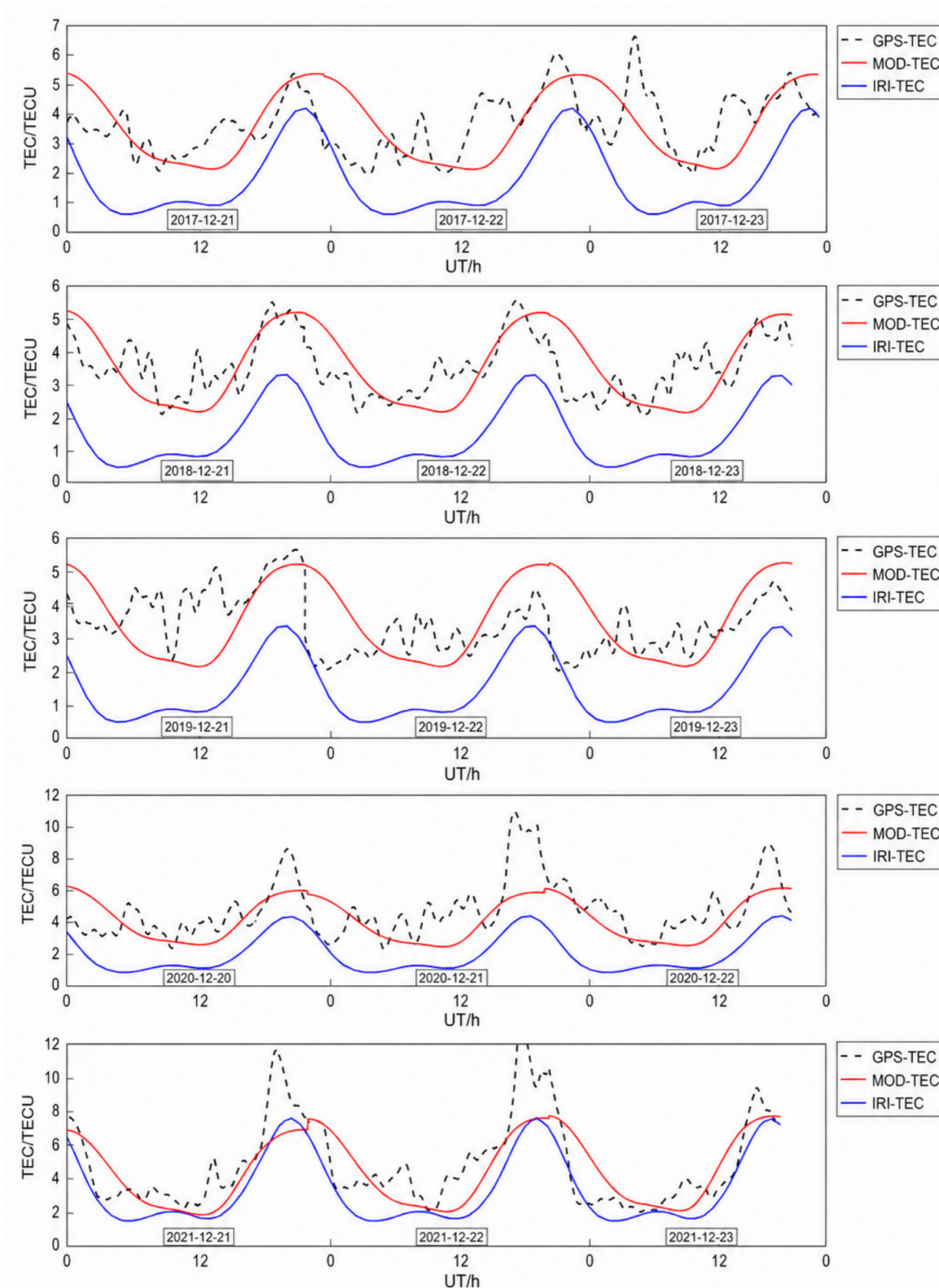


Figure 7. Comparison of NAI-TECEM, GPS-TEC, and IRI2020 at the TUKT station around the winter solstice during 2010–2021.

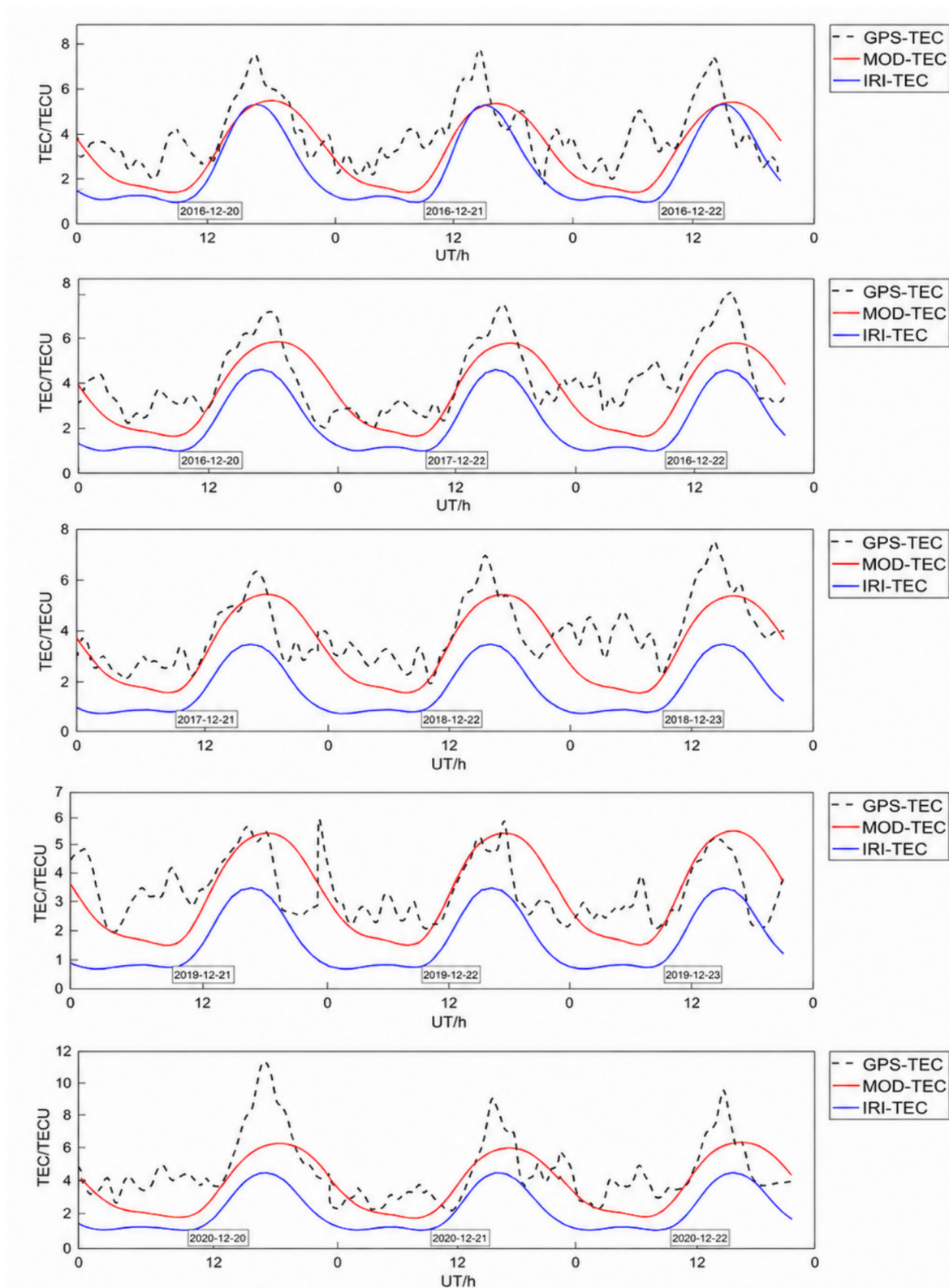


Figure 8. Comparison of NAI-TECEM, GPS-TEC, and IRI2020 at the IQAL station around the winter solstice during 2010–2021.

At the TUKT station, NAI-TECEM shows generally good agreement with GPS-TEC observations and reproduces the typical increase in TEC during daytime and decrease during nighttime around the winter solstice. The model also captures the overall differences in TEC levels among years with different solar activity conditions. Compared with IRI2020,

NAI-TECEM generally agrees more closely with GPS-TEC in terms of daytime peak values, curve shape, and interannual variability.

At the IQAL station, NAI-TECEM also reproduces the diurnal and interannual TEC variations and, in particular, captures the differences in TEC levels between periods of high and low solar activity. In comparison, although IRI2020 reproduces the overall TEC variation trend, noticeable deviations remain in the daytime peak intensity and variation amplitude during some periods. Overall, at both TUKT and IQAL, which were included in the Fusion-TEC construction, NAI-TECEM shows closer agreement with the GPS-TEC observations.

Figure 9 presents the results at the NWOT station, which was not involved in the data fusion. NAI-TECEM shows good overall agreement with GPS-TEC observations and reproduces the characteristic daytime increase and nighttime decrease in TEC around the winter solstice, as well as the interannual differences in TEC levels. In 2016, 2018, and 2019, NAI-TECEM closely follows the timing of the daytime TEC peaks and the overall curve morphology. In 2012 and 2020, stronger fluctuations are observed in the GPS-TEC daytime peaks, and NAI-TECEM underestimates some peak values; nevertheless, its overall variation amplitude and diurnal pattern remain closer to the observations than those of IRI2020.

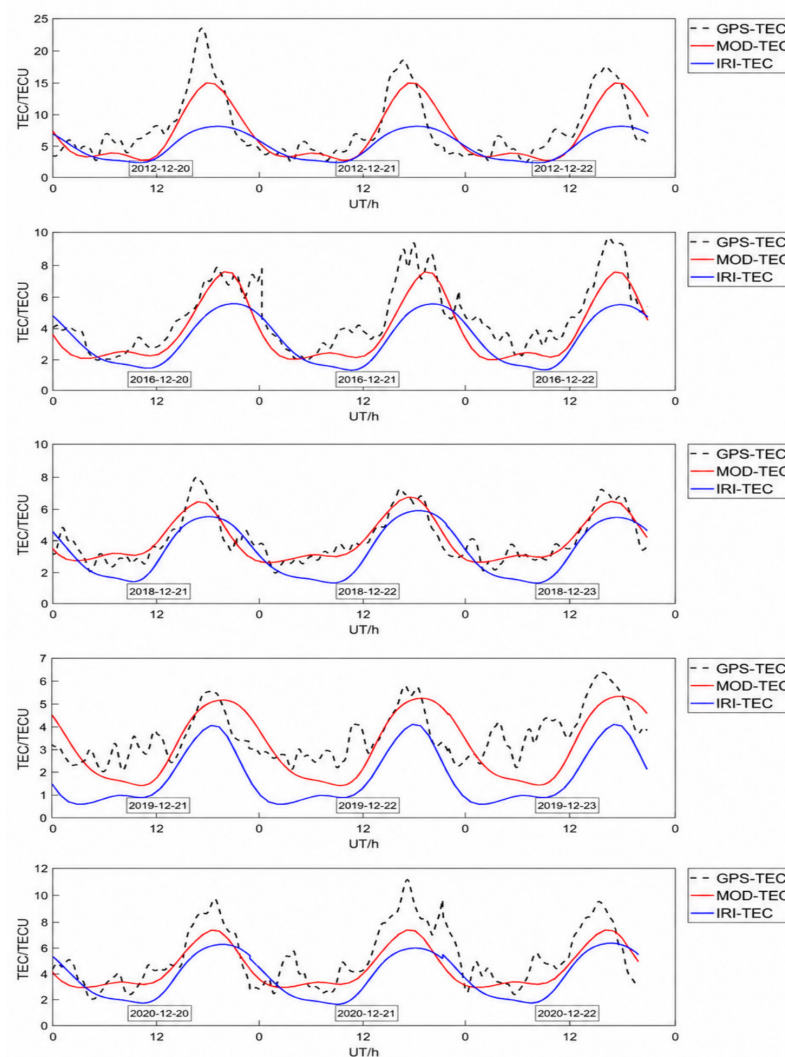


Figure 9. Comparison of NAI-TECEM, GPS-TEC, and IRI2020 at the NWOT station around the winter solstice during 2010–2021.

Because NWOT was not included in the Fusion-TEC dataset used for model construction, the validation results at this station indicate that NAI-TECEM retains a certain degree of spatial generalization capability and regional applicability at an independent location.

3.3.2. Out-of-Period Evaluation of the Winter Anomaly

To further evaluate the capability of NAI-TECEM in representing the winter anomaly over North America, the winter anomaly index (WAI) was used to investigate the model response to winter anomaly variations under different solar activity levels. Following the regression-based approach for winter anomaly analysis, the WAI was calculated under the same solar activity level to reduce the influence of differences in solar activity between winter and summer [28].

The winter anomaly index is defined as:

$$WAI = \frac{TEC_W}{TEC_S} = \frac{a(lat, lon) \times F10.7p + b(lat, lon)}{c(lat, lon) \times F10.7p + d(lat, lon)} \quad (21)$$

where TEC_W and TEC_S represent the TEC values during winter and summer under the same local-time conditions, respectively; a , b , c , d denote the estimated coefficients of the regression equations. A positive WAI indicates that wintertime TEC is higher than summertime TEC, representing the occurrence of the winter anomaly.

First, the WAI variations under different solar activity levels during the modeling period (2010–2021) were analyzed using NAI-TECEM. As shown in Figure 10, NAI-TECEM reproduces clear winter anomaly characteristics under different F10.7p conditions. The winter anomaly intensity exhibits variations with solar activity levels, indicating that the solar activity response term and the winter anomaly parameterization component can jointly characterize the TEC anomaly variations under different solar activity conditions.

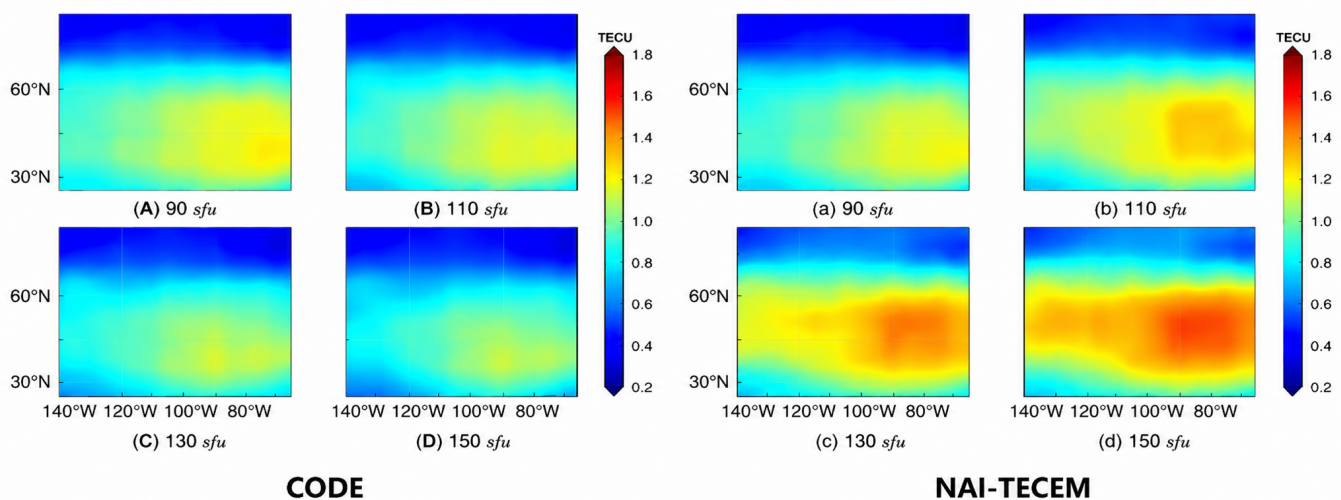


Figure 10. Variations of winter anomaly index under different solar activity levels during the modeling period (2010–2021).

Furthermore, to evaluate the applicability of the model for years not included in parameter estimation, an out-of-period evaluation was conducted using data from 2022–2024. Figure 11 presents the WAI variations under different solar activity levels during the out-of-period validation period. The results demonstrate that NAI-TECEM maintains similar solar activity-dependent characteristics to those obtained during the modeling period, and the variation of WAI remains stable for the independent years.

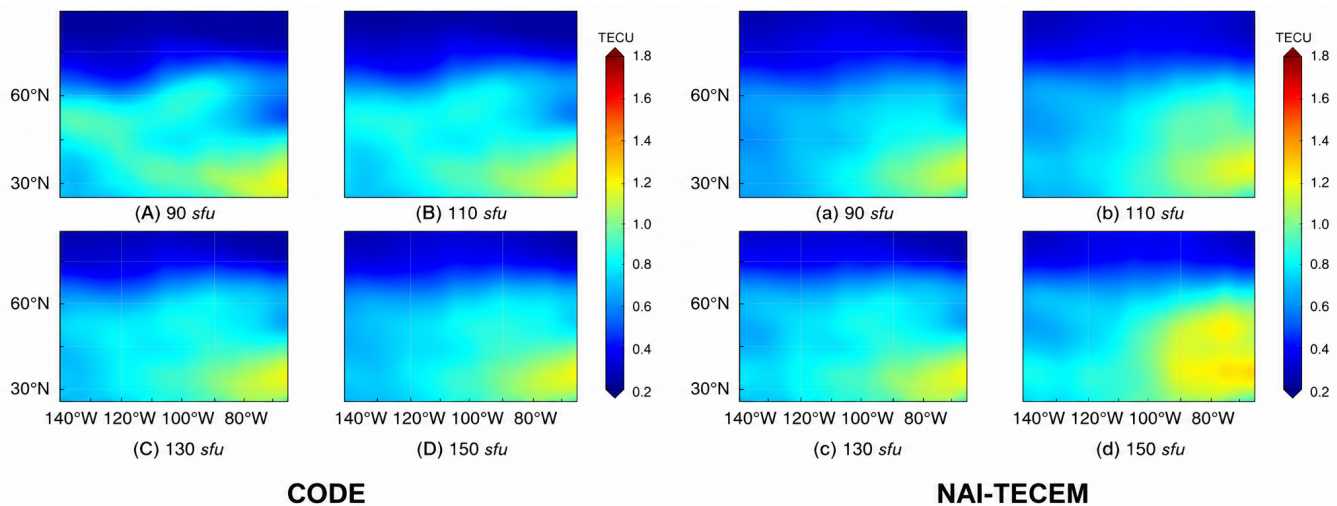


Figure 11. Variations of winter anomaly index under different solar activity levels during the out-of-period evaluation period (2022–2024).

Overall, the results from both the modeling period and the out-of-period evaluation demonstrate that NAI-TECEM can not only reproduce the winter anomaly characteristics under different solar activity conditions during the modeling period but also maintain this relationship during years outside the training period. This indicates that the proposed winter anomaly parameterization component has good temporal extrapolation capability.

4. Discussion

4.1. Solar Activity and Winter Anomaly Terms

As summarized in Table 3, the correlation coefficient between $\hat{c}_{18}$ and $\hat{c}_{19}$ was -0.2308 , indicating a weak pairwise correlation and limited statistical coupling between the two coefficients. The Jacobian retained full column rank (19/19), suggesting no local rank deficiency in parameter estimation. Although the raw Jacobian condition number was relatively large (4.25×10^3), it decreased substantially to 8.75 after column scaling, indicating that the large raw value was mainly associated with differences in parameter scales rather than severe ill-conditioning. In the sensitivity test, the estimate of c_{18} changed only slightly from 0.00424 for the full dataset to 0.00419 after excluding winter observations, corresponding to a relative change of -1.18% . Moreover, the winter-excluded estimate remained within the 95% confidence interval of the full-data estimate, and the two confidence intervals showed substantial overlap. Taken together, these diagnostics indicate that c_{18} and c_{19} can be statistically distinguished and that the estimation of c_{18} remains stable after the exclusion of winter observation.

Table 3. Correlation and collinearity diagnostics for the solar activity and winter anomaly terms.

Diagnostic	Result
Correlation between $\hat{c}_{18}$ and $\hat{c}_{19}$	-0.2308
Jacobian rank	19/19
Raw Jacobian condition number	4.25×10^3
Scaled Jacobian condition number	8.75
Full-data estimate of c_{18}	0.00424
Full-data 95% CI of c_{18}	[0.004033, 0.004447]
Winter-excluded estimate of c_{18}	0.00419
Winter-excluded 95% CI of c_{18}	[0.00396, 0.00442]
Relative change in c_{18}	-1.18%

4.2. Sensitivity to Ap Threshold

A sensitivity analysis was conducted to examine the influence of the Ap threshold on TEC estimation. The TEC values under $Ap \leq 30$ nT and $Ap \leq 20$ nT conditions were compared at four representative grid points covering mid- and high-latitude regions. As listed in Table 4, the differences between the two criteria range from 0.324 to 1.455 TECU, which are smaller than the RMS residual uncertainty of the model (3.29 TECU). This indicates that the use of $Ap \leq 30$ nT as the quiet-time selection criterion does not introduce significant uncertainty into the TEC modeling results.

Table 4. Comparison of TEC values under different Ap filtering thresholds.

Location (Lon,Lat)	Mean TEC($Ap \leq 30$ nT) (TECU)	Mean TEC($Ap \leq 20$ nT) (TECU)	Difference (TECU)
(70°W,75°N)	12.739	11.284	1.455
(90°W,65°N)	10.351	9.568	0.783
(110°W,50°N)	8.793	8.317	0.476
(130°W,40°N)	8.528	8.204	0.324

4.3. Extreme-Condition Test

To further evaluate the physical plausibility and robustness of NAI-TECEM under extreme conditions, three representative high-response scenarios were examined. Since ionospheric TEC generally increases with solar activity, $F_{10.7p} = 200$ sfu was adopted in all three cases to represent a high-solar-activity condition and to examine the upper-end response of the model. Astafyeva et al. [29] reported that maximum daytime VTEC values of approximately 50–60 TECU can occur during geomagnetically quiet conditions. Therefore, a reference threshold of 60 TECU was adopted in this study as a conservative screening criterion for evaluating potential unrealistic TEC amplification. As shown in Table 5, the maximum TEC values obtained under the three extreme scenarios are 49.493, 37.058, and 31.135 TECU, respectively, all of which remain below the 60 TECU reference threshold. These results indicate that, under the tested extreme combinations, the model does not produce anomalous TEC amplification beyond the high-value range reported for geomagnetically quiet conditions, demonstrating that the model maintains a physically reasonable response under these extreme input conditions.

Table 5. Maximum TEC values under representative extreme-condition scenarios.

Extreme Scenarios	$F_{10.7p}$ (sfu)	DOY	Location (Lon,Lat)	LT	TEC(TECU)
High solar + maximum winter anomaly	200	355	(105°W,40°N)	14	49.493
High solar + strong diurnal response	200	81	(110°W,40°N)	14	37.058
High solar + high-latitude F_3 contribution	200	263	(80°W,65°N)	13	31.135

5. Conclusions

In this study, a North American Ionospheric TEC Empirical Model (NAI-TECEM) was developed to characterize TEC variations under winter anomaly conditions over North America by integrating multi-source TEC data and introducing a regional winter anomaly parameterization component. The main conclusions are summarized as follows:

- (1) Five TEC datasets, including GPS-TEC, CODE-GIM, IRI2020, Jason-TEC, and COSMIC-TEC, were integrated to construct the Fusion-TEC dataset. Helmert variance component estimation was employed to determine the relative weights of different data sources. The multi-source fusion approach effectively combines the advantages of

different observation systems in terms of spatial coverage and measurement accuracy, providing a reliable data foundation for regional TEC modeling.

- (2) Based on the Fusion-TEC dataset over North America during 2010–2021, NAI-TECEM was developed by incorporating diurnal variation, seasonal variation, geomagnetic-latitude variation, solar activity response, and winter anomaly correction components. The model fitting results demonstrate that NAI-TECEM can effectively represent TEC variations over North America, with a mean residual of 0.42 TECU, an STD of 3.26 TECU, and an RMSE of 3.29 TECU, indicating good internal consistency with the modeling dataset.
- (3) The applicability of NAI-TECEM was further evaluated through representative grid-point tests and GPS station validations. The results show strong consistency between NAI-TECEM and Fusion-TEC at both mid- and high-latitude grid points. In addition, the model successfully reproduced GPS-TEC variations at the TUKT, IQAL, and NWOT stations, demonstrating its capability for regional TEC representation.
- (4) The capability of NAI-TECEM in representing the winter anomaly was evaluated using the winter anomaly index (WAI) under different solar activity levels. The model successfully reproduced winter anomaly characteristics during the modeling period of 2010–2021 and maintained stable responses during the out-of-period evaluation period of 2022–2024. These results demonstrate that incorporating a regional winter anomaly parameterization component improves the representation capability of empirical models for specific ionospheric phenomena over North America.

Overall, NAI-TECEM improves the representation of TEC variations and winter anomaly characteristics over North America by combining multi-source TEC fusion and regional anomaly parameterization. The proposed model provides a useful reference for regional ionospheric studies and related space environment applications.

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Data Availability Statement: The GPS observation data used in this study are publicly available from UNAVCO through its GNSS data access service at <https://www.unavco.org/> (accessed on 21 March 2025). The CODE-GIM products are publicly available from the Center for Orbit Determination in Europe (CODE) at <http://ftp.aiub.unibe.ch/CODE/> (accessed on 14 April 2025). IRI2020-derived TEC data were generated using the International Reference Ionosphere model provided by the Community Coordinated Modeling Center (CCMC) at <https://ccmc.gsfc.nasa.gov/> (accessed on 5 June 2025). Jason-series satellite altimetry data were obtained from the Radar Altimeter Database System (RADS) at <https://www.star.nesdis.noaa.gov/socd/lisa/RADS.php> (accessed on 24 June 2025). COSMIC radio occultation data were obtained from the UCAR COSMIC Data Analysis and Archive Center (CDAAC) at <https://data.cosmic.ucar.edu/> (accessed on 17 July 2025). The solar and geomagnetic activity indices used in this study, including the F10.7 solar radio flux and the Ap index, were obtained from the OMNIWeb Data Explorer at <https://omniweb.gsfc.nasa.gov/form/dx4.html> (accessed on 28 July 2025).

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Abbreviations

The following abbreviations are used in this manuscript:

AA	Annual Anomaly
Ap	Planetary Geomagnetic Activity Index
CDDIS	Crustal Dynamics Data Information System
CODE	Center for Orbit Determination in Europe
COSMIC	Constellation Observing System for Meteorology, Ionosphere, and Climate
DOY	Day of Year
EIA	Equatorial Ionization Anomaly
EUV	Extreme Ultraviolet
F10.7	10.7 cm Solar Radio Flux Index
F10.7a	81-Day Centered Moving Average of F10.7
F10.7p	Smoothed Solar Radio Flux Index
GIM	Global Ionospheric Map
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HVCE	Helmert Variance Component Estimation
IGRF13	International Geomagnetic Reference Field, 13th Generation
IPP	Ionospheric Pierce Point
IRI	International Reference Ionosphere
IRI2020	International Reference Ionosphere 2020
Jason	Jason Satellite Altimetry Mission
Kp	Planetary Geomagnetic K Index
LT	Local Time
MSNA	Midlatitude Summer Nighttime Anomaly
NAI-TECEM	North American Ionospheric TEC Empirical Model
NTCM-GL	Neustrelitz Total Electron Content Model-Global
RADS	Radar Altimeter Database System
RMSE	Root Mean Square Error
SA	Semiannual Anomaly
STD	Standard Deviation
STEC	Slant Total Electron Content
TEC	Total Electron Content
TECU	Total Electron Content Unit
VTEC	Vertical Total Electron Content
WA	Winter Anomaly
WAI	Winter Anomaly Index

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