PERFORMANCE EVALUATION OF IONOSPHERIC TEC FORECASTING MODELS USING GPS OBSERVATIONS AT DIFFERENT LATITUDES

Shu Wang[1,2], Lilong Liu[1,2,*], Liangke Huang[1,2,3], Yunzhen Yang[1,2], Hua Peng[1,2]

1. College of Geomatic Engineering and Geoinformatics, Guilin University of Technology, Guilin,541004, China
2. Guangxi Key Laboratory of Spatial Information and Geomatics, Guilin, 541004, China
3. GNSS Research Center, WuHan University, WuHan, 430079, China

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ABSTRACT:

In this paper, Holt-Winters model, ARMA model and ARIMA model in time series analysis were used to predict total electron content (TEC).Taking ionospheric grid data of quiet period and active period in different longitude and latitude provided by IGS center as sample data, the TEC data of the first 8 days were used to build four kinds of prediction models and forecast TEC values of the next 6 days, and the results were compared with the observations provided by IGS center. The prediction effects of the four models in different ionospheric environments and different longitude and latitude are emphatically analyzed. The experimental results showed that the average relative accuracy of ARMA, ARIMA and Holt-Winters models in the quiet and active ionospheric periods for the prediction of 6 days was 89.85% in the quiet period, and 88.76% in the active period. In both periods, the higher the latitude, the lower the RMS value. In addition, VTEC from IGS center value and ARMA model and ARIMA model and Holt - Winters in the quiet period and active forecast VTEC values were compared, in the quiet period or active, four models of forecasting value can better reflect the spatial and temporal variation characteristics of TEC three latitude, the prediction results of the ARIMA model can better reflect the spatial and temporal variation characteristics; But compared with the active period, the prediction results of calm period are relatively good.

* Corresponding author. Address: Guilin University of Technology, Guilin,541004, China. Email address: hn_liulilong@163.com.

1. INTRODUCTION

Distance from the ground, about 60 ~ 1000 km, the atmosphere is called the ionosphere, the radiation from the sun and cosmic rays and various kinds of high-energy charged particles under the action of gas molecules in the region of ionization or completely ionization, and release a lot of free electrons, in the process of satellite signal propagation these free electrons on the navigation and positioning accuracy of the deviation of several meters to tens of meters. Therefore, how to simulate and forecast the total electron content (TEC) in ionosphere and analyze the spatial and temporal distribution of ionosphere has become an important research focus. At present, there are mainly two models to predict the total electron content in the ionosphere. One is the empirical ionosphere model, such as Klobuchar(Klobuchar, 1996), Bent(Bent et al., 1975)and IRI(Patel et al.,2018).The other is to use TEC observation data for short-term prediction, such as neural network model (Chen et al.,2005), spectral analysis(Lu et al.,2014), least-squares configuration (Zhang et al.,2014), and time series (Chen et al.,2011; Tang et al.,2013) model. Zhang et al. (2011) analyzed the prediction performance of ARIMA model at different latitudes during calmer and active ionospheric periods, and analyzed the factors affecting the prediction accuracy of this method. Xie et al. (2017) use Holt-Winters addition and multiplication model respectively to the International GNSS Service center (the International GNSS Service, IGS) provide different latitude and longitude ionospheric Total Electron Content (Total Electron Content, TEC) data to carry on the forecast during active and quiet period , the result showed that two kinds of model forecast results are in good agreement with reference, but the additive model can better response change characteristics of the ionosphere TEC. Chen et al. (2018) used SARIMA model, Holt-Winter addition model and multiplication model to predict TEC in different latitudes of the northern hemisphere, and analyzed the variation rule of prediction error with latitude. Elmunim et al. (2017) analyzed and compared Holt-Winter multiplication model and IRI-2012 model under different spatial conditions. Xi et al. (2015) used Holt-Winter model and maldives model to conduct short-term delay modeling and prediction methods in the ionospheric region of mid-latitude region. Kim et al. (2015) proved that satisfactory results can be obtained by using ARMA model to forecast ephemeris and clock correction in satellite enhanced system. Mandrikova et al. (2015) used ARIMA model to

conduct short-term prediction of regional ionospheric parameters, which had a good prediction effect for the study area. Li et al. (2014) accurately simulated TEC data in ionospheric grids by using the ARIMA model of time series theory. Sivavaraprasad et al. (2017) tested the applicability of the ARIMA, ARMA and Holt-Winter addition and multiplication models to predict ionospheric TEC values under different spatial conditions in low latitudes.

Although the current prediction models have been effectively verified, more accurate and in-depth studies are needed to predict the ionospheric morphology at different latitudes. In the future, it is necessary to analyze the validity of these general time series prediction models under different ionospheric conditions. Therefore, in this paper, the global ionospheric map (GIM) provided by the international GNSS (IGS) center will be used to study and analyze the prediction accuracy of ARIMA, ARMA, Holt-Winter addition and multiplication models in different latitudes and ionospheric conditions, in the hope that the study of time series model can promote the development of the prediction of total ionospheric electron content.

2. TIMING MODEL

2.1 Holt-Winters Exponential Smoothing Model

Holt-Winters exponential smoothing model is a prediction model based on time series data, which includes seasonless model, additive model and multiplication model.
Additive model. Applicable to sequences with linear time trends and additive seasonal changes, the formula is:

$$
\begin{cases}
S_t = \alpha(X_t - I_{t-L}) + (1-\alpha)(S_{t-1} - b_{t-1}) \\
I_t = \beta(X_t - S_t) + (1-\beta)I_{t-L} \\
b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1} \\
F_{t+m} = S_t + mb_t + I_{t-L+m}
\end{cases} \quad (1)
$$

The multiplication model. Applicable to sequences with linear time trends and multiplicative seasonal changes, the formula is:

$$
\begin{cases}
S_t = \alpha\frac{X_t}{I_{t-L}} + (1-\alpha)(S_{t-1} - b_{t-1}) \\
I_t = \beta\frac{X_t}{S_t} + (1-\beta)I_{t-L} \\
b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1} \\
F_{t+m} = (S_t + mb_t)I_{t-L+m}
\end{cases} \quad (2)
$$

In equations (1) and (2), X_t are the observed values at time t; S_t is the stable moment at time t; I_t is the seasonal component of the moment t; b_t is the trend component of the moment t; m is the number of prediction periods, $m > 0$; F_{t+m} is the predicted value of the period m; L is seasonal length; α、β、γ is the smoothing parameter, and α、β、γ $\in [0, 1]$.

2.2 ARMA Model

Regressive and Moving Average Model is an important method for predicting time series. It is composed of auto-regressive (AR) and Moving Average (MA). The expression of ARMA model is:

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{3}$$

Where: $\{x_t\}$ is a time series; $\{\varepsilon_t\}$ is white noise sequence; φ_1, $\cdots$, φ_p is the autoregression coefficient; θ_1, $\cdots$, θ_p is the sliding average coefficient.

2.3 ARIMA Model

Autoregressive Integrated Moving Average Model (ARIMA) is an extension of the regressive Moving Average Model (ARMA). ARIMA model can be divided into $ARIMA(p,d,q)$ model and $ARIMA(p,d,q) \times (P,D,Q)_S$ product season model. Stationary series can be obtained by d order difference and D order seasonal difference for non-stationary time series, and the model $ARIMA(p,d,q) \times (P,D,Q)_S$ can be established as follows:

$$\Phi(B)\Phi_S(B)\nabla^d \nabla_S^D x_t = \Theta(B)\Theta_S(B)\varepsilon_t \tag{4}$$

$$\Phi_S(B) = 1 - \varphi_1 B^S - \cdots - \varphi_p B^{PS} \tag{5}$$

$$\Theta_S(B) = 1 - \beta_1 B^S - \cdots - \beta_q B^{QS} \tag{6}$$

Where, ∇_S^D represents the D seasonal difference of order with period S as step length; S is seasonal cycle; $\Phi_S(B)$ is the seasonal autoregressive operator, P is the order of seasonal autoregressive, and φ_1、φ_2、$\cdots$、φ_p is part of the parameters of seasonal autoregressive. $\Theta_S(B)$ is the seasonal moving average operator, Q is the order of the seasonal moving average,

and β_1、β_2、$\cdots$、β_q is part of the parameters of the seasonal moving average.

3. EXPERIMENTAL ANALYSIS

3.1 The Data Source

In this paper, high-precision global ionospheric map (GIM) data provided by IGS center were used as sample sequences. The 2016 annual plot days were 80~93 (2016.03.20-2016.04.02), 174~187 (2016.06.22-2016.07.05), 358-005 (2016.12.23-2017.01.05), and 2017 annual plot days were 201~214 (2017.07.20-2017.08.02) with high latitude (75°N).The data of 120°E), middle latitude (45°N, 120°) and low latitude (5°N, 120°) were used for the prediction and analysis of the ionospheric quiet period. The ionospheric activity period was predicted and analyzed by selecting data from 2014 annual plot days of 139~152 (2014.05.19-2014.06.01), 2015 annual plot days of 196~209 (2015.07.15-2015.07.28), 254~267 (2015.09.11-2015.09.24) with high latitude (75°N, 120°), middle latitude (45°N, 120°) and low latitude (5°N, 120°).

3.2 Accuracy Evaluation Index

TEC values of the first 8 days were used as sample sequences, and the TEC values of the last 6 days were predicted by ARIMA model, ARMA model, Holt-Winter addition model and multiplication model, respectively. The prediction results of the model were compared with the TEC value provided by IGS center (as the reference value), and the average daily relative accuracy and RMS were used to evaluate the prediction accuracy of the model, and the expression was as follows:

$$P = \frac{1}{n}\sum_{t=1}^{n}\left(1 - \frac{|I_{pre} - I_{IGS}|}{I_{IGS}} \times 100\%\right) \tag{7}$$

$$RMS = \sqrt{\frac{1}{n}\sum_{e=1}^{n}(I_{pre} - I_{IGS})^2} \tag{8}$$

Where, I_{pre} is the ionospheric TEC value predicted by the model, I_{IGS} is the observed ionospheric TEC value, e is the observed calendar element, n is the observed calendar element.
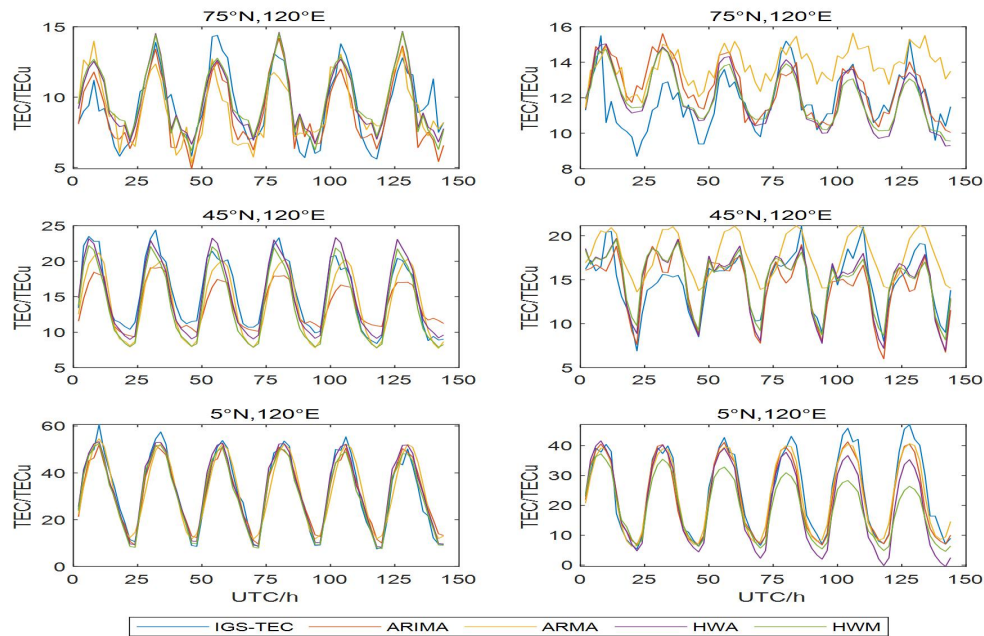
Figure 1. Prediction results of ionospheric TEC in different grid at quiet and active period

Figure 1 shows the comparison between the prediction results in quiet period and active period of different latitudes and the actual observed data. In the figure, the x-coordinate represents the prediction calendar element (one calendar element every 2 hours), and the y-coordinate represents the ionospheric TEC value (unit: TECu).The blue line (IGS-TEC) represents the actual observation value provided by IGS center, the red line (ARIMA) represents the prediction value of ARIMA model, the yellow line (ARMA) represents the prediction value of ARMA model, the purple line (HWA) represents the prediction value of

holt-winter addition model, and the green line (HWM) represents the prediction value of holt-winter multiplication model. It can be seen from figure 1 that in the quiet and active ionospheric periods, ARIMA model, ARMA model, holt-winter addition model and multiplication model can well reflect the temporal and spatial variation characteristics of ionospheric TEC at high, medium and low levels. Compared with the prediction effect of the quiet period and the active period, the prediction effect of the quiet period is better.

day	$\triangle$<1 TECu ARIMA/ARMA/HWA/HWM	1 TECu≤$\triangle$<2 TECu ARIMA/ARMA/HWA/HWM	2 TECu≤$\triangle$<3 TECu ARIMA/ARMA/HWA/HWM	$\triangle$≥3 TECu ARIMA/ARMA/HWA/HWM
1	27.78/22.23/33.34/19.45	33.34/16.67/38.89/22.22	5.55/33.33/22.22/36.11	33.33/27.77/5.55/22.22
2	38.89/25.00/50.00/36.12	27.78/16.68/22.23/25.00	8.33/30.55/19.44/22.22	25.00/27.77/8.33/16.66
3	33.34/22.23/36.12/25.00	19.44/22.22/30.56/33.34	22.22/30.55/13.88/19.44	25.00/25.00/19.44/22.22
4	41.67/27.78/44.45/41.67	22.22/36.12/33.34/30.57	11.11/16.66/19.44/13.88	25.00/19.44/2.77/13.88
5	22.23/25.00/47.23/47.23	25.00/25.00/27.78/30.56	25.00/22.23/8.33/11.11	27.77/27.77/16.66/11.10
6	25.00/27.78/38.89/41.67	19.45/30.56/36.12/36.12	22.22/16.66/2.77/8.33	33.33/25.00/22.22/13.88
mean	31.49/25.00/41.67/35.19	24.54/24.54/31.49/29.64	15.74/25.00/14.35/18.52	28.24/25.46/12.50/16.66

Table 1. Category percentage table of prediction residuals in ionospheric quiet period

day	$\triangle$<1 TECu ARIMA/ARMA/HWA/HWM	1 TECu≤$\triangle$<2 TECu ARIMA/ARMA/HWA/HWM	2 TECu≤$\triangle$<3 TECu ARIMA/ARMA/HWA/HWM	$\triangle$≥3 TECu ARIMA/ARMA/HWA/HWM
1	33.34/30.56/33.34/27.78	19.45/16.67/25.00/22.23	19.44/16.66/22.22/27.77	27.77/36.11/19.44/22.22

2	30.56/5.57/30.56/27.78	25.00/25.00/19.45/33.34	19.44/41.66/33.33/16.66	25.00/27.77/16.66/22.22
3	61.12/8.34/52.78/63.89	25.00/25.00/16.67/11.12	11.11/36.11/5.55/2.77	2.77/30.55/25.00/22.22
4	50.00/22.23/47.23/50.00	19.46/16.67/22.23/16.68	13.88/30.55/8.33/5.55	16.66/30.55/22.21/27.77
5	52.79/16.67/36.12/38.89	16.67/38.89/16.67/22.23	0.00/19.44/11.11/8.33	30.54/25.00/36.1/30.55
6	36.12/19.45/19.45/27.78	25.00/16.67/36.12/30.56	5.55/22.22/8.32/11.11	33.33/41.66/36.11/30.55
mean	43.99/17.14/36.58/39.35	21.76/23.15/22.69/22.69	11.57/27.77/14.81/12.03	22.68/31.94/25.92/25.92

Table 2. Category percentage table of prediction residuals in ionospheric active period

According to the prediction residual statistical results in table 1, the prediction results of the holt-winter addition model in the quiet ionospheric period were the best, with nearly 42% of the prediction residual in 1TECu and 87.5% in 3TECu.The prediction results of holt-winter multiplication model were next, with nearly 35% of the data prediction residua within 1TECu and 84% within 3TECu.The percentage of forecast residua of ARIMA model in each residual interval was slightly lower than that of holt-winter model. The percentage of forecast residua of ARIMA model in 1TECu was 31.5%, and the percentage of forecast residua greater than 3TECu was 28%.According to the prediction residuals statistical results in table 2, the prediction results of ARIMA model are the best in the ionospheric active period, with nearly 44% of the prediction residuals within 1TECu and 77% within 3TECu.The prediction results of holt-winter multiplication model were next, with nearly 40% of the data prediction residua within 1TECu and 74% within 3TECu.The percentage of measured residua in each residual interval of the holt-winter addition model was slightly lower than that of the holt-winter multiplication model. The percentage of predicted residua in the addition model in 1TECu was about 37%, which was about 2% lower than that of the multiplication model. Based on table 1 and table 2, it can be seen that the prediction residual of holt-winter addition model, holt-winter multiplication model and ARMA model in quiet period is relatively better than that in active period. The predicted residual of ARIMA model in active period is better than that in quiet period.

MODEL	GRID	day												
		1d		2d		3d		4d		5d		6d		mean	
		RMS/TECu	P/%	RMS/TECu	P/%	RMS/TECu	P/%	RMS/TECu	P/%	RMS/TECu	P/%	RMS/TECu	P/%	RMS/TECu	P/%
ARIMA	high	1.04	88.79	1.48	88.22	1.51	88.89	1.16	86.94	1.27	88.61	1.89	84.27	1.39	87.62
	middle	3.56	85.26	2.55	88.05	3.30	84.63	2.55	88.39	2.95	82.11	2.25	83.65	2.86	85.35
	low	4.36	89.09	3.38	88.04	3.32	91.36	3.19	86.77	3.79	84.01	4.94	77.24	3.83	86.09
ARMA	high	2.05	79.27	1.41	87.61	2.24	82.81	1.22	86.17	1.53	82.72	1.40	89.15	1.64	84.62
	middle	2.67	84.43	2.97	83.04	2.42	85.23	2.30	87.01	2.27	87.69	1.72	88.75	2.39	86.02
	low	3.92	87.73	4.12	84.45	2.76	87.50	4.19	86.10	5.45	77.89	6.16	78.77	4.43	83.74
HWA	high	1.75	80.70	0.94	92.71	1.20	90.78	1.31	85.98	1.15	86.85	1.54	88.06	1.31	87.51
	middle	1.39	91.97	1.66	90.04	1.98	89.22	1.13	93.56	1.48	92.45	1.36	91.99	1.50	91.54
	low	3.20	91.53	2.45	91.39	3.57	90.55	2.19	92.08	2.52	92.59	4.72	84.91	3.11	90.51
HWM	high	2.01	77.36	0.92	93.90	1.17	90.29	1.25	87.24	1.32	84.70	1.71	86.13	1.40	86.61
	middle	2.10	87.47	2.55	83.75	2.74	83.38	2.04	87.01	1.20	93.35	0.86	94.07	1.91	88.17
	low	3.86	88.29	2.61	93.20	3.90	88.91	2.43	94.28	3.73	91.95	2.92	90.16	3.24	91.13

Table 3. RMS and relative accuracy in ionospheric quiet period

MODEL	GRID	day												
		1d		2d		3d		4d		5d		6d		mean	
		RMS	P/%	RMS	P/%	RMS	P/%	RMS	P/%	RMS	P/%	RMS	P/%	RMS	P/%

		/TECu		/TECu		/TECu		/TECu		/TECu		/TECu		/TECu	
ARIMA	high	2.62	78.43	2.40	79.93	1.22	90.88	0.84	95.32	0.50	96.52	0.74	95.32	1.39	89.40
	middle	2.25	88.59	2.62	84.83	1.03	93.89	1.29	92.82	2.77	83.42	2.14	87.68	2.02	88.54
	low	2.96	84.54	2.65	91.77	1.71	94.71	4.61	85.57	3.27	92.04	5.94	81.41	3.52	88.34
ARMA	high	2.42	80.25	2.35	78.94	2.33	79.96	2.01	84.53	2.10	83.23	2.45	81.08	2.28	81.33
	middle	3.84	71.63	4.43	67.11	3.42	77.83	3.28	78.77	3.17	78.46	3.53	77.00	3.61	75.13
	low	2.26	90.31	2.01	88.72	2.34	87.58	3.55	84.13	3.38	88.24	4.64	79.21	3.03	86.36
HWA	high	2.01	83.99	1.68	86.97	0.79	94.16	0.72	94.72	1.00	93.10	1.24	91.11	1.24	90.67
	middle	2.47	84.96	2.71	84.07	1.07	93.46	1.18	92.81	1.83	89.80	1.70	88.90	1.83	89.00
	low	3.01	85.88	2.22	87.59	3.91	76.01	6.71	66.51	8.44	77.40	10.70	73.12	5.83	77.75
HWM	high	2.02	83.41	1.66	86.94	0.67	94.98	0.76	94.58	0.92	93.30	1.23	91.34	1.21	90.76
	middle	2.61	82.62	2.71	82.83	0.73	96.05	1.18	94.15	1.89	90.23	1.62	91.29	1.79	89.53
	low	3.41	81.99	3.52	89.78	5.63	81.78	7.59	73.07	10.71	68.92	13.45	57.38	7.39	75.49

Table 4. RMS and relative accuracy in ionospheric active period

It can be seen from the statistical table of root mean square value and relative accuracy of the predicted values of ionospheric quiet period given in table 3 that there are significant differences in the root mean square value and relative accuracy of the predicted values of the four models at different latitudes. For the multiplication model, the relative accuracy of the forecast value decreases with the increase of latitude. For the ARMA model and the addition model, the relative accuracy of the prediction value is best in the middle latitude, slightly lower in the low latitude, and worst in the high latitude. The relative accuracy of ARIMA model is the highest in high latitudes, followed by low latitudes and the lowest in middle latitudes. The forecast values of the four models decreased with the increase of latitude. As the ionospheric TEC value is larger in the low latitude area, the prediction residual is larger and the root-mean-square value is larger in this area, while it is opposite in the high latitude area. In addition, the root mean square value of holt-winter addition model is superior to ARIMA model, ARMA model and holt-winter multiplication model in high, middle and low latitude.

According to the statistical table of root mean square value and relative accuracy of the predicted values of ionospheric activity period given in table 4, significant differences exist in the root mean square value and relative accuracy of the four models in different latitudes. For ARIMA model, holt-winter addition model and multiplication model, the relative accuracy of the forecast value increases with the increase of latitude. The relative accuracy of ARMA model is the best in low latitude,

followed by high latitude and the worst in middle latitude. The difference of root mean square value between the four models is not big, which is the largest in the low latitude, the second in the middle latitude and the least in the high latitude.

4. CONCLUSION

In this paper, ARIMA model, ARMA model, holt-winter addition model and multiplication model are adopted to make short-term prediction of ionospheric grid data of IGS center in quiet period and active period of different longitude and latitude, so as to analyze the prediction accuracy of different methods in different space-time environments. The analysis results are as follows:

1) use ARIMA model, ARMA model, holt-winter addition and multiplication model to make short-term prediction of total electron content in the ionosphere, and the prediction results of the four models can reach good accuracy. In the quiet ionospheric period, the average relative accuracy of ARIMA model is better than 86%, while the relative accuracy of holt-winter addition and multiplication model is roughly the same at low latitudes, and the relative accuracy of forecast value is about 91%.In the ionospheric activity period, the average relative accuracy of ARIMA model is better than 88%, and the relative accuracy of holt-winter addition and multiplication model is better than 89% and 90% respectively in middle and high latitudes.

2) in the quiet ionospheric period, the holt-winter addition

model has the best prediction accuracy in mid-latitude area, the holt-winter multiplication model has the best prediction accuracy in low-latitude area, and the ARIMA model has the best prediction accuracy in high-latitude area. The ARMA model performs well in the middle latitude. The prediction effect of ARIMA model is the same in high, medium and low latitudes, and the prediction accuracy is above 85%.In the ionospheric activity period, the prediction effect of the holt-winter addition model and the multiplication model is basically the same, and its relative accuracy is better in the middle and high latitudes, but worse in the low latitudes. In terms of the relative accuracy of ARIMA model, it is better in high, medium and low latitudes, and the accuracy is better with the increase of latitudes. The ARMA model performs well in low latitudes.

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