Towards a GPS-based TEC prediction model for Southern Africa with feed forward networks

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Abstract

In this paper, first results from a national Global Positioning System (GPS) based total electron content (TEC) prediction model over South Africa are presented. Data for 10 GPS receiver stations distributed through out the country were used to train a feed forward neural network (NN) over an interval of at most five years. In the NN training, validating and testing processes, five factors which are well known to influence TEC variability namely diurnal variation, seasonal variation, magnetic activity, solar activity and the geographic position of the GPS receivers were included in the NN model. The database consisted of 1-min data and therefore the NN model developed can be used to forecast TEC values 1 min in advance. Results from the NN national model (NM) were compared with hourly TEC values generated by the earlier developed NN single station models (SSMs) at Sutherland (32.38°S, 20.81°E) and Springbok (29.67°S, 17.88°E), to predict TEC variations over the Cape Town (33.95°S, 18.47°E) and Upington (28.41°S, 21.26°E) stations, respectively, during equinoxes and solstices. This revealed that, on average, the NM led to an improvement in TEC prediction accuracy compared to the SSMs for the considered testing periods.

1. Introduction

The development of reliable models to nowcast and forecast TEC variability remains a challenging task for the ionospheric scientific community. This is partly due to, among other factors, the non-linearity of the physical and geophysical parameters that influence TEC variations and the difficulty in generating accurate measurements for some of these parameters. In addition, a further complication arises from the non uniformity in the time domain for selected periods of some parameters known to influence TEC. This has led to the development of techniques to try and acquire the same temporal resolution for the data which in turn introduces artificial sets of data. Inspite of this, efforts have been made to develop a number of models (single station, regional and global) for nowcasting and forecasting TEC at different time intervals ([Hernandez-Pajares et al., 1997], [Bilitza, 2001], [Tulunay et al., 2006], [Leandro and Santos, 2007] and [Habarulema et al., 2007]) with the most commonly used being the International Reference Ionosphere (IRI). The IRI is updated anually and provides monthly averages of various parameters including TEC (Bilitza, 2001). In the Southern Hemisphere and over South Africa in particular, the IRI under or overpredicts TEC variability during different seasons ([Habarulema et al., 2007] and [Habarulema et al., 2009]) and this has been partly attributed to a lack of data covering this region within the IRI model (McKinnell, 2002). It has, however, been found that the IRI predicts

GPS TEC more accurately than the single station NN models developed over Sutherland (32.38°S, 20.81°E) and Springbok (29.67°S, 17.88°E) to predict TEC at Cape Town (33.95°S, 18.47°E) and Upington (28.41°S, 21.26°E), South Africa, respectively, during spring equinoxes (Habarulema et al., 2009). This work presents the first steps towards the development of a TEC prediction model for Southern Africa. We have utilised the neural network (NN) technique which has been shown to be capable of generalising physical characteristics that exhibit non-linear behaviour and particularly TEC variability ([Hernandez-Pajares et al., 1997], [Leandro and Santos, 2007] and [Habarulema et al., 2007]). Five parameters (seasonal and diurnal variations, magnetic and solar activities, and geographic position of the GPS receiver stations) which influence TEC variability have been used in the NN training, validating and testing. The first two are represented by day number (DN) of the year and hour (HR) of the day, the second two parameters are represented by magnetic index and sunspot number values while the geographic latitude and longitude caters for the locations of the GPS receiver stations. To assess the performance of the NN model, we have predicted TEC variations for days representing equinoxes and solstices in 2002 for the testing stations. For stations where data for the selected testing year (2002) were not available, validation of the model was undertaken for the years 2003 and 2005.

As already mentioned, some work has been done regarding TEC predictions over South Africa using NNs. Previously Habarulema et al. (2007) did a feasibility study into TEC predictions using the NN technique with single station data. In this study it was found that NNs were indeed suitable for predicting South African GPS derived TEC. Habarulema et al. (2009) presented the procedure of using results obtained from the single station NN model to predict TEC for a different station whose data was not included in the training. Furthermore, this work showed that the single station model predicted TEC over a different GPS site relatively well within a geographical latitudinal coverage of ~1–3 degrees beyond which the prediction accuracy began decreasing. In both versions, these authors dealt with hourly GPS TEC data with the corresponding predictions and compared their results with IRI-2001 and ionosonde TEC for validation. The current work is a multi-station model which was developed using a combination of data from different stations at different latitudes and may therefore be used to forecast TEC at any point within South Africa. Where as the previous works were limited to single station predictions, the current work attempts to cover all of South Africa and takes into account 1-min data in contrast with earlier work which dealt with hourly data. Results from the new developed NM were statistically compared with the earlier obtained results from the SSMs that gave TEC predictions over Cape Town (33.95°S, 18.47°E) and Upington (28.41°S, 21.26°E).

2. Data

GPS TEC values at a temporal resolution of 1 min were derived from the dual frequency receivers using the Adjusted Spherical Harmonic Analysis (ASHA) algorithm which utilises a mapping function where the ionosphere is assumed to be a single layer of height 350 km (Opperman et al., 2007). Table 1 and Table 2 show the geographical positions of the GPS receiver stations that were used in the NN training and testing, respectively. Fig. 1 is a South African map showing the training and testing stations. The solar activity and magnetic activity were represented by a 4-month running mean of sunspot number (R4) and the running mean of the previous eight 3-hourly magnetic index values (A8) derived from measurements recorded at a local magnetic Observatory, Hermanus (34.43°S, 19.23°E), South Africa. The choice of R4 and A8 is based on the work done by Habarulema et al. (2007) which showed that these are the optimum parameters for TEC predictions over South Africa. As mentioned before, the diurnal and seasonal variations are represented by DN and HR and these were each split into two cyclic components to allow data continuity ([Poole and McKinnell, 2000] and [McKinnell, 2002]) as follows

$$\mathrm{DNS} = \sin\left(\frac{2\pi \times \mathrm{DN}}{365.25}\right) \mathrm{DNC} = \cos\left(\frac{2\pi \times \mathrm{DN}}{365.25}\right) \tag{1}$$

$$\mathrm{HRS} = \sin\left(\frac{2\pi \times \mathrm{HR}}{24}\right) \mathrm{HRC} = \cos\left(\frac{2\pi \times \mathrm{HR}}{24}\right) \tag{2}$$

where DNS, DNC, HRS and HRC are the sine and cosine components of DN and HR, respectively.

Table 1.

Geographical location of the GPS receiver stations within South Africa and the time period for which training data was available as used in this study.

GPS receiver station	Latitude (°S)	Longitude (°E)	Years for the available data
Bethlehem	28.25	28.33	2001–2004
Bloemfontein	29.10	26.30	2002–2004
Calvinia	31.48	19.77	2002–2004
Ellisras	23.69	27.70	2001–2004
Ermelo	26.50	29.98	2002–2004
Graaff-Reinet	32.25	24.53	2003–2004
Kuruman	27.46	23.43	2002–2004
Pietersburg	23.92	29.47	2002–2004
Springbok	29.67	17.88	2002–2004

GPS receiver station	Latitude (°S)	Longitude (°E)	Years for the available data
Sutherland	32.38	20.81	2000–2004

Table 2.

Geographical location of the GPS receiver stations within South Africa and the time period over which testing data was carried out.

GPS receiver station	Latitude (°S)	Longitude (°E)	Testing data
Aliwal North	30.68	26.72	2003
Cape Town	33.95	18.47	2002
De Aar	30.67	23.99	2002
George	34.0	22.38	2002
Grahamstown	33.3	26.5	2005
Kimberley	28.74	24.81	2002
Middleburg	25.77	29.45	2003
Nelspruit	25.48	30.98	2002
Pietermaritzburg	29.60	30.38	2002
Upington	28.41	21.26	2002

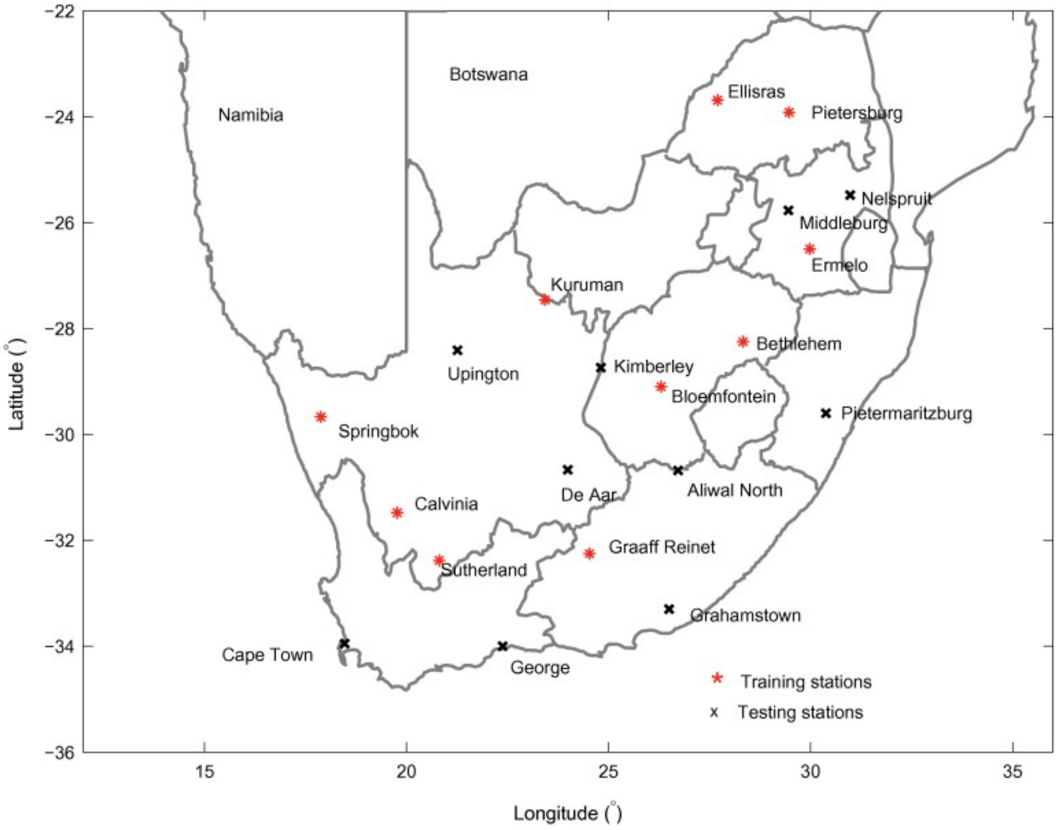

Fig. 1. Map of South Africa showing the training (*) and testing (x) stations.

Therefore the NN input space contained 8 inputs which are used to train the NN and determine the variational trend of the TEC parameter. In this work the predicted TEC is a function of these 8 inputs and can be simply expressed mathematically according to the following expression

$$T_{\mathrm{NN}} \equiv \mathrm{f}(\mathrm{DNS}, \mathrm{DNC}, \mathrm{HRS}, \mathrm{HRC}, \mathrm{R4}, \mathrm{A8}, \mathrm{lat}, \mathrm{long}). \tag{3}$$

where T_{NN} is the TEC predicted by the NN, and lat and long are the geographical latitudes and longitudes of the GPS receiver stations, respectively.

A database of 7 357 341 data points each consisting of 8 input parameters has been used for the training and validating purposes. The choice of training stations depended on two main factors namely;

(1) Identifying GPS receiver stations with sufficient available data within the time range under consideration.

(2) Effort to ensure uniform coverage over South Africa.

The second factor is supported by the recent study done by Habarulema et al. (2009) which clearly demonstrated that it is possible to use single station NN models to predict TEC variability at different stations (with data not used in training) within a latitudinal difference range of ∼1–3 degrees. It is important to point out that this previous work did not include the geogaphical position within the input space since it dealt with single station studies (Habarulema et al., 2009). It was found out that the closer the testing stations are to the stations used in the NN model development, the more effective are the predictions. Thus an effort was made to ensure that the latitudinal difference between the two closest training and testing stations is ∼3°, although this may not always be the case due to a lack of GPS stations with sufficient data within the range. Using the physical and geophysical data information provided to the NN, it is expected that the optimum NN should be able to give an indication of the general TEC patterns at any point within South Africa.

3. Feed forward networks

Various sources extensively describe NNs ([Bishop, 1995], [Haykin, 1994] and [Fausett, 1994]) and give a wide range of their capabilities in empirical modelling. Feed forward networks are a form of NNs that are used to learn the behavioural and variational patterns of the loaded data without the involvement of recurrent cycling within the network connections (Haykin, 1994). This clearly distinguishes feed forward networks from recurrent networks. In simple terms, training is performed to allow the network to learn and generalise the parameter patterns through the non-linear input–output mapping process (Haykin, 1994). In this work, the NN was simply implemented in a topological order, using randomized weights with a feed forward back propagation algorithm. The root mean square error (RMSE) method along with the computation of correlation coefficients (μ) have been used to determine the network architecture. The procedure for determining the optimum architecture was the addition of one hidden node at a time, training the NN, testing it with unseen data and finally computing the RMSE and μ between the GPS TEC and the NN predicted TEC values for a particular dataset (Habarulema et al., 2009). These statistical methods have been used previously in empirical modelling involving NN applications ([Wu and Lundstedt, 1997] and [Oyeyemi et al., 2006]). Results reported in this paper were generated by a NN which consisted of one input layer ($N_i = 8$), two hidden layers ($N_h = 11$ in each layer) and one output layer with one output unit, where N_i and N_h are the input and hidden units, respectively. Since the scope of this paper does not include the description of NNs, and only utilises their role as a tool in non-linear predictions, the reader is referred to the references within this section for more information.

4. Results and discussion

4.1. Diurnal predictions

Fig. 2, Fig. 3, Fig. 4, Fig. 5, Fig. 6, Fig. 7 and Fig. 8 show the variations of 1 min GPS TEC values with the corresponding predictions for equinox and solstice days in 2002 over seven testing GPS receiver stations. The equinoxes in 2002 occured on March 20 (autumn) and September 23 (spring) while the solstices occured on

June 21 (winter) and 22 December (summer). In cases where data for these particular dates were not available, the closest days with data were considered to test the NN model. Of particular interest to compare are the TEC predictions over testing stations located further North or South (referred to as the "extreme end stations") of the country as seen in Fig. 1. With regard to this, the RMSE values between the derived GPS TEC and the predicted NN TEC over Cape Town (CPTN) and Nelspruit (NSPT) are computed to determine where the NN model makes accurate predictions during the equinoxes and solstices as shown in Table 3. A similar analysis was also undertaken for stations that are found within South Africa and tabulated in Table 4. CPTN and NSPT represent the furthest North and South testing stations, respectively while De Aar (DEAR) and Kimberley (KLEY) represent the middle testing stations from the selected testing dataset. Clearly, Table 3 shows that the NN model performs more accurately on average over CPTN compared to NSPT, except for winter solstice. One of the reasons for this difference may be due to the availability of data within the NN model from the nearby stations, since sufficient historic data describing the behavioural pattern of a certain parameter is crucial for effective application of NNs in non-linear modelling (Haykin, 1994). Note that Sutherland had the greatest amount of data within the developed model (see Table 1) and is closer to CPTN than NSPT (see Fig. 1). Also from the geographical location point of view, one would expect the TEC variations at NSPT to be greater due to its proximity to the equator compared to CPTN. This is reflected in Fig. 2 and Fig. 5 especially during summer solstice. An effective comparison in predictions over "extreme end" and "middle" testing stations can be done at best by looking at results that were obtained on the same day. By considering this factor, the difference in RMSE values (Δ RMSE) for June 21 over the "middle" testing stations (DEAR and KLEY) is ∼1.164 TECU compared to ∼1.167 TECU for March 20 over the "extreme end" testing stations (CPTN and NSPT). These values are computed from results shown in Table 3 and Table 4 and demonstrate how close the predictions are on similar days over the considered testing stations. The GPS data available at Aliwal North and Middleburg GPS receiver stations starts from 2003 and therefore the NN model was tested during this year. In 2003, the equinoxes occured on March 21 and September 23, while the solstices occured on June 21 and December 22, respectively. Fig. 9 and Fig. 10 show TEC variations (both observed and predicted) at 1-min interval during equinoxes and solstices over these two GPS receiver stations in 2003. Significant peaks in TEC variability are observed on 23 September at ∼12:00 h UT as seen in Fig. 9 and Fig. 10b. We have not investigated the cause(s) of these peaks in this study. Although the ionosphere is highly variable during equinoxes, it is less likely to be the cause of these peaks given that other datasets at other GPS sites considered do not necessarily exhibit the same TEC variability. Probably these peaks could be associated with the inherent properties of the algorithm used to derive TEC from GPS measurements at these stations. This remains an open question for future investigation. In some cases, the equinox and solstice days in 2003 over these stations are also represented by different days due to data unavailability as earlier mentioned for other selected testing datasets. Fig. 11 shows the diurnal GPS TEC variability and the corresponding NN predictions during equinoxes and solstices over Grahamstown (33.3°S, 26.5°E) in 2005. These results show that the NN overpredicted GPS TEC for this period (especially in Fig. 11a and d), which is an expected outcome since this testing data set fell outside the training period. It is important to note, however, that the trend or shape of the TEC variations is correct and in some cases, almost as accurate as the testing dataset covered in training (for Fig. 11b and c). This illustrates the possibility of developing a model to predict TEC in advance beyond the training set. An important consideration would be to cover all solar activity periods (both maximum and minimum) in our view, since 2005 is near solar minimum compared to the rest of the data used in model development. Thus we suggest that data covering at least an entire solar cycle (∼11 years) may be used to develop a NN model that could probably improve on the accuracy of our present results.

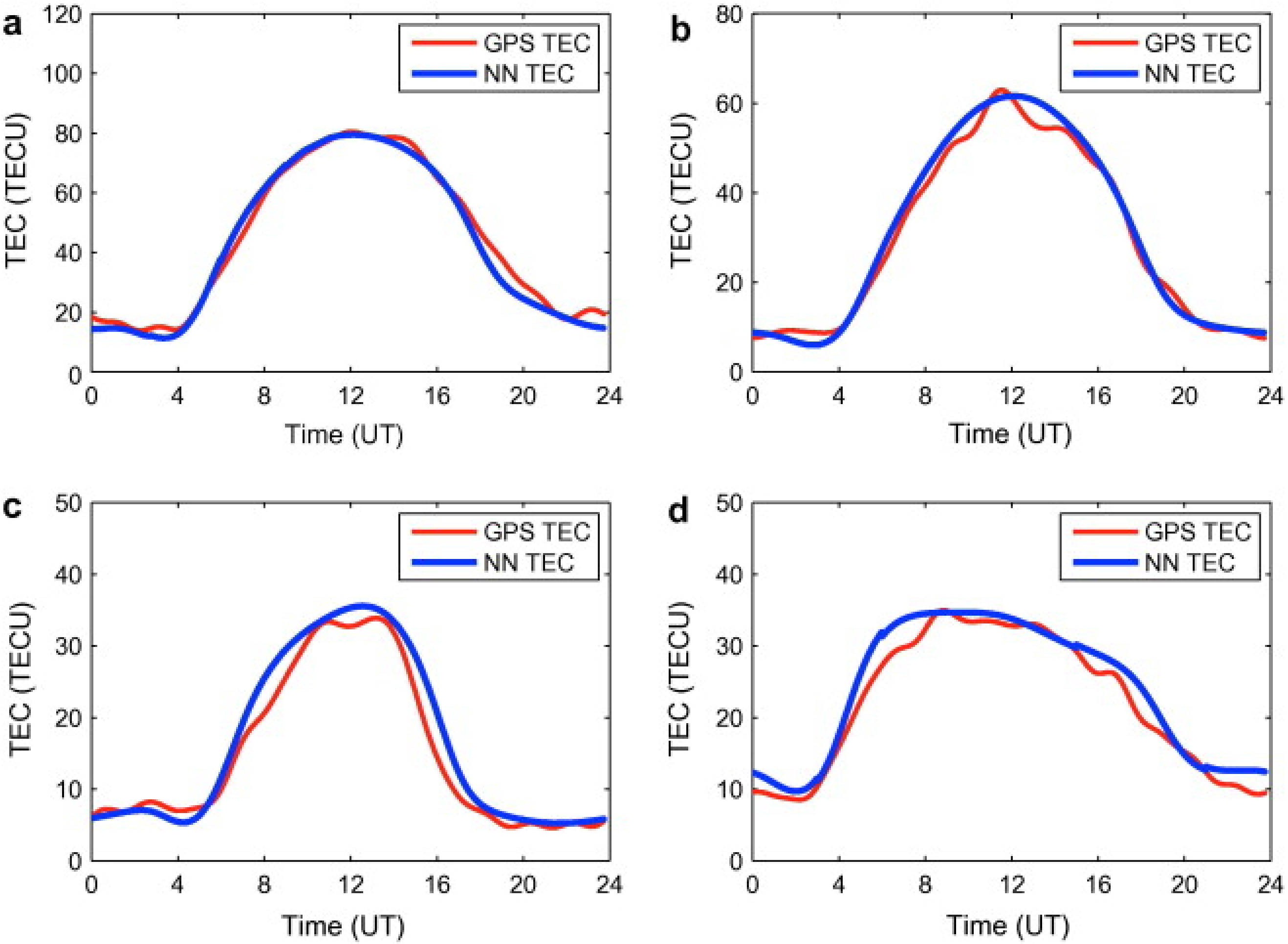

Fig. 2. One-minute GPS TEC with the corresponding predictions for (a) 20 March, (b) 23 September, (c) 22 June, and (d) 21 December; all in 2002 over Cape Town.

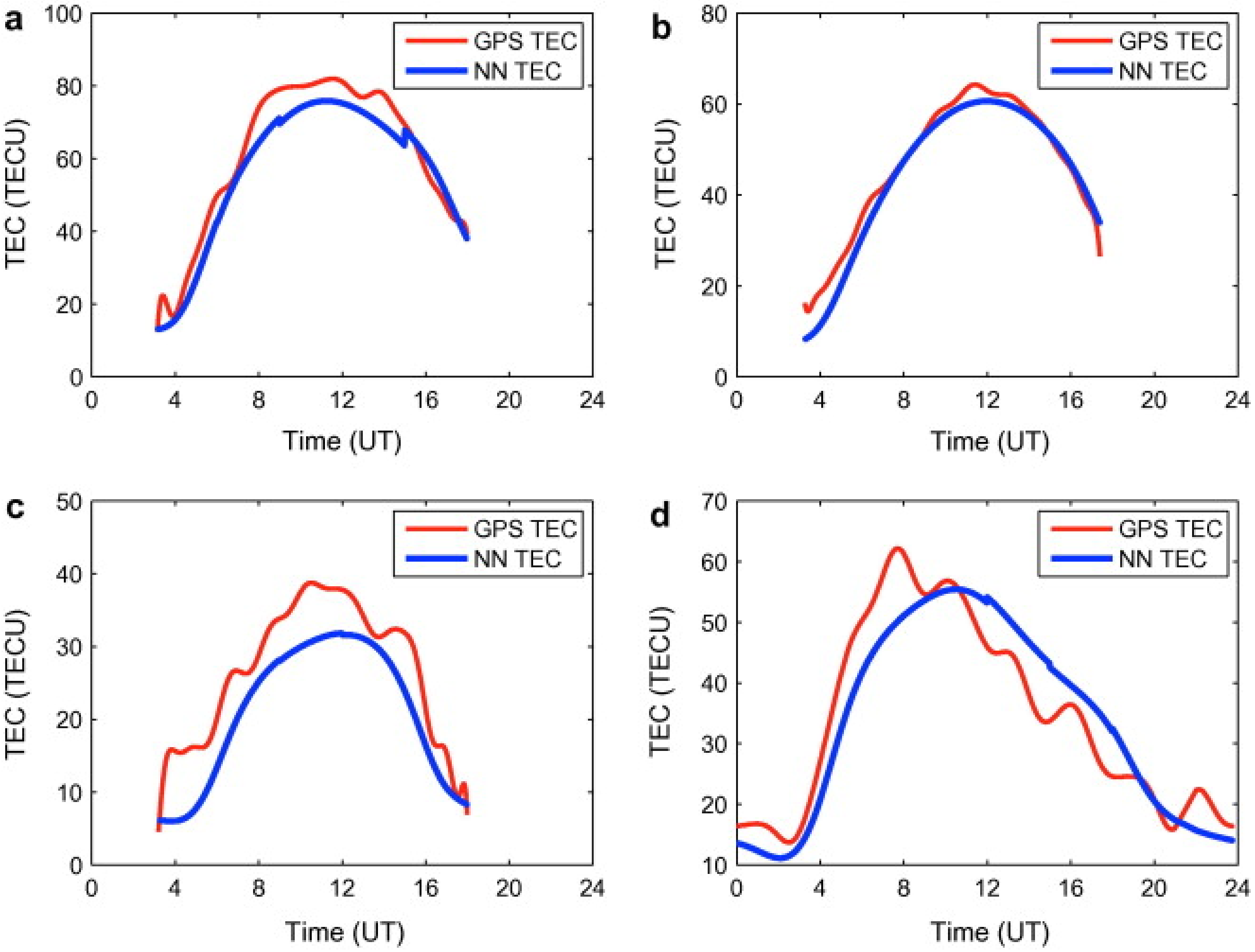

Fig. 3. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 20 March, (b) 23 September; (c) 21 June, and (d) 12 January, respectively, over De Aar GPS receiver station.

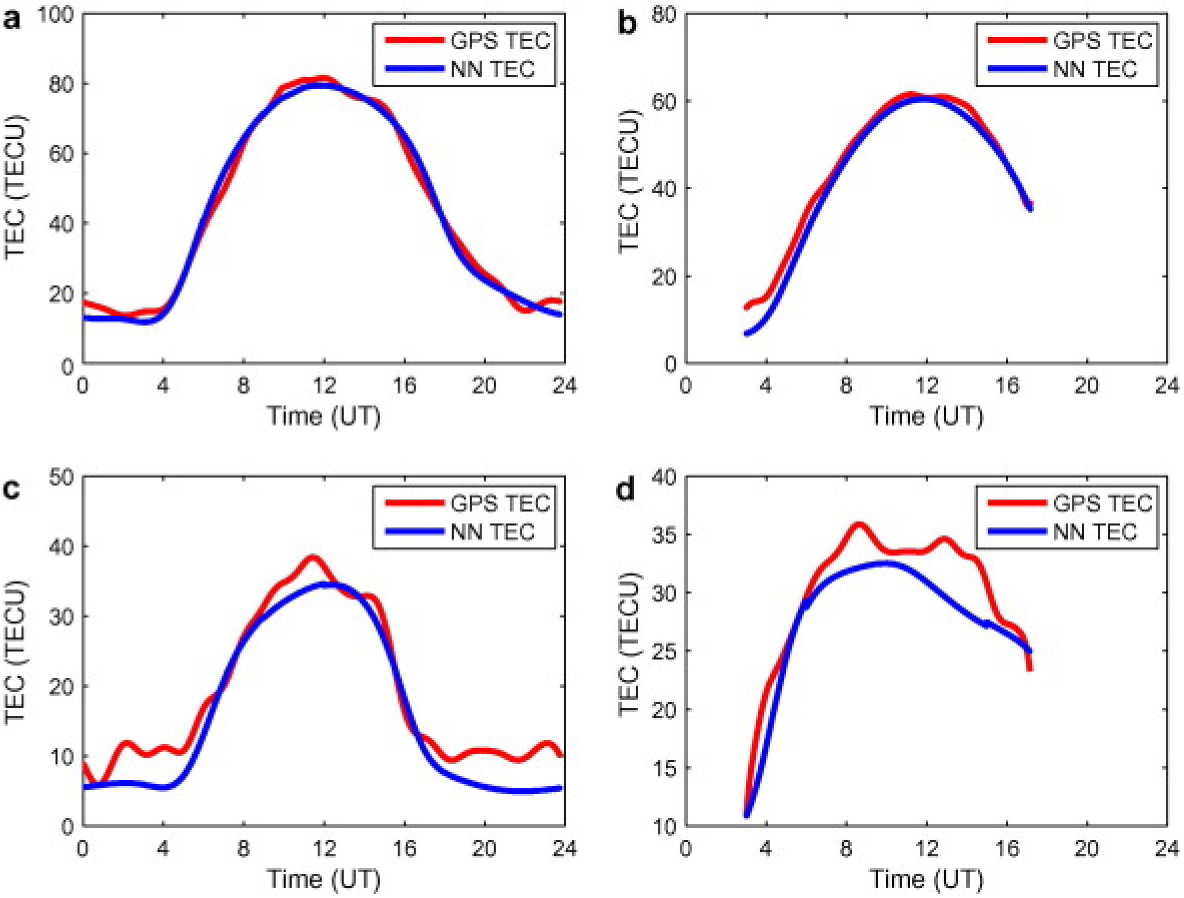

Fig. 4. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 20 March, (b) 26 September; (c) 21 June, and (d) 21 December, respectively, over George GPS receiver station.

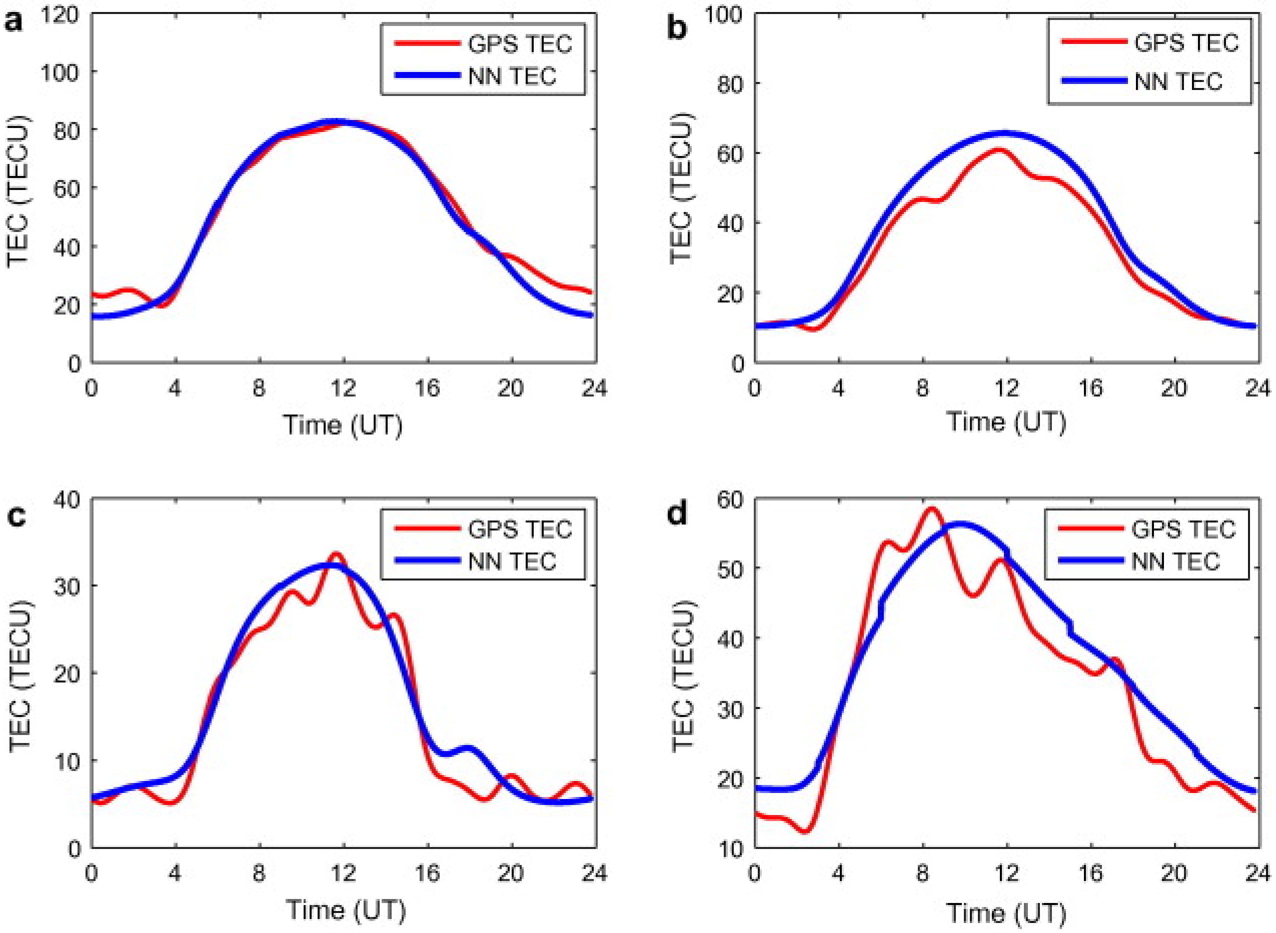

Fig. 5. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 20 March, (b) 22 September; (c) 21 June, and (d) 22 December, respectively, over Nelspruit GPS receiver station.

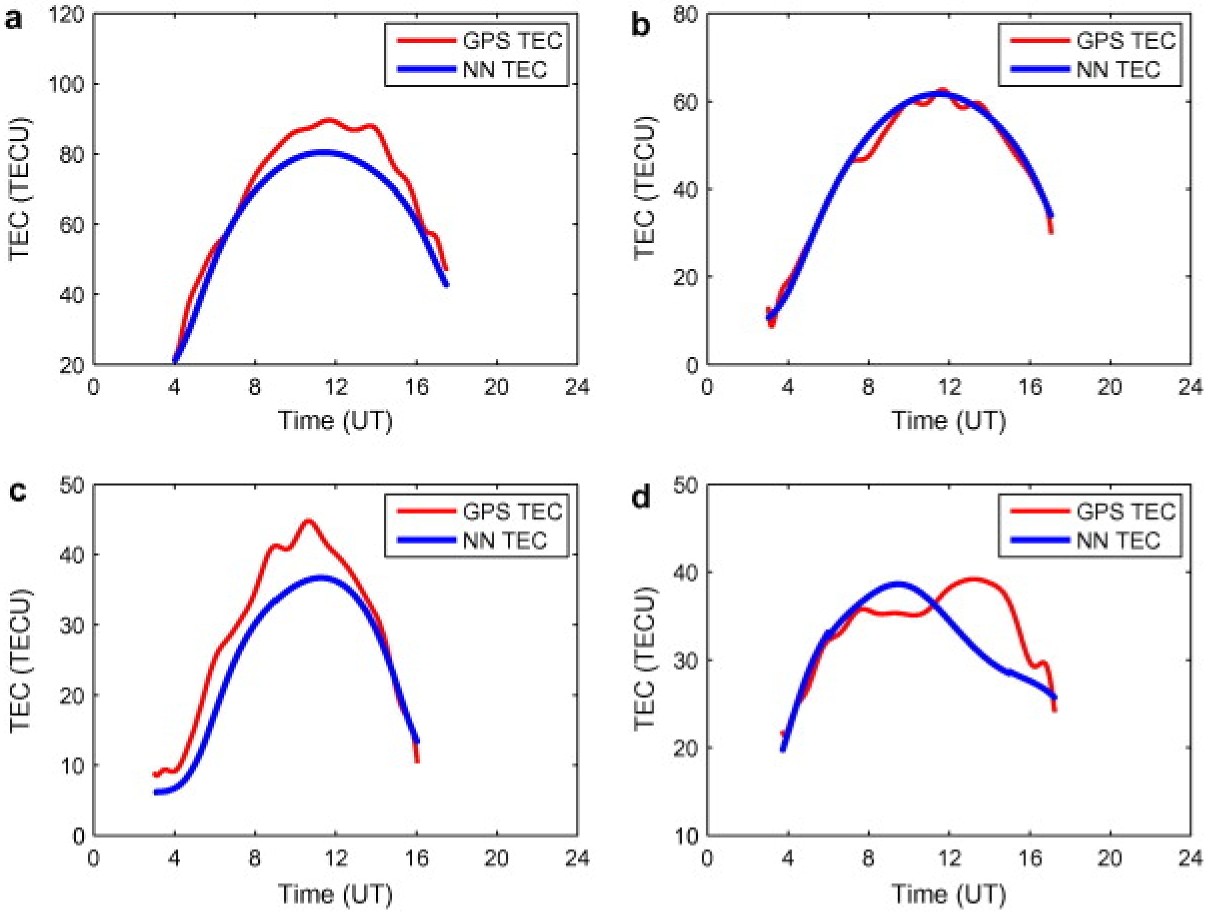

Fig. 6. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 18 March, (b) 26 September; (c) 31 May, and (d) 22 December, respectively, over Pietermaritzburg GPS receiver station.

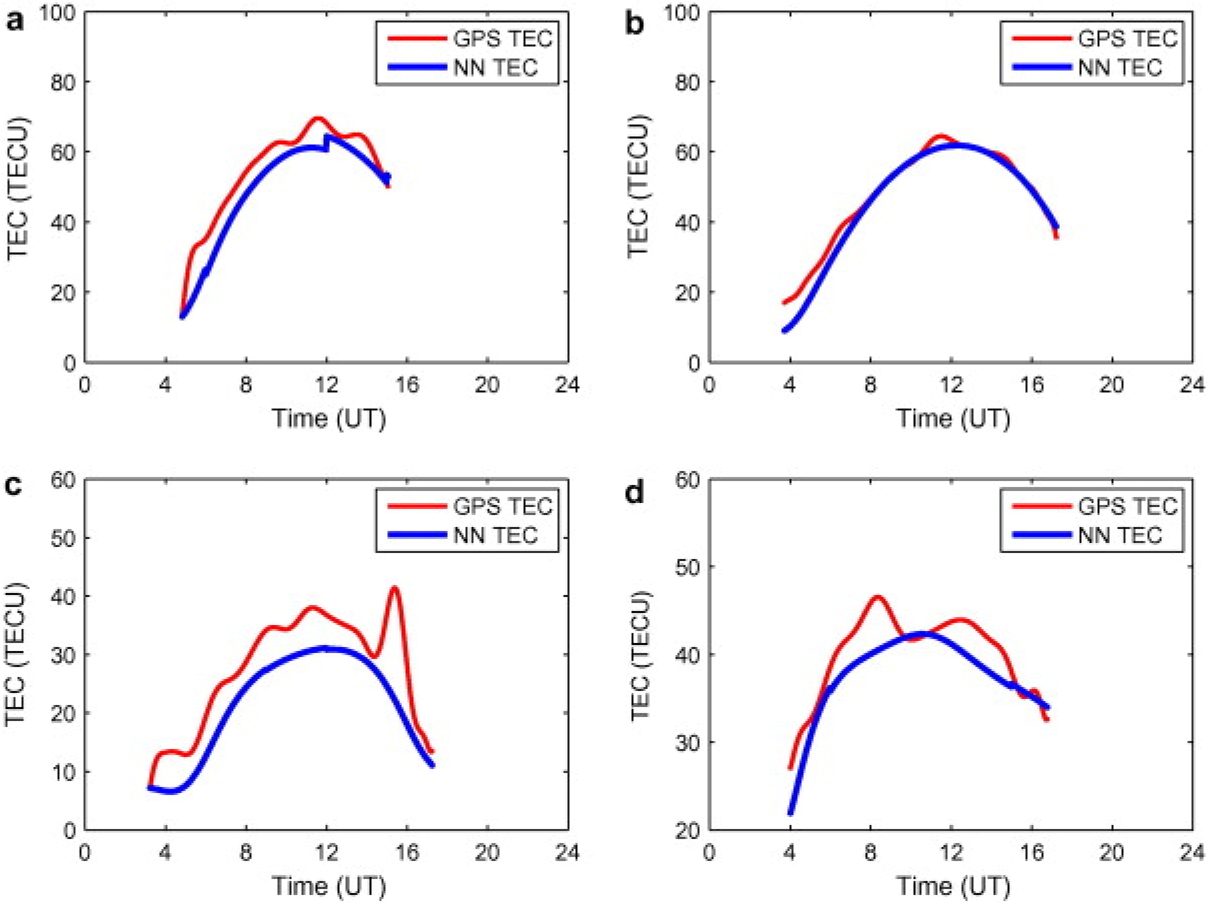

Fig. 7. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 20 April, (b) 23 September; (c) 21 June and (d) 21 December, respectively, over Upington GPS receiver station.

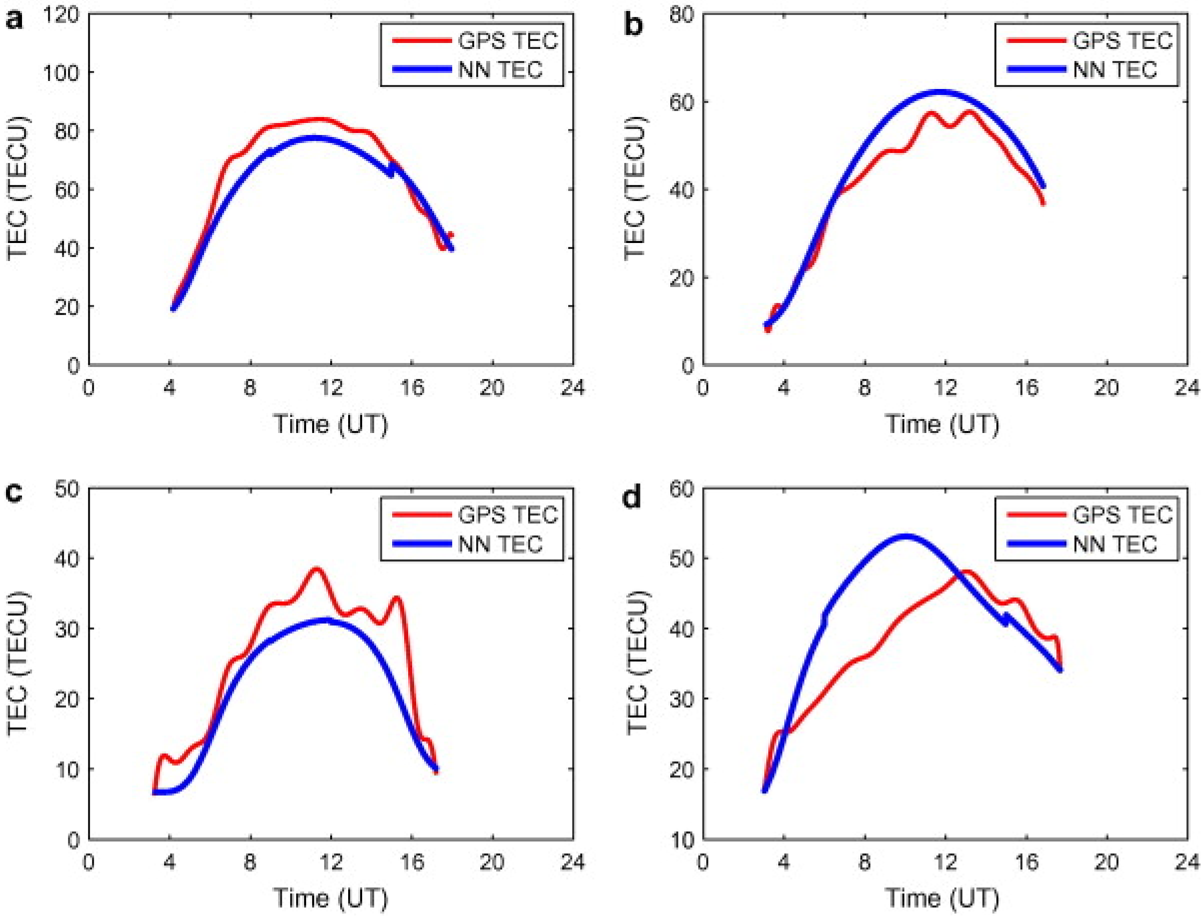

Fig. 8. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 19 March, (b) 28 September; (c) 21 June, and (d) 9 December, respectively, over Kimberley GPS receiver station.

Table 3.

Comparison of RMSE values between GPS TEC and NN TEC over CPTN and NSPT during equinoxes and solstices in 2002.

Equinox and solstice days	**RMSE for CPTN (TECU)**	**RMSE for NSPT (TECU)**
March 20 (both CPTN&NSPT)	3.127	4.294
September 23 (CPTN)/22 (NSPT)	2.375	5.900
June 22 (CPTN)/21 (NSPT)	2.534	2.309
December 21 (CPTN)/22 (NSPT)	2.198	4.975

Table 4.

Comparison of RMSE values between GPS TEC and NN TEC over DEAR and KLEY during equinoxes and solstices in 2002.

Equinox and solstice days	**RMSE for DEAR (TECU)**	**RMSE for KLEY (TECU)**
March 20 (DEAR)/19 (KLEY)	5.982	6.696
September 23 (DEAR)/28 (KLEY)	4.721	5.593
June 21 (both DEAR&KLEY)	6.204	5.040
Jan. 12 (DEAR)/Dec. 9 (KLEY)	6.161	7.764

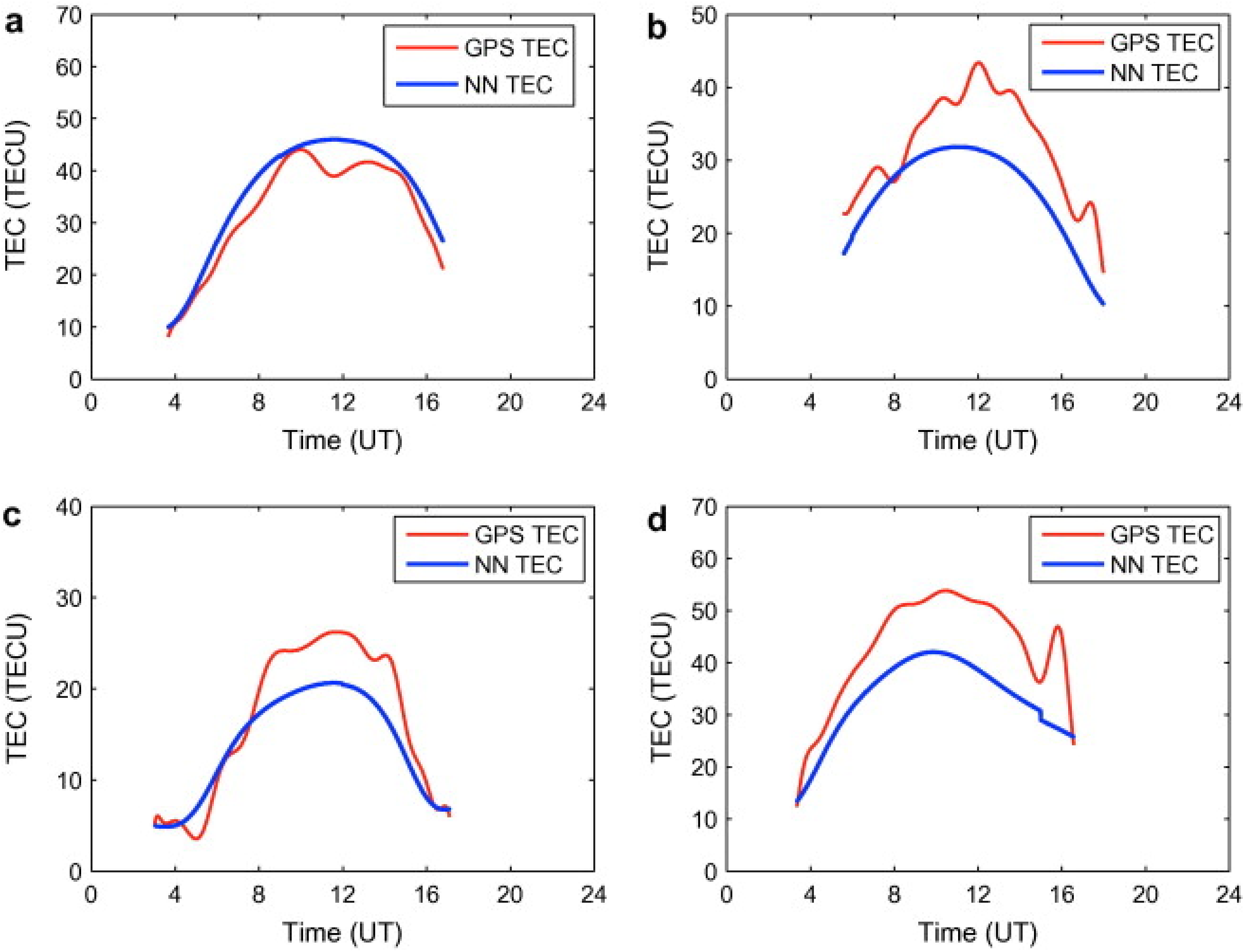

Fig. 9. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 19 March, (b) 23 September; (c) 21 June and (d) 17 January, respectively, over Aliwal GPS receiver station in 2003.

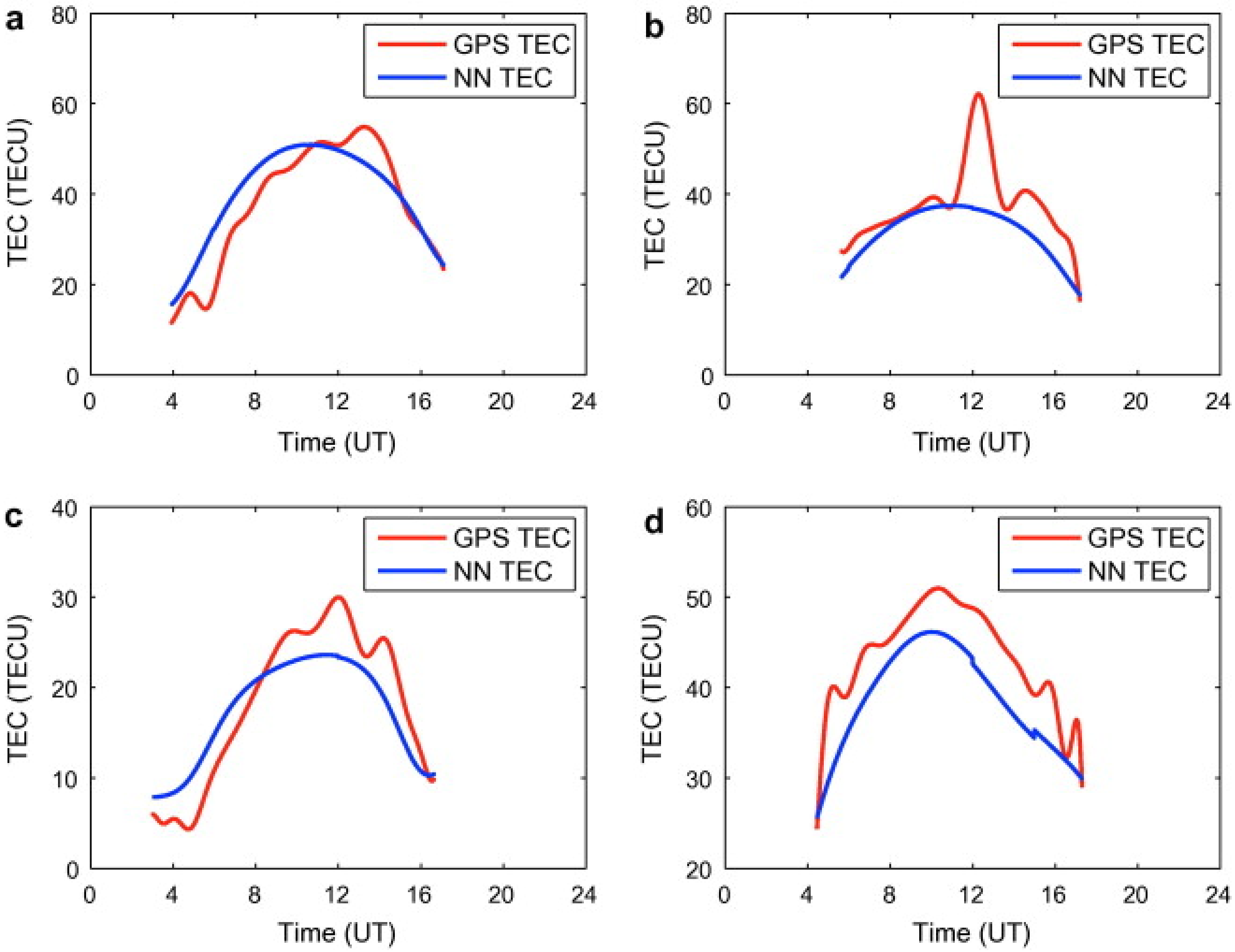

Fig. 10. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 21 March, (b) 23 September; (c) 21 June and (d) 13 January, respectively, over Middleburg GPS receiver station for 2003.

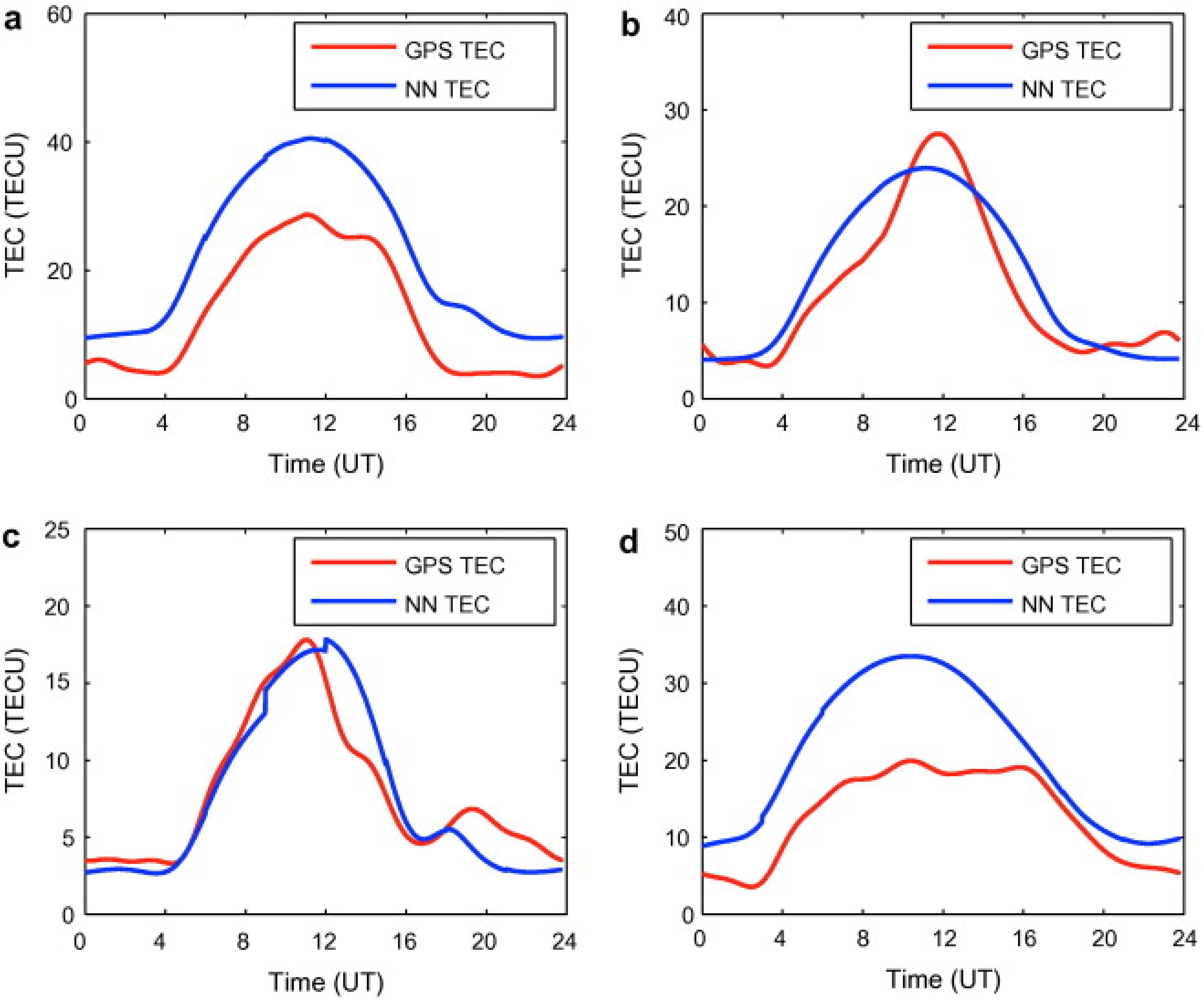

Fig. 11. Similar to Fig. 2, but with equinoxes and solstices represented by (a) 21 March, (b) 23 September; (c) 22 June and (d) 23 December, respectively, over Grahamstown GPS receiver station for 2005.

4.2. Comparison of the national and single station models over Cape Town and Upington

4.2.1. Cape Town (33.95°S, 18.47°E)

In their preliminary work, Habarulema et al. (2009) developed an hourly single station model (SSM) based on the NN technique over Sutherland (32.38°S, 20.81°E) and used it to predict TEC variations at Cape Town (33.95°S, 18.47°E). Table 5 shows the RMSE values as obtained by Habarulema et al. (2009) from the SSM compared to the latest results provided by the national model (NM) for Cape Town during the days representing equinoxes and solstices. The results presented in this paper show that the developed NM leads to an improvement in prediction of ∼19.4%, 41.5% and 12.8%, respectively, over a SSM for March 20, September

23 and December 21 over Cape Town as quantified through the RMSE method. However the prediction accuracy reduces by ∼50.2% for June 22 over the Cape Town GPS receiver station, but still, the NN generates the correct diurnal variational trend for the GPS TEC as shown in Fig. 2c. A significant finding from this study is that the NM improves the prediction accuracy (on average) compared to the SSM and can be used to get an idea of TEC variations at any point within South Africa since it has more coverage than the SSM.

Table 5.

RMSE values between GPS TEC and predicted TEC values obtained by Habarulema et al. (2009) and the developed NM over Cape Town (33.95°S, 18.47°E).

Date	**RMSE (TECU) between GPS TEC and**		
(in 2002)	**NN TEC (SSM)**	**NN TEC (NM)**	**IRI TEC**
March 20	3.880	3.127	15.086
June 22	1.687	2.534	4.690
September 23	4.061	2.375	3.866
December 21	2.520	2.198	2.702

4.2.2. Upington (28.41°S, 21.26°E)

Habarulema et al. (2009) also discussed the development of a SSM over Springbok (29.67°S, 17.88°E) that was used to predict TEC fluctuations over Upington (28.41°S, 21.26°E). These authors used data for three years (2002-2004) to construct an hourly NN model and compared the predictions with results generated by the IRI-2001 model. To expand on their work, we have performed a statistical comparison between the current and the earlier obtained results. An important result to point out here is that the NM provides an improvement in the deviations of the NN TEC from the average TEC values generated by the IRI-2001 model for the spring equinoxes. However, during this season, a consistent result of the IRI-2001 model providing more accurate predictions than both NN models over Upington is observed. Table 6 shows similar comparisons to Table 5 in terms of correlation coefficients for Upington in 2003. From this table, an improvement of ∼0.5% for both March 19 and September 22 is observed while the June 22 prediction improves by ∼0.7% when both the SSM and NM are compared. The prediction for January 2 is reduced by ∼0.1%. Statistically, as it was observed from the prediction results over Cape Town (33.95°S, 18.47°E), the NM also performs more accurately on average than both the SSM and IRI-2001 model over Upington (28.41°S, 21.26°E).

Table 6.

Correlation coefficients between GPS TEC and predicted TEC values as obtained by Habarulema et al. (2009) and the developed NM with a comparison from IRI-2001 model over Upington (28.41°S, 21.26°E).

Date	**Correlation coefficient between GPS TEC and**		
(in 2003)	**NN TEC (SSM)**	**NN TEC (NM)**	**IRI TEC**
March 19	0.985	0.990	0.964
June 22	0.971	0.978	0.970
September 22	0.960	0.965	0.972
January 2	0.973	0.972	0.919

5. Conclusion and future work

Using the regional GPS receiver network, this paper has described the development of a NN-based TEC prediction model over South Africa as a function of diurnal variation, seasonal variation, magnetic activity, solar activity and the geographical position of the GPS receiver stations. We have used data for only five years (2000–2004) from 10 stations distributed over the whole country in training and three years (2002, 2003 and 2005) for testing. Results from the developed NM were compared to the earlier generated results by SSMs over Cape Town and Upington. It is observed that on average, the NM improves the TEC prediction accuracy during equinoxes and solstices in 2002 and 2003 for these GPS receiver stations. However, though the NM provided an improvement in TEC predictions over Springbok compared to the SSM during the spring equinox, the IRI-2001 model still performed more accurately than both the national and single station NN models for this period. It is worth mentioning that the testing data were not used in NN training and validating. In some of our testing datasets, significant peaks in TEC variations were observed and have not been investigated at this stage. Furthermore, the NN model predictions do not accurately reproduce the peaks seen in the measurements. Future work will include the investigation of these peaks and how we can represent TEC variability realistically through NN modelling in cases where these peaks exist. The validation of this model during the disturbed conditions is also an issue for a different paper. It is our intention to develop a comprehensive TEC prediction model for Southern Africa, and therefore, we are currently processing more GPS data to include in NN training which will assist us in covering different solar activity levels and is hence expected to improve the accuracy of the predictions.

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