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Hierarchical Bayesian modeling of ionospheric TEC disturbances as non-stationary processes

Abdu Mohammed Seid [a,*], Tesfahun Berhane [a], Lassi Roininen [b], Melessew Nigussie [c]

[a] *Department of Mathematics, Bahir Dar University, P.O. Box 79, Bahir Dar, Ethiopia*
[b] *Sodankylä Geophysical Observatory, University of Oulu, Tähteläntie 62, FI-99600 Sodankylä, Finland*
[c] *Washera Geospace and Radar Science Laboratory, Bahir Dar University, P.O. Box 79, Bahir Dar, Ethiopia*

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Abstract

We model regular and irregular variation of ionospheric total electron content as stationary and non-stationary processes, respectively. We apply the method developed to SCINDA GPS data set observed at Bahir Dar, Ethiopia (11.6°N,37.4°E). We use hierarchical Bayesian inversion with Gaussian Markov random process priors, and we model the prior parameters in the hyperprior. We use Matérn priors via stochastic partial differential equations, and use scaled $\mathrm{Inv}-\chi^2$ hyperpriors for the hyperparameters. For drawing posterior estimates, we use Markov Chain Monte Carlo methods: Gibbs sampling and Metropolis-within-Gibbs for parameter and hyperparameter estimations, respectively. This allows us to quantify model parameter estimation uncertainties as well. We demonstrate the applicability of the method proposed using a synthetic test case. Finally, we apply the method to real GPS data set, which we decompose to regular and irregular variation components. The result shows that the approach can be used as an accurate ionospheric disturbance characterization technique that quantifies the total electron content variability with corresponding error uncertainties.

Keywords: Ionosphere; TEC; Hierarchical inversion; MCMC; Gaussian process; Non-stationary process

1. Introduction

Ionosphere is the Earth's upper atmosphere which contains significant numbers of free electrons and ions (Schunk and Nagy, 2009). It is very dynamic and affected by the relative position of the Sun and Earth, the solar activity and the interactions among ionosphere, magnetosphere and thermosphere. Sudden events of the Sun and the Earth, geomagnetic storms, solar radio bursts and solar eclipses also cause ionospheric disturbances (Li et al., 2013; Zhang et al., 2005). It has both advantage and disadvantage for ionospheric propagating radio wave technology users. For terrestrial communication, ionosphere can be used as a wave-guide, which enables far-distance communications (Rawer, 1993). It is a threat for trans-ionospheric propagating radio wave dependent applications such as GPS navigation, positioning, surveillance and so on (Tiwari et al., 2013). For example, as GPS signal traverses through the ionosphere, its group and phase velocities delay and advances respectively compared to the velocities in free medium, which results in error in GPS applications. The impact of the ionosphere can be mitigated once its behavior is understood and modeled in a proper way. The basic parameters used to study the dynamics of the ionosphere are electron density and total electron content (TEC), which is defined as the integrated electron density along a signal path of 1 m^2 cross-section between a

* Corresponding author.
E-mail addresses: abdum442@yahoo.com (A.M. Seid), tesfahunb2002@yahoo.com (T. Berhane), lassi.roininen@oulu.fi (L. Roininen), melessewnigussie@yahoo.com (M. Nigussie).

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satellite and a receiver, its unit is TECu (1TECu = 10^{16} electrons per m^2). The temporal behavior of the ionosphere is described by ionospheric TEC.

Many studies have been made to investigate ionospheric TEC short-term and long-term variabilities; to estimate factors affecting the TEC fluctuations; to analyze and develop empirical models (Daniell et al., 1995; Pi et al., 1997; Forbes et al., 2000; Zhang et al., 2005; Chauhan and Singh, 2010; Li et al., 2013; Tiwari et al., 2013). For example, Chauhan and Singh (2010) investigated the diurnal and seasonal variations of TEC at Agra, India using 12 months GPS data. Their result shows the existence of lowest TEC values in winter and largest values in equinox and summer. Their study also reveals the existence of anomalous variations during the period of magnetic disturbances. Li et al. (2013) constructed a linear time series model to study daily averaged TEC variability. They used the model to examine the influences of different factors and its characteristics at different latitudes. Some authors also investigated ionospheric TEC distribution using different tomography techniques (Kunitsyn et al., 2011; Pokhotelov et al., 2011; Van de Kamp, 2013; Ghaffari Razin and Voosoghi, 2016, 2017). For instance, Ghaffari Razin and Voosoghi (2017) studied ionospheric tomography using neural network and particle swarm optimization over the Iranian region. The result gives a regional imaging of ionospheric TEC distributions. However, in all the above studies minimal attention is given to the direct quantification and characterization of TEC disturbances.

Radio signal scintillation and TEC fluctuations have been characterized mostly using the root mean square deviations of the TEC, the rate of TEC (ROT) (in TECU/min) and the rate of TEC index (ROTI) (Pi et al., 1997). The ROTI, defined as the standard deviation of the detrended ROT values over some time interval, is mostly considered to effectively characterize ionospheric fluctuation. Recently, Olwendo et al. (2016) used ionospheric scintillation analysis (S4 index) to study the morphology of ionospheric bubbles over the Kenyan region. Their investigation shows that the scintillation events mainly observed to the northwest and southwest of the sky. Their result, in addition, reveals that the L-band scintillation can last till post-midnight hours (01:00–02:00 LT). Patrick et al. (2016) also used ROTI values with 5-min time intervals to study the trends of ionospheric disturbances during quiet geomagnetic conditions using GNSS-derived TEC data over the African low latitudes. Their result reveals that the strength of the ionospheric disturbance reduces from west to the east in the region.

However, though some studies consider the use of 5-min time intervals for the calculation of ROTI values, there are studies who use different time intervals for the calculation of the ROTI, which may result in different ROTI values in magnitude (Jacobsen, 2014). The choice of time interval is generally a trade-off between time resolution and the quality of the ROTI value, as there should be a sufficient amount of samples per interval for the phenomenon in question to be tractable. Hence, the choice of subjective time intervals in the calculation of ROTI values restricts the use of ROTI only to indicate whether ionospheric irregularity exists or not.

To overcome the problem regarding quality of ROTI values due the subjective choice of time interval, Bires et al. (2016) proposed a new approach using the Bayesian inversion technique to study TEC fluctuation from detrended ROT and ROTI, through the assumption of the TEC as a random stationary process by considering short time scale. However, to consider the TEC as stationary process, how short has to be 'short time scale', depends on the frequency of the fluctuation of the phenomenon of interest. Zhang et al. (2005) had also used the time series of TEC and the autocovariance function of the stationary process to construct independent and identically distributed Gauss samples and used χ^2-test to detect the abnormality hidden in the sequence. In reality, sudden events such as solar flares, geomagnetic storms and Rayleigh-Taylor instability breaks the stationary process. Moreover, the main interest of such studies is the investigation of the TEC disturbances and hence the processes will best be described if both stationarity and non-stationarity are considered in the modeling.

We model TEC fluctuation directly by decomposing the TEC time series into regular and irregular components using hierarchical Bayesian inversion technique. By regular component of the TEC, we mean the component of the TEC that always occur at quiet condition of the ionosphere, such as where there is no sudden solar events and no magnetic storms for ionospheric disturbance to occur and by irregular component of the TEC, we mean the component of the TEC which results in significant disturbance in the ionosphere. Hence, we assume the periodic and trend components of the TEC time series as regular, where as the other fluctuation components of the TEC time series are assumed as irregular in this study. This enables us to propose a stationary and non-stationary prior models separately for the regular and irregular components of the TEC measurement model respectively. Moreover, in this study the regular and irregular variation components of the TEC are directly estimated and quantified from GPS data instead of characterizing them using ROT and ROTI indices indirectly.

We use a three-layer Bayesian hierarchical model: The first level is the data level. The second level is the process level that describes the overall fluctuation of TEC involving the regular and irregular variation components. These two temporal variability determinant components of the TEC are presented respectively, through stationary and non-stationary Gaussian Markov random processes. The third level contains hyperparameters for the first and second level parameters. The posterior distributions of model parameters and hyperparameters are derived by implementing Markov Chain Monte Carlo (MCMC) techniques: