Dynamic Stochastic Model for Tropospheric Delay Estimation from GNSS Observations on UAV

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Title is changed from "NWM/GNSS tightly coupled tropospheric delay estimation and application on an unmanned aerial vehicle (UAV) platform".

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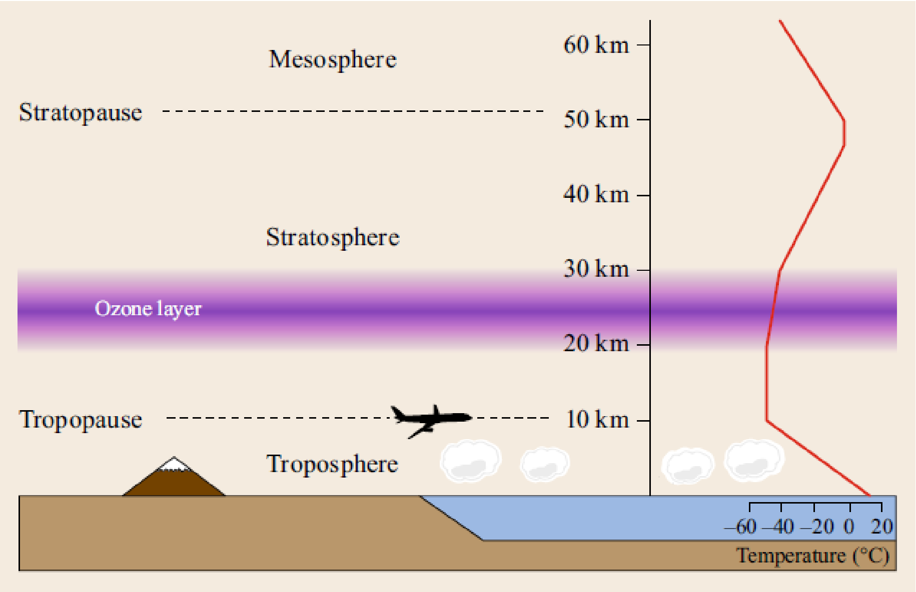
01

Introduction

Introduction

Meteorology concerns

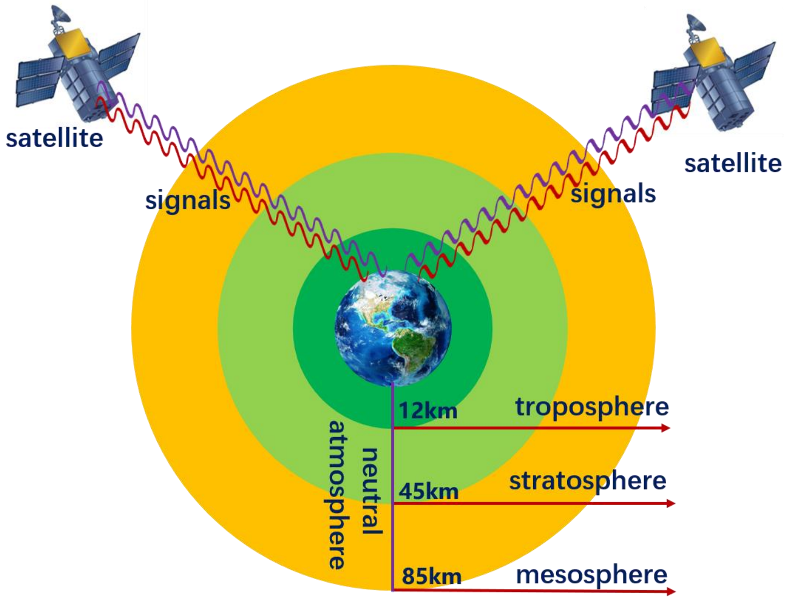
Atmospheric profile information is vital for climate research and weather forecast.



Earth's atmosphere layers

GNSS advance

Global Navigation Satellite Systems (GNSS) can estimate the zenith total delay (ZTD) accurately and further retrieve accumulated atmospheric water vapor.



Satellite Geodesy

Introduction

GNSS application scenarios

	Static platforms	Surface-Kinetic platforms	Aero-Kinetic platforms
Platforms	Permanent stations 	Vehicles, trains, ships… 	Hot-air balloon, Aerial Vehicle 
Advantages	A mature suite of data processing strategy	Horizontal resolution gets improved	Both horizontal and vertical resolution improved. Flexible in time and space.
Defects	Single point and low spatial resolution	Vertical coverage is limited	Calling for advanced GNSS data processing method

Obtaining atmospheric profile information via Aero-kinetic GNSS.

Introduction

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Problems

Issues are found in ZTD estimation from airborne high dynamic platforms, especially around the stochastic processing noise (SPN) model for ZTD parameters.

Current situation

- The ZTD SPN is usually set to be a constant for static stations.
- Hadas et al. (2017a) proposed a locality and time-dependent SPN model for ZTD parameters and improved the accuracy of ZTD estimates by 10% for static stations.
- Vaclavovic et al. (2017) processed GNSS observations from a hot-air balloon, tested a range of SPN values, and demonstrated that there is no unique and optimal SPN.

Challenge and prospect

Properly giving the stochastic model for ZTD parameters and further improving estimation results.

02

Dynamic SPN Modeling Method

Dynamic SPN Modeling Method

Dynamic Stochastic Process Noise (SPN) Modeling Method

The zenith wet delay (ZWD) is commonly modeled as random walking as follows,

$$p_{t+\delta t} = M \cdot p_t + w_t \qquad w_t \sim N(0, \varepsilon\sqrt{\delta t}) \tag{1}$$

SPN depends on parameter variations in both temporal and spatial domains,

$$\varepsilon = \sqrt{\varepsilon_{time}^2 + \varepsilon_{space}^2} \tag{2}$$

<u>Temporal component of the model</u>

Based on the a priori ZWD profile information coming from numerical weather models (NWMs).

$$\varepsilon_{time}(h) = E[ZWD_h^t - ZWD_h^{t+\Delta t}]/\sqrt{\Delta t} \tag{3}$$

$$\varepsilon_{time}(h) = \alpha_t \cdot h^2 + \beta_t \cdot h + \gamma_t \tag{4}$$

Dynamic SPN Modeling Method

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Spatial component of the model

Firstly, considering the variance of ZWD.

$$var(ZWD_h^{\Delta h}) = E\left[(ZWD_h - ZWD_{h+\Delta h})^2\right] \quad (5)$$

$$var(ZWD_h^{\Delta h}) = f(h, \Delta h) \quad (6)$$

Fix Δh to Δh_0, then fit by an exponential function.

$$f(h, \Delta h)|_{\Delta h = \Delta h_0} = \alpha_s \cdot e^{\beta_s h} \quad (7)$$

Introducing a ratio to convert $f(h, \Delta h_0)$ to $f(h, \Delta h)$, fit by a power function.

$$ratio(k) = \frac{E\left[var(ZWD_h^{\Delta h})|_{\Delta h = k \cdot \Delta h_0}\right]}{E\left[var(ZWD_h^{\Delta h})|_{\Delta h = \Delta h_0}\right]} \quad (8)$$

$$ratio(k) = k^{\gamma_s} \quad (9)$$

Dynamic SPN Modeling Method

Spatial component of the model

Lastly, $f(h, \Delta h)$ can be expressed by

$$f(h, \Delta h) = \alpha_s \cdot e^{\beta_s h} \cdot \left(\frac{\Delta h}{\Delta h_0}\right)^{\gamma_s} \tag{10}$$

For simplicity, we set Δh_0 to 1 m since the choice of Δh_0 has no impacts on results.

$$\begin{aligned} f(h, \Delta h) &= f(h, \Delta h)|_{\Delta h = \Delta h_1} \cdot \left(\frac{\Delta h}{\Delta h_1}\right)^{\gamma_s} \\ &= f(h, \Delta h)|_{\Delta h = \Delta h_0} \cdot \left(\frac{\Delta h_1}{\Delta h_0}\right)^{\gamma_s} \cdot \left(\frac{\Delta h}{\Delta h_1}\right)^{\gamma_s} \\ &= f(h, \Delta h)|_{\Delta h = \Delta h_0} \cdot \left(\frac{\Delta h}{\Delta h_0}\right)^{\gamma_s} \end{aligned} \tag{11}$$

Eventually, the concise form is as follows,

$$f(h, \Delta h) = \alpha_s \cdot e^{\beta_s h} \cdot |\Delta h|^{\gamma_s} \tag{12}$$

Dynamic SPN Modeling Method

Spatial component of the model

Recover the spatial SPN model from variance.

$$var(ZWD_h^{\Delta h}) = {\varepsilon_{space}}^2 \cdot t \quad (13)$$

Δh is expressed by the multipliation of vertical velocity v_h and ZTD estimation interval t_0 .

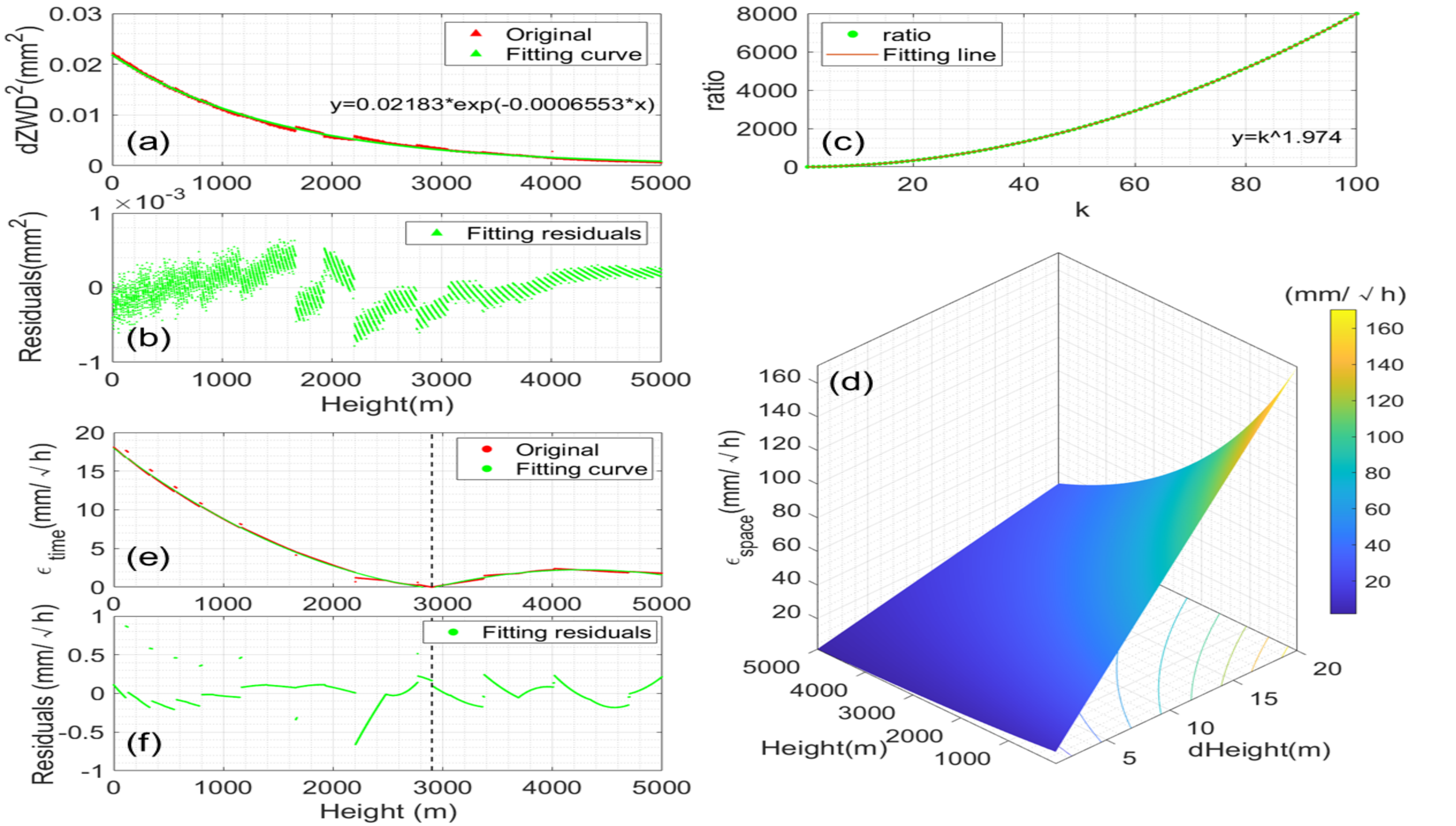
$$\varepsilon_{space} = \sqrt{\alpha_s \cdot e^{\beta_s h} \cdot |v_h \cdot t_0|^{\gamma_s} / t_0} \quad (14)$$

The total SPN model can be finally expressed as,

$$\varepsilon = \sqrt{(\alpha_t \cdot h^2 + \beta_t \cdot h + \gamma_t)^2 + \alpha_s \cdot e^{\beta_s h} \cdot |v_h \cdot t_0|^{\gamma_s} / t_0} \quad (15)$$

Dynamic SPN Modeling Method

Dynamic SPN model in this case



03

Experimental Design

Experimental design

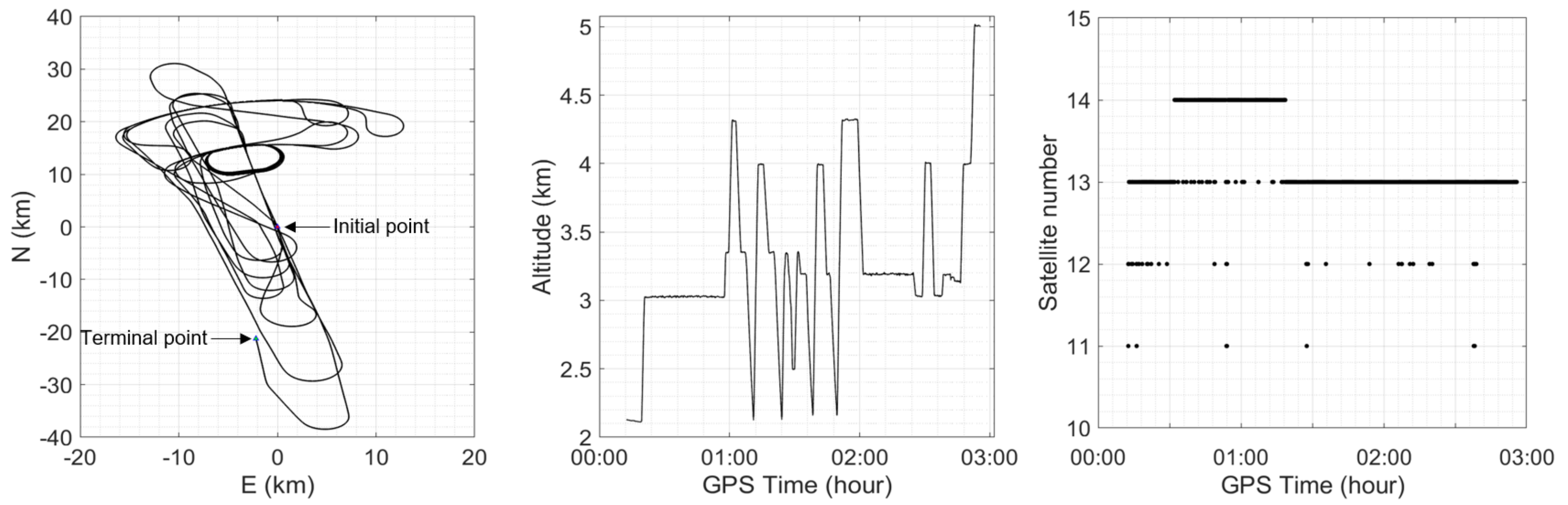
GNSS

- Observations: BeiDou-2, 10HZ, B1I and B2I.
- Products: Archived IGS real-time satellite products from Wuhan University (Gong et al., 2018).
- Strategy: PPP, IF combination, SRIF filter, float ambiguity, Random walking ZTD.

Meteorology

- ERA5: Reanalysis, for assessment.
- GFS: Forecast, (1) SPN modeling, (2) Provide a priori ZTD.

UAV trajectory



Experimental design

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Cases design

Control variables are SPN model for ZTD, a priori ZTD, and initial variance for ZTD.

Case	SPN	A priori ZTD	Initial variance
FS01~FS20	Constant, ranging from 1 to 20mm/$\sqrt{\mathrm{h}}$	Saastamoinen	0.2 m
FS21	Constant, 100mm/$\sqrt{\mathrm{h}}$	Saastamoinen	0.2 m
DS	Dynamic SPN	Saastamoinen	0.2 m
FG	Constant, 12mm/$\sqrt{\mathrm{h}}$	GFS（only for the first epoch)	0.02 m
DG	Dynamic SPN	GFS（only for the first epoch)	0.02 m

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Results and Analysis

Results and Analysis

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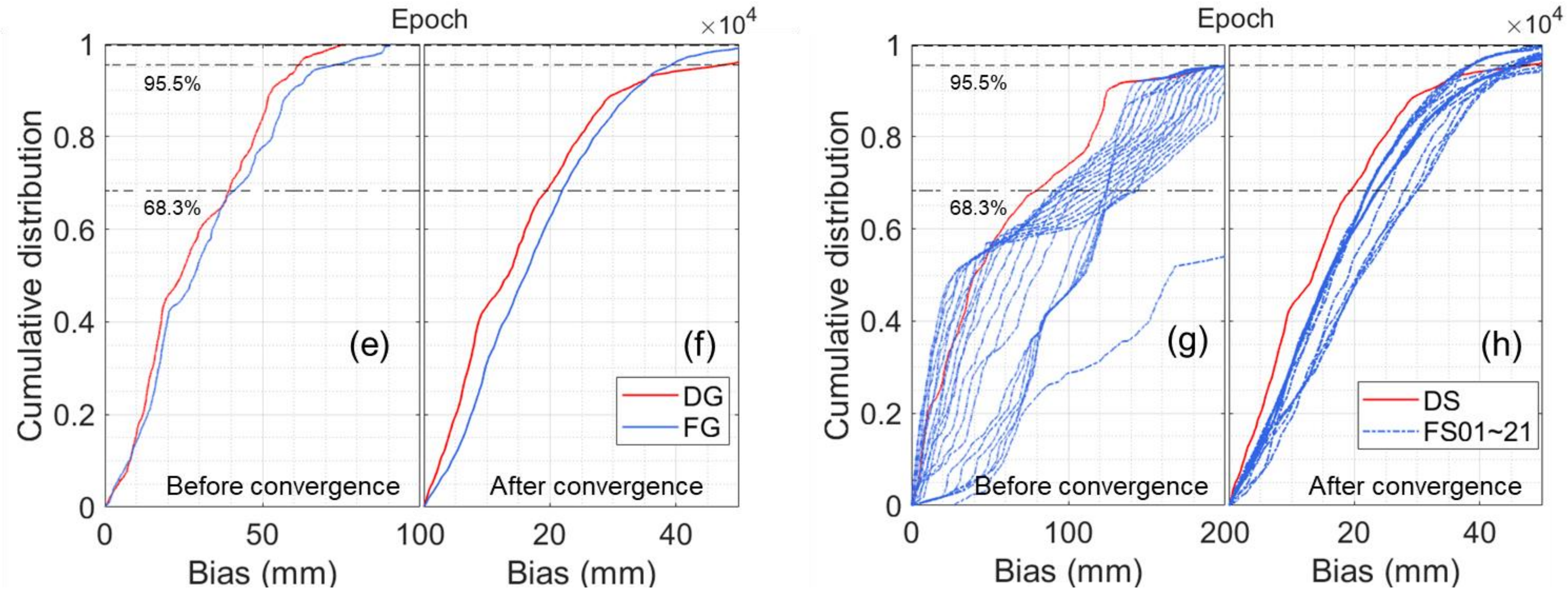
Assessment with ERA5 reanalysis



The dynamic SPN model can speed up the convergence and improve ZTD estimates accuracy.

Results and Analysis

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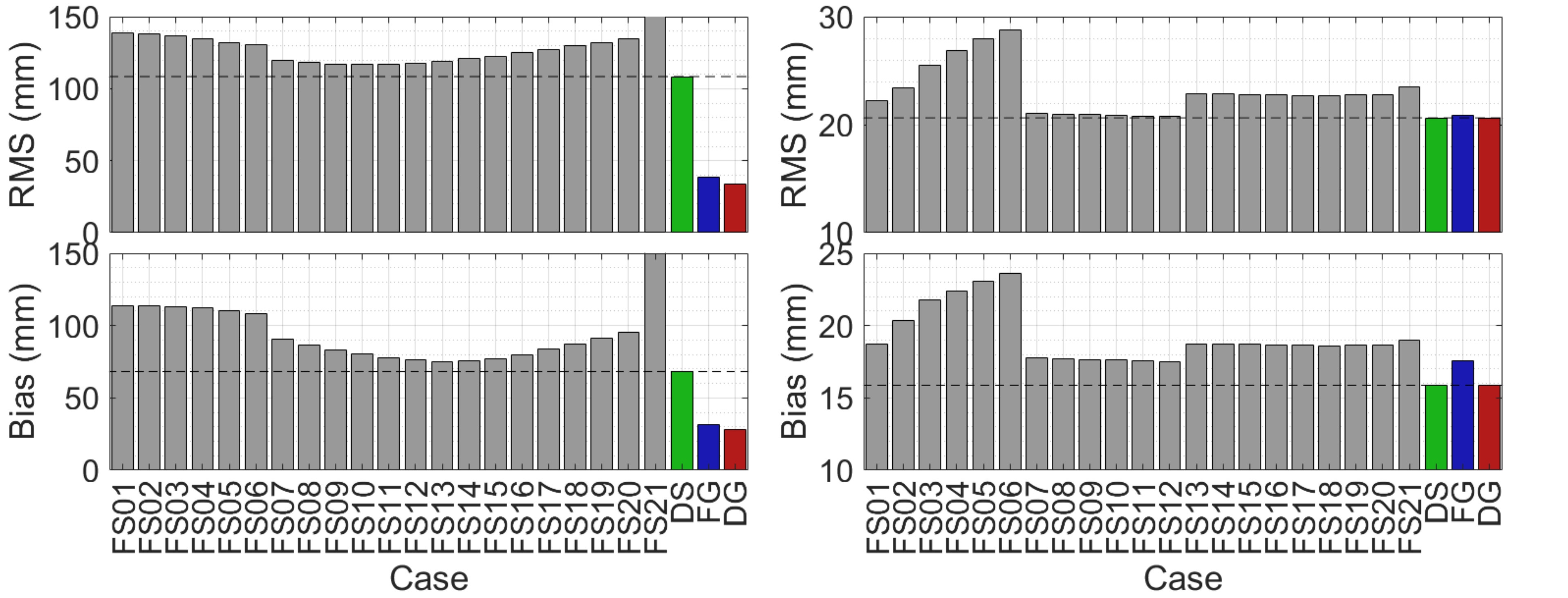
Assessment with ERA5 reanalysis



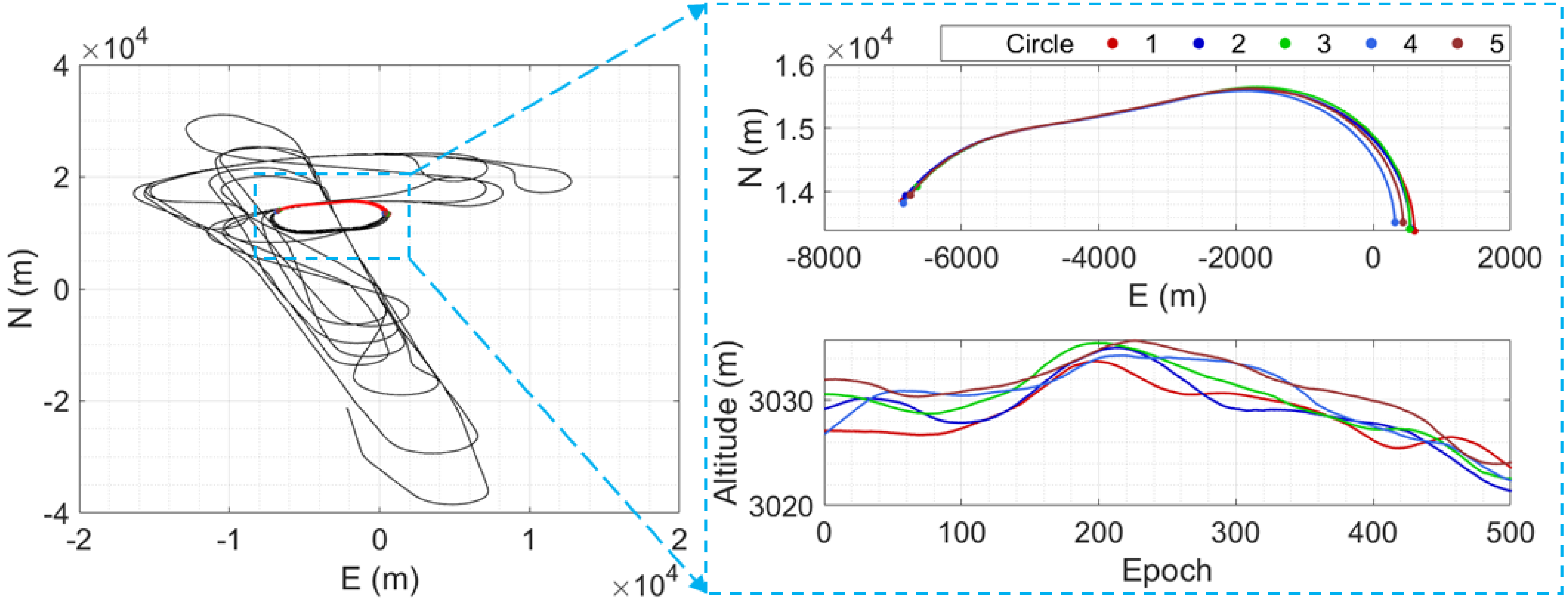
- ✓ The dynamic SPN model leads to smaller RMS and Bias.
- ✓ Introducing a priori ZTD can speed up the convergence but contribute little to the accuracy.

Results and Analysis

Assessment with closed-loop test

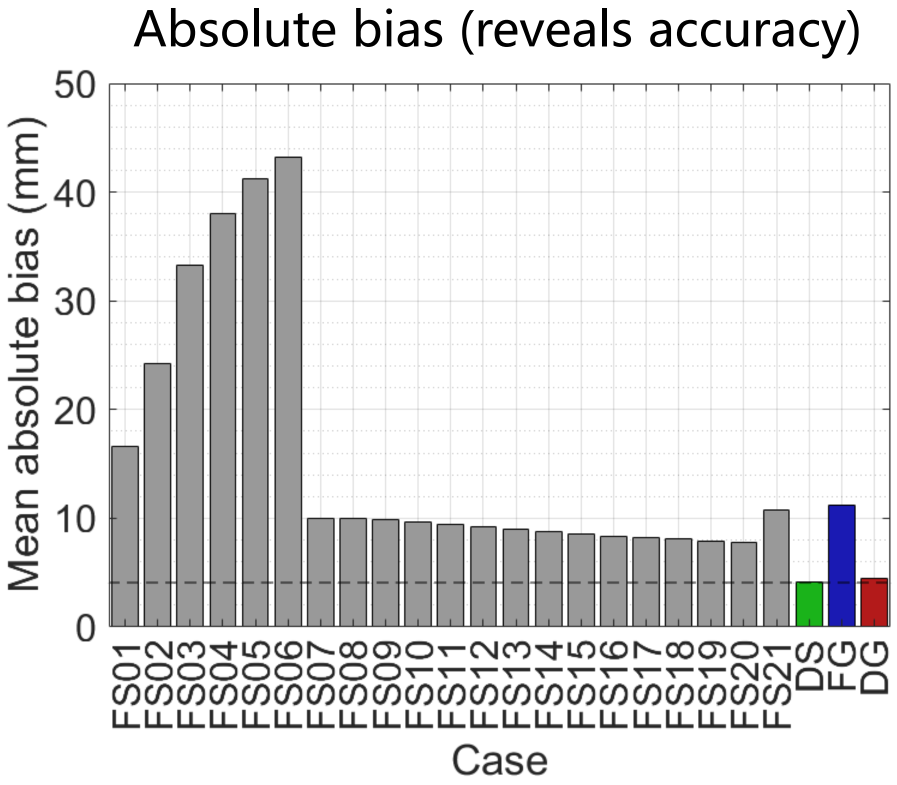
Five repeated routes can be found with in 20 minutes.

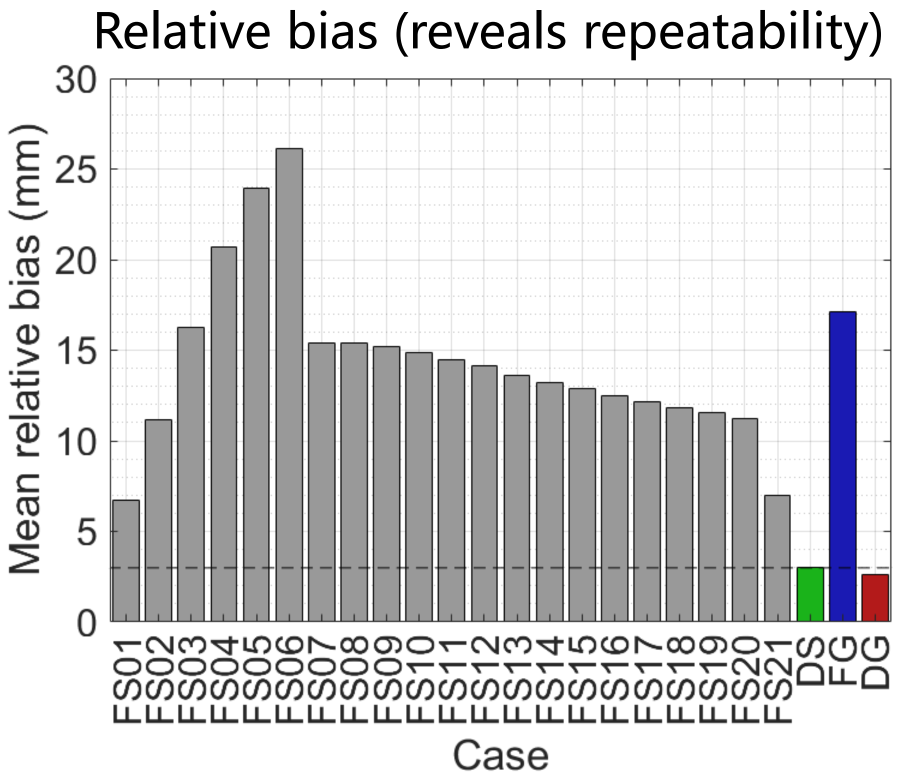
Theoretically, their ZTD series are uniform and the internal overlap accuracy is obtainable.



Results and Analysis

Assessment with closed-loop test





- ✓ The dynamic SPN model outperforms all the fixed ones in both aspects.
- ✓ In this case, the millimeter level accuracy is possible, but only with the proposed dynamic SPN model.

05

Summary and Prospective

Summary and prospective

Significance

- ✓ The proposed dynamic SPN model is prominent, owing to taking both temporal and spatial states of the atmosphere into consideration.
- ✓ High accuracy ZTD profile information is accessible from the airborne GNSS.

Prospective

- ✓ More experiments are required to further assess and support the proposed model.
- ✓ Enhancing the weather forecast and research with the help of the airborne GNSS in practice.

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Thank You!

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