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# Influence of aperiodic non-tidal atmospheric and oceanic loading deformations on the stochastic properties of global GNSS vertical land motion time series

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1           **Influence of aperiodic non-tidal atmospheric and**  
2           **oceanic loading deformations on the stochastic**  
3           **properties of global GNSS vertical land motion time**  
4           **series**

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13           **Key Points:**

- 14           • NTAOL deformations cause a latitudinal bias in parameter estimates of the white  
15           + power-law noise model usually describing GNSS time series.  
16           • Removing NTAOL deformations corrects the latitudinal bias and dramatically re-  
17           duces station velocity uncertainties at high latitudes.  
18           • NTAOL deformations also introduce a seasonal spatial correlation in GNSS ver-  
19           tical land motion time series.

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20 **Abstract**

21 Monitoring vertical land motions (VLMs) at the level of 0.1 mm/yr remains one  
 22 of the most challenging scientific applications of global navigation satellite systems (GNSS).  
 23 Such small rates of change can result from climatic and tectonic phenomena, and their  
 24 detection is important to many solid Earth-related studies, including the prediction of  
 25 coastal sea-level change and the understanding of intraplate deformation. Reaching a level  
 26 of precision allowing to detect such small signals requires a thorough understanding of  
 27 the stochastic variability in GNSS VLM time series. This paper investigates how the aperi-  
 28 odic part of non-tidal atmospheric and oceanic loading (NTAOL) deformations influ-  
 29 ences the stochastic properties of VLM time series. Using the time series of over 10,000  
 30 stations, we describe the impact of correcting for NTAOL deformation on 5 complemen-  
 31 tary metrics, namely: the repeatability of position residuals, the power-spectrum of po-  
 32 sition residuals, the estimated time-correlation properties, the corresponding velocity un-  
 33 certainties, and the spatial correlation of the residuals. We show that NTAOL deforma-  
 34 tions cause a latitude-dependent bias in white noise plus power-law model parameter es-  
 35 timates. This bias is significantly mitigated when correcting for NTAOL deformation,  
 36 which reduces velocity uncertainties at high latitudes by 70%. Therefore, removing NTAOL  
 37 deformation before the statistical analysis of VLM time series might help to detect sub-  
 38 tle VLM signals in these areas. Our spatial correlation analysis also reveals a seasonal-  
 39 ity in the spatial correlation of the residuals, which is reduced after removing NTAOL  
 40 deformation, confirming that NTAOL is a clear source of common-mode errors in GNSS  
 41 VLM time series.

42 **Plain Language Summary**

43 Monitoring vertical land motions (VLMs) at the level of 0.1 mm/yr remains one  
 44 of the most challenging scientific applications of global navigation satellite systems (GNSS).  
 45 Such small rates of change can result from climatic and tectonic phenomena, and their  
 46 detection is important to the prediction of coastal sea-level change and the understand-  
 47 ing of deformation processes acting within tectonic plates. In this paper, we investigate  
 48 to what extent accounting for the deformation of the Earth’s crust due to changes in the  
 49 distribution of the atmospheric and the oceanic pressure helps to detect small vertical  
 50 ground deformation. By analyzing the data from over 10,000 globally distributed GNSS  
 51 stations, we show that accounting for such atmospheric and oceanic deformation can re-  
 52 duce by 70% the uncertainty on the vertical velocity of GNSS stations at high latitudes,  
 53 which could, for instance, improve sea-level change monitoring in these areas.

54 **1 Introduction**

55 Analyzing vertical land motion (VLM) time series estimated from global naviga-  
 56 tion satellite systems (GNSS) provides key information about the deformation of the Earth.  
 57 In particular, estimating GNSS station long-term vertical velocities and their uncertain-  
 58 ties is a crucial step, aiming at giving reliable inputs for the understanding of inter- and  
 59 intraplate tectonic deformation (Elliott et al., 2016; Kreemer et al., 2020), glacial iso-  
 60 static adjustment (Nocquet et al., 2005; Schumacher et al., 2018; Husson et al., 2018),  
 61 and coastal sea-level change (Wöppelmann et al., 2007; Pfeffer & Allemand, 2016; Ballu  
 62 et al., 2019).

63 Measuring vertical deformations at velocities of a few 0.1 mm/yr is one of the most  
 64 challenging scientific applications of GNSS, required to monitor, for instance, slow in-  
 65 traplate (Masson et al., 2019; Craig & Calais, 2014) and climate change-related Earth  
 66 deformations (Wöppelmann & Marcos, 2016). This metrological goal could be met by  
 67 improving the quality of GNSS positioning, the stability of reference frames, and the sta-  
 68 tistical modeling of geodetic time series.

69 To estimate long-term velocities, it is customary to decompose the position time  
70 series as the sum of two parts: a deterministic component and a stochastic variability  
71 (Bos et al., 2020). In practice, the first is described by a trajectory model, whereas the  
72 latter is described by a stochastic model. The trajectory model typically consists of known  
73 parametric functions – trends, offsets, periodic oscillations, and episodic nonlinear motions  
74 – depending on unknown deterministic parameters (Bevis & Brown, 2014). The  
75 stochastic model consists of a set of stochastic processes with known covariance func-  
76 tions depending on unknown stochastic parameters – or variance components – (Bos et  
77 al., 2020).

78 Since the late 1990s, numerous studies demonstrated that the stochastic variabil-  
79 ity of GNSS position time series, often referred to as noise, can be approximated by a  
80 linear combination of white noise (WN) and power-law (PL) processes (Zhang et al., 1997;  
81 Mao et al., 1999; Calais, 1999; Williams et al., 2004; Langbein, 2008; Santamaría-Gómez  
82 et al., 2011). Power-law processes are stochastic processes characterized by their power  
83 spectra  $P(f)$ , which follows a power-law function of the time frequency  $f$ , such that

$$P(f) \approx P_0 \left( \frac{f}{f_0} \right)^\kappa, \quad (1)$$

84 where both  $P_0$  and  $f_0$  are normalization constants, and  $\kappa$  is the so-called spectral index  
85 (Agnew, 1992).

86 The spectral index  $\kappa$  is a scalar identifying the nature of the power-law correlation.  
87 Its reported value usually lies within  $[-3, 1]$  in Earth sciences, and within  $[-2, 0]$  in GNSS  
88 time series analysis. Some power-law processes with integer values of  $\kappa$  are known as white  
89 – that is, uncorrelated – noise ( $\kappa = 0$ ), flicker noise ( $\kappa = -1$ ), and random walk noise  
90 ( $\kappa = -2$ ). The power-law processes with  $\kappa < 0$  are time-correlated. For  $\kappa \leq -1$ , the  
91 power-law process is also non-stationary, and the variance of the process diverges with  
92 time.

93 Accounting for the power-law behavior of the stochastic variability in GNSS po-  
94 sition time series is essential for long-term velocity estimation to obtain realistic estima-  
95 tion of the uncertainties (Williams, 2003a; Santamaría-Gómez et al., 2011). Although  
96 considered in many geodetic studies (Agnew, 1992; Langbein, 2004; Van Camp et al.,  
97 2005), the presence of power-law processes in GNSS position time series remains largely  
98 unexplained (Santamaría-Gómez & Ray, 2021). Given that these power-law processes  
99 are the primary source of uncertainty for velocity estimates, it is crucial to identify their  
100 origin(s) and to reduce their influence on the position time series.

101 The stochastic variability observed in position time series is also spatially corre-  
102 lated (Wdowinski et al., 1997). In global solutions, significant spatial correlations are de-  
103 tected between stations up to a few thousand kilometers apart (Williams et al., 2004;  
104 Amiri-Simkooei, 2009, 2013; Amiri-Simkooei et al., 2017; Benoist et al., 2020). The pres-  
105 ence of large-scale spatial correlations indicates that the stochastic variability cannot be  
106 fully attributed to station-specific errors, and that it probably results from a combina-  
107 tion of large scale positioning errors and non-modelled geophysical or climatic processes  
108 (Amiri-Simkooei et al., 2017; Kreemer & Blewitt, 2021).

109 Possible candidates for explaining large-scale structures in the stochastic variabil-  
110 ity are the non-tidal loading (NTL) deformations, that is, the elastic response of the solid  
111 Earth to changes in the distribution of atmospheric, oceanic, and hydrological loads. Fol-  
112 lowing the International Earth Rotation and Reference System Service (IERS) conven-  
113 tions (Petit & Luzum, 2010), NTL corrections are usually not applied during the esti-  
114 mation of position time series, therefore NTL signals remain in VLMS time series prod-  
115 ucts.

116 Over the last two decades, numerous studies demonstrated that NTL corrections  
 117 derived from numerical climatic load and elastic Earth models help reduce the stochastic  
 118 variability in GNSS VLM time series, whether applied at the GNSS observation level  
 119 – that is, prior to the computation of daily positions – (Gegout et al., 2010; Dach et al.,  
 120 2011; Tregoning & van Dam, 2005; Männel et al., 2019) or at the solution level – that  
 121 is, after computing daily positions – (Van Dam et al., 1994, 2001; Williams & Penna, 2011;  
 122 Van Dam et al., 2012; Martens et al., 2020; Klos et al., 2021). Regarding VLMs, the dif-  
 123 ferences between the two correction strategies seem negligible (Tregoning & Watson, 2009).

124 As numerical climatic load models perform better at retrieving atmospheric and  
 125 oceanic than hydrological loads (Mémin et al., 2020), in this work, we focus on assess-  
 126 ing the effect of non-tidal atmospheric and oceanic loading (NTAOL) deformations on  
 127 the stochastic properties of GNSS VLM time series. NTAOL deformations introduce both  
 128 periodic and aperiodic deformation in VLM time series. Because annual and semi-annual  
 129 signals are always accounted for in the trajectory model, for time series longer than a  
 130 few years, the periodic (i.e., seasonal) part of NTAOL deformations has a negligible in-  
 131 fluence on velocity uncertainties (Blewitt & Lavallée, 2002). This study, therefore, fo-  
 132 cuses on the impact of aperiodic NTAOL deformations.

133 Usually, the influence of NTAOL on the stochastic properties of GNSS time series  
 134 is investigated through the study of change in root mean squared errors (RMSEs) (Tregoning  
 135 & van Dam, 2005; Martens et al., 2020), sometimes at different frequency bands (Mémin  
 136 et al., 2020; Klos et al., 2021). In this work, to further study possible changes in time-  
 137 correlation and try to identify the origin of the stochastic variability in GNSS time se-  
 138 ries, we investigate the influence of correcting for NTAOL deformation (at the solution  
 139 level) on 5 complementary metrics, namely: the repeatability of position residuals, the  
 140 power spectrum of position residuals, their time-correlation properties, the correspond-  
 141 ing velocity uncertainties, and the spatial correlation of position residuals.

142 To describe the stochastic variability and the influence of aperiodic NTAOL defor-  
 143 mations, we investigate each of these metrics using the position time series of over 10,000  
 144 globally distributed GNSS stations. Considering as many stations allows describing with  
 145 an unprecedented resolution the impact of NTAOL deformations on the spatial corre-  
 146 lation of GNSS VLM time series. Besides, systematically analyzing the impact of NTAOL  
 147 deformations on the stochastic properties of each station allows us to evidence previously  
 148 unreported stochastic parameter estimation issues, resulting in recommendations for the  
 149 estimation of velocity uncertainties from global GNSS VLM time series.

## 150 2 Data

### 151 2.1 GNSS position time series

152 We used the North, East, and Up position time series of a total of 10,151 GNSS  
 153 stations processed and distributed by the Nevada Geodetic Laboratory at the Univer-  
 154 sity of Nevada, Reno (Blewitt et al., 2018). This study focuses on the Up coordinates,  
 155 however, the North and East coordinates have been used in the preprocessing for the de-  
 156 tection of discontinuities. NGL’s position time series have been computed using the Jet  
 157 Propulsion Laboratory’s (JPL) GipsyX 1.0 software (Bertiger et al., 2020) based on single-  
 158 station precise point positioning (PPP) with carrier phase ambiguity resolution (Zumberge  
 159 et al., 1997). The satellite orbit and clock used for the PPP processing are JPL’s Re-  
 160 pro 3.0 products. Though we employ the term GNSS for the sake of generality, NGL’s  
 161 processing only exploited observations from the Global Positioning System (GPS). The  
 162 final position time series are expressed in the IGS14 reference frame. Incremental zenith  
 163 wet delays are estimated on top of a priori hydrostatic and wet zenith tropospheric de-  
 164 lays interpolated from the VMF1 grids (Boehm et al., 2006). Both hydrostatic and wet  
 165 zenith delays are mapped to the observation elevations using the Vienna Mapping Func-

166 tion (VMF1). For the ionospheric delays, the first-order effects are removed thanks to  
 167 the use of the ionosphere-free L1/L2 combination and second-order effects are corrected  
 168 using ionospheric TEC maps together with a model of Earth’s magnetic field. For more  
 169 details about NGL’s processing strategy, we refer to <http://geodesy.unr.edu> and Kreemer  
 170 et al. (2020) or Martens et al. (2020).

## 171 2.2 Loading deformation time series

172 To remove NTAOL deformations from GNSS position time series, we used the non-  
 173 tidal atmospheric loading (NTAL) and non-tidal oceanic loading (NTOL) deformation  
 174 time series computed by the Earth System Modelling group of the German Research Cen-  
 175 ter for Geosciences at Potsdam (ESMGFZ) (Dill & Dobsław, 2013). The vertical defor-  
 176 mations caused by NTAL are calculated by the ESMGFZ using the 3-hourly atmospheric  
 177 surface pressure from the European Center for Medium-Range Weather Forecast (ECMWF).  
 178 The vertical deformations caused by NTOL are calculated using the 3-hourly ocean bot-  
 179 tom pressure from the Max-Planck-Institute Meteorology Ocean Model (MPIOM). For  
 180 both load types, vertical displacements are computed using patched Green’s functions  
 181 computed from the ak135 elastic Earth model (Kennett et al., 1995). For more details  
 182 about the ESMGFZ processing strategy, we refer to Dill and Dobsław (2013).

183 NGL’s position time series being expressed in the IGS14 reference frame, we use  
 184 the deformation time series expressed in the center of Earth’s figure frame (CF) (Blewitt,  
 185 2003). Because of the higher sampling rate of ESMGFZ’s NTAOL deformation time se-  
 186 ries, we down-sample ESMGFZ’s time series at NGL’s time series epochs.

## 187 3 Time correlation analysis

### 188 3.1 Position selection

189 For each station, to remove possibly unreliable position estimates, epochs show-  
 190 ing a formal error above 5 mm on any of the three coordinates were ignored. Moreover,  
 191 to eliminate large outliers, the raw position estimates were compared to a running monthly  
 192 median. Any epoch with a position showing a deviation from the median exceeding 5  
 193 times the median absolute deviation, on any of the three coordinates, was discarded (Klos  
 194 et al., 2015).

195 Only position estimates prior to January 2018 were considered in this study. Also,  
 196 as we focus on time correlation, we only used stations presenting time series with over  
 197 1090 daily estimates, that is, more than about 3 years of continuous observations. The  
 198 spans of the considered time series range from 3 to over 20 years, with a median of 8 years.  
 199 The distribution of the GNSS sites with their number of data points are presented in Fig-  
 200 ure S1, provided in the Supporting Information.

### 201 3.2 Trajectory model

202 Noting  $\mathbf{y}$  the  $m \times 1$  observation vector (i.e., a GNSS VLM time series), the tra-  
 203 jectory model describes the expectation  $E\{\cdot\}$  of  $\mathbf{y}$ . To simplify the processing of thou-  
 204 sands of stations, this study only uses linear trajectory models accounting for a linear  
 205 trend, periodic signals, remaining outliers, offsets, and trend discontinuities. The tra-  
 206 jectory model can be expressed as

$$E\{\mathbf{y}\} = \mathbf{A}\mathbf{x}, \quad (2)$$

207 where  $\mathbf{A}$  is the  $m \times n$  design matrix, that is, the Jacobian of the trajectory model, and  
 208  $\mathbf{x}$  is the unknown  $n \times 1$  deterministic parameter vector.

209 The periodic signals accounted for in this trajectory model include the most com-  
 210 monly observed ones in GNSS time series (Ray et al., 2008; Amiri-Simkooei, 2013), namely,  
 211 the annual signal with a period of 365.25 days and its first 2 harmonics, the draconitic  
 212 signal with a period of 351.40 days and its first 7 harmonics, and the 3 fortnightly sig-  
 213 nals with periods of 13.62, 14.17, and 14.76 days.

214 To model the offsets, all the offset dates indicated in the NGL database have been  
 215 considered by default. This database includes dates of known equipment changes and  
 216 possible earthquake-related discontinuities. This database is not necessarily complete for  
 217 all stations, and additional offsets must be detected to improve the trajectory model. This  
 218 issue is addressed using an automatic detection of discontinuities presented in section  
 219 3.6.

### 220 3.3 Stochastic model

221 The stochastic model describes the co-variance  $\text{var}\{\cdot\}$  of the  $m \times 1$  observation vec-  
 222 tor  $\mathbf{y}$ . Under the assumption that the stochastic variability can be approximated by a  
 223 linear combination of homogeneous white noise – that is, uncorrelated with constant vari-  
 224 ance – and a power-law process (WN+PL), the stochastic model reads

$$\text{var}\{\mathbf{y}\} = \mathbf{Q}_y = \sigma_{hw}^2 \mathbf{I} + \sigma_{pl}^2 \mathbf{Q}_\kappa. \quad (3)$$

225 where  $\sigma_{hw}^2$  is the unknown white noise amplitude,  $\mathbf{I}$  is the  $m \times m$  identity matrix,  $\sigma_{pl}^2$   
 226 is the unknown power-law process amplitude,  $\kappa$  is the unknown spectral index, and  $\mathbf{Q}_\kappa$   
 227 is the  $m \times m$  covariance matrix associated to a power-law process of spectral index  $\kappa$   
 228 (Williams, 2003a).

### 229 3.4 Variance component estimation

230 Estimating unknown parameters of the stochastic model can be done using Vari-  
 231 ance Component Estimation (VCE) methods. In this study, we use the Least-Squares  
 232 Variance Component Estimation (LS-VCE) method to estimate the amplitude of each  
 233 process, namely  $\sigma_{hw}^2$  and  $\sigma_{pl}^2$ . Introduced by Teunissen (1988) and further developed by  
 234 Teunissen and Amiri-Simkooei (2008) and Amiri-Simkooei (2007), the LS-VCE method  
 235 is an unbiased and minimum-variance alternative to the more commonly used Maximum  
 236 Likelihood Estimation (MLE) method (Zhang et al., 1997; Williams, 2008; Bos et al.,  
 237 2008; Langbein, 2017) and has already been used in its univariate and multivariate forms  
 238 for GNSS noise analyses (Amiri-Simkooei et al., 2007; Amiri-Simkooei, 2009; Amiri-Simkooei  
 239 et al., 2017).

240 Because the LS-VCE method is unconstrained, it can occasionally return negative  
 241 estimates, which makes no physical sense for stochastic process amplitudes. When en-  
 242 counteracting negative variance estimates, we systematically applied the Non-Negative LS-  
 243 VCE method (NNLS-VCE) introduced in Amiri-Simkooei (2016) to obtain non-negative  
 244 process amplitudes. Though mentioned explicitly in this paper, the non-negativity con-  
 245 straint is the norm, since the nonlinear optimization methods used in most software sim-  
 246 ply do not explore negative solutions (Williams, 2008; Bos et al., 2008; Langbein, 2017).

247 In their linear forms, both the LS-VCE and the NNLS-VCE methods do not al-  
 248 low estimating the unknown spectral index  $\kappa$ . Hence, to assess both the process ampli-  
 249 tudes  $\hat{\sigma}_{hw}^2$  and  $\hat{\sigma}_{pl}^2$ , and the spectral index  $\hat{\kappa}$ , we systematically tested for each time se-  
 250 ries 30 stochastic models with discrete values of  $\kappa$  ranging from  $-1.8$  to  $-0.3$  with a step  
 251 of  $+0.05$ . The most likely  $\hat{\kappa}$  and the corresponding process amplitudes, were chosen as  
 252 those maximizing the restricted likelihood defined in Koch (1986).

253 When VLM is expressed in millimeters (mm), the power-law amplitude estimate  
 254  $\hat{\sigma}_{pl}$  is expressed in (mm yr $^{\kappa/4}$ ) if the scaling of Williams (2003a) is used. Therefore, two  
 255  $\sigma_{pl}$  obtained with different spectral indices are not comparable. To overcome this issue,  
 256 we use a modified standard deviation, noted  $\hat{\sigma}'_{pl}$ , expressed in mm and representing the  
 257 square root of the expected empirical variance of a power-law process over 8 years, which  
 258 is the median cumulative span of the considered VLM time series.

259 Noting  $\mathbf{r}$  a random vector such that  $\mathbf{r} \sim \mathcal{N}(\mathbf{0}, \hat{\sigma}_{pl}^2 \mathbf{Q}_\kappa)$ , the amplitude  $\hat{\sigma}'_{pl}$  is de-  
 260 fined as

$$\hat{\sigma}'_{pl} = \sqrt{\mathbb{E} \left\{ \frac{1}{m'} \sum_{i=1}^{m'} (r_i - \bar{r})^2 \right\}} \quad (4)$$

261 where  $r_i$  is an element of the vector  $\mathbf{r}$ ,  $m'$  is the number of observations for an 8-year long  
 262 time series, and  $\bar{r}$  is the arithmetic mean of the  $r_i$ .

263 As power-law processes with  $\kappa \leq -1$  are non-stationary, their modified standard  
 264 deviations  $\hat{\sigma}'_{pl}$  increase with  $m'$ . Therefore, to allow comparisons between  $\hat{\sigma}'_{pl}$  values,  $m'$   
 265 is kept fixed for all time series.

266 One can show that  $\hat{\sigma}'_{pl}$  can be expressed as

$$\hat{\sigma}'_{pl} = \hat{\sigma}_{pl} \sqrt{\frac{1}{m'} \text{tr}\{\mathbf{Q}'_\kappa\} - \frac{1}{m'^2} \mathbf{u}^T \mathbf{Q}'_\kappa \mathbf{u}} \quad (5)$$

267 with  $\mathbf{u}$  a  $m' \times 1$  vector defined as  $\mathbf{u}^T = [1 \quad 1 \quad \dots \quad 1]$  and  $\mathbf{Q}'_\kappa$  the covariance matrix  
 268 of a power-law process with spectral index  $\kappa$  and length  $m'$ .

### 269 3.5 Residual estimation

270 Part of the investigations presented in this work are based on the analysis of the  
 271 residual VLM time series. Residual time series are computed as the difference between  
 272 the observations and the trajectory model estimated by weighted least-squares (Teunissen,  
 273 2000a). In particular, the residual vector  $\hat{\mathbf{e}}$  is computed from the observation vector  $\mathbf{y}$   
 274 by

$$\hat{\mathbf{e}} = \mathbf{P}_\mathbf{A}^\perp \mathbf{y}, \quad (6)$$

275 in which the  $m \times m$  matrix  $\mathbf{P}_\mathbf{A}^\perp$  is the weighted least-squares orthogonal projector de-  
 276 fined by

$$\mathbf{P}_\mathbf{A}^\perp = \mathbf{I} - \mathbf{A}(\mathbf{A}^T \mathbf{W} \mathbf{A})^{-1} \mathbf{A}^T \mathbf{W}. \quad (7)$$

277 where  $\mathbf{W}$  denotes the  $m \times m$  weight matrix. Hereafter, unless specified otherwise, the  
 278 weight matrix  $\mathbf{W}$  is taken as the inverse of the covariance matrix of the observations:  
 279  $\mathbf{W} = \mathbf{Q}_\mathbf{y}^{-1}$ .

### 280 3.6 Trajectory model improvement

281 As undetected offsets can bias stochastic parameter estimates (Williams, 2003b),  
 282 it is necessary to identify possible additional offsets to the NGL database and to include  
 283 them in the trajectory models. In practice, the offset detection is often done manually,  
 284 since experimented operators tend to perform better than most algorithms (Gazeaux et



285 al., 2013). However, when considering thousands of time series, an automatic detection  
 286 is necessary.

287 Amiri-Simkooei et al. (2019) recently showed that one can improve the automatic  
 288 detection of offsets by accounting for the time-correlated noise, and by analyzing the North  
 289 ( $n$ ), East ( $e$ ), and Up ( $h$ ) coordinates simultaneously. The multivariate LS-VCE used  
 290 in Amiri-Simkooei et al. (2019) assumes constant  $\sigma_{hw}^2/\sigma_{pl}^2$  ratios for all coordinates, which  
 291 might be a risky hypothesis. Here, we relax this hypothesis and adapt the method of Amiri-  
 292 Simkooei et al. (2019) to allow process amplitudes to have different amplitude ratios for  
 293 each coordinate. We then check for discontinuities, including offsets, outliers, and veloc-  
 294 ity changes.

295 The detection method is derived from the Detection Identification Adaptation (DIA)  
 296 procedure introduced by Baarda (1968); Teunissen (2000b). Applied to the detection of  
 297 offsets, outliers, or velocity changes, the DIA procedure consists in testing a null hypoth-  
 298 esis  $H_0 : \mathbf{E}\{\mathbf{y}\} = \mathbf{A}\mathbf{x}$  against an alternative hypothesis  $H_a : \mathbf{E}\{\mathbf{y}\} = \mathbf{A}\mathbf{x} + \mathbf{c}_a(t_k)x_a$ , in  
 299 which  $\mathbf{c}_a(t_k)$  is the known  $m \times 1$  Jacobian vector of a discontinuity of type  $a$  (either an  
 300 offset, an outlier or a velocity change) at time  $t_k$  with an unknown amplitude  $x_a$ . Ac-  
 301 cording to Teunissen (2000b), accepting or rejecting  $H_0$  depends on the value of a  $T$ -statistic  
 302 defined by

$$T_a(t_k) = \frac{(\mathbf{c}_a^T(t_k)\mathbf{Q}_y^{-1}\hat{\mathbf{e}})^2}{\mathbf{c}_a^T(t_k)\mathbf{Q}_y^{-1}\mathbf{P}_A^\perp\mathbf{c}_a(t_k)}. \quad (8)$$

303 Under  $H_0$ , the random variable  $T_a(t_k)$  follows a central chi-squared distribution with  
 304 1 degree of freedom:  $T_a(t_k) \sim \chi^2(1, 0)$ . Hence, for a given confidence level  $\alpha$ , if  $T_a(t_k) >$   
 305  $\chi_\alpha^2(1, 0)$ , the null hypothesis can be rejected and  $\mathbf{c}_a$  can be added to the columns of the  
 306 design matrix  $\mathbf{A}$ .

307 To combine the information of all coordinates, we define the power  $P_a(t_k)$  of a dis-  
 308 continuity  $\mathbf{c}_a(t_k)$  at time  $t_k$  as the sum of the  $T$ -statistics estimated on each coordinate,  
 309 that is

$$P_a(t_k) = \sum_{i \in \{n, e, h\}} T_a^{(i)}(t_k), \quad (9)$$

310 where the residual vector  $\hat{\mathbf{e}}_{(i)}$ , the covariance matrix  $\mathbf{Q}_{y(i)}$ , and the orthogonal projec-  
 311 tor  $\mathbf{P}_{A(i)}^\perp$  are specific to each coordinate ( $i$ ).

312 Assuming that the coordinates are uncorrelated (Amiri-Simkooei, 2009; Benoist et  
 313 al., 2020), under  $H_0$ , the power  $P_a(t_k)$  follows a central chi-squared distribution with 3  
 314 degrees of freedom, that is  $P_a(t_k) \sim \chi^2(3, 0)$ .

315 The chi-squared distribution of  $T_a(t_k)$  and  $P_a(t_k)$  is based on the assumption that  
 316 the covariance matrices  $\mathbf{Q}_{y(i)}$  are known. However, the two variance components  $\sigma_w^2$  and  
 317  $\sigma_{pl}^2$  are unknown and must be estimated. In such a case, the exact distribution of  $T_a(t_k)$   
 318 becomes intractable. Nonetheless, the chi-squared distribution remains a good approx-  
 319 imation, as the redundancy of the trajectory model  $m - n$  is large (Amiri-Simkooei et  
 320 al., 2019).

321 To find a candidate for the alternative hypothesis  $\mathbf{c}_a(t_k)$ , offsets  $\mathbf{c}_o(t_k)$ , outliers  $\mathbf{c}_t(t_k)$ ,  
 322 and velocity changes  $\mathbf{c}_v(t_k)$  were systematically tested for each epoch  $t_k$ . The most-likely  
 323 discontinuity date  $\hat{t}_k$  and type  $\hat{a}$ , were chosen as

$$\hat{a}, \hat{t}_k = \arg \max_{a, t_k} P_a(t_k). \quad (10)$$

324 When the power of the most likely alternative  $P_{\hat{a}}(\hat{t}_k)$  exceeded a given threshold  
 325  $P_{\hat{a}}(\hat{t}_k) > 25$ , the discontinuity  $\mathbf{c}_{\hat{a}}(\hat{t}_k)$  was added to the trajectory model. The thresh-  
 326 old value 25 is arbitrarily chosen and corresponds to a confidence level  $\alpha > 0.9999$  un-  
 327 der the  $\chi^2(3, 0)$  hypothesis. This detection procedure was repeated until no significant  
 328 discontinuities were found anymore. At each iteration, the variance components of the  
 329 stochastic model were (re)estimated for all coordinates. To reduce the computational bur-  
 330 den, and for this detection step only, we used a fixed spectral index  $\kappa = -0.80$  and the  
 331 NNLS-VCE method by default.

332 In the end, an average of 2.49 offsets, 0.67 outliers, and 0.97 velocity changes were  
 333 added to the trajectory model of each station. To compensate for the linearity of the tra-  
 334 jectory model, stations showing nonlinear behaviors such as post-seismic deformation present  
 335 more offsets and velocity changes than the others. But the median number discontinu-  
 336 ity per station is actually 1.0 for the offsets and 0.0 for both the outliers and the veloc-  
 337 ity changes. The imperfect nature of this detection procedure certainly results in an over-  
 338 parameterization of the trajectory model of some stations. However, considering that  
 339 we focus on large scale patterns obtained from a large number of independently processed  
 340 stations, a possible over-parameterization of a few trajectory models is unlikely to af-  
 341 fect the results discussed in section 5.

## 342 4 Spatial correlation analysis

343 Williams et al. (2004) computed the variation of the cross-correlation between pairs  
 344 of residual time series with the station’s separation distance. Amiri-Simkooei (2009); Amiri-  
 345 Simkooei et al. (2017) did a similar analysis but used a particular metric to take time  
 346 correlation into account. However, this metric, based on the multivariate LS-VCE (Amiri-  
 347 Simkooei, 2009), assumes an identical white noise to power-law amplitude ratio and an  
 348 identical spectral index for all the time series. Benoist et al. (2020) assumed a second-  
 349 order stationary spatial distribution of residuals and investigated the spatial correlation  
 350 using variograms (Wackernagel, 2013).

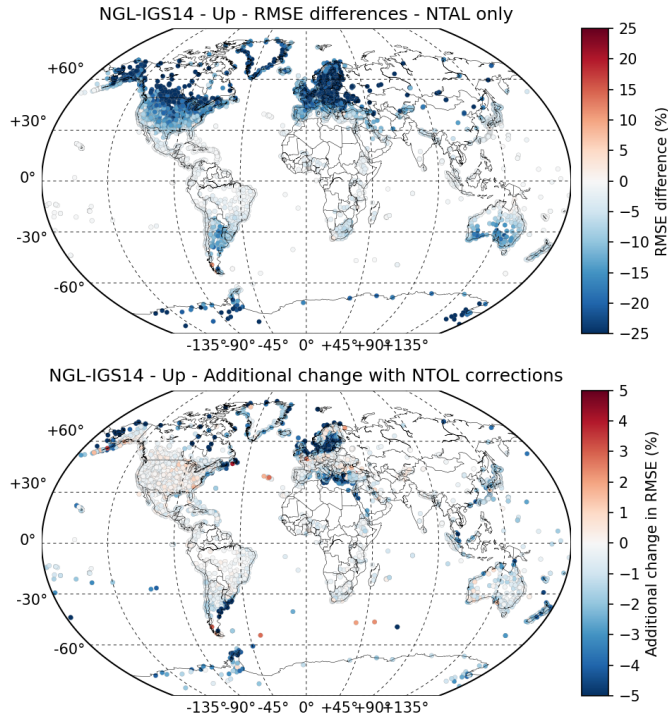
351 In these studies, the spatial correlation coefficients were systematically estimated  
 352 using all observations over a span of a few years. In results, the estimated coefficient was  
 353 an average over the considered span. In practice, for short time scales, let us say a few  
 354 weeks, one would expect the spatial correlation structure to show a time-variable behav-  
 355 ior, especially if position residuals are linked to climate-related mass redistribution.

356 Hence, to investigate the time dependence of the spatial correlation, we computed  
 357 the Pearson correlation coefficients between pairs of residual time series over running win-  
 358 dows of 30 days. We then averaged these pairwise correlation coefficients for 200 inde-  
 359 pendent classes of separation distances, ranging from  $[0, 100]$  to  $[19900, 20000]$  km. Cor-  
 360 relation coefficients obtained from 30-day windows are less precise than those based on  
 361 several years. However, given the number of stations analyzed in this study, the final spa-  
 362 tial correlation estimates result from an average of over a few hundred thousands pairs  
 363 in each distance class, making them robust and interpretable nevertheless.

## 364 5 Influence of aperiodic NTAOL deformations

### 365 5.1 Repeatability

366 To measure the change in repeatability resulting from the correction of either NTAL  
 367 or NTOL deformations, we analyze RMSE reductions. In this part, residuals are com-  
 368 puted using the unweighted least-squares adjustment, that is, using  $\mathbf{W} = \mathbf{I}$  in Equa-  
 369 tion 7. As the trajectory model accounts for annual and semi-annual signals, the changes  
 370 in RMSE do not reflect changes of the seasonal variations in the series, as those are not  
 371 present in the residuals.

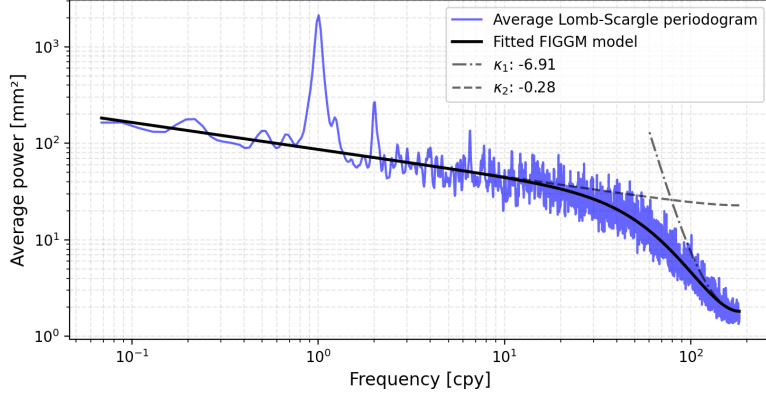


**Figure 1.** Global distribution of change in RMSE after removing ESMGFZ's NTAL deformation predictions only (top), and additional change in RMSE after also removing NTOL deformation predictions (bottom).

372 The global distribution of the change in RMSE obtained after removing NTAL de-  
 373 formations, and the additional change resulting from also removing NTOL deforma-  
 374 tions, are presented in Figure 1. NTAL corrections result in an RMSE reduction for 97.5% of  
 375 the stations. The global-average change in RMSE is  $-11.4\%$ , but the differences are more  
 376 pronounced at latitude over  $\pm 45.0^\circ$  than near the equator, where the atmospheric pres-  
 377 sure is less variable (Van Dam & Wahr, 1987). NTOL corrections result in an additional  
 378 RMSE reduction for 72.8% of the stations. Though lower by a factor 5, the impact of  
 379 NTOL, like that of NTAL, is higher near the poles, but logically confined to coastal ar-  
 380 eas. With an overall reduction of about 30% at high latitudes and about 0% at the equa-  
 381 tor, the high latitude reduction observed here is about 10% better than that reported  
 382 in Fig. 7 in Mémin et al. (2020), probably because their dataset mostly contains coastal  
 383 GNSS stations.

384 Our results show that the correction of either NTAL or NTOL deformations results  
 385 in a quasi-systematic scatter reduction of the aperiodic VLM residual time series. Hence,  
 386 though this dataset aggregates observation from GNSS stations with variable geodetic  
 387 quality, the recently reprocessed NGL's position time series are, nonetheless, of particu-  
 388 lar interest for NTL deformation studies.

389 Because removing NTAL and NTOL deformations results in RMSE reduction for  
 390 the wide majority of stations, in the following, we focus on their combined effect, that  
 391 is, the impact of the non-tidal atmospheric and oceanic loading (NTAOL=NTAL+NTOL)  
 392 on the spectral, temporal, and spatial properties of the stochastic variability in VLM time  
 393 series.



**Figure 2.** Average Lomb-Scargle periodogram of the ESMGFZ’s vertical NTAOL deformation time series (blue solid line). The NTAOL deformation time series have the same sampling and gaps as the GNSS time series. The average power is computed using only time series with a span longer than the considered period. The average power spectrum is approximated by a Fractionally Integrated Generalized Gauss-Markov model (FIGGM, black solid line). The dash dotted black line represents the spectral index  $\kappa_1 = -6.91$  at high frequencies. The dashed black line represents the spectral index  $\kappa_2 = -0.28$  at low frequencies.

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## 5.2 Average power spectrum

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The improved repeatability observed in the previous section does not indicate whether NTAOL deformations are time-correlated. One way to investigate this effect is to analyze the average power spectrum of the NTAOL deformation time series. In Figure 2, we present the average Lomb-Scargle periodogram of the ESMGFZ’s vertical NTAOL deformation time series at the GNSS sites.

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The energy of the spectrum is mainly concentrated at low frequencies and rapidly decreases at high frequencies. This indicates that NTAOL deformations are time-correlated. However, the shape of the power-spectrum does not resemble that expected from the combination of white noise and power-law processes, as it collapses instead of flattening at high frequencies. More precisely, the average power-spectrum shows two distinct slopes above, and below, 20.0 cycles per year [cpy]. Time series presenting such a behavior can be well described by a fractionally integrated generalized Gauss-Markov (FIGGM) process (Bos et al., 2020).

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The power spectrum  $P(f)$  of a discrete FIGGM process reads

$$P(f) = 2 \frac{\sigma^2}{f_s} [1 + \phi^2 - 2\phi \cos(2\pi f/f_s)]^{\kappa_1/2} \times [2 \sin(\pi f/f_s)]^{\kappa_2}, \quad (11)$$

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in which  $\sigma^2$  denotes the amplitude of the process,  $f_s$  denotes the sampling frequency in cpy,  $\kappa_1$  denotes the spectral index at high frequencies,  $\kappa_2$  denotes that at low frequencies, and  $\phi$  denotes the Gauss-Markov parameter controlling the transition between both.

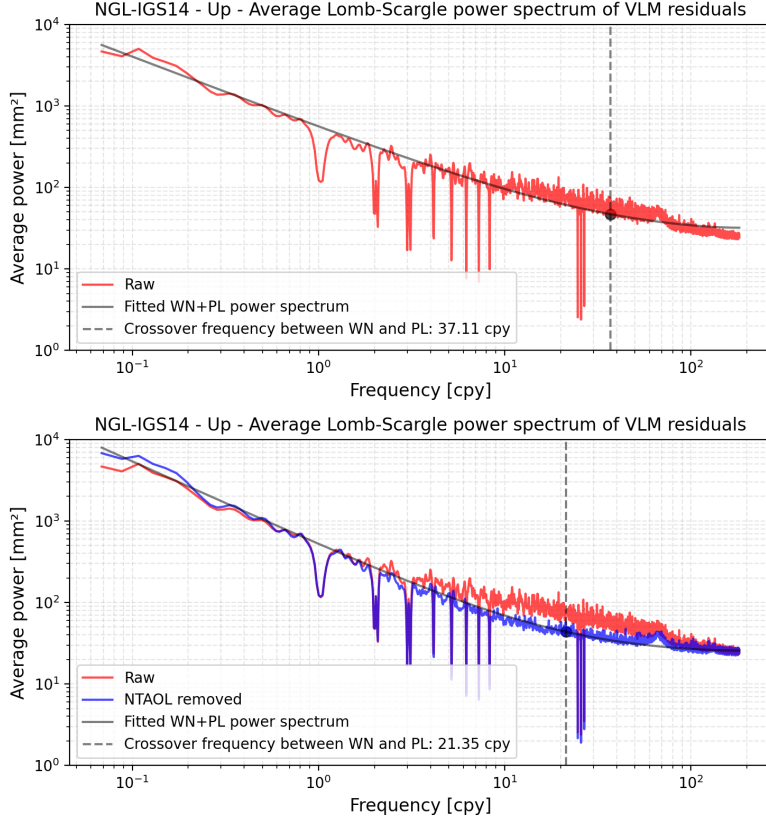
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The estimated low-frequency spectral index of NTAOL deformation is  $\hat{\kappa}_2 = -0.28$  whereas, at high frequencies,  $\hat{\kappa}_1 = -6.91$ . The power-spectrum at high frequencies does not closely follow the steep  $\hat{\kappa}_1$  slope because of the early transition to  $\hat{\kappa}_2$ , due to a small Gauss-Markov parameter ( $\hat{\phi} = 0.18$ ) corresponding to a crossover frequency of 78.8 cpy.



**Figure 3.** Average Lomb-Scargle periodogram of residual GNSS position time series before (top) and after removing the NTAOL deformations (bottom). The average power is computed using only time series with a span longer than the considered period.

416 To investigate how the FIGGM nature of NTAOL deformations affects the spec-  
 417 tral properties of the stochastic variability in GNSS time series, we computed the aver-  
 418 age Lomb-Scargle periodogram of VLM residuals before and after removing NTAOL  
 419 deformations. Unlike in the previous section, hereafter, the VLM residuals are estimated  
 420 using the inverse of the estimated covariance matrix as the weight matrix, that is, us-  
 421 ing  $\mathbf{W} = \mathbf{Q}_y^{-1}$  in Equation 7. Both periodograms are presented in Figure 3.

422 In each plot, we observe power drops at the seasonal, draconitic, and fortnightly  
 423 frequencies accounted for in the trajectory model because the power at these frequen-  
 424 cies is absorbed by the deterministic parameters (see Section 3.2). Besides these frequen-  
 425 cy-specific drops, both power spectra tend to follow that expected from a WN+PL model,  
 426 that is, a slope close to  $-1.00$  (flicker noise) at low frequencies and a flattening at high  
 427 frequencies. Thus, the WN+PL stochastic model used for variance component estima-  
 428 tion (section 5.3) seems well-suited to both cases. To illustrate this, in Figure 3, WN+PL  
 429 power spectra have been adjusted to each average Lomb-Scargle periodogram. The crossover  
 430 frequency – that is, the frequency where the power resulting from white noise equals that  
 431 of the power-law process – is also presented in both cases.

432 Before NTAOL correction, although the WN+PL model approximates the over-  
 433 all shape of the periodogram, it fails to describe the increase in power due to NTAOL  
 434 deformations between 10 cpy and 70 cpy. On the other hand, after NTAOL correction,  
 435 there is a much better agreement between the average periodogram and the WN+PL

436 model. We also observe a more pronounced flattening at high frequencies, which moves  
 437 the estimated crossover frequency between WN and PL from 37.11 cpy to 21.35 cpy. A  
 438 wide spectral peak at 66.4 cpy, already reported in Amiri-Simkooei (2013) and Ray et  
 439 al. (2013), possibly related to the PPP processing (Selle et al., 2014; Amiri-Simkooei et  
 440 al., 2017), is also more visible after NTAOL corrections.

441 The difference in power spectra in Figure 3 differs from that in Fig. 8 in Männel  
 442 et al. (2019), which shows meager differences at high-frequencies and more pronounced  
 443 ones at low-frequencies. There are two possible reasons for the differences at high-frequencies.  
 444 The first one is that we use about 65 times more stations, most of them located in Eu-  
 445 rope and North America. Thus, by averaging, Figure 3 might better reveal NTAOL sig-  
 446 nals in these areas. Another possibility is the use of the Global Mapping Function (GMF)  
 447 (Böhm et al., 2006) by Männel et al. (2019), which might result in tropospheric mod-  
 448 eling errors that partially compensate for the atmospheric loading signal (Steigenberger  
 449 et al., 2009) and reduce the influence of NTAOL corrections on their VLMs time series  
 450 (Martens et al., 2020). The high-frequency flattening of the power-spectrum after NTAOL  
 451 correction presented in this work (Figure 3) seems in better agreement with that pre-  
 452 sented in Fig. 8 of Tregoning and Watson (2009).

453 Regarding the low-frequencies, the more significant differences in Männel et al. (2019)  
 454 are likely due to the correction of hydrology loading, not applied in this work. Also, as  
 455 the spectral properties of the estimated residuals depend on the estimated stochastic model  
 456 (through the weight matrix in Equation 7), the change of slope at low-frequencies in Fig-  
 457 ure 3 is undoubtedly due to the significant changes in spectral indices at mid-latitudes,  
 458 which we present in the following section.

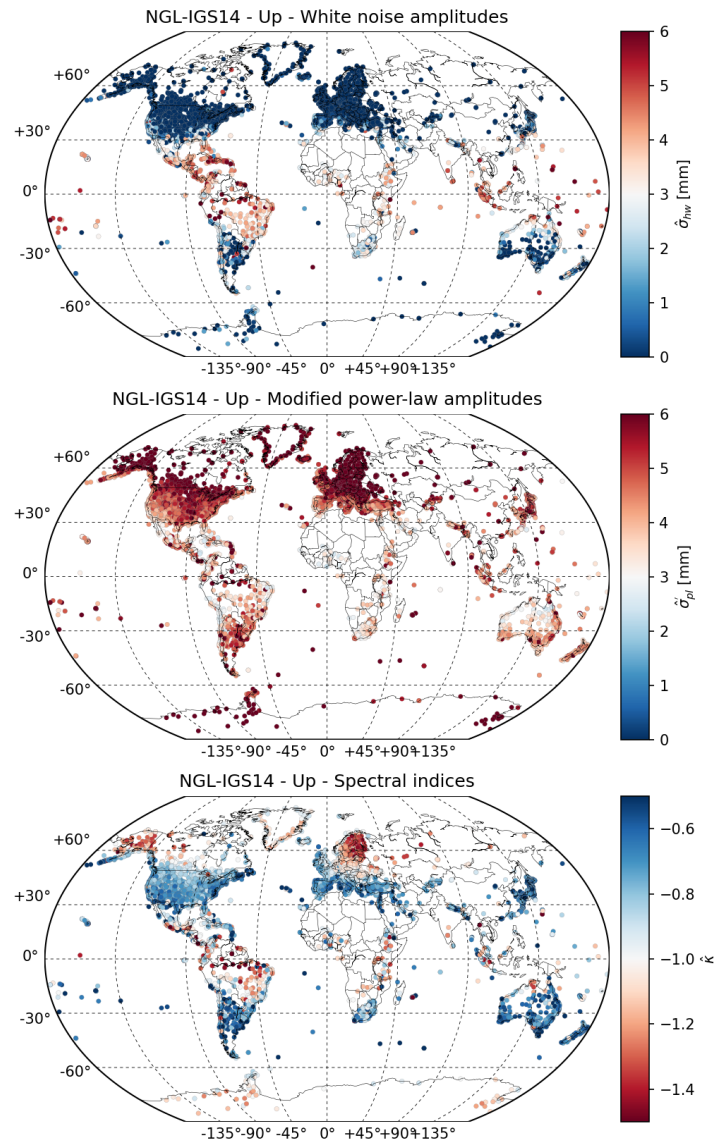
### 459 5.3 Spatial variability of variance components

460 In this section, we present the influence of removing NTAOL deformation on the  
 461 spatial variability of the estimated white noise amplitudes  $\hat{\sigma}_{hw}$ , modified power-law am-  
 462 plitudes  $\hat{\sigma}'_{pl}$ , spectral indices  $\hat{\kappa}$ , and RMSEs.

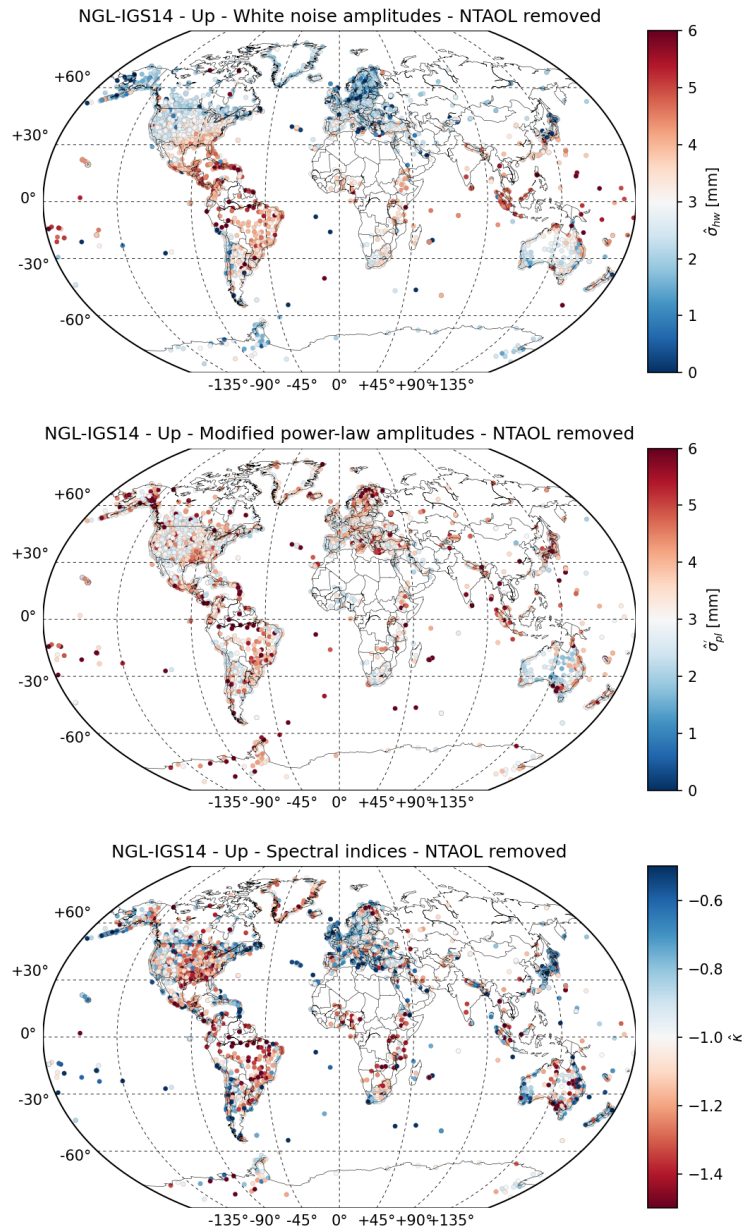
463 The global distribution of the estimated variance components using raw VLM time  
 464 series are presented in Figure 4. That obtained using VLM time series with NTAOL de-  
 465 formations removed are presented in Figure 5. All stochastic parameters show a strong  
 466 global scale variability, mostly characterized by a latitude dependence, which Figure 6  
 467 evidences and compares before and after removal of NTAOL deformation, showing also  
 468 the RMSE changes in parallel. To improve the legibility of Figure 6, we represent run-  
 469 ning medians and interquartile ranges over  $+10.0^\circ$  latitude windows. In the following,  
 470 the quantitative description of the latitude dependence refers to these running medians  
 471 and not the individual station estimates.

472 Before removing NTAOL deformations, the estimated white noise amplitudes reach  
 473 a maximum of about 4.0 mm near the equator and are almost always equal to 0.0 mm  
 474 for latitudes over  $\pm 40.0^\circ$ , forming an equatorial bulge. After the removal of NTAOL de-  
 475 formations, the spatial variability of the stochastic parameters is strongly modified (Fig-  
 476 ure 5). Instead of being null everywhere but at low latitudes, the white noise amplitude  
 477 is now non-zero everywhere. This does not indicate that NTAOL corrections introduce  
 478 additional white noise in the series, but rather that white noise amplitude estimates based  
 479 on the uncorrected series were biased low, due to NTAOL deformations partially hid-  
 480 ding white noise (see Figure 3). The equatorial bulge in white noise amplitudes remains  
 481 visible, with a minimum of 2.0 mm near the poles and a maximum of about 4.0 mm at  
 482 the equator.

483 This bulge was originally pointed out by Williams et al. (2004) but was also more  
 484 recently observed in IGS station position time series by Klos et al. (2019). Williams et  
 485 al. (2004) suggested that the origin of this bulge could reside in mis-modeling of the at-

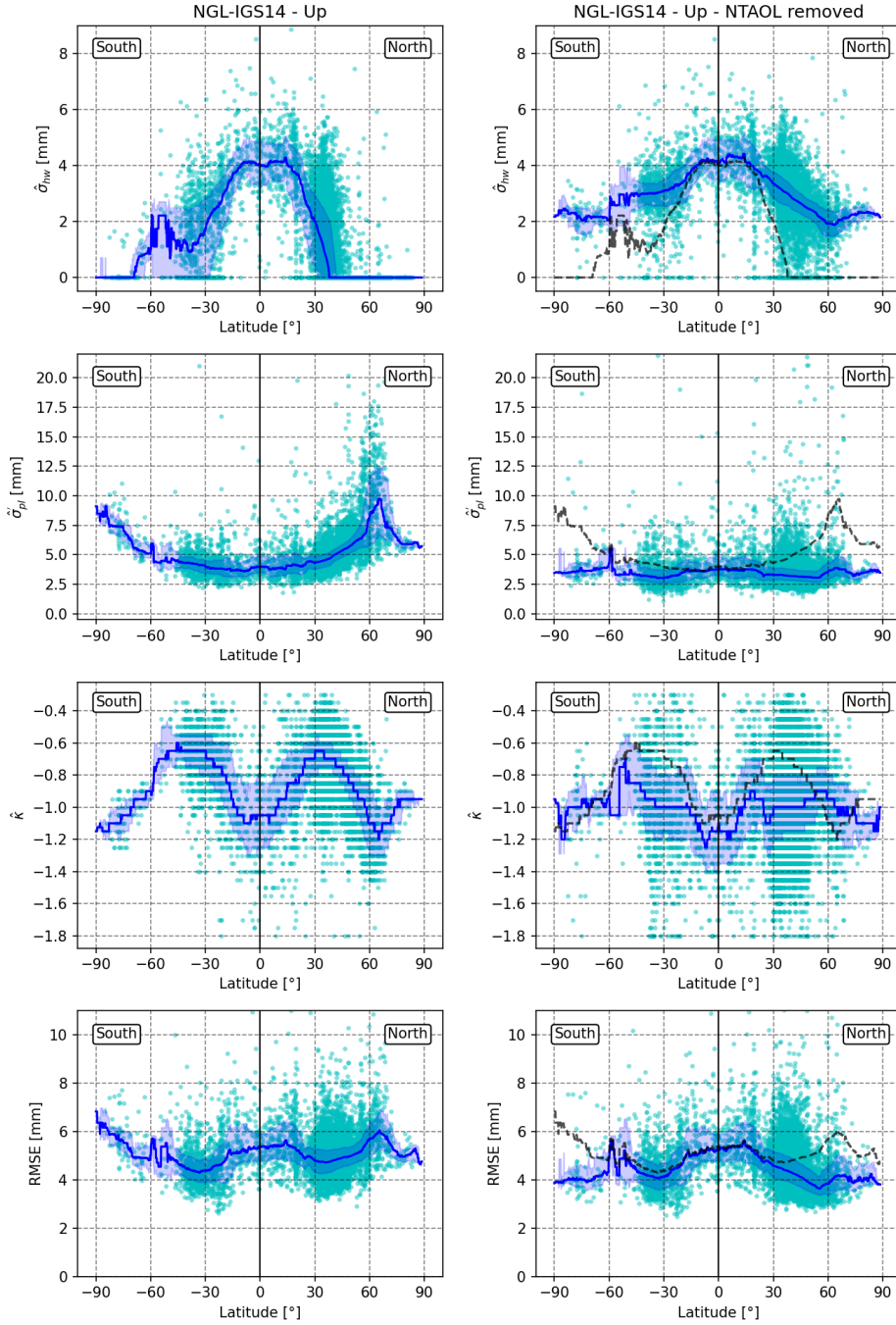


**Figure 4.** Global distribution of stochastic parameters estimated from raw VLM time series. White noise amplitudes (top). Modified power-law amplitudes (middle). Spectral indices (bottom).



**Figure 5.** Global distribution of stochastic parameters estimated from VLM time series with NTAOL deformations removed. White noise amplitudes (top). Modified power-law amplitudes (middle). Spectral indices (bottom).





**Figure 6.** Latitude dependence of white noise amplitudes  $\hat{\sigma}_{hw}$  (top), spectral indices  $\hat{\kappa}$  (upper middle), power-law amplitudes  $\hat{\sigma}'_{pl}$  (lower middle), and RMSEs (bottom), in the presence of NTAOL deformations (left) and with NTAOL deformations removed (right). The dots in cyan represent the station-specific estimates. The continuous blue lines represent running medians over 10° latitude windows. The shaded areas represent the corresponding interquartile ranges. The dashed black lines are the running medians before NTAOL correction, reported in the right plots for comparison with results after NTAOL correction.

486 mospheric delays affecting GNSS observations. Although the NGL-IGS14 solution used  
 487 in this study benefits from recent improvements in the modeling of both tropospheric  
 488 and second-order ionospheric effects, the bulge remains visible in both datasets. Hence,  
 489 further investigations are needed to identify its causes and to reduce its amplitude.

490 Unlike white noise amplitudes, the modified power-law amplitudes before remov-  
 491 ing NTAOL deformations reach a minimum amplitude of 3.5 mm near the equator and  
 492 are maximum at high latitudes, especially near the latitude  $+65.0^\circ$ , where they peak at  
 493 10.0 mm. The estimated spectral indices show a bi-modal distribution with a maximum  
 494 of about  $-0.65$  near  $\pm 40.0^\circ$  and a minimum of about  $-1.10$  near latitudes  $-90.0^\circ$ ,  $0.0^\circ$ ,  
 495 and  $+65.0^\circ$ . In other words, the estimated stochastic variability shows longer memory  
 496 effects near the equator and near the poles than at mid-latitudes. After the removal of  
 497 NTAOL deformations, the modified power-law amplitudes are dramatically reduced at  
 498 middle and high latitudes, making their latitude dependence almost disappear. The power-  
 499 law amplitudes now uniformly lie in a narrow range centered around 3.5 mm. For spec-  
 500 tral indices, as for the other parameters, the latitude dependence is also affected. After  
 501 removing NTAOL deformations, the latitudinal medians of the estimated spectral indices  
 502 no longer show a bi-modal distribution, but a flatter latitude dependence centered on  
 503  $-1.00$ , that is, flicker noise. In addition, their interquartile range shows an increase at  
 504 mid-latitudes, indicating that the spatial distribution is more complex than just a lat-  
 505 itude dependence (see Figure 5).

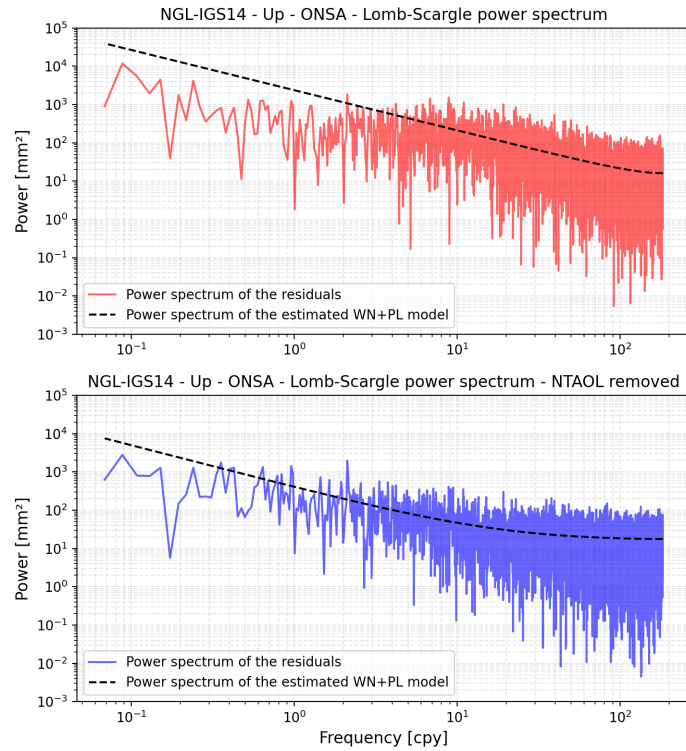
506 The striking latitude dependence of power-law amplitudes and spectral indices  $\hat{\sigma}'_{pl}$   
 507 visible in Figure 4 was not observed by Williams et al. (2004). This difference is likely  
 508 due to the processing improvements having occurred over the past 17 years. Such global  
 509 scale patterns have however been pointed out in Klos et al. (2019, 2020). In Europe, Klos  
 510 and Bogusz (2017); Gruszczynski et al. (2019) and Klos et al. (2021), suggested that NTL  
 511 deformations could be the cause of the spatial variability of stochastic parameters ob-  
 512 served in the Up component. The observed impact of NTAOL corrections at the global  
 513 scale from Figures 5 and 6 is consistent with this hypothesis.

514 Before removing NTAOL deformations, the RMSEs are centered around 5.1 mm  
 515 and reach maxima of about 6.0 mm near the poles and about 5.6 mm near the equator.  
 516 After the removal of NTAOL deformations, they now show a slightly subdued latitudi-  
 517 nal profile mainly resulting from their significant decrease, from 6.0 mm to 4.0 mm, at  
 518 high latitudes, while their values at low latitudes stay unchanged.

519 Note that, at high latitudes, before removing NTAOL deformations, the amplitude  
 520 of power-law processes alone exceeds the RMSE of the residuals (Figure 6). As the RMSE  
 521 accounts for the total effect of white noise plus power-law processes, this indicates that  
 522 there is a bias in the estimation of the power-law parameters. To illustrate how the es-  
 523 timated stochastic parameters change with NTAOL correction, Figure 7 presents the Lomb-  
 524 Scargle periodogram of the VLM residuals along with the WN+PL power spectrum ex-  
 525 pected from the estimated stochastic parameters for station ONSA (Onsala, Sweden),  
 526 both before and after NTAOL correction.

527 Before NTAOL correction, the estimated power spectrum differs from the Lomb-  
 528 Scargle periodogram of the residuals because of the non-modelled variability at sub-annual  
 529 periods resulting from the presence of NTAOL deformations (Figure 2). This illustrates  
 530 that, at high latitudes, where the scatter of the NTAOL deformation is the largest (Tregoning  
 531 & van Dam, 2005), the usual WN+PL stochastic model is not appropriate and the as-  
 532 sociated parameter estimates are not reliable. However, after NTAOL correction, the non-  
 533 modelled sub-annual variability is removed, the stochastic variability resembles more that  
 534 of the WN+PL model, which results in more interpretable parameter estimates.

535 In principle, considering a WN+PL+FIGGM stochastic model instead of a WN+PL  
 536 one could also be a solution to this problem. However, adding a FIGGM process to the



**Figure 7.** Power spectra of the VLM time series of station ONSA (Onsala, Sweden), before (top) and after (bottom) removing NTAOL deformations. The colored lines are the Lomb-Scargle periodograms of the VLM residuals. The black dashed lines are the WN+PL power spectra expected from the estimated stochastic parameters.

537 stochastic model would lead to a more complex and nonlinear variance component es-  
 538 timation problem. Correct for the NTAOL deformations before stochastic parameter es-  
 539 timation is a more efficient and pragmatic solution.

540 Figures 4, 5 and 6 show that all stochastic parameters show a spatial variability,  
 541 both before and after NTAOL correction. Hence, considering spatially variable stochas-  
 542 tic process amplitudes and spectral indices is preferable when analyzing VLM time se-  
 543 ries. In particular, the assumption of a constant spectral index and of a constant power-  
 544 law to white noise amplitude ratio for all stations, as done in Amiri-Simkooei (2013); Amiri-  
 545 Simkooei et al. (2017), seems sub-optimal in global solutions.

546 Although we demonstrated that a large part of the spatial variability of stochas-  
 547 tic parameters can be attributed to the influence of NTAOL deformations, Figure 5 clearly  
 548 shows that non-latitudinal patterns remain. This residual variability could be further  
 549 reduced by improving the accuracy of NTAOL prediction or by accounting also for hy-  
 550 drological loading deformations. Once the strong impact of NTAOL deformation is re-  
 551 moved, detecting the influence of the monumentation quality on the stochastic param-  
 552 eters of individual stations in global solutions might become easier (Langbein & Svarc,  
 553 2019).

#### 554 5.4 Velocity uncertainties

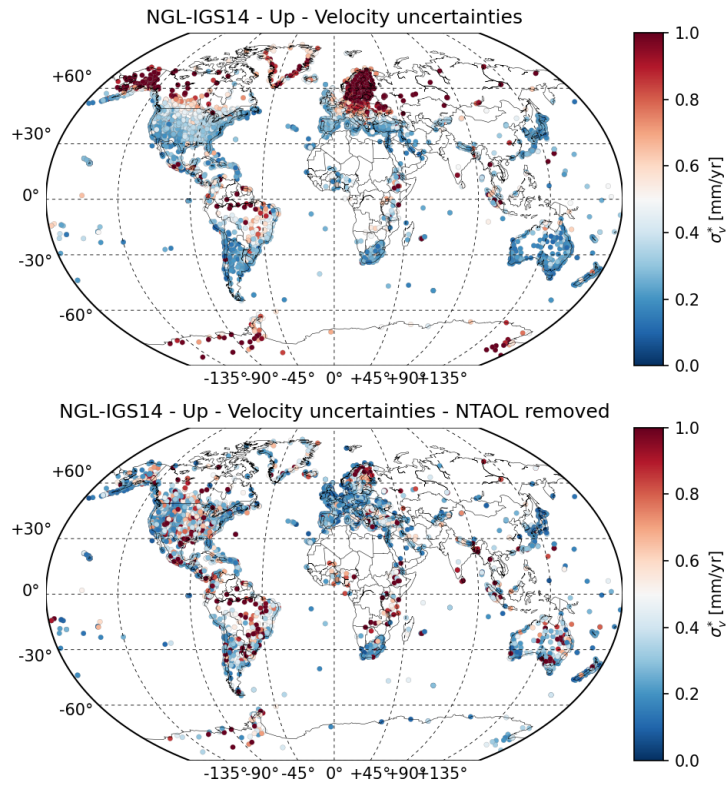
555 Velocity uncertainties depend on the estimated stochastic properties, but also on  
 556 each station’s functional model and span. To isolate the influence of the stochastic prop-  
 557 erties, for a given stochastic model, we define the minimum 8-year velocity uncertainty,  
 558 noted  $\sigma_v^*$ , as the expected standard deviation of the velocity estimated assuming a con-  
 559 tinuous 8-year long time series with a trajectory model consisting of a linear trend and  
 560 the periodic signals presented in section 3.2.  $\sigma_v^*$  is a lower bound estimate because miss-  
 561 ing values and additional deterministic parameters would increase the velocity uncertainty.

562 Figure 8 shows the global distribution of  $\sigma_v^*$  obtained from the stochastic param-  
 563 eters estimated before and after NTAOL correction. Figure 9 depicts their latitudinal  
 564 distributions along with the running medians and the interquartile ranges over  $+10.0^\circ$   
 565 latitude windows. In the Supporting Information, Figure S2 presents an alternative to  
 566 Figure 8, in which the velocity uncertainties account for the full span of each VLM time  
 567 series.

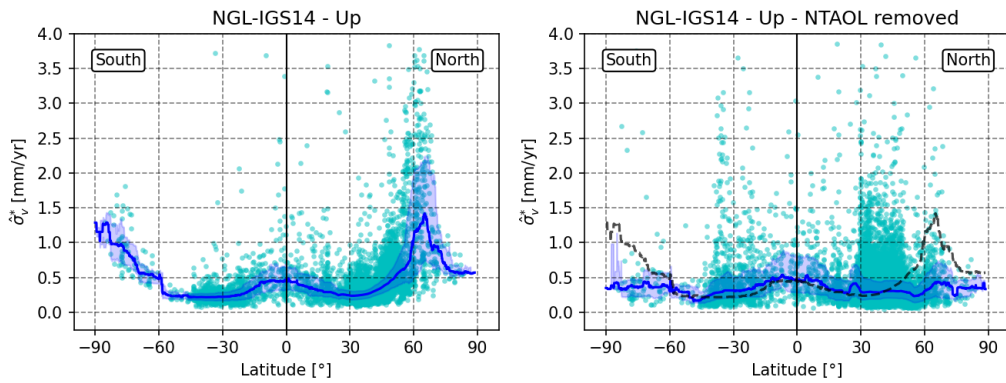
568 Before removing NTAOL deformations  $\sigma_v^*$  is maximum at high latitudes, namely,  
 569 in Alaska, Canada, around the Baltic Sea, Russia, Antarctica, but also within the Ama-  
 570 zon basin. More precisely, the median  $\sigma_v^*$  reaches a maximum of 1.42 mm/yr around the  
 571 latitude  $+65.0^\circ$ , and a minimum of about 0.24 mm/yr near  $\pm 30^\circ$  latitudes.

572 After NTAOL correction, the latitude dependence of  $\sigma_v^*$  is dramatically reduced.  
 573 The median  $\sigma_v^*$  are now centered around 0.37 mm/yr at all latitudes, with a maximum  
 574 of 0.55 mm/yr near the equator and a minimum around 0.26 mm/yr near  $\pm 45^\circ$  latitudes.  
 575 The most dramatic reduction of  $\sigma_v^*$  is observed around the latitude  $+65.0^\circ$ , where  $\sigma_v^*$  drops  
 576 from 1.42 mm/yr to 0.43 mm/yr, that is, a 69.7% decrease. However, the reduction in  
 577 uncertainty is not systematic and concerns only 49.6% of the stations. The other 50.4%  
 578 show a moderate increase in  $\sigma_v^*$  (Figure 9) because of the variance component estima-  
 579 tion bias caused by uncorrected NTAOL deformations, which results in overestimated  
 580 spectral indices at mid-latitudes (e.g., Figure 6).

581 The other stations, mostly localized at mid-latitudes, show a moderate increase in  
 582 uncertainty. An apparent increase in outliers is also observed at mid-latitudes, mainly  
 583 caused by groups of stations near the northern coasts of the Gulf of Mexico, the south  
 584 of Brazil, and Central Africa showing both strong RMSEs and low spectral indices. But  
 585 overall, after NTAOL correction, most stations show more homogeneous  $\sigma_v^*$  estimates



**Figure 8.** Global variability of the minimum velocity uncertainty for 8-year long time series before removing NTAOL deformations (top) and after removing NTAOL deformations (bottom).



**Figure 9.** Latitude dependence of the minimum velocity uncertainty for 8-year long time series before (left) and after (right) removing NTAOL deformations. The dots in cyan represent the station-specific estimates. The continuous blue lines represent running medians over  $10^\circ$  latitude windows. The shaded areas represent the corresponding interquartile ranges. The dashed black lines are the running medians before NTAOL correction, reported on the right plot for comparison with results after NTAOL correction.

Dataset	$\hat{\rho}_c$	$\hat{\rho}_0$	$\hat{\rho}_{\max}$	$\hat{r}$ [km]
Raw	0.01	0.40	0.41	2470
NTAOL removed	0.02	0.27	0.29	2485

**Table 1.** Parameter estimates obtained by fitting the Gaussian correlation model in Equation 12 to the average spatial correlation estimates.

586 and the observed change in  $\sigma_v^*$  mostly highlights the incapacity of the WN+PL model  
 587 to retrieve realistic stochastic parameter estimates, hence realistic velocity uncertainties,  
 588 in the presence of NTAOL deformations.

589 We note that the dramatic change in velocity uncertainty resulting from NTAOL  
 590 corrections at high latitudes does not match the minor shift in uncertainty predicted in  
 591 Santamaría-Gómez and Mémin (2015) from NTAL deformation alone. This difference  
 592 is because the inadequacy of the WN+PL model at high latitudes, and the resulting vari-  
 593 ance component estimation bias, cannot be observed from the analysis of NTAL defor-  
 594 mation time series alone.

595 Given the dramatic reduction in velocity uncertainty observed at high latitudes,  
 596 correcting for NTAOL deformation before the estimation of stochastic parameters in GNSS  
 597 VLM time series will allow a better detection of subtle VLM signals related to glacial  
 598 isostatic adjustment, present-day ice-melting, and improve sea-level change estimates in  
 599 these areas.

## 600 5.5 Spatial correlation

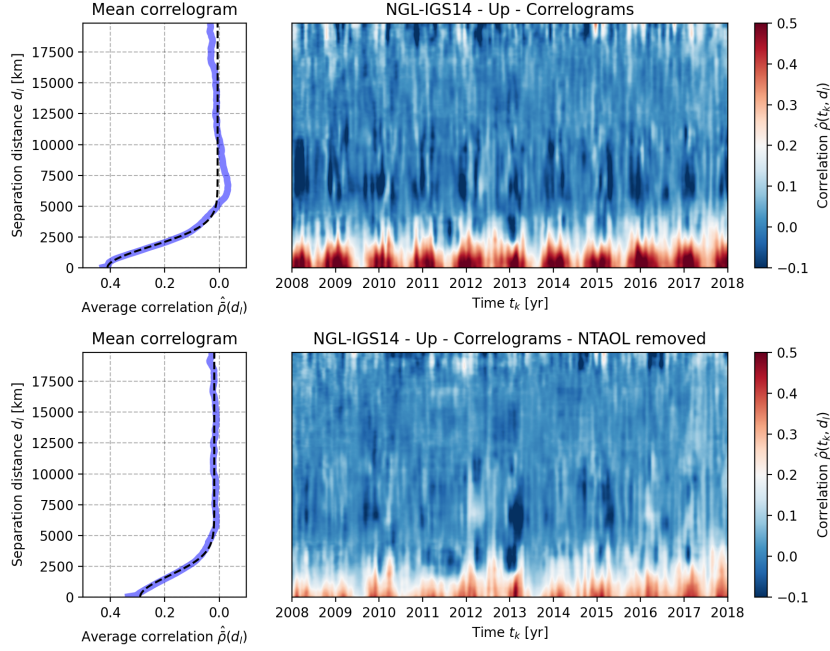
601 For both the raw and the NTAOL-corrected VLM time series, we computed aver-  
 602 aged spatial correlation coefficients  $\hat{\rho}(t_k, d_l)$  for 200 classes of separation distances  $d_l$  rang-  
 603 ing from [0, 100] km to [19900, 20000] km and for 240 epochs  $t_k$  between 2008 and 2018.  
 604 Correlation coefficients between all possible pairs of stations are computed over time win-  
 605 dows of 30 days and averaged within each distance class. The resulting time-variable spa-  
 606 tial correlation estimates  $\hat{\rho}(t_k, d_l)$  are presented, for both cases, in Figure 10. To get a  
 607 clearer picture of the spatial pattern, the spatial correlation averaged over the 2008-2018  
 608 period and denoted  $\bar{\rho}(d_l)$  is also presented in Figure 10.

609 Prior to removing NTAOL deformations, the average spatial correlation  $\bar{\rho}(d_l)$  is close  
 610 to +0.45 for short separation distances (that is,  $d_l < 100$  km) and decreases close to  
 611 zero for larger separation distances (that is,  $d_l \geq 5000$  km). To model this behavior,  
 612 we approximated the average correlogram  $\bar{\rho}(d_l)$  by a Gaussian correlation function de-  
 613 fined by

$$\bar{\rho}(d_l) = \begin{cases} 1, & d_l = 0 \\ \bar{\rho}_c + \bar{\rho}_0 \cdot \exp(-(d_l/\bar{r})^2), & d_l > 0 \end{cases}, \quad (12)$$

614 where  $\bar{\rho}_c$  denotes the distance-independent correlation,  $\bar{\rho}_0$  the distance-variable corre-  
 615 lation, and  $\bar{r}$  the distance range parameter. According to this Gaussian correlation func-  
 616 tion, the maximum correlation for  $d_l > 0$  is  $\bar{\rho}_{\max} = \bar{\rho}_c + \bar{\rho}_0$ .

617 The adjusted parameters of the Gaussian correlation function, with and without  
 618 NTAOL deformations, are presented in Table 1. The graphs corresponding to the ad-  
 619 justed correlation functions are depicted in Figure 10. Although, for the raw VLM resid-



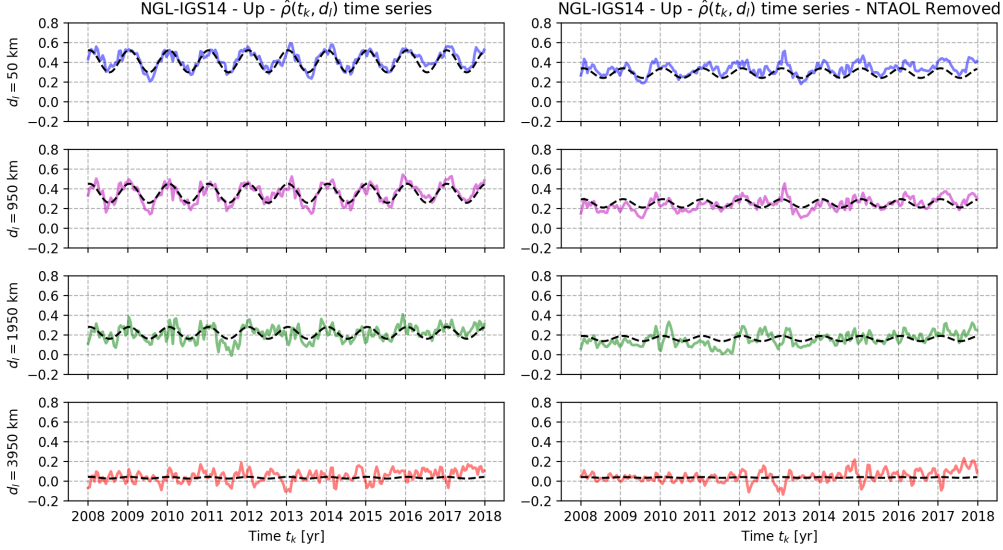
**Figure 10.** Time-variable spatial correlation estimates  $\hat{\rho}(t_k, d_l)$  before (top) and after (bottom) removing NTAOL deformations. The blue curves in the left plots represent the average correlograms over the 2008-2018 period. The dashed black lines represent the adjusted Gaussian correlation models (Equation 12).

620 ual time series, small departures from the observations, inferior to 0.05, are observed for  
 621  $d_l \geq 5000$  km, the Gaussian correlation function is overall a good approximation of the  
 622 correlation curve for both datasets. After the removal of NTAOL deformations, Table  
 623 1 shows that the maximum of correlation for  $d_l > 0.0$  km changed from +0.41 to +0.29,  
 624 that is, a reduction of 29.27%. The average range parameter  $\bar{r}$  is hardly affected by the  
 625 NTAOL corrections.

626 Our results agree with Williams et al. (2004); Amiri-Simkooei et al. (2017) and Benoist  
 627 et al. (2020), evidencing a spatial correlation of the VLM residual time series. However,  
 628 our spatial correlations are slightly smaller, most certainly because we analyze over ten  
 629 thousand recently reprocessed position time series instead of a few hundred (at most).

630 In addition to the approximately Gaussian average spatial correlation, the time-  
 631 variable correlograms in Figure 10 reveal an annual oscillation for short separation dis-  
 632 tances, that is  $d_l < 4000$  km, most visible when NTAOL deformations are not removed.  
 633 The spatial correlation time series  $\hat{\rho}(t_k, d_l)$  for separation distances of 50 km, 950 km,  
 634 1950 km, and 3950 km are presented in Figure 11 to highlight this seasonality. The am-  
 635 plitude of the annual oscillation is maximal for short distances ( $d_l < 100$  km) and syn-  
 636 chronous for all distance classes. Also, both the mean correlation and the annual am-  
 637 plitude get closer to 0.0 for increasing separation distances. To describe the oscillation  
 638 of  $\hat{\rho}(t_k, d_l)$ , we added an annual modulation to the distance-variable part of the mean  
 639 Gaussian correlation function of Equation 12, that is

$$\rho(t_k, d_l) = \begin{cases} 1, & d_l = 0 \\ \rho_c + [\rho_0 + \rho_A \cos(\omega_A t_k - \phi_A)] \cdot \exp(-(d_l/\bar{r})^2), & d_l > 0 \end{cases} \quad (13)$$



**Figure 11.** Time-variable spatial correlation estimates  $\hat{\rho}(t_k, d_l)$  for 4 classes of distances  $d_l$  before (left) and after (right) removing NTAOL deformations. The colored lines represent the estimates for each class of distance  $d_l$ . The dashed black lines represent the corresponding adjusted time-variable Gaussian correlation function (Equation 13).

Dataset	$\hat{\rho}_c$	$\hat{\rho}_0$	$\hat{\rho}_A$	$\hat{\phi}_A$ [day]	$\hat{\rho}_{\min}$	$\hat{\rho}_{\max}$	$\hat{r}$ [km]
Raw	0.01	0.40	0.11	13.8	0.30	0.52	2469
NTAOL removed	0.02	0.27	0.05	22.0	0.24	0.34	2485

**Table 2.** Parameter estimates obtained by fitting the seasonal Gaussian spatial correlation model in Equation 13 to the time-variable spatial correlation estimates.

640 where  $\omega_A$  is the annual angular frequency,  $\rho_A$  is the annual amplitude, and  $\phi_A$  is the cor-  
 641 responding phase. From these estimates, one can define a minimum and a maximum cor-  
 642 relation for  $d_l \approx 0$  as  $\rho_{\min} = \rho_c + \rho_0 - \rho_A$  and  $\rho_{\max} = \rho_c + \rho_0 + \rho_A$ .

643 The adjusted parameters of the time-variable correlation model  $\hat{\rho}_c$ ,  $\hat{\rho}_0$ ,  $\hat{\rho}_A$ ,  $\hat{\phi}_A$ ,  $\rho_{\min}$   
 644 and  $\rho_{\max}$ , estimated with and without NTAOL correction, are presented in Table 2. The  
 645 corresponding graphs are visible in Figure 11.

646 Prior to NTAOL correction, the spatial correlation at short distances shows an an-  
 647 nual amplitude of  $\hat{\rho}_A = 0.11$  and oscillates between +0.30 and +0.52. According to the  
 648 estimated phase  $\hat{\phi}_A$ , the minimum of correlation occurs in July and the maximum in Jan-  
 649 uary. Since most of the stations analyzed are located in the United States and Europe,  
 650 the estimated amplitude and phase of this periodicity are certainly more representative  
 651 of the stochastic variability in these areas but less surely in other parts of the world. Af-  
 652 ter removing NTAOL deformations, we observe a change in annual amplitude, from 0.11  
 653 to +0.05, that is, a 54.55% reduction. The spatial correlation at short distances then os-  
 654 cillates between +0.24 and +0.34. The estimated phase  $\hat{\phi}_A$  remains similar, and the max-  
 655 imum still occurs in January.



656 According to the observed reductions, NTAOL deformation is a significant cause  
 657 of seasonal spatial correlation in GNSS VLM time series. These results support that of  
 658 Gruszczynski et al. (2019), Männel et al. (2019), and Kreemer and Blewitt (2021), who  
 659 pointed out that common mode errors in Europe could be due to NTL deformations.

660 Note that after the NTAOL correction, the spatial correlation at separation dis-  
 661 tances shorter than 100 km still oscillates between +0.24 in July and +0.34 in January  
 662 (e.g., Figure 11 and Table 2). This is expected, as hydrological loading, not corrected  
 663 in this work, also result in spatially correlated deformation (Van Dam et al., 2001; Tre-  
 664 goning et al., 2009; Chanard et al., 2018). Besides, it is also possible that improving the  
 665 quality of NTAOL deformation predictions for instance by computing the dynamic ocean  
 666 response to changes in atmospheric pressure, as done by Mémin et al. (2020), could fur-  
 667 ther reduce the stochastic variability in VLM time series.

668 Nonetheless, considering that orbit and atmospheric positioning errors are other  
 669 known sources of spatially correlated stochastic variability (Amiri-Simkooei et al., 2017),  
 670 it is likely that physical models cannot fully reproduce the spatial correlation in GNSS  
 671 position time series. Hence, further investigating how the remaining spatial correlation  
 672 and its seasonality affect the covariance between GNSS station velocities, similarly as  
 673 Amiri-Simkooei (2009); Razeghi et al. (2016) or Benoist et al. (2020), will undoubtedly  
 674 benefit the study of small deformation signals in global solutions.

## 675 **6 Conclusion**

676 Characterizing and modeling the stochastic variability in GNSS position time se-  
 677 ries is essential to reduce the uncertainty on the estimated station velocities. In this study,  
 678 we investigated how aperiodic non-tidal atmospheric and oceanic loading (NTAOL) de-  
 679 formations influence the stochastic properties of vertical land motion (VLM) time se-  
 680 ries. To do so, we used 10,151 time series processed by the Nevada Geodetic Laboratory  
 681 and NTAOL deformation time series provided the Earth System Modelling team at GFZ  
 682 Potsdam.

683 We first showed that NTAOL deformations exhibit time correlation describable by  
 684 a fractionally integrated Gauss-Markov process. Because this behavior cannot be described  
 685 by the commonly used stochastic model consisting of linear combination of white noise  
 686 and power-law process, the presence of NTAOL deformations in uncorrected VLM time  
 687 series results in biases in white noise amplitude, power-law amplitude, and spectral in-  
 688 dex estimates. In particular, NTAOL deformations cause the power-law parameters to  
 689 display a strong latitude dependence, resulting in a dramatic increase in velocity uncer-  
 690 tainty, exceeding 1.4 mm/yr for 8-year long time series, at high latitudes.

691 Once NTAOL deformations are removed from the VLM time series, we observe a  
 692 drastic reduction of the latitude dependence of all stochastic parameters. This change  
 693 is followed by a significant reduction of velocity uncertainty reaching about 70% in North-  
 694 ern America, Greenland, Fennoscandia, and Antarctica. Therefore, to avoid coping with  
 695 unrealistically high velocity uncertainties, we advise correcting for NTAOL deformation  
 696 prior to the estimation of stochastic parameters in GNSS VLM time series. Doing so will  
 697 certainly allow a better detection of subtle VLM signals related to glacial isostatic ad-  
 698 justment, as well as present-day ice-melting, and improve sea-level change estimates at  
 699 high latitudes.

700 In addition to time-correlation, we investigated how NTAOL deformations influ-  
 701 ence the spatial correlation of aperiodic VLM residuals. First, we demonstrated that,  
 702 before removing NTAOL deformations, VLM residuals are spatially correlated and that  
 703 this spatial correlation shows a Gaussian decay with the separation distance, along with  
 704 a strong seasonality. After removal of NTAOL deformations, the average correlation is

705 reduced by 29.3% and its seasonality by 54.4%, showing that NTAOL deformations are  
706 an important source of spatial correlation.

707 Although NTAOL deformation plays a major role in the stochastic variability in  
708 the VLM time series, it does not fully correct for its power-law behavior or its spatial  
709 correlation. Therefore, further investigations are still needed to identify the physical and  
710 artificial components of the remaining stochastic variability in VLM time series.

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