



# **TED: A global temperature-driven thermoelastic displacement dataset for GNSS reference stations (2000–2023)**

Ran Lu<sup>1,2,3</sup>, Zhao Li<sup>1,2</sup>, Lingfeng Ye<sup>3</sup>, Peng Yuan<sup>4</sup>, Yanming Feng<sup>3</sup>

1. GNSS Research Center, Hubei LuoJia Laboratory, Wuhan University, No. 129 Luoyu Road, Wuhan 430079, China
2. School of Geodesy and Geomatics, Wuhan University, No. 129 Luoyu Road, Wuhan, 430079, China
3. Faculty of Science, Queensland University of Technology, Brisbane, 4000, Australia
4. GFZ Helmholtz Centre for Geosciences, Potsdam, Germany

## **Corresponding Author:**

\* Zhao Li, ✉ [zhao.li@whu.edu.cn](mailto:zhao.li@whu.edu.cn)

## **Abstract**

The nonlinear signals in global GNSS station height time series reflects both non-tidal mass loading (atmospheric, oceanic, and hydrological) and temperature-driven thermoelastic deformation (TED). However, a globally consistent and reproducible TED data product has long been lacking. Here we present a global dataset of vertical TED for ~15,000 GNSS stations spanning 2000–2023, generated using a full-spectrum, layered finite-element model. The model is driven by hourly ERA5 soil-temperature profiles and parameterized with depth-dependent thermophysical properties from the SoilGrids dataset, enabling consistent quantification of TED from semi-diurnal/diurnal variability through seasonal to interannual timescales. Compared with an identical homogeneous-medium benchmark, subsurface stratification typically changes annual amplitudes by ~0.3 mm and shifts the timing of the annual maximum by ~1 month, yielding regionally coherent and smoothly varying spatial patterns. At stations with independent site characterization, the site-constrained solutions agree closely with SoilGrids-based solutions, with annual-amplitude differences of 0.01–0.03 mm and annual-phase differences mostly within 1–3°. Sensitivity tests using ±10% perturbations in thermal expansion, thermal diffusivity, and Young’s modulus indicate that annual-cycle amplitude and phase are robust. Globally, annual TED amplitudes are typically 1–2 mm, exceed 2–3 mm at some stations, and reach peak-to-peak values up to ~5 mm, with the largest signals concentrated in arid inland and continental climate regions. When TED corrections are applied together with non-tidal mass-loading corrections, the residual vertical dispersion decreases at most stations, with vertical scatter reduced by up to ~70% at selected sites. The dataset is publicly available for direct use in GNSS coordinate time series correction and related geophysical applications: <https://doi.org/10.5281/zenodo.18256342> (Lu et al., 2026).

## **1. Introduction**

Global Navigation Satellite System (GNSS) reference-station coordinate time series provide a fundamental observational basis for quantifying crustal deformation, vertical land



39 motion, and surface mass redistribution (Clarke et al., 2005; Jiang et al., 2013; Blewitt et al.,  
 40 2018; Li et al., 2020). In particular, GNSS height records commonly exhibit pronounced  
 41 annual and semiannual signals together with broadband and nonlinear variability, with  
 42 amplitudes ranging from several millimetres to about 2 centimetres. A substantial fraction  
 43 of this variability is non-tectonic, arising from environmental forcing and local site effects,  
 44 including elastic deformation induced by non-tidal atmospheric, oceanic, and hydrological  
 45 loading, as well as temperature-driven thermoelastic deformation (van Dam et al., 2007;  
 46 Fritsche et al., 2012; Fang et al., 2014; Xu et al., 2017; Li et al., 2025). In the absence of  
 47 consistent, reproducible, and scalable corrections for these contributions, seasonal and  
 48 nonseasonal motions can bias velocity estimates, inflate apparent noise levels, and obscure  
 49 subtle geophysical signals, thereby degrading global reference-frame stability and  
 50 subsequent geophysical interpretation (Altamimi et al., 2023).

51 Thermoelastic deformation arises from temperature-driven expansion and contraction  
 52 of the monument and near-surface materials. Temperature perturbations penetrate the  
 53 ground via heat conduction, generating subsurface thermal strain that is subsequently  
 54 expressed as elastic displacement (Biot, 1956; Berger, 1975). GNSS observations indicate  
 55 that shallow thermoelastic effects can explain a substantial portion of the seasonal vertical  
 56 and horizontal variability in some regions (Romagnoli et al., 2003; Prawirodirdjo et al., 2006).  
 57 Importantly, the response is not limited to annual timescales: full-spectrum analyses reveal  
 58 measurable power across a broad frequency range—from semi-diurnal and diurnal bands,  
 59 through weather-driven variability, to seasonal and interannual fluctuations—with  
 60 nonseasonal peak-to-peak motions reaching the millimetre level in some areas and  
 61 therefore detectable by high-precision geodesy (Lei et al., 2020). Thermoelastic deformation  
 62 can also propagate into global geodetic parameter estimation as a non-loading error source.  
 63 For example, Wei et al. (2025) reported that thermoelastic effects contribute significantly to  
 64 the annual variability of the Z component of geocenter motion, implying that improved  
 65 modelling and mitigation may enhance the consistency of GNSS-based geocenter estimates  
 66 across independent solutions.

67 Robust quantification of thermoelastic effects requires temperature forcing that  
 68 resolves the diurnal cycle, together with broad spatial coverage and a long observational  
 69 span. When the forcing is represented only by daily means or by a single fixed-UTC sample,  
 70 diurnal variability is undersampled and can alias into longer periods. Such aliasing can  
 71 introduce longitude-dependent biases in daily GNSS coordinate solutions and generate  
 72 spurious low-frequency variability (from seasonal to interannual), thereby compromising  
 73 cross-regional statistics and hindering robust intercomparisons among correction products  
 74 (Li et al., 2024). At the same time, publicly available global GNSS coordinate archives now  
 75 comprise on the order of 15,000 stations, shifting the need for thermoelastic correction  
 76 from regional case studies toward scalable, operational products. A uniform, reproducible  
 77 dataset with a clear update pathway is therefore required to enable large-scale processing  
 78 workflows and objective cross-product evaluation and intercomparison.

79 Thermoelastic modelling approaches can be broadly categorized into analytical and  
 80 numerical methods. Analytical formulations commonly rely on half-space assumptions and  
 81 idealized boundary conditions; they are compact and computationally efficient and are



therefore well suited for rapid first-order estimates and process interpretation (Dong et al., 2002; Yan et al., 2009, 2010). A key limitation, however, is that many analytical models assume depth-invariant—or effectively homogeneous—thermophysical properties, which restricts their ability to capture the amplitude and phase shifts introduced by soil–bedrock stratification. Recent work has moved toward more realistic representations. For example, full-spectrum frameworks now incorporate both seasonal and nonseasonal temperature variability together with bedrock depth and type information (Li et al., 2024). Other studies assess how thermoelastic signals contribute to nonlinear components in GNSS heights across different products and processing strategies (Lu et al., 2024). Collectively, these advances indicate that the interpretability and practical utility of thermoelastic signals depend not only on the model class, but also on how subsurface structure is parameterized and how temperature forcing is temporally sampled.

Compared with analytical approaches, finite element methods (FEM) more readily accommodate material heterogeneity and interlayer coupling. They naturally represent the coupled processes of heat conduction and elastic deformation, making them well suited for thermoelastic problems in layered media (Lei et al., 2020). Building on this capability, we implement a full-spectrum layered FEM workflow (FEM<sub>FL</sub>) at global scale and release a public dataset of temperature-driven vertical thermoelastic displacement (TED) time series for ~15,000 GNSS stations worldwide over 2000–2023 (Lu et al., 2025). The model is driven in the time domain by hourly ERA5 temperature forcing and parameterized with depth-resolved thermophysical properties from the SoilGrids dataset. The release includes quality-control metrics and technical validation. The dataset is designed as a reusable environmental correction that can be applied alongside non-tidal mass-loading products in GNSS processing workflows, supporting more robust vertical land motion estimation, reference-frame stability assessment, and geocenter-related investigations (Altamimi et al., 2023; Wei et al., 2025).

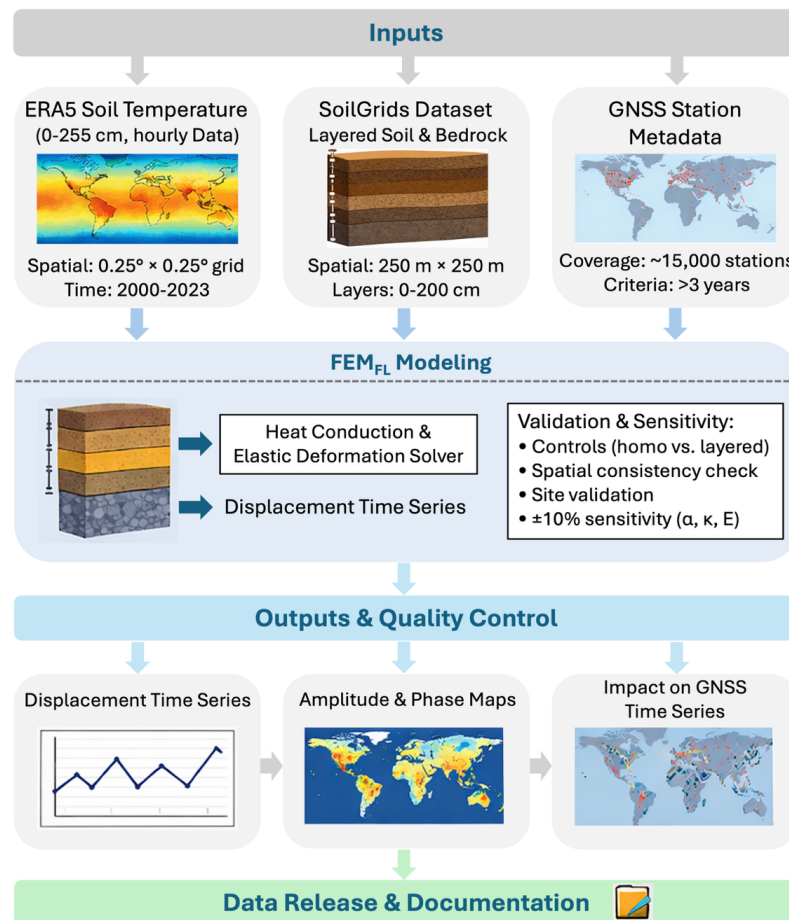
The paper is organized as follows. Section 2 describes the input data, model configuration, and computational workflow. Section 3 presents the main spatiotemporal characteristics of the dataset, provides technical validation, and quantifies its impact on the structure of GNSS vertical residuals. Section 4 documents the data records (file organization, variable definitions, quality flags, and usage guidance) and provides access instructions. Section 5 summarizes applicability and limitations and outlines future updates.

## 2. Materials and methods

This dataset addresses the need for globally consistent modeling and correction of non-tectonic vertical deformation at continuously operating GNSS stations by providing temperature-driven vertical thermoelastic displacement (TED) time series for ~15,000 stations spanning 2000–2023. The product is generated using a standardized end-to-end workflow (Fig. 1). The workflow harmonizes station selection and temporal coverage, constructs and resamples the temperature forcing, parameterizes vertically layered subsurface properties, runs FEM<sub>FL</sub> at scale, and performs quality control and consistency checks prior to packaging and release. Station locations and observation spans are compiled from publicly available GNSS station metadata. Near-surface thermal forcing is derived from



124 ERA5 soil-temperature profiles, and site-specific layered thermo-mechanical properties are  
 125 constructed from SoilGrids and related global datasets. The resulting vertical thermoelastic  
 126 response is computed with the FEM<sub>FL</sub> and distributed in a GNSS-ready, standardized format.



127

128 **Figure 1** Schematic workflow of dataset production: station selection and metadata  
 129 compilation; extraction and resampling of ERA5 temperature forcing; retrieval and unified  
 130 parameterization of layered SoilGrids properties; large-scale FEM<sub>FL</sub> computation; output  
 131 quality control and evaluation; and product release (file organization and metadata  
 132 archiving).

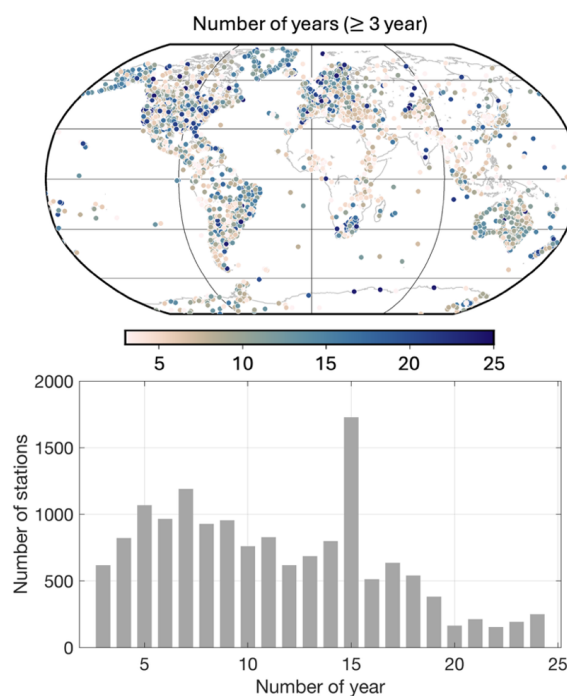
### 133 2.1. GNSS station and temporal coverage

134 GNSS station metadata and coordinate time series are obtained from multi-network  
 135 solutions compiled and maintained by the Nevada Geodetic Laboratory (NGL), which  
 136 integrate continuous observations from the International GNSS Service (IGS) and numerous  
 137 regional and national networks (Blewitt et al., 2018). To support stable estimation of annual  
 138 and semiannual signals—and to facilitate assessment of potential aliased components





139 associated with diurnal temperature variability—we retain continuous stations with at least  
 140 three years of valid observations within 2000–2023, while maximizing the sample size  
 141 subject to broad global coverage. The resulting dataset includes ~15,000 stations distributed  
 142 across the major continents and climate zones (Fig. 2), with particularly dense coverage in  
 143 North America, Europe, East Asia, and Australia. This spatial sampling enables robust  
 144 regional statistics and provides a basis for internal consistency and quality checks.



145

146 **Figure 2** Spatial distribution and temporal coverage of GNSS stations. (a) Global station  
 147 distribution and available record length (color denotes time-series duration); (b) frequency  
 148 distribution of available record length.

## 149 2.2. Temperature forcing data

150 The temperature-driven thermoelastic deformation (TED) is induced by near-surface  
 151 temperature perturbations that propagate downward through heat conduction, generate  
 152 thermal strain, and are expressed as elastic displacement. The reliability of a TED dataset  
 153 therefore depends critically on the temporal resolution and phase fidelity of the  
 154 temperature forcing. We use soil temperatures from ECMWF ERA5 reanalysis as the  
 155 external forcing and adopt the shallowest layer (soil temperature level 1, 0–7 cm) as a  
 156 practical proxy for the surface-temperature boundary condition (Hersbach et al., 2018).

157 To retain sub-daily variability and mitigate the aliasing of diurnal power into lower  
 158 frequencies associated with fixed-UTC sampling, we sample the hourly ERA5 record at 00,  
 159 06, 12, and 18 UTC and apply these values as the upper-boundary forcing at a 6-hour



interval. This strategy maintains global-scale computational tractability while resolving diurnal and semi-diurnal thermal responses. It also reduces spurious seasonal-to-interannual artifacts that can arise when forcing is represented by daily means or by a single-epoch temperature series. In addition to the 0–7 cm layer, we use the full ERA5 soil-temperature profile (0–7, 7–28, 28–100, and 100–255 cm) to better constrain near-surface thermal gradients and to represent background heat transfer at depths.

### 2.3. Layered thermophysical and mechanical properties

The thermal diffusivity, thermal expansion coefficient, and elastic moduli control how temperature perturbations attenuate and phase-lag with depth and how efficiently thermally induced strain is converted into displacement. Globally consistent TED estimates therefore benefit from site-specific, vertically layered parameterization wherever possible. Here we represent the shallow subsurface using the globally gridded, depth-resolved soil information from SoilGrids ([Hengl et al., 2017](#)). SoilGrids provides a suite of soil properties on standard depth intervals (0–5, 5–15, 15–30, 30–60, 60–100, and 100–200 cm), enabling characterization of thermophysical contrasts within the upper ~2 m. We adopted the latest SoilGrids 2.0 dataset that used state-of-the-art machine learning methods to build the required models and produced global maps of soil properties at medium spatial resolution (250 m grid cells) ([Poggio et al., 2021](#)).

For each station, we extract the SoilGrids depth profiles and consistently translate them into the thermophysical parameters required by the model (e.g., thermal conductivity or diffusivity and volumetric heat capacity). Mechanical properties (e.g., Poisson’s ratio) and the linear thermal expansion coefficient are assigned using a uniform, reproducible lookup table. They are then mapped onto the layered structure, so that spatial variations in soil thickness and shallow properties propagate into the coupled thermo-mechanical response. Below 2 m, where globally consistent high-resolution stratigraphic information is generally unavailable, we represent the deeper medium as a bedrock half-space. Its thermophysical and mechanical properties are prescribed using a unified rule set. This parameterization treatment maintains global computational feasibility and reproducibility while retaining the dominant influence of shallow-layer heterogeneity on the modeled response.

### 2.4. TED modeling framework

We compute temperature-driven vertical TED using full-spectrum layered finite element model (FEM<sub>FL</sub>; [Lu et al., 2025](#)). Beneath each station, the subsurface is represented as a one-dimensional, vertically layered soil–bedrock column. Layer-specific thermophysical and mechanical properties are derived from SoilGrids and related datasets and are assumed uniform within each layer. The time-varying near-surface temperature is prescribed as the upper boundary condition. Temperature perturbations then propagate downward through transient heat conduction and attenuate with depth, producing depth-dependent thermal strain. Contrasts in thermal diffusivity, linear thermal expansion, and elastic stiffness among layers control both the amplitude damping and phase lag of the temperature field and the efficiency with which thermal strain is converted into elastic deformation. Together these effects produce a measurable vertical displacement at the surface. This unified framework



enforces heat transfer within layers, continuity across interfaces, and thermo-mechanical coupling, enabling consistent and scalable site-specific TED estimates at the global scale.

In the thermal component, the temperature evolution in each layer follows the one-dimensional transient heat-conduction equation. Continuity of temperature and heat flux is imposed at all layer interfaces, ensuring physically consistent energy transfer through the stratified column. The upper boundary temperature is prescribed from the ERA5 soil-temperature forcing, while the lower boundary condition is formulated to represent a stable deep thermal background, thereby limiting nonphysical drift associated with truncating the domain at finite depth. The model is advanced at the same cadence as the forcing (6-hour time steps), retaining variability from sub-daily to seasonal timescales.

In the mechanical component,  $FEM_{FL}$  treats temperature-induced thermal strain as an eigenstrain term in the constitutive relation and solves the resulting vertical displacement in a one-dimensional layered finite element system. Within each element, thermal strain is determined by the temperature departure from a reference state and the linear thermal expansion coefficient, whereas elastic moduli govern how this strain translates into displacement and how deformation is transmitted across layer interfaces. Solving the assembled layered column yields the surface-node vertical displacement time series directly, rather than relying on simplified depth-integration approximations, and therefore captures stratification effects on both amplitude and phase more consistently. To suppress start-up transients associated with uncertain deep-temperature initial conditions, we apply a spin-up procedure in which a representative year of temperature forcing is repeated until the deep temperature field converges to a stable annually periodic state. The TED series for 2000–2023 is then generated from this equilibrated initialization.

Daily GNSS coordinate solutions are typically referenced to a fixed UTC epoch, whereas sub-daily temperature forcing—and the resulting thermoelastic response—are phased primarily by local solar time. Using a single UTC sampling time can therefore introduce longitude-dependent artifacts and alias diurnal energy into longer periods. To reduce this sensitivity, we drive  $FEM_{FL}$  with temperature forcing sampled at four UTC epochs (00, 06, 12, and 18 UTC). This yields four TED realizations. We then combine them using a phase-consistent strategy. For dominant harmonic components (e.g., annual and semiannual), we apply amplitude–phase vector averaging to preserve both magnitude and phase. The remaining non-harmonic variability is merged on a common sampling basis and added to form the final series. The resulting TED product is less sensitive to the chosen UTC epoch. It is also more compatible with daily GNSS solutions. As a result, it is better suited to large-scale correction workflows.

## 2.5. Quality control and consistency checks

To facilitate reuse, traceability, and verification, all released time series are subjected to multi-level quality control and consistency checks. First, numerical artefacts are screened, including spikes, step-like discontinuities, and unrealistic long-term drift. For the small subset of stations that fail these checks, likely causes are examined (e.g., gaps or interpolation issues in the temperature forcing, fallback/default parameter assignments, or problems in the layered configuration), and the affected records are either assigned quality



243 flags or excluded from the release. Second, spectral consistency is assessed by estimating  
 244 the amplitude and phase of the principal periodic components (semi-diurnal, diurnal,  
 245 semiannual, and annual), and by verifying that these quantities vary smoothly within  
 246 comparable climate regimes; this helps limit spurious spatial discontinuities introduced by  
 247 gridding or parameter transitions. Third, application-oriented checks are performed by  
 248 applying TED together with non-tidal loading corrections at representative stations and  
 249 across regional scales, followed by quantifying the resulting changes in GNSS vertical  
 250 residual statistics (e.g., residual dispersion).

## 251 2.6. Model performance metrics

252 To consistently quantify the key amplitude characteristics of the TED product and its  
 253 correction impact on GNSS vertical time series, we compute the annual-cycle amplitude and  
 254 phase, the nonseasonal variability, and the WRMS improvement of GNSS residuals. For each  
 255 TED series  $u(t)$ , we fit an annual and semiannual harmonic model with a linear term:

$$256 \quad u(t) = a_0 + bt + \sum_{k=1}^2 [c_k \cos(\omega_k t) + s_k \sin(\omega_k t)] + \varepsilon(t) \quad (1)$$

257 where  $a_0$  is the constant term,  $b$  is the linear term,  $\omega_1$  and  $\omega_2$  correspond to the  
 258 annual and semiannual frequencies, respectively, and  $\varepsilon(t)$  denotes the residual. The  
 259 annual amplitude and phase are defined as:

$$260 \quad A_{ann} = \sqrt{c_1^2 + s_1^2} \quad (2a)$$

$$261 \quad \phi_{ann} = \text{atan2}(s_1, c_1) \quad (2b)$$

262 To quantify the remaining variability after removing the linear term and the  
 263 annual/semiannual harmonics, let  $\hat{u}(t)$  denote the fitted reconstruction. The residual is  
 264  $r(t) = u(t) - \hat{u}(t)$ , and the nonseasonal variability is measured by the root-mean-square  
 265 (RMS) of  $r(t)$ :

$$266 \quad RMS_{nonsea} = \sqrt{\frac{1}{N} \sum_{i=1}^N r(t_i)^2} \quad (3)$$

267 where  $N$  is the number of valid samples.

268 For the GNSS vertical time series  $x(t)$ , we quantify scatter using the weighted  
 269 root-mean-square (WRMS):

$$270 \quad WRMS = \sqrt{\frac{\sum_{i=1}^N \omega_i [x(t_i) - \bar{x}_\omega]^2}{\sum_{i=1}^N \omega_i}} \quad (4)$$

$$271 \quad \bar{x}_\omega = \frac{\sum_{i=1}^N \omega_i x(t_i)}{\sum_{i=1}^N \omega_i} \quad (5)$$

272 where the weights are  $\omega_i = 1/\sigma_i^2$ ; when observation uncertainties are unavailable, we use  
 273 equal weights ( $\omega_i = 1$ ). The WRMS reduction rate is defined as:

$$274 \quad \Delta WRMS(\%) = \frac{WRMS_{raw} - WRMS_{corr}}{WRMS_{raw}} \times 100\% \quad (6)$$



where  $WRMS_{raw}$  and  $WRMS_{corr}$  denote the series before and after correction, respectively. We evaluate WRMS improvements for each single correction (NTAL, NTOL, HYDL, and TED) as well as for the combined correction (NTAL+NTOL+HYDL+TED) to quantify the spatially varying contributions of different environmental processes.

In the parameter-sensitivity analysis, we apply a  $\pm 10\%$  relative perturbation to a selected key parameter at each station and recompute TED. The difference between the perturbed and baseline solutions in the annual cycle is then quantified as:

$$\Delta A_{ann} = A_{ann}^{(\pm 10\%)} - A_{ann}, \quad \Delta \phi_{ann} = \phi_{ann}^{(\pm 10\%)} - \phi_{ann} \quad (7)$$

where  $A_{ann}^{(\pm 10\%)}$  denotes the annual-cycle amplitude after applying a  $+10\%$  (or  $-10\%$ ) perturbation to the parameter, and  $\phi_{ann}^{(\pm 10\%)}$  denotes the corresponding annual-cycle phase. For summary statistics, we use the absolute values  $|\Delta A_{ann}|$  and  $|\Delta \phi_{ann}|$  to represent the “sensitivity magnitude.” For the volcano plots, the empirical significance  $p_{emp}$  is defined as the two-sided empirical tail probability within the same (region  $\times$  parameter) subset:

$$p_{emp} = 2\min(F(\Delta), 1 - F(\Delta)) \quad (8)$$

where  $F(\Delta)$  is the empirical cumulative distribution function. We plot  $-\log_{10}(p_{emp})$  as an index of “extremeness” or tail magnitude, emphasizing that it is an empirical measure rather than a hypothesis-test p-value based on a specific statistical assumption.

### 3. Results and analysis

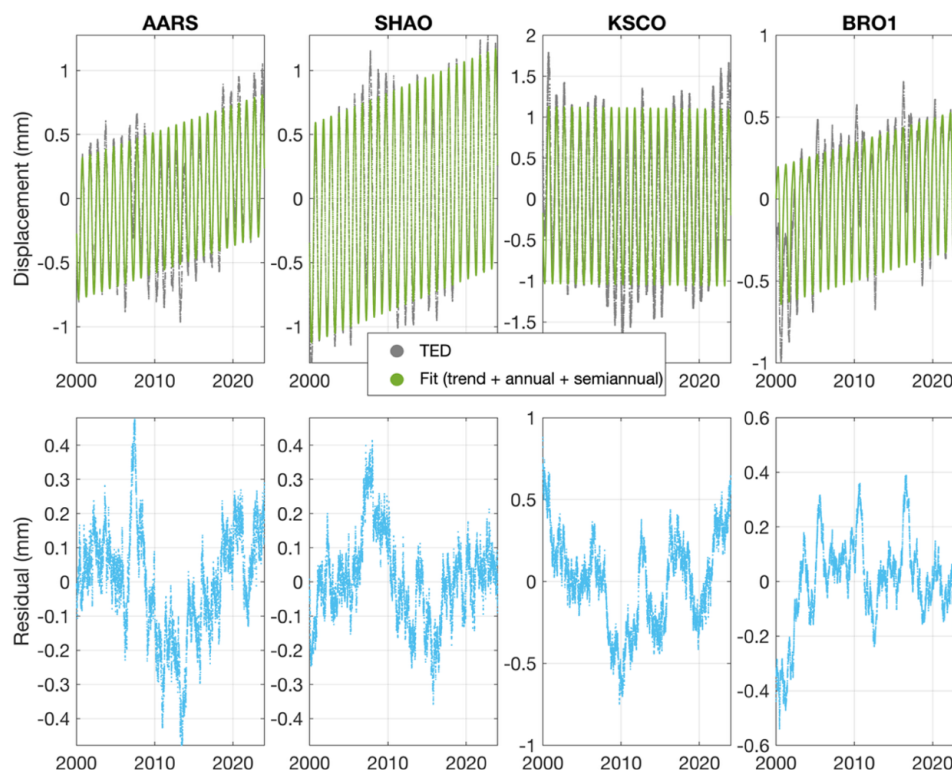
This section summarizes the spatiotemporal characteristics and practical performance of the global TED time series (2000–2023) generated with FEM<sub>FL</sub>. We first use representative stations to illustrate TED variability across multiple timescales, and then present global patterns of annual amplitude, annual phase, peak-to-peak range, and nonseasonal variability. Next, regional transects and validation windows are used to evaluate the sensitivity and internal consistency of the layered parameterization. Finally, using GNSS vertical time-series together with residual-dispersion and spectral analyses, we quantify how applying TED in combination with non-tidal mass-loading corrections reduces residual scatter and apparent noise levels. All metrics and their computations are defined in Section 2.6.

#### 3.1. Thermoelastic displacement characteristics

We illustrate typical temperature-driven vertical thermoelastic displacement (TED) behavior using four representative GNSS reference stations—AARS, SHAO, KSCO, and BRO1 (Fig. 3)—selected to span contrasting climatic regimes. At all sites, TED shows a coherent periodic signal with superimposed short-term fluctuations (upper panels). Residuals after removing a linear trend and the annual and semiannual harmonics are shown in the lower panels. Seasonally, TED closely follows the temperature cycle: warm-season expansion



311 produces uplift, and cold-season contraction produces subsidence. At SHAO, for example,  
 312 TED typically peaks in July–August and reaches a minimum around January, with an annual  
 313 amplitude of  $\sim 1$  mm. Sub-daily variability is also evident, with diurnal fluctuations of  $\sim 0.1$ –  
 314  $0.3$  mm that are particularly clear at arid sites with large day–night temperature contrasts  
 315 (e.g., AARS), highlighting a seasonally dominated signal with detectable sub-daily structure.



316

317 **Figure 3** Examples of vertical thermoelastic displacement series at four representative GNSS  
 318 stations (top: original series with fitted trend plus annual and semiannual harmonics;  
 319 bottom: residuals after removing trend, annual and semiannual harmonics).

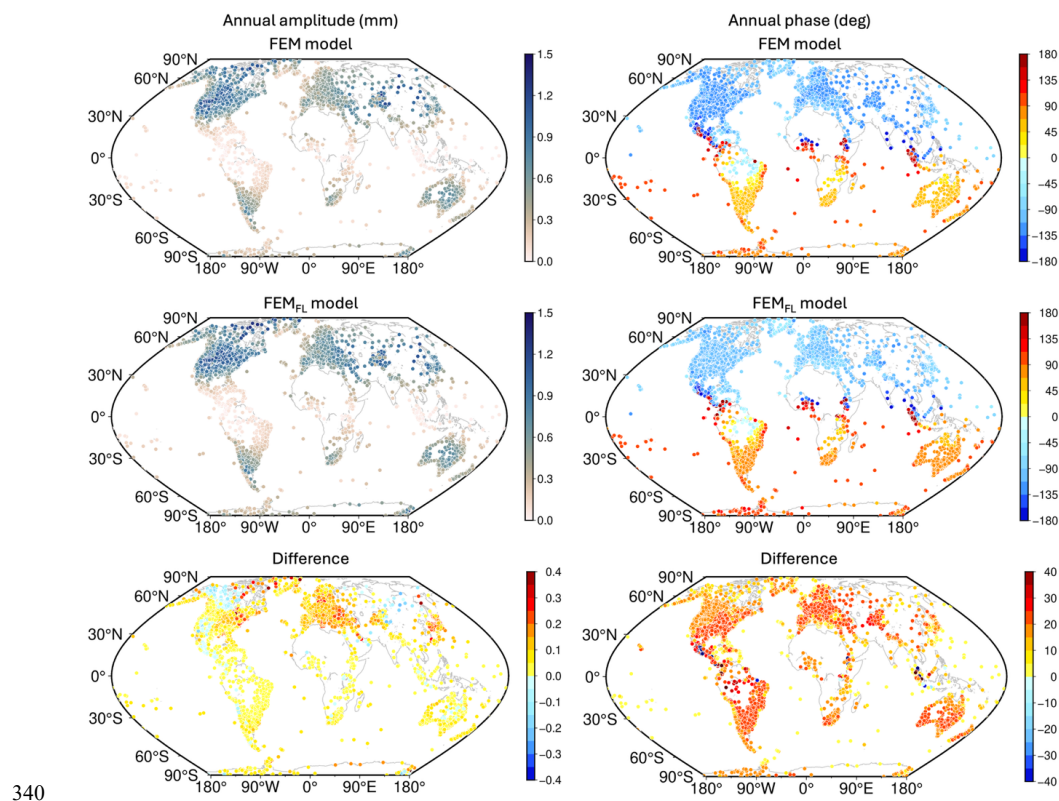
320 To characterize global TED, we decompose the  $FEM_{FL}$  time series at all stations and  
 321 derive four metrics: annual amplitude and phase, peak-to-peak displacement, and  
 322 nonseasonal variability. Figure 4 maps the annual amplitude and phase from the  
 323 homogeneous FEM and layered  $FEM_{FL}$  models, along with their differences. Both models  
 324 display consistent first-order patterns, with larger annual amplitudes over mid–high-latitude  
 325 continents and continental climates, smaller amplitudes in maritime and humid tropical  
 326 regions, and pronounced latitudinal structure in annual phase.

327 Relative to the homogeneous FEM,  $FEM_{FL}$  generally yields modestly larger annual  
 328 amplitudes, most notably in continental interiors. This behavior is physically consistent with  
 329 layered media: reduced near-surface thermal conductivity and diffusivity steepen shallow





330 temperature gradients and concentrate thermal strain closer to the surface, which amplifies  
 331 the vertical response. In contrast, effective homogeneous properties tend to smooth this  
 332 insulating effect. Amplitude differences are predominantly positive, typically  $\sim 0\text{--}0.3$  mm  
 333 and locally up to  $\sim 0.4$  mm and are smaller in humid coastal or densely vegetated regions  
 334 where seasonal temperature forcing is damped. Annual-phase patterns remain broadly  
 335 similar, but  $\text{FEM}_{\text{FL}}$  introduces measurable shifts in some continental interiors: differences  
 336 are mostly within  $\pm 40^\circ$  and commonly on the order of a few to a few tens of degrees (e.g.,  
 337  $10^\circ\text{--}30^\circ$ ). These shifts are consistent with layering-induced changes in the attenuation and  
 338 phase lag of downward-propagating temperature variations, and hence in the timing of  
 339 peak displacement.



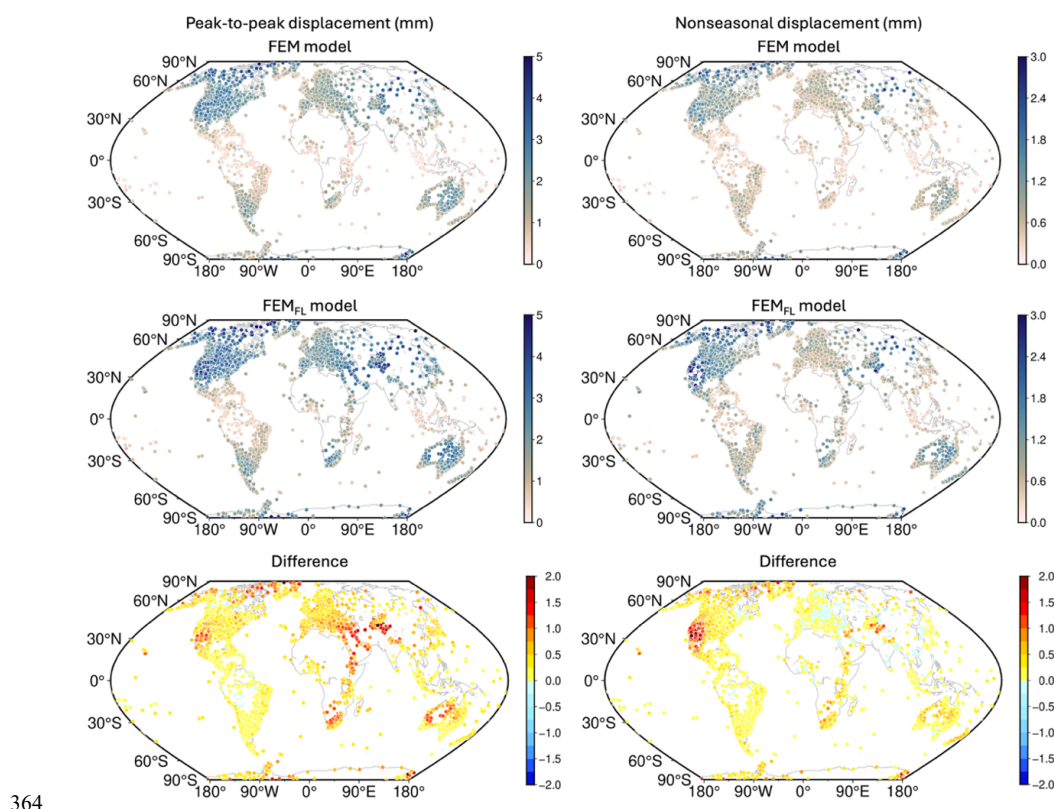
341 **Figure 4** Comparison of annual-cycle amplitude and phase estimated by the homogeneous  
 342 FEM and  $\text{FEM}_{\text{FL}}$ .

343 **Figure 5** shows global distributions of TED peak-to-peak displacement and nonseasonal  
 344 variability by comparing results from the homogeneous FEM and layered  $\text{FEM}_{\text{FL}}$  models.  
 345 Peak-to-peak displacement is defined as the difference between the maximum and  
 346 minimum TED values over 2000–2023, representing the total range at a site due to the  
 347 seasonal cycle together with shorter-period fluctuations. The two models show broadly  
 348 similar spatial patterns, but  $\text{FEM}_{\text{FL}}$  generally yields larger ranges: peak-to-peak values are  
 349 typically  $\sim 2\text{--}4$  mm and reach  $\sim 5$  mm at the upper end. The  $\text{FEM}_{\text{FL}}$  minus FEM differences are



350 predominantly positive, commonly 0–1 mm and locally approaching ~2 mm, indicating that  
 351 layered parameterization tends to increase the total displacement range, particularly where  
 352 short-period temperature variability is strong.

353 Nonseasonal variability is quantified from the residual series after removing a linear  
 354 trend and the annual and semiannual harmonics, and thus reflects TED variations from  
 355 diurnal-to-weather timescales as well as interannual to multi-year fluctuations. Relative to  
 356 the homogeneous FEM,  $FEM_{FL}$  produces slightly higher nonseasonal variability overall: the  
 357 differences are dominated by small positive values, but locally reach contrasts of up to  $\pm 2$   
 358 mm. This pattern is consistent with reduced near-surface conductivity and diffusivity  
 359 concentrating temperature perturbations within shallow layers, which amplifies  
 360 higher-frequency thermoelastic strain and, in turn, increase the residual variance. Figure 5  
 361 therefore indicates that subsurface layering influences not only seasonal amplitudes, but  
 362 also the overall displacement range and nonseasonal variability, with the largest impacts in  
 363 continental interiors.

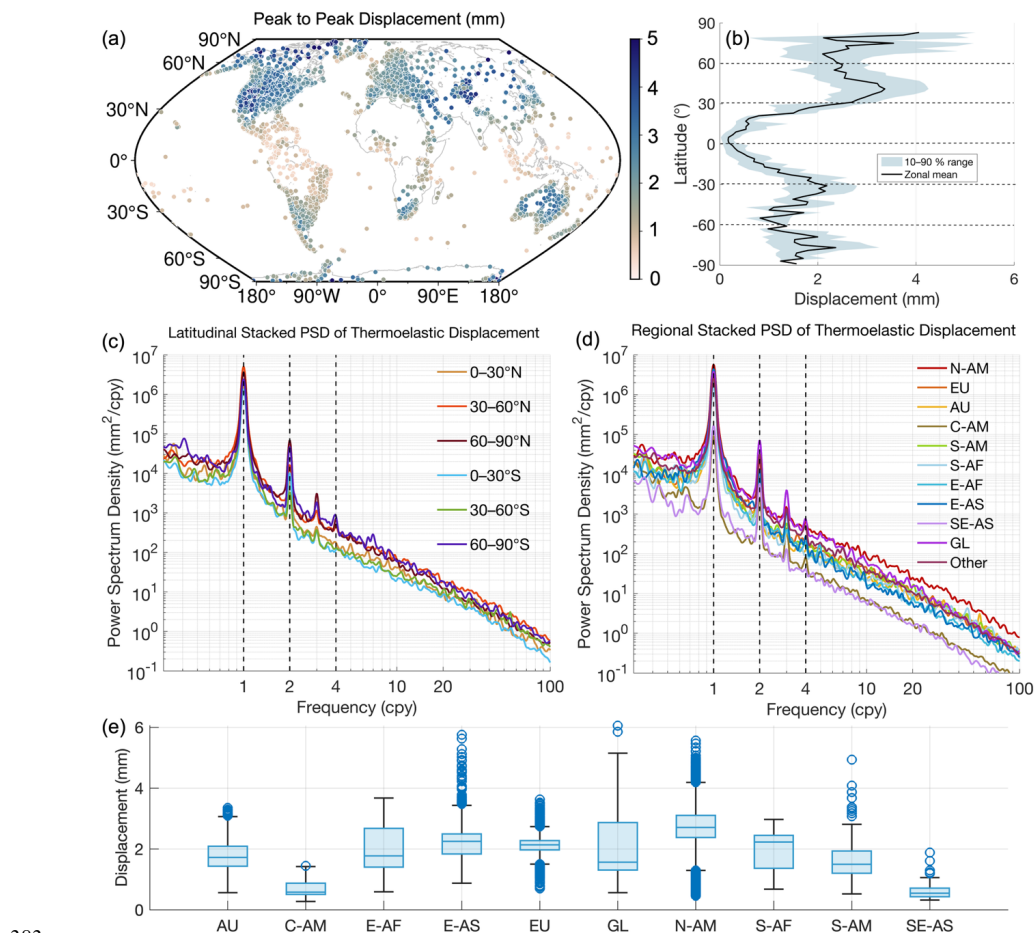


365 **Figure 5** Comparison of peak-to-peak displacement and nonseasonal displacement intensity  
 366 estimated by the homogeneous FEM and  $FEM_{FL}$ .

367 **Figure 6** further summarizes  $FEM_{FL}$ -estimated TED peak-to-peak displacement through (i)  
 368 latitudinal statistics, (ii) regional groupings, and (iii) spectral characteristics. The latitudinal



analysis shows a clear, systematic dependence of peak-to-peak displacement on latitude. However, the substantial within-band spread (10th–90th percentile range) indicates that latitude alone does not control TED magnitude. Regional climate regimes and shallow subsurface conditions also matter, particularly soil–bedrock stratification and its thermophysical properties. Regional boxplots highlight these contrasts: North America and East Asia show higher median peak-to-peak values, whereas Southeast Asia and Central America are lower, consistent with differences in temperature forcing and near-surface thermal responsiveness. To characterize the frequency content, we compute and stack TED power spectral densities (PSDs) across stations within latitude bands and regions. The stacked spectra show a dominant peak near 1 cycle per year (cpy; annual), secondary peaks at 2 cpy (semiannual) and higher-integer harmonics, and a smoothly decaying high-frequency tail. These patterns prove that TED represents a broadband thermoelastic response with a strong seasonal component and appreciable nonseasonal variability extending from monthly to weather timescales.



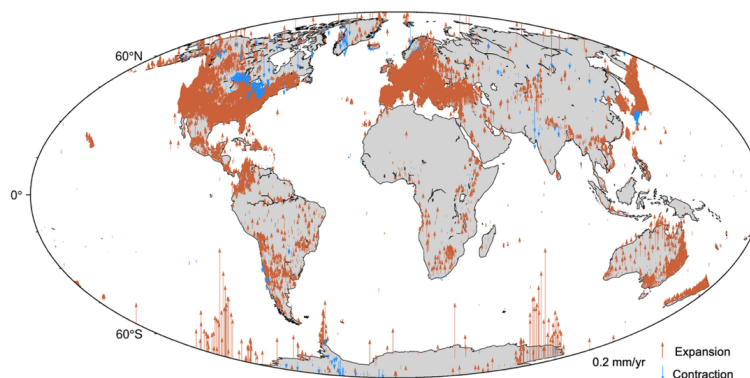
383

384 **Figure 6** Global distribution, regional statistics, and representative PSD characteristics of



385 FEM<sub>FL</sub>-derived TED peak-to-peak displacement. Region abbreviations: N-AM (North America),  
 386 EU (Europe), AU (Australia), C-AM (Central America), S-AM (South America), S-AF (Southern  
 387 Africa), E-AF (Eastern Africa), E-AS (East Asia), SE-AS (Southeast Asia), GL (Greenland).

388 Notably, a weak long-term component is present in TED at some stations. We estimate  
 389 linear trends for the vertical TED series at each site (Fig. 7) and find that they are generally  
 390 small, with the vast majority within  $\pm 0.2$  mm yr<sup>-1</sup>. However, the trends exhibit coherent  
 391 spatial structure instead of random scatter. Positive trends dominate globally, whereas  
 392 negative trends are more localized and may be associated with regional differences in  
 393 climate and surface conditions, including land cover, soil moisture, and snow or freeze–thaw  
 394 regimes. Such trend-like behavior may reflect multi-year non-stationarity in the  
 395 temperature forcing (e.g., regional warming/cooling or long-term drift in reanalysis  
 396 temperatures) and/or gradual adjustment of the shallow soil–bedrock thermal state toward  
 397 a shifting multi-year mean. These signals therefore require cautious interpretation and  
 398 should not be treated as tectonic or other secular geophysical trends. Although small from  
 399 year to year, these effects can accumulate into millimeter-level offsets over years to  
 400 decades, biasing long-term vertical velocity estimates and reference-frame stability metrics.  
 401 We therefore recommend treating the TED trend as a quantifiable temperature-related  
 402 background term in sensitivity analyses and uncertainty budgets for long-term GNSS velocity  
 403 and reference-frame applications.



404

405 **Figure 7** Estimated linear trends of FEM<sub>FL</sub>-derived thermoelastic displacement time series.

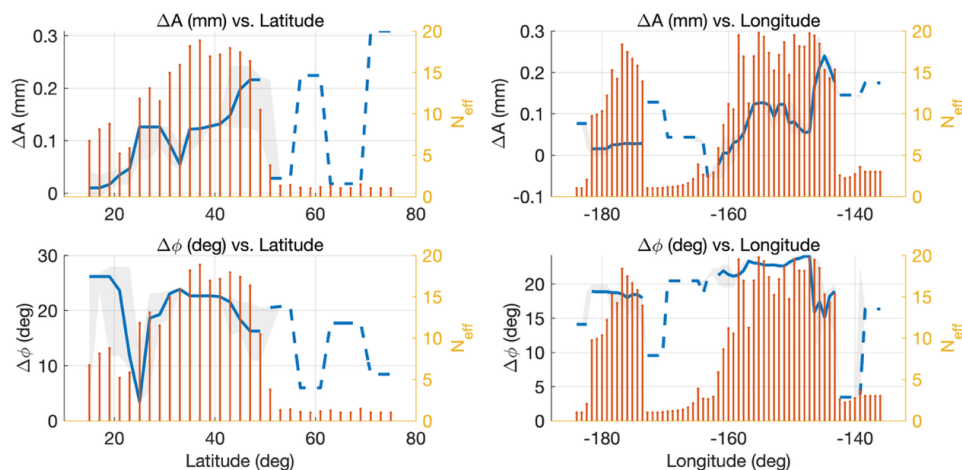
### 406 3.2. Reliability assessment of the thermoelastic dataset

407 To better isolate the influence of subsurface layering on the annual TED signal, we focus  
 408 on North America as a representative subregion and examine meridional and zonal  
 409 transects of the SoilGrids-based layered minus the homogeneous solution differences (Fig.  
 410 8). These transects summarize how the annual vertical amplitude difference ( $\Delta A$ ) and phase  
 411 difference ( $\Delta \phi$ ) vary with latitude and longitude. The blue curve shows the weighted median  
 412 after two-dimensional k-nearest-neighbor (2D-kNN) smoothing, the gray envelope denotes  
 413 the interquartile range (IQR), and the orange tick marks indicate the effective number of  
 414 stations ( $N_{\text{eff}}$ ) contributing within each smoothing window. Segments with  $N_{\text{eff}} < 5$  are



415 plotted as dashed lines and are intended to convey only the broad trend.

416 The layered model yields slightly larger annual amplitudes than the homogeneous  
 417 model across most North America locations. The amplitude difference ( $\Delta A$ ) is predominantly  
 418 positive, typically 0–0.2 mm and reaching  $\sim 0.25$  mm in a few latitude–longitude segments.  
 419 This pattern is consistent with shallow thermophysical contrasts strengthening near-surface  
 420 temperature gradients and concentrating thermoelastic strain toward the surface, thereby  
 421 modestly enhancing the annual vertical response. Phase differences show greater spatial  
 422 variability:  $\Delta\phi$  is generally on the order of tens of degrees (about 10–25° across most  
 423 segments) and forms coherent structures where station density is high. This indicates that  
 424 subsurface layering affects not only the amplitude but also the timing of the annual  
 425 maximum, most likely by modifying the effective penetration depth and phase lag of the  
 426 downward-propagating temperature wave and, in turn, the resulting thermo-mechanical  
 427 coupling. The differences remain modest overall ( $\Delta A$  up to  $\sim 0.3$  mm;  $\Delta\phi$  up to  $\sim 30^\circ$ ).  
 428 Nonetheless, the persistent positive  $\Delta A$  in continental interiors, together with systematic  
 429 phase adjustments, is consistent with the expectation that reduced near-surface thermal  
 430 diffusivity (i.e., stronger insulation) enhances shallow thermoelastic expansion and alters  
 431 the phase lag.



432

433 **Figure 8** North America case study: meridional and zonal profiles of annual amplitude and  
 434 phase differences between the SoilGrids-layered solution and the homogeneous solution:  
 435  $\Delta A = (A_{\text{SoilGrids}} - A_{\text{homo}})$ ,  $\Delta\phi = (\phi_{\text{SoilGrids}} - \phi_{\text{homo}})$ . The blue curve shows the 2D-kNN–  
 436 smoothed weighted median, the gray shading denotes the IQR, and the orange bars indicate  
 437  $N_{\text{eff}}$ ; segments with  $N_{\text{eff}} < 5$  is shown as dashed lines.

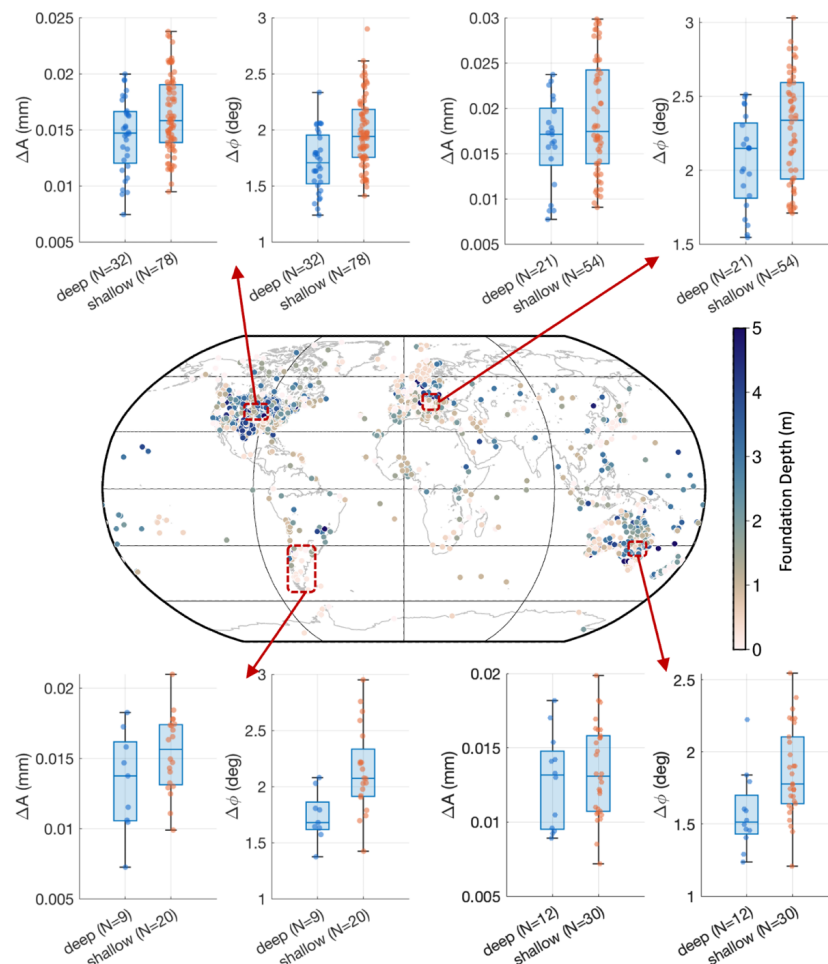
438 To evaluate the robustness of  $\text{FEM}_{\text{FL}}$  across varying site conditions, we select GNSS  
 439 stations with relatively complete site documentation and perform an independent  
 440 comparison within four well-instrumented validation windows (Fig. 9). For each station, we  
 441 construct a site-constrained layered model using available information on



monument/foundation type, embedment depth, and material properties, estimate the annual TED amplitude and phase, and compare these against the SoilGrids-based layered solution. For interpretability, stations are grouped by foundation embedment depth: deep foundations are expected to be more strongly coupled to the stable deeper medium (e.g., bedrock or competent deep soil), whereas shallow foundations are more strongly influenced by near-surface soils. The map in Fig. 9 shows the validation sites and their foundation depths (color-coded), and the boxplots summarize the annual amplitude difference ( $\Delta A$ ) and phase difference ( $\Delta \phi$ ) between the site-constrained and SoilGrids-based solutions for the deep and shallow groups in each window (sample sizes in parentheses).

The two parameterizations agree closely. Across the four validation windows,  $\Delta A$  is on the order of  $10^{-2}$  mm (typically 0.01–0.03 mm) and  $\Delta \phi$  is generally within a few degrees (about  $1\text{--}3^\circ$ ). This indicates that, where site surveys are unavailable, gridded SoilGrids thermophysical properties provide a reasonable statistical representation of typical conditions and that  $FEM_{FL}$  is not unduly sensitive to moderate parameter differences. Shallow-foundation sites show slightly higher medians and larger dispersion in both  $\Delta A$  and  $\Delta \phi$ , consistent with greater sensitivity to near-surface thermal processes and local material heterogeneity, whereas deep-foundation sites exhibit tighter distributions and more consistent behavior across windows. This independent validation supports the transferability of  $FEM_{FL}$  for global application and suggests that incorporating station-specific information, where available, can further refine local estimates of annual amplitude and phase. Since detailed foundation-depth and material metadata remain sparse across global GNSS networks, the small discrepancies observed here also support SoilGrids-based layering as a practical and physically plausible default for global thermoelastic corrections.





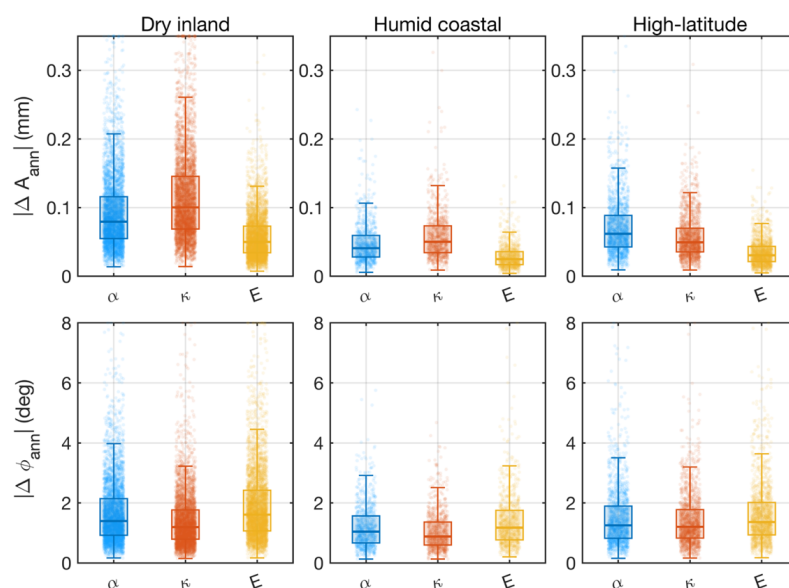
466

467 **Figure 9** Local validation of  $FEM_{FL}$  using stations with known foundation depth and material  
 468 information: the annual amplitude and phase differences between site-specific layered  
 469 solution and the SoilGrids-layered solution, shown separately for deep and shallow  
 470 foundation stations.

471 **Figure 10** summarizes the distribution of absolute changes in annual TED amplitude and  
 472 phase ( $|\Delta A_{ann}|$  and  $|\Delta \phi_{ann}|$ ) induced by  $\pm 10\%$  perturbations to key thermo-mechanical  
 473 parameters, stratified into three representative climate–geographic groups (arid inland,  
 474 humid coastal, and high-latitude). Across all groups, the responses are concentrated at small  
 475 values with a limited long tail, indicating that  $FEM_{FL}$  is generally robust to moderate  
 476 parameter uncertainty while allowing for stronger sensitivity at a small subset of stations.  
 477 The arid-inland group shows the largest dispersion in both  $|\Delta A_{ann}|$  and  $|\Delta \phi_{ann}|$ , consistent  
 478 with stronger annual temperature forcing and steeper near-surface thermal gradients that  
 479 can amplify uncertainty in thermal expansion and diffusivity. The humid-coastal group  
 480 exhibits the tightest distributions (smaller medians and interquartile ranges), reflecting



481 smoother, ocean-moderated forcing and more stable downward propagation of thermal  
 482 signals. The high-latitude group is intermediate overall but displays a more pronounced tail  
 483 at some sites, plausibly linked to snow/freezing-thaw conditions and strong seasonal  
 484 temperature contrasts. In terms of parameter influence, the linear thermal expansion  
 485 coefficient  $\alpha$  most directly controls  $|\Delta A_{\text{ann}}|$  (amplitudes scale approximately with  $\alpha$ ),  
 486 thermal diffusivity  $\kappa$  primarily affects  $|\Delta \phi_{\text{ann}}|$  by governing penetration depth and phase lag,  
 487 and Young's modulus  $E$  modulates amplitudes through material stiffness with typically  
 488 intermediate sensitivity. These patterns provide a basis for uncertainty propagation and  
 489 help prioritize parameters for further refinement.



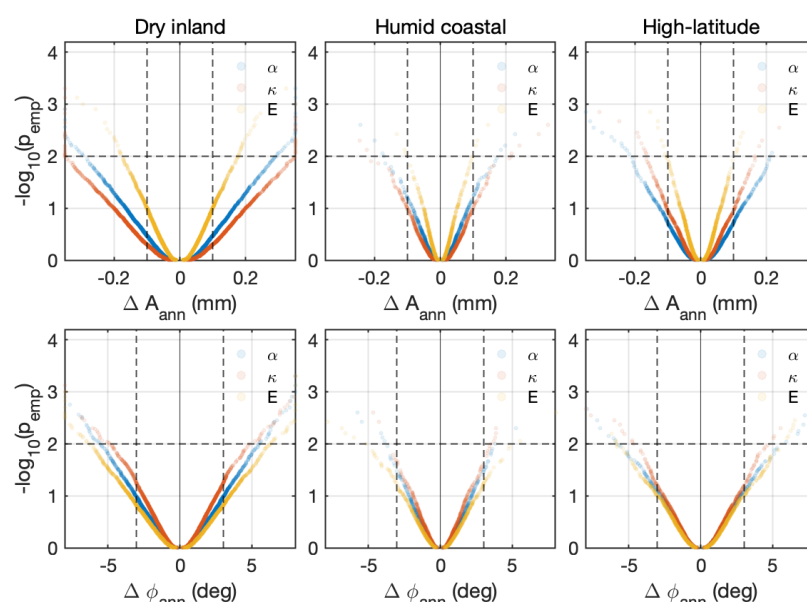
490

491 **Figure 10** Distribution of TED annual-cycle sensitivity under  $\pm 10\%$  parameter perturbations.  
 492 Box-and-scatter summaries for three region types (arid interior, humid coastal, and high  
 493 latitude), showing changes in the TED annual cycle when  $\alpha$  (linear thermal expansion  
 494 coefficient),  $\kappa$  (thermal diffusivity), and  $E$  (Young's modulus) are perturbed by  $\pm 10\%$ .

495 **Figure 11** further quantifies sensitivity using a perturbation-magnitude–  
 496 empirical-significance framework. The x-axis shows the signed perturbation-induced  
 497 changes in annual amplitude and phase ( $\Delta A_{\text{ann}}$  and  $\Delta \phi_{\text{ann}}$ ), and the y-axis plots  $-\log_{10}(p_{\text{emp}})$ ,  
 498 where  $p_{\text{emp}}$  is the within-group empirical tail probability and measures how atypical a  
 499 station's response is for a given (region, parameter) combination. The resulting volcano  
 500 plots exhibit a characteristic V-shape: most stations cluster near zero change (large  $p_{\text{emp}}$ ; low  
 501 significance), whereas a small subset shows larger responses (small  $p_{\text{emp}}$ ; high significance)  
 502 and therefore appears higher on the y-axis. This representation captures both response  
 503 magnitude and relative rarity, separating pervasive low-level variability from a limited  
 504 number of genuinely sensitive sites. It enables efficient global identification of station



505 classes and regions that merit closer scrutiny (e.g., arid-inland and some high-latitude  
 506 environments) and supports rapid screening using threshold lines. The volcano plots are  
 507 consistent with boxplot summaries, indicating that annual TED estimates are generally  
 508 robust to moderate parameter uncertainty while exhibiting interpretable high-sensitivity  
 509 tails under specific environmental conditions, motivating the use of sensitivity flags or  
 510 screening rules in quality control and downstream applications.



511

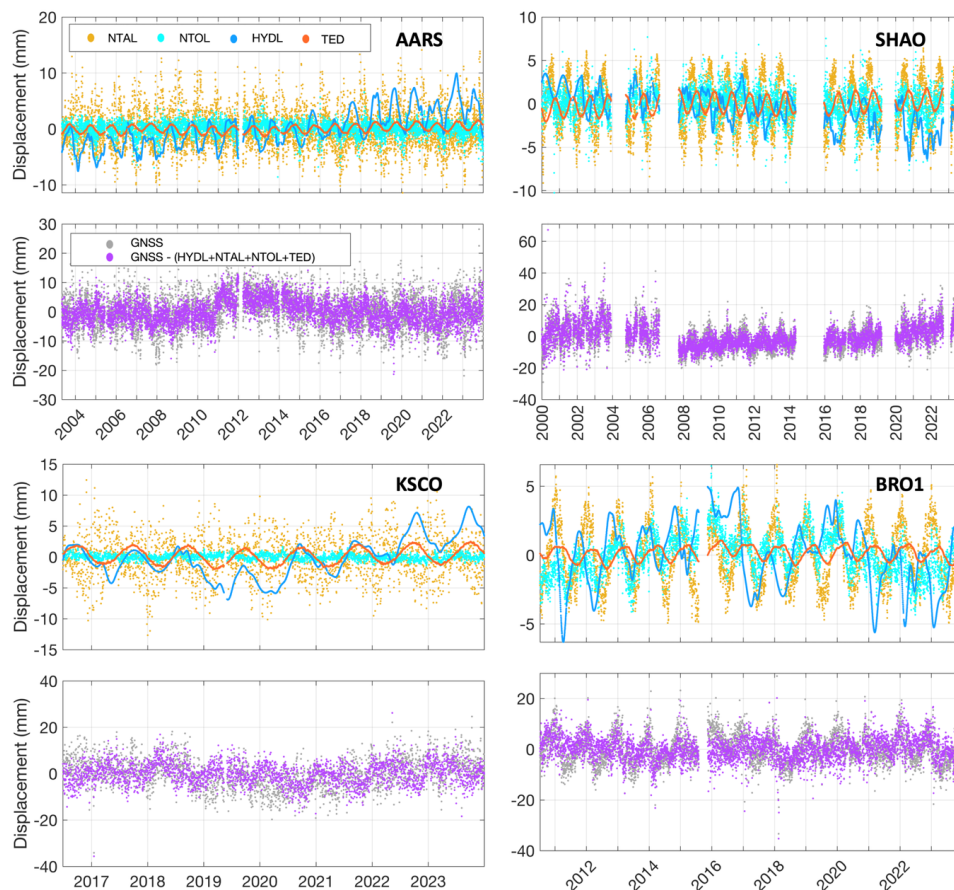
512 **Figure 11** Volcano plots of TED annual-cycle sensitivity:  $\Delta A_{\text{ann}}$  and  $\Delta \phi_{\text{ann}}$  induced by  $\pm 10\%$   
 513 parameter perturbations and their empirical significance ( $p_{\text{emp}}$ ).

### 514 3.3. Contribution of thermoelastic effects to GNSS motion

515 To illustrate how temperature-driven TED and non-tidal mass-loading corrections affect  
 516 GNSS vertical time series, we show examples for four representative stations (AARS, SHAO,  
 517 KSCO, and BRO1; Fig. 12). For each station, the upper panel displays the four environmental  
 518 displacement components (NTAL, NTOL, HYDL, and TED), highlighting their relative  
 519 contributions across seasonal and subseasonal timescales. The lower panel compares the  
 520 original GNSS vertical series with the corrected residual obtained after removing the  
 521 combined signal (NTAL+NTOL+HYDL+TED). Before correction, all stations exhibit  
 522 pronounced seasonal variability along with varying levels of nonseasonal fluctuations; after  
 523 correction, both the residual dispersion and the seasonal peak-to-trough range are  
 524 substantially reduced, indicating that these processes account for a large fraction of the  
 525 non-tectonic vertical signal. At SHAO, for example, the strong annual cycle in the raw series  
 526 is largely suppressed after correction, leaving mainly small-amplitude higher-frequency



variability and slowly varying residual structure. The dominant contributors vary by site: HYDL is often larger in monsoon-influenced regions, TED tends to be more prominent in arid or continental climates, and coastal stations show an additional NTOL contribution.



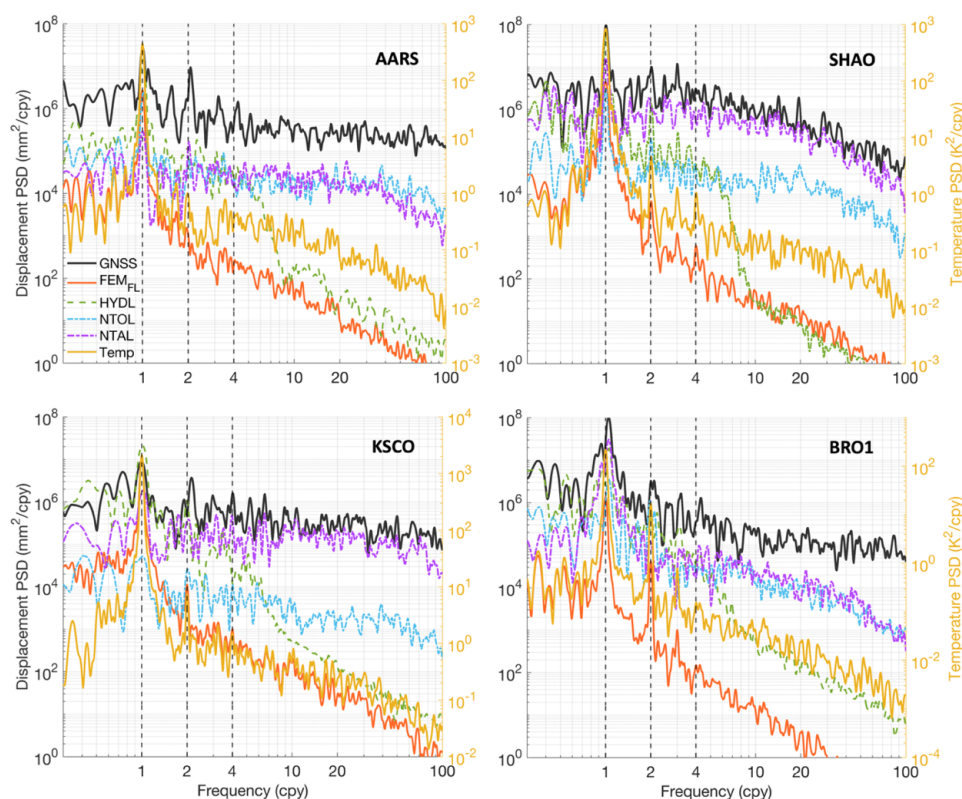
530

**Figure 12** Component comparison and correction effect at four representative stations: the top panels show modeled displacements from NTAL, NTOL, HYDL, and TED, and the bottom panels compare the raw GNSS vertical series with the corrected series after removing these components.

To compare the frequency-domain contributions of TED and non-tidal mass loading to vertical variability of GNSS stations, we compute power spectral densities (PSDs) for four representative stations (Fig. 13). We show PSDs for the raw GNSS height series, the modeled components ( $FEM_{FL-TED}$ , HYDL, NTOL, and NTAL), and the temperature forcing (right axis). The GNSS spectra displays a dominant peak near 1 cpy (annual), with secondary peaks near 2 cpy (semiannual) at some sites, together with elevated power at lower frequencies, indicating the coexistence of seasonal and longer-period variability. The temperature forcing concentrates power near 1 cpy, and TED exhibits a co-located annual peak, indicating that



the surface-temperature cycle is efficiently expressed as thermoelastic motion. HYDL and NTAL (and NTOL at coastal sites) also contribute appreciable power in the same seasonal bands, implying that the observed GNSS seasonal peaks typically reflect superposition of multiple environmental processes. Figure 13 is limited to  $\leq 100$  cpy and therefore does not include diurnal and semi-diurnal frequencies ( $\geq 365$  cpy). For daily solutions, sub-daily thermoelastic variability is more likely to influence this band through aliasing rather than as resolvable spectral peaks. The PSD comparison thus provides complementary evidence that both TED and non-tidal loading contribute substantially to GNSS vertical power at the key seasonal frequencies.



552

**Figure 13** Power spectral density (PSD) comparison for representative GNSS stations: vertical GNSS displacement versus modeled components, including  $FEM_{FL}$  thermoelastic displacement, HYDL, NTOL, NTAL, and the temperature-forcing spectrum.

To quantify the contribution of individual environmental processes to GNSS vertical scatter, we apply four corrections separately at each station—NTAL, NTOL, HYDL, and TED—using an identical processing and evaluation scheme. The benefit of each single correction is quantified as the percentage change in the weighted root-mean-square (WRMS) residual dispersion relative to the uncorrected series. Figure 14 summarizes these changes using global maps and regional boxplots for each component. The correction effectiveness is

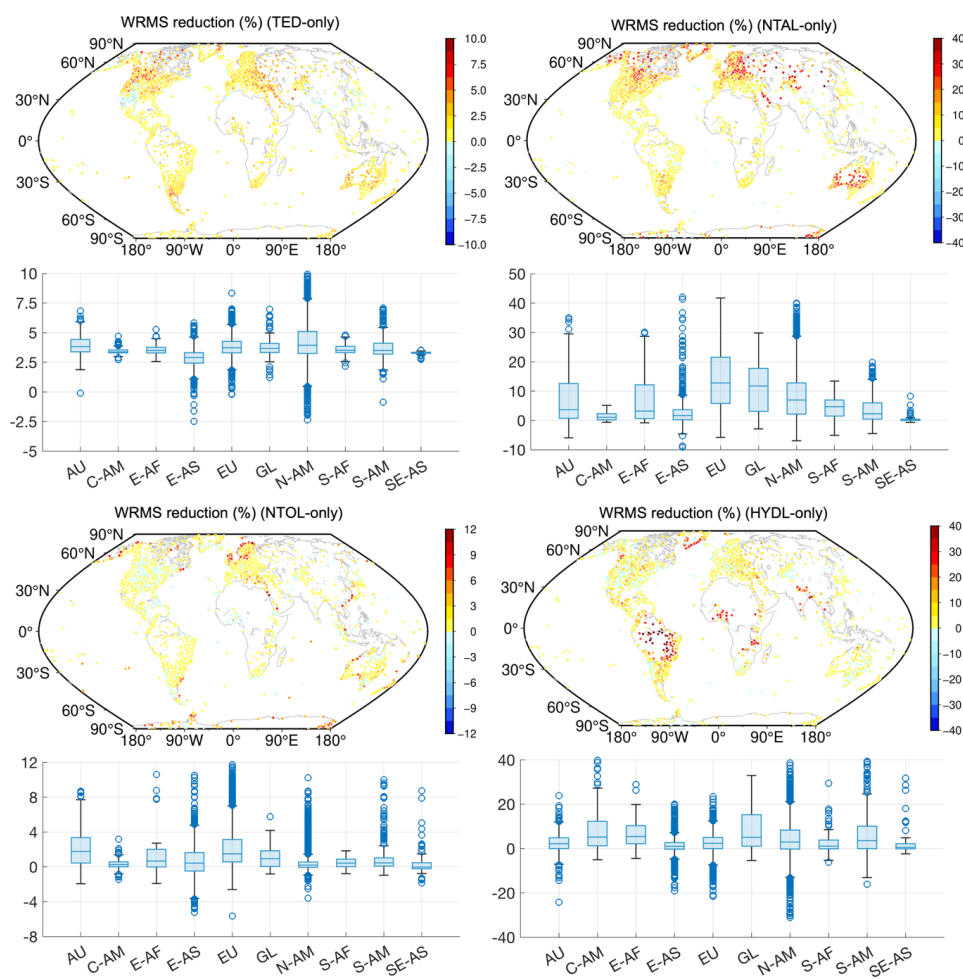
561



strongly region dependent and broadly reflects the underlying forcing. HYDL yields the largest reductions in regions with strong seasonal water-storage variability (e.g., monsoon regions, the Amazon basin, and snow-affected high latitudes), where residual dispersion commonly decreases by ~10–30% and locally by ~30–40%. NTAL shows a more spatially extensive impact, with larger improvements in mid–high latitudes and some high-elevation areas, typically reducing dispersion by a few percent to >10%. NTOL primarily affects coastal and island stations and is weak inland, but can still reduce dispersion by a few percent and locally by up to ~10% near coasts with strong seasonal sea-level variability or complex geometry. TED provides a more ubiquitous but generally modest benefit: dispersion reductions are typically a few percent (often ~5%) and are more pronounced in continental arid/semi-arid interiors with large diurnal temperature ranges. For each component, a small subset of stations shows increased dispersion after correction, indicating limited benefit or slight degradation where local effects dominate, noise levels are high, or the correction is not well matched to site conditions. These results underscore that atmospheric, oceanic, hydrological, and thermoelastic effects dominate in different regions, and that no single correction can substitute for the others at global scale.

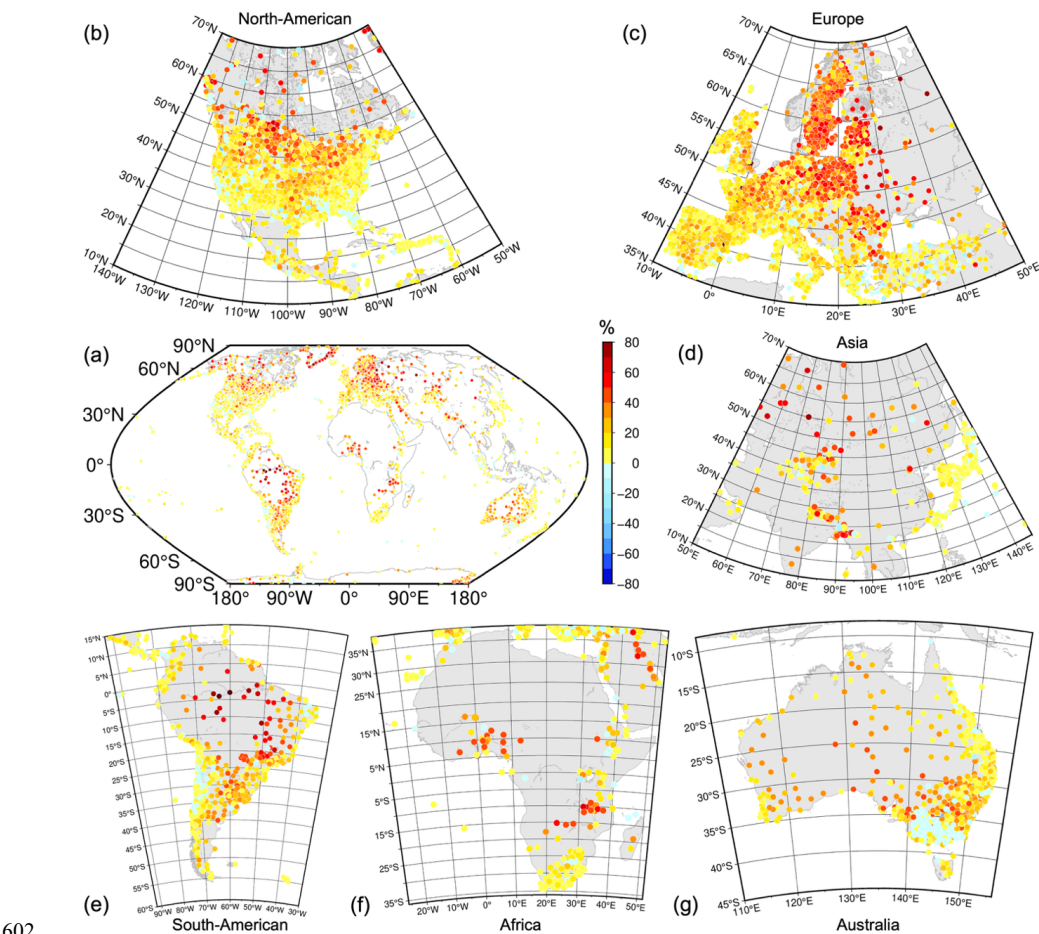
When the major environmental corrections—NTAL, NTOL, HYDL, and TED—are applied jointly, a larger fraction of the seasonal and low-frequency non-tectonic variability in GNSS vertical time series is explained, resulting in a substantial reduction in residual scatter. Figure 15 maps the resulting percentage reduction in WRMS residual dispersion relative to the uncorrected series, with regional zoom-ins for North America, Europe, Asia, South America, Africa, and Australia. Relative to the single-component corrections (Fig. 14), the combined correction produces a more spatially continuous and regionally coherent improvement. WRMS reductions exceed 10% at most stations and are largest where multiple environmental signals are pronounced and station coverage is dense (e.g., North America, Europe, and parts of East Asia), typically reaching 20–35% and peaking at ~70% in the best cases. This pattern indicates that vertical scatter in these regions is largely driven by the superposition of atmospheric, hydrological, oceanic, and temperature-related effects acting within overlapping frequency bands. Improvements are generally smaller in humid tropical regions, some islands, and sparsely instrumented areas, and a small subset of stations shows near-zero or negative changes, consistent with limited benefit where local nonlinear processes, site effects, or observational noise dominate. Applying TED along with non-tidal loading thus provides an effective global strategy for suppressing major non-tectonic signals, reducing residual noise and low-frequency scatter, and yielding cleaner time series for reference-frame stability assessment, vertical land motion studies, and detection of subtler geophysical signals.





598

599 **Figure 14** Percentage reduction in WRMS after applying NTAL, HYDL, NTOL, and TED  
600 corrections individually, shown as global maps and regional boxplots. Regional abbreviations  
601 are consistent with those in Fig. 6e.



**Figure 15** Vertical WRMS reduction after jointly applying NTAL, HYDL, NTOL, and TED corrections: global map and regional zoom-ins.

#### 4. Data availability

The global dataset of temperature-driven vertical thermoelastic displacement (TED) time series for continuous GNSS stations was produced following the workflow described in Section 2 and covers ~15,000 stations for 2000–2023. The archived release is available via Zenodo (DOI: 10.5281/zenodo.18256342; Lu et al., 2026) and is mirrored on the Ground Motion Data Service (GMDS) platform, where users can query by station name and time span and download station-level TED time series together with associated metadata. Data files are organized by station and provide time tags (UTC) and vertical TED displacements (mm), along with essential metadata (e.g., station latitude/longitude, record start/end dates, dataset version, and quality flags), enabling direct alignment with GNSS height time series for correction and evaluation workflows. Users should cite the Zenodo DOI and, when



616 accessing data through GMDS, also cite the GMDS landing page together with the dataset  
617 version (if applicable) and the access date.

## 618 5. Conclusion and discussion

619 Correction-ready, multi-decade non-tectonic displacement time series are essential for  
620 GNSS reference-frame stability assessments and long-term, wide-area deformation analyses.  
621 However, strong heterogeneity in site conditions, temperature forcing, and temporal  
622 sampling has hindered a globally consistent and reproducible characterisation of  
623 temperature-driven thermoelastic deformation. To address this gap, hourly ERA5  
624 soil-temperature forcing is combined with depth-resolved thermophysical properties from  
625 SoilGrids, and a full-spectrum layered finite-element model is implemented globally,  
626 producing a global dataset of vertical thermoelastic displacement (TED) time series for  
627 ~15,000 continuous GNSS stations over 2000–2023, released openly via the GMDS platform.  
628 Methodologically, the dataset couples layered thermo-mechanical physics with a broadband  
629 response spanning semi-diurnal/diurnal through seasonal and interannual timescales. To  
630 mitigate diurnal aliasing and longitude-dependent artefacts associated with fixed-epoch  
631 sampling in daily GNSS solutions, the model is evaluated at four UTC epochs (00/06/12/18)  
632 and the four UTC-epoch realizations are combined using a phase-consistent scheme. This  
633 strategy retains sub-daily variability while reducing undersampling- and aliasing-related  
634 artefacts, yielding daily TED series that align directly with standard daily GNSS height  
635 products for practical correction.

636 Results reveal pronounced regional contrasts in TED. Peak-to-peak displacements are  
637 typically at the millimeter level, generally larger in arid interiors and continental climates,  
638 but smaller in maritime environments and persistently humid regions. Relative to a  
639 homogeneous-medium assumption, incorporating subsurface layering produces systematic  
640 increases in annual amplitude and shifts in the timing of the annual maximum in some areas,  
641 indicating that site-specific parameterization of depth-dependent thermophysical properties  
642 is important for globally consistent TED estimates. Independent validation using 256  
643 stations with site documentation across four well-instrumented regions shows that the  
644 SoilGrids-based layered solution agrees closely with site-constrained layered models, with  
645 annual-amplitude differences typically 0.01–0.03 mm and annual-phase differences  
646 generally within ~1–3° (with a slightly larger spread at shallow-foundation sites). In practical  
647 applications, applying TED together with non-tidal loading corrections (NTAL/NTOL/HYDL)  
648 reduces seasonal—and part of the nonseasonal—variability in GNSS vertical time series at  
649 most stations and produces broadly consistent decreases in residual dispersion, typically  
650 20–35% in densely instrumented regions (e.g., North America, Europe, and parts of East  
651 Asia), reaching ~70% at the best-performing sites. Collectively, these improvements support  
652 more robust tectonic-velocity estimation, cleaner separation of non-tectonic signals, and  
653 millimeter-level reference-frame establishment.

654 Nevertheless, several limitations remain. First, because the dataset relies on globally  
655 uniform inputs, we adopt the simplifying assumption that the monument foundation is  
656 tightly coupled to the surface and shallow subsurface, and we cannot yet incorporate  
657 station-specific engineering information (e.g., foundation type, embedment depth, and



materials) in a systematic way. As a result, the obtained TED amplitude and phase may be biased for rooftop installations, deep-anchored monuments, or other atypical configurations. Users are therefore encouraged to consult site logs or independent metadata to filter stations, stratify analyses, or perform sensitivity tests to mitigate structure-related biases. Second, SoilGrids provides static thermophysical properties, and we do not explicitly represent processes such as time-varying soil moisture, freeze–thaw phase change, or pore-water migration that can modulate effective thermal diffusivity and phase lag. These omissions may increase uncertainty in seasonally frozen or permafrost regions and in strongly monsoonal humid climates. Future work could integrate permafrost, soil-moisture, and snow datasets to develop seasonally varying effective-parameter schemes, thereby improving model fidelity in complex environments. Third, the temperature forcing is derived from reanalysis, and regional biases or surface energy-balance errors may project into weak low-frequency components over multi-year periods. We therefore treat the TED linear term primarily as a diagnostic quantity rather than a tectonic indicator, and recommend consistent detrending in long-term velocity analyses and, where possible, cross-validation against independent temperature or surface energy-flux observations.

#### Author contributions

RL proposed the initial idea, designed the experiments, developed the software, and wrote the manuscript. ZL and YF reviewed and revised the manuscript, focusing on the paper structure, correctness of concept, data, and analysis. LY assisted in developing the GMDS website. PY reviewed and revised the manuscript. All authors approved of the manuscript.

#### Competing interests

The contact author has declared that none of the authors has any competing interests.

#### Disclaimer

Publisher's note: Copernicus Publications remains neutral with regard to jurisdictional claims made in the text, published maps, institutional affiliations, or any other geographical representation in this paper. While Copernicus Publications makes every effort to include appropriate place names, the final responsibility lies with the authors.

#### Acknowledgments

We gratefully acknowledge the Nevada Geodetic Laboratory (NGL) for providing the GNSS coordinate time series, GFZ for the non-tidal atmospheric and ocean loading displacement products (NTAL and NTOL), and the GRACE/GRACE-FO Mascon solutions provided by NASA that were used to derive the hydrological loading (HYDL). We also thank ECMWF for the ERA5 temperature datasets. Figures were generated using the Generic Mapping Tools (GMT) software (Wessel et al., 2013). Ran Lu thanks the China Scholarship Council (CSC) for supporting the portion of this work carried out at the Queensland University of Technology (QUT), Australia.



## 695 Financial support

696 This research was supported in part by the National Natural Science Foundation of China  
 697 (grant nos: [424B2026](#), [42574041](#), [42192531](#), [42388102](#)) and by the Scientific Research  
 698 Innovation Capability Support Project for Young Faculty (grant no: [SRICSPYF-ZY2025007](#)),  
 699 and by the Wuhan Natural Science Foundation (grant no: [2024040701010029](#)).

## 700 References

- 701 Altamimi Z, Rebischung P, Collilieux X, Métivier L, Chanard K (2023). ITRF2020: an  
 702 augmented reference frame refining the modeling of nonlinear station motions.  
 703 *Journal of Geodesy*, 97.
- 704 Biot MA (1956) Thermoelasticity and irreversible thermodynamics. *Journal of Applied*  
 705 *Physics*, 27:240–253.
- 706 Berger J (1975) A note on thermoelastic strains and tilts. *Journal of Geophysical Research*,  
 707 80(2), 274– 277. <https://doi.org/10.1029/JB080i002p00274>
- 708 Blewitt G, Hammond W, Kreemer C (2018) Harnessing the GPS Data Explosion for  
 709 Interdisciplinary Science. *Eos*, 99. <https://doi.org/10.1029/2018eo104623>
- 710 Clarke PJ, Lavallée DA, Blewitt G, van Dam TM, Wahr JM (2005) Effect of gravitational  
 711 consistency and mass conservation on seasonal surface mass loading models.  
 712 *Geophysical Research Letters* 32(L08306).
- 713 Dong D, Fang P, Bock Y, Cheng M. K, Miyazaki S. I (2002) Anatomy of apparent seasonal  
 714 variations from GPS-derived site position time series. *Journal of Geophysical Research*,  
 715 107(B4), ETG-9. <https://doi.org/10.1029/2001JB000573>
- 716 Fritsche M, Döll P, Dietrich R (2012) Global-scale validation of model-based load  
 717 deformation of the Earth’s crust from continental watermass and atmospheric pressure  
 718 variations using GPS. *Journal of Geodynamics*, 59–60(1):133–142.  
 719 <https://doi.org/10.1016/j.jog.2011.04.001>
- 720 Fang M, Dong D, Hager H (2014) Displacements due to surface temperature variation on a  
 721 uniform elastic sphere with its centre of mass stationary. *Geophysical Journal*  
 722 *International*, 196:194–203. <https://doi.org/10.1093/gji/ggt335>
- 723 Hersbach H, Bell B, Berrisford P, Biavati G, Horányi A, Muñoz-Sabater J, Nicolas J, Peubey C,  
 724 Radu R, Rozum I, Schepers D, Simmons A, Soci C, Dee D, Thépaut JN (2018). ERA5  
 725 hourly data on single levels from 1940 to present [Dataset]. Copernicus Climate Change  
 726 Service (C3S) Climate Data Store (CDS).
- 727 Hengl T, de Jesus JM, Heuvelink GBM, Ruiperez Gonzalez, M, Kilibarda M, Blagotić A,  
 728 Shangguan W, Wadoux A, Ribeiro E, Kempen B, Leenaars J, Walsh MG, Gonzalez MR  
 729 (2017). SoilGrids250m: Global gridded soil information based on Machine Learning.  
 730 *PLoS ONE*, 12(2), e0169748.
- 731 Jiang W, Li Z, van Dam T, Ding W (2013) Comparative analysis of different mass loads  
 732 methods and their impacts on the GPS height time series. *Journal of Geodesy*, 87(7),  
 733 687– 703. <https://doi.org/10.1007/s00190-013-0642-3>



- 734 Lei J, Chen W, Li Z, Li F, Zhang S (2020) A full-spectrum bedrock thermal expansion model  
735 and its impact on the global positioning system height time series. *Geophysical*  
736 *Research Letters*, 47(1). <https://doi.org/10.1029/2019GL086022>
- 737 Li Z, Chen W, van Dam Tonie, Rebischung Paul, Altamimi Zuheir (2020) Comparative analysis  
738 of different atmospheric surface pressure models and their impacts on daily ITRF2014  
739 GNSS residual time series. *Journal of Geodesy*, 94(4), 1-20.  
740 <https://doi.org/10.1007/s00190-020-01370-y>
- 741 Li Z, Lu R, Jiang W, Dong D, Lei J, Lu Y, Ding X, Yang C, Chen H, Chen Q (2024) A refined  
742 full-spectrum temperature-induced subsurface thermal expansion model and its  
743 contribution to the vertical displacement of global GNSS reference stations. *Journal of*  
744 *Geodesy*, 98, 25. <https://doi.org/10.1007/s00190-024-01834-5>
- 745 Li Z, Jiang W, van Dam T, Zou X, Chen Q, Chen H (2025) A Review on Modeling  
746 Environmental Loading Effects and Their Contributions to Nonlinear Variations of  
747 Global Navigation Satellite System Coordinate Time Series. *Engineering*, 47, 26-37.  
748 <https://doi.org/10.1016/j.eng.2024.09.001>
- 749 Lu R, Li Z, Chen Q, Ding X, Yang C, Zhang M, Lu Y, Fan W, Chen H, Jiang W (2024) On the  
750 contributions of refined thermal expansion model to nonlinear variations in different  
751 GNSS height time series products. *GPS Solutions*, 28, 80.  
752 <https://doi.org/10.1007/s10291-024-01625-7>
- 753 Lu R, Li Z, Ye L, Wang J, Yuan P, Ding X, Zhang M, Feng Y (2025) Diurnal temperature forcing  
754 and subsurface stratification drive thermoelastic displacements at global GNSS stations,  
755 *Journal of Geophysical Research: Solid Earth* (Under Review)
- 756 Lu, R., Li, Z., Feng, Y. (2026). TED: A global temperature-driven thermoelastic displacement  
757 dataset for GNSS reference stations (2000–2023) [Data set]. Zenodo.  
758 <https://doi.org/10.5281/zenodo.18256342>
- 759 Romagnoli C, Zerbini S, Lago L, Richter B, Simon D, Domenichini F, Elmi C, Ghirotti M (2003)  
760 Influence of soil consolidation and thermal expansion effects on height and gravity  
761 variations. *Journal of Geodynamics*, 35(4-5), 521-539.  
762 [https://doi.org/10.1016/S0264-3707\(03\)00012-7](https://doi.org/10.1016/S0264-3707(03)00012-7)
- 763 Prawirodirdjo L, Ben-Zion Y, Bock Y (2006) Observation and modeling of thermoelastic strain  
764 in southern California integrated GPS network daily position time series. *Journal of*  
765 *Geophysical Research*, 111, B02408. <https://doi.org/10.1029/2005JB003716>
- 766 Poggio L, de Sousa L M, Batjes N H, Heuvelink G B M, Kempen B, Ribeiro E, Rossiter D (2021)  
767 SoilGrids 2.0: producing soil information for the globe with quantified spatial  
768 uncertainty, *SOIL*, 7, 217–240, <https://doi.org/10.5194/soil-7-217-2021>.
- 769 van Dam T, Wahr J, Lavallée D (2007) A comparison of annual vertical crustal displacements  
770 from GPS and Gravity Recovery and Climate Experiment (GRACE) over Europe. *Journal*  
771 *of Geophysical Research: Solid Earth*, 112(B3).
- 772 Wessel P, Smith WHF, Scharroo R, Luis J, Wobbe F (2013) Generic mapping tools: improved  
773 version released. *Eos Trans AGU* 94(45):409–410.





- 774 Wei N, Zhou Y, Shi C, Xu X, Rebischung P, Liu J (2025) Toward a refined estimation of  
775 geocenter motion from GNSS displacements: Mitigating thermoelastic deformation and  
776 systematic errors. *Journal of Geophysical Research: Solid Earth*, 130(7),  
777 e2024JB028967.
- 778 Xu X, Dong D, Fang M, Zhou Y, Wei N, Zhou F (2017) Contributions of thermoelastic  
779 deformation to seasonal variations in GPS station position. *GPS Solutions*, 21(3), 1265–  
780 1274. <https://doi.org/10.1007/s10291-017-0609-6>
- 781 Yan H, Chen W, Zhu Y, Zhang W, Zhong M (2009) Contributions of thermal expansion of  
782 monuments and nearby bedrock to observed GPS height changes. *Geophysical*  
783 *Research Letters*, 36. <https://doi.org/10.1029/2009GL038152>
- 784 Yan H, Chen W, Shu Y, Zhang W, Zhong M, Liu G (2010) Thermal effects on vertical  
785 displacement of GPS stations in China. *Chinese Journal of Geophysics (in Chinese)*,  
786 53(4): 825-832.