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GPS displacement dataset for study of elastic surface mass variations

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Abstract

Quantification of uncertainty in surface mass change signals derived from GPS measurements poses challenges, especially when dealing with large data sets with continental or global coverage. We present a new GPS station displacement data set that reflect surface mass load signals and their uncertainties. We assess the structure and quantify the uncertainty of vertical land displacement derived from 3045 GPS stations distributed across the continental US. Monthly means of daily positions are available for 15 years. We list the required corrections to isolate surface mass signals in GPS estimates and screen the data using GRACE(-FO) as external validation. Evaluation of GPS timeseries is a critical step, which identifies a) corrections that were missed; b) sites that contain non-elastic signals (e.g., close to aquifers); and c) sites affected by background modelling errors (e.g., errors in the glacial isostatic model). Finally, we quantify uncertainty of GPS vertical land displacement (VLD) estimates through stochastic modeling and quantification of spatially correlated errors. Our aim is to assign weights to GPS estimates of VLD, which will be used in a joint solution with GRACE(-FO). We prescribe white, colored and spatially correlated noise. To quantify spatially correlated noise, we build on the common mode imaging approach adding a geophysical constraint (i.e., surface hydrology) to derive an error estimate for the surface mass signal. We study the uncertainty derived using each technique and find that three techniques exhibit an average noise level between 2-3 mm: white noise, flicker noise, and RMS of residuals about a seasonality and trend fit. Prescribing random walk noise increases the error level such that half of the stations have noise > 4 mm, which is systematic with the noise level derived through modeling of spatial correlated noise. The new data set is suitable for use in a future joint solution with GRACE(-FO)-like observations.

Keywords: GPS uncertainty | vertical land displacement | GRACE-FO | surface mass change

1. Introduction

For more than two decades, the Gravity Recovery and Climate Experiment (GRACE) space gravity mission and its nearly identical successor mission, GRACE-Follow on (GRACE-FO), have provided mass change estimates through tracking the time-variable part of the Earth's gravity field (Landerer et al., 2020). Mass change products are typically given on a monthly basis and have been used to study a variety of critical climate-related factors (Tapley et al., 2019), such as sea level rise (Frederikse et al., 2020); ice mass change (Velicogna et al., 2020); prolonged drought periods (Thomas et al., 2014) and regional flood potentials (Reager et al., 2014). The measurement geometry of GRACE(-FO) limits the study of geophysical processes to spatial scales of ~300 km and larger, for monthly timespans. Recent community reports (Pail et al., 2015, Wiese et al., 2022) have highlighted the utility and need of mass change observations at improved spatial resolutions to address a number of science and applications objectives. Examples include closure of the terrestrial water budget for small to medium sized river basins, and separation of surface mass balance from ice dynamic processes at the scale of individual outlet glacier systems.

The spatial resolution of gravity maps derived from satellite measurements is limited by sampling at altitude. Fusion with external geodetic data sources, however, can improve spatial resolution over what can be achieved only with satellite gravimetry. GPS position timeseries have been used widely to study the elastic response of Earth's surface to mass loading (e.g., Argus et al., 2017; Fu and Freymueller, 2012) and can provide information at short wavelengths (~100km) (Argus et al., 2021). Solid Earth responds elastically to changes in the surface load of water, snow, ice, and atmosphere. When the Earth's surface is loaded with mass (e.g., snow and water) it subsides; and when mass loads are removed the surface rises. Thus, the Earth's response follows the water cycles such that: precipitation and snow accumulation subside the surface and snow melt, evaporation and water run off allow the Earth's surface to bounce back (uplift). Focus is typically placed on the radial direction (vertical), due to the rapid decrease of vertical land displacement (VLD) with the distance from a surface load (Argus et al., 2017), which leads to high fidelity estimates in the space domain. Note that across certain geological formations such as aquifers, subduction zones and regions with volcanic activity surface loading is mixed with other solid Earth/geophysical processes making it difficult to isolate the elastic component. Therefore, GPS sites located at the vicinity of such formations are omitted from further analyses.

GPS VLDs (i.e., displacement between two epochs) have many different signals embedded in them; i.e., those related to atmospheric and oceanic loading, solid Earth phenomena such as tectonics, glacial isostatic adjustment (GIA), and others related to surface mass changes. With the proper treatment (see Sec.2) GPS stations can capture local surface mass changes. We are interested in isolating the signals that reflect the Earth's elastic response to mass variations, thus we apply a set of corrections to GPS VLD estimates, and then we screen the data for outliers or potential errors. The data screening process checks for consistency between GPS and GRACE(-FO) VLD estimates (similar analysis has been performed by Yin et al., 2020; Blewitt et al., 2001; van Dam et al., 2001; Becker and Bevis, 2004; Davis, 2004; Tregoning et al., 2009; Tsai, 2011 and Chew et al., 2014) and identifies outliers that statistical tests fail to pick up (He et al., 2018).

The last step is to estimate uncertainty in the screened data set. Since our purpose is to isolate surface mass load signals, we define *error* as any VLD signal that does not reflect an elastic surface mass load. The reported uncertainty of a measurement reflects the sum of all error sources to the measurement, and is the final product of this study. Error correlation (temporal and spatial) and the deficiency of stochastic noise models to describe the error realistically are the main challenges in this uncertainty quantification task.

Error sources include errors driven by satellite antenna phase centre offsets (Santamaria-Gomez et al., 2012); atmospheric pressure models (Kumar et al., 2020); non-tidal ocean loading (Jiang et al., 2013); satellite orbits (Ray et al., 2008; Amiri-Simkooei ,2013); earth orientation parameters (Rodriguez-Solano et al., 2014); and tectonic trends and post-seismic relaxation after earthquake activity (Ji and Herring, 2013; Crowell et al., 2016).

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Most of these errors are also spatially coherent, and their sum is usually referred to as common-mode noise (CMN) (Kreemer and Blewitt; 2021). Mitigation of CMN is usually done by means of spatial filtering (Wdowinski et al. 1997), a technique that needs to be applied with caution, due to the assumptions made when applying a spatial filter (see e.g., Williams, 2004; Tian and Shen 2016). Recent developments of spatial filtering algorithms include principal component analysis (PCA) or independent component analysis (ICA). PCA decomposes residual time-series (relative to a deterministic model) into various principal/independent components based on their variance and identifies the components that reflect CMN (Serpelloni et al., 2013; Li and Shen, 2018). ICA is different than PCA in that it finds the maximum independence of the components instead of minimum correlation (Milliner et al., 2019; Liu et al., 2015). One of the main limitations of PCA/ICA is their susceptibility to dismiss CMN reflected in a relatively small number of stations. Therefore, in many occasions a subset of stations is studied independently (Wu et al., 2019).
Considering the increased number of GPS stations and the limitations posed by the existing methodologies, Kreemer and Blewitt (2021) developed a robust methodology to estimate the common spatial components of GPS residuals (i.e., the remaining signals of a time-series after subtraction of a deterministic model). The so-called common mode component (CMC) imaging technique quantifies the spatial correlation of the residuals (position or VLD time-series anomaly with respect to a deterministic model) of unequal-length time-series using information from neighbor stations. It is important to note that CMC reflects both spatially correlated noise and spatially correlated signals, including elastic displacements, that a deterministic model fails to describe.
Spectral analysis of the residuals (with respect to a deterministic model, see Eq.2) is an alternative way to estimate the noise level of VLD series for each GPS station. The spectrum of the residuals can be approximated by white or colored noise (flicker, random walk, power law approximation, generalized gauss markov etc.), or by a combination of white and colored noise (Williams et al., 2004; Bos et al., 2008; Klos et al., 2014). A summary of the different noise models and their power distribution can be found in He et al. (2018). Several standard GPS time series analysis packages are available to perform such an analysis, e.g., CATS (Williams, 2008) and Hector (Bos et al. 2013). Various studies in the past suggested that the residuals are better described by a combination of white and flicker noise (see e.g., Klos et al., 2014; Argus et al., 2017), with the latter contributing the most (Argus and Peltier, 2010). Recently, Argus et al. (2022), showed that the longer the timeseries the more the spectrum of GPS residuals converges with the noise model of random walk.

In this contribution, we outline a comprehensive framework for processing large data sets (continental and/or global) of GPS VLD timeseries, to derive VLD estimates that only reflect surface mass signals, for use in a joint inversion with GRACE(-FO) measurements. Originally, we layout the corrections required to capture local surface mass changes (Section 2.1). Our interest is to make the process as automated as possible, thus we set a number of evaluation metrics to detect outliers among all candidate (for the joint inversion) sites. Stations flagged as outliers are further evaluated for extra corrections (e.g., offsets; poor site maintenance etc.). Finally, we assign weights to each GPS VLD record. We test the most popular methodologies to quantify the error, considering time-correlation, spatial-correlation and/or white noise (Section 3). Note that for spatially correlated noise the commonly used PCA/ICA is not as applicable to our use case, because our data set extends over very large spatial areas (continental). CMC imaging (Kreemer and Blewitt; 2020) fits our needs better. We overcome CMC's limitation of include spatially correlated hydrology signals in the error estimate by deriving surface loading signals from a hydrology

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model and removing them. The final product is a new data set with GPS VLD estimates that reflect elastic mass variations and their uncertainties.

2. GPS data processing and screening

2.1 Isolating surface mass loading fingerprint from GPS VLD

The 3054 GPS position time-series used in this study are a product of Jet Propulsion Laboratory (JPL) (Bertiger et al., 2020) and Nevada Geodetic Laboratory reprocessed GPS solutions (Blewitt et al., 2018). GPS satellite orbits, clocks, and core site positions are estimated consistently using the latest techniques and GipsyX software (Bertiger et al., 2020). Displacement signals driven by solid earth, oceanic and pole tides are corrected according to International Earth Rotation Service (IERS) standards.
We process the GPS series similar to Argus et al. (2017; 2022), that is, we correct for atmospheric loading signals using the ECMWF weather model (Simmons et al., 2007) and for GIA, using the ICE-6G_D model (Peltier et al., 2018). GIA modelling errors affect GPS and GRACE(-FO) VLD predictions in opposite sense. Overestimation of GIA translates to subsidence when we correct GPS. The same overestimation predicts too much mass gain and shows as water loss when we correct GRACE(-FO), which eventually translates to land uplift. The same analogy applies to underestimation of GIA, which is mapped as uplift on GPS and as subsidence on GRACE(-FO) VLD predictions.
Estimates prior to or after a significant earthquake event, or biased by a significant post-seismic transient are discarded. Stations with non-elastic response (e.g., porous) located at aquifers, volcanically active regions and oil extraction sites are also removed from the data record (see Argus et al. (2017) for details). An interseismic strain accumulation correction across the Cascadia is also applied (Argus et al., 2021). The model (Li et al. 2018) consists of both elastic and viscous components (2/3 elastic and 1/3 viscous). All estimates are given in the International Terrestrial Reference Frame 2014 (Altamimi et al., 2016).
Finally, we solve for and remove an offset (Argus et al., 2010) if an estimated offset is greater than 8 mm in the radial direction. In most cases, estimating the offset reduces the root mean square dispersion (in mm) of the position estimates about a fit of the position, velocity and sinusoid with an annual frequency, by more than 5 percent. Daily solutions are averaged into monthly means, and are available for different durations over a span of fifteen years starting from 2006.
To compare GPS with GRACE(-FO) VLD estimates we reference all VLD data to the epoch with the most GPS site records, which is September 2012. This process results in an 11% loss of stations (i.e., no available measurement on 09/2012). Similar to Yin et al. (2020), detrended monthly estimates of each station that are larger than 3σ relative to the mean of the time-series are considered outliers and removed from the data set. Statistical outliers comprise ~0.5% of the records.
2705 (or 88.8%) of GPS stations remain after the choice of reference epoch, the 3σ test and the removal of sites with non-elastic loading response. The distribution of sites is denser along the East and West coasts, and fairly sparse in the central-north US (Fig.1). Series of two arbitrary stations (hivi and njwt) located at the West and East coast respectively, are shown in Fig. 1. The response of the Earth on the extensive drought period in California between 2011.5-2015.5 is captured in the uplift trend mapped by hivi station (Fig.1, top right panel; dashed blue line).

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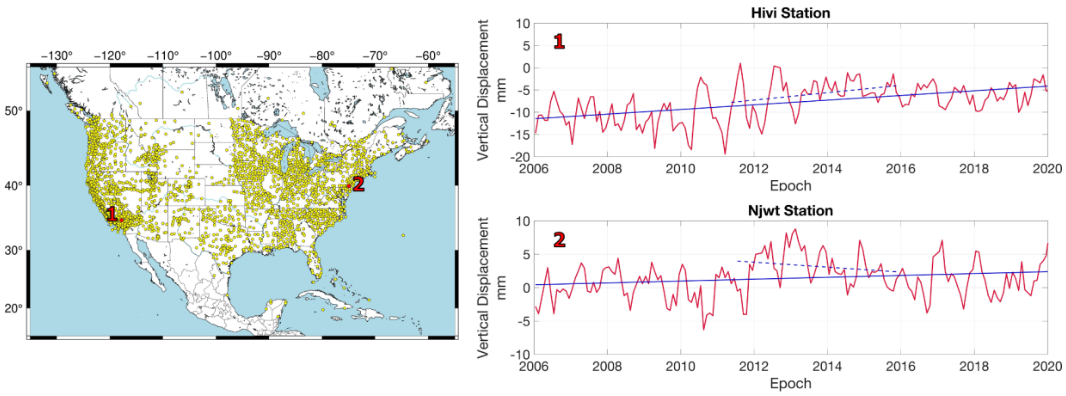

Figure 1: Left panel) Map of study area. GPS stations are shown in yellow; Right panel) Vertical displacement timeseries of two random stations (red line). Solid blue line denotes the overall trend of the timeseries and dashed blue line the trend between (2011.5-2015.5). Note the significant uplift of the hivi station located in southern California.

2.2 External validation data sets - Time-variable gravity field

We employ GRACE(-FO) mascon solutions developed at the Jet Propulsion Laboratory that resolve mass changes using 3-degree spherical cap basis functions (Wiese et al., 2016; Watkins et al., 2015) as a validation tool for the GPS data. The effect of postglacial rebound is removed from GRACE(-FO) products using ICE-6G_D model estimates (Peltier et al., 2017). The geocentre motion (degree 1) coefficient is replaced with the estimated coefficient from Sun et al. (2016), using TN-13. The Earth's oblateness coefficient (C20) is replaced by an estimate derived from Satellite Laser Ranging observations for all months (Loomis et al., 2019), as is the C30 coefficient for all months after August 2016, due to only having a single functioning accelerometer. GPS position timeseries do not include the linear trend of the geocentre motion (i.e., the linear trend of the ITRF14 frame is approximately zero, Altamimi et al. (2014)), as opposed to GRACE(-FO), thus we remove it from GRACE(-FO). The annual signal of the geocentre (as realized by ITRF14) projected on the up component in north America can explain up to 20% of the GPS VLD signal.
GRACE(-FO) VLD monthly estimates are derived as follows (e.g., Davis et al., 2004):

$$U(\phi,\lambda) = a\sum_{l,m}\left(\frac{h_l^E}{1+k_l^E}\right)P_{lm}(sin\lambda)\times[C_{lm}cosm\phi + S_{lm}sinm\phi] \qquad (1)$$

Where, U is the estimate of vertical displacement, a denotes the Earth's radius, ϕ, λ denote the latitude and longitude, respectively; are the associated Legendre polynomials, and are the elastic and vertical Love numbers (PREM; Wang et al., 2012), respectively, and C and S are the spherical harmonic coefficients derived from GRACE(-FO) monthly solutions with respect to degree l and order m. Similar to GPS, we subtract September 2012 values from the rest of the series for a common reference basis.

2.3 Screening metrics

GPS VLD estimates are evaluated against the ones derived from GRACE(-FO), to assist in identifying outliers or further corrections that may be needed. We employ a number of different metrics to evaluate the agreement between the two data sets, and to determine whether to include it in the joint solution or not. Similar to Yin et al. (2020) we quantify correlation and variance reduction between GPS and GRACE(-FO) VLDs. The structure of surface mass periodic signals (e.g., annual cycles, trends) as picked up by the two measurement platforms, also entails critical information regarding mismodelled offsets, and is evaluated as well.
This process flags sites that need correction and corroborates joint inversion's hypothesis (Argus et al., 2021), that a basic level of agreement is needed for the GPS data to be used to infer surface mass change.

Correlation

First, we specify the level of agreement between the data sets by estimating the Pearson correlation coefficient between GPS & GRACE(-FO) VLD timeseries. On average the correlation is 62%, but stations located on the West coast exhibit an agreement higher than 80%, which in most cases is driven by the larger annual signal amplitude. A more detailed look into the correlation metric is performed to evaluate the agreement of GPS/GRACE(-FO) in retrieving the seasonal cycle amplitude in different watersheds. We fit and remove a deterministic model $y(t)$:

$$y = a + bt + A + Bcos(2\pi t), \tag{2}$$

with a being the intercept; b being the trend and A and B being the amplitude and phase of a periodic function with annual frequency.

We classify stations in watersheds and plot the GPS-GRACE(-FO) correlation coefficient (R) of each station in different watershed against the amplitude of annual signals (Fig. 2b). To quantify the relationship between magnitude of the annual cycle and correlation between the two data sets we fit a linear function between the magnitude of the annual signals and the GPS-GRACE(-FO) VLD correlations for each watershed, separately. A steep slope ($\boldsymbol{a}$) of the fit ($\boldsymbol{a}$>0.5) indicates an agreement between the two data sets, which depends on the magnitude of the annual cycle. This relationship breaks when stations of a basin exhibit smaller annual cycles. We discuss an interesting case in Supplements, where stations located in the St. Lawrence basin demonstrate a negative trend $\boldsymbol{a} = -1.26$. The disagreement is even more pronounced while assessing the second metric (i.e., trends). Both metrics, when taken together, helped us identify the source problem (i.e., unlogged offset) and take corrective actions (see Supplements for more details). Note that for Figs. 2 and 3 the corrected data were used.

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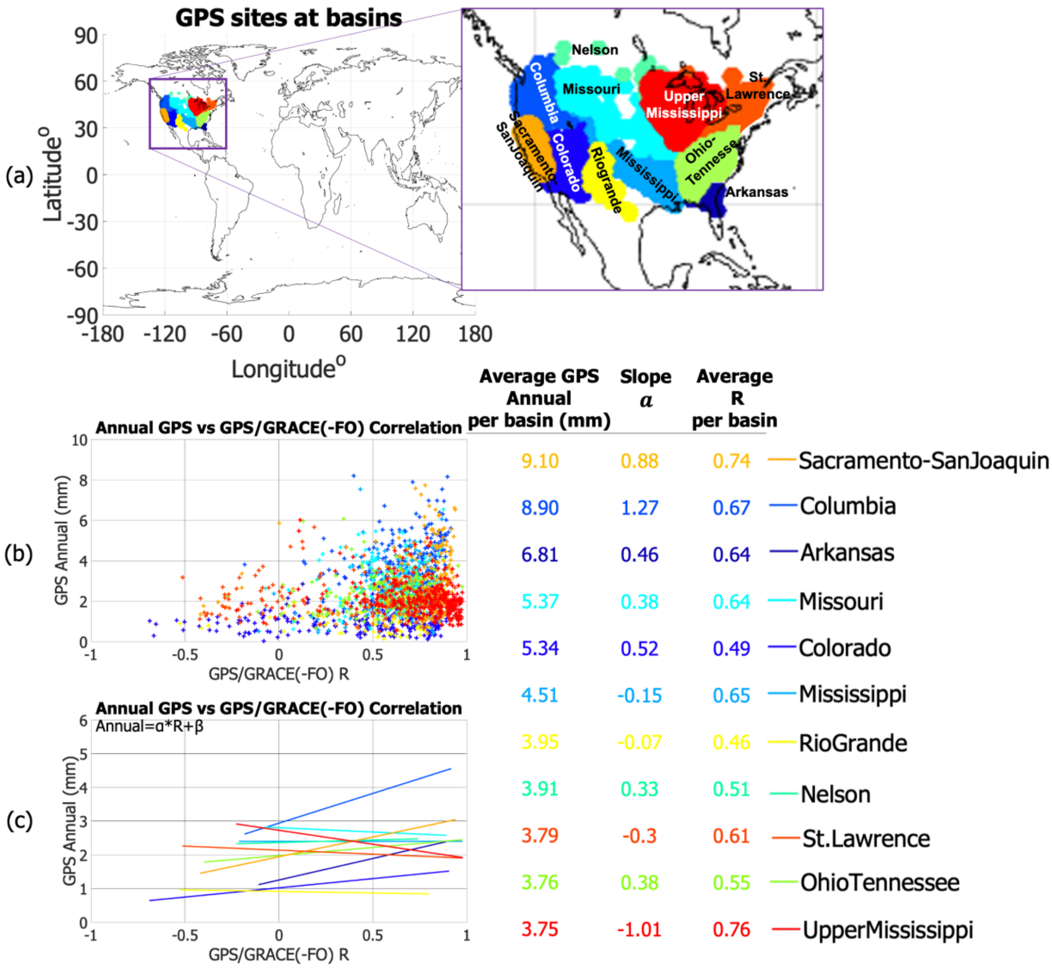

Figure 2: a) GPS sites clusters at watersheds in the US. Each watershed has a different color; b) Magnitude of annual GPS VLD cycles derived with respect to GPS-GRACE(-FO) correlation; c) Linear fit between magnitude of the annual GPS VLD cycles and GPS-GRACE(-FO) correlation.

Trends

In order to study the agreement between GPS/GRACE(-FO) in more detail, we split the timeseries of each station into non-overlapping intervals of 36 months, and fit Eq.2 for each station during each time-window. Different time-lengths of the GPS series may lead to misinterpretation of the geophysical content. For example, a station that has records only for the first 13 months out of the total of 36 months window may reflect different fit constituents compared to a neighbor station with full records, if the actual behavior of Earth's response changes during the 36-months window. Although in our data set this case is fairly rare, we proceed with deriving the rate (slope) and the annual cycles only for stations that have records for at least 28 out of the 36 months. As expected, GPS rates feature higher spatial variability than GRACE(-FO). However, both platforms capture large-scale quasi-periodic variations every 3 years (Fig. 3), an agreement that is noteworthy. The effect of this metric to detect outliers is pronounced when the two platforms show flipped trends.

Regions with pronounced trend disagreement:

- Great Lakes area (St. Lawrence watershed). The trend during 2015-2018 was flipped between GPS and GRACE(-FO). We discovered a missed offset in the series occurring in April 2016, and corrected for it, which the agreement in the trend (see Supplements).
- Cascadia region (northwest coast). The disagreement is evident in maps spanning 2009-2012, 2015-2018 and 2018-2021.5. GPS sites record a large surface uplift, which over the course of 15 years sums to 60 mm in sites located in Vancouver Island. GRACE(-FO) does not capture any such behavior. We attribute this disagreement partly on 1) GIA modeling error which manifests oppositely on two platforms. ICE6G_D predicts too much subsidence, thus when we correct GPS we find too much uplift and when we correct GRACE(-FO) we find too much water gain which predicts too much subsidence; and partly on 2) the interseismic strain accumulation correction applied in the GPS data set over this area (Argus et al., 2021). The sites have been flagged and are not going to be used in the joint inversion.
- San Andreas Fault (Southern California). Sites located in a vicinity of the Parkfield segment of the fault (Carrizon plain), exhibit consistent disagreement in the trend. More investigation is required to understand the mechanism that the fault presents on GPS/GRACE(-FO) VLD estimates. The disagreement is also seen in Argus et al. (2022, Fig. S12). The sites have been flagged and are not going to be used in the joint inversion.

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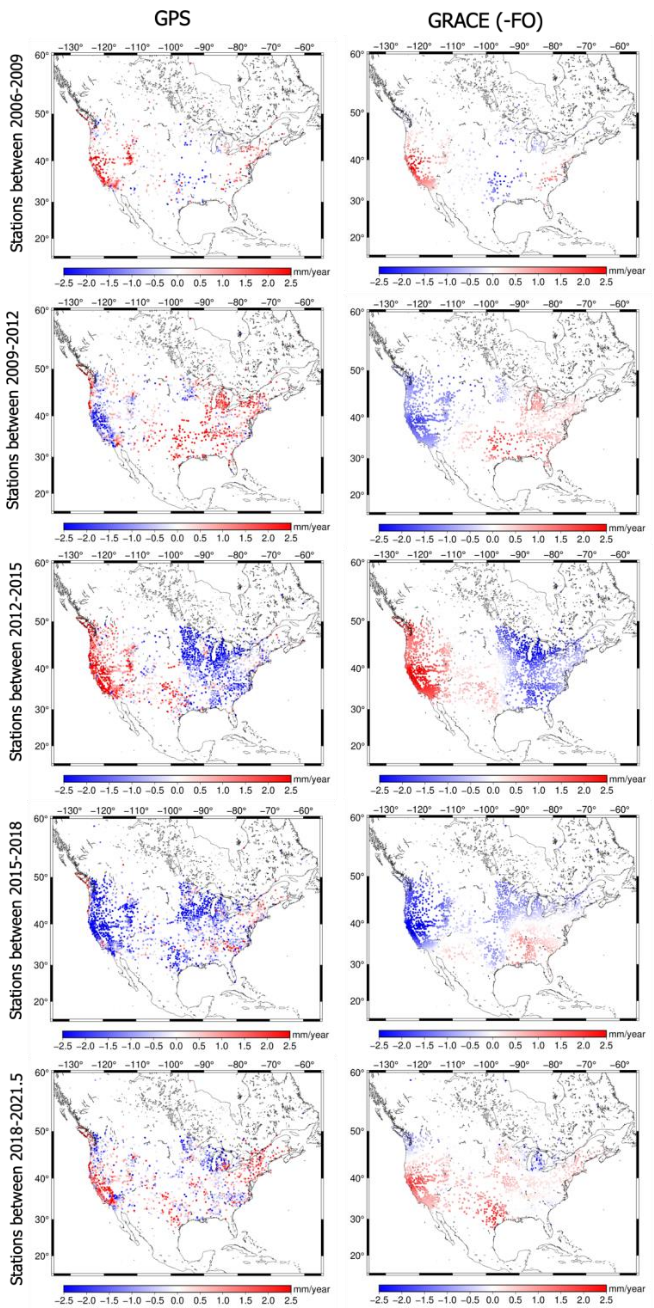

Figure 3: Rates of vertical displacements derived by GPS and GRACE. The rates are calculated every 36-months (3 years) between 2006-2021.

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Variance Reduction

Similarity in both amplitude and phase between two quantities is quantified via the variance attenuation factor (Gaspar and Wunsch, 1989; Fukumori et al., 2015):

$$var_{red} = \left(1 - \frac{var(GPS - GRACE(-FO))}{var(GPS)}\right) \times 100 \qquad (3)$$

The higher the agreement in phase and amplitude between GPS and GRACE(-FO), the closer the metric gets to 100%. var_{red} may also be negative when the differences in amplitude and/or phase are large. Overall, GPS and GRACE(-FO) are consistent when var_{red} exceeds 50%. The areas of main disagreement are near coasts, especially along the Atlantic Ocean. This inconsistency can be partly explained by modeling errors of the non-tidal oceanic and atmospheric loading model (e.g., Klos et al., 2021; van Dam et al., 2007). Additionally, agreement is poor for sites located in the vicinity of the Parkfield segment (specific regions across the fault perform poorly), which is consistent with the disagreement shown in Fig. 3.

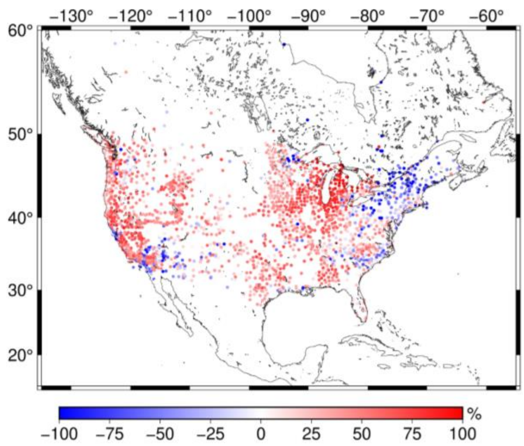

Figure 4: Variance reduction between GPS and GRACE(-FO) VLD

We also compared the amplitudes of GPS and GRACE(-FO) VLD periodic cycles. This analysis was not informative for the presence of outliers or errors.

Overall, the screening process not only assisted in outlier detection, but it also allowed for a deeper look into the structure of VLD periodic signals. We identified the need for antenna offset corrections (in the case of Great Lakes); removed sites affected by GIA and interseismic modeling errors; and sites located at the Parkfield segment of San Andreas Fault.

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3. Uncertainty Quantification

With the updated data set we are now ready to proceed with the uncertainty quantification of the GPS VLD timeseries. We apply different error characterization schemes consisting of a root sum square of a random error, white noise error, power law noise error (flicker noise and random walk) and spatially coherent error.

3.1 Methods

Root Mean Square Error

Residuals r of a series with respect to a deterministic model (Eq. 2) are often used as a first approximation of noise in VLD series (e.g., Bos et al., 2013; Michel et al., 2021). Practically, r shows how well a deterministic model can describe the original time-series. Therefore, the root mean square (rms) of r can give a first approximation of the noise floor of each station.

Spectral Analysis, White, Flicker and Random Walk Noise

Power distribution of residuals and its agreement with noise models, is another popular way to quantify uncertainty of GPS time-series (e.g., Klos et al., 2019; Argus et al., 2022). Typically, GPS series are evaluated for white, flicker and random walk noise, or combination of them. The Hector software (Bos et al., 2013) is used to estimate full noise covariance information by means of a maximum likelihood estimator. The covariance matrix C from a combination of white and power law (i.e., flicker and random walk) noise is given as:

$$C = a \times \mathbf{I} + b \times \boldsymbol{J} \qquad \text{Eq. 4}$$

Where a is the amplitude of white noise, $\boldsymbol{I}$ is the identity matrix of size N (number of samples/epochs in the series), b is the amplitude and $\boldsymbol{J}$ the covariance matrix of power law noise. $\boldsymbol{J}$ matrix is a full covariance matrix that describes the time-correlated error (as the data record length increases, the displacement uncertainty changes (Bos et al., 2008 Eqs. 8-11)). The optimal selection of the noise models is done via two optimality criteria, namely the Akaike Information Criterion (Akaike, 1974) and the Bayesian Criterion (Schwarz, 1978).

In this study, we consider three cases:

a) White Noise (WN)
b) Combination of WN and Flicker Noise (WN+FN)
c) Combination of WN, FN and Random Walk Noise (WN+FN+RW)

We take the root-sum-squares of the noise magnitudes as our noise floor. For example, for the case of WN+FN noise, noise is derived as $\sigma = \pm\sqrt{\sigma_{WN}^2 + \sigma_{FN}^2}$. Our data are sampled on a monthly basis, thus

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σ_{FN} needs to be scaled appropriately, i.e., $\sigma_{FN} = \sigma_{PL}(\frac{1}{12})^{-\frac{k}{4}}$, where, σ_{PL} is the uncertainty of power-law (PL) and k the spectral index, outputted from Hector (more information on power-law noise estimation can be found in Bos et al., 2008, and Williams, 2003).

Common Mode Noise

The Common Mode Component (CMC) is derived following the processing scheme suggested by Kreemer and Blewitt (2021), which can be summarized as:

1) Input GPS VLD time-series (referenced to Sep 2012) for j stations (l_j)
2) Derive each station's residuals by removing the deterministic part of the series ($l_j(t) - y_j(t)$)
3) Quantify the correlation coefficient r_{MAD} using robust statistics. r_{MAD} is defined as:
$$r_{MAD} = \frac{MAD^2(u) - MAD^2(v)}{MAD^2(u) + MAD^2(v)} \quad \text{Eq. 5}$$

   where MAD is the median absolute value and u and v are derived as:
$$u = \frac{p - median(p)}{\sqrt{2}MAD(p)} + \frac{q - median(q)}{\sqrt{2}MAD(q)} \quad \text{Eq. 6}$$
$$v = \frac{p - median(p)}{\sqrt{2}MAD(p)} - \frac{q - median(q)}{\sqrt{2}MAD(q)} \quad \text{Eq. 7}$$

   with p and q being the residual series of the reference station and the neighbor station, respectively. For each station there are $j - 1$ correlation coefficients r_{MAD}. In order to decide the cut-off distance that a neighbor station will be considered in the analysis we plot r_{MAD} coefficient against its distance from the reference station (Fig. 5). Based on results from all stations we decide to set a cut-off at 1500 km, slightly higher than the 1350 km suggested by Kreemer and Blewitt (2021). The 1500 km cut-off allows us to separate stations between east and west coast, as spatially coherent signals at stations located across the continent are negligible.
4) Derive the median slope estimator ccs using Theil-Sen median trend.
5) Derive the zero-distance intercept cci_j for each station as median$(r_{MAD} - ccs * d)$, with d being the distance between the station of reference and the neighbor station (maximum d = 1500 km).

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6) Construct CMC: Calculate the cumulative (c_j) and percentile (p_j) weights for each station and then find the weighted median that corresponds to p_j = 50%. This weighted median represents the CMC of the station (Fig. 6).

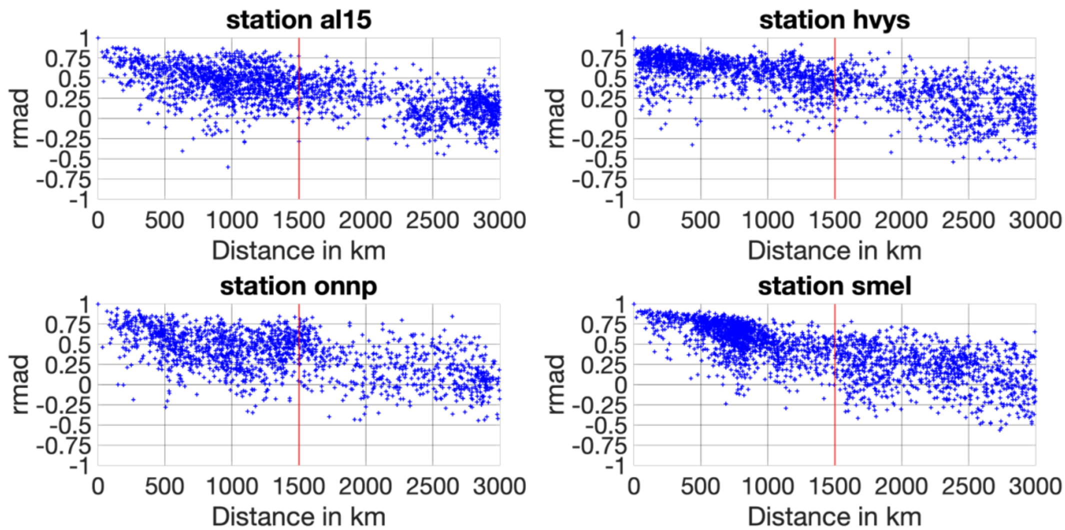

Figure 5: coefficient of four random stations with the rest of the station sample, plotted against the distance of the reference station with the rest of the stations. Each cross resembles the of the reference station with a station located at distance d.

CMC is limited in providing a realistic error approximation, in that the technique cannot isolate spatially correlated noise from signal (e.g., hydrology signals not described by the deterministic model are present in the residuals fed into CMC). Under the realistic assumption that a component of the high frequency signal contained in CMC reflects real hydrological processes, we remove the contribution of surface hydrology using Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004) VLD predictions. GLDAS does not model deep groundwater and open surface water, so these signals remain in the residual (Scanlon et al., 2018). VLD predictions driven by surface hydrology are derived similar to GRACE(-FO) (Section 2.2). We use Noah v2.1 monthly estimates of soil moisture storage given at 0.25-degree grids (Beaudoing and Rodell, 2016), convert the fields from terrestrial water storage (kg/m^2) to units of equivalent water height, and predict the elastic response of the Earth (Eq. 1). Finally, we remove the reference epoch (09/2012) similar to GPS VLDs and derive the residuals relative to the deterministic model (Eq. 2). GLDAS (surface hydrology) residuals should ideally reflect high frequency hydrological processes and are therefore removed from GPS residuals. Overall, CMC of surface hydrology residuals exhibits a fairly small magnitude (~0.5 mm). We remove the contribution of surface hydrology within the CMC algorithm by first subtracting GLDAS VLD predictions from GPS, and next inputting the residuals of this difference into the algorithm. The output of this process (CMC_{HF}) slightly decreases the magnitude of CMC and expresses a more realistic representation of spatially correlated noise.

3.2 Results

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VLD uncertainty of each station is estimated by means of all the different approaches discussed in Section 3. The mean value and standard deviation are shown in Table 1. On average, an assumption of white noise shows slightly reduced uncertainty compared to the other techniques, followed by RMSE. When flicker noise is considered in addition to white noise (WN+FN) the average uncertainty increases by nearly 0.8 mm compared to the white noise only. Noise level from combination of all three noise models (WN+FN+RW) is somewhat less than 4 mm on average. CMC noise floor is 3.6 mm on average with a relatively large standard deviation (±1.6 mm) which suggests that spatially correlated noise has higher variability than time-correlated noise (± 1.6 mm as opposed to ~±1 mm). When surface hydrology is removed (CMC_{HF}) the noise floor drops by a fraction of a mm on average compared to CMC.

Table 1: Different uncertainty quantification cases

	μ (mm)	median (mm)	± std (mm)
RMSE	2.8	2.7	0.8
WN	2.4	2.2	0.8
WN+FN	3.2	3.1	0.7
WN+FN+RW	3.8	3.5	1.1
CMC	3.6	3.2	1.6
CMC_{HF}	3.5	3.1	1.6

RMSE and WN exhibit a smooth transition among the regions, which indicates the presence of spatially coherent regime signal mostly driven by hydrology (Fig. 6). The combination of WN+FN is mostly dominated by FN and the uncertainty exhibits local (in space) coherence. The uncertainty is larger when random walk is included in the combination (WN+FN+RW). A recent study from Argus et al. (2022) on groundwater flux in Central Valley (California) suggests that noise on GPS-derived uplift motion can be well described by a combination of flicker noise and random walk, due to the ability of these noise models to reflect low frequency noise. When a simulated contribution of the surface hydrological component is removed from the series, CMC_{HF} reflects a more realistic picture of the noise. Arguably the level of change compared to CMC is sub-millimeter. Signal contributions from un-modelled groundwater variations are potentially still present, but groundwater changes are typically slower in time.

We obtain the relative likelihood of each uncertainty quantification method by estimating the probability density function (PDF) (Fig. 7). White noise has a flat power spectrum, having the same amplitude across frequencies. Estimating a best fit for a flat spectrum doesn't allow for capturing the long tail skew of the residuals (low frequency), which are biased towards their mean. Thus, the amplitude of white noise is smaller compared to the rest of the techniques (Table 1). Flicker and random walk noise models add to the long tail of the power distribution, that is they allow more low frequency noise, which explains the higher amplitude of the uncertainty when these two noise types are considered.
RMSE and WN show a 50% probability of a station having an uncertainty (σ) between 1.5-2 mm and less than 10% of a station exceeding σ=4 mm. The noise level fells within [2 4] mm for ~93% of the stations when we consider combination of WN+FN. PDF of RMSE, WN and WN+FN resemble a normal distribution, with the mean being shifted for each case. When random walk is also considered (WN+FN+RW) 64% of the stations exhibit noise within [2 4] mm. In this case, the distribution is more spread resembling a gamma-like distribution, with a peak being at 3 mm (18%). CMC and CMC_{HF} PDF

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also follow a gamma-shape, and the probability of the uncertainty ranging between [2 4] mm is nearly 60% for CMC and 65% when surface hydrology is removed.

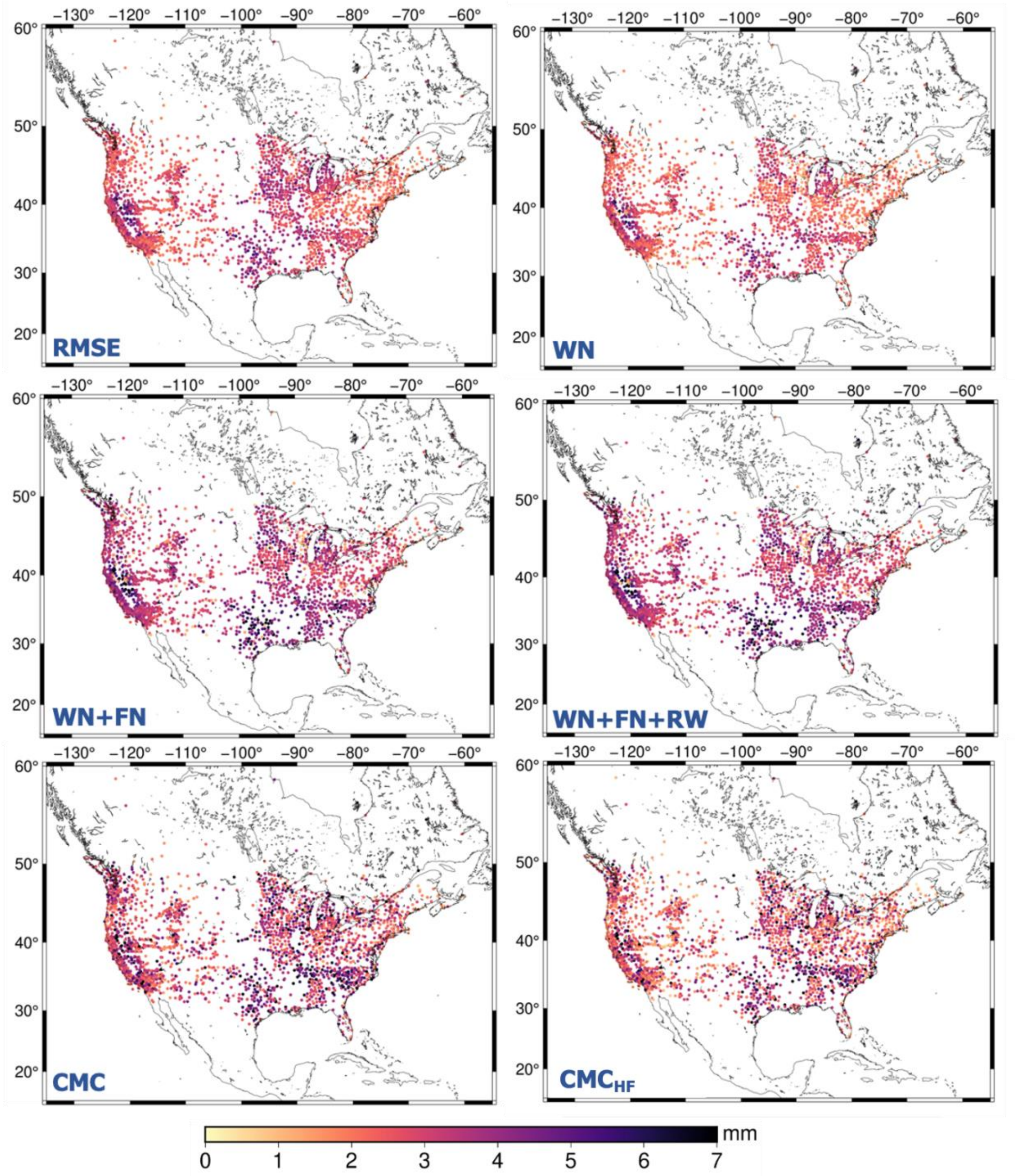

Figure 6: Uncertainty of GPS sites estimated using various techniques

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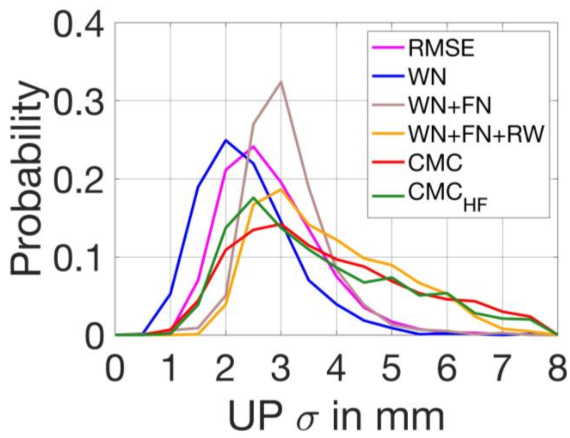

Figure 7: Probability density function of VLD estimates uncertainty

4. Discussion

GPS VLD observations are very useful to supplement GRACE(-FO) gravity products to infer mass change signals at spatial scales smaller than what can typically be achieved with current satellite gravimetry alone (i.e., < 300km). This work provides a general workflow on isolating surface mass signals, developing processing standards and uncertainty quantification schemes of GPS VLD estimates, with the ultimate goal of merging them with satellite-gravimetry observations. First, we provide a list of corrections needed for isolating surface mass following recommendations outlined in Argus et al. (2017; 2022). Additionally, detailed investigation of trends, correlation, and variance reduction, accentuates the need for better background modeling (GIA and interseismic strain), as the two observation platforms respond differently in the presence of such errors. At this point the recommendation is to remove sites located in the vicinity of regions where background models are known to perform poorly, before any joint inversion. Except detecting outlier stations, screening metrics point to extra corrections that need to be applied in certain sites (e.g., missed antenna offset in sites located in Michigan).
Several uncertainty quantification schemes have been tested to prescribe weights on GPS VLD estimates for the joint inversion. The noise level is centered at 2 and 2.5 mm when uncertainty is derived as the RMSE of residuals or as white noise, respectively. Error increases when lower frequencies are included in the noise estimation. When we account for flicker noise, one third of the sites exhibits noise levels of up to 3 mm. The average noise increases significantly in presence of random walk, as more power of the lower frequencies gets into the estimations, and the distribution of noise is more dispersed. In this case, half of the stations are prescribed with > 4 mm uncertainty. Argus et al. (2022), suggests that random walk is the most realistic representation of noise based on postfit residuals. We notice that the spectrum of CMC provides similar uncertainties to random walk, which implies that despite the different characterization procedure, CMC is able to provide equally realistic noise estimates of GPS VLD timeseries. We strived to minimize lingering hydrology signals embedded in CMC, through reducing the GPS VLD observations with VLD from the GLDAS hydrology model. The average noise floor dropped slightly (~0.5 mm drop in sigma). Future work will potentially provide further information of GPS station errors when the weight of each GPS site is also considered based on its impact on the performance in a

formal data combination of GPS-GRACE(-FO). The suggested framework can be easily adjusted to account for global data sets. The new data set provides GPS vertical displacements of elastic mass variations in North America and their uncertainties.

Data Availability: The data product described in the manuscript is available in zenodo (doi: 10.5281/zenodo.8184285)**.** GPS timeseries are provided by the Global Station List from the Nevada Geodetic Laboratory (http://geodesy.unr.edu/; Blewitt et al., 2018). Non atmospheric and oceanic tidal aliasing product (AOD1B RL06) is provided by GFZ's Information System and Data Center (ftp://isdc.gfz-potsdam.de/grace/Level-1B/GFZ/AOD/RL06, Dobslaw et al., 2017). GRACE and GRACE-FO Level 2 products are available from podaac (https://doi.org/10.5067/GFL20-MJ060).

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