Drought-induced vertical displacements and water loss in the Po river basin (Northern Italy) from GNSS measurements

F. Pintori[1], E. Serpelloni[1]

[1]Istituto Nazionale di Geofisica e Vulcanologia (INGV), Bologna, 40128, Italy.

Corresponding author: Francesco Pintori (francesco.pintori@ingv.it)

Key Points:

- Vertical ground displacements are used as an independent measure of terrestrial water storage variations.
- Interannual changes of vertical displacements are a reliable near real-time indicator of drought severity.
- The inversion of GNSS displacements shows that about 70 billion tons of water is lost during the 2021-2022 drought in the Po river basin.

Abstract

We study vertical ground displacement time series from GNSS stations to measure deformation associated with hydrological drought in the Po river basin. Focusing on interannual trend changes, rather than seasonal (annual) components, we found a clear spatially correlated deformation signal that is temporally (anti)correlated with changes in the Po river level and the SPEI-12 drought index, with stations moving upward during periods of river/index level decrease and vice versa. In the 2021-2022 time span, which culminated in the most severe drought of the last two centuries, we estimate the amount and spatial distribution of water loss in the basin and its surroundings. Excluding the seasonal signals, between January 2021 and August 2022, the GNSS stations underwent uplift, up to 7 mm, which corresponds to ~70 Gtons of water loss. Compared to GLDAS and GRACE estimates, GNSS results show a similar temporal evolution of water content but a more heterogeneous distribution of values. Dense GNSS networks provide an effective way to monitor multiannual trend changes in water storage even in small water basins and serve as a reliable indicator of drought severity.

Plain Language Summary

This study looks at the way the ground moves up and down in the Po river basin, in northern Italy, using Global Navigation Satellite System (GNSS) stations. We measure how much water was lost during a big drought in the area, which occurred from January, 2021 to August, 2022. During this time interval, the GNSS stations show that the ground mostly moved upwards, which means that water was being lost. Besides the annual water storage variations, we estimate that about 70 billion tons was lost during that time, in agreement with other ways of measuring terrestrial water variations. This study shows that GNSS stations can be an alternative way to measure how much water is being lost during drought in small areas and common vertical displacement signals are a good approximation of drought indexes.

1 Introduction

Drought is one of the most complex recurring natural disasters, defined by a deficiency of precipitations that causes prolonged water scarcity. Failure to manage drought risk has the potential to have dire consequences for people, livelihoods, economy and ecosystems. During the summer of 2022, Italy faced the most severe drought in the last two centuries, where the dry conditions were related to several drivers, the most relevant being the changes in the precipitation regime, resulting in a decline of snow fraction and snowmelt, and an increasing evaporation rate (Montanari et al., 2023). The drought significantly impacted the largest Italian river, the Po, whose level has significantly decreased from the summer of 2021 to the autumn of 2022 (Fig. 1). In summer 2022 several regions declared a state of emergency, and drinking water has been rationed in hundreds of municipalities in northern Italy.

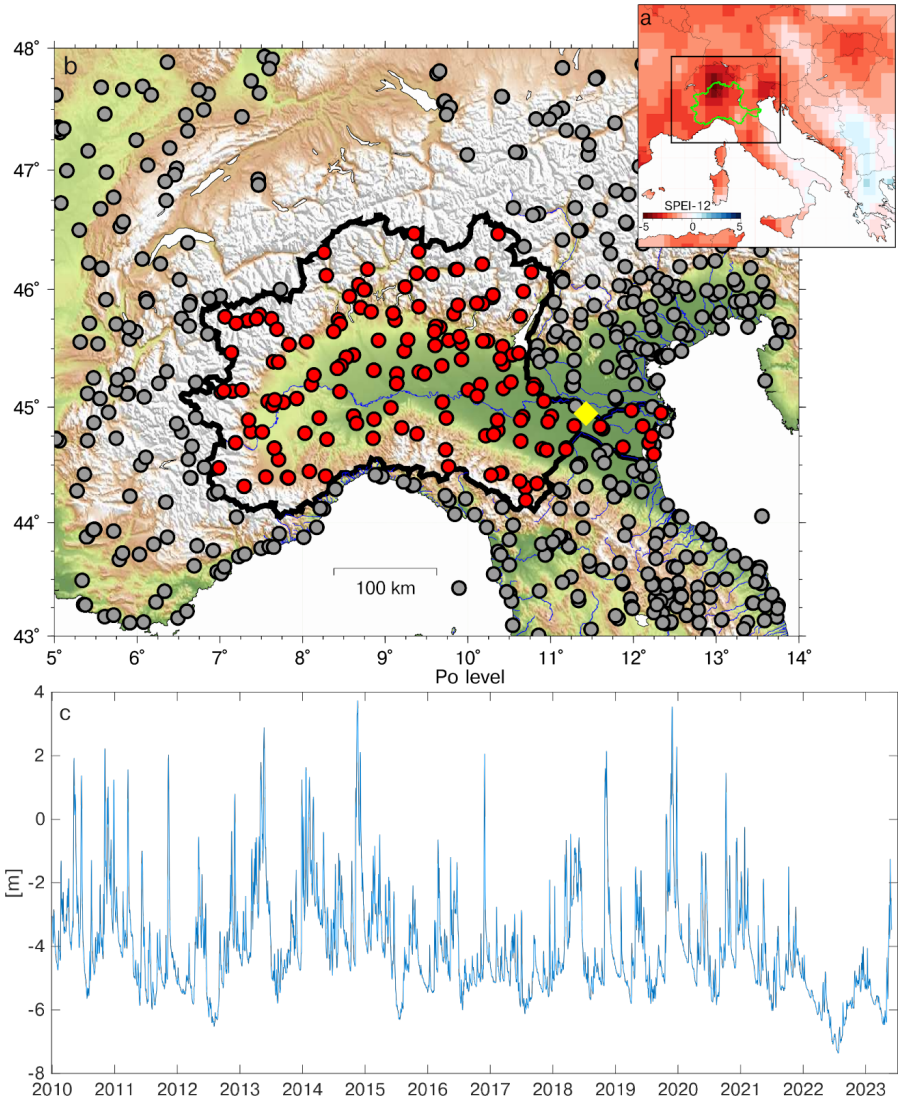

Figure 1. a) Map of the SPEI-12 values at August 2022. b) The study area: the black line represents the Po river (thick blue line) basin; the dots show the positions of the GNSS stations used in the analysis, the reds are the ones inside the basin, the gray the ones outside; the yellow diamond shows the location of the Po level measurement point. c) Po river level changes.

The effects of droughts are particularly dangerous in the Po river basin, which has an extension of ~$74 \cdot 10^4$ km^2, for various reasons: drought threatens the crops in the Po Valley, which are around 40% of the total food produced in Italy, and impacts energy production, since a reduced river flow causes deficiencies in hydropower generation and cooling of thermal plants (Boyko et al., 2022).

Due to global warming, more frequent, longer and severe droughts are likely to occur in the future (Boyko et al., 2022). In order to evaluate the best policies to address the problems caused by water scarcity, it is crucial to measure and monitor variations in terrestrial water storage (TWS). For drought monitoring, in fact, changes or anomalies in TWS provide direct observations of total water availability, complementing model-based measures such as drought severity indices. Taking into account the anomalies of both precipitation and potential evapotranspiration, Vicente-Serrano et al. (2010) proposed the Standardised Precipitation-Evapotranspiration Index (SPEI) drought index. In particular, the SPEI-12 quantifies the drought level of the previous 12 months, considering the precipitation and potential evapotranspiration anomalies over 12 months (Fig. 1a). However, meteorological drought indices, such as the SPEI, and other drought indices, like the Standardized Precipitation Index (SPI) or the Palmer Drought Severity Index (PDSI), estimate droughts based on precipitation and temperature anomalies, so they do not allow to quantify TWS anomalies. TWS, in general, is hard to quantify because it is the sum of many components, including groundwater, surface water, vegetation and soil moisture, ice and snow. Piezometers, for example, effectively monitor groundwater level variations but not the other water storage components, and evaluating the water volume changes from them is not straightforward. On the other hand, the Global Land Data Assimilation System (GLDAS) model provides daily variations of the soil moisture and snow water equivalent, but it can not take into account the groundwater stored more than 2 m below the surface (Argus et al., 2014; Jiang et al., 2021). Geodetic techniques have a distinctive role in monitoring the hydrological cycle, as they are the sole means of directly observing TWS anomalies and they can

function across local to global scales. TWS anomalies can be estimated at global scale by using Gravity Recovery and Climate Experiment (GRACE) measurements, which allow modeling water storage changes by inverting the spatiotemporal variations of the Earth's gravity field. Unlike GLDAS, GRACE accounts for all the components of TWS, but it provides a spatial resolution of ~300-400 kilometers, which is insufficient for monitoring smaller watersheds (Fu et al., 2015; Knappe et al., 2019), particularly in mountainous regions where TWS gradients are steep, as highlighted in Argus et al. (2017). Moreover, due to the monthly nature of GRACE observations they are not suitable for assessing water availability and flood risk during and following brief, intense precipitation events.

TWS variations are indirectly detectable not only through gravity data but also by measuring ground deformation through geodetic observations: an increase of the water content, in the absence of poroelastic processes, causes an increasing load on the Earth surface, which subsides elastically; while when the water content decreases the crust moves upward because of the water content decrease. Global Navigation Satellite System (GNSS) measurements, for example, provide daily measurements of ground displacements, at mm precisions, that can be used to measure ground deformation associated with TWS variations. Argus et al. (2014) inferred the spatial distribution of the TWS seasonal amplitude, expressed in terms of equivalent water height (EWH), by inverting the seasonal vertical displacements of the ground in California. Fu et al. (2015) estimated TWS variations from GNSS measurements of vertical displacement in Washington and Oregon, finding that the largest seasonal variations of water content were localized in the mountain areas. GNSS displacements have been inverted to estimate the TWS also by Jin and Zhang (2016) in the southwestern United States, by Zhang et al. (2016) over the Yunnan Province in China and by Ferreira et al. (2019) in the entire South America.

Carlson et al. (2022) computed TWS in California using a joint inversion method combining the GRACE products with the results of the inversion of GNSS data, taking advantage of the dense spatial distribution of GNSS data together with GRACE's ability to provide regional closure of the water budget. While most of the above mentioned studies dealt with seasonal fluctuations of TWS, here we focus on multi-annual trends. We model displacement time-series looking for trend changes in the vertical component, with the goal of

114 studying the non-seasonal deformation signals caused by interannual TWS variations, similarly
115 to Borsa et al. (2014), focusing in particular on the most recent and severe 2021-2022 drought.

116 In Section 2 we describe the GNSS data used and the methods applied to analyze the
117 vertical displacement time series; in Section 3 we show the relationship between geodetic and
118 hydrological observations and provide a quantitative estimation of the evolution of the TWS. In
119 Section 4 we discuss the results, in light of alternative estimates of water storage variations.

120 **2 Data and Methods**

121 We consider ~180 daily GNSS vertical ground displacement time series from January,
122 2010 to June, 2023 of continuous stations located in the Po river basin (see Fig. 1). We also
123 include in the analysis ~280 stations located within 1° of the catchment limits in order to reduce
124 inversion artifacts near the boundaries of the study region (Fu et al. 2015). This is part of a larger
125 geodetic solution encompassing the whole Euro-Mediterranean region, obtained following the
126 approach detailed in Serpelloni et al. (2022). We remove the long-term linear trend from the time
127 series using the Median Interannual Difference Adjusted for Skewness (MIDAS) estimator
128 (Blewitt et al. 2016) and filter the contribution of the non-tidal atmospheric loading (NTAL), as
129 suggested by White et al. (2022), since they can produce displacements of several millimeters at
130 daily-weekly timescales that can interfere with the hydrological signal. The NTAL-induced
131 vertical displacements are evaluated from the daily 0.5° x 0.5° gridded solution of the Earth-
132 System-Modeling Group at the German Research Center for Geosciences (Dill and Dobslaw,
133 2013) and its contribution in each site is calculated considering the nearest grid point where the
134 displacements associated with NTAL are computed. The resulting GNSS vertical displacements
135 time series are then analyzed using a trend filtering approach, which performs an extensive
136 analysis using a L1 norm regularization model to identify the seasonal components, offsets and
137 linear trend changepoints in the GNSS time series (Wu et al. 2018). The piecewise trend x is
138 estimated by minimizing the weighted sum objective function:
139 $(1/2)\|y-x-s-w\|_2^2+\lambda\left\|D^{(2)}x\right\|_1+\rho\left\|D^{(1)}w\right\|_1$
140 where y is the original time series, w indicates the level component associated with the offsets, s
141 is the seasonal term, $\|.\|_1$ represents the L1 norm and $D^{(n)}$ are the n-th difference matrix defined
142 as in Wu et al. (2018). λ and ρ are positive parameters controlling the knots of the estimation
143 trend and the frequency of level shifts, respectively (we choose λ=2000 and ρ=80). Figure 2

144 shows an example of output of this analysis. Focusing on transients and interannual variations,
145 we only consider the extracted piecewise trends, not the seasonal terms having annual and semi-
146 annual frequencies. For some stations level changes (i.e., offsets) not associated with tectonic
147 events or equipment changes are highlighted, which mostly represent fast variations in ground
148 displacements (see Fig. 2 in 2012). For this reason, in the further steps we consider the piecewise
149 trend as the sum of the trend and level components. As it can be seen in Fig. 2, there is an
150 increase in uplift starting from 2021, which is a common feature in GNSS stations within the Po
151 river basin. Fig. 2e shows the stacking of the vertical piecewise trend time-series for all stations
152 analyzed, which is performed by averaging, for each epoch, the residuals of all the time series
153 resulting by removing the mean and linear trend terms. In order to better characterize the spatial
154 distribution of this deformation signal, we use a multivariate statistical approach, similarly to
155 what is used for tectonic deformation studies (Kositsky and Avouac, 2010; Gualandi et al. 2014).

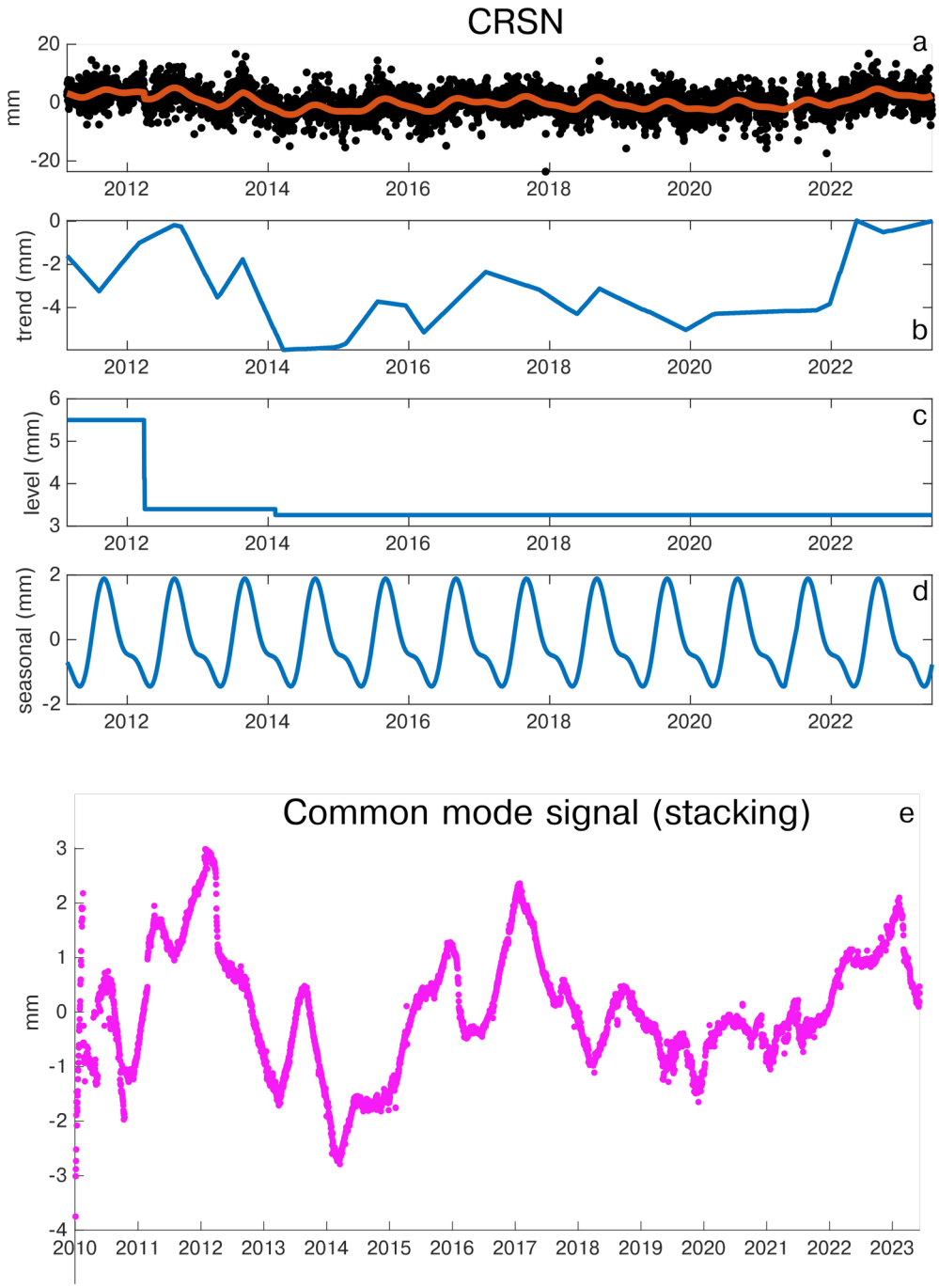

Figure 2. Example of GNSS time series decomposition performed using the L1-norm trend filtering approach. In a) the black dots represent the original time series, the red line the model obtained as the sum of the trend (b), level (c) and seasonal component (d). Panel (e) shows the result of the stacking on the piecewise vertical trends of all the stations inside the Po river basin.

3 Results

3.1 Comparison between geodetic and hydrological measurements

We adopt an approach similar to the one described in Jiang et al. (2022), using as input of a principal component analysis (PCA) the piecewise vertical trends described in the previous section rather than the raw time-series that also include the seasonal terms. We decompose the dataset using one PC in order to identify the most important common signal of the GNSS stations in the Po basin and retrieve its spatial pattern (i.e., amplitude and sign). However, the first principal component (PC1) obtained performing a PCA using 2 components is almost identical to the PC1 obtained performing a one-component decomposition, both in terms of temporal evolution (Fig. S1) and spatial distributions (Fig. S2). The temporal evolution of PC1 (Fig. 3a) well resembles the common mode signal resulting from a stacking of the vertical trend time-series for all stations (Fig. 2e and Fig. S3). However, the advantage of the PCA is to provide the spatial information on the displacement amplitudes (Fig. S2a). We compare the temporal evolution of PC1 with the SPEI-12 index value, averaged over the Po river basin, and with the Po river level measurements provided by the Regional Agency for Environmental Protection of Veneto region (ARPAV; https://wwwold.arpa.veneto.it/arpavinforma/bollettini/dati-storici, Last Access: 24-07-2023). The Po river level time series is filtered adopting the same approach used for the GNSS time-series, retaining only the piecewise trend component (Fig. S4) and not the seasonal ones. On the other hand, SPEI-12 time series does not contain annual variations, since the index is computed as an anomaly over 12 months, then the time series has not been filtered. Figure 3a shows that the geodetic (sign inverted), climatic and hydrological time series are highly temporally correlated, so that geodetic uplift is observed coeval with the drop of the Po river level and the SPEI-12 index, while the geodetic subsidence is instead observed coeval with the increase of the Po river level and SPEI-12 index, respectively. Focusing on the time interval covering the last drought, we observe that the three de-seasoned time series start decreasing from the beginning of 2021 to mid-2022, after which they invert their sign. As a result, we set the time limits of the drought as 2021.00 and 2022.58 (January 1st, 2021 - August 1st, 2022), which is represented as the yellow area in Fig. 3a.

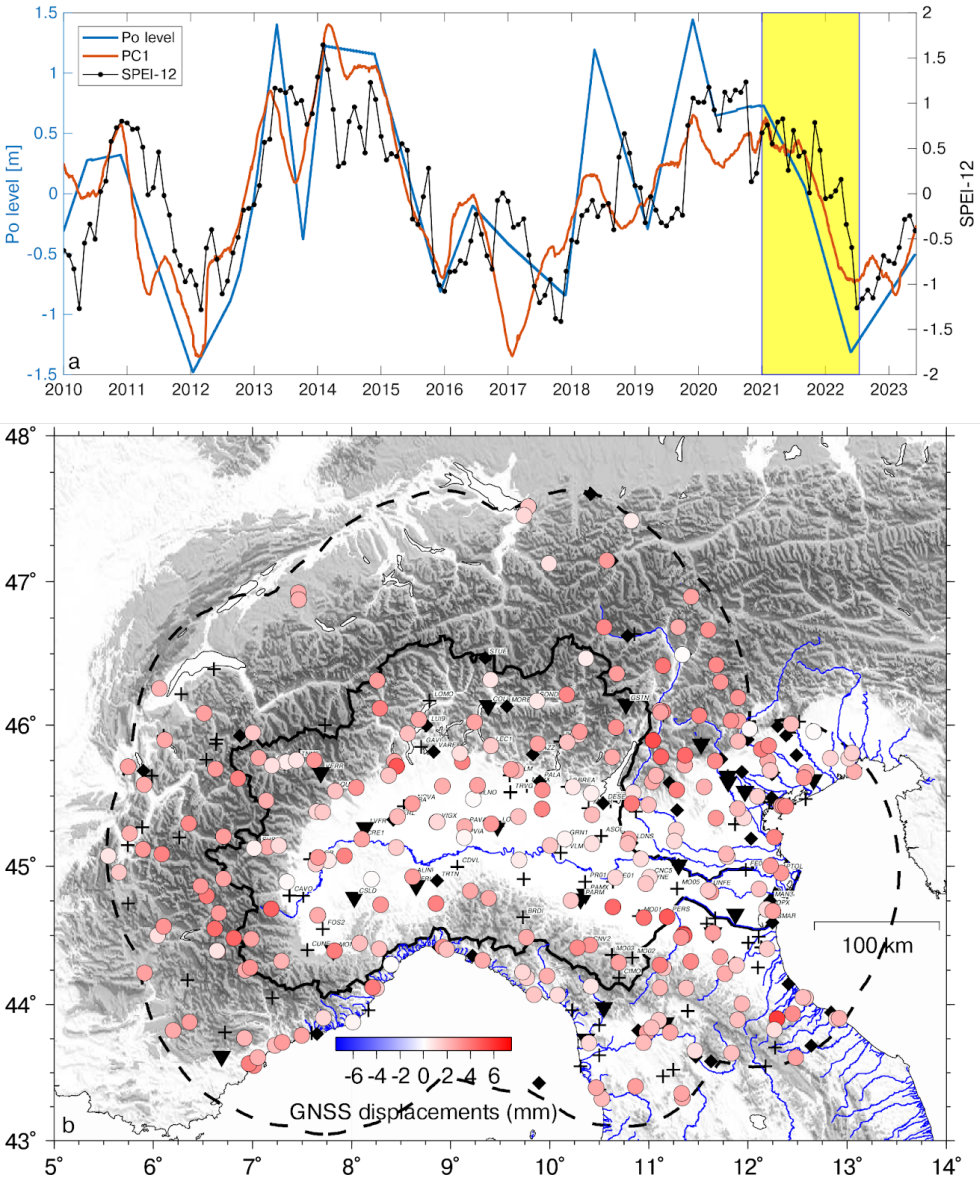

Figure 3. a) Comparison between the PC1 temporal evolution, the SPEI-12 index and the Po river level. Since PC1 is obtained from detrended GNSS time series, Po river level and SPEI-12 have also been detrended for consistency. b) Vertical displacements associated with PC1 during the 2021.00 (January, 2021) - 2022.58 (August, 2022) time interval (yellow panel). The dashed line represents the boundary of the Po river basin, extended by 1°. Black triangles indicate the 22 stations excluded because they show negative displacements; black crosses represent sites with more than 75% of missing data and black diamonds the stations with no records after 2021.0.

The vertical displacements associated with PC1 from 2021.00 to 2022.58 are shown in Fig. 3b. Most of the stations show positive values (uplift), in accordance with the hypothesis that in dry periods, when the water load is reduced, the GNSS stations record uplift, while in wet periods the water load increases causing a downward motion of the Earth's surface. We find that this is not true for 22 sites, which show an opposite behavior (black triangles in Fig. 3b). Maximum uplift, of the order of 7 mm, is observed in the south-eastern portion of the basin and in the northern portion of the Po basin, which correspond to uplift rates, in the considered two years, that are much faster than the long-term ones (e.g., Pintori et al., 2022).

3.2 Inversion of vertical ground displacements

The displacements associated with PC1 are inverted using the approach described in Jiang et al. (2022), which estimates water storage variations assuming an elastic response of the Earth to the hydrological load. In order to avoid misinterpretation of the spatial variations of the water storage changes, we exclude from the inversion the 22 stations showing negative vertical displacements (i.e., subsidence, Fig. S5) in the investigated time interval that, following Carlson et al. (2022), are possibly affected by poroelastic processes, causing vertical displacements in the opposite direction compared to the elastic ones. We also exclude from the inversion the GNSS stations that have no observations recorded in the 2021.00-2022.58 time-span (i.e., do not register displacements potentially associated with the last drought episode investigated in this work). The total number of stations used for the inversion is then 257.

The relationship between the vertical displacements measured by GNSS x and the water mass load u, expressed as EWH, is

$$x = Gu$$

where G is the Green's function matrix using load Love numbers of the preliminary reference earth model (PREM) (Dziewonski and Anderson, 1981) as commonly used in many recent works (e.g. Carlson et al. 2022, Jiang et al. 2021). The final solution for the daily estimates of EWH changes u is

$$u = \left(G^T G + \alpha^2 L^T L\right)^{-1} G^T x$$

where L is the Laplacian smoothing matrix and α is the smoothing factor controlling the relative weight between model roughness and data misfit.

We invert the displacements associated with PC1 to estimate EWH on a 0.25°x0.25° grid. We choose α=0.0030, which is the minimum in the line showing the relation between the sum of squared residuals from cross-validation (CVSS) and the smoothing factor (Fig. S6), and use 4 neighbor points for calculating the Laplacian matrix during the least-squares inversion. Fig. 3a shows the temporal evolution of the EWH averaged over the study area, while Fig. 3b is a map of the EWH variations that occurred in the 2021.00 - 2022.58 time interval (yellow box in Fig. 3a).

A checkerboard test using synthetic inputs is performed to show the ability of the inversion method and the distribution of the GNSS stations to resolve spatial features of water mass variation in a checkerboard pattern, where each mass has dimensions of 1° × 1° and an EWH change of 300 mm (Fig. 4a). The inversion performance is evaluated estimating the agreement dR between each grid point of the checkerboard synthetic model within the Po river basin and the results of the inversion (Fig. 4a) using the following equation, which estimates the percentage of accuracy:

$$dR = 1 - \frac{|input - output|}{max\left(input\right)}$$

where *input* is the value of the checkerboard synthetic model, *output* the value resulting from the inversion and $max(input)$ the maximum value of *input*, i.e. 300 mm. The mean value of *dR* computed over all the grid points is 0.67, then we can conclude that the accuracy of our inversion, at the resolution of 1° x 1°, is 67%. By using smaller patches we find a rapid degradation of the spatial accuracy (Fig. 4a-b).

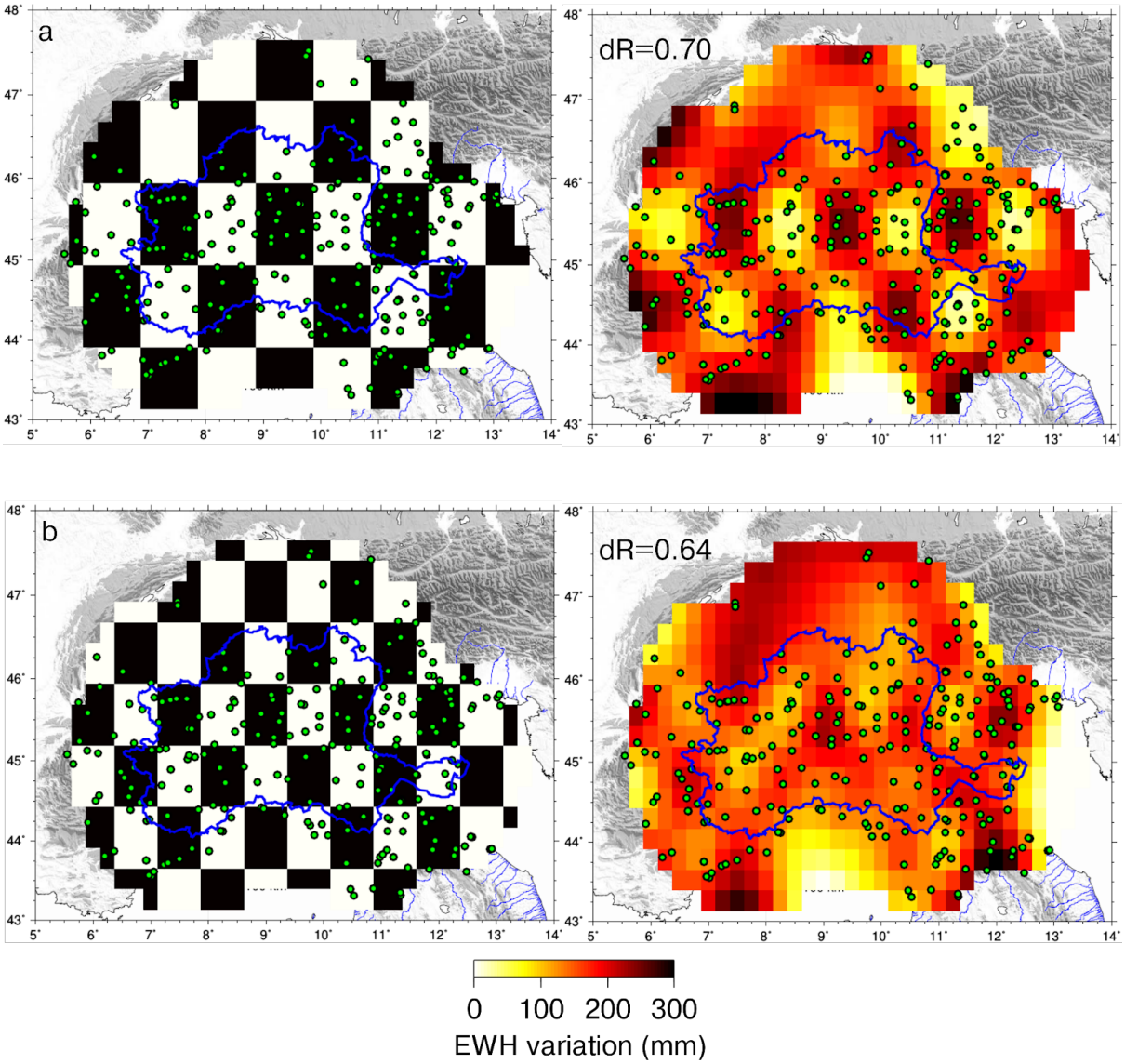

Figure 4. Checkerboard test using synthetic data. a) Comparison between the checkerboard synthetic model (left) and the results using the inversion method (right) considering a 1.00° spatial resolution. b) Same as a) but considering a 0.75° spatial resolution.

4 Discussion

We compare the EWH obtained by inverting the GNSS displacements (EWH_{gnss}) with surface water content from GLDAS (SWC) and with Liquid Water Equivalent Thickness (LWE) from GRACE. The GLDAS products provide the soil moisture content in the first 2 m of the subsurface, the snow depth water equivalent, the plant canopy surface water and the root zone soil moisture (Rodell et al., 2004). We consider as SWC the sum of these four components, which are provided as 0.25°x0.25° gridded dataset and 3-hours temporal resolution, which are transformed into daily time series by averaging the 3-hourly time series to make them consistent with the daily resolution of EWH_{gnss}.

LWE is computed using the NASA Jet Propulsion Laboratory (JPL) GRACE and GRACE-FO RL06 Mascon solutions (Watkins et al. 2015), but we also show the results obtained using other GRACE products in the supplementary material. While the data are here analyzed in a 0.25°x0.25° grid for consistency with SWC and EWH_{gnss} , the current resolution is 300 km. The temporal resolution of LWE data is monthly and data are missing in correspondence with the gap between the GRACE and GRACE-FO missions, which results in a 11 month gap, from July 2017 to May 2018.

The GLDAS products allow an estimate of the water content with a better nominal spatial resolution of EWH_{gnss}, even though the disadvantage is that GLDAS does not take into account groundwater. Importantly, while the GLDAS nominal spatial resolution is 0.25°, its effective resolution may be different due to the assimilation process and the interpolation techniques used to generate gridded datasets. Furthermore, the nominal spatial resolution of GLDAS may not represent the true spatial variability of soil moisture in a context such as the Po river basin, characterized by high topographic gradients. The correct determination of the soil types in regions characterized by heterogeneous landscapes, elevation and land cover, in fact, is complex and this can lead to errors in soil moisture modeling (Bi et al., 2016). LWE takes into account all TWS components, but with a spatial and temporal resolution much poorer than EWH_{gnss}. We point out that while EWH_{gnss} is inverted on a 0.25°x0.25° grid, the results of the checkerboard test show that the actual spatial resolution is ~1°, corresponding to about 100 km (Section S1 of the Supporting Information). This is consistent with the resolution achieved by Zhang et al. (2016) in the Yunnan region of China and by Fu et al. (2015) in

Washington and Oregon. The high spatial density of the southern California GNSS network allowed Carlson et al. (2022) to reach a spatial resolution of 80 km, while when considering larger study areas as in Borsa et al. (2014) and in Ferreira et al. (2019) the spatial resolution decreases to 200-300 km.

We remove the annual and semiannual components in SWC time series using the same approach used for GNSS displacement and Po river level measurements (see Fig. S7), and apply a PCA using one PC on the trend components. Because of the monthly temporal resolution of the GRACE products, LWE data are analyzed using a slightly different strategy: we remove the annual and semiannual components from the original time series instead of estimating the trend components, as done for GNSS and GLDAS time-series. As for the GLDAS and GNSS datasets, the filtered time series are analyzed with a PCA with one PC. Fig. 5a shows the temporal evolutions of the basin-averaged water content expressed as EWH_{gnss}, SWC from GLDAS and LWE from GRACE, while Fig. 5b-d shows the spatial distributions of water loss from January, 2010 to August, 2022 (2021.00-2022.58, yellow box in Fig. 5a), estimated from GNSS, GLDAS and GRACE, respectively. Fig. 5a shows that the drought time interval, previously defined considering the SPEI-12, Po level and GNSS data, is also consistent in SWC and LWE time series from GLDAS and GRACE, respectively.

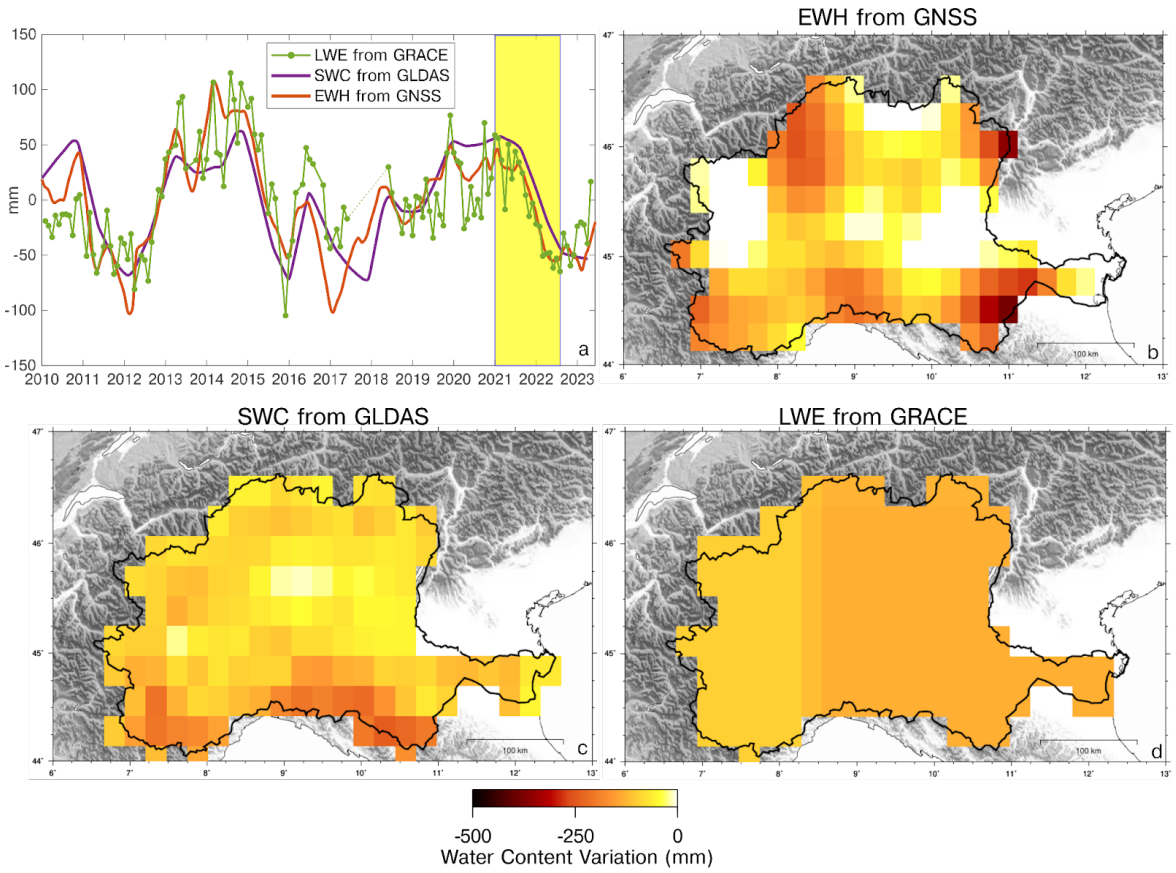

Figure 5. a) Comparison among the temporal evolutions of the regional-averaged water content expressed as EWH_{gnss} (red), SWC (purple) and LWE (green). Since EWH is obtained from GNSS detrended data; both GLDAS and GRACE data have also been detrended for consistency. b) Water loss occurred in the 2021.00 - 2022.58 time interval in terms of EWH from GNSS, c) SWC from GLDAS and d) LWE from GRACE.

The temporal evolution of the basin-averaged water content estimated by the three models is very similar (Fig. 5a), suggesting that the water storage variations may be dominated by its superficial content, captured by GLDAS. The spatial distribution of the water loss occurring in the 2021.00 - 2022.58 time interval (Fig. 5b-d) is different depending on the considered dataset; nonetheless, averaging on the Po basin surface, we obtain water loss values of the order of about 69, 73 and 90 Gtons from GNSS, GLDAS and GRACE, respectively in this period. Figure S8 in the supplementary material shows a comparison in terms of regional-averaged water loss and spatial distribution of LWE thickness change in the 2021.00 - 2022.58 time interval obtained using the Gravity Information Service of the German Research Centre for Geosciences (GRAVIS) and the Center for Space Research of the University of Texas (CSR) GRACE products. Regional averaged water loss values according to CSR and GRAVIS products are 139 and 124 Gtons, respectively. However, because of a higher temporal variability of LWE values from GRACE, and in particular of CSR products, the water loss estimation may vary significantly with small changes in the considered time interval.

The poor spatial resolution of GRACE measurements makes LWE spatial distribution more uniform than the other two products and not able to detect possible concentrations of water loss at the scale of the Po river basin. Both SWC and EWH_{gnss} show the largest values in the southern portion of the basin, but EWH_{gnss} is large also in the north-central portion of the basin, in agreement with the SPEI-12 map (Fig. 1), and very small in the eastern and western portions. The reason for the observed spatial discrepancy can be a consequence of the GLDAS limitations in resolving the spatial distribution of the water loss in the mountain sectors. It is also worth considering that GNSS vertical displacements can contain signals that might cause an incorrect estimation of the water content. In fact, the inversion is made on the displacements reconstructed by the PC1. This statistical approach allows us to identify a common displacement signal that has the same temporal evolution in all the GNSS stations, but different amplitudes. The amplitude associated with this signal might be imprecise, especially in GNSS sites characterized by noisy time-series or for stations affected by local processes.

Importantly, estimates of water loss values depend on the Green's function used to invert the displacements data. Several authors (e.g., Argus et al., 2017; Chanard et al., 2014), point out that a gravitating, spherical Earth model is preferred in this context, since non gravitating, half-space models, can understate elastic vertical displacements up to a factor of 2.5. Moreover, the

results are not very sensitive to the Earth's structure: assuming two different models for the Earth, PREM and the Gutenberg Bullen A Earth structure (Farrell, 1972), Argus et al. (2017) find that the difference between the displacements caused by a 450 km × 60 km load is only 4%.

5 Conclusions

We analyze vertical ground displacements from GNSS stations located in the Po river basin, a significant European district with industrial and agricultural settlements. We find that inter-annual and multi-annual changes in vertical trends clearly respond to meteo-climatic forcing and serve as a reliable, near real-time, independent approximation of drought indexes. Differently from meteorological drought indicators, the measure of vertical displacements allows estimating the severity of drought in terms of spatial and temporal evolution of water volume loss, which is crucial for managing the problem of water scarcity. During the last dry period that has affected the study region, from the beginning of 2021 to the summer of 2022, we observe a regional uplift signal. This uplift reaches values of up to 7 mm and exhibits spatial variations across the area. We interpret this phenomenon as a result of variable water loss and subsequent reduced load, enabling us to estimate the spatial distribution of EWH. We estimate that approximately 70 Gtons of water was lost in the Po river basin from 2021 to August 2022. This estimate aligns with values obtained from GLDAS but is lower than the estimate derived from GRACE. Additionally, while the temporal evolution of EWH estimated by GNSS, GLDAS, and GRACE shows similarities, the spatial patterns differ significantly.

Our findings are also relevant for studying active tectonics and geodynamics. The Apennines and Alps, in fact, exhibit long-term uplift signals resulting from various multiscale processes (Sternai et al., 2019). Accounting for the hydrological origins of trend variations is crucial to improve accuracy and prevent misinterpretation of transient signals or biases in velocity estimates, especially in case of short time-series.

Future works will integrate GNSS with InSAR data to improve the spatial resolution of EWH to a few tens of meters, as demonstrated by Ghorbani et al. (2022). This integration would enhance our understanding of the phenomenon and provide more detailed information on water loss and recharge dynamics.

Acknowledgments

We thank GNSS data providers (see Serpelloni et al. 2022 for references), and in particular private networks providers. Some of the figures are created using the Generic Mapping Tools (GMT) software (Wessel et al., 2013).

Open Research

The EWH is estimated by inverting the GNSS data using the GNSS2TWS software (https://github.com/jzshhh/gnss2tws).

The trend filtering on the GNSS vertical displacements time series is performed using the L1tool software (https://github.com/wudingcheng/l1tool).

The stacking of the GNSS time series is performed using the GNSS_TS_NRS code (https://github.com/CL-Xiong/GNSS-TS-NRS, He et al., 2020).

GLDAS data was downloaded from https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.1/summary?keywords=GLDAS.

GRACE data was downloaded from http://www2.csr.utexas.edu/grace.

SPEI-12 data was downloaded from https://spei.csic.es/map/maps.html#months=1#month=0#year=2023GNSS.

GNSS time series data are available from https://doi.pangaea.de/10.1594/PANGAEA.958598.

The maps have been made using the GMT software (Wessel et al. 2019).

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