

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

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Key Points:

- Vertical ground displacements are used as an independent measure of terrestrial water storage variations.
- Trend changes of vertical displacements are a reliable near real-time indicator of drought severity.
- About 80 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 in the Po river basin to measure deformation signals associated with the severe drought occurring since 2021 and estimate the spatial distribution of water loss. The detection of vertical ground displacement trend changes allows us to extract a spatially correlated signal that follows the Po level trend changes and SPEI-12 drought index. GNSS stations in the basin mostly underwent uplift, up to 7 mm, since 2021, which corresponds to ~80 Gtons of water loss. Compared to GLDAS and GRACE, the GNSS results show a similar temporal evolution of water content, but a different spatial distribution. Our study indicates that using dense GNSS networks is an effective way to monitor long-term 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 since 2021. We find that the GNSS stations show that the ground mostly moved upwards since 2021, which means that water was being lost. We estimate that about 80 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 a severe drought, where the dry conditions were related to a persistent lack of precipitation since December 2021. The level of the largest Italian river, the Po, has been significantly decreasing since the summer of 2021 (Fig. 1). Several regions declared a state of emergency, and drinking water has been rationed in hundreds of municipalities in northern Italy. Figure 1 shows a map of the Standardised Precipitation-

Evapotranspiration Index (SPEI-12, Vicente-Serrano et al. 2010), which quantifies the drought level of the last 12 months taking into account both precipitation and potential evapotranspiration.

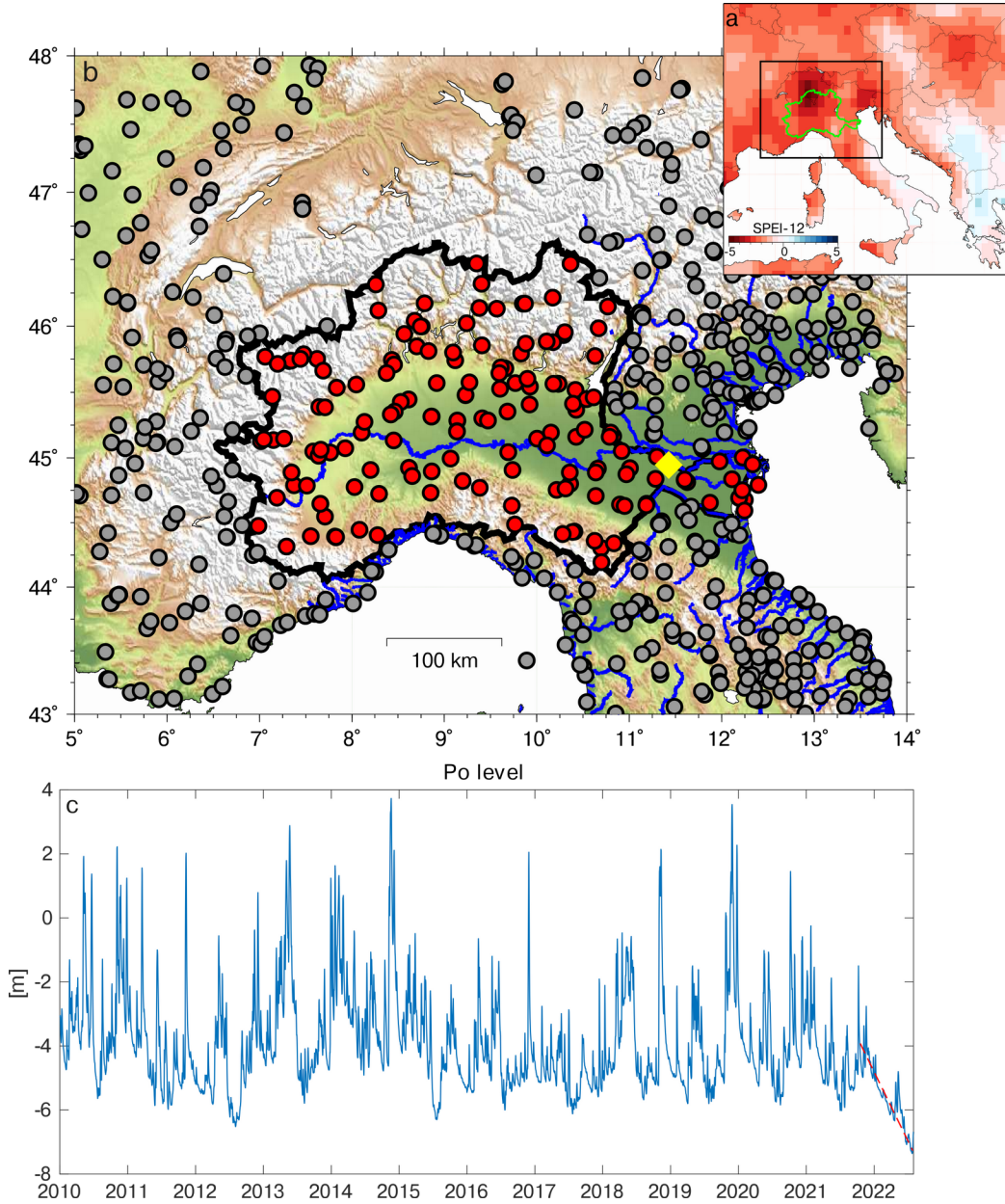


Figure 1. a) SPEI-12 computed on August 2022. b) The study area: the black line represents the Po river (thick blue line) basin; the dots show the positions of the GNSS stations used in the analysis, the reds are the ones inside the basin, the gray the ones outside; the yellow diamond shows the location of the Po level measurement point. c) Po river level changes. The rapid level drop between 2021 and 2022 is shown by the red dashed line.

54 The effects of droughts are particularly dangerous in the Po river basin for various
55 reasons: drought threatens the crops in the Po Valley, which are around 40% of the total food
56 produced in Italy, and impacts energy production, since a reduced river flow causes
57 deficiencies in hydropower generation and cooling of thermal plants (Boyko et al., 2022).

58 Due to global warming, more frequent and severe droughts are likely to occur in the
59 next future (Boyko et al., 2022). For this reason, while it is necessary to measure and monitor
60 variations in terrestrial water storage (TWS) in order to evaluate the best policies to address
61 the problems caused by water scarcity, it is difficult to get measurements of all the TWS
62 components, which include groundwater, surface water, vegetation and soil moisture, ice and
63 snow. Piezometers, for example, effectively monitor groundwater level variations but not the
64 other water storage components, and evaluating the water volume changes from them is not
65 straightforward. On the other hand, the Global Land Data Assimilation System (GLDAS)
66 model provides daily variations of the soil moisture and snow water equivalent, but it can not
67 take into account the groundwater stored more than 2 m below the surface (Argus et al., 2014;
68 Jiang et al., 2021). TWS can also be estimated using Gravity Recovery and Climate
69 Experiment (GRACE) measurements, which allow modeling water storage changes by
70 inverting the spatiotemporal variations of the Earth's gravity field. Unlike GLDAS, all the
71 components of TWS are taken into account by GRACE, nonetheless its spatial resolution
72 (300-400 km) and its temporal resolution (monthly) are too coarse for many regional or local
73 studies (Fu et al., 2015; Knappe et al., 2019).

74 TWS variations are indirectly detectable not only through gravity data but also by
75 measuring ground displacements through geodetic observations: a water content increase
76 causes an increasing load on the Earth surface, which subsides elastically; while when the
77 water content decreases the crust moves upward because of the water content decrease. Global
78 Navigation Satellite System (GNSS) measurements, for example, provide daily measurements
79 of ground displacements, at mm precisions, that can be used to measure ground deformation
80 associated with TWS variations. Argus et al. (2014) inferred the spatial distribution of the
81 TWS seasonal amplitude, expressed in terms of equivalent water height (EWH), by inverting
82 the seasonal vertical displacements of the ground in California. Fu et al. (2015) estimated
83 TWS variations from GNSS measurements of vertical displacement in Washington and
84 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.

In this work we estimate the amount of water loss in the Po river basin, extending $\sim 7.4 \cdot 10^5 \text{ km}^2$, by inverting vertical ground displacements measured by continuous GNSS stations. We consider stations inside the basin, but also stations located within 1° from the basin boundaries, in order to reduce inversion artifacts near the boundaries of the study region (Fu et al. 2015). We focus on long-term, inter-annual, changes, rather than seasonal (i.e., annual) variations, by modeling displacement time-series looking for trend changes in the vertical component, with particular focus on the most recent and severe 2021-2022 drought.

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

2 Data and Methods

We consider ~180 daily GNSS vertical ground displacement time series from January, 2010 to September, 2022 of continuous stations located in the Po river basin (see Fig. 1). We also include in the analysis ~280 stations located within 1° of the catchment limits. This is part of a larger geodetic solution encompassing the whole Euro-Mediterranean region, obtained following the approach detailed in Serpelloni et al. (2022). We remove the long-term linear trend from the time series using the Median Interannual Difference Adjusted for Skewness (MIDAS) estimator (Blewitt et al. 2016) and filter the contribution of the non-tidal atmospheric loading (NTAL), as suggested by White et al. (2022), since they can produce displacements of several millimeters at daily-weekly timescales that can interfere with the hydrological signal. The NTAL-induced vertical displacements are evaluated from the daily 0.5° x 0.5° gridded solution of the Earth-System-Modeling Group at the German Research Center for Geosciences (Dill and Dobsław, 2013) and its contribution in each site is calculated considering the nearest grid point where the displacements associated with NTAL are computed.

The resulting GNSS vertical displacements time series are then analyzed using a trend filtering approach, which performs an extensive analysis using a L1 norm regularization model to identify the seasonal components, offsets and linear trend changepoints in the GNSS time series (Wu et al. 2018). The piecewise trend x is estimated by minimizing the weighted sum objective function:

$$(1/2)\|y - x - s - w\|_2^2 + \lambda \|D^{(2)}x\|_1 + \rho \|1 + D^{(1)}w\|_1$$

where y is the original time series, w indicates the level component associated with the offsets, s is the seasonal term, $\|\cdot\|_1$ represents the L1 norm and $D^{(n)}$ are the n -th difference matrix defined as in Wu et al. (2018). λ and ρ are positive parameters controlling the knots of the estimation trend and the frequency of level shifts, respectively (we choose $\lambda=2000$ and $\rho=80$). Figure 2 shows an example of output of this analysis. Focusing on transients and interannual variations, we only consider the extracted piecewise trends, not the seasonal terms having annual and semi-annual frequencies. For some stations level changes (i.e., offsets) not associated with tectonic events or equipment changes are highlighted, which mostly represent fast variations in ground displacements (see Fig. 2 in 2012). For this reason, in the further steps we consider the piecewise trend as the sum of the trend and level components. As it can be seen in Fig. 2, there is an increase in uplift starting from 2021, which is a common feature in GNSS stations within the Po river basin. Fig. 2e shows the stacking of the vertical piecewise trend time-series for all stations analyzed, which is performed by averaging, for each epoch, the residuals of all the time series resulting by removing the mean and linear trend terms. In order to better characterize the spatial distribution of this deformation signal, we use a multivariate statistical approach, similarly to what is used for tectonic deformation studies (Kositsky and Avouac, 2010; Gualandi et al. 2014).

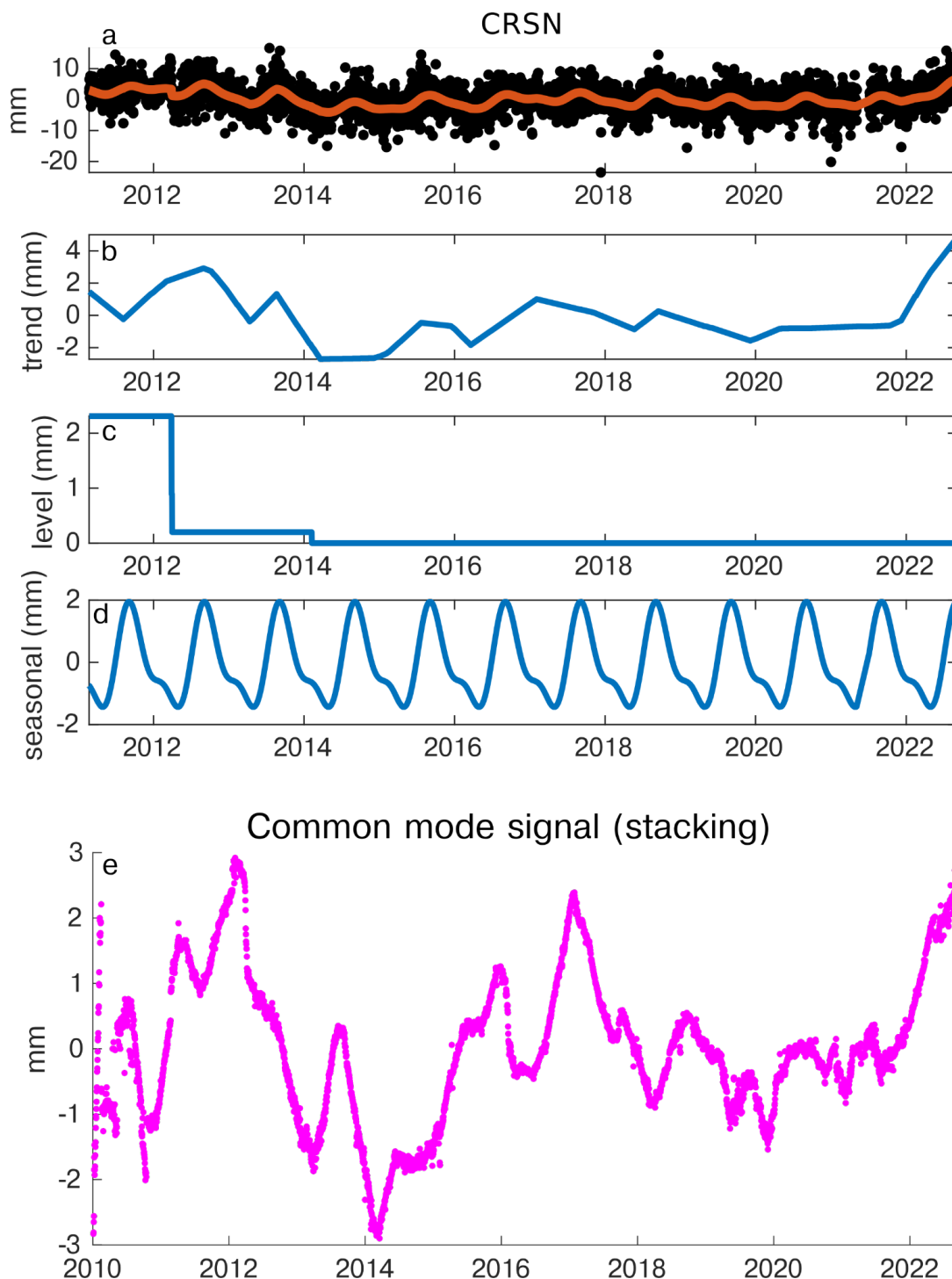


Figure 2. Example of GNSS time series decomposition performed using the L1-norm trend filtering approach. In a) the black dots represent the original time series, the red line the model obtained as the sum of the trend (b), level (c) and seasonal component (d). Panel (e) shows the result of the stacking 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), but we use as input of a principal component analysis (PCA) the piecewise vertical trends described in the previous section, rather than the raw time-series. 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 or 3 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: 20-12-2022). The Po river level time series is filtered adopting the same approach used for the GNSS time-series, and retaining only the piecewise trend component (Fig. S4). 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, climatic and hydrological time series are highly temporally correlated.

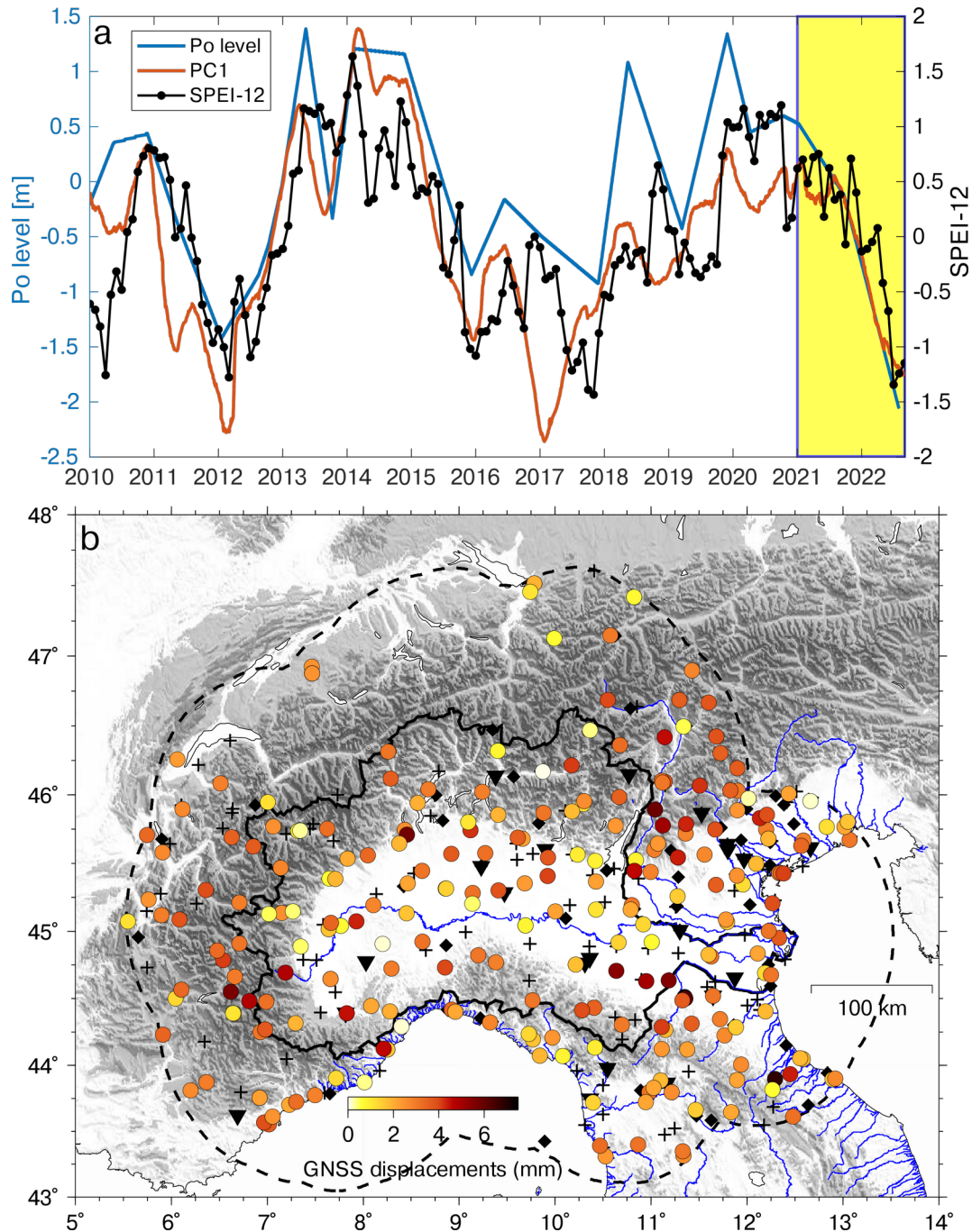


Figure 3. a) Comparison between the PC1 temporal evolution, the SPEI-12 index and the Po river level. Since PC1 is obtained from detrended GNSS time series, Po river level and SPEI-12 have also been detrended for consistency. b) Vertical displacements associated with PC1 during the 2021.00 (January, 2021) - 2022.67 (September, 2022) time interval (yellow panel). The dashed line represents the boundary of the Po river basin, extended by 1°. Black triangles indicate the 21 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 2022.67 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 21 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 21 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 2021.00-2022.67 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 250.

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

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

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 $0.25^\circ \times 0.25^\circ$ grid. We choose $\alpha = 0.0034$, 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 - 2022.67 time interval (yellow box in Fig. 3A).

Text S1 presents the results of checkerboard tests, showing that our inversion is well resolved at the spatial resolution of $1^\circ \times 1^\circ$.

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 $0.25^\circ \times 0.25^\circ$ 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 GRACE and GRACE-FO RL06 Mascon solutions from the Center for Space Research (Save et al., 2016; Save, 2020). While the data are provided in a grid with the same size as the GLDAS one, which corresponds to a resolution of about 25 km, the current resolution is 300-400 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 months gap, from July 2017 to May 2018.

The GLDAS products allow an estimate of the water content with a better nominal spatial resolution of EW_{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 EW_{gnss} . We point out that while EW_{gnss} is inverted on a $0.25^\circ \times 0.25^\circ$ grid, the results of the checkerboard test show that the actual spatial resolution is $\sim 1^\circ$, 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 filter the annual and semiannual signals in SWC time series using the same approach used for GNSS displacement and Po river level measurements (see Fig. S8), 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, removing the annual and semiannual components from the original time series instead of estimating the trend components, as done for GNSS and GLDAS time-series. In fact, the trend variations observed in EW_{gnss} occur also at a monthly timescale, but the temporal resolution of LWE is also monthly, so it is unnecessary to estimate the LWE trend variations. As for the GLDAS and GNSS datasets, the filtered time series are analyzed with a PCA with one PC. Fig. 4a shows the temporal evolutions of the basin-averaged water content expressed as EW_{gnss} , SWC from GLDAS and LWE from GRACE, while Fig. 4b-d shows the spatial distributions of water loss from January, 2010 to September, 2022 (yellow box in Fig. 4a), estimated from GNSS, GLDAS and GRACE, respectively.

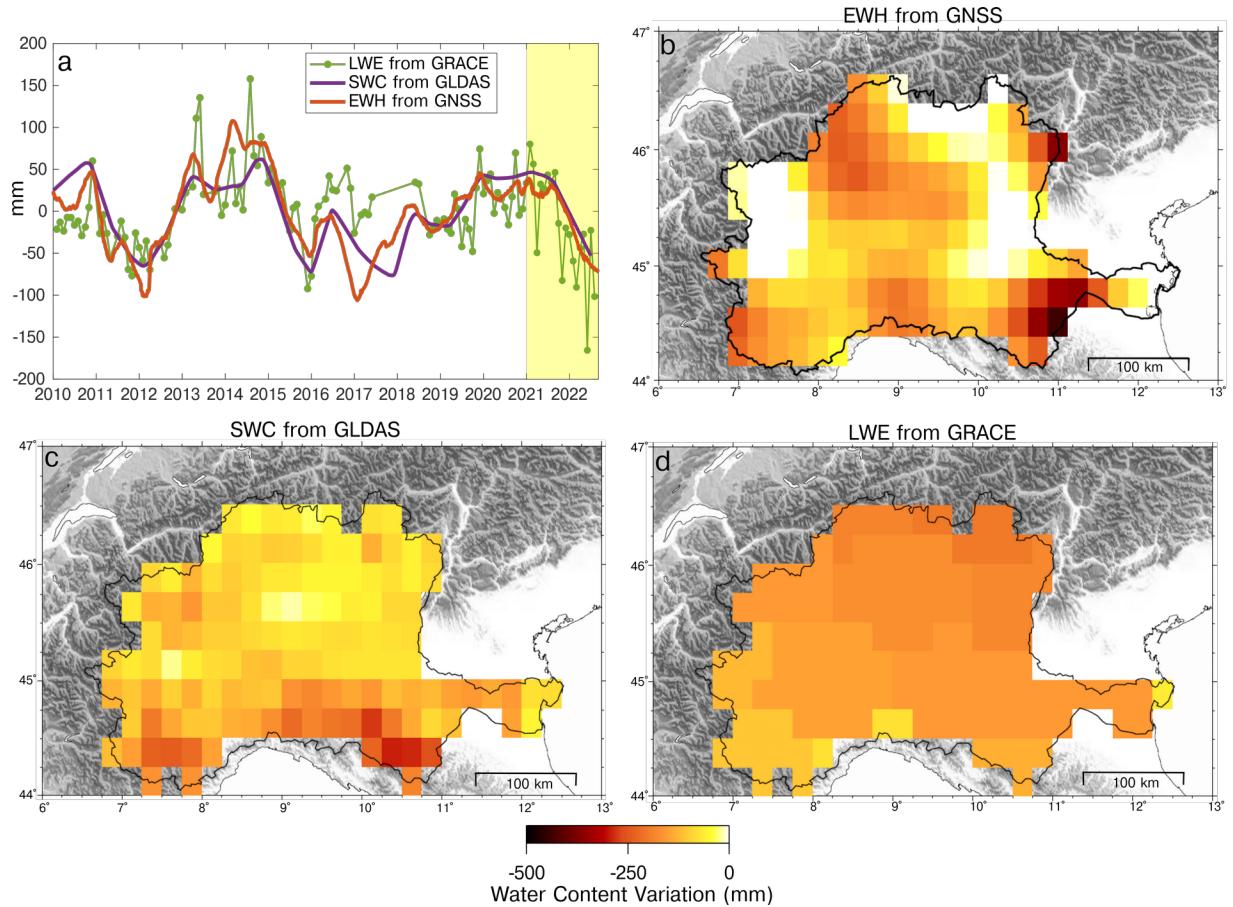


Figure 4. a) Comparison among the temporal evolutions of the regional-averaged water content expressed as EWH_{gnss} (red), SWC (purple) and LWE (green). Since EWH is obtained from GNSS detrended data; both GLDAS and GRACE data have also been detrended for consistency. b) Water loss occurred in the 2021.00 - 2022.67 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, especially between EWH_{gnss} and SWC (Fig. 4a), 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 - 2022.67 time interval (Fig. 4b-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 80, 82 and 115 Gtons from GNSS, GLDAS and GRACE, respectively in this period.

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

290 Importantly, estimates of water loss values depend on the Green’s function used to
291 invert the displacements data. Several authors (e.g., Argus et al., 2017; Chanard et al., 2014),
292 point out that a gravitating, spherical Earth model is preferred in this context, since non
293 gravitating, half-space models, can understate elastic vertical displacements up to a factor of
294 2.5. Moreover, the results are not very sensitive to the Earth’s structure: assuming two
295 different models for the Earth, PREM and the Gutenberg Bullen A Earth structure (Farrell,
296 1972), Argus et al. (2017) find that the difference between the displacements caused by a 450
297 $\text{km} \times 60 \text{ km}$ 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. Our study demonstrates that changes in vertical trends respond to meteo-climatic forcing and serve as a reliable, near real-time, independent approximation of drought indexes. During the drought that has affected the region since 2021, 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. GNSS observations indicate that an estimated average of approximately 80 Gtons of water was lost in the Po river basin from 2021 to the end of summer 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 research 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

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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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