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

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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.

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2 **(Northern Italy) from GNSS measurements**

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6 **Key Points:**

7 • Vertical ground displacements are used as an independent measure of terrestrial water
8   storage variations.

9 • Trend changes of vertical displacements are a reliable near real-time indicator of
10   drought severity.

11 • About 80 billion tons of water is lost during the 2021-2022 drought in the Po river
12   basin.

13

14

15 **Abstract**

16 We study vertical ground displacement time-series from GNSS stations in the Po river basin to

17 measure deformation signals associated with the severe drought occurring since 2021 and

18 estimate the spatial distribution of water loss. The detection of vertical ground displacement

19 trend changes allows us to extract a spatially correlated signal that follows the Po level trend

20 changes and SPEI-12 drought index. GNSS stations in the basin mostly underwent uplift, up to

21 7 mm, since 2021, which corresponds to ~80 Gtons of water loss. Compared to GLDAS and

22 GRACE, the GNSS results show a similar temporal evolution of water content, but a different

23 spatial distribution. Our study indicates that using dense GNSS networks is an effective way to

24 monitor long-term changes in water storage even in small water basins and serve as a reliable

25 indicator of drought severity.

26 **Plain Language Summary**

27 This study looks at the way the ground moves up and down in the Po river basin, in northern

28 Italy, using Global Navigation Satellite System (GNSS) stations. We measure how much

29 water was lost during a big drought in the area since 2021. We find that the GNSS stations

30 show that the ground mostly moved upwards since 2021, which means that water was being

31 lost. We estimate that about 80 billion tons was lost during that time, in agreement with other

32 ways of measuring terrestrial water variations. This study shows that GNSS stations can be an

33 alternative way to measure how much water is being lost during drought in small areas and

34 common vertical displacement signals are a good approximation of drought indexes.

35 **1 Introduction**

36   Drought is one of the most complex recurring natural disasters, defined by a deficiency

37 of precipitations that causes prolonged water scarcity. Failure to manage drought risk has the

38 potential to have dire consequences for people, livelihoods, economy and ecosystems. During

39 the summer of 2022 Italy faced a severe drought, where the dry conditions were related to a

40 persistent lack of precipitation since December 2021. The level of the largest italian river, the

41 Po, has been significantly decreasing since the summer of 2021 (Fig. 1). Several regions

42 declared a state of emergency, and drinking water has been rationed in hundreds of

43 municipalities in northern Italy. Figure 1 shows a map of the Standardised Precipitation-

44 Evapotranspiration Index (SPEI-12, Vicente-Serrano et al. 2010), which quantifies the drought

45 level of the last 12 months taking into account both precipitation and potential
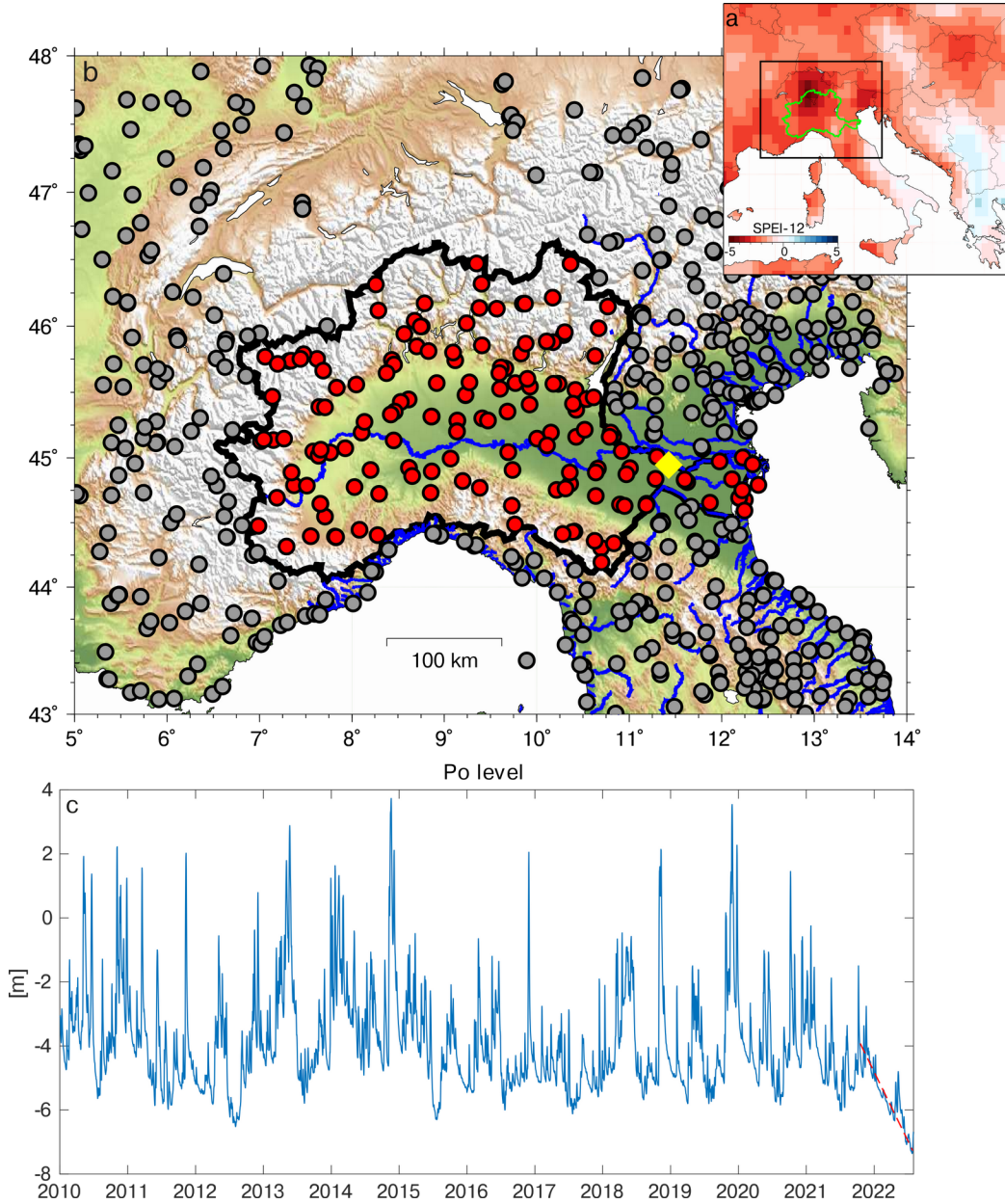
46 evapotranspiration.

47

48 **Figure 1. a) SPEI-12 computed on August 2022. b) The study area: the black line**

49 **represents the Po river (thick blue line) basin; the dots show the positions of the GNSS**

50 **stations used in the analysis, the reds are the ones inside the basin, the gray the ones**

51 **outside; the yellow diamond shows the location of the Po level measurement point. c) Po**

52 **river level changes. The rapid level drop between 2021 and 2022 is shown by the red**

53 **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

85 mountain areas. GNSS displacements have been inverted to estimate the TWS also by Jin and
86 Zhang (2016) in the southwestern United States, by Zhang et al. (2016) over the Yunnan
87 Province in China and by Ferreira et al. (2019) in the entire South America.

88 Carlson et al. (2022) computed TWS in California using a joint inversion method
89 combining the GRACE products with the results of the inversion of GNSS data, taking
90 advantage of the dense spatial distribution of GNSS data together with GRACE's ability to
91 provide regional closure of the water budget.

92 In this work we estimate the amount of water loss in the Po river basin, extending
93 $\sim 7.4 \cdot 10^5$ km^2, by inverting vertical ground displacements measured by continuous GNSS
94 stations. We consider stations inside the basin, but also stations located within 1° from the
95 basin boundaries, in order to reduce inversion artifacts near the boundaries of the study region
96 (Fu et al. 2015). We focus on long-term, inter-annual, changes, rather than seasonal (i.e.,
97 annual) variations, by modeling displacement time-series looking for trend changes in the
98 vertical component, with particular focus on the most recent and severe 2021-2022 drought.

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

103 **2 Data and Methods**

104   We consider ~180 daily GNSS vertical ground displacement time series from January,
105 2010 to September, 2022 of continuous stations located in the Po river basin (see Fig. 1). We
106 also include in the analysis ~280 stations located within 1° of the catchment limits. This is part
107 of a larger geodetic solution encompassing the whole Euro-Mediterranean region, obtained
108 following the approach detailed in Serpelloni et al. (2022). We remove the long-term linear
109 trend from the time series using the Median Interannual Difference Adjusted for Skewness
110 (MIDAS) estimator (Blewitt et al. 2016) and filter the contribution of the non-tidal
111 atmospheric loading (NTAL), as suggested by White et al. (2022), since they can produce
112 displacements of several millimeters at daily-weekly timescales that can interfere with the
113 hydrological signal. The NTAL-induced vertical displacements are evaluated from the daily
114 0.5° x 0.5° gridded solution of the Earth-System-Modeling Group at the German Research
115 Center for Geosciences (Dill and Dobslaw, 2013) and its contribution in each site is calculated
116 considering the nearest grid point where the displacements associated with NTAL are
117 computed.

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

123 $(1/2)\|y - x - s - w\|_2^2 + \lambda\|D^{(2)}x\|_1 + \rho\|1 + D^{(1)}w\|_1$

124   where y is the original time series, w indicates the level component associated with the

125   offsets, s is the seasonal term, $\|.\|_1$ represents the L1 norm and $D^{(n)}$ are the n-th difference

126   matrix defined as in Wu et al. (2018). λ and ρ are positive parameters controlling the knots of

127   the estimation trend and the frequency of level shifts, respectively (we choose $\lambda= 2000$ and $\rho=$

128   80). Figure 2 shows an example of output of this analysis. Focusing on transients and

129   interannual variations, we only consider the extracted piecewise trends, not the seasonal terms

130   having annual and semi-annual frequencies. For some stations level changes (i.e., offsets) not

131   associated with tectonic events or equipment changes are highlighted, which mostly represent

132   fast variations in ground displacements (see Fig. 2 in 2012). For this reason, in the further

133   steps we consider the piecewise trend as the sum of the trend and level components. As it can

134   be seen in Fig. 2, there is an increase in uplift starting from 2021, which is a common feature

135   in GNSS stations within the Po river basin. Fig. 2e shows the stacking of the vertical

136   piecewise trend time-series for all stations analyzed, which is performed by averaging, for

137   each epoch, the residuals of all the time series resulting by removing the mean and linear trend

138   terms. In order to better characterize the spatial distribution of this deformation signal, we use

139   a multivariate statistical approach, similarly to what is used for tectonic deformation studies

140   (Kositsky and Avouac, 2010; Gualandi et al. 2014).
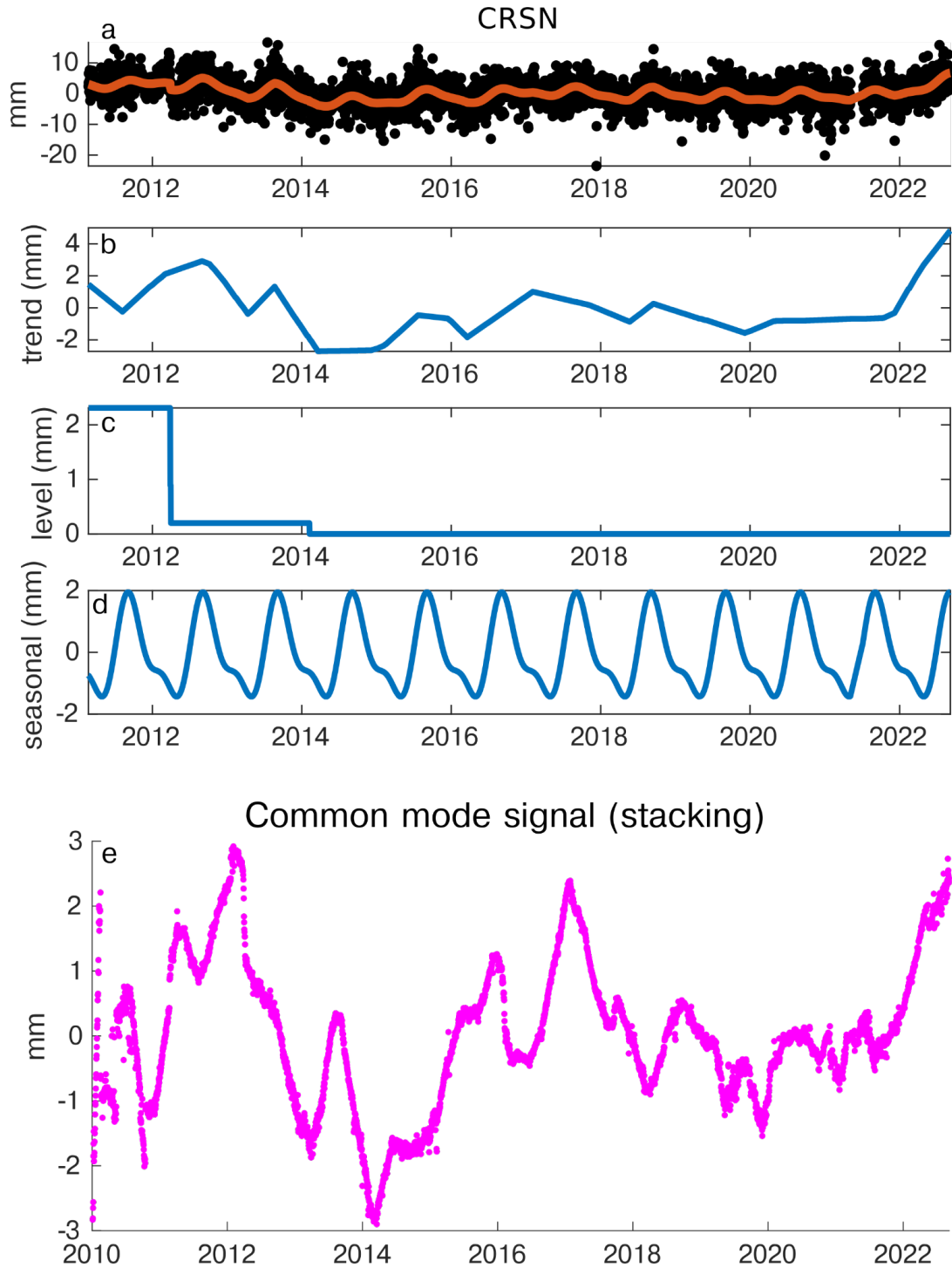
141

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.

148 **3 Results**

149   3.1 Comparison between geodetic and hydrological measurements

150   We adopt an approach similar to the one described in Jiang et al. (2022), but we use as
151 input of a principal component analysis (PCA) the piecewise vertical trends described in the
152 previous section, rather than the raw time-series. We decompose the dataset using one PC in
153 order to identify the most important common signal of the GNSS stations in the Po basin and
154 retrieve its spatial pattern (i.e., amplitude and sign). However, the first principal component
155 (PC1) obtained performing a PCA using 2 or 3 components is almost identical to the PC1
156 obtained performing a one-component decomposition, both in terms of temporal evolution
157 (Fig. S1) and spatial distributions (Fig. S2).

158   The temporal evolution of PC1 (Fig. 3A) well resembles the common mode signal
159 resulting from a stacking of the vertical trend time-series for all stations (Fig. 2e and Fig. S3).
160 However, the advantage of the PCA is to provide the spatial information on the displacement
161 amplitudes (Fig. S2A).

162   We compare the temporal evolution of PC1 with the SPEI-12 index value, averaged
163 over the Po river basin, and with the Po river level measurements provided by the Regional
164 Agency for Environmental Protection of Veneto region (ARPAV;
165 https://wwwold.arpa.veneto.it/arpavinforma/bollettini/dati-storici, Last Access: 20-12-2022).
166 The Po river level time series is filtered adopting the same approach used for the GNSS time-
167 series, and retaining only the piecewise trend component (Fig. S4). On the other hand, SPEI-
168 12 time series does not contain annual variations, since the index is computed as an anomaly
169 over 12 months, then the time series has not been filtered. Figure 3A shows that the geodetic,
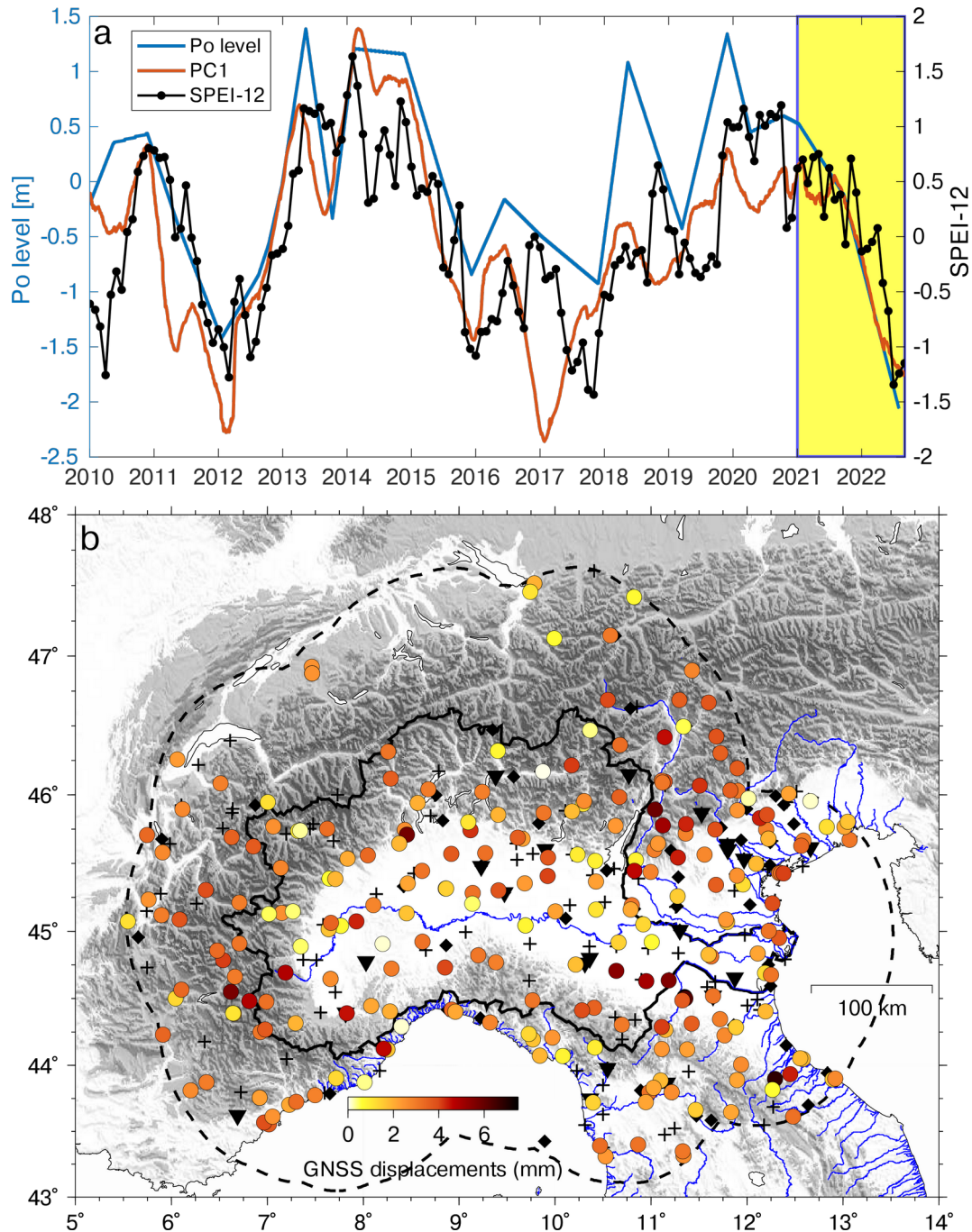170 climatic and hydrological time series are highly temporally correlated.

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

177 **displacements; black crosses represent sites with more than 75% of missing data and**

178 **black diamonds the stations with no records after 2021.0.**

179   The vertical displacements associated with PC1 from 2021.00 to 2022.67 are shown in

180 Fig. 3B. Most of the stations show positive values (uplift), in accordance with the hypothesis

181 that in dry periods, when the water load is reduced, the GNSS stations record uplift, while in

182 wet periods the water load increases causing a downward motion of the Earth's surface. We

183 find that this is not true for 21 sites, which show an opposite behavior (black triangles in Fig.

184 3B). Maximum uplift, of the order of 7 mm, is observed in the south-eastern portion of the

185 basin and in the northern portion of the Po basin, which correspond to uplift rates, in the

186 considered two years, that are much faster than the long-term ones (e.g., Pintori et al., 2022).

187   3.2 Inversion of vertical ground displacements

188   The displacements associated with PC1 are inverted using the approach described in

189 Jiang et al. (2022), which estimates water storage variations assuming an elastic response of

190 the Earth to the hydrological load. In order to avoid misinterpretation of the spatial variations

191 of the water storage changes, we exclude from the inversion the 21 stations showing negative

192 vertical displacements (i.e., subsidence, Fig. S5) in the investigated time interval that,

193 following Carlson et al. (2022), are possibly affected by poroelastic processes, causing vertical

194 displacements in the opposite direction compared to the elastic ones. We also exclude from the

195 inversion the GNSS stations that have no observations recorded in the 2021.00-2022.67 time-

196 span (i.e., do not register displacements potentially associated with the last drought episode

197 investigated in this work). The total number of stations used for the inversion is then 250.

198   The relationship between the vertical displacements measured by GNSS x and the

199 water mass load u, expressed as EWH, is

200 $x=Gu$

201 where G is the Green's function matrix using load Love numbers of the preliminary reference

202 earth model (PREM) (Dziewonski and Anderson, 1981) as commonly used in many recent

203 works (e.g. Carlson et al. 2022, Jiang et al. 2021). The final solution for the daily estimates of

204 EWH changes u is

205 $$u = \left(G^T G + \alpha^2 L^T L \right)^{-1} G^T x$$

206 where L is the Laplacian smoothing matrix and α is the smoothing factor controlling the

207 relative weight between model roughness and data misfit.

208 We invert the displacements associated with PC1 to estimate EWH on a 0.25°x0.25°

209 grid. We choose $\alpha=0.0034$, which is the minimum in the line showing the relation between the

210 sum of squared residuals from cross-validation (CVSS) and the smoothing factor (Fig. S6),

211 and use 4 neighbor points for calculating the Laplacian matrix during the least-squares

212 inversion. Fig. 3A shows the temporal evolution of the EWH averaged over the study area,

213 while Fig. 3B is a map of the EWH variations that occurred in the 2021.00 - 2022.67 time

214 interval (yellow box in Fig.3A).

215 Text S1 presents the results of checkerboard tests, showing that our inversion is well

216 resolved at the spatial resolution of 1°x1°.

217 **4 Discussion**

218 We compare the EWH obtained by inverting the GNSS displacements (EWH$_{gnss}$) with

219 surface water content from GLDAS (SWC) and with Liquid Water Equivalent Thickness

220 (LWE) from GRACE.

221 The GLDAS products provide the soil moisture content in the first 2 m of the

222 subsurface, the snow depth water equivalent, the plant canopy surface water and the root zone

223 soil moisture (Rodell et al., 2004). We consider as SWC the sum of these four components,

224 which are provided as 0.25°x0.25° gridded dataset and 3-hours temporal resolution, which are

225 transformed into daily time series by averaging the 3-hourly time series to make them

226 consistent with the daily resolution of EWH$_{gnss}$.

227   LWE is computed using the GRACE and GRACE-FO RL06 Mascon solutions from

228   the Center for Space Research (Save et al., 2016; Save, 2020). While the data are provided in a

229   grid with the same size as the GLDAS one, which corresponds to a resolution of about 25 km,

230   the current resolution is 300-400 km. The temporal resolution of LWE data is monthly and

231   data are missing in correspondence with the gap between the GRACE and GRACE-FO

232   missions, which results in a 11 months gap, from July 2017 to May 2018.

233   The GLDAS products allow an estimate of the water content with a better nominal

234   spatial resolution of EWH_{gnss}, even though the disadvantage is that GLDAS does not take into

235   account groundwater. Importantly, while the GLDAS nominal spatial resolution is 0.25°, its

236   effective resolution may be different due to the assimilation process and the interpolation

237   techniques used to generate gridded datasets. Furthermore, the nominal spatial resolution of

238   GLDAS may not represent the true spatial variability of soil moisture in a context such as the

239   Po river basin, characterized by high topographic gradients. The correct determination of the

240   soil types in regions characterized by heterogeneous landscapes, elevation and land cover, in

241   fact, is complex and this can lead to errors in soil moisture modeling (Bi et al., 2016).

242   LWE takes into account all TWS components, but with a spatial and temporal

243   resolution much poorer than EWH_{gnss}. We point out that while EWH_{gnss} is inverted on a

244   0.25°x0.25° grid, the results of the checkerboard test show that the actual spatial resolution is

245   ~1°, corresponding to about 100 km (Section S1 of the Supporting Information). This is

246   consistent with the resolution achieved by Zhang et al. (2016) in the Yunnan region of China

247   and by Fu et al. (2015) in Washington and Oregon. The high spatial density of the southern

248   California GNSS network allowed Carlson et al. (2022) to reach a spatial resolution of 80 km,

249   while when considering larger study areas as in Borsa et al. (2014) and in Ferreira et al. (2019)

250   the spatial resolution decreases to 200-300 km.

251   We filter the annual and semiannual signals in SWC time series using the same

252   approach used for GNSS displacement and Po river level measurements (see Fig. S8), and

253   apply a PCA using one PC on the trend components. Because of the monthly temporal

254   resolution of the GRACE products, LWE data are analyzed using a slightly different strategy,

255   removing the annual and semiannual components from the original time series instead of

256   estimating the trend components, as done for GNSS and GLDAS time-series. In fact, the trend

257   variations observed in EWH_{gnss} occur also at a monthly timescale, but the temporal resolution

258   of LWE is also monthly, so it is unnecessary to estimate the LWE trend variations. As for the

259   GLDAS and GNSS datasets, the filtered time series are analyzed with a PCA with one PC.

260   Fig. 4a shows the temporal evolutions of the basin-averaged water content expressed as

261   EWH_{gnss}, SWC from GLDAS and LWE from GRACE, while Fig. 4b-d shows the spatial

262   distributions of water loss from January, 2010 to September, 2022 (yellow box in Fig. 4a),

263   estimated from GNSS, GLDAS and GRACE, respectively.
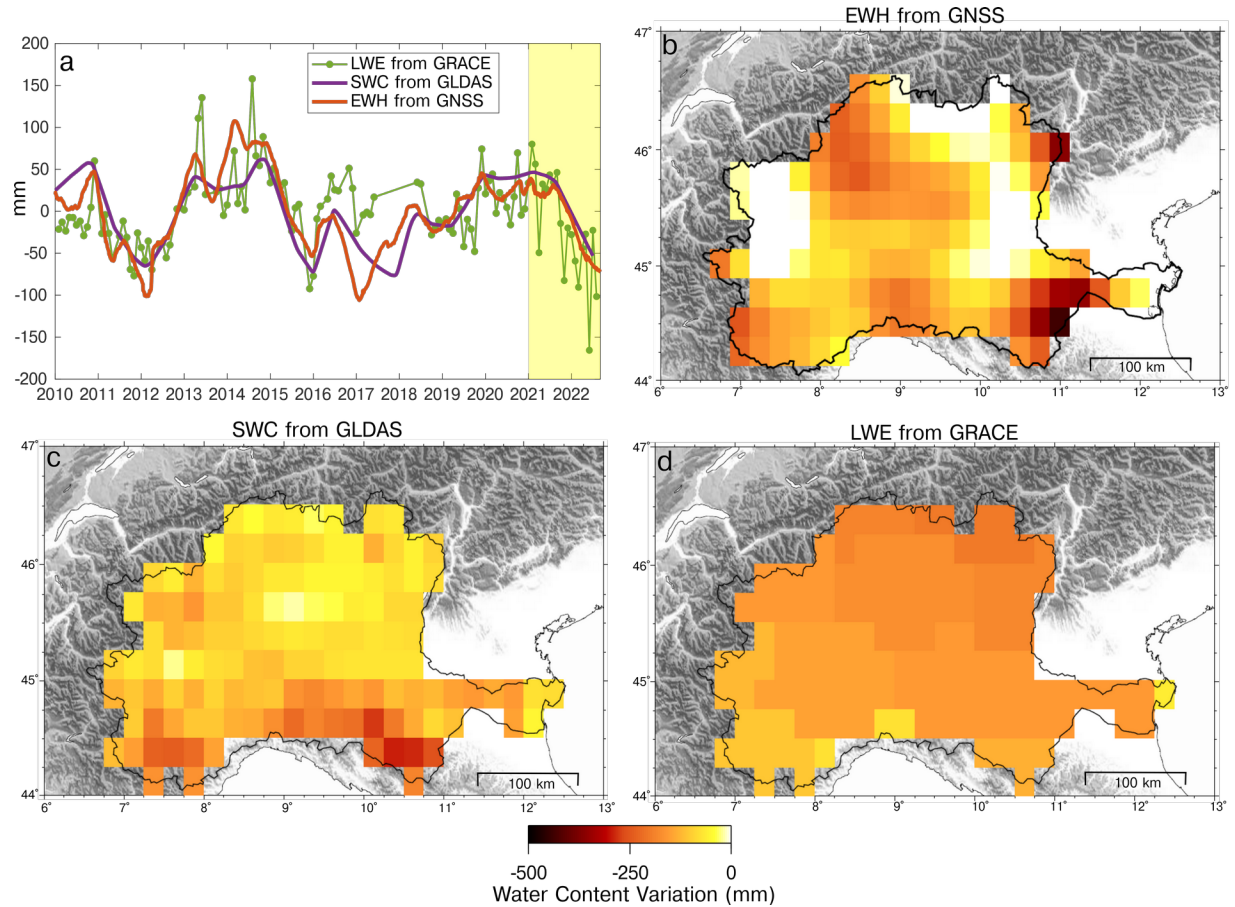
Figure 4. a) Comparison among the temporal evolutions of the regional-averaged water content expressed as EWH$_{gnss}$ (red), SWC (purple) and LWE (green). Since EWH is obtained from GNSS detrended data; both GLDAS and GRACE data have also been detrended for consistency. b) Water loss occurred in the 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   km × 60 km load is only 4%.

298 **5 Conclusions**

299   We analyze vertical ground displacements from GNSS stations located in the Po river

300 basin, a significant European district with industrial and agricultural settlements. Our study

301 demonstrates that changes in vertical trends respond to meteo-climatic forcing and serve as a

302 reliable, near real-time, independent approximation of drought indexes. During the drought

303 that has affected the region since 2021, we observe a regional uplift signal. This uplift reaches

304 values of up to 7 mm and exhibits spatial variations across the area. We interpret this

305 phenomenon as a result of variable water loss and subsequent reduced load, enabling us to

306 estimate the spatial distribution of EWH. GNSS observations indicate that an estimated

307 average of approximately 80 Gtons of water was lost in the Po river basin from 2021 to the

308 end of summer 2022. This estimate aligns with values obtained from GLDAS but is lower than

309 the estimate derived from GRACE. Additionally, while the temporal evolution of EWH

310 estimated by GNSS, GLDAS, and GRACE shows similarities, the spatial patterns differ

311 significantly.

312   Our findings are also relevant for studying active tectonics and geodynamics. The

313 Apennines and Alps, in fact, exhibit long-term uplift signals resulting from various multiscale

314 processes (Sternai et al., 2019). Accounting for the hydrological origins of trend variations is

315 crucial to improve accuracy and prevent misinterpretation of transient signals or biases in

316 velocity estimates, especially in case of short time-series.

317   Future research will integrate GNSS with InSAR data to improve the spatial resolution

318 of EWH to a few tens of meters, as demonstrated by Ghorbani et al. (2022). This integration

319 would enhance our understanding of the phenomenon and provide more detailed information

320 on water loss and recharge dynamics.

326 the figures are created using the Generic Mapping Tools (GMT) software (Wessel et al.,

327 2013).

Open Research

329 The EWH is estimated by inverting the GNSS data using the GNSS2TWS software

330 (https://github.com/jzshhh/gnss2tws).

331 The trend filtering on the GNSS vertical displacements time series is performed using

332 the L1tool software (https://github.com/wudingcheng/l1tool).

333 The stacking of the GNSS time series is performed using the GNSS_TS_NRS code

334 (https://github.com/CL-Xiong/GNSS-TS-NRS, He et al., 2020).

335 GLDAS data was downloaded from

336 https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.1/summary?keywords=GLDAS.

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

338 SPEI-12 data was downloaded from

339 https://spei.csic.es/map/maps.html#months=1#month=0#year=2023GNSS.

340 GNSS time series data are available from

341 https://doi.pangaea.de/10.1594/PANGAEA.958598.

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

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1
2 **Drought-induced vertical displacements and water loss in the Po river basin (Northern Italy) from GNSS measurements**

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6 **Key Points:**

7   • Vertical ground displacements are used as an independent measure of terrestrial water
8   storage variations.

9   • Trend changes of vertical displacements are a reliable near real-time indicator of
10   drought severity.

11   • About 80 billion tons of water is lost during the 2021-2022 drought in the Po river
12   basin.

13

14

15 **Abstract**

16 We study vertical ground displacement time-series from GNSS stations in the Po river basin to

17 measure deformation signals associated with the severe drought occurring since 2021 and

18 estimate the spatial distribution of water loss. The detection of vertical ground displacement

19 trend changes allows us to extract a spatially correlated signal that follows the Po level trend

20 changes and SPEI-12 drought index. GNSS stations in the basin mostly underwent uplift, up to

21 7 mm, since 2021, which corresponds to ~80 Gtons of water loss. Compared to GLDAS and

22 GRACE, the GNSS results show a similar temporal evolution of water content, but a different

23 spatial distribution. Our study indicates that using dense GNSS networks is an effective way to

24 monitor long-term changes in water storage even in small water basins and serve as a reliable

25 indicator of drought severity.

26 **Plain Language Summary**

27 This study looks at the way the ground moves up and down in the Po river basin, in northern

28 Italy, using Global Navigation Satellite System (GNSS) stations. We measure how much

29 water was lost during a big drought in the area since 2021. We find that the GNSS stations

30 show that the ground mostly moved upwards since 2021, which means that water was being

31 lost. We estimate that about 80 billion tons was lost during that time, in agreement with other

32 ways of measuring terrestrial water variations. This study shows that GNSS stations can be an

33 alternative way to measure how much water is being lost during drought in small areas and

34 common vertical displacement signals are a good approximation of drought indexes.

35 **1 Introduction**

36   Drought is one of the most complex recurring natural disasters, defined by a deficiency

37 of precipitations that causes prolonged water scarcity. Failure to manage drought risk has the

38 potential to have dire consequences for people, livelihoods, economy and ecosystems. During

39 the summer of 2022 Italy faced a severe drought, where the dry conditions were related to a

40 persistent lack of precipitation since December 2021. The level of the largest italian river, the

41 Po, has been significantly decreasing since the summer of 2021 (Fig. 1). Several regions

42 declared a state of emergency, and drinking water has been rationed in hundreds of

43 municipalities in northern Italy. Figure 1 shows a map of the Standardised Precipitation-

44   Evapotranspiration Index (SPEI-12, Vicente-Serrano et al. 2010), which quantifies the drought

45   level of the last 12 months taking into account both precipitation and potential
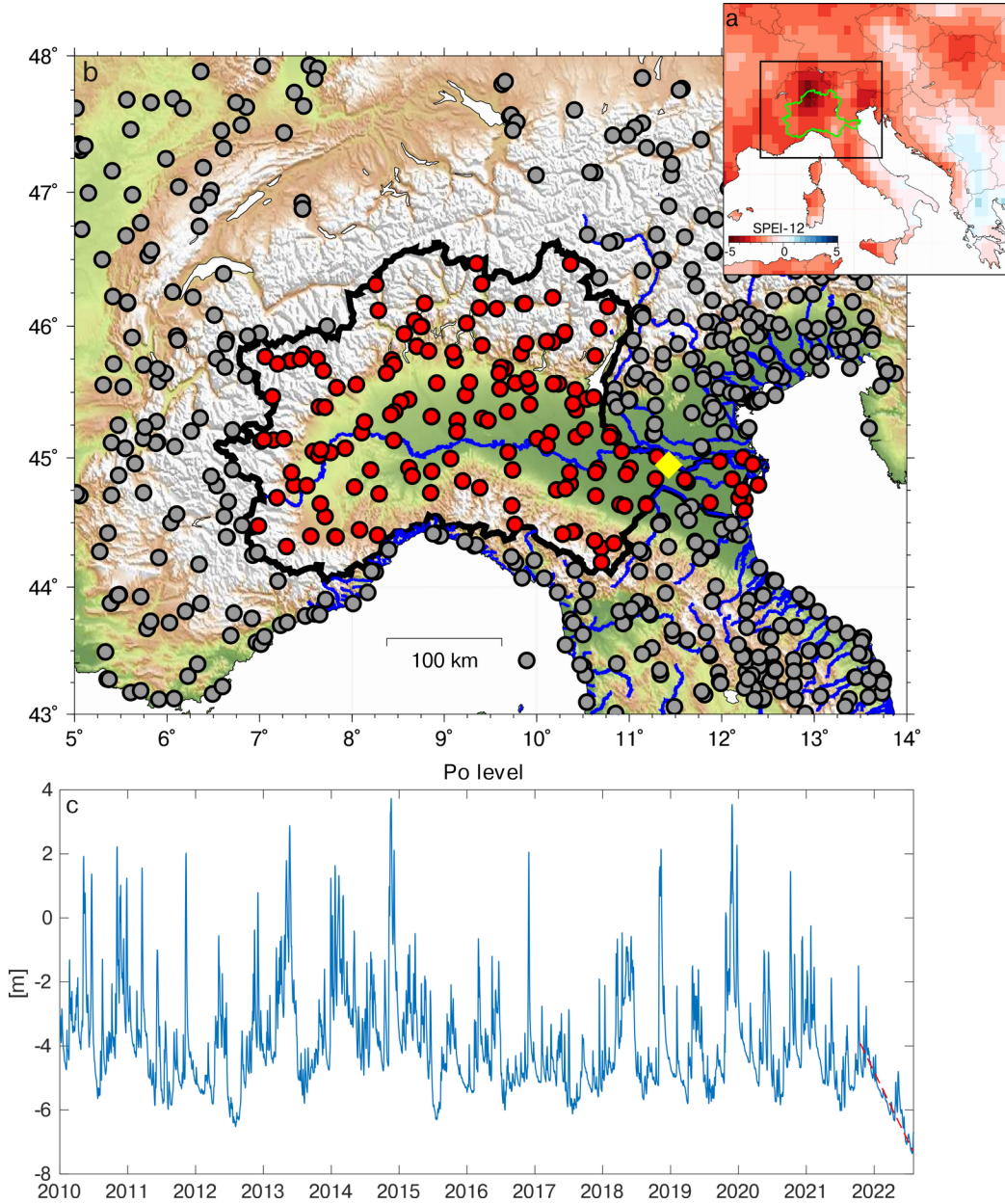
46   evapotranspiration.

47

48   **Figure 1. a) SPEI-12 computed on August 2022. b) The study area: the black line**

49   **represents the Po river (thick blue line) basin; the dots show the positions of the GNSS**

50   **stations used in the analysis, the reds are the ones inside the basin, the gray the ones**

51   **outside; the yellow diamond shows the location of the Po level measurement point. c) Po**

52   **river level changes. The rapid level drop between 2021 and 2022 is shown by the red**

53   **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

85   mountain areas. GNSS displacements have been inverted to estimate the TWS also by Jin and

86   Zhang (2016) in the southwestern United States, by Zhang et al. (2016) over the Yunnan

87   Province in China and by Ferreira et al. (2019) in the entire South America.

88   Carlson et al. (2022) computed TWS in California using a joint inversion method

89   combining the GRACE products with the results of the inversion of GNSS data, taking

90   advantage of the dense spatial distribution of GNSS data together with GRACE's ability to

91   provide regional closure of the water budget.

92   In this work we estimate the amount of water loss in the Po river basin, extending

93     $\sim 7.4 \cdot 10^5$ km^2, by inverting vertical ground displacements measured by continuous GNSS

94   stations. We consider stations inside the basin, but also stations located within 1° from the

95   basin boundaries, in order to reduce inversion artifacts near the boundaries of the study region

96   (Fu et al. 2015). We focus on long-term, inter-annual, changes, rather than seasonal (i.e.,

97   annual) variations, by modeling displacement time-series looking for trend changes in the

98   vertical component, with particular focus on the most recent and severe 2021-2022 drought.

99   In Section 2 we describe the GNSS data used and the methods applied to analyze the

100   vertical displacement time series; in Section 3 we show the relationship between geodetic and

101   hydrological observations and provide a quantitative estimation of the evolution of the TWS.

102   In Section 4 we discuss the results, in light of alternative estimates of water storage variations.

103 **2 Data and Methods**

104   We consider ~180 daily GNSS vertical ground displacement time series from January,

105 2010 to September, 2022 of continuous stations located in the Po river basin (see Fig. 1). We

106 also include in the analysis ~280 stations located within 1° of the catchment limits. This is part

107 of a larger geodetic solution encompassing the whole Euro-Mediterranean region, obtained

108 following the approach detailed in Serpelloni et al. (2022). We remove the long-term linear

109 trend from the time series using the Median Interannual Difference Adjusted for Skewness

110 (MIDAS) estimator (Blewitt et al. 2016) and filter the contribution of the non-tidal

111 atmospheric loading (NTAL), as suggested by White et al. (2022), since they can produce

112 displacements of several millimeters at daily-weekly timescales that can interfere with the

113 hydrological signal. The NTAL-induced vertical displacements are evaluated from the daily

114 0.5° x 0.5° gridded solution of the Earth-System-Modeling Group at the German Research

115 Center for Geosciences (Dill and Dobslaw, 2013) and its contribution in each site is calculated

116 considering the nearest grid point where the displacements associated with NTAL are

117 computed.

118   The resulting GNSS vertical displacements time series are then analyzed using a trend

119 filtering approach, which performs an extensive analysis using a L1 norm regularization

120 model to identify the seasonal components, offsets and linear trend changepoints in the GNSS

121 time series (Wu et al. 2018). The piecewise trend x is estimated by minimizing the weighted

122 sum objective function:

123 $(1/2)\|y - x - s - w\|_2^2 + \lambda\|D^{(2)}x\|_1 + \rho\|1 + D^{(1)}w\|_1$

124   where y is the original time series, w indicates the level component associated with the

125   offsets, s is the seasonal term, $\|.\|_1$ represents the L1 norm and $D^{(n)}$ are the n-th difference

126   matrix defined as in Wu et al. (2018). λ and ρ are positive parameters controlling the knots of

127   the estimation trend and the frequency of level shifts, respectively (we choose $\lambda = 2000$ and $\rho =$

128   80). Figure 2 shows an example of output of this analysis. Focusing on transients and

129   interannual variations, we only consider the extracted piecewise trends, not the seasonal terms

130   having annual and semi-annual frequencies. For some stations level changes (i.e., offsets) not

131   associated with tectonic events or equipment changes are highlighted, which mostly represent

132   fast variations in ground displacements (see Fig. 2 in 2012). For this reason, in the further

133   steps we consider the piecewise trend as the sum of the trend and level components. As it can

134   be seen in Fig. 2, there is an increase in uplift starting from 2021, which is a common feature

135   in GNSS stations within the Po river basin. Fig. 2e shows the stacking of the vertical

136   piecewise trend time-series for all stations analyzed, which is performed by averaging, for

137   each epoch, the residuals of all the time series resulting by removing the mean and linear trend

138   terms. In order to better characterize the spatial distribution of this deformation signal, we use

139   a multivariate statistical approach, similarly to what is used for tectonic deformation studies

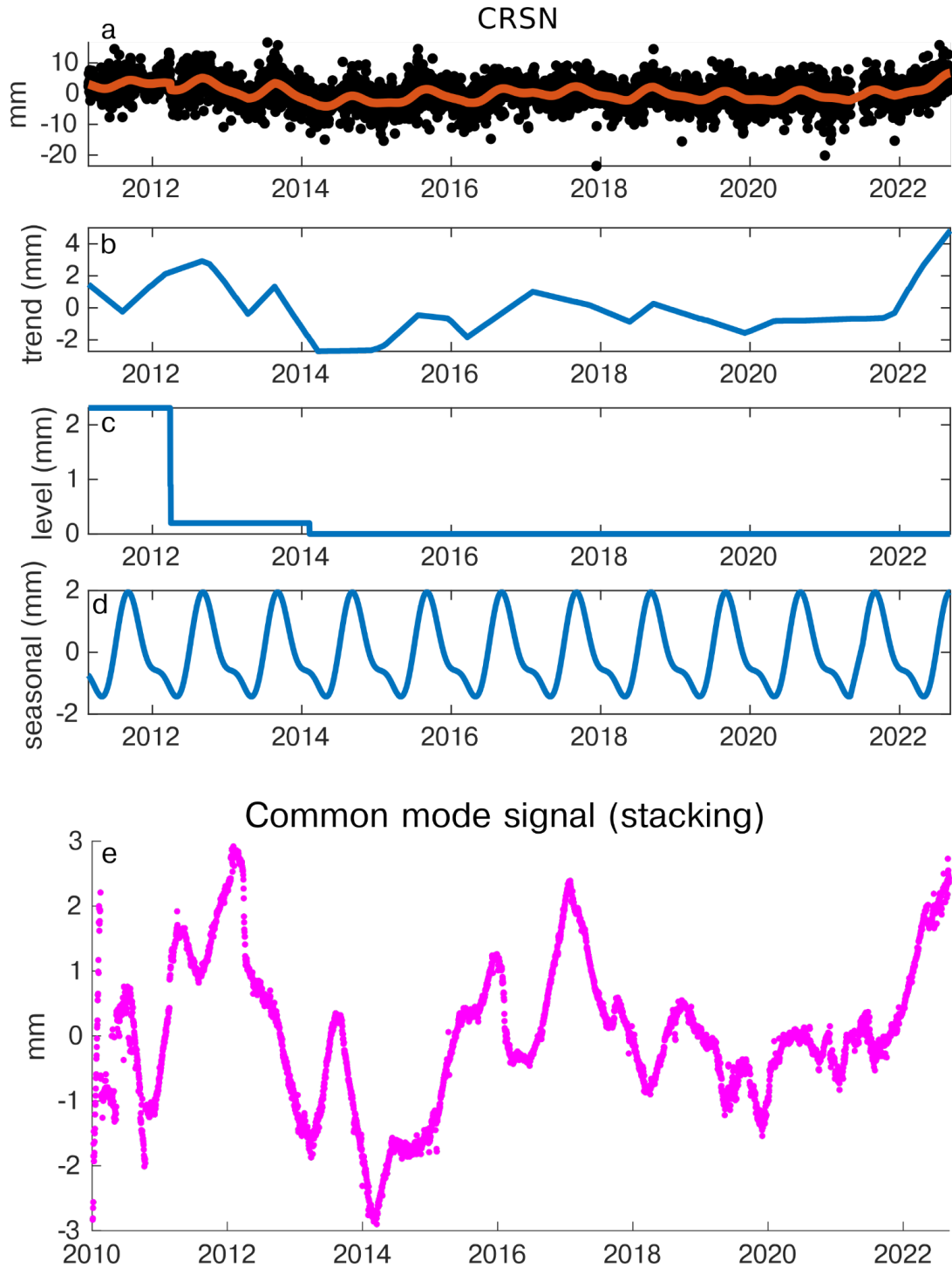140   (Kositsky and Avouac, 2010; Gualandi et al. 2014).

141

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.

148 **3 Results**

149   3.1 Comparison between geodetic and hydrological measurements

150   We adopt an approach similar to the one described in Jiang et al. (2022), but we use as
151 input of a principal component analysis (PCA) the piecewise vertical trends described in the
152 previous section, rather than the raw time-series. We decompose the dataset using one PC in
153 order to identify the most important common signal of the GNSS stations in the Po basin and
154 retrieve its spatial pattern (i.e., amplitude and sign). However, the first principal component
155 (PC1) obtained performing a PCA using 2 or 3 components is almost identical to the PC1
156 obtained performing a one-component decomposition, both in terms of temporal evolution
157 (Fig. S1) and spatial distributions (Fig. S2).

158   The temporal evolution of PC1 (Fig. 3A) well resembles the common mode signal
159 resulting from a stacking of the vertical trend time-series for all stations (Fig. 2e and Fig. S3).
160 However, the advantage of the PCA is to provide the spatial information on the displacement
161 amplitudes (Fig. S2A).

162   We compare the temporal evolution of PC1 with the SPEI-12 index value, averaged
163 over the Po river basin, and with the Po river level measurements provided by the Regional
164 Agency for Environmental Protection of Veneto region (ARPAV;
165 https://wwwold.arpa.veneto.it/arpavinforma/bollettini/dati-storici, Last Access: 20-12-2022).
166 The Po river level time series is filtered adopting the same approach used for the GNSS time-
167 series, and retaining only the piecewise trend component (Fig. S4). On the other hand, SPEI-
168 12 time series does not contain annual variations, since the index is computed as an anomaly
169 over 12 months, then the time series has not been filtered. Figure 3A shows that the geodetic,
170 climatic and hydrological time series are highly temporally correlated.
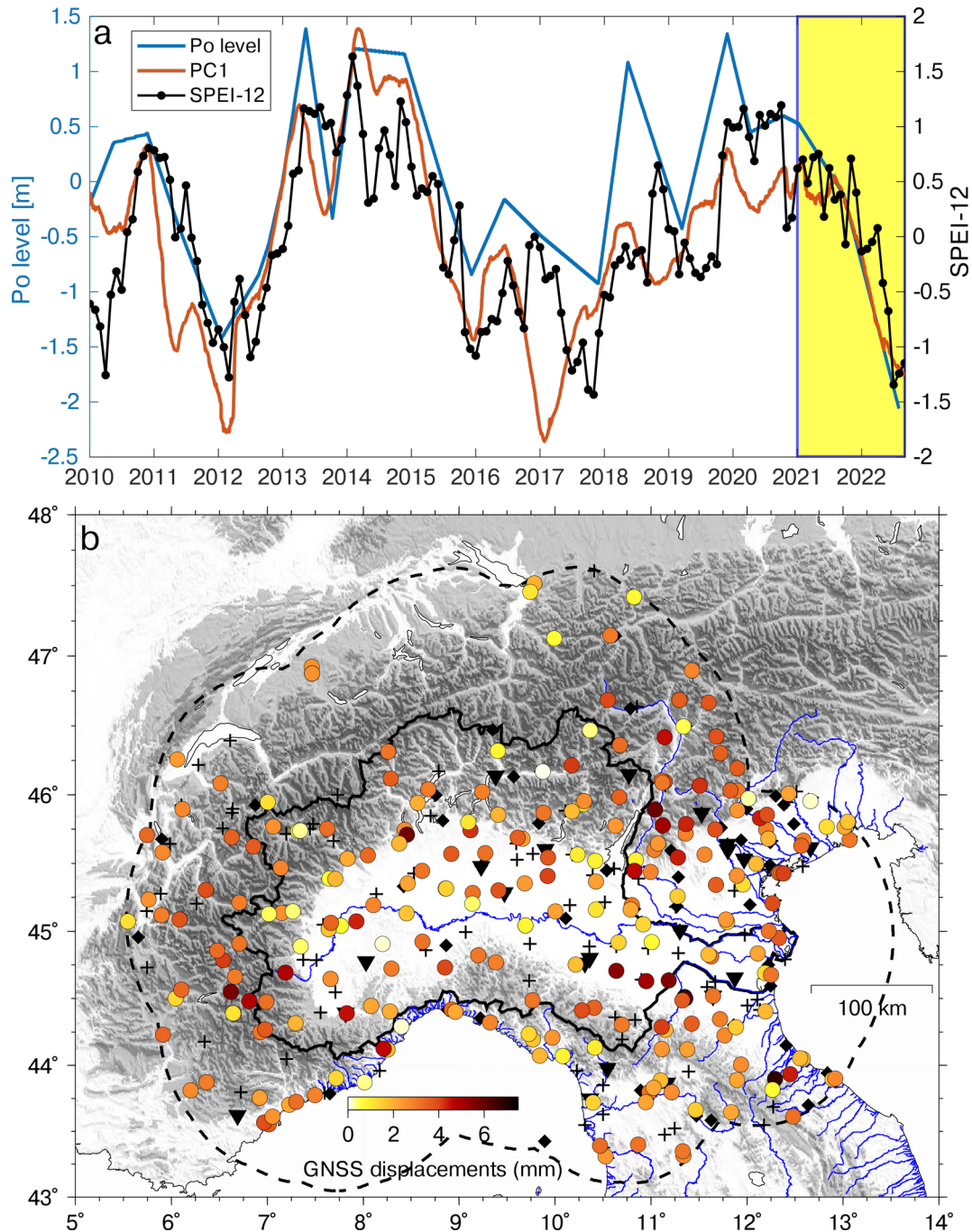
Figure 3. a) Comparison between the PC1 temporal evolution, the SPEI-12 index and the Po river level. Since PC1 is obtained from detrended GNSS time series, Po river level and SPEI-12 have also been detrended for consistency. b) Vertical displacements associated with PC1 during the 2021.00 (January, 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

177 **displacements; black crosses represent sites with more than 75% of missing data and**

178 **black diamonds the stations with no records after 2021.0.**

179   The vertical displacements associated with PC1 from 2021.00 to 2022.67 are shown in

180 Fig. 3B. Most of the stations show positive values (uplift), in accordance with the hypothesis

181 that in dry periods, when the water load is reduced, the GNSS stations record uplift, while in

182 wet periods the water load increases causing a downward motion of the Earth's surface. We

183 find that this is not true for 21 sites, which show an opposite behavior (black triangles in Fig.

184 3B). Maximum uplift, of the order of 7 mm, is observed in the south-eastern portion of the

185 basin and in the northern portion of the Po basin, which correspond to uplift rates, in the

186 considered two years, that are much faster than the long-term ones (e.g., Pintori et al., 2022).

187   3.2 Inversion of vertical ground displacements

188   The displacements associated with PC1 are inverted using the approach described in

189 Jiang et al. (2022), which estimates water storage variations assuming an elastic response of

190 the Earth to the hydrological load. In order to avoid misinterpretation of the spatial variations

191 of the water storage changes, we exclude from the inversion the 21 stations showing negative

192 vertical displacements (i.e., subsidence, Fig. S5) in the investigated time interval that,

193 following Carlson et al. (2022), are possibly affected by poroelastic processes, causing vertical

194 displacements in the opposite direction compared to the elastic ones. We also exclude from the

195 inversion the GNSS stations that have no observations recorded in the 2021.00-2022.67 time-

196 span (i.e., do not register displacements potentially associated with the last drought episode

197 investigated in this work). The total number of stations used for the inversion is then 250.

198   The relationship between the vertical displacements measured by GNSS x and the

199 water mass load u, expressed as EWH, is

200 $x = Gu$

201 where G is the Green's function matrix using load Love numbers of the preliminary reference

202 earth model (PREM) (Dziewonski and Anderson, 1981) as commonly used in many recent

203 works (e.g. Carlson et al. 2022, Jiang et al. 2021). The final solution for the daily estimates of

204 EWH changes u is

205 $$u = \left(G^T G + \alpha^2 L^T L \right)^{-1} G^T x$$

206 where L is the Laplacian smoothing matrix and α is the smoothing factor controlling the

207 relative weight between model roughness and data misfit.

208 We invert the displacements associated with PC1 to estimate EWH on a 0.25°x0.25°

209 grid. We choose $\alpha=0.0034$, which is the minimum in the line showing the relation between the

210 sum of squared residuals from cross-validation (CVSS) and the smoothing factor (Fig. S6),

211 and use 4 neighbor points for calculating the Laplacian matrix during the least-squares

212 inversion. Fig. 3A shows the temporal evolution of the EWH averaged over the study area,

213 while Fig. 3B is a map of the EWH variations that occurred in the 2021.00 - 2022.67 time

214 interval (yellow box in Fig.3A).

215 Text S1 presents the results of checkerboard tests, showing that our inversion is well

216 resolved at the spatial resolution of 1°x1°.

217 **4 Discussion**

218 We compare the EWH obtained by inverting the GNSS displacements (EWH$_{gnss}$) with

219 surface water content from GLDAS (SWC) and with Liquid Water Equivalent Thickness

220 (LWE) from GRACE.

221 The GLDAS products provide the soil moisture content in the first 2 m of the

222 subsurface, the snow depth water equivalent, the plant canopy surface water and the root zone

223 soil moisture (Rodell et al., 2004). We consider as SWC the sum of these four components,

224 which are provided as 0.25°x0.25° gridded dataset and 3-hours temporal resolution, which are

225 transformed into daily time series by averaging the 3-hourly time series to make them

226 consistent with the daily resolution of EWH$_{gnss}$.

227   LWE is computed using the GRACE and GRACE-FO RL06 Mascon solutions from

228   the Center for Space Research (Save et al., 2016; Save, 2020). While the data are provided in a

229   grid with the same size as the GLDAS one, which corresponds to a resolution of about 25 km,

230   the current resolution is 300-400 km. The temporal resolution of LWE data is monthly and

231   data are missing in correspondence with the gap between the GRACE and GRACE-FO

232   missions, which results in a 11 months gap, from July 2017 to May 2018.

233   The GLDAS products allow an estimate of the water content with a better nominal

234   spatial resolution of EWH_{gnss}, even though the disadvantage is that GLDAS does not take into

235   account groundwater. Importantly, while the GLDAS nominal spatial resolution is 0.25°, its

236   effective resolution may be different due to the assimilation process and the interpolation

237   techniques used to generate gridded datasets. Furthermore, the nominal spatial resolution of

238   GLDAS may not represent the true spatial variability of soil moisture in a context such as the

239   Po river basin, characterized by high topographic gradients. The correct determination of the

240   soil types in regions characterized by heterogeneous landscapes, elevation and land cover, in

241   fact, is complex and this can lead to errors in soil moisture modeling (Bi et al., 2016).

242   LWE takes into account all TWS components, but with a spatial and temporal

243   resolution much poorer than EWH_{gnss}. We point out that while EWH_{gnss} is inverted on a

244   0.25°x0.25° grid, the results of the checkerboard test show that the actual spatial resolution is

245   ~1°, corresponding to about 100 km (Section S1 of the Supporting Information). This is

246   consistent with the resolution achieved by Zhang et al. (2016) in the Yunnan region of China

247   and by Fu et al. (2015) in Washington and Oregon. The high spatial density of the southern

248   California GNSS network allowed Carlson et al. (2022) to reach a spatial resolution of 80 km,

249   while when considering larger study areas as in Borsa et al. (2014) and in Ferreira et al. (2019)

250   the spatial resolution decreases to 200-300 km.

251   We filter the annual and semiannual signals in SWC time series using the same

252   approach used for GNSS displacement and Po river level measurements (see Fig. S8), and

253   apply a PCA using one PC on the trend components. Because of the monthly temporal

254   resolution of the GRACE products, LWE data are analyzed using a slightly different strategy,

255   removing the annual and semiannual components from the original time series instead of

256   estimating the trend components, as done for GNSS and GLDAS time-series. In fact, the trend

257   variations observed in EWH_{gnss} occur also at a monthly timescale, but the temporal resolution

258   of LWE is also monthly, so it is unnecessary to estimate the LWE trend variations. As for the

259   GLDAS and GNSS datasets, the filtered time series are analyzed with a PCA with one PC.

260   Fig. 4a shows the temporal evolutions of the basin-averaged water content expressed as

261   EWH_{gnss}, SWC from GLDAS and LWE from GRACE, while Fig. 4b-d shows the spatial

262   distributions of water loss from January, 2010 to September, 2022 (yellow box in Fig. 4a),

263   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   km × 60 km load is only 4%.

298 **5 Conclusions**

299   We analyze vertical ground displacements from GNSS stations located in the Po river

300 basin, a significant European district with industrial and agricultural settlements. Our study

301 demonstrates that changes in vertical trends respond to meteo-climatic forcing and serve as a

302 reliable, near real-time, independent approximation of drought indexes. During the drought

303 that has affected the region since 2021, we observe a regional uplift signal. This uplift reaches

304 values of up to 7 mm and exhibits spatial variations across the area. We interpret this

305 phenomenon as a result of variable water loss and subsequent reduced load, enabling us to

306 estimate the spatial distribution of EWH. GNSS observations indicate that an estimated

307 average of approximately 80 Gtons of water was lost in the Po river basin from 2021 to the

308 end of summer 2022. This estimate aligns with values obtained from GLDAS but is lower than

309 the estimate derived from GRACE. Additionally, while the temporal evolution of EWH

310 estimated by GNSS, GLDAS, and GRACE shows similarities, the spatial patterns differ

311 significantly.

312   Our findings are also relevant for studying active tectonics and geodynamics. The

313 Apennines and Alps, in fact, exhibit long-term uplift signals resulting from various multiscale

314 processes (Sternai et al., 2019). Accounting for the hydrological origins of trend variations is

315 crucial to improve accuracy and prevent misinterpretation of transient signals or biases in

316 velocity estimates, especially in case of short time-series.

317   Future research will integrate GNSS with InSAR data to improve the spatial resolution

318 of EWH to a few tens of meters, as demonstrated by Ghorbani et al. (2022). This integration

319 would enhance our understanding of the phenomenon and provide more detailed information

320 on water loss and recharge dynamics.

321 **Acknowledgments**

326   the figures are created using the Generic Mapping Tools (GMT) software (Wessel et al.,

327   2013).

328   **Open Research**

329   The EWH is estimated by inverting the GNSS data using the GNSS2TWS software

330   (https://github.com/jzshhh/gnss2tws).

331   The trend filtering on the GNSS vertical displacements time series is performed using

332   the L1tool software (https://github.com/wudingcheng/l1tool).

333   The stacking of the GNSS time series is performed using the GNSS_TS_NRS code

334   (https://github.com/CL-Xiong/GNSS-TS-NRS, He et al., 2020).

335   GLDAS data was downloaded from

336   https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.1/summary?keywords=GLDAS.

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

338   SPEI-12 data was downloaded from

339   https://spei.csic.es/map/maps.html#months=1#month=0#year=2023GNSS.

340   GNSS time series data are available from

341   https://doi.pangaea.de/10.1594/PANGAEA.958598.

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

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

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Contents of this file

Introduction

We provide additional figures to better explain how the time series are analyzed. These figures also support the inversion strategy employed to estimate the terrestrial water storage variations and what is presented in the discussion. Furthermore, Text S1 provides a detailed description of the checkerboard tests used to determine the spatial resolution of the terrestrial water storage variations.

Figure S1. Comparison of the temporal evolution of the PC1 obtained considering 1 (blue), 2 (red) and 3 (yellow) total principal components.

Figure S2. Comparison of the spatial responses of the PC1 obtained considering 1 (a), 2 (b) and 3 (c) total principal components.

Figure S3. Comparison of the temporal evolution of the PC1 (red) with the common mode signal of the network obtained by performing a weighted stacking (blue).
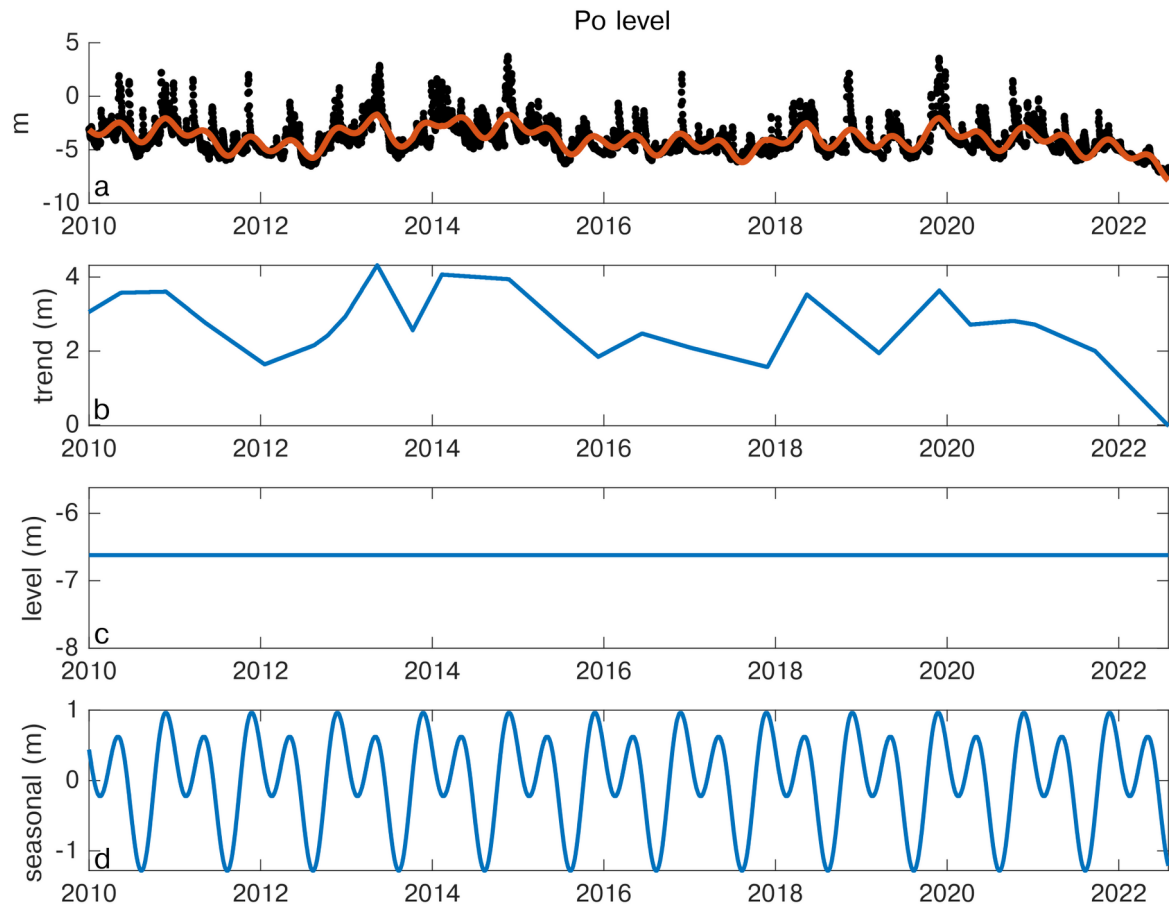
Figure S4. Decomposition of the Po river level measurements, performed using the L1 tool software. In a) the black dots represent the original time series, the red line the L1 tool model, which is the sum of the trend (b), level (c) and seasonal component (d).

Figure S5. Vertical displacements associated with PC1 during the 2021.00 (January, 2021) - 2022.67 (September, 2022) time interval.

Figure S6. Relation between the sum of squared residuals from cross-validation (CVSS) and the smoothing factor.

Text S1.

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. S7a). 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. S7a) using the following equation, which estimates the percentage of accuracy:

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

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. S7a-b).
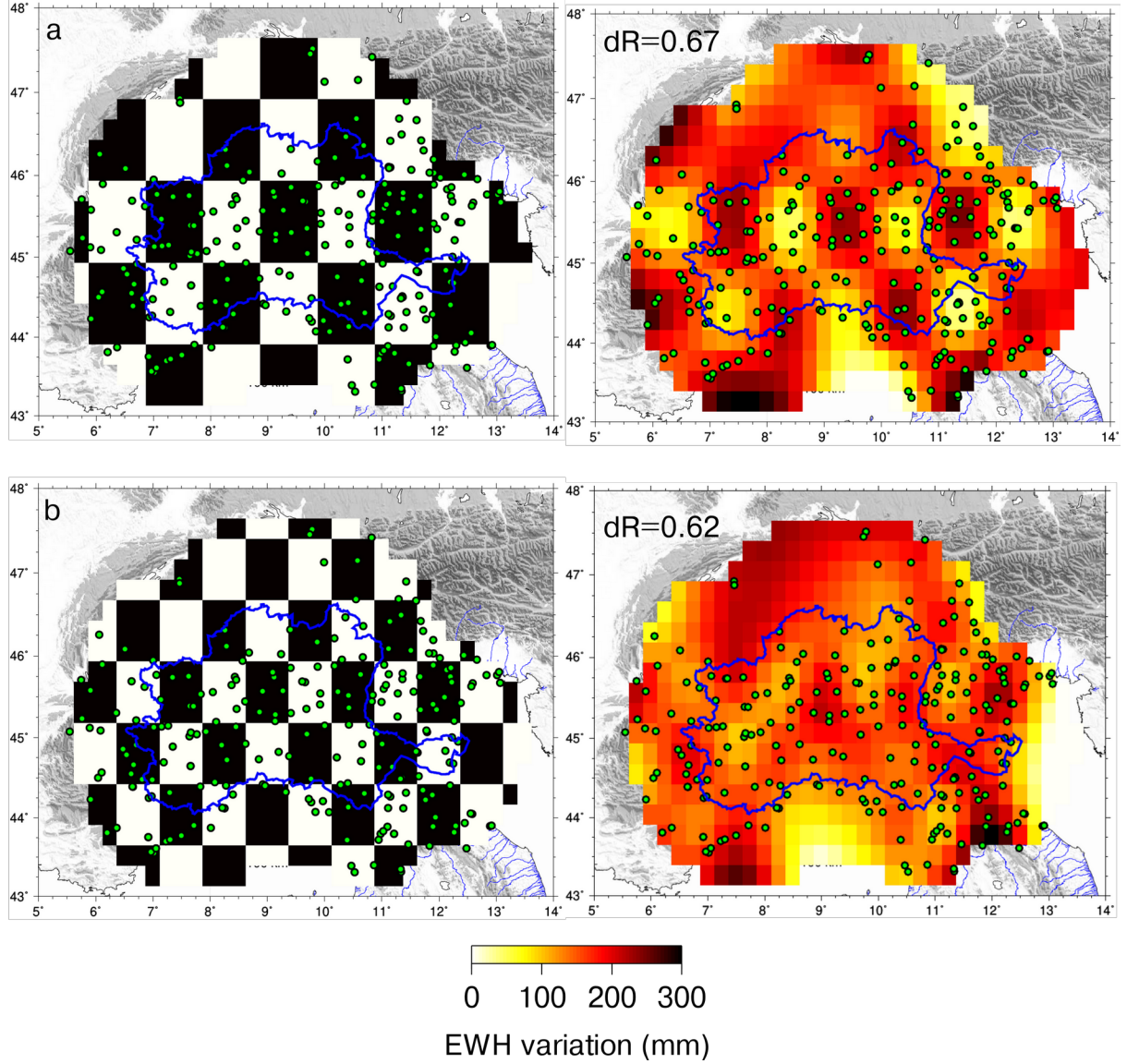

Figure S7. Checkerboard test using synthetic data. a) Comparison between the checkerboard synthetic model (left) and the results using the GNSS2TWS inversion method (right) considering a 1.00° spatial resolution. b) Same as a) but considering a 0.75° spatial resolution.
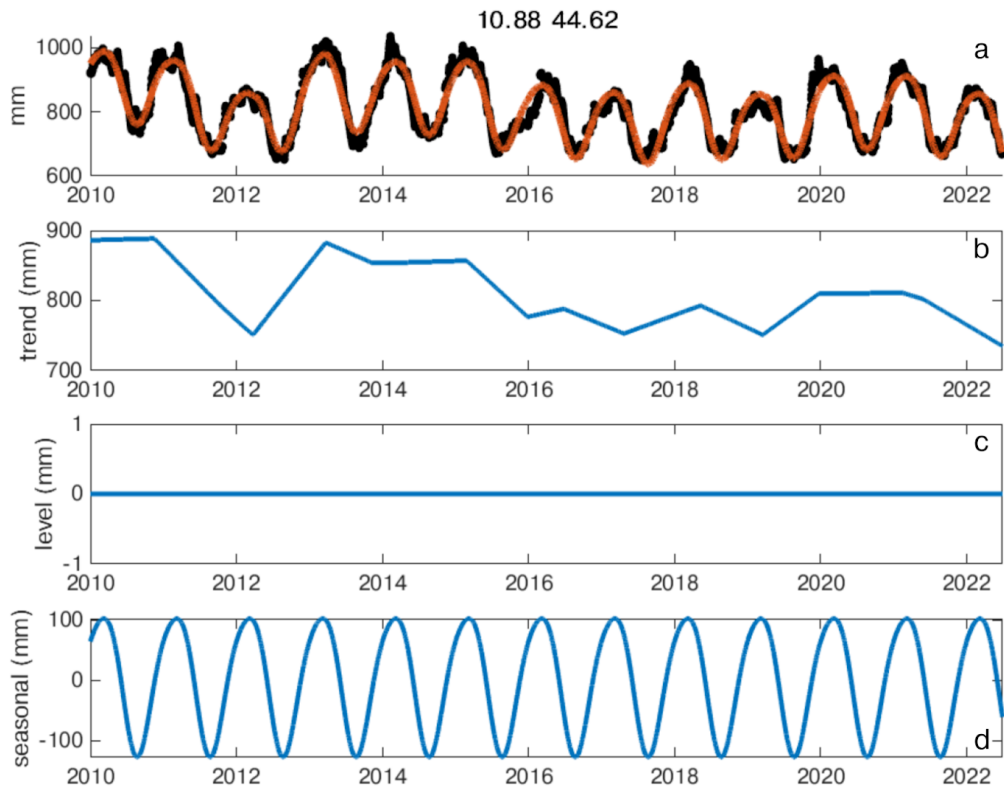
Figure S8. Decomposition of the GLDAS surface water content time series, associated with the cell with coordinates lon= 10.88°, lat= 44.62°, performed using the L1 tool software. In a) the black dots represent the original time series, the red line the L1 tool model, which is the sum of the trend (b), level (c) and seasonal component (d).
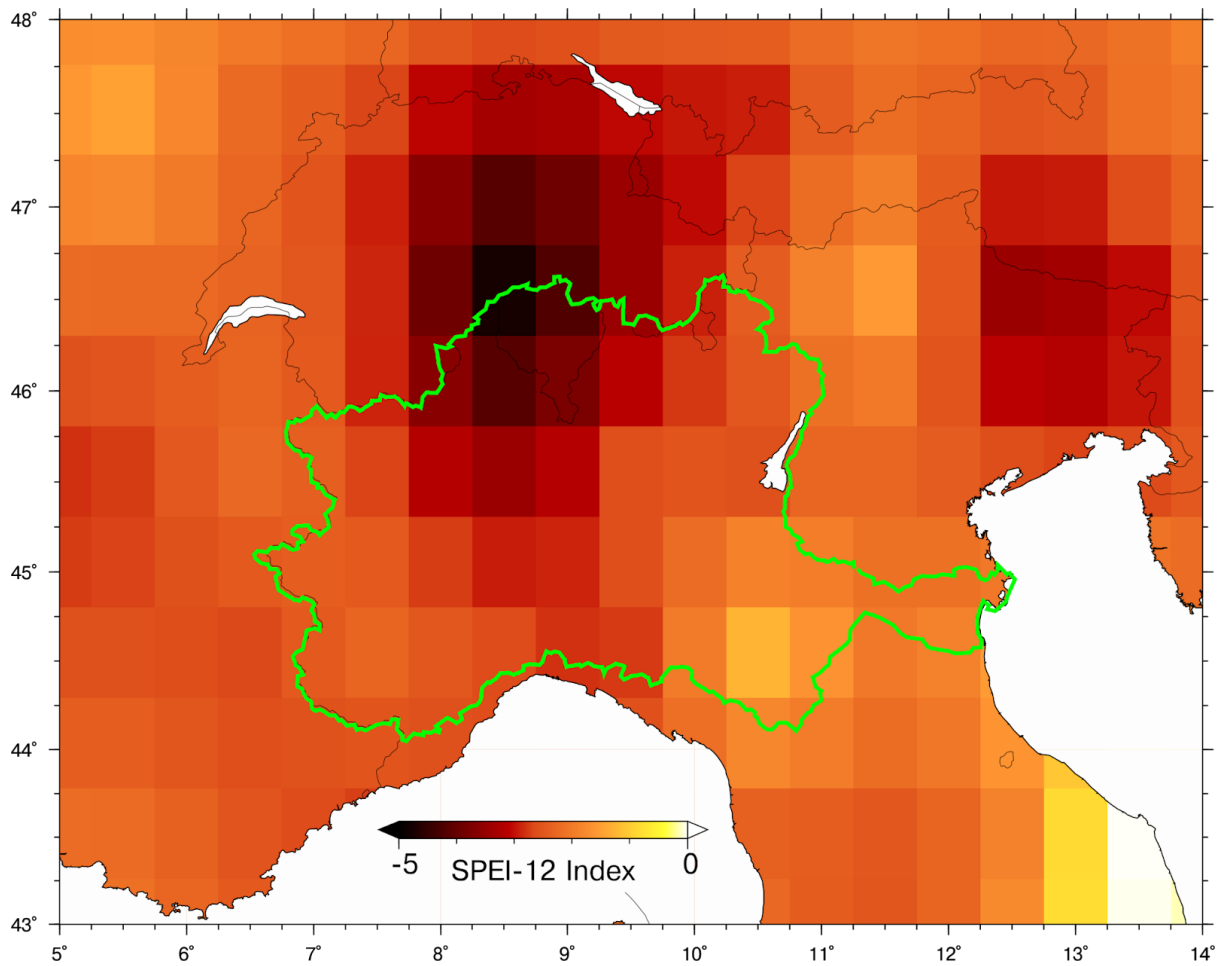
Figure S9. Zoom of the SPEI-12 maps, computed in August 2022, shown in Fig.1, considering only the negative values and the same color palette of Fig. 4.