remote sensing

Communication

Drought in Northern Italy: Long Earth Observation Time Series Reveal Snow Line Elevation to Be Several Hundred Meters Above Long-Term Average in 2022

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Abstract: The hydrological drought in Northern Italy in 2022 was, in large part, the consequence of a snow drought in the Italian Alps in the winter of 2021/22 and the resulting deficit of melt water runoff. In this communication, we assessed the snow-cover dynamics in nine Alpine Italian catchments using long time series of satellite-derived snow line elevation (SLE) measurements. We compared the SLE of the hydrological year 2021/22 to the long-term dynamics of 1985–2021. In early 2022, the SLE was located several hundred meters above the expected median values in all of the nine catchments. This resulted in deficits of snow-covered area of up to 83% in the Western Alps (catchment of Sesia, March 2022) and up to 61% in the Eastern Alps (Brenta, March 2022) compared to the long-term median. Although snow-cover data from optical satellite imagery do not contain information about snow depth and water content, in a preliminary qualitative analysis, the derived SLE dynamics show good agreement with the Standardized Snowpack Index (SSPI) which is based on the snow water equivalent (SWE). While the exact relationships between SLE, SWE, and runoff have to be explored further on the catchment basis, long-time series of SLE may have potential for use in drought early warning systems.

Keywords: drought; snow; Alps; Italy; Landsat; Earth Observation; time series; climate change

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1. Introduction

In the summer of 2022, Northern Italy was suffering an exceptional hydrological drought that particularly affected the basin of Italy's largest river, the Po. A discharge deficit of 66% (264 m^3/s instead of the expected 819 m^3/s) has been reported at the station in Piacenza for the month of March 2022, and even higher deficits of around 75% have been observed in the Po's Alpine tributaries Dora Baltea, Adda, and Ticino [1,2]. By July 2022, official drought emergencies and water restrictions had been issued in five Italian regions, affecting 42% of the Italian population [3]. The lack of available fresh water had impacts on Italy's agricultural sector, negatively affecting plant productivity and irrigation potential. The Soil Moisture Index was below −2.0 in many areas, indicating extreme drought. At the same time, salt water intrusion in the Po river delta was at an all-time high [1,4–6]. Meanwhile, hydroelectric reservoirs in Northern Italy were 34.8% below the 8-year minimum energy potential experienced in 2021 [4]. This shortage of fresh water was the result of an exceptionally dry and mild winter 2021/22. Compared to the average of 1991–2020, the temperature was 2.1 °C higher, while at the same time, precipitation was 65% lower. Between December 2021 and February 2022, only 25% of the expected precipitation was recorded [1]. The situation was exacerbated by multiple heat waves at the end of May, the middle of June, and July, due to the persistence of one of the most extreme geopotential height anomalies over Europe since 1950 [4,7], which potentially further increased runoff deficits through evaporation enhancement [8].

In the context of this drought, the seasonal Alpine snowpack of 2021/22 played a crucial role [9]. Similar to many other mountainous regions in the world, the Alps serve as water towers to Northern Italy [10], in which the snowpack is an important water buffer. Fresh water is accumulated and stored in the winter months and gradually released in spring and summer to meet the increased water demand in these seasons. The winter precipitation deficit in combination with mild temperatures had led to a reduced snow accumulation in the Southern Alps from which the western and northern tributaries of the Po draw their water. The Snow Water Equivalent (SWE) in the Italian Alps was only at 40% of the usual median conditions (2009–2021) at the end of February [1,9].

Snow drought is usually assessed by monitoring SWE, which measures the amount of water released when a snow pack melts instantaneously [11,12]. However, SWE measurements are either performed as in-situ measurements and thus lack spatial coverage or are derived from space-borne passive microwave sensors at coarse spatial resolutions at the kilometer scale which is unreliable over mountainous terrain [13]. Optical remote sensing enables the spatially continuous observation of snow-cover dynamics across variable scales [14]. Long time series of almost 40 years generated from multispectral high-resolution Earth Observation (EO) missions such as Landsat enable the timely comparison of current snow-cover dynamics, with long-term observations even in inaccessible mountain areas. In comparison to other multispectral sensors, such as MODIS, VIIRS, or AVHRR, with 30–60 m, Landsat offers the spatial resolution of greater than 100 m required for snow cover mapping in complex terrain as defined by the Global Climate Observing System (GCOS) [15]. The snow line elevation (SLE), i.e., the elevation of the border between snow-free and snow-covered elevation ranges in mountainous areas [16], enables the estimation of snow-covered areas even under partially cloudy conditions. The SLE can be retrieved on a catchment basis from snow-classifications in combination with a Digital Elevation Model (DEM) [17,18] and, thus, might complement the challenging SWE retrieval in the context of snow-drought monitoring.

The goal of this study was to assess the spatiotemporal dynamics of the SLE in the context of the drought in Northern Italy in 2022. To do so, we derived the SLE for nine Italian catchments located in the Alps (Figure 1) for the hydrological year 2021/22 (October to September). We compared these observations to the SLE values retrieved from the entire Landsat archive between 1985 and 2021. Based on the SLE and the topography, we calculated the areas covered by snow in winter and spring 2021/22 and analyzed the snow-cover deficit on a catchment basis. Finally, we discuss our findings in the context of the current drought situation in Northern Italy, as well as the potential of SLE information as a complementing data source to SWE for drought monitoring.

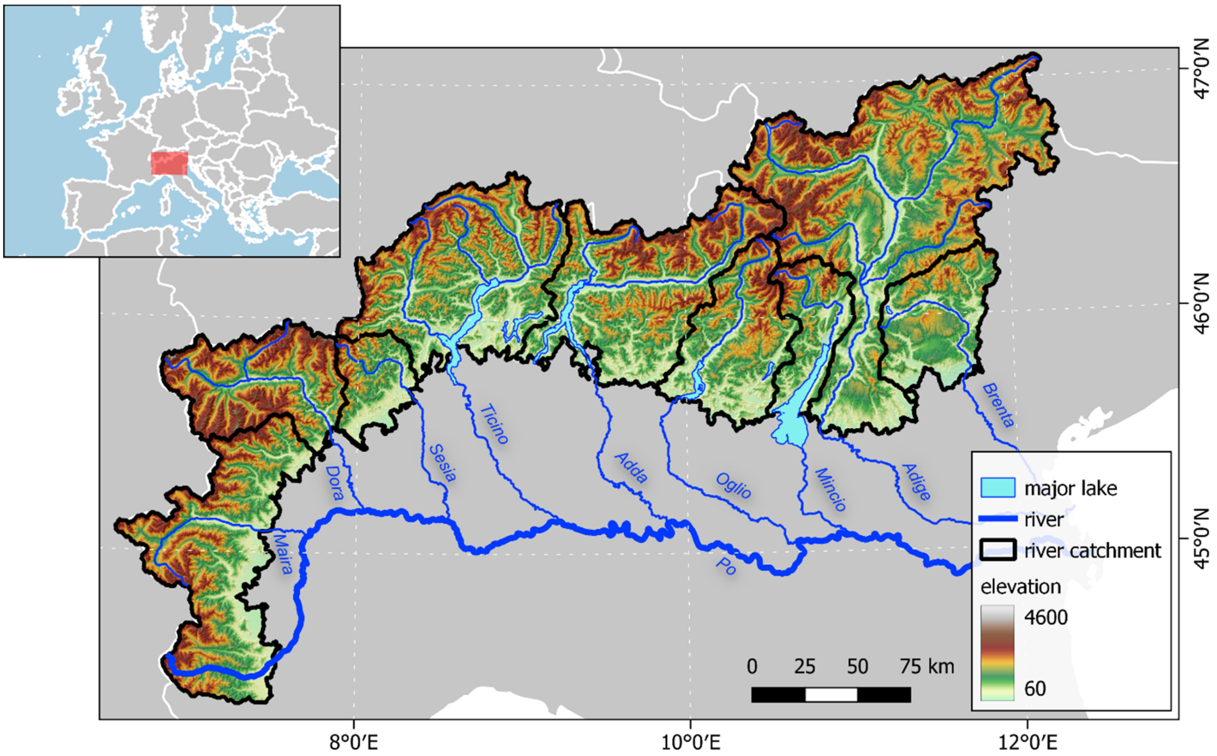

Figure 1. Location and topography of the Alpine reaches of the nine Italian catchments analyzed in this study.

2. Materials and Methods

To analyze recent and long-term snow-cover dynamics, we generated SLE time series from multispectral Landsat data ranging from 1985 to August 2022 for each catchment, as described in detail in Koehler et al. [17]. The SLE retrieval approach is based on an algorithm developed by Hu et al. [18–20]. We acquired all available Landsat Collection-2, Level-2, Tier 1 Surface Reflectance scenes by the sensors TM, ETM+, and OLI covering the analyzed catchments [21–23]. Each scene was classified by applying the temperature and shadow thresholding used in the Snow Product Intercomparison and Evaluation Exercise (SnowPEx) [24] and utilizing the spectral bands and the normalized difference vegetation index (NDVI), normalized difference snow index (NDSI), and normalized difference water index (NDWI) [25–27]. In total, 6421 Landsat scenes were processed. From the land-cover classes "snow" and "clear land", the SLE was estimated by using the GLO-30 Copernicus DEM [28] for each scene and catchment [16]. The SLE is defined as the elevation below which there are as few "snow" pixels as possible and above which there are as few "clear land" pixels as possible. To generate a regular time series, the retrieved SLE estimates were filtered for reliability by rejecting observations that contained less than 20% of valid pixels (snow and clear land), e.g., due to cloud cover. For each catchment ~890 SLE measurements were generated of which ~83% met the quality standard. The remaining observations were aggregated on a monthly basis, and the remaining data gaps were filled by using linear interpolation, providing an estimation of the spatial average of the SLE in each catchment. Of the 452 SLE observations of each monthly time series, 18% of the values are interpolated on average, particularly before the year 2000. We created time series for the Alpine reaches of the catchments of the Po tributaries Maira, Dora Baltea, Sesia, Ticino, Adda, Oglio, and Mincio, as well as Adige and Brenta. The outlines of the catchments were derived from the HydroBASINS dataset [29] and cropped to the extent of the Alpine region, as defined by the Alpine Convention [30]. Data preprocessing and the SLE retrieval were performed by using the Python 3.8 programming language [31], while time-series generation and analysis were conducted in R [32]. For the following analysis, we compared the SLE of the hydrological year 2021/22 starting in October 2021 with the long-term observations covering 1985 to September 2021. Furthermore, we calculated the fractional snow cover (FSC), i.e., the percentage of area covered with snow of the total area of a catchment, using the derived SLE and the DEM, in order to assess the spatial effects of the observed SLE dynamics.

3. Results

The SLE in Northern Italy exceeded the 75th percentile of the of the long-time observations (1985–2021) for most of the hydrological year 2021/22 (October 2021–August 2022, Figure 2). Until December 2021, the SLE was well within the expected elevation range, and in some cases (Dora, Sesia, Brenta), even below. However, starting with January 2022, it was located several hundred meters above the expected median value in all of the catchments (Table 1). This was especially pronounced in Northwestern Italy (Maira, Dora, Sesia, Ticino, and Adda), where the SLE exceeded even the historical 75th percentile value for at least three consecutive months. The highest deviation in spring was observed in Sesia in March, where the SLE was located 802 m above the long-term median. In summer, the SLE was even 1056 m above the median in Ticino (June), exceeding the historical maximum in that month by 543 m (Supplementary Table S1). The SLE difference was less extreme in Oglio, Mincio, Adige, and Brenta, where a snowfall event in February had shifted the SLE downward. However, the SLE still exceeded the long-term mean throughout the first three months of 2022. Further snowfall was observed in April, which briefly brought the SLE close to the long-term median; however, it rapidly retreated to higher elevations above the historical 75th percentiles in all catchments afterward.

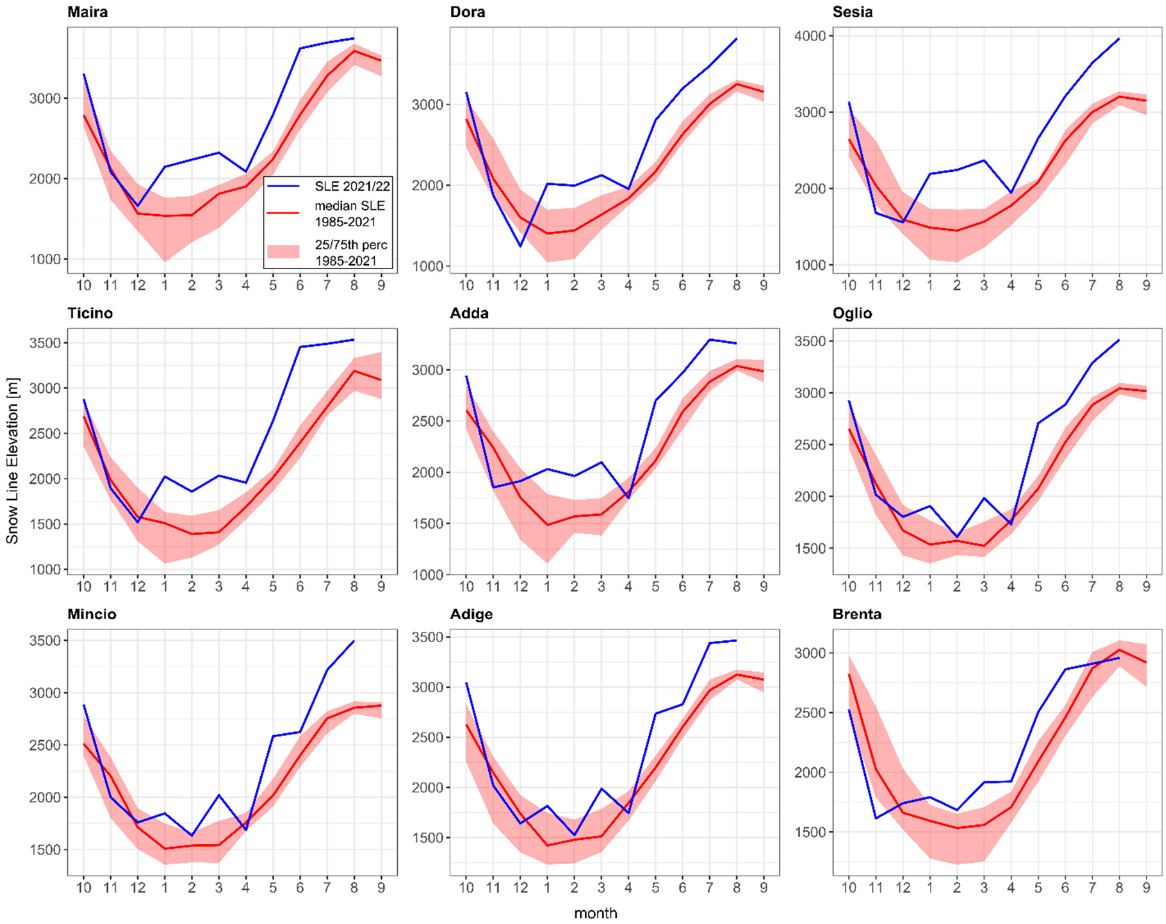

Figure 2. SLE of the hydrological year 2021/22 (blue line) in comparison to the median (red line) and 25th and 75th percentiles (red area) between 1985 and 2021 for nine Italian catchments.

Table 1. Deviation of the SLE in early 2022 from the long-term (1985–2021) median in meters. See Supplementary Table S1 for all months of the hydrological year 2021/22.

Catchment	January 2022	February 2022	March 2022	April 2022
Maira	+609	+690	+509	+186
Dora Baltea	+616	+555	+489	+116
Sesia	+703	+794	+802	+168
Ticino	+515	+469	+625	+267
Adda	+546	+395	+508	−62
Oglio	+372	+35	+462	−42
Mincio	+337	+96	+477	−71
Adige	+393	+46	+475	−102
Brenta	+199	+151	+357	+216

This SLE deviation from the long-term median results in a deficit of snow-cover area, as illustrated for the example of Dora Baltea in March 2022 (Figure 3). Here, the snow-covered area is visible in the underlying false-color satellite image from 26 March 2022. In this case, the SLE is averaged over three satellite observations acquired in the same month. Although over- and underestimations of the SLE occur locally, mainly due to different aspects and slopes of the terrain, the approach models the actual snow-cover outline quite accurately across the entire catchment. The lack of snow-cover area is clearly visible between the lines of the 2022 SLE and the long-term median.

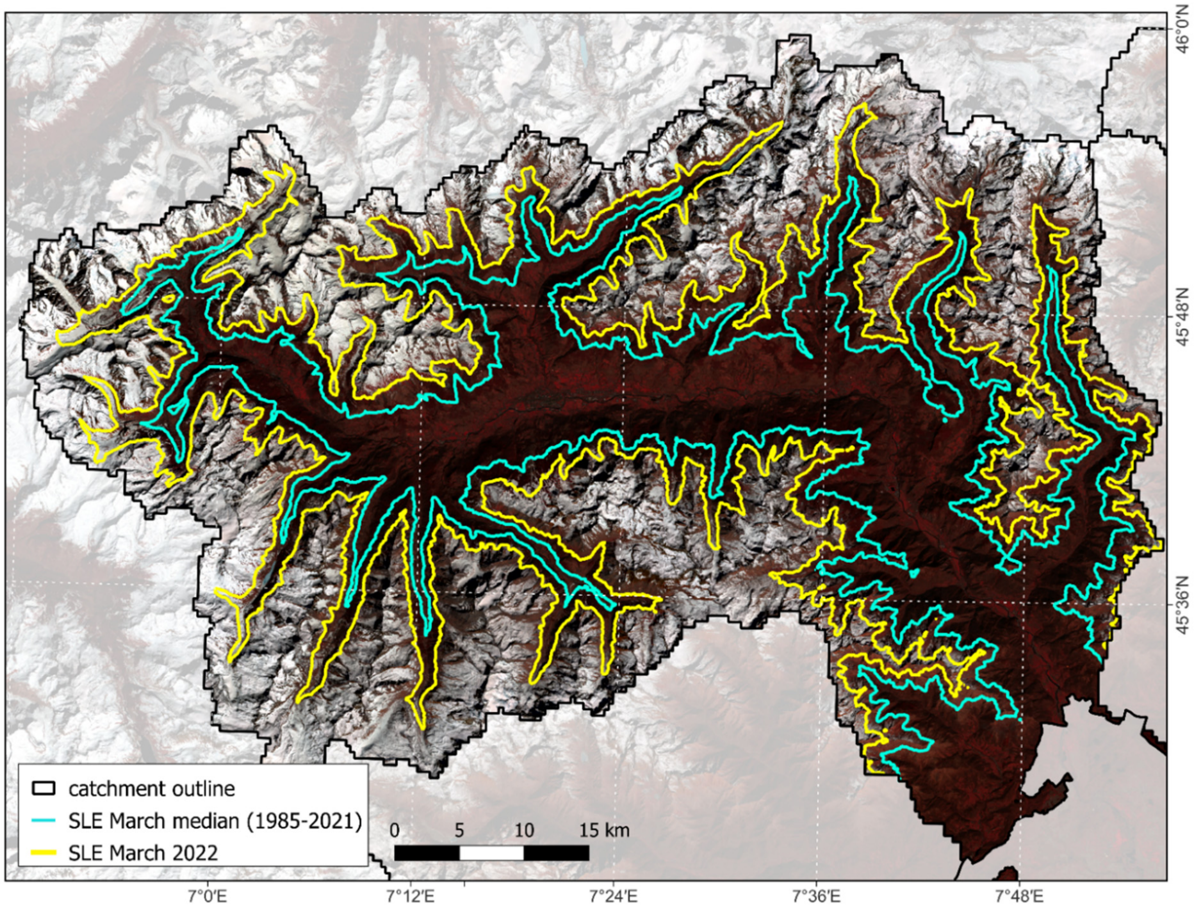

Figure 3. Location of the SLE in March 2022 (2125 m.a.s.l.) compared to the SLE median (1636 m.a.s.l., 1985–2021) in the catchment of Dora Baltea. Background: Landsat 8 false-color image of 26 March 2022 (R, Band 5; G, Band 4; B, Band 3).

To further assess the impact of the observed SLE dynamics on the area covered by snow, the FSC was calculated for the months January to April, usually the season with the highest rates of snow accumulation (Table 2). All catchments show a large FSC deficit in 2022 compared to the expected median FSC (1985–2021). The deficit was larger in the western catchments, Maira, Dora Baltea, Sesia, Ticino, and Adda, than in the eastern catchments, where a snowfall event in February had reduced the SLE briefly to the expected degree. The highest FSC deficit was observed in Sesia, where, from January to March, only 5–8% of the entire catchment was covered by snow. In the Western Alps, Dora Baltea was least affected by the snow-cover deficit (28–31%), while in the Eastern Alps, it was Adige (4–43%).

Table 2. Expected fractional snow cover (FSC, median 1985–2021), observed FSC (2022), and difference between observation and expected values (bold) in each catchment.

Catchment	January			February			March 2022			April 2022		
	Exp. FSC	FSC 2022	Difference	Exp. FSC	FSC 2022	Difference	Exp. FSC	FSC 2022	Difference	Exp. FSC	FSC 2022	Difference
Maira	48%	24%	**−50%**	48%	21%	**−57%**	37%	17%	**−54%**	34%	26%	**−22%**
Dora Baltea	79%	55%	**−31%**	78%	56%	**−28%**	72%	50%	**−31%**	64%	58%	**−8%**
Sesia	30%	8%	**−74%**	32%	7%	**−79%**	27%	5%	**−83%**	19%	14%	**−28%**
Ticino	43%	21%	**−50%**	48%	28%	**−41%**	47%	21%	**−56%**	35%	24%	**−32%**
Adda	49%	28%	**−43%**	46%	30%	**−34%**	45%	25%	**−44%**	37%	39%	**+6%**
Oglio	34%	20%	**−41%**	33%	31%	**−4%**	35%	17%	**−50%**	25%	27%	**+6%**
Mincio	29%	18%	**−39%**	28%	25%	**−12%**	28%	14%	**−51%**	21%	23%	**+12%**
Adige	59%	39%	**−33%**	56%	54%	**−4%**	54%	31%	**−43%**	38%	43%	**+13%**
Brenta	22%	13%	**−40%**	25%	17%	**−30%**	24%	9%	**−61%**	16%	9%	**−45%**

4. Discussion

The SLE is a convenient metric to model the spatiotemporal dynamics of snow cover. It is derived from EO data and can be estimated even under partially cloudy conditions. As a continuous numerical metric, it can be easily modeled in a time series, which facilitates the comparison of single observations to multi-decadal reference periods and the detection of long-term trends. In combination with a DEM of the respective catchment, the snow-covered area and, thus, the FSC can be estimated from the SLE. However, SLE and the snow-covered area are not necessarily representative of the actual amount of water stored in the snowpack since snow accumulation and depth cannot be quantified from multispectral remote sensing data alone. For that, the SWE is the more relevant parameter that can be derived from passive microwave sensors as used in the GlobSnow [13] and EUMETSAT SWE-E [33] products, from in situ measurements, or from climate [34] and hydrological models [35]. While the passive microwave data have severe limitations in Alpine terrain due to their coarse spatial resolution, ground-based stations lack the spatially continuous coverage of remote sensing data. Hydrological models, on the other hand, strongly depend on the accuracy of the meteorological inputs [36]. Current research is directed into innovative remote sensing SWE retrieval methods, using higher spatial resolutions, e.g., using SAR backscatter [37] or time-lapse photography [38]. Despite promising first results, the approaches are still experimental and therefore lack either temporal or spatial coverage.

Nonetheless, in the case of Northern Italy in 2022, the SLE clearly exhibited the patterns expected to precede a hydrological drought. Its dynamics in January, February, and June 2022 reflected the reported mild temperatures and the lack of precipitation [1,4]. To verify this observation, we compared the recent SLE dynamics with the monthly averaged Standardized Snowpack Index (SSPI) between January 2020 and August 2022 in each catchment. The SSPI is a dimensionless metric of the SWE standardized over a 40 year reference period (1981–2020) [39]. Positive values indicate that more snow than usual is present, while negative values represent a lack of snow compared to the reference period. The SSPI data were provided by the Alpine Drought Observatory (ADO) dataset (https://ado.eurac.edu/ (accessed on 6 October 2022)). The SWE data used as input for the calculation of the SSPI are derived by using a modified version of the deterministic snow model SNOWGRID-CL [40] driven by downscaled ERA5 data (1979 to today) provided by the Copernicus Climate Change Service. For each catchment, we used the spatial median of the 30-day aggregated variant of the SSPI. Note that, as modelled values, these data cannot be considered ground truth and are affected by the issues discussed above. In the context of this discussion, however, the comparison of SLE dynamics with an established and evaluated SWE dataset can give some indication toward a potential linkage between snow cover and runoff.

The absolute SLE values were compared to the deviation of the SLE from the long-term mean and the SSPI for the example of Adda (Figure 4) and the other catchments (Supplementary Figures S1–S8). In general, the SSPI inversely mirrors the deviation of the SLE from the mean. For example, the unusually low SLE in winter 2020/21 is accompanied by positive SSPI values in the same months, while the long period of exceptionally high SLE values in the first half of 2022 is reflected by a consistent spell of negative SSPI values. This indicates that the SLE is, to a certain degree, representative of the amount of potential melt water within a catchment despite offering no information about snow depth. However, the exact statistical relationship between SLE, SWE, and actual runoff within a catchment has yet to be explored further. For example, it may strongly depend on the unique topography of the respective basin. In a topography with steep slopes, even high SLE fluctuations may cause relatively small changes in snow-covered areas (and thus, potentially, SWE), while the relation is much stronger in more even terrain. This effect can be observed by comparing the catchments Maira and Dora Baltea. Both exhibited a similar SLE change (Table 1), but the affected area and, thus, the SCF deficit were much greater in Maira, which has a much lower elevation difference compared to Dora Baltea (Table 2).

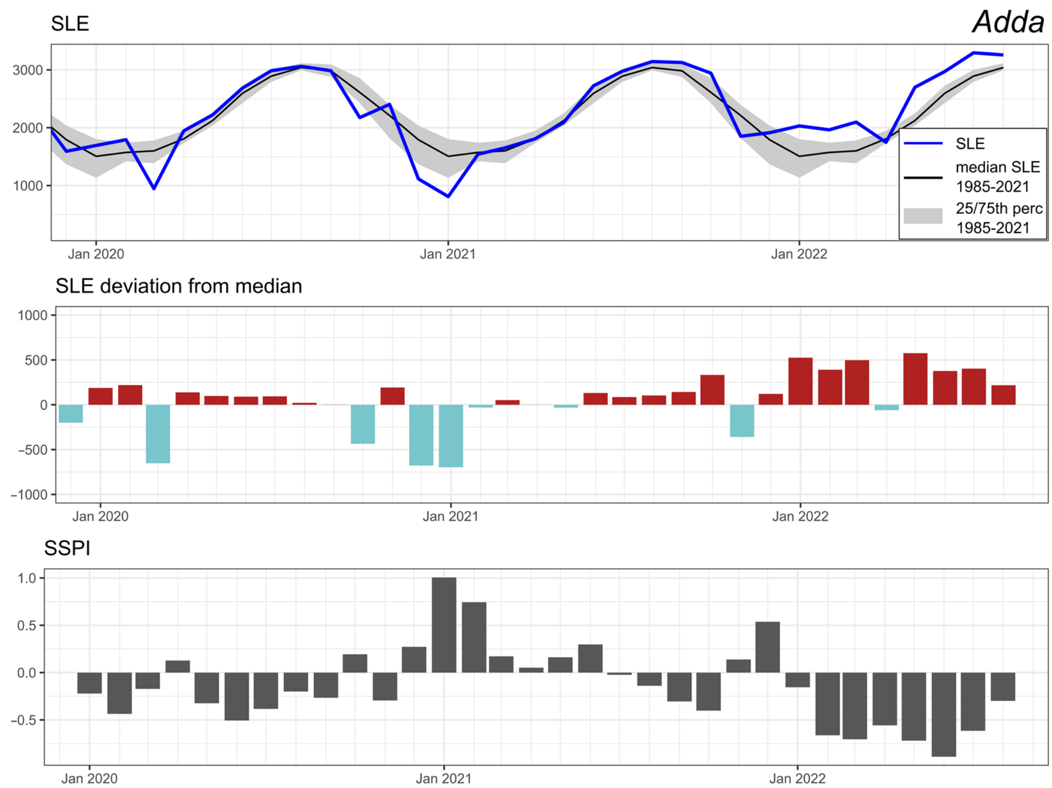

Figure 4. Snow line elevation (**top**), SLE deviation from the long-term median (**center**), and SSPI (**bottom**) for the catchment Adda 2020–2022.

5. Conclusions

In the context of drought monitoring, long, continuous time series acquired by remote sensing have great potential, especially in inaccessible regions where timely in situ data are sparse and unevenly distributed. Multiple decades of continuous observations, as offered by the Landsat mission, enable the comparison of the severity of recent dynamics, e.g., of the SLE, to long-term observations. An unusually high SLE in the early season, such as in 2022, acquired in a timely manner can then serve as an indicator for an upcoming drought in a near-real-time drought early warning system and complement in situ or passive microwave-based SWE approaches that offer a higher temporal resolution [12]. Furthermore, long time series facilitate the detection of long-term trends and the modeling of future snow conditions [17], which are important factors for estimating the frequency of future drought events. Finally, these time series can contribute to the implementation of catchment-based runoff or discharge models by integrating further explanatory variables, such as SWE or precipitation. The majority of the Alps is already facing a retreat of the snow line to higher elevations at rates of several meters per year [17], and runoff regimes in mountainous catchments are projected to dramatically change in the future [41]. Particularly in regions in which the freshwater supply is strongly dependent on snow melt, spatially and temporally continuous remote sensing data on snow-cover dynamics can help adapt to and mitigate the effects of climate change.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs14236091/s1, Figure S1: Snow Line Elevation, SLE deviation from the long-term median, and SSPI for Adige; Figure S2: Snow Line Elevation, SLE deviation from the long-term median, and SSPI for Brenta; Figure S3: Snow Line Elevation, SLE deviation from the long-term median, and SSPI for Dora Baltea; Figure S4: Snow Line Elevation, SLE deviation from the long-term median, and SSPI for Maira; Figure S5: Snow Line Elevation, SLE deviation from the long-term median, and SSPI for Mincio; Figure S6: Snow Line Elevation, SLE deviation from the long-term median, and SSPI for the catchment Oglio; Figure S7: Snow Line Elevation, SLE deviation from the long-term median, and SSPI for Sesia; Figure S8: Snow Line Elevation, SLE deviation from the long-term median, and SSPI for Ticino; Table S1: Deviation of the SLE in the hydrological year 2021/22 from the long-term (1985–2021) median in Meters.

Author Contributions: Conceptualization, J.K. and A.J.D.; data curation, J.K., P.Z., L.C., Ž.V., M.H.A., K.M., K.H. and G.B.; formal analysis, J.K.; investigation, J.K.; methodology, J.K., A.J.D., C.A.B. and M.D.; resources, C.A.B., P.Z. and L.C.; software, J.K., P.Z., L.C., Ž.V., M.H.A., K.M. and K.H.; supervision, A.J.D., A.J. and C.K.; visualization, J.K.; writing—original draft, J.K.; writing—review and editing, A.J.D., C.A.B., G.B., A.J. and C.K. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The SLE data presented in this study are available upon request from the corresponding author. The data are not publicly available due to their volume. SSPI data can be retrieved from the ADO project platform: https://ado.eurac.edu/ (accessed on 6 October 2022).

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