



1 **MSDT v1.0: An Open-source Multi-method Snow Drought Toolbox**

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11



12 **Abstract**

13 Snow drought, characterized by anomalously low snow water equivalent (SWE) relative to
14 climatological conditions, has become an increasingly important cryospheric hazard with
15 substantial environmental and socio-economic impacts. Although numerous snow drought
16 identification methods have been developed, existing implementations are typically fragmented into
17 independent scripts and region-specific workflows, hindering methodological consistency,
18 reproducibility, and systematic intercomparison. Here we present the Multi-method Snow Drought
19 Toolbox (MSDT), an open-source Python software package that provides an end-to-end workflow
20 for snow drought research, encompassing SWE data acquisition, multi-method identification, data
21 visualization, and comparative analysis through an intuitive graphical user interface. MSDT
22 integrates seven widely adopted snow drought identification methods spanning yearly, monthly, and
23 daily temporal scales, with flexible and adjustable parameters that enable users to tailor analyses to
24 different climatic regions and research objectives. The toolbox streamlines data access by
25 supporting automated downloading of state-of-the-art SWE datasets together with a curated catalog
26 of commonly used products, and further supports interactive geospatial visualization for data
27 exploration and methodological comparison. In addition, the toolbox adopts a memory- and
28 performance-efficient architecture that supports large spatiotemporal datasets while maintaining
29 responsive snow drought computing. Its modular architecture enables straightforward integration of
30 additional datasets and identification algorithms. We demonstrate the capability of MSDT using
31 ERA5-Land SWE data to reproduce global snow drought climatology, temporal variability, and
32 representative historical events documented in previous studies. The results show that MSDT
33 consistently reproduces published snow drought characteristics while substantially improving
34 computational efficiency, workflow reproducibility, and methodological comparability. By
35 providing a standardized, extensible, and user-friendly platform, MSDT lowers technical barriers
36 and facilitates reproducible snow drought monitoring, model evaluation, and impact assessment.

37 **Key words:** snow drought, snow water equivalent, multi-method, toolkit, open-source

38



39 1. Introduction

40 Snow drought, characterized by anomalously low snow water equivalent (SWE) relative to
41 climatological conditions, has emerged as a critical component of global change. Recent decades
42 have witnessed a succession of high-impact snow drought events across the western United States
43 (Harpold et al., 2017; Dye et al., 2023), Central Asia (Bair et al., 2018), the European Alps (Colombo
44 et al., 2023), and the Hindu Kush-Himalaya region (ICIMOD, 2025), underscoring the global scope
45 and increasing severity of this hazard. Reduced snowpack generates cascading impacts through
46 altered snow-atmosphere coupling and surface energy balance (Henderson et al., 2018; Collow et
47 al., 2022; Li and Wang, 2022), diminished warm-season soil-moisture recharge and streamflow in
48 snow-dominated water supplies (Barnett et al., 2005; Immerzeel et al., 2010; Liu et al., 2024; Han
49 et al., 2025), elevated wildfire risk (Abolafia-Rosenzweig et al., 2022), and disruption of snow-
50 dependent tourism economies (Falk and Lin, 2021; Moscovici, 2022; Leal Filho et al., 2024;
51 Vorkauf et al., 2024), with far-reaching implications for water security, ecosystem functioning,
52 agricultural productivity, hydropower generation, and winter tourism (Siirila-Woodburn et al., 2021;
53 Sturm et al., 2017; Gottlieb and Mankin, 2022).

54 The growing prominence of snow drought has stimulated the development of diverse identification
55 methods that characterize different aspects of snow deficiency across multiple temporal scales.
56 Annual-scale approaches generally evaluate whether seasonal snow metrics, such as 1 April SWE,
57 peak SWE magnitude, peak SWE timing, seasonal accumulated SWE, or average SWE, fall below
58 climatological thresholds (Harpold et al., 2017; Dierauer et al., 2019; Marshall et al., 2019; Li et al.,
59 2024). Monthly-scale methods, represented by the Standardized Snow Water Equivalent Index
60 (SWEI), extend the standardized precipitation index (SPI) framework by transforming cumulative
61 SWE anomalies into standardized probability distributions, thereby enabling consistent assessment
62 of prolonged snow deficits (Huning and AghaKouchak, 2020b). At finer temporal resolution, daily-
63 scale approaches such as the Phase Diagram Method (PDM) simultaneously track the evolution of
64 SWE and precipitation percentiles, allowing the onset, development, transition, and recovery of
65 snow drought events to be monitored in near real time (Hatchett et al., 2022). Together, these
66 complementary methods provide a comprehensive characterization of snow drought evolution from
67 seasonal accumulation deficits to intra-seasonal persistence and short-term snowpack dynamics.



68 Despite these methodological advances, practical application remains constrained by the lack of
69 unified computational tools. Unlike meteorological and hydrological drought indices, which benefit
70 from mature, widely adopted computational packages (Hao et al., 2017; Hayes et al., 2011), snow
71 drought analyses remain dependent on ad hoc, investigator-specific scripts written in Python, R, or
72 MATLAB. Differences in implementation details, parameter settings, climatological baselines,
73 temporal aggregation strategies, and output formats frequently lead to inconsistent results among
74 studies, reducing methodological transparency, reproducibility, and comparability (Gottlieb and
75 Mankin, 2022; Fang and Leung, 2023). Moreover, constructing complete snow drought analysis
76 workflows—including data acquisition, preprocessing, identification, visualization, and result
77 export—typically requires considerable programming expertise, creating substantial barriers for
78 hydrologists, cryosphere scientists, operational agencies, and resource managers. Although
79 platforms such as Google Earth Engine, Microsoft Planetary Computer, and Copernicus Climate
80 Data Store have provided scalable cloud computing environments and facilitate retrieval and
81 preprocessing of snow datasets, none currently provides standardized implementations of multiple
82 snow drought identification methods, integrated comparison among alternative definitions, or
83 dedicated graphical workflows tailored to snow drought analysis.

84 To bridge this gap, we developed the Multi-method Snow Drought Toolbox (MSDT), an open-
85 source Python-based software package that provides an integrated and standardized platform for
86 snow drought analysis. MSDT implements seven widely adopted snow drought identification
87 methods across yearly, monthly, and daily temporal scales within an intuitive graphical user
88 interface (GUI). The toolbox supports automated downloading of ERA5-Land and GlobSnow SWE
89 datasets, flexible parameter customization, multi-file comparison, interactive geospatial
90 visualization, and standardized NetCDF output with embedded metadata to facilitate reproducible
91 downstream analyses. Its modular software architecture separates computational algorithms, data
92 management, visualization, and interface components, allowing new datasets and identification
93 methods to be incorporated with minimal modification. By integrating data acquisition, processing,
94 visualization, and multi-method comparison into a unified workflow, MSDT substantially lowers
95 technical barriers while improving methodological consistency and computational reproducibility
96 for snow drought research and operational applications.



To address the lack of standardized software for snow drought research, this paper presents the Multi-method Snow Drought Toolbox (MSDT), an open-source Python package that integrates multiple snow drought identification methods, automated SWE data acquisition, interactive visualization, and standardized data management within a unified workflow. Sect. 2 introduces the implemented snow drought identification methods together with the software architecture and graphical interface. Sect. 3 demonstrates the capability of MSDT using global analyses and representative historical snow drought events. Sect. 4 examines the scientific implications, computational performance, current limitations, and future development of the toolbox.

2. Method and software

2.1 Snow drought identification method

We group existing methods by temporal scale: point-in-time methods for yearly conditions, standardized index methods for monthly anomalies, and diagram methods for daily evolution (Table 1).

Table 1. Snow drought identification methods

Categories	Reference	Descriptor	Metric	Default threshold in original method (user-configurable in MSDT)
Point-in-time method (Yearly)	Harpold et al. (2017)	1AprSWE	1 April SWE	< user-defined fraction of climatological mean (default: 1.0 x mean)
	Dierauer et al. (2019)	PeakSWEMean	Peak SWE	< user-defined fraction of climatological mean (default: 1.0 x mean)
	Marshall et al. (2019)	PeakSWE Pctl	Peak SWE	< user-defined lower-tail percentile (default: 25th percentile)
	Marshall et al. (2019)	PeakSWE Date	Date of peak SWE	< user-defined lower-tail percentile of peak date (default: 25th percentile)
	Li et al. (2024)	AccSWE	Accumulated SWE	User-defined percentile classes (default: 50th-25th, 25th-15th, 15th-5th, and <5th percentiles)
Standardized index method (SI, Monthly)	Huning and AghaKouchak (2020b)	SWEI	n-month accumulated SWE	User-defined standardized SWEI threshold and severity classes (default detection threshold: SWEI



Categories	Reference	Descriptor	Metric	Default threshold in original method (user-configurable in MSDT)
				≤ -0.5
Phase diagram method (PDM, Daily)	Hatchett et al. (2022)	PDM	SWE	User-defined SWE percentile threshold and severity classes (default: 30th, 20th, 10th, 5th, and 2nd percentiles)

111
112 2.1.1 Point-in-time method (yearly)

113 Point-in-time methods identify snow drought when snow metrics, such as 1 April SWE, peak SWE,
114 peak SWE date, or annual accumulated SWE, fall below local climatology or lower-tail percentiles.
115 The 1 April SWE metric is widely used in the western United States because it often approximates
116 maximum seasonal snowpack and separates accumulation from melt seasons (Harpold et al., 2017;
117 Huning and AghaKouchak, 2020a; Pagano et al., 2004; Zeng et al., 2018). Its transferability is
118 limited, however, because peak timing varies across regions and elevations (Gottlieb and Mankin,
119 2022; Harpold et al., 2012; Musselman et al., 2021). Alternative approaches use peak SWE, peak
120 timing, or annual accumulated SWE relative to climatological means, medians, or percentiles
121 (Cooper et al., 2016; Dierauer et al., 2019; Heldmyer et al., 2023; Li et al., 2024; Marshall et al.,
122 2019; Shrestha et al., 2021).

123 In MSDT, the thresholds listed in Table 1 are implemented as documented defaults rather than hard-
124 coded constants. Users can define the mean multiplier used by 1AprSWE and PeakSWEMean, the
125 lower-tail percentile used by PeakSWEPctl, PeakSWEDate, AccSWE, and PDM, and the SWEI
126 threshold used for standardized monthly anomalies. These settings are stored in output metadata to
127 support sensitivity analysis and reproducibility.

128 The point-in-time methods are advantageous for interpreting the state of snowpack in a simple and
129 practical way. Peak SWE, for example, is widely used for revealing interannual changes in snow
130 conditions (Cowherd et al., 2023; Heldmyer et al., 2023; Yeşilköy et al., 2024). The primary
131 limitation is that these methods do not account for the dynamics of snow cover (i.e., the onset,
132 development, and cessation process).

133
134 2.1.2 Standardized index method (SI, monthly)



SI methods treat snow drought as a sub-seasonal period of low snowpack. The Standardized Snow Water Equivalent Index (SWEI), inspired by SPI (Keyantash, 2021), describes snow drought using probability-transformed cumulative SWE anomalies (Huning and AghaKouchak, 2020b). In the original SWEI method, a three-month sliding accumulation is performed on monthly SWE datasets to obtain accumulated SWE records:

$$A_{k,i} = \sum_{k=-2}^0 SWE_k$$

the probabilities of cumulative SWE were subsequently determined by computing the empirical Gringorten plotting position (Gringorten, 1963):

$$p(A_{k,i}) = \frac{i - 0.44}{N + 0.12}$$

where i represent the i -th rank of $A_{k,i}$ sorted in ascending order, N is the number of samples in the ranked list. The inverse cumulative distribution function is used to transform the empirical probability, p , into the standard normal distribution to obtain SWEI:

$$SWEI = \Phi^{-1}(p)$$

SI methods provide a measure reflecting the combined effects of SWE amount and its persistence over any desired timescale. They allow a more flexible characterization of the temporal evolution of snow drought. In addition, SI values are comparable across regions with different climates, since they are essentially the standardized SWE anomalies after the normalization (Keyantash, 2021). These advantages potentially support their widespread adoption, similar to other drought indices (Hao et al., 2017; Hayes et al., 2011).

2.1.3 Phase Diagram method (PDM, daily)

Hatchett and McEvoy (2018) noted that point-in-time and SI methods do not fully represent the real-time onset, evolution, and termination of snow drought, which can limit impact-oriented interpretation. Hatchett et al. (2022) therefore applied a phase diagram to examine the daily co-variation of SWE and accumulated precipitation. The method basically follows the following steps: (1) calculating daily percentiles for SWE and precipitation. The accumulated SWE and accumulated precipitation since the first day of winter period is calculated first, and a 7-d moving window centered on each calendar day is applied to reduce seasonality effects. (2) scattering and connecting daily percentiles on the phase diagram in chronological order. (3) days falling between the 30th–



163 20th, 20th–10th, 10th–5th, and 5th–2nd percentiles, and below the 2nd percentile, are identified as
164 abnormally dry, moderate drought, severe drought, extreme drought, and exceptional drought,
165 respectively.

166 The PDM provides more than a snow drought identification method and an illustration of variation,
167 it offers a potential tool to link snow drought to its impacts on meteorology, water resources,
168 ecosystems, and recreation within the system of interest. However, because it explicitly includes
169 precipitation but not other drivers such as temperature, solar radiation, humidity, or light-absorbing
170 particles, it cannot represent all snow-evolution mechanisms (Fang and Leung, 2023; Hatchett et al.,
171 2022; Wang et al., 2024).

172 **2.2 Identification of snow-covered area**

173 Accurate snow drought identification requires prior establishment of valid snow persistence zones.
174 Following Li and Wang (2022), we first calculate 3-month rolling snow cover fraction climatology
175 from MODIS/Terra observations (2000–2022), then apply a 5% threshold to remove ephemeral
176 snow regions. Monthly SWE records from the land component of the fifth generation of European
177 ReAnalysis (ERA5-Land, 1980–2024) are further used to retain pixels where snow is present for at
178 least 75% of a given month across the study period.

179 **2.3 Multi-method snow drought toolbox, MSDT**

180 **2.3.1 Software architecture**

181 The MSDT is designed as a modular, end-to-end software framework that integrates SWE data
182 preparation, multi-scale snow drought analysis, visualization, and standardized output generation
183 within a unified workflow (Fig. 1). The software adopts a layered architecture in which individual
184 functional components communicate through standardized NetCDF-based data structures rather
185 than method-specific intermediate files, ensuring consistency, extensibility, and reproducibility.

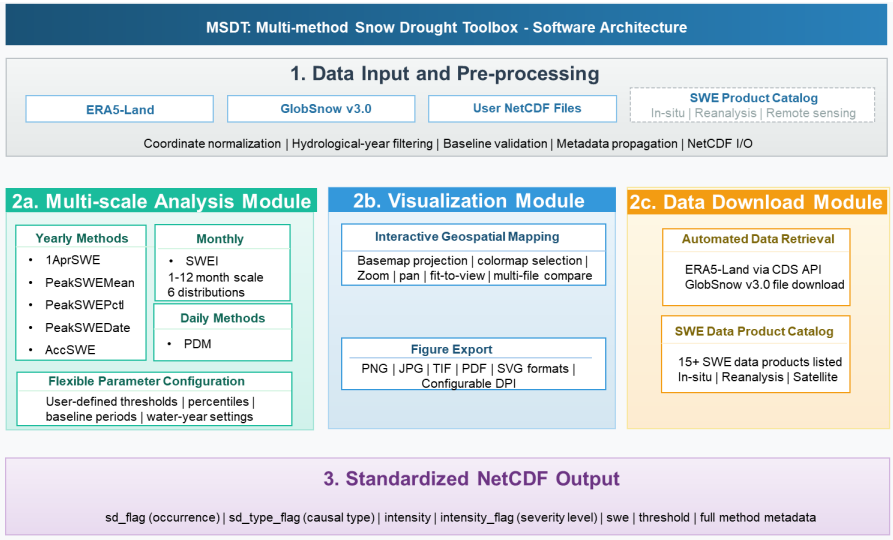


Figure 1. Overall software architecture of MSDT.

The workflow begins with a data input and preprocessing layer. During data ingestion, coordinate systems, temporal dimensions, hydrological-year definitions, baseline periods, and metadata are automatically validated and standardized. This shared preprocessing framework ensures that all subsequent analysis modules operate on consistent data structures regardless of the original data source. After preprocessing, users access three independent yet interconnected functional modules through the graphical user interface. The Multi-scale Analysis Module performs snow drought identification using multiple methods at yearly, monthly, and daily temporal scales. The Visualization Module enables interactive inspection of both original SWE datasets and derived snow drought products through synchronized geospatial mapping and comparison tools. The Data Download Module provides automated retrieval of selected SWE datasets together with a curated catalog of commonly used snow products for convenient data discovery. Finally, all analysis results are exported through a standardized NetCDF output layer, which stores snow drought occurrence, drought type, intensity, SWE values, thresholds, and complete method metadata using a unified data model (Table 2). By separating data management, computational algorithms, visualization, and user-interface components, the architecture facilitates future integration of new datasets and identification algorithms while maintaining a consistent and reproducible workflow.



Table 2. Main characteristics for different snow drought definitions. sd_flag: binary records of snow drought; sd_type_flag: causes of snow drought; intensity: SWE, date, or SWEI anomaly of each record; intensity_flag: severity level of snow drought; swe: SWE when snow drought occurs; threshold: threshold used to identify snow drought.

Categories	Descriptor	Snow drought characteristics					
		sd_flag	sd_type_flag	intensity	intensity_flag	swe	threshold
Yearly	1AprSWE	✓		✓		✓	✓
	PeakSWEMean	✓		✓		✓	✓
	PeakSWEpctl	✓		✓		✓	✓
	PeakSWEDate	✓		✓		✓	✓
	AccSWE	✓		✓	✓	✓	✓
Monthly	SWEI	✓		✓	✓		✓
Daily	PDM	✓	✓	✓	✓		✓

208

2.3.2 Multi-scale analysis module

The Multi-scale Analysis Module constitutes the computational core of MSDT (Fig. S1). It integrates seven widely adopted snow drought identification methods spanning yearly, monthly, and daily temporal scales. Five yearly point-in-time methods (1AprSWE, PeakSWEMean, PeakSWEpctl, PeakSWEDate, and AccSWE) characterize seasonal snow deficits from complementary perspectives, including snow accumulation, peak magnitude, and peak timing. The monthly module implements SWEI method, allowing users to choose the accumulation window from 1 to 12 months and to fit the cumulative SWE series using either the empirical Gringorten plotting position or parametric distributions commonly used in drought-index calculations, including Gamma, Pearson type III, normal, lognormal, and Weibull distributions (McKee et al., 1993; Guttman, 1999; Vicente-Serrano et al., 2010; Stagge et al., 2015). For parametric SWEI fitting, positive-support distributions use a zero-probability adjustment before cumulative distribution transformation, whereas real-support distributions are fitted directly to finite accumulated SWE values. If a fitted distribution is numerically unstable or has too few valid samples at a grid cell, MSDT falls back to the empirical estimator and records the selected distribution in the output metadata. At the daily scale, the PDM method identifies the onset, evolution, and termination of snow drought events based on the joint evolution of SWE and precipitation percentiles.



226 Despite their methodological differences, all identification methods follow a common
227 computational workflow consisting of data loading, parameter validation, algorithm execution,
228 metadata generation, and standardized output. This unified processing framework enables direct
229 comparison among snow drought definitions, climatological baselines, threshold selections,
230 temporal scales, and input datasets. Users can flexibly configure baseline periods, winter period
231 definitions, drought thresholds, accumulation windows, and probability distributions through the
232 graphical interface. To minimize invalid parameter combinations, the graphical interface
233 dynamically activates only the configuration options required by the selected identification method.
234 The software also automatically determines the default winter period according to the hemisphere
235 of the input dataset, adopting July–June (Northern Hemisphere) and January–December (Southern
236 Hemisphere) for yearly-scale analyses, and November–March and May–September for daily-scale
237 analyses, respectively. Furthermore, the Intensity outputs generated by the AccSWE, SWEI, and
238 PDM methods support user-defined reclassification, enabling direct comparison of snow drought
239 severity across methods, datasets, and study regions.

240 **2.3.3 Visualization module**

241 The Visualization Module provides an integrated environment for interactive exploration of SWE
242 datasets and snow drought products without requiring external geographic information system (GIS)
243 software (Fig. S2). Multiple NetCDF files can be opened simultaneously, allowing direct
244 comparison among datasets, identification methods, variables, and parameter settings. The module
245 synchronizes temporal selection, map projection, color mapping, and navigation across multiple
246 visualization panels, facilitating evaluation of methodological differences and spatial consistency.

247 Interactive geospatial visualization is implemented using Matplotlib and Basemap, supporting
248 zooming, panning, fit-to-view, and rapid switching between variables and time steps. Variable
249 metadata are displayed within the interface and can be customized to improve figure readability.
250 Final figures can be exported in PNG, JPG, TIF, PDF, and SVG formats with user-defined
251 resolutions, enabling publication-quality graphics to be generated directly within MSDT.

252 **2.3.4 Data download module**

253 The Data Download Module integrates automated data acquisition with a comprehensive SWE
254 product catalog to simplify data preparation for snow drought analysis (Fig. S2). Downloaded



255 datasets are automatically organized using the standardized data structure adopted throughout
256 MSDT and can be transferred directly to the analysis and visualization modules without additional
257 preprocessing.

258 Currently, MSDT supports automated retrieval of ERA5-Land SWE through the Copernicus
259 Climate Data Store (CDS) API and downloading of GlobSnow v3.0 products (Pulliainen et al., 2020;
260 Muñoz-Sabater et al., 2021). Users specify the spatial domain, temporal range, variables, local
261 storage location, and API credentials (where required), while download progress and execution
262 status are displayed in real time within the application.

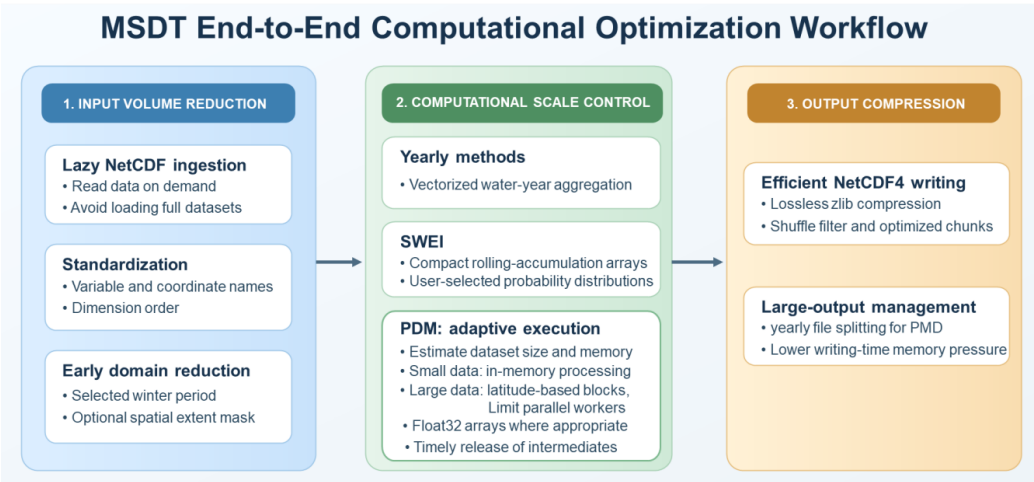
263 To facilitate broader data selection, MSDT also includes a curated SWE product catalog covering
264 more than 9 commonly used in-situ observations, reanalysis and data-assimilation products, and
265 satellite-derived datasets (Table S1). For each product, the catalog summarizes the temporal
266 coverage, spatial resolution, provider, available variables, and access information, enabling users to
267 efficiently identify suitable datasets for regional applications, intercomparison studies, and
268 validation analyses (Robinson et al., 1993; Gelaro et al., 2017; Bormann et al., 2018; Che et al.,
269 2019; Rodell et al., 2004; Takala et al., 2011; Pulliainen et al., 2020; National Operational
270 Hydrologic Remote Sensing Center, 2004).

271 **2.3.5 Computational optimization**

272 To improve computational efficiency and memory stability, MSDT adopts an end-to-end
273 optimization strategy covering the entire workflow from data input to result export (Fig. 2). During
274 data ingestion, NetCDF files are loaded lazily to reduce memory pressure and standardized to
275 consistent variable names, coordinate conventions, and dimension orders, thereby eliminating
276 redundant preprocessing in subsequent computational steps. The input data are further constrained
277 to the optionally selected winter period and user-defined spatial extent, minimizing the volume of
278 data processed throughout the workflow. During computation, optimization strategies are tailored
279 to different identification methods. Yearly methods rely primarily on vectorized hydrological-year
280 aggregation with low memory overhead, whereas SWEI employs compact rolling-accumulation
281 arrays with user-selectable probability distributions. For the computationally intensive daily PDM
282 method, MSDT automatically estimates dataset size and available memory to determine the
283 execution mode. Small datasets are processed entirely in memory, whereas large datasets are



284 partitioned into latitude-based spatial blocks with adaptive parallelization to avoid excessive
285 memory consumption. Intermediate arrays are stored as float32 where appropriate, and temporary
286 variables are released immediately after completing percentile calculation, intensity classification,
287 and drought-type identification. During output, results are written using lossless NetCDF4
288 compression with optimized chunking, reducing storage requirements while preserving efficient
289 data access. For large daily PDM outputs, optional yearly file splitting further decreases file size
290 and memory pressure during writing. Together, these optimizations enable MSDT to efficiently
291 process large spatiotemporal SWE datasets on standard desktop computers while maintaining
292 computational performance and memory stability.



293

294 **Figure 2.** End-to-End Computational Optimization Workflow of MSDT

295 **3 Experimental study**

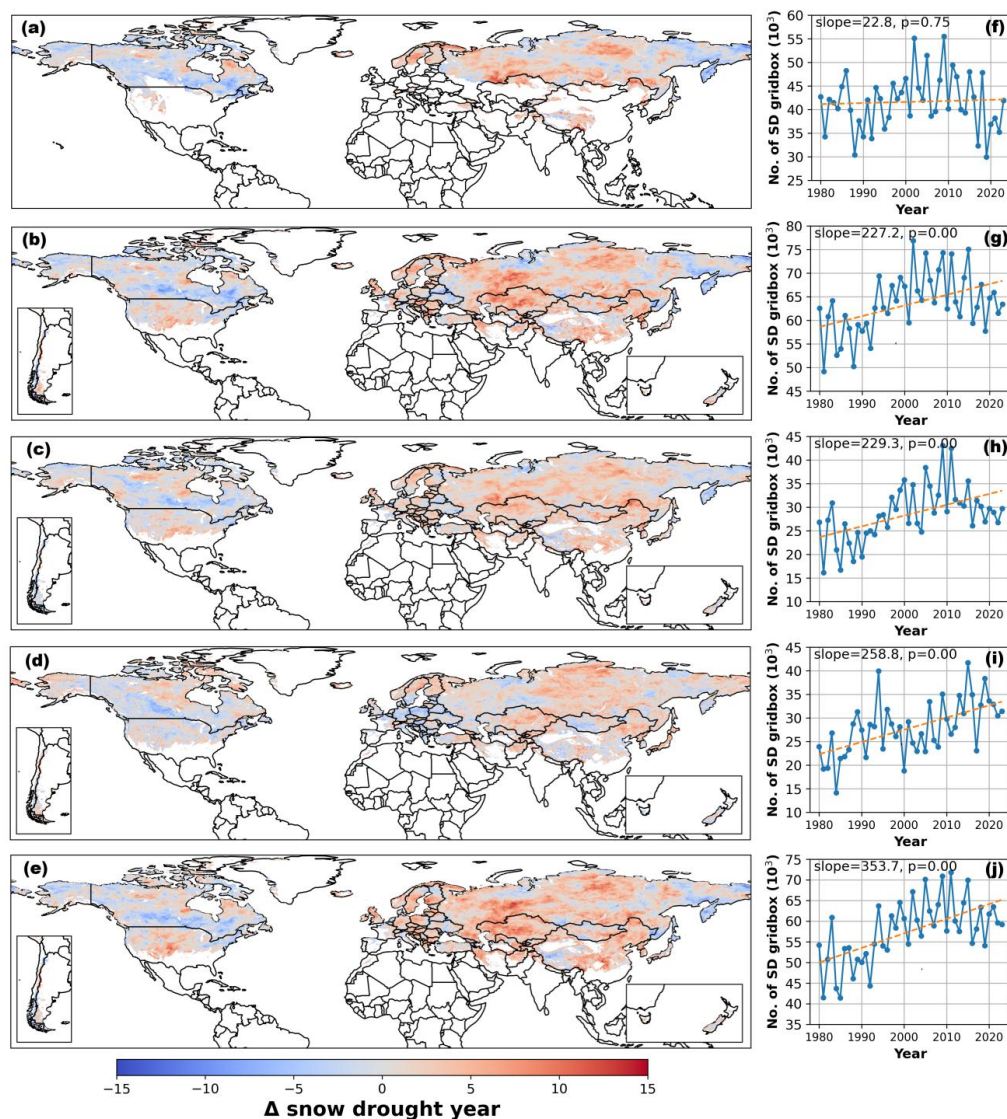
296 **3.1 Global SD characteristics**

297 To demonstrate the capabilities of MSDT, we analyzed global snow drought characteristics across
298 yearly, monthly, and daily scales. Snow drought characteristics were calculated from ERA5-Land
299 SWE data at 0.25° spatial resolution for 1980-2024. The default parameters were used for each
300 method.

301 Figs. 3a-e shows the relative changes in snow drought years across the world from 1980 to 2024



302 using yearly-scale methods. Positive and negative values indicate increases and decreases in snow
303 drought years during the latter 22 years relative to the first 22 years, respectively. Globally, the
304 methods revealed spatially consistent patterns, with hotspots in western CONUS, eastern Russia,
305 Europe, eastern Siberia, Central Asia, and East Asia, demonstrating the ability of MSDT to
306 reproduce established large-scale snow drought patterns. The temporal evolution of snow drought
307 spatial extent is shown in Figs. 3f-j. Over the past 45 years, snow droughts exhibited significant
308 spatial expansion across all methods except 1AprSWE, potentially reflecting earlier snowmelt
309 timing. The 1AprSWE method, originally designed for western CONUS, showed smaller spatial
310 coverage than the other four methods (Figs. 3a-e) because valid snowpack is often absent on 1 April
311 in southern or low-elevation regions of the Northern Hemisphere. Similarly, PeakSWEpctl showed
312 smaller changes in drought years and spatial extent than PeakSWEMean (Figs. 3b-c, 3g-h),
313 reflecting its stricter drought identification threshold.



314

315 **Figure 3.** Global changes in snow drought year between the first and last 22 years (a-e) and the
 316 timeseries of the number of SD grid box (f-j) using yearly-scale methods: (a, f) 1AprSWE, (b, g)
 317 PeakSWEMean, (c, h) PeakSWEPctl, (d, i) PeakSWEDate, and (e, j) AccSWE.

318 Fig. 4 displays the spatiotemporal characteristics of snow drought duration derived from the SWEI
 319 and PDM methods. Snow drought duration exhibited distinct latitudinal and altitudinal gradients,
 320 with Arctic and mountainous regions experiencing prolonged drought conditions (Fig. 4a). Over the
 321 past 45 years, the global mean snow drought duration doubled from 2 to 4 months, accompanied by



a significant increase in drought days (Fig. 4d). The strongest intensification occurred across Eurasia (Fig. 4c). Fig. 5 presents the spatial distribution and temporal trends of snow drought intensity calculated with the monthly and daily methods. Intensity patterns were related to snow climate regimes: coastal and intermountain regions exhibited more severe droughts than continental zones (Fig. 5a). Concurrently, global snow drought intensification was evident from declining SWEI values and daily intensity metrics (Figs. 5b-d), consistent with previous studies (Cowherd et al., 2023; Huning and AghaKouchak, 2020b). The spatial patterns of duration and intensity changes closely matched those of snow drought occurrence (Figs. 3a-e, 4c, and 5c), indicating systematic aggravation of snow droughts across the globe.

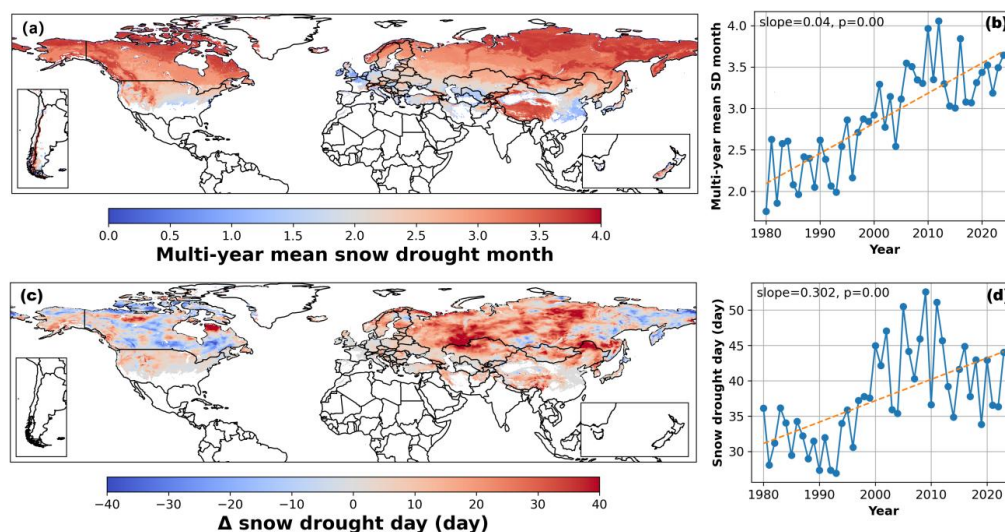


Figure 4. Global map and timeseries of multi-year mean snow drought (SD) month (a, b) and snow drought day (c, d). Δ snow drought day is the difference between the later and first 22-years during 1980-2024.

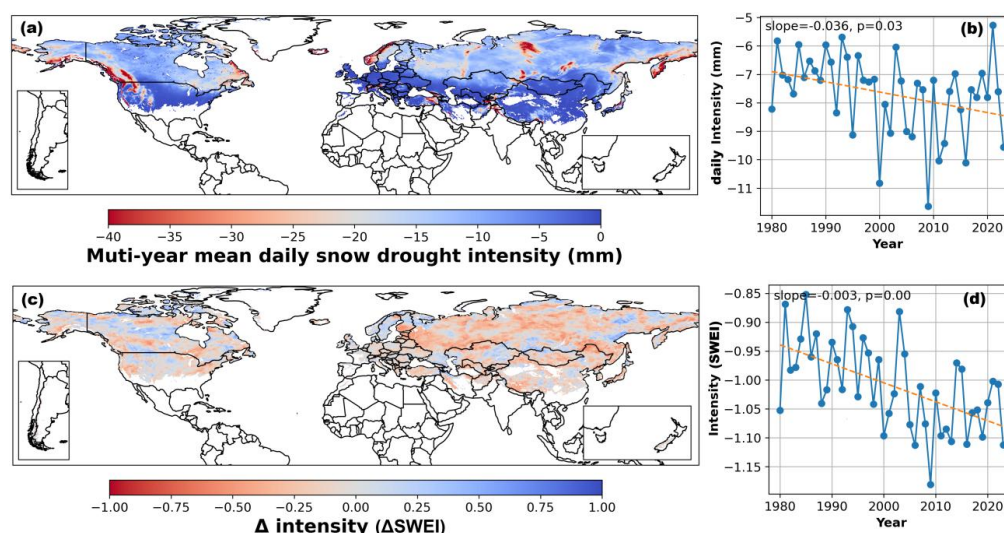


Figure 5. Global map and timeseries of daily (a, b) and monthly (c, d) snow drought intensity. Δ intensity is the difference of SWEI values between the later and first 22-years during 1980-2024.

3.2 High-impact SD characteristics

Three recent high-impact snow drought events were selected to further demonstrate the applicability of MSDT: the 2014/15 and 2016/17 events in the contiguous United States (CONUS) and the 2017/18 event in Central Asia. Statistics for these events are presented below, and the consistency among different snow drought identification methodologies was evaluated.

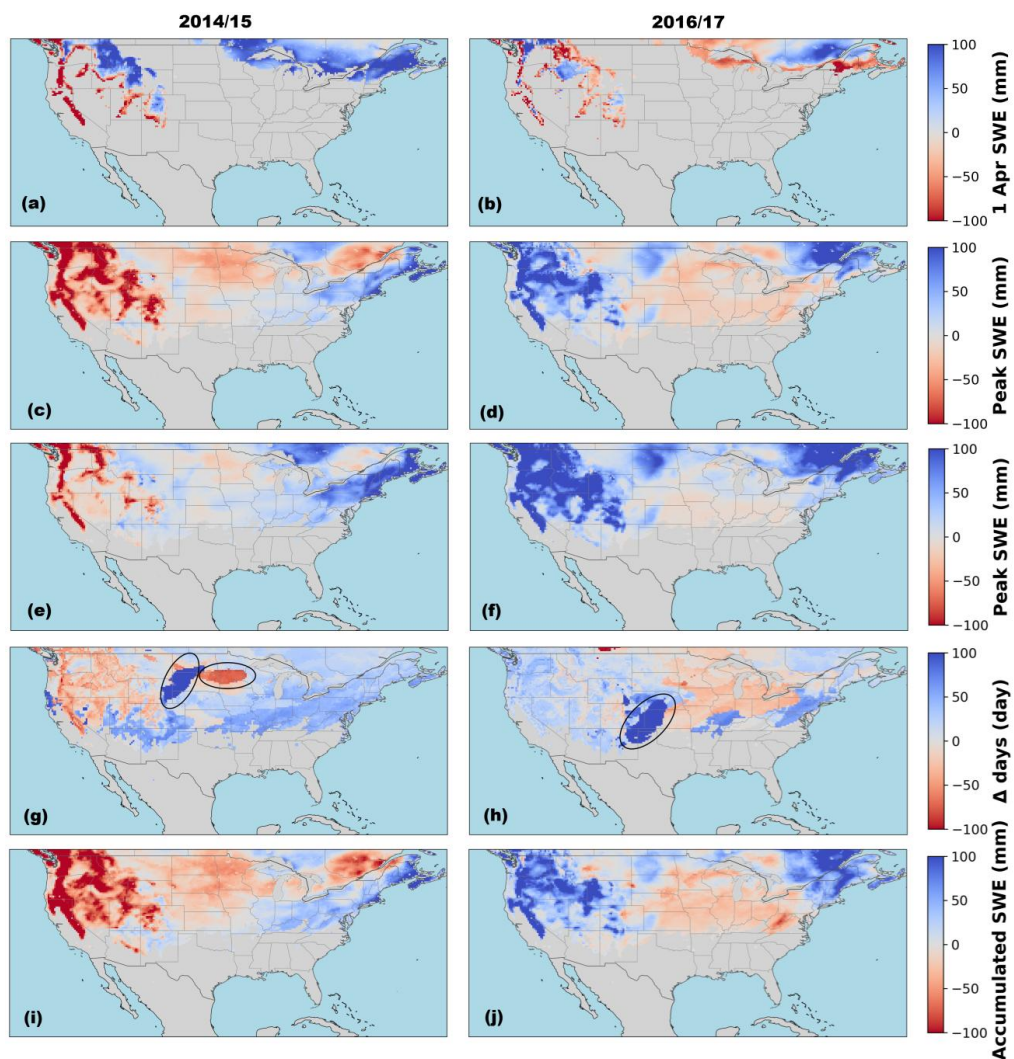
3.2.1 Snow drought in the contiguous United States (CONUS)

The CONUS has suffered from chronic snow droughts over recent decades. The 2014/15 winter saw unprecedented and widespread snow drought in western CONUS, breaking records of the past three to four centuries (Fosu et al., 2016; Margulis et al., 2016; Dye et al., 2023; Harley et al., 2020). Driven by anomalously high temperatures in the Pacific Northwest and precipitation deficits in the Sierra Nevada, the 2014/15 snow drought triggered abnormal winter streamflow and extreme summer water shortages, prompting drought emergency declarations in Washington and Oregon (Cooper et al., 2016; Harley et al., 2020). In contrast, the 2016/17 winter brought substantial snowpack recovery to western CONUS following a series of winter storms (Folger, 2017), while an



352 atypical snow drought emerged in eastern regions (Huning and AghaKouchak, 2020b; Koch and
353 Coulston, 2020).

354 Fig. 6 maps snow drought intensity across the CONUS during the 2014/15 and 2016/17 water years,
355 with negative values denoting drought conditions. Method-specific intensities are not directly
356 comparable because the methods use different thresholds and measurement dimensions. All yearly-
357 scale methods effectively detected the 2014/15 western drought and eastern wet anomalies. Snow
358 drought intensity varied among methods in central CONUS, reflecting differences in snow drought
359 definitions (Figs. 6a, c, e, g, i). In 2016/17, most methods captured the "wet west, dry east" pattern
360 across CONUS, except for 1AprSWE, which showed "dry west, no data in the east". This result
361 indicates that 1AprSWE can overestimate snow drought in western CONUS and is less suitable for
362 regions with early snowmelt, such as eastern CONUS. The encircled anomalies in Figs. 6g-h further
363 mark strong peak-SWE timing deviations, with early peaks in the north-central United States and
364 late peaks in the northern and central Great Plains. These align well with the November 2014 storms
365 in central Minnesota (National Weather Service, 2014), blue (late) aligns with May 2015 heavy
366 snow in South Dakota and April 2017 blizzards in Kansas-Colorado (National Weather Service,
367 2015, 2017), demonstrating the PeakSWEDate method's capability to detect anomalous snow timing
368 compared with the other yearly methods.

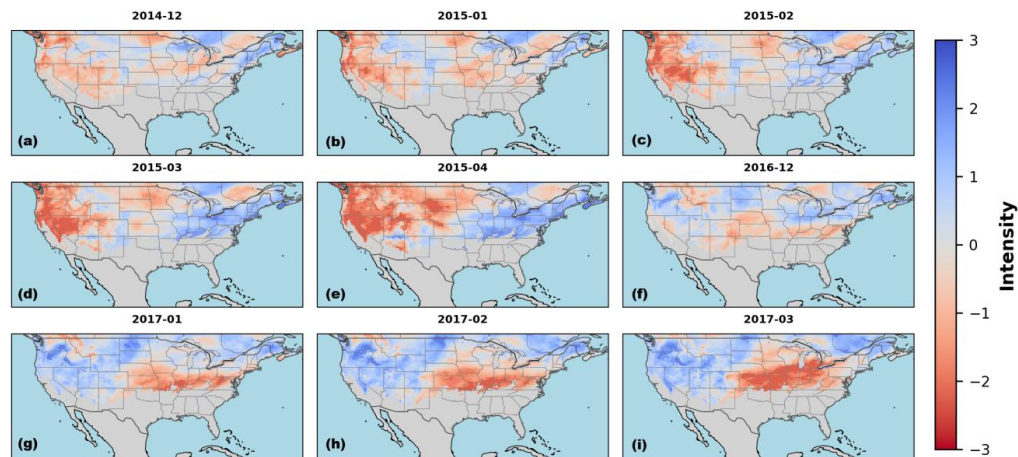


369
370 **Figure 6.** Snow drought intensity (negative values) in CONUS during the water year of 2014/15
371 (left) and 2016/17 (right) using yearly-scale methods: (a, b) 1AprSWE, (c, d) PeakSWE Mean, (e, f)
372 PeakSWE Pctl, (g, h) PeakSWE Date, and (i, j) AccSWE.

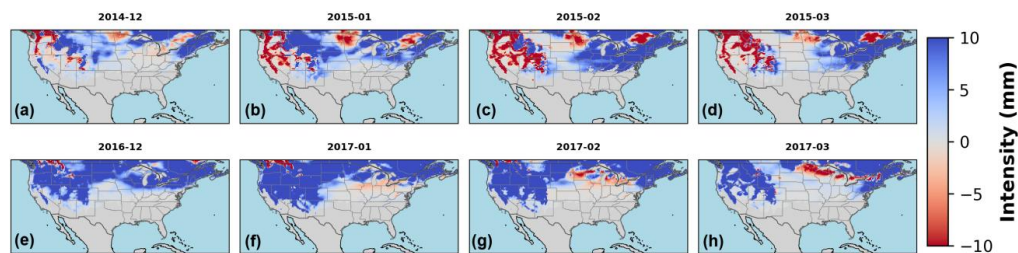
373 The evolution patterns of the 2014/15 and 2016/17 snow droughts are depicted in Figs. 7 and 8.
374 During the 2014/15 water year, concurrent snow droughts initiated in both western and eastern
375 CONUS, escalating and expanding westward while subsiding eastward in the following months
376 (days). In contrast, the 2016/17 water year began with opposing anomalies: drought developing in
377 eastern CONUS and wet conditions in the west. These patterns progressively worsened and spatially



378 expanded in subsequent months (days).



379
380 **Figure 7.** Snow drought intensity across CONUS during the water year of 2014/15 (a-e) and
381 2016/17 (f-i) using monthly-scale method.



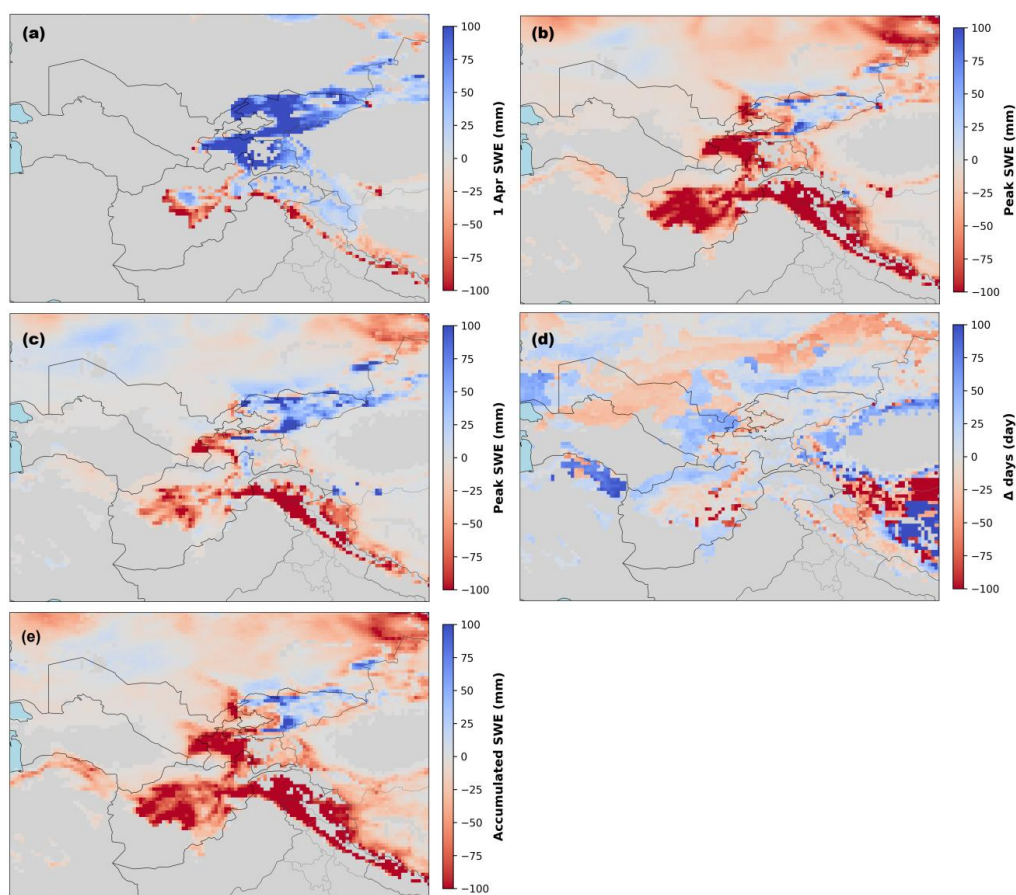
382
383 **Figure 8.** Snow drought intensity across CONUS during the water year of 2014/15 (a-d) and
384 2016/17 (e-h) using daily-scale method.

385 3.2.2 Snow drought in Central Asia (2017/18)

386 During the 2017-2018 winter, Central Asia experienced an extraordinary snow drought event, with
387 the most pronounced deficits extending from the western Tianshan Mountains through Afghanistan's
388 high-altitude regions to the northwestern Himalayas. More than three-quarters of Afghanistan's
389 snow-covered districts experienced snow drought intensities fourfold higher than average. The snow
390 drought led to drying of wells and rivers, widespread crop failures, livestock losses, and
391 displacement of more than 260,000 people, severely disrupting agricultural production and
392 contributing to a humanitarian crisis (Bair et al., 2018; Muhammad et al., 2017).



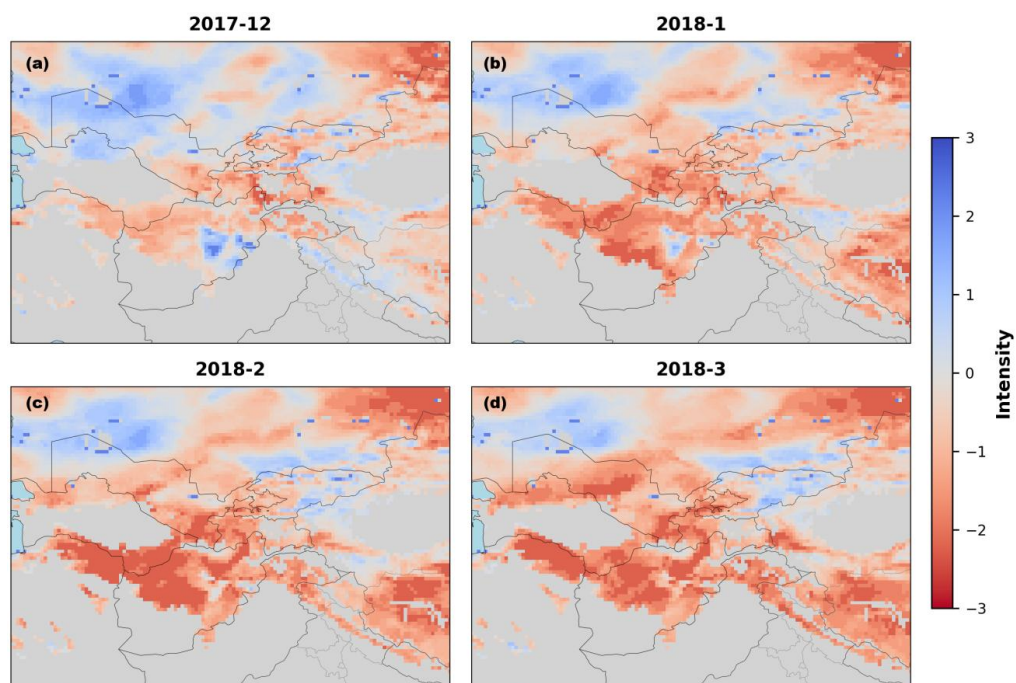
393 Fig. 9 displays the spatial distribution of yearly snow drought intensity across Central Asia during
 394 the 2017/18 water year. Snow droughts are represented as negative values. All methods consistently
 395 identified Tianshan wet anomalies in the north and Himalayan-Afghan drought signals in the south.
 396 The 1AprSWE method yielded the most limited spatial extent (Fig. 9a), followed by PeakSWEDate
 397 (Fig. 9d), while PeakSWEMean, PeakSWEpctl, and AccSWE showed comparable snow drought
 398 coverage (Figs. 9b, c, e). Temporal analysis revealed initially normal snowpack conditions in the
 399 Himalayas and southeastern Afghanistan at the onset of the 2017/18 water year, followed by
 400 progressive drought intensification. Conversely, the Tianshan Mountains exhibited a gradual
 401 wetting trend from December 2017 to March 2018 (Fig. 10). These asymmetric patterns were
 402 corroborated by daily-scale snow drought analyses (Fig. 11).



403
 404 **Figure 9.** Snow drought intensity in Central Asia during the water year of 2017/18 using yearly-



405 scale methods: (a) 1AprSWE, (b) PeakSWEMean, (c) PeakSWEpctl, (d) PeakSWEDate, and (e)
406 AccSWE.
407



408
409 **Figure 10.** Snow drought intensity in Central Asia during the water year of 2017/18 using monthly-
410 scale method.

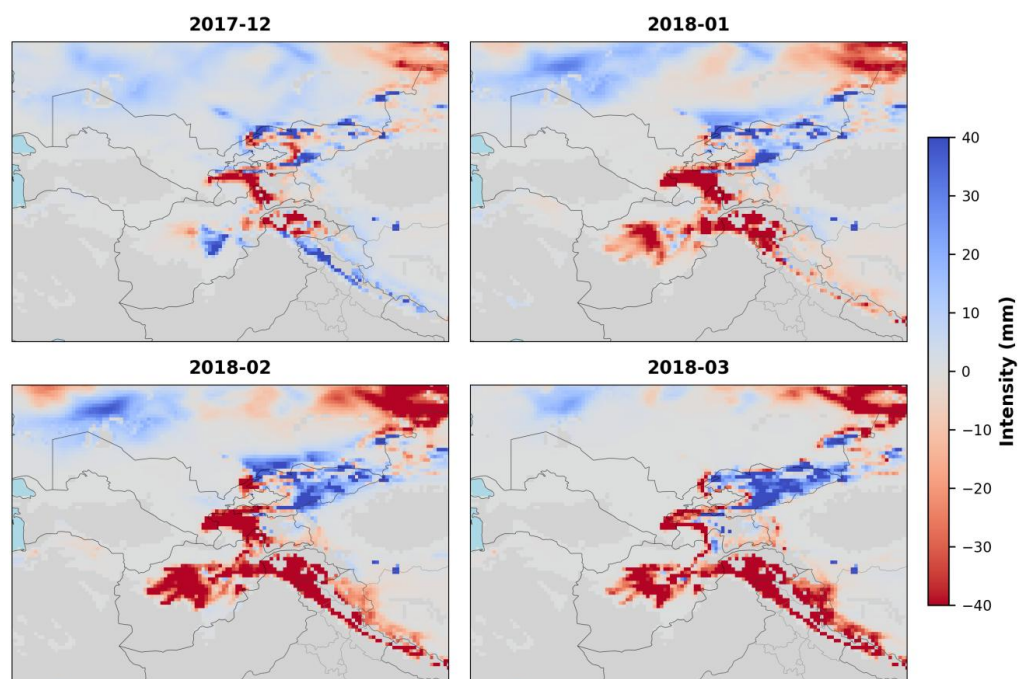


Figure 11. Snow drought intensity in Central Asia during the water year of 2017/18 using daily-scale method.

4 Discussion and Conclusions

This study presents the MSDT, an open-source Python software package that provides an integrated platform for standardized snow drought identification, visualization, and SWE data management across yearly, monthly, and daily temporal scales. MSDT integrates seven widely adopted snow drought identification methods within a unified graphical interface, enabling reproducible workflows for data acquisition, preprocessing, multi-method analysis, visualization, and standardized NetCDF export. Its modular software architecture supports future extension to additional datasets and algorithms while ensuring methodological consistency and reproducibility (Hao et al., 2017; Gottlieb and Mankin, 2022).

Application of MSDT to ERA5-Land SWE data for 1980-2024 showed that the toolbox reproduced previously reported global snow drought characteristics and representative historical events, while also providing a unified framework for interpreting methodological differences among existing snow drought definitions (Figs. 3-11). Although the seven implemented methods differ in their



conceptual basis and therefore produce different estimates of drought intensity, spatial extent, and evolution, they consistently identified the major global snow drought hotspots and long-term intensification trends, indicating that the principal signals of snow drought are robust across methodologies. Rather than competing alternatives, these methods should be regarded as complementary tools addressing different scientific questions, consistent with previous work showing that point-in-time metrics, standardized SWE anomalies, and daily phase-diagram approaches emphasize different aspects of snow drought development (Harpold et al., 2017; Huning and AghaKouchak, 2020b; Hatchett et al., 2022; Fang and Leung, 2023). Annual point-in-time methods are most appropriate for seasonal water-resource assessments based on representative snow metrics, monthly SWEI is better suited for monitoring persistent snow deficits and interregional comparison through standardized anomalies, and the daily PDM provides detailed characterization of drought onset, development, and recovery for operational monitoring and impact assessment. By integrating these complementary methods into a standardized computational framework, MSDT enables reproducible multi-method analyses and facilitates more comprehensive understanding of snow drought processes than any individual method alone.

Beyond software implementation, MSDT provides a standardized computational framework that improves the reproducibility and comparability of snow drought research. Such standardization follows broader recommendations for operational drought monitoring systems and drought-index implementation (Hayes et al., 2011; Hao et al., 2017). By adopting unified parameter management, metadata recording, and standardized NetCDF outputs, the toolbox facilitates integration with GIS analyses, hydrological modelling, climate model evaluation, and climate-impact assessment. The availability of a common multi-method platform also enables more rigorous intercomparison among alternative snow drought definitions, supporting future methodological development and community benchmarking. As snow droughts become increasingly frequent under continued climate warming, MSDT provides an open and extensible platform for both scientific research and operational monitoring.

The computational performance of MSDT depends mainly on the spatial resolution, temporal coverage, and selected identification method. Annual methods are generally efficient, followed by the monthly SWEI analyses which require additional processing for rolling accumulation and



457 probability fitting. The daily PDM method is the most computationally demanding because it
458 involves repeated moving-window and grid-wise percentile calculations. According to the end-to-
459 end optimization strategy of MSDT (Fig. 2), users are advised to define an appropriate winter period
460 and apply an extent mask where possible before calculation. For large-domain or long-term daily
461 analyses, memory allocation and parallel execution are adaptively configured according to the input
462 data volume and the available hardware resources of the local computing environment. Because
463 each worker requires its own data block and temporary arrays, increasing the number of workers
464 may therefore not always improve performance and can substantially increase peak memory use. In
465 practice, moderate block sizes and a small number of parallel workers generally provide a more
466 stable configuration. Nevertheless, large-scale, high-resolution analyses remain mainly constrained
467 by NetCDF input/output and grid-wise statistical calculations.

468 There remains considerable scope for future development of MSDT. Future versions will extend
469 support beyond SWE-based diagnostic methods by incorporating additional snow datasets,
470 emerging snow drought identification algorithms, and predictive capabilities. Planned
471 improvements also include parallel and distributed computing, cross-platform and containerized
472 deployment, enhanced visualization functionality, and community-contributed modules enabled by
473 the modular software architecture. These extensions will help the toolbox support drought
474 monitoring across different hydrological regimes and user communities (Baez-Villanueva et al.,
475 2024). Through continuous community development and methodological expansion, MSDT is
476 expected to evolve into a comprehensive open-source platform supporting both scientific research
477 and operational applications in snow drought monitoring and cryosphere studies.

478

479 **Code availability**

480 The source code for MSDT is publicly available at <https://zenodo.org/records/21396772> (Li and
481 Tian, 2026a).

482 **Data availability**

483 The produced global snow drought characteristics, together with the input SWE and precipitation
484 data, are publicly available at <https://zenodo.org/records/21396300> (Li and Tian, 2026b). The case-



485 study analyses use ERA5-Land SWE data obtained from the Copernicus Climate Data Store
486 ([https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanal-ysis-era5-land-monthly-](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanal-ysis-era5-land-monthly-means?tab=overview)
487 [means?tab=overview](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanal-ysis-era5-land-monthly-means?tab=overview)). The snow-covered area extraction uses the MODIS Snow Cover data from
488 National Snow and Ice Data Center (<https://nsidc.org/data/MOD10CM/versions/6>). Additional
489 SWE product links listed in the MSDT catalog are provided for user discovery and intercomparison;
490 users should cite the relevant product provider when using those datasets.

491 **Author contributions**

492 XL and JT conceived the study, developed the software, and carried out the test application. XL and
493 CW processed data and drafted the manuscript. SW and LZ revised the manuscript. All authors
494 contributed to manuscript writing and approved the final version.

495 **Competing interests**

496 The contact author declares that none of the authors has any competing interests.

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