



1 **Review article: Remote sensing methods for snowline dynamics detection in the Andes:**
2 **a critical review**

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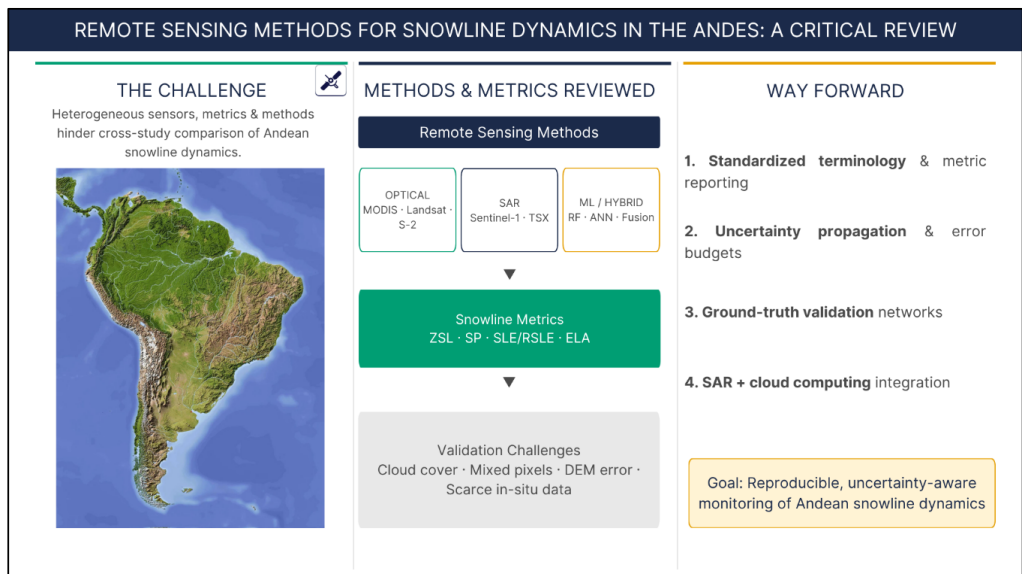
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13 **Graphical Abstract**





17 **Abstract**

18

19 Remote sensing has become a key tool for monitoring snowline dynamics in the Andes, yet
20 cross-study comparison remains limited by heterogeneous definitions, sensors, classification
21 schemes and spatial scales. Drawing on more than 60 studies covering satellite data from
22 1984 to 2025, spanning optical, SAR and hybrid approaches, and following a PRISMA-
23 informed structure, this review examines how snowline-related metrics are defined, applied
24 and interpreted in Andean research, with emphasis on local snowline altitude, snow
25 persistence and catchment- to regional-scale snowline elevation. Andean applications rely
26 predominantly on MODIS-derived snow products and snow-persistence approaches, whereas
27 fewer studies exploit Landsat, Sentinel-2 or SAR workflows to derive transferable metrics or
28 uncertainty-aware frameworks. Reported trends in the extratropical Andes (29° - 37° S) range
29 from 10 to 30 m yr⁻¹, but these estimates are not directly comparable because they derive
30 from different metrics, sensors, temporal windows and aggregation rules. Comparability is
31 further constrained by inconsistent terminology, variable thresholding, limited treatment of
32 digital elevation model and mixed-pixel effects, and scarce in situ validation. Rather than
33 identifying a single optimal metric, the evidence indicates that different approaches suit
34 different objectives: local metrics for event-scale analyses, snow persistence for
35 climatological zonation, and regional snowline elevation for basin-to-regional trend
36 assessment. We identify four priorities: standardized terminology and metric reporting;
37 explicit propagation of uncertainty; systematic ground-truth validation; and stronger
38 integration of SAR and cloud-computing workflows. Reframing snowline monitoring as a
39 problem of metric selection, scale, uncertainty and application provides a basis for more
40 reproducible and hydrologically meaningful assessments of Andean snowline dynamics.

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54 **Keywords:** *Andes; Snowline elevation; Snow persistence; Mountain hydrology; Climate*
55 *change.*



56 1. Introduction

57 Mountain snow, and particularly the position of the snowline, exerts a first-order control on
58 the timing and magnitude of meltwater delivery to downstream basins worldwide, not only
59 in South America (Masiokas et al., 2020; Schauwecker et al., 2022). The Andean cryosphere
60 spans seasonal snow cover, glaciers, mountain permafrost and specialized ice forms such as
61 penitentes, making it one of the most diverse cryospheric settings on Earth (Masiokas et al.,
62 2020; Dussailant et al., 2019). In semi-arid catchments, where precipitation falls in only a
63 handful of winter storms, the altitude of the snowline and its seasonal evolution determine
64 how much water is stored as snow and subsequently released during the spring and summer
65 melt (Masiokas et al., 2020).

66 This hydrological role is most acute in central Chile and western Argentina, where snow and
67 ice underpin urban supply, irrigation and hydropower (Masiokas et al., 2006; Masiokas et al.,
68 2020; McCarthy et al., 2022). Between roughly 30° and 37°S, winter snow accumulation
69 explains more than 85% of the interannual variability in mountain river discharge, a striking
70 measure of how completely regional water security depends on seasonal snow storage
71 (Masiokas et al., 2006). The recent central-Chile drought has exposed both sides of this
72 dependence: the cryosphere buffers supply yet is itself highly vulnerable, and snow-
73 dominated basins in the extratropical Andes display a long hydrological memory that
74 prolongs runoff deficits under sustained precipitation shortfalls (Garreaud et al., 2017;
75 McCarthy et al., 2022; Álvarez-Garretón et al., 2021).

76 Against this backdrop, satellite remote sensing has become the primary source of information
77 on snow cover and snowline dynamics in the Andes, especially in data-scarce mountain
78 regions (Dietz et al., 2012; Masiokas et al., 2020; Gascoin et al., 2024). Andean studies
79 nonetheless diverge widely in their choice of sensors, spectral indices, cloud treatment,
80 elevation models, thresholds and snowline metrics, which makes cross-study comparison
81 difficult and often methodologically ambiguous (Dietz et al., 2012; Gascoin et al., 2024).
82 This heterogeneity is not merely technical but conceptual: terms such as ZSL, SLA, TSL,
83 SLE, RSLE, snow persistence, ELA and even the 0 °C isotherm is frequently treated as
84 interchangeable despite denoting different processes, spatial supports and temporal meanings
85 (Schauwecker et al., 2022; Hu et al., 2019; Dietz et al., 2025).

86 Existing reviews offer valuable overviews of snow remote sensing, ranging from early
87 syntheses of remote sensing, GIS and GPS in glaciology (Gao and Liu, 2001) and of global
88 satellite-derived snow products (Frei et al., 2012) to more recent assessments of mountain-
89 snow methods (Dietz et al., 2012; Nolin, 2010; Hammond et al., 2018; Gascoin et al., 2024).
90 They tend, however, to emphasize sensors or broad cryospheric change rather than
91 systematically comparing how individual snowline metrics perform under Andean
92 conditions. The unresolved problem is therefore not a shortage of studies but the absence of
93 an explicit methodological framework for comparing robustness, reproducibility,
94 uncertainty, scalability and operational relevance across snowline approaches. That gap is
95 especially consequential in the Andes, where high relief, aridity, cloud contamination, mixed
96 pixels, DEM sensitivity and scarce in situ validation strongly condition the interpretation of
97 snowline products (Dietz et al., 2012; Choubin et al., 2019; Gascoin et al., 2024).

98 This review addresses that gap by positioning itself explicitly as a methodological review of
99 Andean snowline monitoring rather than a general cryospheric or climatic overview.



100 Following a PRISMA-informed reporting structure, we make the identification, selection and
101 synthesis of studies transparent, and we compare snowline-related metrics and remote-
102 sensing methods by their definitions, scale dependence, uncertainty sources, validation
103 requirements and fitness for different hydrological and climatic objectives (Page et al., 2021).
104 Three questions organize the review: (1) how do local snowline altitude, snow persistence
105 and SLE/RSLE-type metrics differ in conceptual meaning and robustness; (2) what
106 methodological limitations affect optical, SAR and hybrid approaches in the Andes; and (3)
107 what elements would constitute a more reproducible, uncertainty-aware and operationally
108 relevant multi-sensor framework for Andean snowline monitoring (Page et al., 2021;
109 Masiokas et al., 2020; Gascoin et al., 2024).

110 **2. Materials and methods.**

111 This review was structured using a PRISMA-oriented approach to improve transparency,
112 reproducibility, and consistency in the identification, screening, classification, and synthesis
113 of studies addressing snowline monitoring in the Andes and comparable mountain
114 environments (Page et al., 2021). In this context, the review was designed not only to compile
115 Andean case studies, but also to compare the methodological performance of snowline-
116 related metrics and sensors under the specific environmental constraints of high-relief, data-
117 scarce mountain regions (Masiokas et al., 2020; Gascoin et al., 2024).

118 **2.1 Literature search strategy.**

119 The literature search was conducted using major scientific databases such as Web of Science,
120 Scopus, and Google Scholar, which together provide broad coverage of remote-sensing,
121 cryosphere, hydrology, and mountain-environment studies. Search strings combined
122 geographic, methodological, and metric-related terms, including “Andes”, “snowline”,
123 “snowline elevation”, “regional snowline elevation”, “snow persistence”, “remote sensing”,
124 “optical”, “SAR”, “Sentinel-2”, “Landsat”, and “MODIS”, together with commonly used
125 metric variants such as ZSL, SLA, TSL, SLE, and RSLE (Hu et al., 2019; Dietz et al., 2025;
126 Schauwecker et al., 2022). Because snowline terminology is not standardized across the
127 literature, the search strategy explicitly incorporated synonymous or partially overlapping
128 expressions to avoid excluding relevant studies that use different conceptual labels for similar
129 snow-no snow interface metrics.

130 **2.2 Screening and eligibility criteria**

131 The search was designed to capture both Andean applications and methodological studies
132 from other mountain regions, provided the latter offer transferable approaches to snowline
133 detection, uncertainty assessment or metric evaluation (Tang et al., 2014; Hu et al., 2020; Liu
134 et al., 2021). This broader inclusion is warranted because several methods now applied in the
135 Andes, regional snowline elevation, scene-based optical delineation and snow-persistence
136 zoning, were first developed or comparatively tested in other mountain settings before being
137 adapted to Andean conditions (Krajčič et al., 2014; Moore et al., 2015; Aranda et al., 2023).
138 The regional snowline-elevation approach, for instance, has been extended to characterize
139 snowmelt-runoff events across European basins (Parajka et al., 2019) and combined with
140 snow persistence to map snow regimes in the Himalaya (Dixit et al., 2024), illustrating the
141 cross-regional transferability that this review exploits. The exact search period, the date of
142 the last search and any language restrictions applied are reported in accordance with PRISMA
143 principles (Page et al., 2021).



144 Study selection was performed in two consecutive stages: an initial title and abstract
145 screening, followed by full-text assessment of potentially relevant records (Page et al., 2021).
146 Studies were included when they: (i) address snowline, snow-cover dynamics, or snow
147 persistence in mountain environments; (ii) use remote sensing, DEM-based analysis, or
148 related geospatial methods; (iii) report or enable interpretation of metrics such as ZSL, SLA,
149 TSL, SLE, RSLE, or SP; and (iv) either focus directly on the Andes or provide methods that
150 are demonstrably transferable to Andean mountain conditions. Studies were excluded when
151 they are purely climatological without a snowline-related metric, when they lack sufficient
152 methodological detail, when they are duplicates, or when their scope does not contribute to
153 the comparative methodological objectives of the review. Additionally, prior to formal title
154 and abstract screening, 1,227 records retrieved by the database queries were excluded at a
155 pre-screening stage because they addressed snowlines in non-terrestrial contexts (planetary
156 bodies, comets, and stellar astrophysics), which fall outside the scope of this review. This
157 pre-screening step reduced the de-duplicated pool from 1,781 to 554 records that underwent
158 formal title and abstract assessment (see Figure 1 and Table 1).

159 This screening logic is particularly important in the present review because the review
160 distinguishes among multiple non-equivalent concepts, including ZSL, SLA, Transient
161 Snowline (TSL), SLE, RSLE, ELA, and the 0 °C isotherm altitude, which are sometimes
162 used inconsistently in the literature (Schauwecker et al., 2022; Hu et al., 2019; Dietz et al.,
163 2025). A PRISMA flow diagram (Figure 1) summarizes the number of records identified,
164 screened, excluded, and finally included, thereby making the literature selection process
165 explicit and reproducible.

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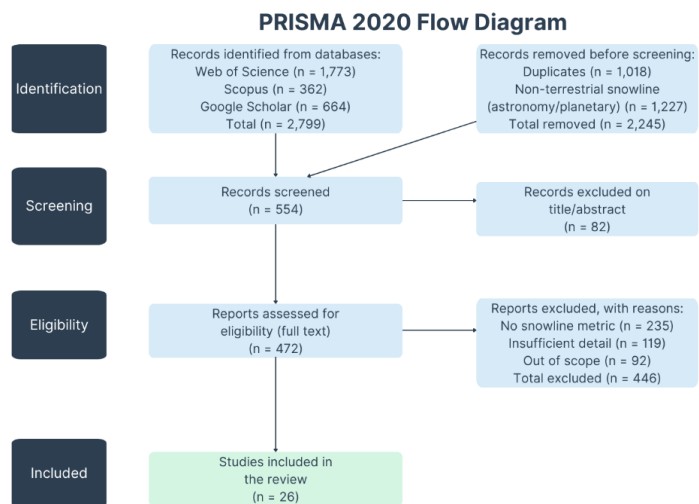


167 **Table 1. Literature search and screening summary**

Databa se	Search date	Time windo w	Search string / keywords	Record s retriev ed	Duplicat es removed	Record s screen ed	Full- text assesse d	Full- text exclud ed	Final include d studies
Web of Science	Januar y-2026	2000- 2026	("snowline" OR "snow line" OR "snowline elevation" OR "regional snowline elevation" OR "snow persistence ") AND ("Andes" OR "Andean" OR mountain) AND ("remote sensing" OR optical OR SAR OR MODIS OR Landsat OR Sentinel)	1773	0	546	464	446	18
Scopus	Januar y-2026	2000- 2026	("snowline" OR "snow line" OR "snowline elevation" OR "regional snowline elevation" OR "snow persistence	362	354	8	8	0	8



			" AND (Andes OR Andean OR mountain) AND ("remote sensing" OR optical OR SAR OR MODIS OR Landsat OR Sentinel))						
Google Scholar	March 2026	2000- 2026	"Snowline " OR "snow persistence " OR "regional snowline elevation" Andes "remote sensing" (MODIS OR Landsat OR Sentinel OR SAR)	664	664	0	0	0	0
Total	2026	26		2799	1018	554	472	446	26



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170 **Figure 1.** PRISMA 2020 flow diagram for the identification, screening, eligibility
171 assessment, and inclusion of studies on remote sensing methods for Andean snowline
172 monitoring. Records were retrieved from Web of Science ($n = 1,773$), Scopus ($n = 362$), and
173 Google Scholar ($n = 664$) in January-March 2026. Prior to formal title/abstract screening,
174 1,227 records addressing non-terrestrial snowlines (astronomy and planetary science) were
175 excluded at a pre-screening stage. A total of 26 studies met all inclusion criteria and are
176 synthesized in this review. Full search strings and record counts by database are provided in
177 Table 1.

178 2.3 Study classification framework

179 After screening, the selected studies were classified using a structured framework that reflects
180 the analytical goals of this review rather than purely chronological or regional ordering. At
181 minimum, the classification includes the following dimensions: (i) metric type, including
182 local snowline metrics and temporally integrated metrics; (ii) satellite platform or sensor,
183 such as MODIS, Landsat (sensors MSS/TM/ETM+/OLI), Sentinel-2 (sensor MSI), SAR, or
184 multi-sensor fusion; (iii) spatial scale, from slope or glacier scale to basin and regional scale;
185 (iv) validation approach, including in situ observations, photographs, reanalysis products, or
186 indirect hydrological consistency; and (v) uncertainty treatment, including threshold
187 sensitivity, DEM sensitivity, cloud contamination, mixed pixels, and cross-sensor
188 inconsistencies (Dietz et al., 2012; Choubin et al., 2019; Gascoin et al., 2024).

189 An additional classification level distinguishes studies according to their primary application
190 objective, such as event-based snowline detection, climatological zonation, long-term trend
191 analysis, or operational hydrological support. This distinction is necessary because there is
192 no single universally best method for determining the snowline; rather, metric suitability
193 depends strongly on the temporal scale, spatial scale, and decision context of the analysis.



194 **Table 2. Classification framework of reviewed studies**

Author (Year)	Region / sector	Metric type	Satellite (sensor) / data source	Resolution	Validation	Uncertainty treatment	Reported trend / change	Primary application
Saavedra et al. (2017)	Andes (tropical-Patagonia), Andes (8-55°S)	SP	MODIS	500 m / Daily → seasonal	Climatological consistency	Cloud gaps, temporal sampling	-	Climatological zoning
Saavedra et al. (2018)	Extratropical Andes, Andes (south of 29°S)	SP / SLE	MODIS	500 m / 2000-2016	Indirect / climatological	Limited explicit propagation	+10-30 m yr ⁻¹ SLE	Trend
Aranda et al. (2023)	Central Andes (~33°S), Yeso River basin	SP / SLE	MODIS	500 m / 2000-2021	Basin consistency	Cloud, DEM	+21 m yr ⁻¹ SLE	Trend
Dietz et al. (2025)	Central Chilean Andes, Aconcagua-Maipo	SLE	Landsat	30 m / 1985-2024	Noted in study	Method-dependent	+9.8-15.6 m yr ⁻¹ SLE	Trend
Saavedra et al. (2026)	Andes (Chile)	SP / SCA	MODIS	500 m / 2000-2025	Cloud-reduction validation	Cloud (49→29 %)	Continued snow decline	Zoning / trend
Schauwecker et al. (2022)	Dry subtropical Andes, Subtropical Chilean Andes	ZSL / Z0°	Sentinel-2 + stations + ERA5	10-20 m / 2011-2021 events	Citizen science + stations	Event-scale	ZSL below Z0°	Event
Cordero et al. (2019)	Andes (tropical-extratropical), Andes (18-40°S)	SCA (ZSL proxy)	Landsat / MODIS	30-500 m / 1986-2018	Limited	Fixed-threshold bias	Declining snow-cover extent	Trend
Cortés et al. (2014)	Extratropical Andes (32-38°S)	FSC (sub-pixel)	Landsat 5/7	30 m / 1986-2013	High-resolution imagery	Unmixing / endmember	Declining min. snow/ice	Trend
Cortés and Margulis (2017)	Extratropical Andes	SWE (assimilation)	Landsat + reanalysis	~100-500 m / 1985-2015	Reanalyses / in situ	Model + observation error	-	Hydrology



Veettil et al. (2016)	Tropical Andes (Peru), Cordillera Blanca	Annual max snowline (TSL)	Landsat	30 m / 1984-2015	Glacier records	Scene availability	Rising end-of-summer snowline	Trend
Klein and Isacks (1999)	Tropical Andes (Bolivia/Peru), Zongo / Quelccaya	TSL (spectral unmixing)	Landsat TM	30 m / Event	Mass-balance ELA	Endmember selection	-	Event
Rabatel et al. (2012)	Tropical Andes, Outer tropics	TSL → ELA	Landsat / SPOT	10-30 m / Annual	Glacier mass balance	Snowline-ELA offset	-	Zoning
Carrasco et al. (2008)	Southern Andes, western side	ELA (0 °C isotherm)	Radiosonde + surface	-	Surface stations	-	Rising ELA (secular)	Trend (atmospheric proxy)
MacFee et al. (2025)	SH glaciers (incl. Andes)	Glacier snowline altitude	MODIS	500 m	-	-	Broadly rising SLA	Trend (hemispheric)
Krajčič et al. (2014)	Analogue (Europe) Carpathians	RSLE	MODIS	500 m / Daily	Runoff consistency	DEM, classification	-	Trend
Parajka et al. (2019)	Analogue (Europe) European basins	RSLE	MODIS	500 m / Daily (events)	Runoff	DEM, clouds	-	Hydrology
Hu et al. (2019)	Analogue (Europe) European mountains	RSLE	Landsat	30 m / 1984-2018	-	DEM, classification	-	Trend
Hu et al. (2020)	Analogue (Alps) European Alps	RSLE	Landsat	30 m / 1985-2018	-	DEM, clouds	-	Trend
Tang et al. (2014)	Analogue (HMA), Tibetan Plateau	SLA	MODIS FSC	500 m / 2001-2013	-	Cloud, DEM	-	Trend
Liu et al. (2021)	Analogue (HMA), Eastern Tibetan Plateau	SLA	Landsat (GEE / Otsu)	30 m / 1995-2016	-	Threshold, geometry	-	Trend
Dixit et al. (2024)	Analogue (HMA), Indus-Ganga-	SP / RSLE	MODIS	500 m / 2003-2021	Köppen zones	Cloud, threshold	-	Zoning / trend



	Brahmaputra							
Racoviteanu et al. (2019)	Analogue (HMA), Karakoram-E. Himalaya	SLA (automated)	Landsat / ASTER	15-30 m / End-of-season	DEM visual	DEM, clouds	-	Event
Wu et al. (2014)	Analogue (HMA), Tien Shan	SLA → ELA	HJ-1	30 m / 2009-2010	In situ ELA	SLA-ELA mismatch	-	Event
Hammond et al. (2018)	Analogue (global)	SP	MODIS	500 m / 2001-2016	-	Gap-filling	-	Zoning / trend
Callegari et al. (2016)	Analogue (Alps), European Alps	TSL (PolSAR)	SAR (RADAR SAT-2)	~10 m / Event	Reference maps	Geometry, classification	-	Event
Snauffer et al. (2018)	Analogue (N. America), British Columbia	SWE (ML fusion)	Multi-source + ML	Gridded / Annual	Station SWE	Training bias	-	Hydrology
Bonnell (2024)	Analogue (N. America), Western US	SWE (L-band InSAR)	Airborne / UAVSAR	<500 m / Weekly	In situ / GPR	Phase, snow density	-	Snow-state
Portenier et al. (2022)	Analogue (Alps), Swiss Alps	RSLE (webcams)	Public webcams	Variable / Sub-daily	DEM-projected	Viewpoint, mapping	-	Event

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196 2.4 Evidence synthesis criteria

197 The synthesis of evidence was guided by a comparative methodological perspective focused
 198 on robustness, reproducibility, uncertainty, scalability, and suitability for trend detection. In
 199 practical terms, each study was assessed according to its sensitivity to cloud contamination,
 200 topographic shadowing, DEM quality, threshold choice, mixed-pixel effects, temporal
 201 compositing strategy, and validation support, because these factors strongly affect the
 202 interpretation of snowline products in the Andes (Dietz et al., 2012; Harer et al., 2018;
 203 Choubin et al., 2019; Gascoin et al., 2024).

204 Within this framework each metric is treated as a distinct analytical tool rather than a label
 205 for a single phenomenon; the metric-by-metric comparison is developed in Section 4, and the
 206 classification dimensions are summarized in Table 2. Where persistent cloud cover limits
 207 optical products, SAR and optical-SAR fusion is noted as complementary sources, although
 208 their Andean use remains comparatively limited. The aim of overarching is to identify which
 209 combinations of metrics, sensors and processing strategies are most reproducible and
 210 operationally meaningful for Andean snowline monitoring.



211 **3. Conceptual framework: Andean cryosphere and snowline metrics.**

212 **3.1 The Andean cryosphere and its hydrological role**

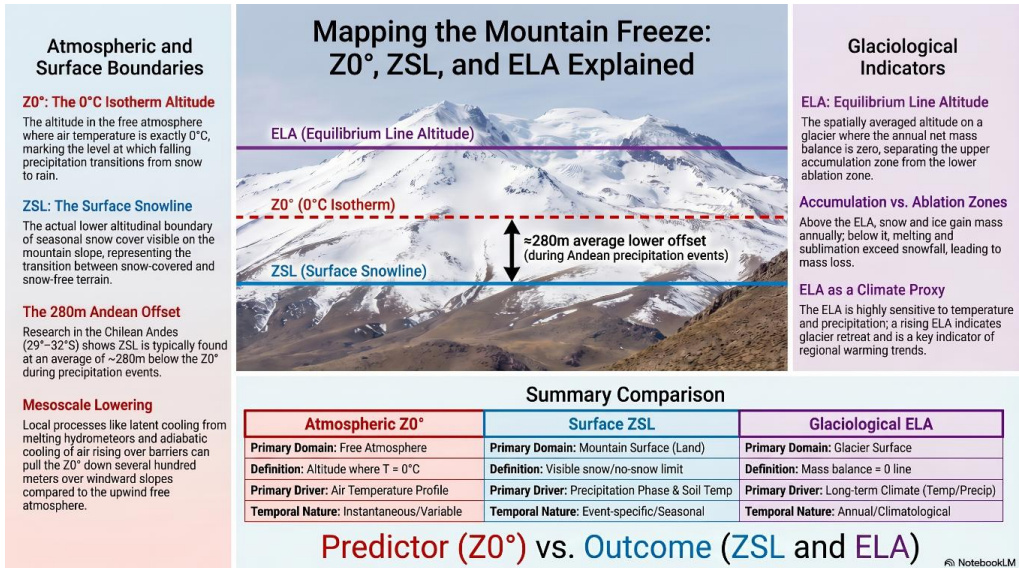
213 The Andean cryosphere encompasses every component of the Earth system in which water
214 occurs in solid form, seasonal snow, glaciers, permafrost and other frozen materials in the
215 atmosphere, on land and in the oceans (Masiokas et al., 2020). Spanning more than 60° of
216 latitude, this domain is exceptionally diverse, ranging from tropical high-elevation glaciers
217 through the extensive temperate ice fields of Patagonia, where twentieth-century glacier
218 recession is well documented (Masiokas et al., 2008), to the seasonally snow-covered
219 mountains of the semi-arid sectors (Masiokas et al., 2020; Dussailant et al., 2019). The
220 resulting latitudinal and altitudinal gradients generate a strongly heterogeneous cryospheric
221 mosaic in which snow and ice regimes change markedly both along and across the range
222 (Masiokas et al., 2020). In the tropical Andes this gradient is also ecological: the snowline
223 and the treeline together bound the habitable mountain landscape and respond jointly to
224 climate variability (Young et al., 2016).

225 Hydrologically, the Andean cryosphere acts at once as a seasonal snow reservoir and as a
226 longer-term ice store that buffers downstream flow (Masiokas et al., 2020). This dependence
227 is strongest in the semi-arid sectors of central Chile and western Argentina, where solid
228 precipitation above the snowline governs most of the interannual variability in river discharge
229 (Masiokas et al., 2006). Changes in snow and ice storage therefore propagate directly to urban
230 supply, irrigation, hydropower and other water-dependent sectors in the adjacent lowlands
231 (Masiokas et al., 2020; McCarthy et al., 2022).

232 The recent central-Chile drought has laid bare the vulnerability of this system: as snowfall
233 declined, glacier melt became a non-negligible contributor to river flow during prolonged
234 precipitation deficits (Garreaud et al., 2017; McCarthy et al., 2022). Snow-dominated
235 catchments between about 30° and 35°S likewise reveal a long hydrological memory, in
236 which groundwater-supported baseflow and carry-over snowmelt amplify runoff deficits
237 during extended dry spells (Álvarez-Garretón et al., 2021). Within this setting, the altitude of
238 the snowline and its seasonal evolution emerge as sensitive indicators of both climate forcing
239 and hydrological response in Andean basins (Masiokas et al., 2020).



240 3.2 Snowline, freezing level and equilibrium line altitude



241
242 **Figure 2.** Conceptual diagram illustrating the vertical relationships among three key
243 mountain cryosphere metrics over the central Chilean Andes (29°-37°S). The Equilibrium
244 Line Altitude (ELA, purple line) marks the glacier surface where annual mass accumulation
245 equals ablation. The 0°C isotherm altitude (Z0°, red dashed line) represents the altitude in
246 the free atmosphere where air temperature is exactly 0°C, marking the level at which falling
247 precipitation transitions from snow to rain. The Local Snowline Altitude (ZSL, blue line) is
248 the actual lower boundary of visible seasonal snow cover on the mountain slope. During
249 precipitation events, ZSL is observed at an average of ~280m below Z0° due to mesoscale
250 cooling from melting hydrometeors and adiabatic cooling of orographically lifted air
251 (Schauwecker et al., 2022). The vertical arrow indicates this mean offset. The summary table
252 (bottom) compares the three metrics by domain, definition, primary driver, and temporal
253 scale.

254 The snowline is most defined as the lower altitudinal limit of seasonal snow cover on a
255 mountain slope after a precipitation or melt event, that is, the visible surface boundary
256 between snow-covered and snow-free terrain (Schauwecker et al., 2022). Its position
257 integrates the atmospheric and surface controls operating during storm and melt episodes,
258 precipitation phase, advection, radiative exchange and terrain-controlled microclimates
259 (Schauwecker et al., 2022). Importantly, the climatic sensitivity of this boundary is not fixed
260 but varies with the moisture regime. In the central Andes, Klein et al. (1999) showed that
261 snowlines in the humid eastern cordillera lie close to the mean annual 0 °C isotherm and
262 respond mainly to temperature, whereas in the more arid western cordillera they rise far
263 higher and are governed primarily by accumulation. ZSL therefore captures an instantaneous,
264 event-specific boundary whose very drivers are spatially variable, whereas snow-persistence
265 and regional-elevation metrics integrate this signal over longer windows and broader spatial
266 supports.



267 The altitude of the 0 °C isotherm (Z0°) is frequently used as a proxy for the rain-snow
268 transition, yet it is not equivalent to the surface snowline (Minder et al., 2011; Minder and
269 Kingsmill, 2013; Schauwecker et al., 2022). Mesoscale processes, isothermal layers, variable
270 lapse rates, windward -leeward contrasts and cold-air pooling, can displace the freezing level
271 from the actual surface snowline by several hundred meters, particularly in the steep, narrow
272 valleys typical of the Andes (Minder et al., 2011; Minder and Kingsmill, 2013; Schauwecker
273 et al., 2022). This offset is not merely theoretical: in the dry subtropical Chilean Andes,
274 Schauwecker et al. (2022) found that event snowlines typically lie below the 0 °C isotherm,
275 so substituting Z0° directly for snowline position introduces systematic conceptual and
276 operational mismatches.

277 The snowline is likewise related to, but not interchangeable with, the equilibrium-line altitude
278 (ELA) of glaciers. Whereas ZSL marks an instantaneous lower boundary of seasonal snow,
279 the ELA is the spatially averaged altitude at which glacier surface mass balance is zero over
280 a defined interval, separating the accumulation and ablation zones (Masiokas et al., 2020).
281 The two are physically coupled: Condom et al. (2007) reconstructed the ELA across the entire
282 Andes (10°N-55°S) from the 0 °C isotherm altitude and precipitation, and the end-of-summer
283 transient snowline is widely treated as a proxy for the ELA on individual glaciers. That proxy
284 relationship is not universal, however. Wu et al. (2014) demonstrated in the Tien Shan that
285 the optically derived snowline can depart substantially from the in-situ ELA where
286 accumulation and ablation occur simultaneously throughout the year, a caveat that is directly
287 relevant to the semi-arid Andes. In the central Chilean Andes, ELA reconstructions from
288 atmospheric variables reveal upward shifts consistent with regional warming since the late
289 twentieth century (Carrasco et al., 2005, 2008; Barría et al., 2019). Hydrologically, the
290 snowline and the ELA jointly govern the altitudinal distribution of seasonal snow and
291 perennial ice, and hence the timing and magnitude of meltwater delivery to rivers (Masiokas
292 et al., 2006; McCarthy et al., 2022).

293 Throughout this review, ZSL denotes local, scene-based estimates of the lower snow
294 boundary, whereas SLE and RSLE are reserved for catchment- and regional-scale metrics
295 derived from the joint elevation distribution of snow-covered and snow-free pixels (Hu et al.,
296 2019; Dietz et al., 2025). The distinction matters because the single term “snowline” can
297 denote different spatial supports and aggregation rules depending on the method applied.
298 Table 3 fixes these conceptual differences before the methodological comparison developed
299 in Section 4.



300 **Table 3. Conceptual distinctions among snowline-related metrics used in this review**

Concept / metric	Operational definition	Spatial scale	Temporal scale	Relation to snowline	Main sensitivity	Best suited use
Local Snowline Altitude (ZSL)	Lower boundary of visible seasonal snow in a single scene, derived from direct delineation or thresholding of the snow-land transition.	Hillslope / sub-basin / single glacier	Event / instantaneous	Direct surface snowline estimate	Clouds, shadows, subjective delineation, sub-pixel heterogeneity	Event-based monitoring and individual storm or melt episodes
Snowline Altitude / Transient Snowline (SLA / TSL)	Snowline extracted from an individual optical image, often after cloud masking and elevation filtering.	Hillslope / glacier / small catchment	Event / seasonal	Direct but scene-specific snowline estimate	Viewing geometry, cloud contamination, pixel mixing	Short-term snowline dynamics and seasonal melt evolution
0 °C Isotherm Altitude (Z0°)	Altitude in the free atmosphere where air temperature reaches 0 °C.	Atmospheric column / basin	Hourly to daily	Proxy, not equivalent to surface snowline	Lapse rate variability, cold-air pooling, terrain effects	Meteorological context for rain-snow transition
Equilibrium Line Altitude (ELA)	Altitude where glacier mass balance is zero over a defined period, separating accumulation and ablation zones.	Glacier / glacierized basin	Annual to multiyear	Related to snowline, but not equivalent	Climate forcing, glacier geometry, accumulation-ablation balance	Glacier-climate studies and long-term mass-balance interpretation
Snowline Elevation (SLE) / Regional Snowline Elevation (RSLE)	Catchment- or region-scale snowline derived from the elevation distribution of snow-covered and	Catchment / regional	Seasonal / multiyear	Regional snowline metric	DEM quality, classification errors, topographic heterogeneity	Trend detection and inter-basin comparison



	snow-free pixels.					
Snow Persistence (SP)	Fraction of a period during which a pixel remains snow covered.	Pixel / grid-cell / region	Seasonal / annual	Indirect snowline descriptor through snow zoning	Cloud gaps, temporal sampling, gap-filling assumptions	Snow-climate zonation and climatological snow distribution

301

302 3.3 Recent snowline changes: climatic drivers and global context

303 Snowline variability in the Andes is governed by regional and large-scale climate models
 304 that modulate both precipitation and temperature. The El Niño-Southern Oscillation (ENSO)
 305 and the Southern Annular Mode (SAM) strongly condition snow accumulation by shifting
 306 storm tracks, moisture transport and freezing-level heights (Garreaud, 2009; Masiokas et al.,
 307 2020). South of about 35°S, the extratropical westerlies dominate, delivering abundant
 308 snowfall on the windward Chilean flank while casting a heavy rain shadow over leeward
 309 Argentina (Viale et al., 2019b). Over recent decades a positive SAM trend has pushed the
 310 westerlies poleward, reducing cold-season precipitation and raising freezing levels across
 311 central Chile (Cordero et al., 2019; Garreaud et al., 2017).

312 These circulation changes coincided with the onset, since 2010 of the unprecedented central-
 313 Chile megadrought-sustained precipitation deficits, elevated temperatures and a marked
 314 decline in low-elevation snow events (Cordero et al., 2019; Garreaud et al., 2017). Under
 315 such conditions the snowline migrates upward, the snow season shortens and the extent of
 316 seasonal snow contracts, most sharply in basins whose climatological snowline already sits
 317 close to the 0 °C isotherm (Masiokas et al., 2020). The consequences are amplified in semi-
 318 arid basins, where snow storage carries a disproportionate share of the seasonal water supply
 319 and small upward shifts in snowline position translate into large changes in meltwater
 320 availability.

321 Satellite-based analyses for the extratropical Andes between roughly 29° and 36°S have
 322 reported upward trends in snowline metrics on the order of 10-30 m yr⁻¹ over recent decades,
 323 consistent with regional warming and rising freezing-level heights (Saavedra et al., 2018;
 324 Dietz et al., 2025). However, these rates should be interpreted cautiously because they are
 325 not directly comparable across metrics, sensors, time periods or aggregation rules. For that
 326 reason, this review treats the reported trends as evidence of a persistent upward tendency
 327 rather than as a single uniform rate for the entire Andes.

328 Comparable patterns of rising snowlines and shortening snow seasons have been documented
 329 across other mountain ranges, including the European Alps and High Mountain Asia, where
 330 regional snowline-elevation metrics prove especially sensitive to warming in mid-latitude
 331 and maritime-influenced settings (Hu et al., 2020; Prein and Heymsfield, 2020; Liu et al.,
 332 2021; Bernat et al., 2025). Indeed, the upward migration of the high-mountain snowline has
 333 been characterized as a global imprint of atmospheric warming (Li et al., 2026), while snow
 334 droughts have lengthened and intensified across several hotspots over recent decades
 335 (Huning and AghaKouchak, 2020). These analogues situate the Andean signal within a



336 broader global pattern and reinforce the value of robust, regionally consistent metrics such
337 as SLE and RSLE for detecting and comparing change across climatic regimes.

338

339 **4. Remote sensing methods for snowline detection**

340 Remote sensing products such as MODIS were designed to provide automated, consistent
341 inputs for climate studies, with improved snow-cloud discrimination and quality-assessment
342 information compared with earlier operational products (Hall et al., 2002). Building on this
343 foundation, Krajčů et al. (2014) introduced Regional Snowline Elevation (RSLE) as a
344 catchment-scale metric derived from MODIS imagery for seasonally snow-covered
345 mountain basins. Their method identifies the elevation at which the number of snow-covered
346 pixels below a given altitude equals the number of snow-free pixels above it, thereby
347 maximizing the correspondence between topography and snow-cover patterns. RSLE
348 therefore provides a topography-aware snowline metric that integrates information from
349 many pixels and reduces sensitivity to local cloud contamination and small-scale terrain
350 effects.

351 **4.1 Historical development of optical snowline metrics**

352 The most widely used technique for snow cover mapping from optical satellite sensors is the
353 Normalized Difference Snow Index (NDSI), which exploits the high reflectance of snow in
354 visible wavelengths and its strong absorption in shortwave infrared bands. Salomonson and
355 Appel (2004) showed that MODIS-based NDSI, when combined with threshold tests,
356 provides robust automated binary mapping of snow cover and established relationships
357 between NDSI values and fractional snow cover within 500 m pixels. This work extended
358 the binary snow-mapping approach underlying operational products such as MOD10A1 (Hall
359 et al., 2002) and marked a transition from binary snow/no-snow classification toward sub-
360 pixel representations of snow cover that are essential for snowline detection in heterogeneous
361 terrain.

362 Binary snow maps alone, however, do not resolve the geometry of the snowline, especially
363 in narrow valleys, complex topography, and partially cloud-covered scenes. This limitation
364 motivated the development of metric-specific approaches such as Regional Snowline
365 Elevation (RSLE), snowline altitude (SLA) and transient snowline (TSL), which use
366 elevation information to translate snow-cover distributions into snowline estimates.

367 Complementary scene-based approaches extract snowline altitude from individual optical
368 images, typically combining cloud-filtered fractional snow-cover products with digital
369 elevation models. An early Andean example is the spectral mixture analysis of Klein and
370 Isacks (1999), who unmixed Landsat TM imagery to locate the transient snowline on tropical
371 glaciers in Bolivia and Peru and showed that the end-of-summer snowline approximates the
372 equilibrium line. Subsequent work has automated the delineation: Tang et al. (2014) derived
373 a snowline-altitude field over the Tibetan Plateau for 2001-2013 from cloud-removed
374 MODIS fractional snow cover and a DEM, revealing strong seasonal and interannual SLA
375 variability and high correlations with melt-season temperature, while Racoviteanu et al.
376 (2019) developed an automated algorithm to estimate snowline altitudes from optical
377 imagery across High Mountain Asia. Comparable automated pipelines have been built
378 specifically for glaciers: Rastner et al. (2019) mapped glacier snow cover and computed
379 snowline altitudes from multi-temporal Landsat, and Shea et al. (2013) derived regional snow

lines from MODIS to constrain glacier mass change in western North America; earlier still, Turpin et al. (1997) used satellite-observed snowline rise to calibrate a glacier runoff model, an early demonstration of the metric’s hydrological value. Together these developments mark the shift from mapping snow presence alone toward deriving standardized, comparable snowline metrics across seasons, basins and climate regimes.

‘Monitoring the Andean Cryosphere: A Multi-Sensor Snowline Framework’

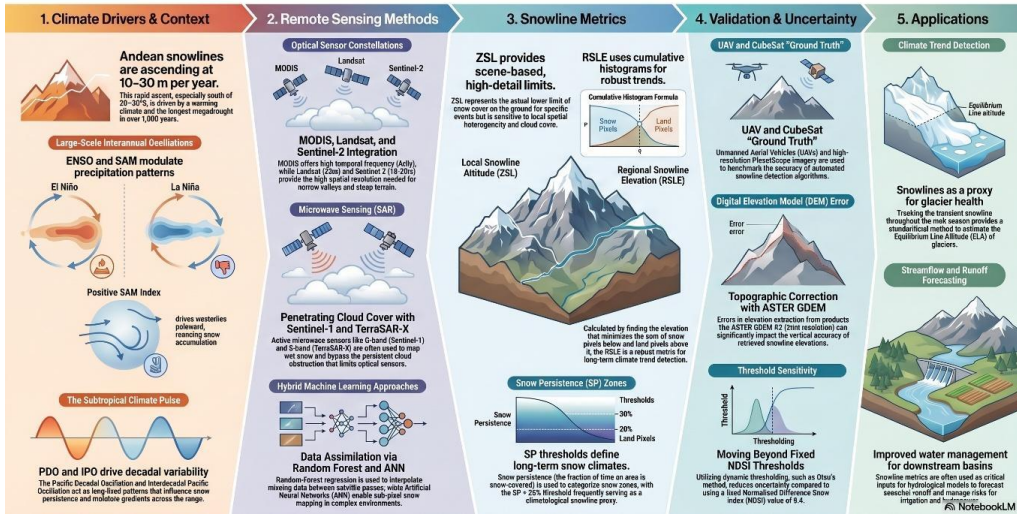


Figure 3. Integrated multi-sensor framework for Andean snowline monitoring, organized into five thematic blocks: (1) climate drivers and context (ENSO, SAM, PDO/IPO and the subtropical megadrought); (2) remote-sensing methods (optical constellations, microwave/SAR sensing and hybrid machine-learning approaches); (3) snowline metrics (ZSL, RSLE and snow-persistence zones); (4) validation and uncertainty (UAV/CubeSat ground truth, DEM error and threshold sensitivity); and (5) applications (climate-trend detection and streamflow forecasting).

4.2 Snowline metrics and their robustness under Andean conditions

Although several remote-sensing metrics are used to characterize the snowline, they are not methodologically equivalent and should not be interpreted as interchangeable under Andean conditions (Krajčič et al., 2014; Hu et al., 2019; Dietz et al., 2025). A central issue for this review is therefore not only how each metric is calculated, but also how each one responds to the main sources of uncertainty that affect snowline monitoring in the Andes, including cloud contamination, mixed pixels, DEM quality, threshold dependence and limited ground validation (Dietz et al., 2012; Choubin et al., 2019; Gascoin et al., 2024). From this perspective, the robustness of a snowline metric depends on its sensitivity to local noise, its capacity to scale across basins and climatic sectors, and its suitability for detecting long-term changes rather than isolated events.

Local snowline altitude (ZSL) is the most intuitive metric because it attempts to delineate the visible transition between snow-covered and snow-free terrain in individual scenes (Schauwecker et al., 2022; Tang et al., 2014). This makes ZSL useful for event-based analyses, storm reconstruction and high-resolution interpretation of hillslope-scale



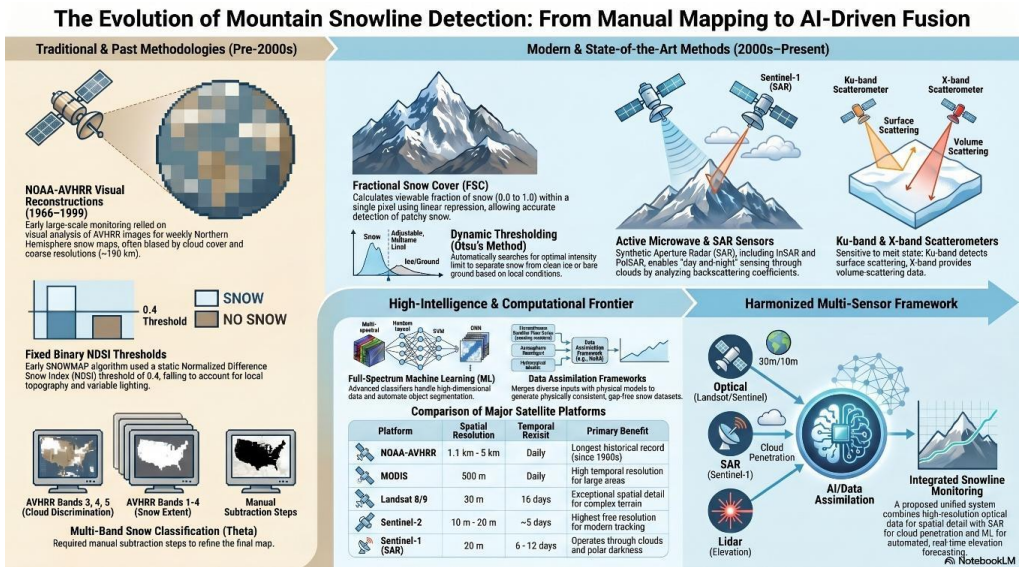
variability, particularly when Landsat or Sentinel-2 imagery is available (Tang et al., 2014; Xiao and Liang, 2024). However, its apparent simplicity masks substantial methodological fragility: ZSL is highly sensitive to partial cloud cover, terrain shadows, viewing geometry, sub-pixel heterogeneity and operator decisions regarding which boundary pixels represent the actual snowline (Dietz et al., 2012; Choubin et al., 2019; Gascoin et al., 2024). In steep Andean terrain, these factors can introduce strong scene-to-scene noise and limit the reproducibility of multi-decadal time series based on local delineations alone (Dietz et al., 2012; Choubin et al., 2019).

Catchment- and regional-scale metrics such as SLE and RSLE were developed to reduce this sensitivity to local noise by aggregating snow-cover information across many pixels and explicitly linking snow distribution to elevation (Krajčič et al., 2014; Hu et al., 2019; Dietz et al., 2025). In RSLE, the objective is not to trace a visible line on a single slope, but to identify the elevation that best separates snow-covered terrain below from snow-free terrain above at the basin or regional scale (Krajčič et al., 2014). This aggregation reduces the influence of local cloud contamination, isolated misclassified pixels and small-scale terrain heterogeneity, making SLE/RSLE more suitable for interannual comparison and trend detection across multiple basins (Krajčič et al., 2014; Aranda et al., 2023; Dietz et al., 2025). Even so, these metrics are not uncertainty-free, because their performance depends strongly on DEM resolution, vertical accuracy and the way snow/no-snow classifications are generated from optical data (Choubin et al., 2019; Dietz et al., 2012). In the Andes, where slopes are steep and relief is high, DEM errors and threshold choices can propagate into vertical snowline uncertainties of tens to hundreds of metres if they are not explicitly evaluated (Choubin et al., 2019; Harer et al., 2018). A recent Andean refinement of this family is the Maximum Dissimilarity Method (MDM) of Aranda et al. (2023), which retrieves SLE from MODIS even on cloudy days and over largely snow-covered basins by selecting the elevation that maximizes the statistical dissimilarity between snow and snow-free bands. Benchmarked against the regional snow-line elevation estimation method in a snowmelt-driven basin of the central Chilean Andes, the MDM recovered a coherent 22-year series and an upward SLE trend of about 21 m per year, illustrating how Andean studies are beginning to adapt, rather than merely import, regional snowline algorithms.

Snow persistence (SP) metrics provide a different but complementary perspective by integrating snow occurrence through time rather than estimating a snowline from a single image (Moore et al., 2015; Saavedra et al., 2017; Hammond et al., 2018). In this framework, the relevant variable is the fraction of a season or year during which each pixel remains snow-covered, allowing the delineation of intermittent, transitional and persistent snow zones (Moore et al., 2015; Saavedra et al., 2017). Because SP reduces dependence on individual scenes, it is less vulnerable than ZSL to transient cloud conditions and isolated classification errors, and it is especially useful for climatological zonation and long-term regional comparison (Saavedra et al., 2017; Hammond et al., 2018; Aranda et al., 2023). This is particularly relevant in the Andes, where SP-based approaches have been used to define snowline elevation from persistence thresholds and to detect upward migration of snow zones over recent decades (Saavedra et al., 2017; Saavedra et al., 2018). Nevertheless, SP is not a direct event-scale snowline metric, and its interpretation depends on the selected temporal window, gap-filling strategy and persistence threshold, so comparisons across studies can also become inconsistent when reporting standards are weak (Hammond et al., 2018; Aranda et al., 2023; Dietz et al., 2025).



454 Taken together, these contrasts show that metric selection should follow the research
455 objective rather than convention: ZSL suits event-scale or slope-specific analyses,
456 SLE/RSLE basin- to regional-scale trend assessment, and SP climatological zonation and
457 temporally integrated monitoring (Krajčič et al., 2014; Saavedra et al., 2017; Hu et al., 2019;
458 Dietz et al., 2025). Because each metric operates on a different spatial and temporal support,
459 the resulting Andean trends are not directly comparable even when all are labelled “snowline
460 change”; they must be treated as distinct analytical tools with their own uncertainty
461 structures, scaling properties and interpretive limits. This principle, developed once here,
462 underpins the methodological reading of observed trends in Section 5 and the
463 recommendations in Section 6. The consolidated metric- and approach-level comparison is
464 presented in Table 4 (Section 4.5).



465
466 **Figure 4.** Evolution of mountain snowline detection, from traditional manual interpretation
467 of coarse NOAA-AVHRR imagery and fixed NDSI thresholding (pre-2000s) toward
468 fractional snow cover, dynamic (Otsu-type) thresholding, active microwave and SAR
469 sensing, and AI-driven multi-sensor data assimilation (2000s-present). The lower table
470 compares the main satellite platforms (NOAA-AVHRR, MODIS, Landsat 8/9, Sentinel-2
471 and Sentinel-1) in terms of spatial resolution, temporal revisit and principal benefit for
472 snowline monitoring.

473 4.3 Optical methods and snow indices under Andean constraints

474 Optical methods remain the backbone of snowline monitoring in the Andes because they
475 provide long time series, relatively high spatial detail, and direct sensitivity to surface snow
476 cover conditions (Salomonson and Appel, 2004; Saavedra et al., 2017; Hall et al., 2002).
477 However, their performance in the Andes is constrained by persistent cloud cover, strong
478 topographic shading, aridity, and high surface reflectance from bare rock and soil, all of
479 which complicate the interpretation of snow masks and the derivation of snowline metrics
480 (Dietz et al., 2012; Gascoin et al., 2024). For this reason, optical methods should be treated
481 not as a single universal solution, but as a family of approaches whose suitability depends on



482 the metric being estimated, the spatial scale of the analysis, and the level of uncertainty that
483 can be tolerated.

484 Traditional applications commonly use fixed NDSI thresholds to derive binary snow maps
485 from MODIS, Landsat, or Sentinel-2 data, but these thresholds can be problematic in semi-
486 arid Andean environments where bright non-snow surfaces are frequent (Dietz et al., 2012;
487 Salomonson and Appel, 2004; Saavedra et al., 2017). Threshold choice should not be treated
488 as a minor technical detail, because it directly affects robustness, reproducibility, and
489 comparability across studies. In steep terrain, small shifts in classification can translate into
490 large changes in estimated snowline elevation, so threshold sensitivity should be treated
491 explicitly as a source of methodological uncertainty rather than as a background issue
492 (Choubin et al., 2019; Harer et al., 2018).

493 Adaptive approaches such as Otsu-based thresholding and multi-index classification can
494 reduce some of these biases by allowing thresholds to respond to local scene conditions rather
495 than imposing a fixed global cutoff (Otsu, 1979; Masson et al., 2018; Bhardwaj et al., 2015).
496 This is particularly relevant in the Andes, where illumination, land cover, and snow
497 properties vary strongly with elevation and exposure, and where a single binary threshold
498 may not transfer well across catchments or seasons. At the same time, adaptive methods
499 introduce their own challenges, because they may improve local classification while reducing
500 direct comparability across time or between basins if the decision rules are not reported
501 transparently.

502 **4.3.1 Fractional snow cover approaches**

503 Fractional snow-cover (FSC) products provide a firmer basis for snowline analysis than
504 binary snow/no-snow maps because they resolve the sub-pixel heterogeneity that pervades
505 mountain terrain (Salomonson and Appel, 2004; Rittger et al., 2013). This is critical in the
506 Andes, where the snowline frequently falls within mixed pixels, in narrow valleys, on steep
507 slopes and across the transition between persistent snow and exposed ground (Saavedra et
508 al., 2017). Cloud-removed MODIS FSC data have been used to derive snowline-altitude
509 fields and quantify seasonal variability over large mountain regions, a useful analogue for
510 Andean applications (Tang et al., 2014). The approach has also been demonstrated directly
511 in the Andes: Cortés et al. (2014) applied spectral unmixing to the historical Landsat archive
512 to retrieve sub-pixel snow and ice extent over the extratropical Andes, validating the
513 retrievals against high-resolution imagery and extracting multidecadal trend evidence that
514 FSC unmixing is viable for long-term Andean snowline monitoring.

515 Fractional snow cover is also helpful for connecting local snowline estimates with regional
516 metrics such as SLE and RSLE, because it provides a more continuous representation of the
517 snow-no snow transition than binary classification alone. Recent assessments of snow-cover
518 mapping algorithms indicate that multi-index and fractional approaches generally outperform
519 simple fixed-threshold methods in heterogeneous terrain, especially when forests, shadows,
520 or bright rock surfaces are present (Masson et al., 2018; Teleubay et al., 2022). For the Andes,
521 this suggests that FSC-based workflows should be prioritized where the goal is
522 methodological robustness rather than simply maximizing operational simplicity.



523 **4.3.2 DEM dependence and topographic sensitivity**

524 The estimation of snowline elevation from optical imagery depends strongly on the quality
525 of the underlying DEM because elevation is the vertical reference used to locate the snowline
526 boundary (Choubin et al., 2019). In steep Andean terrain, even moderate vertical errors can
527 produce substantial horizontal displacement of the snowline boundary, which affects both
528 ZSL and elevation-based metrics such as SLE and RSLE. This issue is central to a rigorous
529 treatment of uncertainty propagation, encompassing DEM sensitivity, mixed pixels, and
530 threshold effects.

531 The manuscript should therefore avoid presenting DEM use as a routine preprocessing step
532 and instead describe it as a source of structural uncertainty that must be documented, tested,
533 and, where possible, propagated into the final snowline estimates (Choubin et al., 2019).
534 Studies in high-relief environments show that DEM errors, terrain ruggedness, and the choice
535 of elevation binning rules can alter reported snowline values enough to affect multi-year trend
536 interpretation, particularly when the analysis seeks to compare basins or sensors. This is one
537 of the reasons why RSLE and SP-based metrics are often more defensible for long-term
538 comparisons than single-scene ZSL estimates.

539 **4.3.3 Cloud gaps and compositing**

540 Cloud contamination is one of the principal limitations of optical snowline detection in the
541 Andes because it reduces the number of usable scenes and increases the risk of biased
542 snowline estimates in storm-prone or persistently cloudy seasons (Dietz et al., 2012;
543 Saavedra et al., 2017; Gascoin et al., 2024). Temporal compositing, cloud masking, and gap-
544 filling strategies can partially alleviate this problem, but they also introduce assumptions that
545 should be stated explicitly in any scientific studies. Snowline studies should not overstate the
546 precision of optical snowline estimates without acknowledging that scene availability itself
547 can control the reliability of the resulting trend analysis.

548 Recent work in the tropical Andes shows that MODIS MOD10A1 products processed in
549 Google Earth Engine can yield long snow-cover-area time series when paired with Landsat-
550 based validation masks, underscoring the value of cloud-based workflows for large-scale
551 monitoring (Calizaya et al., 2023). Cloud contamination itself can be mitigated rather than
552 merely tolerated: Saavedra et al. (2026) applied multi-step spatio-temporal gap-filling to
553 MODIS snow products over the central Andes, substantially increasing the number of cloud-
554 free observations available for trend analysis and reducing the bias that intermittent cloud
555 cover imposes on snowline estimates. These results indicate that operational optical
556 workflows in the Andes are most effective when they couple automated processing and
557 explicit cloud reduction with a metric that absorbs residual missing-data effects, such as SP
558 or RSLE. Optical methods are therefore best framed not as a standalone solution but as a core
559 component of a multi-metric monitoring system.

560 **4.4 SAR and microwave methods for snowline detection**

561 Synthetic Aperture Radar (SAR) is a valuable complement to optical methods because it can
562 acquire data regardless of daylight and cloud cover, which is a major advantage in
563 mountainous environments with frequent winter cloud contamination (Tsai et al., 2019). Its
564 signal is sensitive to snow dielectric properties, grain structure, and especially liquid water
565 content, meaning that wet snow typically produces much lower backscatter than dry snow or
566 bare ground, which can be exploited to identify the transient snowline (TSL) (Tsai et al.,



567 2019). In a review focused on the Andes, this advantage should be framed carefully: SAR is
568 not universally superior, but it is particularly useful when optical observations are incomplete
569 or temporally sparse.

570 The main methodological challenge is that SAR interpretation in steep terrain is strongly
571 affected by geometric distortions such as layover and foreshortening, as well as by
572 shadowing, incidence angle variability, and coherence loss (Callegari et al., 2016; Tsai et al.,
573 2019). These effects are especially relevant in the Andes because extreme relief can distort
574 the radar geometry enough to complicate the separation between snow, ice, rock, and
575 vegetation. For that reason, SAR-based snowline products should always be presented
576 together with a clear discussion of topographic correction and scene geometry, otherwise the
577 method can appear more robust than it really is

578 Polarimetric SAR improves snowline detection by adding scattering information that helps
579 separate wet snow from other surfaces. Li et al. (2012) proposed glacier snowline detection
580 using polarimetric SAR and Support Vector Machine (SVM) classification, defining the TSL
581 as the boundary between wet snow and ice on the classification map. Callegari et al. (2016)
582 showed that topographic correction and polarimetric decomposition features improve
583 classification performance, with accuracy gains over backscatter-only methods and higher
584 performance for fully polarimetric configurations than for simpler dual-pol setups. Although
585 these examples are not Andean, they are methodologically relevant because they show that
586 SAR is most effective when geometry, scattering mechanism and surface state are handled
587 explicitly rather than treated as secondary details. Beyond mapping, the transient snowline
588 retrieved from such imagery can itself constrain glacier mass balance: Barandun et al. (2018)
589 reconstructed multi-decadal mass-balance series for Kyrgyz glaciers in the Tien Shan from
590 transient-snowline observations, illustrating how snowline products feed directly into
591 climate-relevant variables in data-sparse high mountains.

592 Interferometric SAR (InSAR) has been explored for snow-depth and snow-water-equivalent
593 (SWE) retrieval, which can indirectly support snowline analysis by improving snow-state
594 characterization in space and time (Schaffhauser et al., 2008). Interest has intensified with
595 longer-wavelength sensors: L-band InSAR penetrates the snowpack more effectively and has
596 emerged as a promising route to spatially distributed SWE, although retrievals still hinge on
597 phase-unwrapping accuracy and on changes in snow density and stratigraphy between
598 acquisitions; assessments over shallow, heterogeneous snowpacks confirm both the promise
599 and the strong sensitivity of these retrievals to snow state (Bonnell, 2024; Palomäki and
600 Sproles, 2023). These applications nonetheless remain difficult, because temporal
601 decorrelation, variable snow metamorphism and complex scattering reduce retrieval stability,
602 particularly in operational settings. In the Andes, InSAR is therefore best presented as an
603 emerging complement rather than a routine snowline-monitoring solution, pending further
604 validation and a stronger empirical record in steep mountain terrain gap that upcoming L-
605 and S-band missions are well placed to fill.

606 Overall, SAR is best treated in this review as the most promising all-weather alternative for
607 cloud-prone periods, but also as a method whose usefulness depends heavily on terrain
608 correction, acquisition geometry, and the snow condition being observed (Tsai et al., 2019).
609 In practical terms, SAR is most valuable when it is used to support optical snowline metrics,
610 not to replace them entirely, and when the review explicitly distinguishes wet-snow
611 detection, dry-snow ambiguity, and geometry-driven uncertainty.



612 **4.5 Hybrid, data-assimilation and machine-learning approaches**

613 Hybrid approaches combine optical, microwave, atmospheric, and model-based information
614 to infer snowline behavior indirectly through snow cover depletion, snow water equivalent,
615 or snow-state transitions when direct optical detection is limited by cloud cover or complex
616 terrain (Dietz et al., 2012; Cortés and Margulis, 2017). In the Andes, this type of integration
617 is especially relevant because snowline monitoring is constrained by persistent cloud
618 contamination, strong topographic gradients, limited in situ validation, and the coexistence
619 of multiple non-equivalent metrics such as ZSL, SLE/RSLE and SP. Rather than replacing
620 snowline metrics, hybrid systems should be understood as frameworks that improve their
621 consistency, spatial continuity and operational usability across time and space.

622 Cortés and Margulis (2017) illustrated this logic by assimilating Landsat-derived snow
623 depletion information into a high-resolution SWE reanalysis over the extratropical Andes,
624 showing that remote sensing can effectively constrain model estimates in data-sparse basins.
625 This is important for the present review because it demonstrates that snowline-related
626 observations can play a role beyond mapping: they can also serve as boundary conditions,
627 validation layers, or calibration targets for hydrological and land-surface models. In that
628 sense, hybrid methods are not merely technical add-ons, but an avenue for connecting
629 snowline monitoring with runoff prediction and climate-impact assessment.

630 Data-assimilation and data-fusion approaches are particularly useful when the snowline is
631 intermittently obscured or when the objective is a continuous basin-scale variable rather than
632 a scene-based boundary. Merging Landsat, MODIS, reanalysis and land-surface-model
633 outputs reduce uncertainty relative to any single source, especially where cloud gaps, spatial
634 aliasing or sensor-specific biases would otherwise dominate the signal. Spatio-temporal
635 fusion offers a complementary route to the same end: Yang et al. (2024) fused polar-orbiting
636 Sentinel-3 with geostationary Himawari-9 imagery and found that an enhanced spatio-
637 temporal adaptive reflectance fusion model (ESTARFM) reconstructed cloud-gap snow
638 cover in mountainous terrain more faithfully than a simpler multi-temporal scheme,
639 recovering sub-daily snow dynamics that any single sensor would miss. Such methods
640 nonetheless demand care: they add robustness only when the target variable, the error
641 structure and the validation strategy are explicitly defined.

642 Machine-learning methods extend this logic by learning relationships among optical, SAR,
643 topographic, and climatic predictors, with the goal of improving snow classification, gap-
644 filling, or sub-pixel snow-cover retrieval. Snauffer et al. (2018) showed that neural-network
645 fusion of multiple SWE products and covariates can outperform individual products and
646 simpler regression approaches, suggesting a potentially valuable pathway for Andean
647 applications where complex terrain and sparse observations limit conventional calibration.
648 At the same time, the Andes still lack dense high-elevation training and validation datasets,
649 which means that machine-learning outputs should be interpreted as model-assisted estimates
650 rather than direct observations.

651 From a methodological standpoint, the most promising hybrid workflow for the Andes is not
652 a fully generic “black box” fusion system, but a tiered framework in which optical
653 ZSL/SLE/RSLE or SP products are first derived, then corrected or complemented using SAR
654 and model-based information and finally evaluated against any available in situ or
655 photographic evidence. This tiered logic responds directly to the need for a more operational



656 and reproducible framework, because it links metric selection, uncertainty handling and data
657 fusion within a single methodological pathway (Dietz et al., 2012; Gascoin et al., 2024). In
658 this review, hybrid approaches are therefore positioned as the most flexible route toward
659 near-real-time, cloud-resilient and basin-scale snowline monitoring, if uncertainties are
660 explicitly propagated and the limits of each input source are documented.

661 To compare the available snowline monitoring approaches in a meaningful way, the review
662 organizes them according to the criteria most relevant to a methodological assessment: spatial
663 scale, temporal scale, principal strengths, key limitations, dominant sources of uncertainty,
664 and best-suited analytical objective.

665 As Table 4 makes explicit, these approaches are complementary rather than interchangeable:
666 local optical estimates give the most direct but least reproducible boundary, SP best captures
667 regime zonation, SLE/RSLE are most robust for multi-decadal trends, and SAR and fusion
668 extend observation under persistent cloud (Krajčič et al., 2014; Saavedra et al., 2017; Hu et
669 al., 2019; Dietz et al., 2025).

670 The comparison also makes clear that sensor choice cannot be separated from metric choice.
671 Optical approaches offer higher geometric fidelity and direct boundary visualization, but they
672 are constrained by aridity, cloud cover and threshold sensitivity; SAR adds all-weather
673 capability, yet introduces its own geometric and interpretive uncertainties in steep Andean
674 terrain; and hybrid or data-assimilation approaches improve continuity and operational
675 relevance only when their input data, target variable and uncertainty structure are explicitly
676 defined (Tsai et al., 2019; Hu et al., 2019; Gascoin et al., 2024). In that sense, the table is not
677 only a summary of methods, but a decision framework for matching each approach to a
678 specific monitoring objective.



Table 4. Comparative evaluation of snowline metrics and monitoring approaches in the Andes

Approach	Metric / output	Main data sources	Spatial scale	Temporal scale	Main strengths	Main limitations	Key uncertainty sources	Best suited for	Relative robustness
Local optical snowline	ZSL / SLA / TSL	Landsat, Sentinel-2, MODIS FSC	Hillslope, glacier, sub-basin	Event to seasonal	High spatial detail, direct boundary observation	Sensitive to clouds, shadows, subjective delineation, mixed pixels	Cloud gaps, threshold choice, DEM quality, sub-pixel heterogeneity	Event-scale snowline mapping, storm response	Low to moderate
Snow persistence	SP zones	MODIS, Landsat time series, Sentinel-2 composites	Pixel, basin, regional zonation	Seasonal to multiannual	Integrates snow dynamics through time, useful for snow regime zonation	Not a direct elevation metric, depends on compositing and data continuity	Temporal gap filling, cloud masking, compositing rules	Climatic zoning, snow regime classification	Moderate to high
Regional snowline elevation	SLE / RSLE	MODIS, Landsat, Sentinel-2, DEM	Catchment to regional	Seasonal to multiannual	More stable for trend detection, less sensitive to local clouds and heterogeneity	Depending on DEM accuracy, may smooth local variability	DEM vertical error, elevation binning, classification error	Long-term trend detection, basin comparison	High
Fixed-threshold optical	Binary snow map	MODIS, Landsat, Sentinel-2	Scene to regional	Daily to seasonal	Simple, operational, long archives	Threshold transferability poor in arid/high	NDSI threshold sensitivity, brightness confusions	Broad snow cover mapping	Low



						-relief terrain	n, shadow effects		
Dynam ic optical	Adapti ve snow map / FSC	Landsat, Sentinel- 2, MODIS FSC	Scene to region al	Daily to season al	Better scene adaptatio n, improved snow discrimin ation	More complex and less standardi zed	Algorith m choice, training data, validatio n scarcity	Comple x terrain, heteroge neous land cover	Moder ate
SAR backsc atter	Wet- snow / snow state map	Sentinel- 1, TerraSA R-X	Scene to region al	Event to sub- weekly	All- weather, day/night capabilit y	Dry snow ambiguit y, geometr y distorti ons, interpret ation com plexity	Layover, foreshort ening, incidence angle, coherenc e loss	Cloud- prone periods, wet- snow detectio n	Moder ate
PolSA R	Wet snow / TSL	Fully polarime tric SAR	Scene to glacie r / basin	Event to season al	Stronger surface discrimin ation than backscatt er-only	Limited availabil ity, higher processi ng burden	Polarime tric decompo sition, topograp hic correctio n, classifica tion error	Researc h- focused snowline mapping	Moder ate
InSAR	Snow depth / SWE proxy	Interfero metric SAR	Scene to basin	Event to season al	Indirect snow- state informati on, complem entary to other data	Tempora l decorrela tion, complex interpret ation	Phase noise, coherenc e decay, snow metamor phism	Experim ental snow- state estimati on	Low to moder ate



Hybrid assimilation	Continuous snow state	Optical + SAR + reanalyses + models	Basin to regional	Continuous or gap-filled	Best continuity, supports forecasting and calibration	Model dependence, calibration burden	Model structure error, observation error, forcing uncertainty	Operational hydrology, forecasting	High if well validated
Machine learning fusion	Gap-filled snowline / FSC / SWE proxy	Optical + SAR + terrain + climate covariates	Basin to regional	Continuous or near-real-time	Nonlinear integration of predictors, gap filling	Training data scarcity, interpretability issues	Training bias, overfitting, domain transfer	Regional mapping and automation	Moderate to high

681

682 No single approach is therefore optimal across all Andean applications; the practical mapping
683 of method to objective is summarized in Table 4 and revisited as operational guidance in
684 Table 6 (Section 6.6).

685 **5. Observed snowlines change in the Andes and global context**

686 Satellite remote sensing has revealed coherent evidence of upward snowline shifts across
687 large portions of the Andes, together with shorter snow seasons and a lower frequency of
688 snow occurrence at low elevations (Saavedra et al., 2018; Cordero et al., 2019; Masiokas et
689 al., 2020). In the extratropical Andes between about 29° and 36°S, MODIS- and Landsat-
690 based analyses indicate increases in snowline-related metrics on the order of 10-30 m yr⁻¹,
691 although the magnitude and interpretation of these trends depend on the metric, study period,
692 and analytical approach used (Saavedra et al., 2018; Dietz et al., 2025). This distinction is
693 essential for the present review, because a trend derived from SP-based snow zones is not
694 directly equivalent to a trend based on scene-scale ZSL or basin-scale RSLE (Saavedra et al.,
695 2017; Hu et al., 2019; Dietz et al., 2025).

696 **5.1 Observed changes across the Andes**

697 Across the central and extratropical Andes, the dominant signal is an upward displacement
698 of the snowline, particularly in semi-arid sectors where the seasonal snow cover is highly
699 sensitive to changes in freezing level and precipitation phase (Masiokas et al., 2020; Dietz et
700 al., 2025). In these regions, reductions in low-elevation snow occurrence and contractions of
701 intermittent snow zones have been documented using both persistence-based and elevation-
702 based metrics, indicating that the most climate-sensitive portions of the snow regime are
703 shifting upslope (Saavedra et al., 2017; Saavedra et al., 2018; Aranda et al., 2023). Reported
704 changes are nevertheless spatially heterogeneous, reflecting differences in latitude, relief,
705 storm exposure, basin size and sensor availability across the Andes (Masiokas et al., 2020;
706 Gascoin et al., 2024).

707 The tropical Andes and Patagonia likewise show snow-cover and snowline changes, but their
708 observational density, sensor strategies and climatic interpretation differ from those of the



709 semi-arid central Andes, making direct comparison less straightforward (Masiokas et al.,
710 2020; Gascoin et al., 2024). In the tropical Andes, glacier-scale studies report rising end-of-
711 summer snowlines against a broader, multi-decadal decline of tropical snow and ice (Rabatel
712 et al., 2013; Vuille et al., 2018): Veettil et al. (2016), for example, documented an upward
713 shift of the annual maximum snowline on Cordillera Blanca glaciers (Peru) between 1984
714 and 2015. At the extratropical end, the Landsat-based sub-pixel record of Cortés et al. (2014)
715 revealed widespread declines in minimum annual snow and ice extent over 1986-2013. Even
716 so, the strongest synthesis currently available concerns the extratropical Andes, where longer
717 time series and more consistent use of MODIS-based products have enabled clearer
718 identification of multi-decadal tendencies (Saavedra et al., 2018; Aranda et al., 2023; Dietz
719 et al., 2025). This uneven regional evidence base reinforces the need to distinguish a robust
720 regional pattern of rising snowlines from the far more variable confidence attached to local
721 magnitudes and specific trend estimates.

722

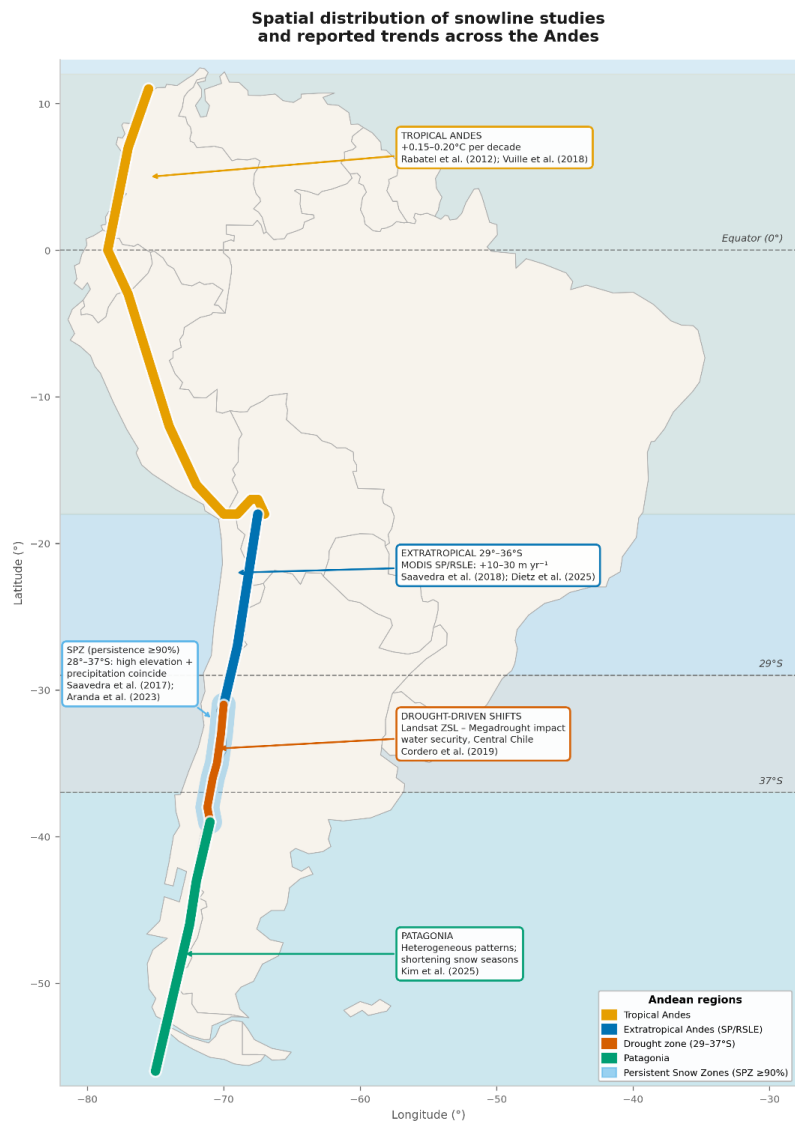


Figure 5. Spatial distribution of snowline studies and reported trends across the Andes. Key patterns include the rapid decline of tropical snow and ice, MODIS SP/RSLE increases of 10-30 m yr⁻¹ in the extratropical Andes (29-36°S), drought-driven snowline shifts associated with the central-Chile megadrought, persistent snow zones (SP ≥ 90%) concentrated between 28° and 37°S, and heterogeneous snow-season patterns across Patagonia.



729 5.2 Drivers and regional contrasts

730 The main climatic controls on Andean snowline change are temperature, precipitation
731 amount, precipitation phase and large-scale circulation variability, especially through ENSO,
732 PDO and SAM influences on storm tracks, atmospheric-river activity and freezing-level
733 altitude (Garreaud, 2009; Garreaud et al., 2017; Masiokas et al., 2020; Viale et al., 2018,
734 2019a). In central Chile, the persistent megadrought since 2010 has been associated with
735 warmer conditions, reduced cold-season precipitation and fewer low-elevation snowfall
736 events, all of which favor upward migration of the snowline (Garreaud et al., 2017; Cordero
737 et al., 2019; Masiokas et al., 2020). These mechanisms are especially important in basins
738 where climatological snowlines lie close to the freezing-level transition zone, because
739 relatively small atmospheric shifts can produce strong altitudinal responses in snow
740 occurrence (Masiokas et al., 2020; Pepin et al., 2015).

741 At the same time, the expression of these drivers depends on the metric used to summarize
742 snowline behavior (Hu et al., 2019; Dietz et al., 2025). SP-based approaches tend to
743 emphasize persistent changes in the temporal frequency of snow cover, whereas ZSL-type
744 products are more sensitive to event-scale conditions and RSLE-type metrics capture
745 integrated basin- or region-scale elevation responses (Saavedra et al., 2017; Saavedra et al.,
746 2018; Krajčič et al., 2014; Hu et al., 2019). As a result, the same underlying climatic forcing
747 may appear as a contraction of intermittent snow zones, an upward migration of a local snow
748 boundary, or a gradual increase in regional snowline elevation depending on the
749 observational framework adopted (Saavedra et al., 2018; Aranda et al., 2023; Dietz et al.,
750 2025).

751 5.3 Global comparison

752 The Andean evidence is broadly consistent with findings from other mountain systems. In
753 the European Alps, snow cover is receding and snow seasons are shortening (Beniston, 2012;
754 Hu et al., 2020), while in High Mountain Asia satellite analyses report upward snowline shifts
755 and reduced snow persistence (Prein and Heymsfield, 2020; Liu et al., 2021; Pandey et al.,
756 2024; Bernat et al., 2025). The pattern extends to the Mediterranean mountains, where snow
757 is a critical but increasingly stressed water resource (Fayad et al., 2017), and to the Southern
758 Hemisphere, where four decades of observations in the New Zealand Southern Alps reveal a
759 rising snowline and coherent glacier-climate responses (Lorrey et al., 2022), and a satellite
760 census of Southern Hemisphere glaciers documents broadly rising snowline altitudes from
761 2000 to 2023 (MacFee et al., 2025). On the global scale, satellite records document a broad
762 decline in snow cover over recent decades (Young, 2023). This convergence supports
763 interpreting Andean snowline rise as part of a wider pattern of elevation-dependent warming
764 on mountain cryospheres (Pepin et al., 2015; Arias et al., 2021). Cross-regional comparison
765 must nonetheless remain cautious, because snowline sensitivity reflects not only climate
766 forcing but also relief, cloud regime, precipitation seasonality, sensor selection and the metric
767 chosen to define snowline change (Hu et al., 2019; Gascoin et al., 2024; Dietz et al., 2025).

768 For this reason, the global comparison is useful primarily as contextual support rather than
769 as proof of strict equivalence between regional trends. The Andes share the general direction
770 of change reported elsewhere, but the interpretation of magnitude remains conditioned by
771 uneven validation, high-relief terrain, data scarcity and methodological heterogeneity
772 (Masiokas et al., 2020; Gascoin et al., 2024). Cross-regional comparability thus depends as



773 much on metric standardization as on shared climatic signals (Hu et al., 2019; Dietz et al.,
774 2025).

775 Because the metrics summarized above operate on different spatial and temporal supports
776 (Section 4.2), the trends they yield cannot be pooled into a single value. Accordingly, the
777 most defensible conclusion from the available evidence is not that a single number
778 summarizes Andean snowline change, but that multiple snowline formulations consistently
779 indicate an upward tendency, while differing in the magnitude, uncertainty and interpretation
780 of that change (Saavedra et al., 2018; Aranda et al., 2023; Dietz et al., 2025).

781 **6. Methodological gaps and future directions**

782 The current Andean literature demonstrates substantial progress in satellite-based snowline
783 monitoring, but it still falls short of a fully standardized, reproducible and operational
784 framework for comparing snowline dynamics across basins and sensors (Masiokas et al.,
785 2020; Gascoin et al., 2024). The main limitation is not the absence of observations, but the
786 lack of methodological harmonization in how snowline metrics are defined, extracted,
787 validated and interpreted (Saavedra et al., 2018; Hu et al., 2019; Dietz et al., 2025). For that
788 reason, future work should prioritize conceptual clarity, consistent reporting and explicit
789 uncertainty treatment rather than simply expanding the number of case studies.

790 **6.1 Harmonizing snowline definitions and reporting**

791 A first priority is to standardize snowline terminology and report metrics so that studies
792 remain comparable across the Andes and beyond (Krajčič et al., 2014; Saavedra et al., 2017;
793 Hu et al., 2019). Existing studies deploy ZSL, SLA, TSL, SLE, RSLE and SP-based zones
794 in ways that are sometimes operationally similar yet conceptually distinct, which hampers
795 synthesis and invites incorrect cross-study comparisons (Saavedra et al., 2018; Choubin et
796 al., 2019; Dietz et al., 2025). Progress toward standardization is feasible: Wayand et al.
797 (2018) defined a set of globally scalable alpine snow metrics computed automatically from
798 Landsat-8 and Sentinel-2 in Google Earth Engine, showing that consistent, transferable
799 definitions can be applied across disparate mountain ranges. Building on such efforts, this
800 review recommends that every study explicitly reports the metric definition, spatial
801 aggregation unit, temporal window, snow-map source and elevation reference used to derive
802 its snowline products (Hu et al., 2019; Dietz et al., 2025).

803 In practice this means avoiding generic statements such as “the snowline rose” unless the
804 underlying metric, sensor and uncertainty are specified, so that a ZSL trend is never equated
805 with an SP or RSLE trend. Standardized terminology is, in this sense, a prerequisite for any
806 credible benchmarking effort in the Andes.

807 **6.2 Formal uncertainty propagation**

808 A second priority is the explicit quantification and propagation of uncertainty, which remains
809 underdeveloped in most Andean studies despite being central to the interpretation of
810 snowline trends (Choubin et al., 2019; Gascoin et al., 2024). Optical snowline products are
811 affected by cloud contamination, shadowing, mixed pixels and threshold sensitivity, while
812 RSLE and SLE add DEM-related uncertainty and sensitivity to elevation binning (Dietz et
813 al., 2012; Harer et al., 2018; Choubin et al., 2019). SAR-based methods face a different
814 uncertainty structure, dominated by layover, foreshortening, incidence-angle effects, wet-
815 snow ambiguity and coherence loss in steep terrain (Tsai et al., 2019; Callegari et al., 2016).



The review should therefore encourage studies to report uncertainty budgets rather than only final snowline values or trends. At minimum, this includes sensitivity tests for thresholds, DEM quality, cloud masking choices and pixel aggregation rules, together with error propagation derived into trend estimates (Dietz et al., 2012; Choubin et al., 2019; Gascoin et al., 2024). For Andean applications, uncertainty reporting is particularly important because small vertical changes can produce large apparent shifts in snowline position in steep slopes and narrow valleys.

Table 5. Main uncertainty sources across snowline methods

Uncertainty source	Affects most strongly	Effect on result	Typical mitigation
Cloud contamination	Optical ZSL, FSC, SLE/RSLE	Missing or biased snow boundaries	Cloud masking, compositing, SAR fusion
DEM vertical error	SLE, RSLE, ZSL	Elevation bias, boundary displacement	Higher-quality DEMs, sensitivity analysis
Threshold choice	Optical binary and fractional products	Snow over/underestimation	Adaptive thresholds, multi-index schemes
Mixed pixels	Optical ZSL, FSC	Boundary smoothing, uncertainty in transition zone	High-resolution data, fractional products
Topographic shadow	Optical methods	False snow/no-snow classification	Terrain correction, illumination normalization
Layover / foreshortening	SAR	Geometric distortion of terrain response	Terrain correction, acquisition planning
Coherence loss	InSAR	Reduced retrieval stability	Short revisit times, scene selection
Cross-sensor inconsistency	Multi-sensor fusion	Non-comparable outputs	Harmonized preprocessing and validation

824

825 6.3 Improving validation and ground truth

826 Validation remains one of the weakest parts of the current literature, largely because in situ
827 observations near the seasonal snowline are sparse and unevenly distributed across the Andes
828 (Masiokas et al., 2020; McCarthy et al., 2022). Most studies report trends but do not provide
829 systematic pixel-level validation against independent field data, high-resolution imagery or
830 UAV surveys, which limit confidence in their derived products (Dietz et al., 2012; Gascoin
831 et al., 2024). This remains a key gap for improving validation, reproducibility and operational
832 credibility.

833 Future work should combine station observations, snow courses, UAV mapping, very-high-
834 resolution satellite imagery and, where available, airborne data to validate ZSL, SLE and
835 RSLE products across representative elevation bands (Rittger et al., 2013; Choubin et al.,
836 2019; Özen et al., 2024). Emerging Andean datasets already point the way: satellite tri-stereo
837 photogrammetry has been used to map high-elevation snow depth in the central Chilean
838 Andes (Shaw et al., 2020), providing a spatially distributed reference against which snowline
839 retrievals can be checked, while networks of public webcam images have been shown to
840 yield regional snowline-elevation estimates at low cost (Portenier et al., 2022), a particularly
841 attractive option for the data-scarce Andes. A practical strategy is to locate validation sites
842 around the climatological snowline and to report standard performance metrics, overall



843 accuracy, precision, recall, Dice coefficient and F1-score, rather than relying on visual
844 agreement alone (Gascoin et al., 2024; Özen et al., 2024).

845 **6.4 Strengthening SAR and multi-sensor workflows**

846 SAR remains underused in the Andes despite its clear potential under cloudy conditions and
847 its ability to complement optical observations when cloud cover limits scene availability
848 (Tsai et al., 2019; Gascoin et al., 2024). The current challenge is not whether SAR is useful
849 in principle, but how to adapt its processing to steep Andean terrain without overclaiming
850 robustness. Future studies should address geometry correction, wet-snow classification and
851 cross-sensor harmonization more explicitly, especially when comparing SAR backscatter
852 with optical snow indices and elevation-based metrics (Callegari et al., 2016; Tsai et al.,
853 2019).

854 A promising direction is the construction of multi-sensor workflows that integrate optical
855 snow extent, SAR wet-snow information, DEM constraints and meteorological forcing into
856 a single reproducible processing chain (Lievens et al., 2019; Gascoin et al., 2024). Such
857 workflows are especially relevant for cloud-prone periods and for basins where operational
858 snow monitoring is required at near-real-time cadence.

859 **6.5 Toward operational and reproducible monitoring**

860 The final gap concerns operationalization. The review shows that many studies remain
861 research-oriented and do not yet provide workflows that are easily transferable to water
862 management, drought monitoring or forecasting applications (Cortés and Margulis, 2017;
863 Saavedra et al., 2018; Gascoin et al., 2024). This is important because the hydrological
864 relevance of snowline change in the Andes depends not only on scientific accuracy, but also
865 on how readily the output can be used in seasonal runoff forecasting and adaptation planning
866 (Masiokas et al., 2006; McCarthy et al., 2022).

867 To move in that direction, future studies should favor transparent code, cloud-computing
868 platforms, reproducible preprocessing and explicit documentation of all thresholds and
869 parameters used (Gascoin et al., 2024; Altemus Cullen, 2023). Google Earth Engine and
870 similar environments can support this transition, but only if they are used within a clearly
871 defined methodological framework that links data ingestion, classification, validation and
872 uncertainty reporting. In short, operational relevance in the Andes will come from
873 reproducible methods and consistent metrics, not simply from more satellite data.

874 **6.6 Synthesis**

875 The most robust path for Andean snowline monitoring combines standardized metric
876 definitions, explicit uncertainty propagation, stronger validation and multi-sensor
877 integration. Table 6 condenses the four priorities of this section into operational guidance,
878 mapping each analytical objective to its best-suited metric and method (Saavedra et al., 2018;
879 Hu et al., 2019; Dietz et al., 2025).



Table 6. Recommended method by analytical objective

Objective	Recommended metric / method	Why
Event-scale storm analysis	ZSL / SLA with high-resolution optical imagery	Captures the actual snow boundary at fine spatial detail
Seasonal regime characterization	SP zones	Integrates snow presence through time
Long-term trend detection	SLE / RSLE	More robust to clouds and local terrain effects
Cloud-dominated conditions	SAR or optical-SAR fusion	Maintains observations when optical data fail
Operational hydrology	SLE / RSLE + SP + model assimilation	Links snowline dynamics to runoff and forecasting
Research on snow state processes	PolSAR / InSAR	Useful where detailed scattering or phase information is needed

7. Conclusions

The main contribution of this review is methodological. Across the Andes, snowline monitoring is best understood not as a single measurement but as a choice among non-equivalent metrics, each tied to a particular scale, definition and uncertainty structure. This distinction matters beyond methodology. In a cordillera where seasonal snow sustains the water security of tens of millions of people, the snowline is a decision-relevant indicator, and the way it is measured shapes what water managers, forecasters and policymakers can act upon.

For the study region of this work, the semi-arid and Mediterranean Andes between roughly 29° and 36° S, these distinctions point to a clear preference. The combination of steep terrain and persistent winter cloud cover makes scene-based local snowline altitude too noisy for reliable multi-decadal trends, so a regional, elevation-aggregated metric such as the regional snowline elevation (RSLE) is better suited as the primary indicator of change, with ZSL reserved for event-scale analysis. No single sensor is sufficient either: a continuous MODIS record provides the long baseline, Landsat and Sentinel-2 add spatial detail, and Sentinel-1 SAR fills the winter cloud gaps that most affect this latitude band. The strongest configuration for 29 - 36° S therefore couples RSLE-type metrics with optical-SAR fusion in a reproducible cloud-based workflow, ideally assimilating the resulting snow-depletion information into a snow water equivalent reanalysis, so that the snowline is tied directly to the volume and timing of meltwater, the variable that matters most for water management in this drought-exposed region.

This framing has direct operational value. In the semi-arid central Andes, where the recent megadrought showed how abruptly snow storage can fail, snowline and snow-persistence products can inform reservoir operation, irrigation scheduling, hydropower planning and drought early warning, provided their uncertainty is quantified rather than hidden. Because a rising snowline translates almost directly into a shorter, earlier melt season and a smaller seasonal reservoir, consistent regional metrics give water agencies a spatially explicit early signal of change that sparse station networks cannot provide on their own.



910 Turning this potential into practice requires embedding snowline products in climate services
911 and in durable monitoring infrastructure. Snowline elevation is a sensitive, physically
912 interpretable climate indicator, and it can be assimilated into national water and climate
913 services, seasonal forecasts and adaptation planning, narrowing the gap between satellite
914 research and operational decisions. What is needed is a coordinated, multi-sensor Andean
915 snowline observatory built on harmonized, openly documented processing chains, which
916 cloud platforms such as Google Earth Engine now make increasingly feasible. Such a system
917 would fuse optical and SAR observations, anchor them to in-situ, UAV and even citizen-
918 science or webcam references, and deliver near-real-time products with explicit error bounds.
919 Infrastructure of this kind would turn the standardization advocated here into shared regional
920 practice rather than a study-by-study choice.

921 The methods reviewed here, including automated snowline delineation, optical-SAR fusion
922 and L-band interferometry for snow water equivalent, are arriving alongside a new generation
923 of L-band SAR missions such as NISAR and ROSE-L, which should markedly improve all-
924 weather monitoring of the steep, cloud-prone Andes. Detecting snowline change is, for the
925 most part, no longer the obstacle. The harder task is for the Andean scientific and operational
926 community to build the shared metrics, validation networks and reproducible pipelines
927 needed to monitor that change consistently and to feed it into water-security and climate-
928 adaptation decisions. How well the region meets that task will determine the value of
929 snowline remote sensing for the Andes.

930

931 **8. Code and data availability**

932 This review article did not generate new code or datasets. All data and studies discussed
933 derive from previously published literature and publicly available satellite products (MODIS,
934 Landsat, Sentinel-2, Sentinel-1) accessible through their respective distribution platforms
935 and from the original publications listed in the reference list. No new data were created or
936 analysed in this study.

937

938 **9. Author contributions**

939 CR conceptualized the review, performed the literature search and synthesis, and wrote the
940 original draft. FS supervised the work, contributed to the conceptual framework and
941 methodology, and reviewed and edited the manuscript. PCP co-supervised the work and
942 reviewed and edited the manuscript. All authors have read and agreed to the submitted
943 version of the manuscript.

944

945 **10. Competing interests**

946 The authors declare that they have no competing interests.

947

948



949

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960

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964

965 **13. References**

966 Altemus Cullen, A. L.: Remote sensing of climate-related extreme events in the Andean
967 region: a semi-systematic review, *Frontiers in Environmental Science*, 11, 1154686,
968 <https://doi.org/10.3389/fenvs.2023.1154686>, 2023.

969 Álvarez-Garretón, C., Boisier, J. P., Garreaud, R., Seibert, J., and Vis, M.: Progressive water
970 deficits during multiyear droughts in basins with long hydrological memory in Chile,
971 *Hydrology and Earth System Sciences*, 25, 429–446, [https://doi.org/10.5194/hess-25-429-](https://doi.org/10.5194/hess-25-429-2021)
972 2021, 2021.

973 Aranda, F., Medina, D., Castro, L., Ossandón, Á., Ovalle, R., Flores, R. P., and Bolaño-Ortiz,
974 T. R.: Snow persistence and snow line elevation trends in a snowmelt-driven basin in the
975 Central Andes and their correlations with hydroclimatic variables, *Remote Sensing*, 15, 4461,
976 <https://doi.org/10.3390/rs15184461>, 2023. Arias, P. A. et al.: Technical summary, in: *Climate*
977 *Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth*
978 *Assessment Report of the Intergovernmental Panel on Climate Change*, edited by: Masson-
979 Delmotte, V. et al., Cambridge University Press, 2021.

980 Barandun, M., Huss, M., Berthier, E., Kääb, A., Azisov, E., Bolch, T., Usabaliev, R., and
981 Hoelzle, M.: Multi-decadal mass balance series of three Kyrgyz glaciers inferred from
982 transient snowline observations, *The Cryosphere*, 12, 1899–1916, [https://doi.org/10.5194/tc-](https://doi.org/10.5194/tc-12-1899-2018)
983 12-1899-2018, 2018.

984 Barría, I., Carrasco, J., Casassa, G., and Barría, P.: Simulation of long-term changes of the
985 equilibrium line altitude in the central Chilean Andes mountains derived from atmospheric
986 variables during the 1958–2018 period, *Frontiers in Environmental Science*, 7, 161,
987 <https://doi.org/10.3389/fenvs.2019.00161>, 2019.

988 Beniston, M.: Is snow in the Alps receding or disappearing?, *Wiley Interdisciplinary*
989 *Reviews: Climate Change*, 3, 349–358, <https://doi.org/10.1002/wcc.179>, 2012.



- 990 Bernat, M., Miles, E. S., Kneib, M., Fujita, K., Sasaki, O., Shaw, T. E., and Pellicciotti, F.:
991 Precipitation phase drives seasonal and decadal snowline changes in high mountain Asia,
992 Environmental Research Letters, 20, 064039, <https://doi.org/10.1088/1748-9326/adcf39>,
993 2025.
- 994 Bhardwaj, A., Joshi, P. K., Sam, L., and Snehmani: Remote sensing of alpine glaciers in
995 visible and infrared wavelengths: a survey of advances and prospects, Geocarto International,
996 <https://doi.org/10.1080/10106049.2015.1059903>, 2015.
- 997 Bonnell, R.: Evaluating L-band radar for the future of snow remote sensing, Doctoral
998 dissertation, Colorado State University, Mountain Scholar, 2024.
- 999 Calizaya, E., Laqui, W., Sardón, S., Calizaya, F., Cuentas, O., Cahuana, J., Mindani, C., and
1000 Huacani, W.: Snow cover temporal dynamic using MODIS product, and its relationship with
1001 precipitation and temperature in the tropical Andean glaciers in the Alto Santa sub-basin
1002 (Peru), Sustainability, 15, 7610, 2023.
- 1003 Callegari, M., Carturan, L., Marin, C., Notarnicola, C., Rastner, P., Seppi, R., and Zucca, F.:
1004 A Pol-SAR analysis for alpine glacier classification and snowline altitude retrieval, IEEE
1005 Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9, 3106-
1006 3121, <https://doi.org/10.1109/JSTARS.2016.2587819>, 2016.
- 1007 Carrasco, J. F., Casassa, G., and Quintana, J.: Changes of the 0 °C isotherm and the
1008 equilibrium line altitude in central Chile during the last quarter of the 20th century,
1009 Hydrological Sciences Journal, 50, 933-948, 2005.
- 1010 Carrasco, J. F., Osorio, R., and Casassa, G.: Secular trend of the equilibrium-line altitude on
1011 the western side of the southern Andes, derived from radiosonde and surface observations,
1012 Journal of Glaciology, 54, 538-550, <https://doi.org/10.3189/002214308785837002>, 2008.
- 1013 Choubin, B., Khalighi-Sigaroodi, S., Malekian, A., Ahmad, S., and Danesh, M.: Snow cover
1014 mapping using MODIS and Landsat imagery in a mountainous basin, Journal of Hydrology,
1015 573, 123-137, <https://doi.org/10.1016/j.jhydrol.2019.03.033>, 2019.
- 1016 Condom, T., Coudrain, A., Sicart, J. E., and Théry, S.: Computation of the space and time
1017 evolution of equilibrium-line altitudes on Andean glaciers (10° N-55° S), Global and
1018 Planetary Change, 59, 189-202, <https://doi.org/10.1016/j.gloplacha.2006.11.021>, 2007.
- 1019 Cordero, R. R., Asencio, V., Feron, S., Damiani, A., Llanillo, P. J., Sepulveda, E., Jorquera,
1020 J., Carrasco, J., and Casassa, G.: Dry-season snow cover losses in the Andes (18°-40° S)
1021 driven by changes in large-scale climate modes, Scientific Reports, 9, 16945,
1022 <https://doi.org/10.1038/s41598-019-53486-7>, 2019.
- 1023 Cortés, G. and Margulis, S. A.: Impacts of El Niño and La Niña on interannual snow
1024 accumulation in the Andes: results from a high-resolution 31 year reanalysis, Geophysical
1025 Research Letters, 44, 6859-6867, <https://doi.org/10.1002/2017GL073826>, 2017.
- 1026 Cortés, G., Giroto, M., and Margulis, S. A.: Analysis of sub-pixel snow and ice extent over
1027 the extratropical Andes using spectral unmixing of historical Landsat imagery, Remote
1028 Sensing of Environment, 141, 64-78, <https://doi.org/10.1016/j.rse.2013.10.023>, 2014.
- 1029 Dietz, A. J., Kuenzer, C., Gessner, U., and Dech, S.: Remote sensing of snow - a review of
1030 available methods, International Journal of Remote Sensing, 33, 4094-4134,
1031 <https://doi.org/10.1080/01431161.2011.640964>, 2012.
- 1032 Dietz, A. J., Köhler, J., Obrecht, L., Rößler, S., Baumhoer, C. A., Cereceda-Balic, F., and
1033 Saavedra, F.: Snow cover trends in the Chilean Andes derived from 39 years of Landsat data
1034 and a projection for the year 2050, Remote Sensing, 17, 1651, 2025.
- 1035 Dixit, A., Goswami, A., Jain, S., and Das, P.: Assessing snow cover patterns in the Indus-
1036 Ganga-Brahmaputra river basins of the Hindu Kush Himalayas using snow persistence and



- 1037 snow line as metrics, *Environmental Challenges*, 14, 100834,
1038 <https://doi.org/10.1016/j.envc.2023.100834>, 2024.
- 1039 Dussailant, I., Berthier, E., Brun, F., Masiokas, M. H., Hugonnet, R., Favier, V., Rabatel,
1040 A., Ruiz, L., Pitte, P., and Maturana, D.: Two decades of glacier mass loss along the Andes,
1041 *Nature Geoscience*, 12, 802-808, <https://doi.org/10.1038/s41561-019-0432-5>, 2019.
- 1042 Fayad, A., Gascoin, S., Faour, G., López-Moreno, J. I., Drapeau, L., Le Page, M., and
1043 Escadafal, R.: Snow hydrology in Mediterranean mountain regions: a review, *Journal of*
1044 *Hydrology*, 551, 374-396, <https://doi.org/10.1016/j.jhydrol.2017.05.063>, 2017.
- 1045 Frei, A., Tedesco, M., Lee, S., Foster, J., Hall, D. K., Kelly, R., and Robinson, D. A.: A
1046 review of global satellite-derived snow products, *Advances in Space Research*, 50, 1007-
1047 1029, <https://doi.org/10.1016/j.asr.2011.12.021>, 2012.
- 1048 Gao, J. and Liu, Y.: Applications of remote sensing, GIS and GPS in glaciology: a review,
1049 *Progress in Physical Geography*, 25, 520-540,
1050 <https://doi.org/10.1177/030913330102500404>, 2001.
- 1051 Garreaud, R. D.: The Andes climate and weather, *Advances in Geosciences*, 22, 3-11,
1052 <https://doi.org/10.5194/adgeo-22-3-2009>, 2009.
- 1053 Garreaud, R. D., Alvarez-Garreton, C., Barichivich, J., Boisier, J. P., Christie, D.,
1054 Galleguillos, M., LeQuesne, C., McPhee, J., and Zambrano-Bigiarini, M.: The 2010-2015
1055 megadrought in central Chile: impacts on regional hydroclimate and vegetation, *Hydrology*
1056 *and Earth System Sciences*, 21, 6307-6327, <https://doi.org/10.5194/hess-21-6307-2017>,
1057 2017.
- 1058 Gascoin, S., Aït Hssaine, A., André, S., Deems, J. S., Dehecq, A., Deschamps-Berger, C.,
1059 Dumont, M., Filhol, S., Girod, L., Hagenmuller, P., Malbéqui, F., Marty, M., Revuelto, J.,
1060 Rittger, K., Gruppe, P., Berthier, E., Lamare, M., López-Moreno, J. I., and Nheili, R.: Remote
1061 sensing of seasonal snow in mountains: a review of methods, products and applications,
1062 *Hydrology and Earth System Sciences*, 28, 5347-5405, 2024.
- 1063 Hall, D. K., Riggs, G. A., and Salomonson, V. V.: MODIS/Terra snow cover products,
1064 *Remote Sensing of Environment*, 83, 181-194, 2002.
- 1065 Hammond, J. C., Saavedra, F. A., and Kampf, S. K.: Global snow zone maps and trends in
1066 snow persistence (2001-2016), *International Journal of Climatology*, 38, 4374-4388, 2018.
- 1067 Harer, S., Bernhardt, M., and Schulz, K.: Impact of hourly and daily meteorological forcing
1068 data on simulating an alpine snowpack, *Frontiers in Earth Science*, 6, 3, 2018.
- 1069 Hu, Z., Dietz, A. J., and Kuenzer, C.: Deriving regional snow line dynamics during the
1070 ablation seasons 1984-2018 in European mountains, *Remote Sensing*, 11, 933,
1071 <https://doi.org/10.3390/rs11080933>, 2019.
- 1072 Hu, Z., Dietz, A., Zhao, A., Rutzinger, M., and Kuenzer, C.: Snow moving to higher
1073 elevations: analyzing three decades of snowline dynamics in the Alps, *Geophysical Research*
1074 *Letters*, 47, e2019GL086259, 2020.
- 1075 Huning, L. S. and AghaKouchak, A.: Global snow drought hot spots and characteristics,
1076 *Proceedings of the National Academy of Sciences*, 117, 19753-19759,
1077 <https://doi.org/10.1073/pnas.1915921117>, 2020.
- 1078 Klein, A. G. and Isacks, B. L.: Spectral mixture analysis of Landsat thematic mapper images
1079 applied to the detection of the transient snowline on tropical Andean glaciers, *Global and*
1080 *Planetary Change*, 22, 139-154, [https://doi.org/10.1016/S0921-8181\(99\)00032-6](https://doi.org/10.1016/S0921-8181(99)00032-6), 1999.
- 1081 Klein, A. G., Seltzer, G. O., and Isacks, B. L.: Modern and last local glacial maximum
1082 snowlines in the central Andes of Peru, Bolivia, and northern Chile, *Quaternary Science*
1083 *Reviews*, 18, 63-84, [https://doi.org/10.1016/S0277-3791\(98\)00095-X](https://doi.org/10.1016/S0277-3791(98)00095-X), 1999.



- 1084 Krajčí, P., Holko, L., Perdigão, R. A. P., and Parajka, J.: Estimation of regional snowline
1085 elevation (RSLE) from MODIS images for seasonally snow covered mountain basins,
1086 *Journal of Hydrology*, 519, 1769-1778, <https://doi.org/10.1016/j.jhydrol.2014.08.064>, 2014.
- 1087 Li, J., Tang, S., He, T., Liang, W., Ren, H., Xu, J., Liu, J., Li, F., and Chen, Y.: The rising
1088 high-mountain snowline - a global imprint of climate warming, *The Innovation Geoscience*,
1089 4, 100223, <https://doi.org/10.59717/j.xinn-geo.2026.100223>, 2026.
- 1090 Li, Z., Huang, L., Chen, Q., and Tian, B.-S.: Glacier snow line detection on a polarimetric
1091 SAR image, *IEEE Geoscience and Remote Sensing Letters*, 9, 584-588,
1092 <https://doi.org/10.1109/LGRS.2011.2175697>, 2012.
- 1093 Lievens, H., Demuzere, M., Marshall, H.-P., Reichle, R. H., Brucker, L., Brangers, I., de
1094 Rosnay, P., Dumont, M., Giroto, M., Immerzeel, W. W., Jonas, T., Kim, E. J., Koch, I.,
1095 Marty, C., Saloranta, T., Schöber, J., and De Lannoy, G. J. M.: Snow depth variability in the
1096 Northern Hemisphere mountains observed from space, *Nature Communications*, 10, 4629,
1097 <https://doi.org/10.1038/s41467-019-12566-y>, 2019.
- 1098 Liu, Y., Chen, D., Zhang, T., and Li, L.: Variability of the snowline altitude in the eastern
1099 Tibetan Plateau from 1995 to 2016 using Google Earth Engine, *Remote Sensing*, 13, 1565,
1100 2021.
- 1101 Liu, Y., Fang, Y., and Margulis, S. A.: Spatiotemporal distribution of seasonal snow water
1102 equivalent in High Mountain Asia from an 18-year Landsat-MODIS era snow reanalysis
1103 dataset, *The Cryosphere*, 15, 5261-5280, <https://doi.org/10.5194/tc-15-5261-2021>, 2021.
- 1104 Lorrey, A. M., Vargo, L., Purdie, H., Anderson, B., Cullen, N. J., Sirguey, P., Mackintosh,
1105 A., Willsman, A., Macara, G., and Chinn, W.: Southern Alps equilibrium line altitudes: four
1106 decades of observations show coherent glacier-climate responses and a rising snowline trend,
1107 *Journal of Glaciology*, 68, 1127-1140, <https://doi.org/10.1017/jog.2022.27>, 2022.
- 1108 MacFee, M., Carrivick, J. L., and Quincey, D. J.: Rising snowline altitudes across Southern
1109 Hemisphere glaciers from 2000 to 2023, *Scientific Reports*, 15, 35683,
1110 <https://doi.org/10.1038/s41598-025-19486-6>, 2025.
- 1111 Masiokas, M. H., Villalba, R., Luckman, B. H., Le Quesne, C., and Aravena, J. C.: Snowpack
1112 variations in the central Andes of Argentina and Chile, 1951-2005: large-scale atmospheric
1113 influences and implications for water resources in the region, *Journal of Climate*, 19, 6334-
1114 6352, <https://doi.org/10.1175/JCLI3969.1>, 2006.
- 1115 Masiokas, M. H., Villalba, R., Luckman, B. H., Lascano, M. E., Delgado, S., and Stepanek,
1116 P.: Twentieth-century glacier recession and regional hydroclimatic changes in northwestern
1117 Patagonia, *Global and Planetary Change*, 60, 85-100, 2008.
- 1118 Masiokas, M. H., Rabatel, A., Rivera, A., Ruiz, L., Pitte, P., Ceballos, J. L., Barcaza, G.,
1119 Soruco, A., Bown, F., Berthier, E., Dussaillant, I., and MacDonell, S.: A review of the current
1120 state and recent changes of the Andean cryosphere, *Frontiers in Earth Science*, 8, 99,
1121 <https://doi.org/10.3389/feart.2020.00099>, 2020.
- 1122 Masson, T., Dumont, M., Dalla Mura, M., Sirguey, P., Gascoin, S., Dedieu, J.-P., and
1123 Chanussot, J.: An assessment of existing methodologies to retrieve snow cover fraction from
1124 MODIS data, *Remote Sensing*, 10, 619, <https://doi.org/10.3390/rs10040619>, 2018.
- 1125 McCarthy, M., Pritchard, H., Dinkel, C., Fahnestock, M., Wiens, D., and Heckel, A.: Glacier
1126 contributions to river discharge during the current Chilean megadrought, *Earth's Future*, 10,
1127 e2022EF002873, 2022.
- 1128 Minder, J. R. and Kingsmill, D. E.: Mesoscale variations of the atmospheric snow line over
1129 the northern Sierra Nevada: multiyear statistics, case study, and mechanisms, *Journal of the*
1130 *Atmospheric Sciences*, 70, 916-938, 2013.



- 1131 Minder, J. R., Durran, D. R., and Roe, G. H.: Mesoscale controls on the mountainside snow
1132 line, *Journal of the Atmospheric Sciences*, 68, 2107-2127, [https://doi.org/10.1175/JAS-D-](https://doi.org/10.1175/JAS-D-10-05006.1)
1133 10-05006.1, 2011.
- 1134 Moore, C., Kampf, S., Stone, B., and Richer, E.: A GIS-based method for defining snow
1135 zones: application to the western United States, *Geocarto International*, 30, 62-81,
1136 <https://doi.org/10.1080/10106049.2014.885089>, 2015.
- 1137 Nolin, A. W.: Recent advances in remote sensing of seasonal snow, *Journal of Glaciology*,
1138 56, 1141-1150, <https://doi.org/10.3189/002214311796406077>, 2010.
- 1139 Otsu, N.: A threshold selection method from gray-level histograms, *IEEE Transactions on*
1140 *Systems, Man, and Cybernetics*, 9, 62-66, 1979.
- 1141 Özen, B., Schellenberger, T., Kinar, N., and Kääh, A.: Deep learning for snow cover mapping
1142 from Sentinel-2 in complex mountain terrain, *Remote Sensing of Environment*, 312, 114295,
1143 2024.
- 1144 Palomäki, R. T. and Sproles, E. A.: Assessment of L-band InSAR snow estimation techniques
1145 over a shallow, heterogeneous prairie snowpack, *Remote Sensing of Environment*, 296,
1146 113744, <https://doi.org/10.1016/j.rse.2023.113744>, 2023.
- 1147 Pandey, A., Parashar, D., Palni, S., Sarkar, M. S., Mishra, A. P., and Singh, A. P.:
1148 Spatiotemporal snowline status and climate variability impact assessment: a case study of
1149 Pindari River Basin, Kumaun Himalaya, India, *Environmental Sciences Europe*, 36, 104,
1150 <https://doi.org/10.1186/s12302-024-00924-7>, 2024.
- 1151 Parajka, J., Bezak, N., Burkhart, J., Hauksson, B., Holko, L., Hundecha, Y., Jenicek, M.,
1152 Krajčí, P., Mangini, W., Molnar, P., Riboust, P., Rizzi, J., Sensoy, A., Thirel, G., and
1153 Viglione, A.: MODIS snowline elevation changes during snowmelt runoff events in Europe,
1154 *Journal of Hydrology and Hydromechanics*, 67, 101-109, [https://doi.org/10.2478/johh-2018-](https://doi.org/10.2478/johh-2018-0011)
1155 0011, 2019.
- 1156 Pepin, N., Bradley, R. S., Diaz, H. F., Baraer, M., Cáceres, E. B., Forsythe, N., Fowler, H.,
1157 Greenwood, G., Hashmi, M., Liu, X. D., Miller, J. R., Ning, L., Ohmura, A., Palazzi, E.,
1158 Rangwala, I., Schöner, W., Severskiy, I., Shahgedanova, M., Wang, M. B., ... and Yili, Z.:
1159 Elevation-dependent warming in mountain regions of the world, *Nature Climate Change*, 5,
1160 424-430, 2015.
- 1161 Portenier, C., Hasler, M., and Wunderle, S.: Estimating regional snow line elevation using
1162 public webcam images, *Remote Sensing*, 14, 4730, <https://doi.org/10.3390/rs14194730>,
1163 2022.
- 1164 Prein, A. F. and Heymsfield, A. J.: Increased melting level height impacts surface
1165 precipitation phase and intensity, *Nature Climate Change*, 10, 771-776,
1166 <https://doi.org/10.1038/s41558-020-0825-x>, 2020.
- 1167 Rabatel, A., Bermejo, A., Loarte, E., Soruco, A., Gomez, J., Leonardini, G., ... and Sicart, J.
1168 E.: Can the snowline be used as an indicator of the equilibrium line and mass balance for
1169 glaciers in the outer tropics?, *Journal of Glaciology*, 58, 1027-1036,
1170 <https://doi.org/10.3189/2012JoG12J027>, 2012.
- 1171 Rabatel, A., Francou, B., Soruco, A., Gomez, J., Caceres, B., Ceballos, J. L., Basantes, R.,
1172 Vuille, M., Sicart, J. E., Huggel, C., Scheel, M., Lejeune, Y., Arnaud, Y., Collet, M.,
1173 Condom, T., Consoli, G., Favier, V., Jomelli, V., Galarraga, R., ... and Wagnon, P.: Current
1174 state of glaciers in the tropical Andes: a multi-century perspective on glacier evolution and
1175 climate change, *The Cryosphere*, 7, 81-102, 2013.



- 1176 Racoviteanu, A. E., Rittger, K., and Armstrong, R.: An automated approach for estimating
1177 snowline altitudes in the Karakoram and eastern Himalaya from remote sensing, *Frontiers in*
1178 *Earth Science*, 7, 220, <https://doi.org/10.3389/feart.2019.00220>, 2019.
- 1179 Rastner, P., Prinz, R., Notarnicola, C., Nicholson, L., Sailer, R., Schwaizer, G., and Paul, F.:
1180 On the automated mapping of snow cover on glaciers and calculation of snow line altitudes
1181 from multi-temporal Landsat data, *Remote Sensing*, 11, 1410,
1182 <https://doi.org/10.3390/rs11121410>, 2019.
- 1183 Rittger, K., Painter, T. H., and Dozier, J.: Assessment of methods for mapping snow cover
1184 from MODIS, *Advances in Water Resources*, 51, 367-380, 2013.
- 1185 Saavedra, F. A., Kampf, S. K., Fassnacht, S. R., and Sibold, J. S.: A snow climatology of the
1186 Andes Mountains from MODIS snow cover data, *International Journal of Climatology*, 37,
1187 1520-1539, 2017.
- 1188 Saavedra, F. A., Kampf, S. K., Fassnacht, S. R., and Sibold, J. S.: Changes in Andes snow
1189 cover from MODIS data, 2000-2016, *The Cryosphere*, 12, 1027-1043, 2018.
- 1190 Saavedra, F., Hernández-Duarte, A., Caro, A., Rabatel, A., Fassnacht, S., Condom, T.,
1191 Kampf, S., Masiokas, M., Romero, C., Aguirre, Y., González, D., Contreras, V., Medina, J.,
1192 and Arancibia, P.: Spatial and temporal variability of snow in the Andes using MODIS snow
1193 product 2000-2025, *Frontiers in Earth Science*, 14, 1564035,
1194 <https://doi.org/10.3389/feart.2026.1564035>, 2026.
- 1195 Salomonson, V. V. and Appel, I.: Estimating fractional snow cover from MODIS using the
1196 normalized difference snow index, *Remote Sensing of Environment*, 89, 351-360,
1197 <https://doi.org/10.1016/j.rse.2003.10.016>, 2004.
- 1198 Schaffhauser, A., Adams, M., Fromm, R., Jörg, P., Luzi, G., Noferini, L., and Sailer, R.:
1199 Remote sensing-based retrieval of snow-cover properties, *Cold Regions Science and*
1200 *Technology*, 54, 164-175, <https://doi.org/10.1016/j.coldregions.2008.07.007>, 2008.
- 1201 Schauwecker, S., Palma, G., MacDonell, S., Ayala, Á., and Viale, M.: The snowline and 0
1202 °C isotherm altitudes during precipitation events in the dry subtropical Chilean Andes as seen
1203 by citizen science, surface stations, and ERA5 reanalysis data, *Frontiers in Earth Science*, 10,
1204 875795, 2022.
- 1205 Shea, J. M., Menounos, B., Moore, R. D., and Tennant, C.: An approach to derive regional
1206 snow lines and glacier mass change from MODIS imagery, western North America, *The*
1207 *Cryosphere*, 7, 667-680, <https://doi.org/10.5194/tc-7-667-2013>, 2013.
- 1208 Snauffer, A. M., Hsieh, W. W., Cannon, A. J., and Schnorbus, J. O.: Improving gridded snow
1209 water equivalent products in British Columbia, Canada: multi-source data fusion by neural
1210 network models, *The Cryosphere*, 12, 891-905, <https://doi.org/10.5194/tc-12-891-2018>,
1211 2018.
- 1212 Tang, Z., Wang, J., Li, H., Liang, J., Li, C., and Wang, X.: Extraction and assessment of
1213 snowline altitude over the Tibetan plateau using MODIS fractional snow cover data (2001 to
1214 2013), *Journal of Applied Remote Sensing*, 8, 084689,
1215 <https://doi.org/10.1117/1.JRS.8.084689>, 2014.
- 1216 Teleubay, Z., Fahnestock, M. A., Liang, S., Xiao, X., and Yegorov, A.: Assessment of snow
1217 cover mapping algorithms from high-resolution satellite data: application to snow depth
1218 modeling, *Sustainability*, 14, 9643, 2022.
- 1219 Tsai, Y.-L., Dietz, A., Oppelt, N., and Kuenzer, C.: Remote sensing of snow cover using
1220 spaceborne SAR: a review, *Remote Sensing*, 11, 2101, 2019.



- 1221 Turpin, O. C., Ferguson, R. I., and Clark, C. D.: Remote sensing of snowline rise as an aid
1222 to testing and calibrating a glacier runoff model, *Physics and Chemistry of the Earth*, 22, 279-
1223 283, [https://doi.org/10.1016/S0079-1946\(97\)00144-4](https://doi.org/10.1016/S0079-1946(97)00144-4), 1997.
- 1224 Veettil, B. K., Wang, S., Bremer, U. F., de Souza, S. F., and Simões, J. C.: Recent trends in
1225 annual snowline variations in the northern wet outer tropics: case studies from southern
1226 Cordillera Blanca, Peru, *Theoretical and Applied Climatology*,
1227 <https://doi.org/10.1007/s00704-016-1775-0>, 2016.
- 1228 Viale, M., Garreaud, R. D., and Rondanelli, R.: Rainfall and snowfall distribution over the
1229 Andes: from satellite observations to regional modeling, *Frontiers in Earth Science*, 7, 108,
1230 2019a.
- 1231 Viale, M., Bianchi, E., Cara, L., Ruiz, L. E., Villalba, R., Pitte, P., Masiokas, M., Rivera, J.,
1232 and Zalazar, L.: Contrasting climates at both sides of the Andes in Argentina and Chile,
1233 *Frontiers in Environmental Science*, 7, 69, <https://doi.org/10.3389/fenvs.2019.00069>, 2019b.
- 1234 Viale, M., Valenzuela, R., Garreaud, R. D., and Ralph, F. M.: Impacts of atmospheric rivers
1235 on precipitation in southern South America, *Journal of Hydrometeorology*, 19, 1671-1687,
1236 2018.
- 1237 Vuille, M., Carey, M., Huggel, C., Buytaert, W., Rabatel, A., Jacobsen, D., Soruco, A.,
1238 Villacis, M., Yarleque, C., Condom, T., Salzmann, N., and Sicart, J. E.: Rapid decline of
1239 snow and ice in the tropical Andes - impacts, uncertainties and challenges ahead, *Earth-
1240 Science Reviews*, 176, 195-213, 2018.
- 1241 Wayand, N. E., Marsh, C. B., Shea, J. M., and Pomeroy, J. W.: Globally scalable alpine snow
1242 metrics, *Remote Sensing of Environment*, 213, 61-72,
1243 <https://doi.org/10.1016/j.rse.2018.05.012>, 2018.
- 1244 Wu, Y., He, J., Guo, Z., and Chen, A.: Limitations in identifying the equilibrium-line altitude
1245 from the optical remote-sensing derived snowline in the Tien Shan, China, *Journal of
1246 Glaciology*, 60, 1093-1100, <https://doi.org/10.3189/2014JoG13J221>, 2014.
- 1247 Xiao, X. and Liang, S.: Assessment of snow cover mapping algorithms from Landsat surface
1248 reflectance data and application to automated snowline delineation, *Remote Sensing of
1249 Environment*, 310, 114163, <https://doi.org/10.1016/j.rse.2024.114163>, 2024.
- 1250 Yang, R., Zhang, Y., Wei, Q., Liu, F., and Li, K.: Comparison of two data fusion methods
1251 from Sentinel-3 and Himawari-9 data for snow cover monitoring in mountainous areas,
1252 *Research in Cold and Arid Regions*, <https://doi.org/10.1016/j.rcar.2024.12.010>, 2024.
- 1253 Young, K. R., Ponette-González, A. G., Polk, M. H., and Lipton, J. K.: Snowlines and
1254 treelines in the tropical Andes, *Annals of the American Association of Geographers*, 107,
1255 429-440, <https://doi.org/10.1080/24694452.2016.1235479>, 2016.
- 1256 Young, S. S.: Global and regional snow cover decline: 2000-2022, *Climate*, 11, 162,
1257 <https://doi.org/10.3390/cli11080162>, 2023.