

Review

# Remote Sensing Techniques for Assessing Snow Avalanche Formation Factors and Building Hazard Monitoring Systems

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**Abstract:** Snow avalanches, one of the most severe natural hazards in mountainous regions, pose significant risks to human lives, infrastructure, and ecosystems. As climate change accelerates shifts in snowfall and temperature patterns, it is increasingly important to improve our ability to monitor and predict avalanches. This review explores the use of remote sensing technologies in understanding key geomorphological, geobotanical, and meteorological factors that contribute to avalanche formation. The primary objective is to assess how remote sensing can enhance avalanche risk assessment and monitoring systems. A systematic literature review was conducted, focusing on studies published between 2010 and 2025. The analysis involved screening relevant studies on remote sensing, avalanche dynamics, and data processing techniques. Key data sources included satellite platforms such as Sentinel-1, Sentinel-2, TerraSAR-X, and Landsat-8, combined with machine learning, data fusion, and change detection algorithms to process and interpret the data. The review found that remote sensing significantly improves avalanche monitoring by providing continuous, large-scale coverage of snowpack stability and terrain features. Optical and radar imagery enable the detection of crucial parameters like snow cover, slope, and vegetation that influence avalanche risks. However, challenges such as limitations in spatial and temporal resolution and real-time monitoring were identified. Emerging technologies, including microsatellites and hyperspectral imaging, offer potential solutions to these issues. The practical implications of these findings underscore the importance of integrating remote sensing data with ground-based observations for more robust avalanche forecasting. Enhanced real-time monitoring and data fusion techniques will improve disaster management, allowing for quicker response times and more effective policymaking to mitigate risks in avalanche-prone regions.

**Keywords:** snow avalanche; remote sensing; formation factors; hazard monitoring systems



**Citation:** Denisova, N.; Nurakynov, S.; Petrova, O.; Chepashev, D.; Daumova, G.; Yelisseyeva, A. Remote Sensing Techniques for Assessing Snow Avalanche Formation Factors and Building Hazard Monitoring Systems. *Atmosphere* **2024**, *15*, 1343. <https://doi.org/10.3390/atmos15111343>

Academic Editor: Tin Lukić

Received: 30 September 2024

Revised: 1 November 2024

Accepted: 3 November 2024

Published: 9 November 2024



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## 1. Introduction

In recent years, human activities have exacerbated global warming, leading to more frequent and severe weather-related calamities, including unusual patterns of temperature and precipitation, specifically rainfall and snowfall, which can escalate into serious natural catastrophes [1]. Avalanches are catastrophic natural phenomena characterized by the sudden release of snow, ice, and sometimes rocks, soil, and vegetation from mountain slopes [2]. Avalanches occur predominantly in mountainous areas with steep terrains and are triggered by a complex interplay of meteorological conditions, terrain features, and snowpack characteristics [3]. Typically, they form during or after heavy snowfall when new snow layers accumulate, adding significant weight to the existing snowpack. This accumulation destabilizes the snowpack, causing a large mass of snow to break

away and slide down the slope, sweeping along additional snow and debris in its path [4]. Despite the low frequency of occurrence, avalanches are catastrophic natural events that can significantly affect lives, infrastructure, and ecosystems [3]. Therefore, studying avalanches is a form of risk research aimed at reducing their impact by examining how they form in relation to meteorological conditions and snowpack triggers.

Conventionally, researchers have investigated avalanche formation by field testing snow properties, on-site assessments of avalanche activities and dynamics, and modeling these factors [5]. Field-based methods for studying avalanches face limitations due to high risks and observational biases toward objects that are easily seen in accessible areas under favorable weather conditions and snow stability [6,7]. Many avalanche and snow parameters are measured on-site following industry standards set by organizations like the American Avalanche Association, the Canadian Avalanche Association, and the European Avalanche Warning Services [8,9]. This results in significant uncertainties and gaps in both time and space regarding the mapping of avalanche activity, which obstructs effective data analysis, risk assessments, and detailed comparisons with meteorological triggers [5]. Employing ground-based, aerial, and satellite remote sensing could address these deficiencies, offering more precise measurements of avalanche activity and dynamics.

The adoption of remote sensing (RS) technologies not only enhances avalanche monitoring but also offers insights into the broader geological environment through advanced imaging and analysis techniques—often termed “remote sensing of the geological environment” (GERS). This approach utilizes sophisticated image processing to identify geological features that might influence avalanche behavior, such as terrain structure, fault lines, and underlying rock formations. These capabilities are crucial in both GERS and avalanche monitoring for understanding the surface characteristics that predispose certain areas to avalanches [10,11].

RS technologies enable comprehensive coverage across vast and often unreachable areas. Traditionally, high-resolution optical data from aircraft and satellites have been utilized to identify avalanche debris in clear conditions [12,13]. The continuous advancements in remote sensing technologies, including high-resolution, multi-source RS images from satellites like Landsat, Worldview, and Gaofen, have significantly bolstered our ability to conduct extensive geological surveys. These surveys are instrumental in mapping areas prone to natural disasters, including avalanches, thereby facilitating more effective disaster management and environmental protection efforts. However, the availability of these data is typically restricted to specific areas, and obtaining them promptly can be challenging. Recent advancements have seen Unmanned Aerial Systems (UAS) documenting specific avalanche incidents, although their regional coverage is limited by legal and operational constraints [14].

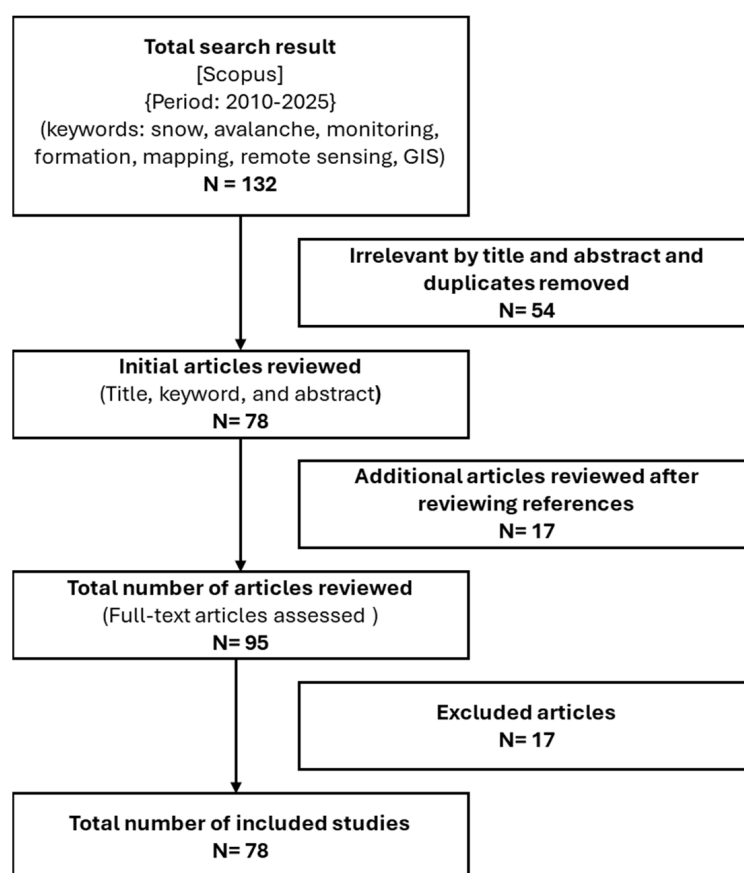
Radar satellite technology addresses some limitations of optical data by acquiring images through clouds and without the need for daylight, enhancing the mapping of avalanche areas [15]. Nevertheless, the coarser resolution of radar data (3–30 m) and complications such as radar shadow and layover restrict its effectiveness, especially for detecting smaller avalanches or those involving dry snow. These factors are crucial for the accurate statistical analysis of avalanche occurrences [5]. Efforts are ongoing to integrate various remote sensing tools to improve avalanche detection. For example, Sentinel-2 satellites provide high temporal resolution with lower spatial detail under open data policies and are being explored to augment avalanche detection capabilities, complementing other tools like Sentinel-1 [13]. The integration of diverse remote sensing technologies holds the promise of advancing our capacity to map avalanches consistently and extensively, thereby enhancing both immediate response strategies and foundational avalanche research.

This review aims to systematically assess how remote sensing techniques can be applied to understand the formation factors of avalanches and enhance hazard monitoring systems. We have explored a variety of remote sensing technologies, including satellite imagery and advanced data analysis methods, to examine the geomorphological, geobotanical, and meteorological factors that influence avalanche risks. Our analysis covers

different geographic regions, focusing on how variations in terrain and atmospheric conditions can be discerned through remote sensing data to predict avalanche occurrences. The primary objectives of this review are to elucidate the capabilities and limitations of current remote sensing technologies in capturing essential data on avalanche formation factors and to explore how these technologies can be integrated to improve avalanche risk assessments. We have also addressed the technical challenges and research gaps within the field, suggesting potential future advancements in remote sensing that could further enhance our ability to monitor and predict avalanches effectively. This review culminates in a comprehensive discussion of the key findings and their implications for disaster management and policymaking, offering recommendations for future research directions in this critical area of geoscience.

## 2. Scientometric Review of Remote Sensing in Snow Avalanche Research

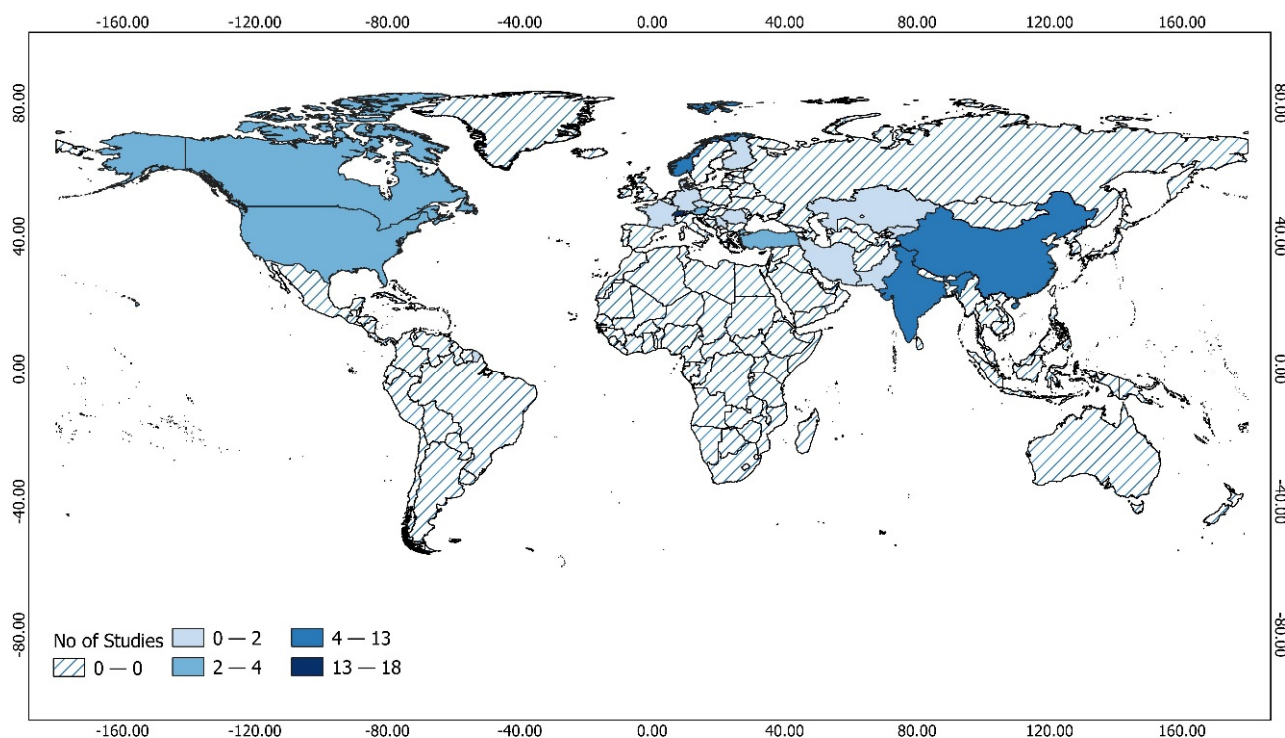
The objective of this systematic review was to assess the application of remote sensing techniques in the monitoring and formation of avalanches with the literature sourced from studies published between 2010 and 2024. We adopted a structured approach to the literature search, selection, and synthesis guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Figure 1) to ensure thoroughness and reproducibility. The literature search was conducted using the Scopus database, employing a defined set of keywords to ensure comprehensive coverage of relevant topics. The keywords used included “snow”, “avalanche”, “avalanches”, “monitoring”, “formation”, “mapping”, “remote sensing”, and “GIS”. These keywords were combined using “AND” and “OR” operators in the following manner to optimize the search: (“snow”) AND (“avalanche” OR “avalanches”) AND (“monitoring” OR “formation” OR “mapping”) AND (“remote sensing” OR “GIS”).



**Figure 1.** Flow chart of the literature search strategy.

The search initially yielded a total of 132 articles. To refine the search results, titles and abstracts were screened for relevance to the topics of avalanche monitoring and formation using remote sensing. Articles were also checked for duplicates during this phase. This initial screening process resulted in the exclusion of 54 articles, leaving 78 articles for more detailed review. The selected articles underwent a thorough review based on their abstracts, titles, and keywords to further assess their suitability for inclusion in the study. This review was complemented by an additional screening of references from these articles, identifying 17 more articles potentially relevant to the research questions. A total of 95 articles, including those identified through reference checking, were subjected to a full-text review to determine their direct relevance to the scope of this review. This stage assessed each article's content in depth to ensure that it provided significant insights into the use of remote sensing in avalanche research. Articles that did not meet the specific criteria for relevance and scientific rigor were excluded from the review. This process resulted in the exclusion of 17 articles, culminating in 78 articles being included in the final analysis.

The geographical distribution of the relevant literature (Figure 2) on remote sensing in snow avalanche studies was mapped using QGIS, employing a classification approach based on natural Jenks symbology. This classification highlighted five distinct classes of publication frequency across various countries: 0, 0–2, 2–4, 4–13, and 13–18 publications. The geographical analysis of the relevant literature reveals a broad global engagement in avalanche research using remote sensing technologies, with Switzerland, China, and India leading in contributions. These countries show a higher concentration of studies, indicating established research communities and ongoing projects. Norway also contributes significantly, reflecting robust research activities. Countries such as Canada and Turkey demonstrate steady involvement, while Austria, the United States, France, Iran, Kazakhstan, Pakistan, and Romania show lighter yet meaningful participation. Further, nations like the Czech Republic, Germany, Denmark, Finland, Kyrgyzstan, and Serbia are identified as having emerging interests in this field, each contributing foundational studies that may pave the way for increased research efforts.



**Figure 2.** Geographic distribution of study areas where relevant literature was found.

For this review, we selected publications from 2010 to 2024, a period marked by significant advancements in remote sensing technology and a growing focus on climate-related phenomena. This timeframe aligns with rapid developments in remote sensing applications for snow avalanche monitoring and mapping. A bar graph (Figure 3) displaying the annual number of publications reveals a clear upward trend, illustrating increasing research activity. This growth reflects enhancements in sensor accuracy and data processing capabilities, which have bolstered the use of remote sensing in avalanche studies. The increasing volume of publications underscores the expanding reliance on these technologies for effective risk assessment and improved understanding of avalanche dynamics under changing climatic conditions. Furthermore, to analyze the frequency of specific terms used in research publications over several years, we employed a structured approach using Python for data extraction, processing, and analysis. Our results (Table 1) highlight notable trends and shifts in research focus. The emergence of terms like “remote”, “sensing”, and “data” across several years points to an increasing reliance on technological advancements and data-driven methodologies in conducting research.

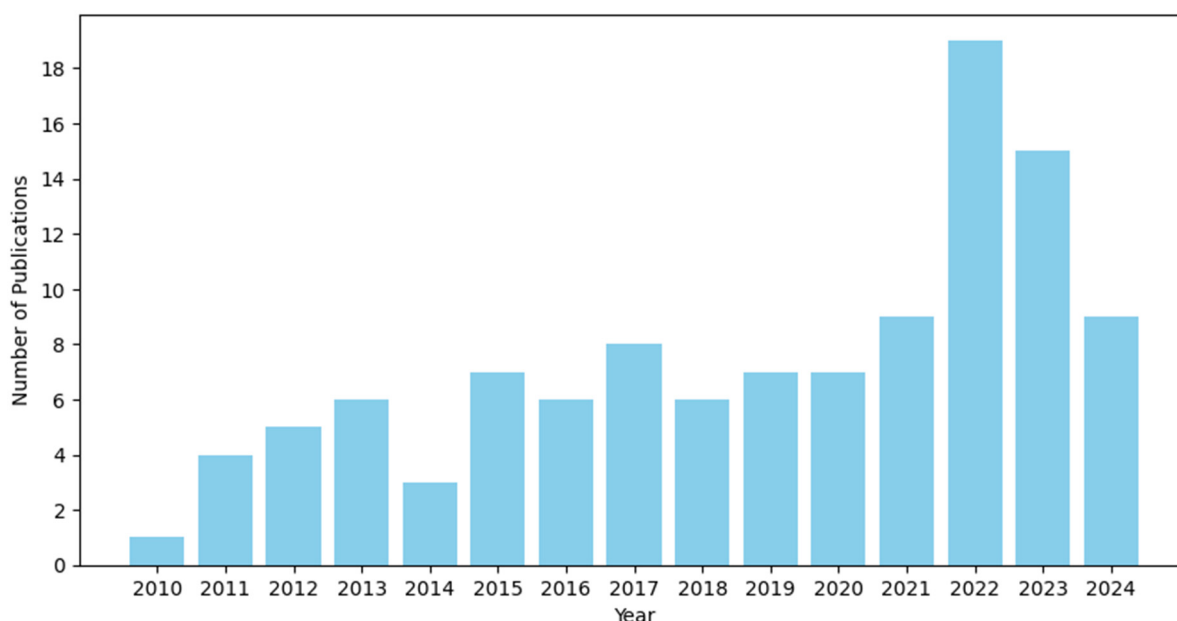


Figure 3. Number of publications per year.

Table 1. Frequency of key terms in compiled publications annually.

Year	Terms (Frequency)
2010	[("snow", 12), ("density", 6), ("data", 5), ("using", 3), ("polarization", 3), ("algorithm", 3), ("hh", 3), ("radar", 2), ("estimating", 2), ("scattering", 2)]
2011	[("avalanche", 20), ("la", 15), ("de", 14), ("des", 12), ("snow", 11), ("à", 10), ("les", 7), ("pour", 7), ("using", 6), ("model", 6)]
2012	[("avalanche", 22), ("snow", 15), ("avalanches", 10), ("curvature", 9), ("risk", 8), ("wet", 8), ("high", 6), ("slush", 6), ("including", 5), ("based", 5)]
2013	[("avalanche", 31), ("snow", 30), ("triggering", 12), ("high", 11), ("using", 10), ("release", 8), ("areas", 8), ("cover", 8), ("remote", 8), ("avalanches", 7)]
2014	[("snow", 5), ("terrestrial", 4), ("potential", 4), ("avalanche", 3), ("changes", 3), ("local", 3), ("monitoring", 2), ("automated", 2), ("laser", 2), ("scanner", 2)]
2015	[("snow", 45), ("avalanche", 29), ("depth", 11), ("instability", 9), ("using", 7), ("use", 7), ("field", 6), ("data", 6), ("resolution", 6), ("sar", 5)]

Table 1. Cont.

Year	Terms (Frequency)
2016	[("snow", 18), ("avalanche", 17), ("depth", 11), ("data", 8), ("remote", 8), ("avalanches", 7), ("sensing", 7), ("spatial", 6), ("detection", 6), ("high", 5)]
2017	[("avalanche", 47), ("snow", 26), ("using", 13), ("avalanches", 11), ("data", 9), ("detection", 9), ("used", 8), ("method", 7), ("remote", 7), ("climate", 6)]
2018	[("avalanche", 28), ("snow", 22), ("data", 12), ("mapping", 10), ("potential", 10), ("recurrence", 7), ("cover", 6), ("avalanches", 6), ("based", 6), ("image", 6)]
2019	[("avalanche", 46), ("snow", 34), ("using", 11), ("data", 11), ("study", 9), ("remote", 9), ("sensing", 9), ("cover", 9), ("livelihood", 8), ("monitoring", 8)]
2020	[("avalanche", 53), ("snow", 21), ("avalanches", 18), ("forest", 17), ("using", 10), ("mapping", 10), ("model", 10), ("remote", 9), ("sensing", 9), ("results", 9)]
2021	[("snow", 64), ("avalanche", 57), ("low", 15), ("avalanches", 14), ("spectral", 14), ("double", 13), ("results", 13), ("density", 12), ("using", 10), ("snowpack", 10)]
2022	[("avalanche", 99), ("snow", 82), ("avalanches", 39), ("results", 24), ("method", 23), ("susceptibility", 20), ("data", 20), ("model", 19), ("high", 19), ("using", 18)]
2023	[("avalanche", 72), ("snow", 59), ("avalanches", 31), ("data", 25), ("study", 15), ("mapping", 13), ("remote", 12), ("high", 12), ("models", 12), ("sensing", 11)]
2024	[("avalanche", 61), ("snow", 25), ("using", 16), ("model", 15), ("avalanches", 9), ("vegetation", 9), ("density", 8), ("coupled", 8), ("data", 7), ("detection", 7)]

In our systematic review focusing on the application of remote sensing techniques in avalanche monitoring, the use of a word cloud provides an intuitive and visual summary of the thematic focus within the compiled literature. This word cloud (Figure 4) was developed using Python 3.9.0 libraries (Rispy and Word Cloud). It was specifically generated from terms extracted from the titles of the reviewed articles, with the font size of each term in the cloud corresponding to its frequency of occurrence. This visual representation allows for the immediate recognition of the most emphasized topics within the field. In the word cloud, the term "snow avalanche" appears as the most frequently used, prominently displayed due to its larger font size. This highlights the central focus of the collected literature, underscoring the primary subject of study. Following closely are "remote sensing" and "mapping", which also appear in larger fonts, reflecting their significant roles in the research landscape. These terms, along with others in the word cloud, outline the key methodologies and areas of interest that researchers have focused on over the selected period.

In the context of our systematic review of remote sensing techniques for avalanche monitoring, the clustered co-occurrence map (Figure 5) serves as a pivotal analytical tool, providing a visual representation of the relationships and thematic concentrations within the collected literature. The map was developed using VOSviewer version 1.6.20, which is an open-source software used for bibliometric analysis. This map is constructed using terms extracted from the titles, abstracts, and keywords of the compiled articles, revealing the intricate network of topics that form the foundation of the current research in this field. Node size in this map corresponds to the frequency of term occurrence across the literature, highlighting the most prominent topics discussed within the field. Each node represents a unique term, with its size reflecting how often the term appears, thus indicating its relevance and popularity in avalanche-related studies. Edges between nodes depict the co-occurrence of terms within the same papers, providing insights into how concepts are interconnected. The physical proximity of nodes on the map, determined by the strength of term associations, illustrates the closeness of the relationship between different research themes. Significantly, the map is organized into seven distinct clusters, each representing a cohesive theme within avalanche research as informed by remote sensing techniques. The blue and green clusters are particularly notable, emerging as the largest clusters with "remote sensing" positioned as a central hub. This central positioning underscores the



This review adopts a narrative synthesis approach, systematically organizing and integrating the findings based on the type of remote sensing technology used and its application in understanding avalanche dynamics and monitoring. This approach allows for a nuanced discussion of remote sensing tools' effectiveness and technological advancements in avalanche research. By adhering to this structured approach, this review aims to provide a comprehensive overview of how remote sensing has been applied to enhance our understanding and monitoring of avalanches. It focuses on summarizing technological advancements, assessing the effectiveness of different remote sensing tools, and identifying areas for further research within this crucial area of geoscience.

### 3. Major Factors Influencing Avalanche Formation

#### 3.1. Geomorphological Factors

The geomorphological characteristics of a landscape play a pivotal role in influencing the stability of snowpacks and the initiation of avalanches. The interplay of several key terrain features such as slope, elevation, aspect, curvature, and terrain roughness determine the conditions under which avalanches are most likely to occur. In this subsection, we discussed the importance of the formerly mentioned factors in influencing avalanche formation.

##### 3.1.1. Slope and Its Influence

The slope of the terrain is one of the most significant geomorphological factors considered in snow and avalanche studies. The inclination of a slope critically influences avalanche dynamics. Avalanches are predominantly triggered on slopes angled between  $25^\circ$  to  $50^\circ$ , where the gravitational pull on the snowpack exceeds the frictional resistance of the snow layer [16,17]. As slope gradients increase, particularly beyond  $36^\circ$ , the likelihood of avalanches escalates due to altered force distributions within the snow layer and variations in snowpack thickness. This alteration not only impacts the stability by increasing the shear stress but also by varying the depth and density of the snowpack due to uneven snow deposition [18]. This is corroborated by extensive studies indicating that slopes between  $28^\circ$  and  $60^\circ$  are particularly prone to avalanches, as steeper slopes may not allow for sufficient snow accumulation, while gentler slopes below  $10^\circ$  typically do not support enough snow load for avalanche occurrence [19–21]. Several research studies highlight that under certain conditions, particularly with wetter snow or during rapid temperature rises, even slight changes in slope can drastically increase avalanche probability [22,23].

##### 3.1.2. Elevation and Avalanche Activity

Elevation serves as a critical modifier of environmental conditions that dictate snowpack characteristics essential for avalanche activity [19]. It affects avalanche formation by influencing climatic conditions like snowfall, wind, and temperature. Generally, higher elevations are associated with greater snowfall and prolonged snow cover, increasing the likelihood of avalanches during the winter season [2]. However, at elevations below 1000 m, the warmer conditions often lead to less cohesive snow layers, reducing the frequency and intensity of avalanches [3]. The variability in climatic conditions at different elevations directly influences the spatial distribution of avalanche occurrences, making elevation a key factor in avalanche risk assessment [24].

##### 3.1.3. Aspect and Snowpack Stability

Aspect, or the directional orientation of a slope, significantly impacts snowpack conditions and avalanche potential. Aspect determines the amount of sunlight a slope receives, profoundly affecting the snowpack's thermal regime [3]. North-facing slopes in the Northern Hemisphere, for example, typically exhibit stronger temperature gradients due to reduced sunlight exposure, fostering the formation of weak snow layers. This can lead to the development of weak, faceted snow crystals beneath the surface, which are structurally poor at bonding and contribute to slab avalanches [7,25]. In contrast, south-



facing slopes might experience more melt–freeze cycles, leading to firmer and often more stable snowpacks. Recognizing this aspect is crucial in predicting the areas that are most likely to accumulate unstable snow layers and thus where avalanche mitigation efforts should be concentrated [26].

#### 3.1.4. Curvature and Its Effects on Snow Movement

The curvature of the slope influences how snow accumulates and how it is released once an avalanche is triggered [27]. Concave slopes tend to gather more snow, creating deeper and potentially more unstable snowpacks, while convex slopes promote the shedding of snow, reducing load but also potentially triggering avalanches by overloading downslope areas [28]. The interaction between slope curvature and snow distribution plays a vital role in determining the initiation zones of avalanches and the pathways they will follow [29].

#### 3.1.5. Terrain Roughness and Avalanche Dynamics

The physical texture of the terrain, or terrain roughness, significantly affects the mechanical stability of the snowpack. It encompasses the irregularity and variability of the surface and affects the formation of cohesive weak layers within the snowpack. Rough surfaces with irregular features such as rocks, gullies, or outcrops can anchor the snowpack, preventing widespread slab release [21]. They interrupt the continuity of the snow layer, thereby reducing the likelihood of large-scale slab avalanches. However, in scenarios where the snow is deep and smooths over rough terrain, these features can contribute to instability by creating stress concentrations that facilitate cracking and sliding [7]. Understanding the role of terrain roughness in avalanche formation is essential for predicting potential release areas and for designing effective avalanche control measures.

### 3.2. Land Cover and Vegetation

Land or ground cover and vegetation cover significantly influence avalanche dynamics by altering snow deposition and the mechanical stability of snowpacks [30]. This section explores the multifaceted roles of land cover and vegetation in avalanche formation and the interactions between avalanches and vegetation.

#### 3.2.1. Influence of Land Cover and Vegetation on Avalanche Formation

Vegetation significantly impacts avalanche dynamics, acting both as a mitigative barrier and as a factor that can potentially increase avalanche susceptibility [31]. The role of vegetation in avalanche formation is complex and multifaceted, influenced by the type of vegetation, its density, and the structure of the land cover. Dense forests, for example, provide a substantial defense against avalanche initiation by intercepting snowfall, reducing ground snow accumulation, and thereby diminishing avalanche potential [3,32]. The irregular snow deposition under forest canopies results in a more stable snowpack. Conversely, sparse or bare areas allow for uniform snow accumulation, increasing the risk of forming unstable snowpacks and facilitating avalanche occurrences [7].

The structure and density of forest vegetation directly influence the dynamics of avalanches [24]. Heterogeneous forests, characterized by a mix of species and tree structures, disrupt the continuity of the snowpack, preventing the formation of weak layers critical for slab avalanches. On the other hand, open areas with smooth and low vegetation facilitate the creation of a compact and homogeneous snow layer, which can be more susceptible to releasing in glide snow avalanches. Such environments provide less natural resistance to avalanche initiation and progression [33].

Forests not only reduce the amount of snow that settles on the terrain but also impact the internal energy dynamics of the snowpack [31]. By limiting the direct energy input from the environment, such as sunlight and wind, forests foster smoother variations in snow characteristics, leading to more homogeneous and stable snow conditions. This stability is

crucial in preventing the sudden release of avalanches, especially in regions where snowfall is heavy and frequent [27,34].

### 3.2.2. Mutual Relationship Between Avalanches and Vegetation

The interaction between avalanches and vegetation dynamically influences both landscape ecology and avalanche behavior [35,36]. Avalanches shape vegetation distribution and structure, with frequent events fostering resilient floristic communities such as shrubs and early successional species, while large, infrequent avalanches can drastically change forest structures, significantly altering ecological dynamics [31,37]. Over time, as the frequency of avalanches decreases, these areas can evolve from being dominated by shrubs to hosting mature forest ecosystems. This progression illustrates the powerful role avalanches play in ecological succession and landscape shaping [32].

Conversely, dense forests can mitigate avalanche runouts, especially in small-to-medium events, by acting as physical barriers that decrease the momentum of moving snow. While the impact on large avalanches is less significant, forest structure still helps reduce travel distance and influences snow deposition and weak layer formation within the snowpack, thus affecting avalanche dynamics [7,32].

### 3.3. Meteorological Factors

Meteorological conditions significantly influence avalanche dynamics through a complex interplay of snowfall, wind, and temperature changes [38]. Each factor has a distinct impact on the stability of the snowpack and the likelihood of avalanche occurrences. Both wet snow and slab avalanches are strongly connected to meteorological variables, and the monitoring of these factors is essential for forecasting and managing avalanche risks.

#### 3.3.1. Temperature

Temperature is a decisive factor in snowpack stability, affecting it through direct and indirect interactions [16]. Fluctuations in temperature, particularly rapid warming, can critically weaken the snowpack by causing meltwater to percolate through the snow layers, lubricating and weakening the bonds between them [39]. This is most notable during late winter and early spring, leading to an isothermal snowpack that is uniform yet fragile and prone to sliding. Extended periods of high temperatures are known precursors to wet avalanches, significantly weakening the snowpack structure [19,40].

Diurnal temperature variations also induce freeze–thaw cycles that compromise structural integrity, forming crust layers that become weak as new snow accumulates. These conditions foster slab avalanches, particularly when a rapid temperature drop follows warming, creating a brittle surface crust likely to fracture under stress [41,42].

#### 3.3.2. Precipitation: Snowfall and Rainfall

Snowfall is one of the most direct and potent causes of avalanches [43]. Heavy snowfall increases the load on a snowpack, directly contributing to avalanche risk by adding weight and altering the internal stress distribution. The western Tianshan Mountains, for example, experience a higher frequency of avalanches during periods of intense snowfall in early February [19]. Rapid accumulation destabilizes the snowpack by altering its internal stress distribution, where the added weight of new snow may overwhelm the snowpack's structural integrity, leading to fresh snow avalanches [16]. Additionally, wind redistributes snow, creating uneven and unstable wind slabs on slopes that are prone to triggering under minor disturbances [44,45].

Rainfall can critically destabilize snowpacks by adding weight and introducing liquid water, which reduces friction between snow grains [22]. This is especially dangerous when rain falls on a snowpack that is already near its melting point, as it can rapidly increase the likelihood of snowpack failure. Rain-on-snow events are particularly associated with wet avalanches, where the snowpack becomes saturated and heavy, leading to potentially large and destructive avalanches [46].

### 3.3.3. Wind

Wind plays a crucial role in shaping the snowpack and influencing avalanche conditions [45]. It can transport snow from the windward sides of terrain features and deposit it on the leeward sides, creating wind slabs that are often denser and more prone to sliding. These slabs form over weaker, looser snow layers and can be triggered by further snowfall, additional wind loading, or even temperature changes. Wind patterns that favor the accumulation of snow on certain slopes significantly increase the risk of avalanches in those areas [46].

Moreover, wind can exacerbate avalanche conditions by stripping snow from some areas and loading others with windblown snow [22]. This process creates a heterogeneous snowpack with varying densities and strengths, which can lead to unexpected avalanche releases. The direction and speed of the wind are therefore critical factors in avalanche forecasting [23].

### 3.3.4. Integrating Meteorological Data for Avalanche Prediction

Understanding and monitoring these meteorological factors is essential for accurate avalanche forecasting [18]. Their complex interactions determine the stability of the snowpack and the subsequent risk of avalanche occurrences. As climate patterns continue to evolve, the role of advanced monitoring and forecasting technologies becomes increasingly important in mitigating avalanche risks and safeguarding human lives and property in vulnerable mountainous regions [38,47]. Remote sensing tools, including satellite imagery and ground-based radar, allow for the continuous observation of snowpack conditions across vast and inaccessible areas. These technologies provide data on snow depth, snow water equivalent, and temperature profiles of the snowpack, which are integral to predicting when and where avalanches are likely to occur [13,42].

## 4. Remote Sensing Techniques

Remote sensing technologies have become an invaluable tool in monitoring avalanche formation and predicting high-risk zones. These technologies offer various platforms, including satellites, drones, and aircraft, that provide data on snow cover, snowpack stability, and terrain features. This section outlines the primary remote sensing techniques used in avalanche monitoring, focusing on satellite imagery, aerial photography, and the data analysis methods applied to these technologies.

### 4.1. Satellite Imagery: Overview of Satellite Technologies Used for Avalanche Monitoring

Satellites equipped with both optical and radar sensors (Table 2) have been instrumental in tracking avalanche-prone areas over large and inaccessible terrains. Their ability to capture data consistently across different weather conditions makes them a key component of modern avalanche forecasting.

**Table 2.** Overview of satellite datasets for avalanche monitoring.

Satellite	Sensor	Resolution	Type	Key Features	Application
Sentinel-1	Synthetic Aperture Radar (SAR) (C-band)	5–20 m	Radar	All-weather, day and night imaging; interferometric capabilities	Snow cover mapping, avalanche detection, terrain mapping
TerraSAR-X	SAR (X-band)	1–40 m	Radar	High-resolution, all-weather imaging	Avalanche debris detection, terrain mapping
Sentinel-2	Multispectral Imager (MSI)	10–60 m	Optical	Multi-spectral, frequent revisits, wide area coverage	snow cover, avalanche debris mapping, snow albedo tracking, vegetation assessment

Table 2. Cont.

Satellite	Sensor	Resolution	Type	Key Features	Application
Landsat-8	Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	30 m	Optical/Thermal	Long-term record of Earth's surface, ideal for studying historical avalanche patterns, thermal infrared data, long-term records	Historical snowpack analysis, climate change impact analysis, vegetation Monitoring
SPOT-6	High-Resolution Visible (HRV)	1.5 m	Optical	High-resolution, fast revisit	Avalanche path mapping, snow cover monitoring, land use mapping
RADARSAT-2	SAR (C-band)	3–100 m	Radar	Flexible imaging options, fine resolution capabilities; all-weather, day and night imaging	Detailed terrain analysis, change detection in avalanche-prone areas, snow depth measurement
WorldView	HRV	0.31 m panchromatic, 1.24 m multispectral	Optical	Very high spatial resolution, high Accuracy	High-precision mapping, avalanche risk zoning
Pleides	HRV	0.5 m panchromatic, 2 m multispectral	Optical	High-resolution imagery, fast revisit	Snow cover mapping, avalanche detection, detailed terrain analysis
Planet	HRV	3–5 m	Optical	Daily revisit, global coverage	Snowpack monitoring, avalanche risk assessment, vegetation assessment
ALOS-PALSAR	SAR (L-band)	10–100 m	Radar	Penetrates vegetation, wide-area mapping	Avalanche susceptibility, terrain roughness analysis
ASTER GDEM	VNIR, TIR	30 m	Optical	Digital elevation model (DEM)	Topography mapping, avalanche runout zones
ALOS World 3D	SAR (L-band)	5 m	SAR	3D terrain model	High-accuracy terrain mapping, avalanche risk
SuperView-1	HRV	0.5 m panchromatic, 2 m multispectral	Optical	High-resolution, short revisit time	Snow cover mapping, avalanche detection, detailed terrain analysis
Rapid Eye	HRV	5 m panchromatic, 15 m multispectral	Optical	Large-area monitoring, daily revisit	Snow and ice monitoring, avalanche risk
Super Dove	HRV	3 m panchromatic, 12 m multispectral	Optical	Daily global coverage, high revisit	Snow cover tracking, terrain mapping

Optical satellite systems, like the Sentinel-2 and Landsat-8 platforms, utilize visible and infrared wavelengths to capture high-resolution images of snow-covered landscapes. Sentinel-2 offers a spatial resolution ranging from 10 to 60 m, while Landsat-8 provides a 30 m resolution for multispectral imagery. These satellites are effective in identifying snow albedo, snow cover, and snow accumulation [48]. Optical data play a vital role in monitoring changes in snowpack and vegetation, which is essential for understanding

avalanche risks. For instance, Sentinel-2 provides frequent revisits and wide area coverage, useful for monitoring snow conditions in vast mountainous areas.

However, optical imagery has inherent limitations during cloudy conditions or periods of low visibility, which are common in winter months. Cloud cover frequently hampers the acquisition of optical imagery, especially during winter months when avalanches are most likely to occur [49]. Additionally, avalanches often have small spatial footprints, sometimes only a few meters wide, which makes them difficult to detect with medium-resolution optical satellites like Sentinel-2 and Landsat-8. While these satellites are excellent for broader snowpack analysis, they may not provide the spatial granularity required to detect finer-scale snow avalanches [12,44]. Avalanches may go undetected if their footprint is smaller than the resolution of the satellite, highlighting the inadequacy of medium-resolution products for precise avalanche detection.

In contrast, high-resolution optical sensors, such as those on SPOT-6 and WorldView, offer much finer detail, with resolutions as high as 1.5 m and 0.31 m, respectively. These satellites can map snow accumulation, snow cover, and avalanche paths with far greater precision, making them ideal for areas where avalanches have smaller footprints [50]. The high spatial resolution of WorldView and Skyview allows them to capture even small-scale changes in the snowpack, providing a more accurate representation of avalanche-prone areas [51]. However, like Sentinel-2, these sensors are still limited by cloud cover and the need for daylight [52].

Radar imagery, especially from synthetic aperture radar (SAR) systems like Sentinel-1, TerraSAR-X, RADARSAT-2, offers a complementary solution to optical data by providing reliable all-weather, day-and-night observations [5,53,54]. SAR technology can penetrate cloud cover and is particularly sensitive to surface roughness, enabling it to detect changes in snowpack stability and identify avalanche deposition zones [15,53]. This also makes SAR technology particularly useful in winter months when there is a possibility of unavailability of optical imageries due to cloud cover. The C-band SAR used by Sentinel-1 offers a medium resolution of 5 to 20 m, while TerraSAR-X and RADARSAT-2 (X-band and C-band, respectively) can achieve resolutions as fine as 1 m. These radar satellites are particularly sensitive to surface roughness, which enables them to detect changes in snowpack stability and identify avalanche deposition zones.

While Sentinel-1 has a revisit time of six days and provides extensive coverage, its medium resolution limits its ability to detect smaller avalanches. Small avalanches, which may have footprints less than 10 m wide, could be missed by Sentinel-1 due to its spatial resolution, despite its excellent temporal coverage [50]. On the other hand, higher-resolution radar systems like TerraSAR-X provide much better spatial detail, making them more suitable for identifying smaller avalanches and subtle changes in snow conditions [15]. However, these high-resolution radar systems may come with higher operational costs and limited coverage areas compared to Sentinel-1 [55,56].

Therefore, the relationship between spatial resolution and avalanche detection is critical. Medium-resolution satellites such as Sentinel-2 and Landsat-8 are valuable for broad-scale snow cover monitoring, but their resolutions are often too coarse for detecting smaller avalanches. High-resolution optical and radar satellites, such as SPOT-6, WorldView, and TerraSAR-X, provide more precise data, but their utility is often constrained by weather conditions (in the case of optical satellites) or high operational costs (in the case of radar systems). Combining optical and radar data is essential for comprehensive snow avalanche monitoring, especially in areas with small-scale avalanches and variable weather conditions.

To better understand how remote sensing datasets correspond to different factors influencing avalanche formation, it is helpful to break these down into geomorphological, geobotanical, and meteorological factors. Each of these factors can be monitored through a range of satellite datasets and technologies, as summarized in Table 3.

**Table 3.** Remote sensing datasets for avalanche-influencing parameters.

Parameter	Influence	RS Dataset Available	Literature
<b>Geomorphological</b>			
Slope	Influences snow stability and avalanche dynamics based on steepness.	Sentinel-1, TerraSAR-X, ALOS-DEM, LiDAR (drones), ASTER GDEM, SRTM DEM	[21,28,51,57–59]
Elevation	Affects snow accumulation, temperature gradients, and avalanche frequency.	Sentinel-1, ALOS-DEM, ASTER GDEM, RADARSAT-2	[2,19,59,60]
Aspect	Determines snow stability through exposure to sunlight, influencing melt.	Sentinel-1, ALOS-DEM, ASTER GDEM, SRTM DEM	[3,7,25,28,59]
Curvature	Influences snow accumulation and release; convex/concave slopes.	Sentinel-1, TerraSAR-X, ALOS-DEM, ASTER GDEM	[27–29,58]
Terrain Roughness	Affects snow cohesion and avalanche release by interrupting snow layers.	Sentinel-1, ALOS-DEM, ASTER GDEM, SRTM DEM, TerraSAR-X, LiDAR (drones)	[7,21]
<b>Geobotanical</b>			
Land Cover	Influences snow deposition and stability by interrupting snow accumulation.	Sentinel-1, Sentinel-2, Landsat-8, WorldView, Planet, RapidEye	[30,34,58,59]
Vegetation	Reduces or exacerbates avalanche risk through interception or windbreaks.	Sentinel-1, SPOT-6, LiDAR, Landsat-8, WorldView, Planet, RapidEye	[7,31,61]
<b>Meteorological</b>			
Precipitation	Directly increases snowpack load, influencing avalanche likelihood.	Weather Radar, GPM (Global Precipitation Measurement), TRMM, MODIS	[16,22,51]
Wind Speed and Direction	Redistributes snow, forming dangerous wind slabs.	Weather Radar, Wind LiDAR, ESA's Aeolus	[44,46]
Temperature	Affects snowmelt and refreeze cycles, destabilizing snowpack.	Weather Radar, Sentinel-3, Landsat-8, MODIS	[23,41,42,62]

Major snow avalanche factors have been highlighted in bold.

Table 3 provides an overview of the key parameters influencing avalanche formation and the remote sensing (RS) datasets available to monitor them. By using the appropriate RS datasets, researchers can monitor these parameters with varying levels of spatial and temporal resolution [34,35,56,63,64].

Geomorphological factors include slope, elevation, and aspects that influence the mechanical behavior of the snowpack. Slope directly affects snow stability and avalanche behavior, as steeper slopes tend to be more unstable, especially when subjected to rapid snow accumulation or warming. Remote sensing datasets such as Sentinel-1, TerraSAR-X, ALOS-DEM, LiDAR, ASTER GDEM, and SRTM DEM are instrumental in providing detailed slope analysis through elevation data and SAR technologies. Meanwhile, datasets such as Sentinel-1, ALOS-DEM, ASTER GDEM, and RADARSAT-2 are valuable for capturing elevation data and have been used extensively in studies such as those by Refs. [2,60] to model snowpack and avalanche risk. Aspect, or the orientation of the slope, is another critical factor, as it determines snow stability through its exposure to sunlight, influencing snowmelt and freeze cycles. Remote sensing datasets such as Sentinel-1, ALOS-DEM, ASTER GDEM, and SRTM DEM are used to monitor snowpack dynamics based on aspect.

Curvature—whether a slope is convex or concave—also influences snow accumulation and release. Convex slopes are more prone to avalanche triggering, while concave slopes tend to retain snow. Sentinel-1, TerraSAR-X, ALOS-DEM, and ASTER GDEM datasets provide valuable data for analyzing curvature [27,29]. Lastly, terrain roughness affects snow cohesion and avalanche release by interrupting snow layers. Rough terrain may prevent snow from forming stable layers, thereby increasing avalanche risk. Datasets such as Sentinel-1, ALOS-DEM, ASTER GDEM, SRTM DEM, TerraSAR-X, and LiDAR provide essential data for analyzing terrain roughness. The studies by Refs. [12,21] show the critical role that terrain roughness plays in influencing avalanche behavior.

Geobotanical factors such as land cover and vegetation can stabilize or destabilize snowpacks. Land cover, such as forests and shrubs, can interrupt snow accumulation, while barren or sparsely vegetated areas may allow snow to accumulate more uniformly, increasing avalanche risk. Remote sensing datasets like Sentinel-2, Landsat-8, WorldView, Planet, and RapidEye have proven useful in monitoring these land cover changes. For instance, Refs. [30,34,58] have effectively used these datasets to study the influence of land cover on avalanche susceptibility. Vegetation can also either reduce or exacerbate avalanche risk by intercepting snow or creating windbreaks that affect snow distribution. Datasets such as Sentinel-1, SPOT-6, LiDAR, Landsat-8, WorldView, Planet, and RapidEye provide insights into the role of vegetation in stabilizing or destabilizing snowpacks, as demonstrated by studies such as those by Refs. [7,31].

Meteorological factors include precipitation, wind, and temperature—all critical elements in determining snowpack stability and avalanche risk [22,65–67]. Weather radar, GPM (Global Precipitation Measurement), TRMM, and MODIS datasets are widely used to track precipitation and snowpack load. Wind speed and direction redistribute snow, forming dangerous wind slabs that can trigger avalanches. Remote sensing datasets such as weather radar, Wind LiDAR, and ESA's Aeolus have been employed to monitor wind effects on snow stability. Temperature affects snowmelt and refreeze cycles, which can destabilize snowpacks. Remote sensing datasets such as weather radar, Sentinel-3, Landsat-8, and MODIS are essential in tracking temperature variations and their impact on snow stability.

In conclusion, by utilizing the appropriate RS datasets for each parameter, researchers can effectively monitor snowpack dynamics and better understand avalanche risks. Sentinel-1, for example, provides radar imagery that is particularly useful for detecting avalanche deposits even in cloudy conditions, while Sentinel-2 offers detailed optical imagery of snow cover, which is vital for tracking snow distribution across various elevations [68]. The combination of these datasets ensures a comprehensive approach to snow avalanche monitoring and risk assessment.

#### *4.2. Aerial Photography and Drones: Use of High-Resolution Imagery from Drones and Aircraft*

Beyond satellite-based observation, aerial photography and drones offer higher-resolution imagery for avalanche monitoring, particularly in small-scale, high-risk areas [14]. Aerial surveys conducted by manned aircraft remain a conventional method for obtaining high-resolution images of snow-covered terrains [69,70]. These surveys are beneficial in capturing large areas quickly and are particularly useful for post-avalanche assessment [71]. However, adverse weather conditions and high operational costs limit their frequent use [15].

Drones have increasingly become a vital tool for avalanche monitoring due to their ability to navigate difficult terrains, low operational costs, and the flexibility of acquiring real-time data [47]. Drones equipped with cameras, multispectral sensors, and LiDAR (Light Detection and Ranging) can gather high-resolution data on snow depth, snow distribution, and terrain roughness [30,72]. Drones allow for detailed avalanche mapping at a local scale, offering insights into the snowpack's behavior in real-time [22]. These instruments enable drones to collect granular data on snow depth, snow distribution, and the roughness of the terrain, providing researchers and responders with detailed, real-time maps of avalanche sites. This capability is pivotal for conducting localized avalanche

risk assessments and understanding dynamic changes within the snowpack just before an avalanche occurs [73].

Complementing aerial techniques, ground-based time-lapse cameras and seismic sensors offer additional layers of monitoring that enhance the understanding of avalanche dynamics. Time-lapse cameras installed at strategic locations continuously record the evolving conditions of snowpacks, capturing incremental changes that might not be evident from periodic observations [74]. These continuous visual data are crucial for identifying subtle precursors to avalanche events, such as snowpack settling or cracking [11,75]. Seismic sensors, strategically placed around avalanche-prone slopes, monitor ground vibrations indicative of avalanche movements [76]. These sensors are sensitive to the initial rumblings that precede an avalanche, providing early warning signals that can be crucial for activating emergency response plans [77]. Furthermore, seismic data help in quantifying the force and frequency of avalanches, contributing significantly to long-term avalanche prediction models and safety measures.

Together, these ground-based technologies synergize with aerial data, offering a comprehensive toolkit for avalanche monitoring. By integrating data from multiple remote sensing technologies, researchers can achieve a more nuanced understanding of avalanche triggers and develop more effective strategies for risk mitigation and disaster response.

#### 4.3. Data Analysis Methods: Processing and Analyzing Remote Sensing Data

Remote sensing generates vast amounts of data, necessitating advanced processing and analysis techniques. These methods include the use of machine learning algorithms, data fusion techniques, and change detection algorithms, all of which significantly improve the detection, classification, and prediction of avalanche risks [78,79]. Modern developments in artificial intelligence (AI) and big data analytics have further accelerated these capabilities, enabling the integration of multi-sensor data for a more holistic view of snowpack conditions.

##### 4.3.1. Machine Learning Techniques

Machine learning (ML), and more specifically deep learning, plays an essential role in processing the complex datasets produced by remote sensing technologies [74,80]. Deep learning models, such as convolutional neural networks (CNNs), have been particularly effective in identifying patterns in snow cover and terrain features that are not easily detectable by traditional methods [61]. These models are capable of classifying snow types and predicting avalanche risks by analyzing patterns in the data that are invisible to the human eye [81,82]. For example, SAR data from Sentinel-1 has been used to automatically detect snow avalanche deposits using machine learning techniques, improving both detection accuracy and processing speed [57,60]. The types of machine learning models used in avalanche monitoring are shown in Table 4.

**Table 4.** Types of machine learning models used in avalanche monitoring.

Machine Learning Model	Application in Avalanche Monitoring	Key Advantages	References
Support Vector Machines (SVMs)	Classifying snow types and avalanche risks	High accuracy, works well with limited data	[17,83]
Convolutional Neural Networks (CNNs)	Detecting avalanche deposits in SAR data	Superior in feature extraction, deep layers for complex data	[61,74]
Random Forests	Predicting high-risk avalanche zones	Handles large datasets, robust to overfitting	[81,84,85]
Object-Based Image Analysis (OBIA)	Segmenting snow-covered areas in satellite imagery	Good for high-resolution imagery	[71,86]



Machine learning algorithms can classify various snow types based on remote sensing data, including optical and radar imagery. For example, Sentinel-1 SAR data has been used extensively to detect snow avalanche deposits through machine learning techniques that automatically classify disturbed and undisturbed snow areas [55]. By analyzing backscatter variations in radar images, these algorithms can discern the structural differences in snow layers, improving both detection accuracy and processing speed. This approach reduces the need for human intervention, making the entire process more efficient [12,15].

Machine learning models are also crucial in predicting avalanche risks by identifying key snowpack and terrain parameters [11,26]. For instance, models trained on historical datasets can forecast high-risk zones by analyzing the interplay of geomorphological factors such as slope and curvature and meteorological conditions such as temperature and precipitation [17,87]. The integration of support vector machines (SVMs) and random forests has further enhanced prediction capabilities, as these models can process large datasets from multiple sensors, detecting even subtle changes in snow stability [83].

Another important application of machine learning is object-based image analysis (OBIA), where machine learning techniques segment satellite images into meaningful objects (e.g., snow-covered vs. non-snow-covered regions) [71]. This approach has been effective in detecting snow avalanches from optical satellite imagery and aerial images by identifying abrupt changes in surface characteristics [88]. For instance, optical data from QuickBird can be segmented into different snow types, and any anomalies (e.g., disturbed snow following an avalanche) can be flagged for further analysis [89].

#### 4.3.2. Data Fusion

With advancements in remote sensing, data fusion has become an essential tool for enhancing the spatial and temporal resolution of avalanche monitoring [62]. By combining datasets from different remote sensing platforms, analysts can obtain more accurate and reliable insights into snowpack stability.

One of the main challenges in avalanche monitoring is the variability in data availability due to weather conditions. For example, optical satellite imagery (such as from Sentinel-2) is limited during cloudy conditions, whereas SAR data from Sentinel-1 can provide all-weather coverage [12]. Data fusion techniques combine these datasets to fill in gaps, enabling continuous monitoring of snowpack conditions. By integrating both optical and radar data, researchers can generate more detailed snowpack models that account for factors such as snow depth, density, and spatial distribution [59].

The fusion of datasets from various platforms also helps overcome the limitations of temporal and spatial resolution. For instance, high-resolution data from TerraSAR-X can be combined with the frequent revisit capabilities of Sentinel-1 to monitor rapid snowpack changes and predict avalanches more accurately [15]. This combination provides a more complete picture of the snowpack's behavior, allowing for more timely risk assessments.

Data fusion is also used to integrate remote sensing data with ground-based measurements, such as those from weather stations and snow pits, to enhance terrain and snowpack models [13,46,47]. This fusion allows for a more accurate simulation of snow distribution and stability, improving the prediction of avalanche risks in real-time. Machine learning algorithms can further analyze these fused data to detect patterns that indicate impending snow instability.

Table 5 provides a quick overview of the different types of remote sensing data fusion used for avalanche monitoring and highlights their specific applications. For example, multi-sensor fusion combines radar and optical imagery to overcome weather limitations, while temporal-spatial fusion leverages the frequent revisits of one satellite with the high resolution of another to provide continuous snow monitoring.

**Table 5.** Types of remote sensing data fusion for avalanche monitoring.

Remote Sensing Data Fusion Type	Sensors Combined	Application	Example of Use Case
Multi-Sensor Fusion	Sentinel-1 (SAR) + Sentinel-2 (Optical)	Continuously monitor snow cover in variable weather conditions	Monitoring snow cover in cloudy conditions with Sentinel-1 and Sentinel-2 for clear days
Temporal–spatial Fusion	TerraSAR-X + Sentinel-1	Enhanced temporal resolution for rapid snow changes	Sentinel-1’s frequent revisits combined with TerraSAR-X’s high resolution for precise detection
Ground-Based and Satellite Fusion	Weather stations + SAR data	Enhanced snowpack models by combining in situ measurements and satellite data	Integrating SAR data with snow pit observations for real-time avalanche predictions

#### 4.3.3. Change Detection Algorithms

Change detection algorithms play a critical role in identifying snowpack changes that may signal avalanche activity. These algorithms analyze differences in remote sensing data collected over time, making it possible to detect events such as snow accumulation, snowmelt, or snow disturbances caused by avalanches [90].

By comparing pre- and post-event satellite imagery, change detection algorithms can identify areas where snow conditions have changed significantly, such as areas affected by recent avalanches [55]. This approach has been particularly effective when applied to radar imagery, such as data from TerraSAR-X, which can capture surface roughness and detect disruptions caused by avalanches [15]. The integration of change detection with machine learning models can also automate the identification process, reducing the time required for avalanche detection [80,91].

Synthetic aperture radar (SAR) data are especially useful for monitoring snowpack changes, as they can detect differences in snow structure by measuring backscatter intensity. SAR-based change detection algorithms have been used successfully to monitor snow depth variations, snow compaction, and other snowpack properties that are indicative of avalanche risk. These algorithms are often applied to areas that experience frequent avalanches to provide early warnings and to assess the extent of snow damage post-event [15].

#### 4.4. Building Hazard Monitoring Systems

The combination of advanced remote sensing technologies and data analysis methods discussed above lays the foundation for building robust avalanche hazard monitoring systems. These systems can integrate multi-sensor data from satellite imagery, drones, and ground-based observations, offering real-time insights into snowpack stability and avalanche risks. Machine learning algorithms, such as those using support vector machines (SVMs) and convolutional neural networks (CNNs), can automate the detection of hazardous snow conditions, while change detection algorithms can provide early warnings by identifying areas of significant snowpack changes that could trigger avalanches [12,57].

Multi-sensor fusion is critical in enhancing the accuracy and reliability of hazard monitoring systems, particularly in areas with variable weather conditions or limited satellite coverage [68]. By integrating radar, optical, and thermal data with ground-based measurements, these systems can deliver early warnings and real-time risk assessments, significantly improving preparedness in avalanche-prone regions. Furthermore, the increasing use of drones in capturing high-resolution local data allows for finer-scale monitoring, ensuring even small, localized avalanches are detected promptly [92].

Implementing these hazard monitoring systems in high-risk areas can mitigate the impact of avalanches by providing timely alerts to local authorities and residents, allowing for

quick evacuation or mitigation measures. Systems like these are already being developed and deployed in several avalanche-prone regions across the world, as demonstrated by the work of Refs. [13,30,38]. As remote sensing technologies and machine learning models continue to evolve, these hazard monitoring systems will become more refined, offering enhanced precision and better predictive capabilities.

## 5. Challenges and Future Directions

Despite the progress made in remote sensing technologies, several technical limitations still hinder the full potential of avalanche monitoring. One of the most prominent challenges is the balance between spatial resolution and temporal coverage [55,93]. High-resolution satellites like TerraSAR-X provide detailed data, but their relatively long revisit times make it difficult to monitor rapidly changing snow conditions. In contrast, lower-resolution satellites like Sentinel-1 offer frequent updates but at the cost of reduced spatial detail, potentially missing smaller avalanches that can still pose significant risks [15,57]. Optical satellite imagery, such as data from Sentinel-2, is highly dependent on weather conditions and often becomes ineffective in cloudy or stormy weather—periods when avalanche risks are most critical [48,68]. Although radar satellites can overcome these limitations, their data often lack the finer resolution necessary for precise avalanche path mapping [94]. Integrating satellite data with ground-based observations (e.g., weather stations, snow pits) presents significant challenges. Discrepancies in data resolution and format, as well as the complexity of processing radar data, require advanced computational infrastructure and expertise, which may not always be available in regions prone to avalanches [57]. While remote sensing excels in detecting large avalanches, the detection of smaller avalanches, especially in steep or heavily shadowed areas, remains a challenge [95]. Radar imagery often fails to capture these smaller events due to resolution constraints, leading to an incomplete assessment of avalanche risk. Although remote sensing provides valuable data for avalanche monitoring, real-time systems remain scarce. Developing near-real-time data processing systems capable of providing immediate analysis and alerts could significantly improve response times and risk mitigation efforts in avalanche-prone regions [55]. Future research should focus on integrating data from various platforms, such as ground-based sensors, drones, and satellites. This comprehensive approach would provide a holistic view of the snowpack, enabling better prediction and mitigation of avalanche risks.

Furthermore, the current machine learning models, while useful, struggle to process heterogeneous datasets from multiple sources [96]. More advanced algorithms that can handle diverse datasets, such as combining optical, radar, and ground-based data, need to be developed for more accurate avalanche prediction [74,86]. Looking ahead, several technological advancements hold promise for improving avalanche monitoring capabilities. Hyperspectral imaging, which captures a wide range of wavelengths, could offer new insights into snowpack composition and stability by providing detailed chemical and physical data [97]. This would allow for a more granular analysis of snow conditions, potentially improving avalanche prediction accuracy. Furthermore, improvements in data fusion techniques, particularly in merging radar and optical data, will be critical in overcoming the current limitations in spatial and temporal resolution. This will enable a more detailed and frequent assessment of snowpack conditions, enhancing the overall avalanche monitoring capabilities.

## 6. Conclusions

This review highlights the pivotal role that remote sensing technologies play in understanding the complex factors influencing avalanche formation and improving hazard monitoring systems. Through a comprehensive exploration of geomorphological, geobotanical, and meteorological parameters, this study has demonstrated how optical and radar satellite imagery, combined with advanced data analysis techniques like machine learning and data fusion, are integral in enhancing avalanche prediction and risk assessment.

The key findings indicate that while traditional methods of avalanche monitoring, such as field-based measurements, provide valuable localized data, they are limited by accessibility, operational costs, and temporal coverage. Remote sensing, particularly through platforms like Sentinel-1, TerraSAR-X, and Landsat-8, offers a more scalable, cost-effective, and continuous monitoring solution. These technologies enable detailed mapping of key factors such as slope, aspect, curvature, and terrain roughness, all of which are critical in assessing snowpack stability and avalanche susceptibility.

The integration of ground-based measurements with satellite data is crucial for improving real-time avalanche forecasting. Remote sensing can cover large, inaccessible areas and provide essential data in all weather conditions, particularly through radar imaging, which functions effectively during cloudy or low-light conditions. This integration strengthens our ability to anticipate avalanche risks and respond quickly, thus minimizing the impacts on human lives and infrastructure.

Despite these advancements, several persistent challenges and gaps need addressing to further leverage remote sensing's capabilities in avalanche research. These include the need for higher-resolution data to detect small-scale avalanche phenomena and monitor rapid changes in snowpack conditions that precede avalanches. The complexity of processing and integrating data from diverse remote sensing sources remains a significant hurdle, requiring ongoing advancements in computational methods and algorithms.

Moreover, there is a significant gap in the absence of effective real-time monitoring systems in many avalanche-prone areas. Developing real-time systems that can process and analyze data will enable quicker responses to emerging avalanche threats. Additionally, enhancing the capability to integrate and synthesize data from various sources, including hyperspectral imaging, ground sensors, and existing satellite platforms, will improve the accuracy and reliability of avalanche forecasts.

Considering these findings, future research should focus on improving the integration of diverse datasets, advancing real-time avalanche monitoring systems, and developing more robust machine learning models capable of processing heterogeneous data sources. These efforts will be instrumental in enhancing our predictive capabilities and mitigating avalanche risks, especially as climate change continues to alter snowpack dynamics and avalanche behavior globally.

**Author Contributions:** Conceptualization, N.D. and S.N.; software, D.C. and G.D.; formal analysis, N.D., O.P. and G.D.; investigation, N.D., O.P. and G.D.; writing—original draft preparation, O.P., D.C. and G.D.; writing—review and editing, N.D. and S.N.; visualization, D.C. and A.Y.; supervision, S.N.; project administration, D.C.; funding acquisition, S.N. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was supported by project IRN BR21882022 “Research of avalanche activity in the East Kazakhstan region for the development of monitoring systems and scientific justification for their placement”, funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan. The APC was funded by the projects budget.

**Data Availability Statement:** Data are contained within this article.

**Acknowledgments:** We are grateful to all the authors of the articles that were discussed in this review.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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