Monitoring Cryospheric Environment at a Regional Scale: Big Data from Sensor Networks and Experimental AI Applications in the Framework of the Glarisk-cc FESR Project

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Abstract

In recent years, monitoring of glacial hazards has gained increasing relevance in the context of climate change and associated cryospheric dynamics. Among these hazards, the formation and evolution of supraglacial and proglacial lakes represent a growing risk due to their potential for sudden outburst floods. This study explores the integration of remote sensing data and artificial intelligence to detect and monitor glacial lakes in alpine environments, with a focus on the Italian Alps. After years of manual lake mapping, we tested for the first time in 2024 a semi-automated procedure based on thresholding of spectral indices (NDWI and NDSI), cloud masking, and spatial filtering to generate a seasonal lake map. The results were compared with a manually compiled inventory and a statistical analysis shows a good agreement between the two. Although the model demonstrates promising performance, limitations remain due to image resolution, weather conditions, and fixed threshold-based constraints. In the final section, we discuss how advanced Machine Vision (MV) approaches—such as convolutional neural networks and temporal image analysis—can be leveraged to enhance the robustness of lake detection and reduce both false positives and false negatives. This work underlines the potential of AI-driven methodologies for improving early warning systems and long-term monitoring strategies in glaciated regions.

Keywords

AI, Environmental Monitoring, Glacial Lakes, Machine Vision, Image Segmentation.

1. Introduction

Mountain glaciers are the main source of freshwater for human activities in the surrounding regions. Furthermore, glaciological processes (e.g., ice break-offs, glacier outbursts, snow/ice avalanches) can threaten populations, urban areas and infrastructure 0. In densely populated areas, such as the European Alps, the interaction between glaciers and anthropic activities is very frequent [2] and is of crucial importance in the study of glaciers in order to understand their evolution and as a response to climate change. Moreover, glaciers are expected to reduce their area coverage and increase their instability [3]. The long-term monitoring of glaciological processes is often complicated and expensive, especially in remote areas and inaccessible terrains, which are common in mountain environments [4]. A practical approach is the adoption of remote sensing instrumentation that

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allows for the observation of glacial processes with minimal risk for scientists and technicians. On the other hand, these instruments and the derived processing produce large amounts of data.
The Aosta Valley (Italian: Valle d'Aosta) is a mountainous autonomous region in northwestern Italy. Covering an area of 3,263 km^2 and with a population of approximately 128,000, it is the smallest, least populous, and least densely populated region in Italy. The Aosta Valley is an Alpine valley which, with its tributary valleys, includes the Italian slopes of Mont Blanc, Monte Rosa, Gran Paradiso and the Matterhorn; its highest peak is Mont Blanc (4810 m). With about 40% of the regional territory above 2500 m, the presence of glaciers is widespread around the whole region. In this high alpine environment, 4% of the Aosta Valley territory is still covered by glaciers (2015). The Regional Glacier Inventory, with its update to 2019, counts 184 glaciers.
In this setting, Aosta Valley region has a large historical record of glacial destabilizations [5] and therefore the management of glacial risk has been managed continuously since 2012 with an organized Regional Risk monitoring Plan [6]. In this frame, the monitoring methodologies, monitoring sensor networks and monitoring data have been continuously evolving and multiplying thus generating more and more data, transitioning from an era of qualitative observations into numerical analysis generating Big Data flows from monitoring instruments, UAVs and satellites.
The aim of this paper is to present the current methodologies and datasets used for glacial hazard monitoring at a regional scale, highlighting the extensive data collection efforts that have enabled analytical approaches to be applied for lake detection. We describe recent results obtained using spectral indices, spatial filters, and thresholding techniques to map glacial lakes from satellite imagery. Building on these findings, the paper outlines ongoing experimental activities that investigate the use of Artificial Intelligence (AI) and Machine Vision (MV) techniques—such as convolutional neural networks—for more robust, automated analysis. These approaches are intended to improve the detection and temporal monitoring of glacial lakes, ultimately contributing to more effective early warning systems and long-term risk management.

2. Monitoring plan: methodologies and materials

The Fondazione Montagna sicura has managed a regional glacial risk monitoring plan on behalf of the Aosta Valley region since 2012. The first case study of glacial risk in Aosta Valley is, in fact, represented by the Whymper Serac ice avalanche monitoring of 1998 [7]. In 2009, the monitoring of the Whymper Serac on a 24/7 basis began, becoming the first site-specific, high-frequency glacial risk monitoring plan in the Aosta Valley region and in Italy [8]. Together with

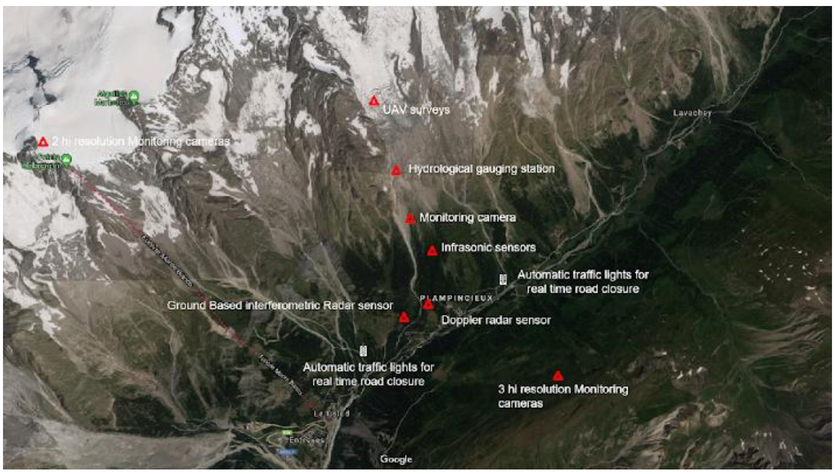

Figure 1: localization of the monitoring instruments in the Val Ferret.

Table 1
Timeline of the introduction of principal monitoring systems. (*Operative range in terms of distance from Planpincieux hamlet/Mont de La Saxe crest).

Apparatus	Monitored Area	Survey Period	Operative Range
RTS	Whymper Serac	October 2010 – present	4800 m
GNSS	Whymper Serac	October 2010 – 2012	–
TLC	Montitaz Lobe	August 2013 – present	3800 m
TLC	Whymper Serac	August 2016 – present	4800 m
TRI	Montitaz Lobe	9 August 2013 (2h) 7 August 2014 (2h)	2500 m/3800 m *
TRI	Whymper Serac	9 August 2013 (2h) 8 August 2014 (3h)	4800 m/5400 m *
TRI	Montitaz Lobe	2 September – 14 October 2015	2500 m
TRI	Montitaz Lobe	13 – 19 June 2016	2500 m
TRI	Montitaz Lobe	26 September 2019 – present	2500 m
TRI	Whymper Serac	16 January 2020 - present	4800 m

Table 2
Example of data acquired for single event description. (*These apparatuses belong to the monitoring network of the Planpincieux Glacier).

Monitoring system	Products	Application
S2 satellite	Orthoimage NDWI	Site state before the event
Pleiades satellite	Stereo imagery Orthorectified image DEM	Site state before the event
Planetscope	Orthoimage NDWI	Site state before the event
UAV	Orthoimage DEM	Site state before and after the event Debris flow mapping Debris flow volume estimation DEM coregistration, Satellite image orthorectification
Aerial Lidar	DEM	Satellite image orthorectification
Aerial photogrammetry	Orthoimage	DEM error quantification
RTK GNSS	Ground control points	
AXIS camera*	Hourly photographs	Site state before and after the event
Bridge survey webcam*	Live video	Timing of the event
AWS	Semi-hourly rainfall data	Environmental conditions
Doppler radar*	Ice avalanche detection	
GB-SAR*	Near-real time glacier displacement	State of glacier activity
TLCs*	Daily glacier displacement Hourly photographs	State of glacier activity Ice avalanche/GLOF occurrence

the expertise of Prof. Martin Funk, a full Regional Monitoring Plan of Glacial Risk was set up in order to cover the entire regional area with low frequency monitoring and to have a framework to implement site-specific, high-frequency monitoring if needed [6]. The structure of the plan was built on experience from the Swiss territory, where a certain number of sites and events had been monitored in recent decades [9]. The very first large-scale action, started by the Fondazione in 2005, was the institution of a regular regional glacier inventory with the aim of having a more frequent update with respect to the national and global inventories, and that would serve as the database on which to construct the regional glacial risk monitoring plan. The second large-scale action included in the plan was the scheduling of a yearly screening of all the glacial bodies in the region, by means of a photographic helicopter flight over the whole regional area. Since 2010, systematic implementation (**Table 1**) of automated time lapse cameras, robotized topographic station, GNSS networks, hydrological gauging station, Doppler radar systems, Interferometric radar systems, especially in the Grandes Jorasses glacier complex (**Figure 1**), has increased exponentially the quantity of monitoring data. In addition to fixed terrestrial systems, specific surveys, acquisitions or processing of data has been introduced for the analysis of single events or the evolution of specific processes. Typical data acquired on purpose are summarized in **Table 2.**

2.1. Data usage

In this study, the main data sources, included in the regional glacial risk monitoring plan, have been analysed and an overview of the data flows involved in the different operational processes has been provided. **Figure 2** illustrates the general workflow of the actions implemented within the monitoring plan. Additionally, **Figure 3** outlines the workflow adopted to periodically update the monitoring strategy, integrating new technologies and methodologies as they become available. **Table 3** summarizes the key data flows currently used in the management of the regional glacial

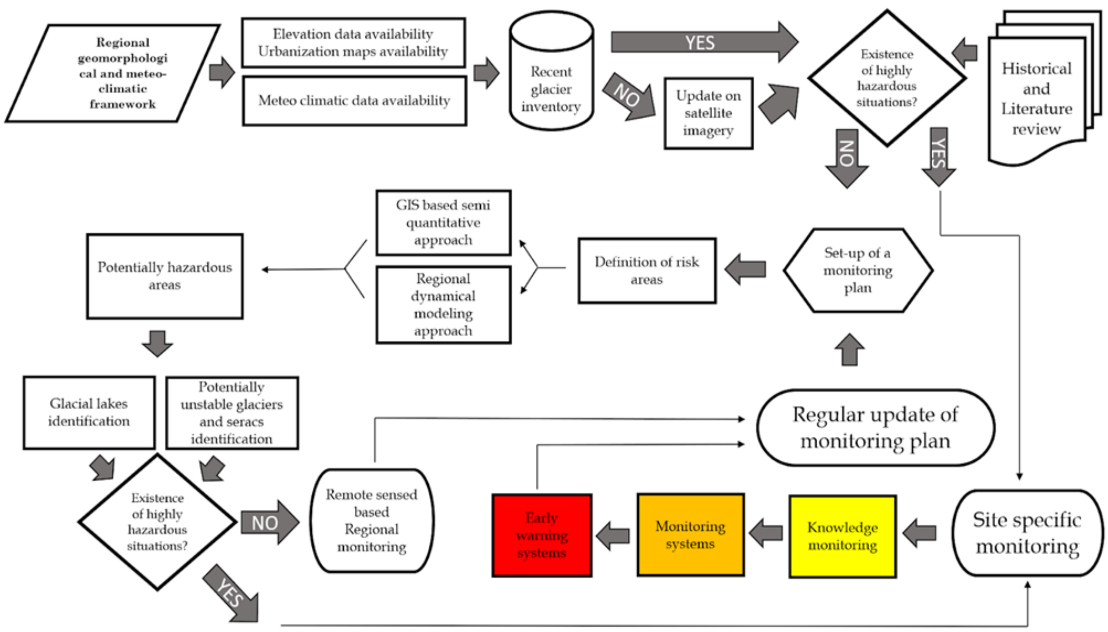

Figure 2: workflow procedure of the monitoring plan.

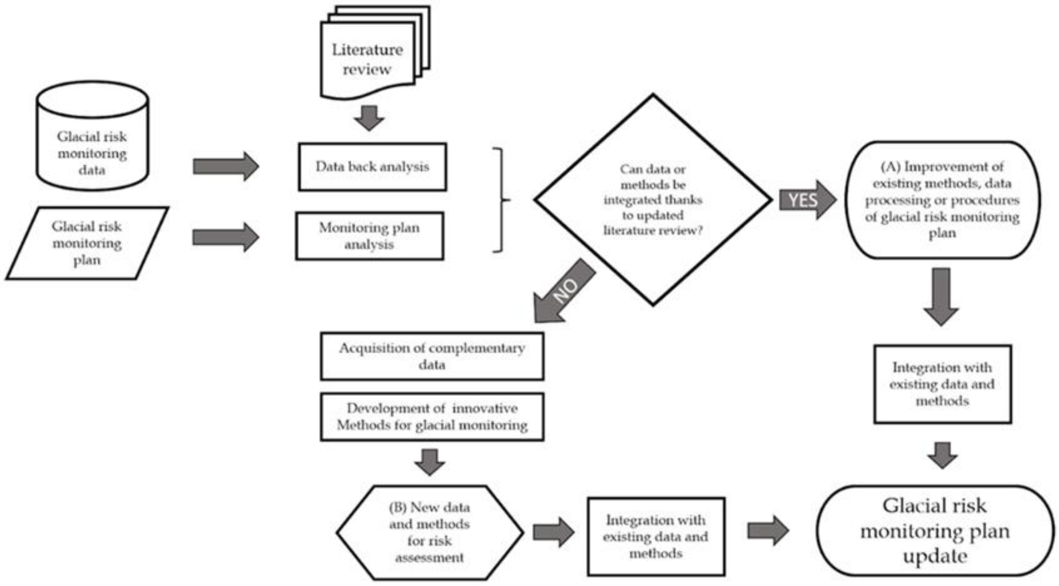

Figure 3: workflow adopted to periodically update the monitoring strategy.

Table 3
Summary of data acquisitions.

Data source	Data type	Yearly data flow	Expected evolution
GB-SAR interferometry	csv	4 TB	0.2x year
GNSS	csv	0.2 TB	steady
TLC	raster	1 TB	1.5x year
UAV	raster	1 TB	2x year
Satellite imagery	raster	2 TB	1.5x year

hazard monitoring plan. Given the large volume of data collected annually, the integration of Artificial Intelligence (AI) techniques into these workflows is being explored. Three main areas of application have been identified:

i. Digital camera image processing: automatic recognition of three-dimensional features (e.g., glacier surfaces and morphological changes) and image enhancement using super-resolution techniques.
We started testing super resolution algorithms instead of classic interpolation methods for the up sampling of digital images for the monitoring of glaciers with time lapse cameras. Major differences are present in the glaciological features appearance (**Figure 4**) with sharper pixel clusters appearing in the AI approach. This could be relevant in the processing of the images for detection of surface displacements and will be the object of further tests and developments.
ii. Deformation data analysis: automated identification of kinematic domains, aimed at detecting areas with significant surface deformation; traditional glacier monitoring methods are limited to tracking feature patterns without semantic information, restricting the analysis to displacement, velocity, and acceleration of pre-defined areas rather than monitoring specific critical features like seracs prone to collapse or crevasses. Additionally, detecting serac failures or other critical events is mainly carried out by manual inspection. Recent advancements in computer vision (CV) and deep learning (DL) could significantly enhance monitoring systems' accuracy and predictive capabilities. However, while well-established in computer science, these

advanced techniques are still underutilised in glaciology due to a technical divide between these disciplines.

In the future we could employ cutting-edge DL segmentation and tracking algorithms to enable object-level tracking rather than pixel-level. This effectively complements traditional methods for deriving movements in challenging dynamic scenes, e.g., with deforming objects or with temporary occlusions. Additionally, DL integration could help introduce strong automatization in data processing, reducing required supervision.

iii. Satellite-based water detection: AI-based methods for identifying and monitoring glacial lakes from optical satellite imagery.

Due to the strategic importance and potential impact of the third application, a dedicated analysis was conducted to evaluate the performance of a large-scale automated screening process for glacial lake evolution using time-series of satellite images.

3. Glacial lake mapping: analytical method

Large-scale screening of the evolution of glacial lakes from continuous analysis of optical satellite images has been implemented. In fact, in the last decade, the possibility to successfully detect water bodies in mountain regions with the use of remotely sensed data grew interest. When dealing with freely available datasets, ground resolution and revisit time of Landsat satellites that were available before the Sentinels launch (2015) was not suited to the identification of newly formed glacial lakes in an alpine environment. With the availability of Sentinel-2 (S2) datasets, we conceived an experimental activity of a possible semi-automatic classification of newly formed glacial lakes to be possibly integrated into the glacial risk monitoring plan. The development of the research plan was inserted into the framework of the WP3 of the Interreg Alcotra 2014-2020 (IT-FR) RISK-ACT-PITEM RISK project. This financed the experiments to validate a procedure based on the analysis of updated NDWI index maps (**Equation 1**)[10]:

$$NDWI_{S2} = \frac{B03-B08}{B03+B08} \tag{1}$$

on the regional territory for every low cloud cover percentage image acquired by the S2 satellites. The procedure has been integrated in the glacial risk monitoring plan as an experimental monitoring procedure and is currently active and ongoing.

3.1. Automatic lake detection: procedure

In summer 2024, in the framework of the PNRR project "Agile Arvier. La cultura del cambiamento", this procedure has been updated. **Figure 5** shows a flowchart illustrating the current updated procedure for the automatic detection of glacial lakes in the Aosta Valley. This workflow is based on a daily-updated archive of S2 satellite imagery, specifically leveraging its multispectral data. The analysis is restricted to a buffered area around glaciers, defined as a 500-meter buffer from the glacier outlines mapped in 2019. When the procedure is initiated, it automatically searches for the necessary spectral bands to compute two key indices: the Normalized Difference Water Index (NDWI) and the Normalized Difference Snow Index (NDSI). In particular, bands B3 (green) and B8 (near infrared) are used to compute the NDWI (see **Equation 1**), while bands B3 and B11 (shortwave infrared) are used for the NDSI, defined as follows (**Equation 2**):

$$NDSI_{S2} = \frac{B03-B11}{B03+B11} \tag{2}$$

It is worth noting that the two indices come with different spatial resolutions, since B11 is not available at 10 m resolution. Therefore, a downscaling algorithm from 20 m to 10 m resolution is applied to the NDSI.

S2 data also include a Scene Classification Layer (SCL), which provides useful information about cloud cover for each image. Based on this layer, and considering the classes related to clouds (specifically 3, 8, 9, 10, 11), a cloud mask can be derived and applied to the buffered NDWI and NDSI data. This process results in raster layers with masked (i.e., removed) cloudy areas. Also in this case, since the original resolution of the SCL is 20 m, a downscaling to 10 m is required.

The NDWI is primarily computed to highlight areas containing water. Based on literature, a

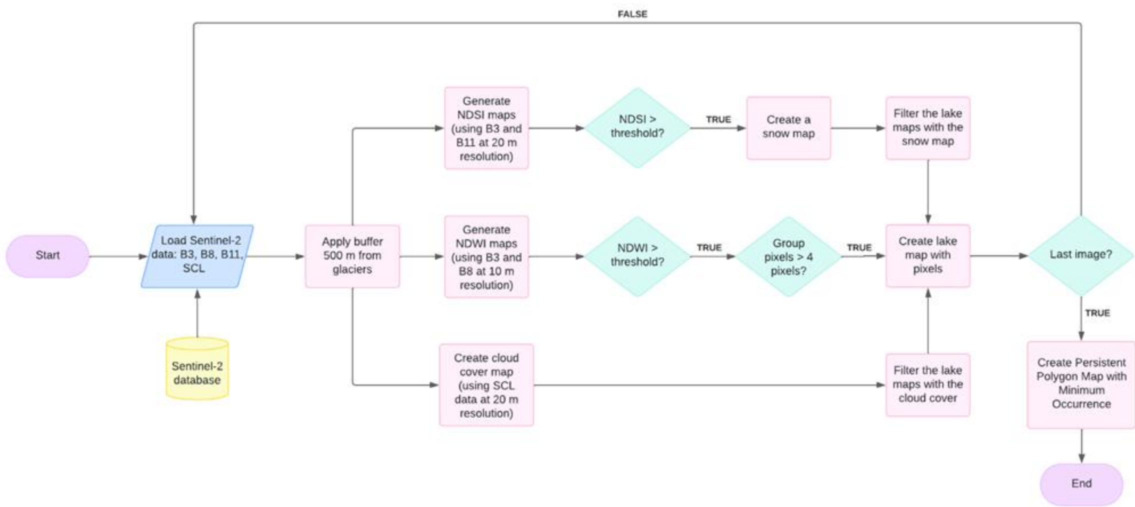

Figure 5: flowchart of the actual automatic procedure for glacial lakes detection in Aosta Valley.

threshold of 0.5 is commonly adopted to identify water bodies. However, due to recent updates in the processing baseline of Sentinel-2 Level 1C products, the dynamic range of NDWI values has been shrank, and the threshold had to be adjusted. In this implementation, the NDWI threshold was lowered to 0.2, which allowed for the identification of a greater number of glacial lakes. Nevertheless, this lower threshold also increases the risk of false positives, particularly toward the end of the summer season when the glacier surface undergoes significant melt. In such cases, the NDWI may erroneously detect portions of glacier ice as lakes. To mitigate this issue, a secondary filtering step based on the NDSI is applied. Specifically, areas with NDSI values greater than 0.5—typically corresponding to snow or ice—are removed from the lake maps, improving the reliability of the final

detection. The cloud mask has been applied too, to remove the artefacts produced by water vapour or the shadows projected on the ground.
After the production of the map containing the perimeters of the detected lakes, a filter based on the aera has been applied, setting the minimum area at 400 m^2, equals to 4 pixels.
Once the lake map of an image is produced and filtered for snow and cloud cover, the procedure is iterated over the full set of available S2 images for the selected period—typically covering the summer season, from July to September. For each acquisition, a water mask is generated using the same processing steps, resulting in a series of binary lake presence maps over time.
At the end of this iterative process, a temporal comparison is performed across all the maps to identify the most persistent water bodies. The idea behind this post-processing step is to reduce false positives, which may occur due to transient artifacts or temporary meltwater on glacier surfaces. For example, polygons (i.e., detected lake areas) that appear in only one single image are likely to be false detections and are therefore removed. Conversely, features that appear repeatedly in multiple images are retained, as they are more likely to correspond to actual glacial lakes.
The minimum number of occurrences required for a polygon to be considered a "likely lake" can be customized. In order to reduce the risk of underestimating lake presence, a conservative threshold of 2 has been adopted in this study.

3.2. Automatic lake detection: results

After several years of manual mapping of the glacial lakes, the procedure was tested for the first time in 2024. Following the steps outlined above, the analysis produced an overall lakes map for the timeframe between July and September (just before the first snowfall of the season, which occurred between September 10th and 15th). The resultant map successfully identified lakes within the buffer zone, which were then compared to the manual cadastre. An example of part of the outcoming map is reported in **Figure 6**, where the inventory and the automatic map are shown in red and yellow, respectively. Considering the Aosta Valley, the comparison showed 46 lakes were successfully mapped (true positives), 32 lakes were detected by the procedure but not present in the cadastre (false positives), and 38 lakes were not detected by the procedure but are present in the cadastre (false negatives).
Statistically, the model's precision, which measures the accuracy of positive predictions, is 59%. The recall, which measures the model's ability to identify all actual positive cases but may also lead to false positives, is 57%. These metrics indicate a balance between precision and coverage.
Although the results are promising and give confidence in the procedure, the number of false positives and false negatives remains relatively high. Several factors may contribute to this. One of the main reasons is the recursive nature of the procedure: when generating the final map, some lakes may be excluded due to bad weather conditions (clouds, shadows, snow) in certain images. Another limitation is the presence of small lakes manually mapped, which may not be detected due to the

Figure 6: Extract of the lake map produced for the summer season 2024. In red, the lakes mapped manually. The yellow areas, instead, are the auto-detected water zones.

pixel threshold. Additionally, since the image resolution is 10 meters, the borders of lakes have lower reflectance, which may cause them to fall below the detection threshold.
All these limitations may be solved with the use of more sophisticated algorithms, using the Artificial Intelligence trained by these final maps and inventories.

4. Future developments and implementation of AI algorithms

The implementation of advanced Machine Vision (MV) tools for identifying and monitoring proglacial, marginal, and supraglacial lakes using satellite data is made possible by the extensive dataset and long-term data collection as described in the previous sections. Machine Vision refers to the technology and methods which involve capturing visual data through imaging devices, processing this data using algorithms to extract meaningful information, and making decisions based on the analysis. In the context of environmental monitoring, MV has been effectively utilized to assist in biodiversity preservation[13][14], monitor ecosystems and in the context of glacial lake mapping [15][16][17][18].
As part of the ERDF-funded project Glarisk-cc, MV will be applied to analyse satellite imagery for the identification and monitoring of proglacial, marginal, and supraglacial lakes.
Traditional methods, such as manual digitization and thresholding techniques, often struggle with the complex and variable appearances of glacial lakes, particularly when dealing with small or debris-covered bodies of water. To overcome these challenges, advanced machine vision approaches, particularly those leveraging deep learning, have been developed [19][20]. For instance, convolutional neural networks (CNNs) can be trained on annotated datasets to recognize the distinct features of glacial lakes, allowing for automated and accurate segmentation [21].
Integrating multiple satellite data sources, including optical and radar imagery, further enhances detection accuracy. Optical images provide detailed visual information, while radar imagery offers the advantage of penetrating cloud cover and detecting surface changes under various weather conditions. By employing a supervised learning approach, these algorithms can be trained on previously validated datasets, such as those created using the Normalized Difference Water Index (NDWI), to improve their performance in accurately identifying and monitoring glacial lakes over time.
The training and validation of these algorithms will be supported through access to satellite images and geospatial data. Additionally, automated recognition algorithms will be used to classify lake

characteristics via supervised learning techniques. These models will be trained on existing and supplementary datasets to ensure the relevance and reliability of the territorial information. The validation process will incorporate technical expertise for model evaluation and may include reinforcement learning (see for instance [16][18][21]) benefiting from extensive experience of the group in glacier monitoring and geospatial data management. Once validated, the segmentation algorithms will be applied repeatedly over time to monitor changes in the formation and extent of glacial lakes, using new satellite imagery. This iterative approach will provide updated insights into glacial conditions and evolution. Finally, a potential web service may also be developed to integrate the algorithms and visualization tools, offering wider access to the monitoring capabilities.

5. Conclusion

In this study, we presented the current methodologies employed for monitoring glacial hazards in Aosta Valley, focusing on the detection of glacial lakes in the Italian Alps through the analysis of optical satellite imagery. We demonstrated a semi-automated workflow based on spectral indices, cloud masking, and spatial filtering, and compared its results to manual inventories, showing promising alignment. The paper also introduced future directions involving the integration of Artificial Intelligence and Machine Vision techniques to enhance the accuracy and scalability of lake detection and monitoring over time.

Given the volume and complexity of data involved in regional-scale environmental monitoring, our findings highlight the necessity of adopting AI-based solutions to support the processing, interpretation, and operational use of remote sensing datasets. To achieve meaningful progress, collaboration between AI developers, field experts, and environmental researchers is essential. Such interdisciplinary efforts will be key to developing robust, adaptive tools that support both early warning systems and long-term climate resilience strategies in glaciated regions.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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