SkiSlo: Leveraging Digital Twins to improve Ski Safety

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Abstract

The rising popularity of winter sports has led to an increase in the frequency and severity of skiing accidents. This issue is intensified by the lack of standardized regulations for route-setting and protection placement, processes which currently rely heavily on the subjective experience of course setters and safety managers. Consequently, enhancing safety measures on ski slopes is a critical priority. In this work, we propose **SkiSlo**, a framework that provides efficient, objective support for safer route-setting decision-making. **SkiSlo** utilizes a digital twin of the slope to pinpoint high-risk zones and guide the placement of protection devices. The framework follows a three-phase protocol: digital twin construction, descent simulation, and data-driven risk estimation. We demonstrate the practical application of **SkiSlo** through ongoing testing at the *Sestriere* ski facility on the *Kandahar* slope.

Keywords

Digital Twin, Digital Surface Model, Ski Safety, Risk Modelling

1. Introduction

In recent years, advancements in materials, construction, and geometry have defined modern ski performance, allowing athletes to constantly push the limits of their equipment (Coupe [1]). However, this evolution has led to substantially higher speeds and load-intensive turning in alpine ski racing, culminating in an increased injury rate among elite athletes (Gilgien et al. [2]). Furthermore, the incidence of skiing-related accidents has also risen in the recreational sector, driven by the growing popularity of winter sports [3, 4, 5, 6, 7]. To address this, we propose a novel framework designed to detect and mitigate slope hazards, thereby raising awareness of the potential risks skiers face during descent.

We propose the SkiSlo framework (a more detailed description is provided in Section 3) including:

Mountain digital twin: a digital representation of the slope to achieve greater realism in modelling the path geometry and snow conditions.

Skier descent simulations: to adequately comprehend the stresses skiers experience, without hindering their safety, we perform descent simulations. We leverage our own custom model, realistically mimics the skier's physical behaviour during descent, to compute the acting forces given the skiers trajectory on the slope.

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Objective risk quantification: based on a *risk index*, an objective risk quantification is given, enabling a highly interpretable graphical representation of high-risk areas.

We selected the *Kandahar* slope at the *Sestriere* ski area for the initial experimental evaluation of our framework, primarily due to the research team's extensive prior knowledge of the site's topological characteristics. To date, an experimental campaign featuring several data measurements have been conducted to test a diverse range of equipment and methodologies, with further trials scheduled for the near future.

2. Related Work

This section provides a brief overview of the state of the art in the fields related to three main aspects of the SkiSlo framework (addressed in section 1).

2.1. Mountain Digital Twin

Several works in the literature present frameworks for analysing mountain slopes serving many different purposes. Many of them focus on the use of digital twins to predict and estimate hydrological risk (as Zhang et al. [8]), where the implementation of neural network algorithms for dynamic prediction of geological disasters is proposed. Others, such as Liu et al. [9], are committed to enhancing the performance of the digital twin of geo-hazard slopes by combining monitoring data and slope survival records to probabilistically update the model and predict its stability.
Papers such as the work from Izumida et al. [10], instead, demonstrate the use of high-resolution topographic datasets to produce accurate digital surface models (DSMs) of the research area. This result is accomplished through the combination of structure-from-motion (SfM) photogrammetry and aerial light detection and ranging (LiDAR) data, both derived from sensors carried by an unmanned aerial vehicle (UAV). Further evidence of how the advancements in UAV technology have led to their widespread adoption across various scenarios is discussed by Liu et al. [11]. Their work highlights the efficiency of LiDAR-based UAV systems for capturing detailed information about inspection sites, such as in agricultural monitoring, search-and-rescue missions, and industrial inspections.
Finally, Avanzi et al. [12] present the accuracy of snow-depth measurements from Unmanned-Aerial-Sytems (UAS) photogrammetry compared with the latest high-resolution laser-scanning device (MultiStation) relying on manual probing. Results show a Root Mean Square Error (RMSE) between UAS data and manual probing in the order of $0.20 - 0.30\ m$, or even lower $0.06 - 0.17\ m$ when areas of potential outliers are excluded, demonstrating the reliability of compact and portable remote-sensing devices like UASs.
Our work further contributes to assessing the current surface modelling technique for the Digital Twin, based on aerophotogrammetry and LiDAR sensors (section 3.1), given its proven repeatability and vertical centimetric accuracy.

2.2. Descent Simulations

Although the aims of the works are extremely various, the main references for the descent modelisation were the following ones: Li et al. [13] studied the influence of wind coming from the four cardinal directions and how it influenced the descent time of the skier. In our case study, we limited the analysis to the case in which the air is still. Gao et al. [14] developed a model that incorporates a full 3D musculoskeletal model, a flexible ski model, a ski-snow contact model and an air resistance model. Then, using the acquired experimental data and inverse kinematics, they were able to optimize the friction coefficient parameters, also accounting for the skier's skill level. Cai and Yao [15] numerically studied the optimal descent trajectory that minimizes the descent time; they modelled the skier as a rigid body, in particular a rod that connects the center of mass to the skies. The same authors in Cai and Yao [16] proposed an improved retractable body model that uses a spring to simulate the flexion and extension motion of the skier's legs. While these models allow for realistic mechanical simulations, they often require significant computational effort, particularly when simulating a descent on a large-scale real slope. The contribution of this work will be to investigate the effectiveness of a simplified modeling approach, less complex than those previously discussed, applied directly to real terrain data. The goal is to achieve a suitable balance between computational efficiency and physical accuracy, enabling feasible large-scale simulations while preserving the essential dynamics of the motion. The physical formulation adopted in this work draws its main theoretical inspiration from D. Lind and S. Sanders, The Physics of Skiing [17].

2.3. Risk Prediction

Radovanovic et al. [18] build a decision model for the prediction of ski injuries using pre-collected data. Although their aim is, similarly to ours, to propose a tool that supports decision-making processes, their approach efficiently exploits data mining techniques to predict injury rates throughout the analysis of historical data. Thus, our work is substantially different in the type of risk predicted and in the scope; we limit our scope to a single slope, analysing it at a finer grain. While Wang et al. [19] attempt to model injury risk rates using weather data.

While some works on risk analysis and skiing are present in the literature, none of them address the problem posed in this document.

To our knowledge, the present proposal is the first of its kind. Different from those in literature, it provides a complete solution integrating data gathering, data processing and output to the final user. In particular, we exploit existing technology to build a digital twin, we engineered our physical model to perform simulations, and with these data, we propose our novel approach to predict areas of higher risk.

3. The SkiSlo Vision

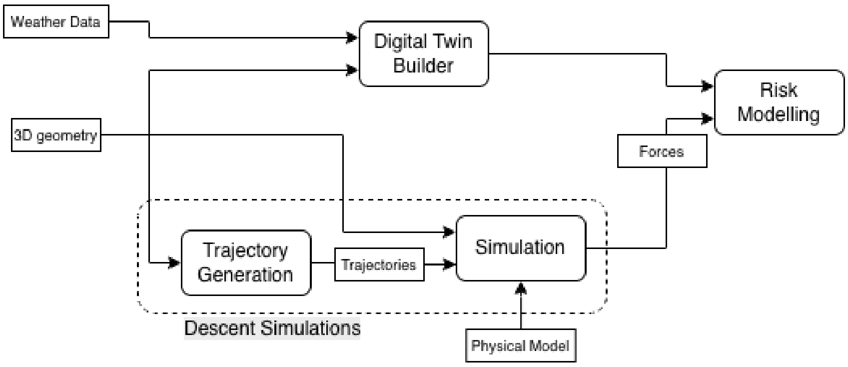

Figure 1: The SkiSlo pipeline: *Digital Twin Builder*, *Descent Simulations* and *Risk Modelling*

The objective of this research is to provide a tool to inform and assist the risk evaluation in competitive skiing. SkiSlo can help assess dangerous areas along the slope, potentially assisting ski technicians in their evaluations and enhancing athletes' awareness.

We present the tool as composed of three different components (depicted in Fig. 1): the *Digital Twin Builder*, the *Simulation* module and the *Risk Modelling* block. Raw data are gathered and fed to the *Digital Twin Builder*, which outputs a complete digital twin for the slope. The geometry of the mountain acts as input also in the *Simulation* module that generates a bundle of trajectories and performs simulations on them, obtaining a representation of the forces acting on the skier during the descent. Finally, the outputs of the former blocks are fed into the *Risk Modelling* unit that highlights the most dangerous areas of the slope.

Considering that the project is still ongoing, we present the components in the order of their progress at the time of writing. In particular, while studies regarding the *Digital Twin Builder* and the *Simulation* module have already been carried out, the *Risk Modelling* block is not yet implemented. For these reasons, we describe the first two modules in this section and the last in the discussion section 4.2.

3.1. Mountain Digital Twin

An accurate Digital Surface Model (DSM) is needed in order for the descent simulations to also be accurate. Already available geometric models were considered. Models generated through satellite imaging, as those used by *Google Earth*, were discarded because of the accuracy that is highly variable and can be biased depending on the region of interest. Satellite imagery accuracy has improved over the years, but the error magnitude remains in the meter range [20]. Ski resort managers also have surface models of their slopes, which are used by modern snowcats to efficiently distribute snow during snow grooming operations. Snowcat software also has the capability of producing a geometric model of the snow-covered slope through the interpolation of GNSS RTK data.

3.1.1. Data Collection: Aerial Scan

To have the most accurate geometric representation of the geometry and to have total control over the data, an independent aerial scan was chosen as the Digital Surface Model data source. A first aerial scan on the dry slope has been conducted, using both aerophotogrammetry and a LiDAR sensor to define the site topography and the reference, bare surface. A second survey is then carried out to produce an updated DSM of the snow-covered slope in order to calculate an accurate snow distribution profile. Later on, it is validated against the profile generated by the snowcat software, which compares the aforementioned dry DSM owned by the resort manager with the snowcat GNSS RTK data.

3.1.2. Point Cloud Generation

The dry scan was conducted using a `DJI Matrice 300 RTK` drone. Ten markers were distributed along the ski slope in order to use them as a fixed reference for the aerophotogrammetry. Each marker was anchored to the ground, and their positions were measured via a `Leica GS14` GNSS RTK Receiver. A high-resolution camera (`DJI ZenMuseP1`) was mounted on the drone and a reasonable flight altitude has been selected. The selected flight height was 200 m, resulting in a flight time of 20 minutes and a pixel resolution of 1.2 cm. The selected height was a trade-off, allowing a reasonable flight time while still maintaining the desired accuracy. More than 700 pictures were taken by the drone. The pictures were associated by the drone flight computer itself with GNSS RTK and inertial data, which are enough to produce a point cloud. The ground markers were still used to enhance the accuracy of the generated point cloud. The point cloud was generated using the *Agisoft Metashape PRO* software. The output point cloud is composed of 950 million points. The required computational time was 20 minutes[1]. The result is presented in Fig. 3. A 12.5 cm accuracy was estimated by the software, but it is worth noting that the errors were mostly in the z direction and probably due to a GNSS bias, since the closest RTK station was located far from the site. The bias implicates all the points being shifted vertically, but this does not affect the relative positions of the points, and thus will not result in a significant error in the descent simulations.

A second point cloud was generated using the `DJI L1` Lidar senso. LiDAR imaging do not require any ground marker. The LiDAR-generated point cloud, obtained via the *DJI Terra* software, is shown in Fig 2.

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[1] Running on a PC with the following specifications: AMD Ryzen 9 7950X3D 16-Core CPU, 192 GB DDR5 RAM, SSD M.2 NVME Gen 5

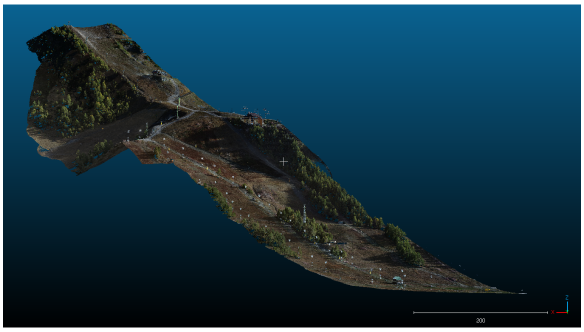

Figure 2: The point cloud generated via LiDAR imaging

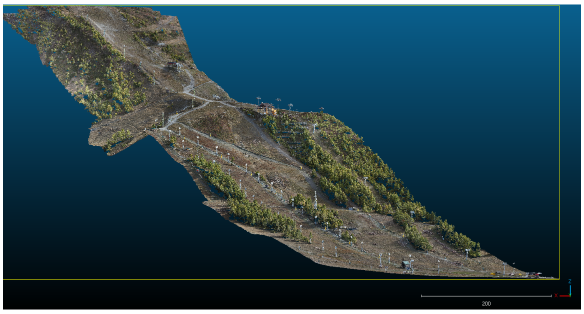

Figure 3: The point cloud generated via aero-photogrammetry

Fig. 4 shows the comparison elaborated through the *CloudCompare* software. Cloud-to-cloud distances were computed using the method proposed by [21], as implemented in *CloudCompare*. The two different point clouds are consistent, with errors concentrated in highly vegetated zones and scan area borders. Finally, the photogrammetry point cloud was compared to the dry point cloud used as a reference in the snowcat computers and owned by the managers. Fig. 5 shows the distance between the clouds, denoting an altitude shift in the point clouds, which, again, could be a GNSS bias. Further refinement is necessary to mitigate this bias and operationalize the use of photogrammetry alongside snowcat data. Once the Digital Surface Model (DSM) of the snow-covered slope is generated, this framework will facilitate a comparative analysis between the calculated snow profile and the operational data used by the snowcats.

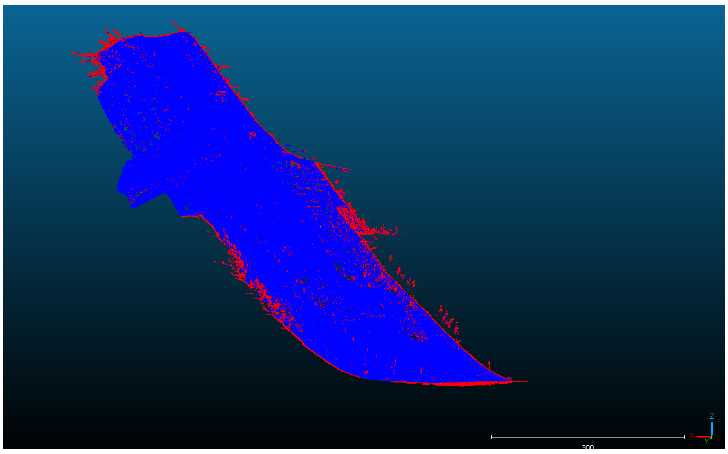

Figure 4: Point cloud comparison. Blue areas indicates less than $5\ mm$ distance between the LiDAR and photogrammetry point clouds

The finalized digital model should also include the snow physical properties, as discussed in section 4.1 .

3.2. Descent Simulations

In SkiSlo, the skier is modelled as a point mass moving along a three-dimensional surface representing the slope. Unlike complex rigid body dynamics, this particle-based approach focuses on the trajectory and all the forces are applied at the skier's snow interface. To accurately analyse the descent, we establish a non-inertial local reference system attached to the moving skier. In this frame, it is possible to decompose the acting forces relative to the direction of motion and the terrain topology.

In particular, the model computes the interplay between gravitational forces, aerodynamic drag, friction with terrain and the apparent forces resulting from the non-inertial frame of reference. A crucial aspect of this analysis is the estimation of the effective load. The load is calculated not merely as

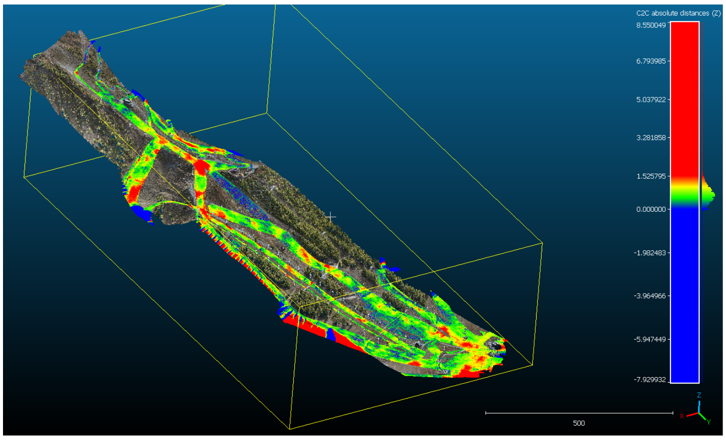

Figure 5: The cloud to cloud distance between the photogrammetry output and the dry scan use by the resort manager

the perpendicular component of gravity, but as the vector sum of the gravitational normal force and the lateral forces induced by the skier's turning motion (centrifugal force). By accounting for the local radius of curvature at every point along the path, the simulation determines the total force pressing the skis against the snow, which directly influences the available friction and, consequently, the skier's ability to maintain control.

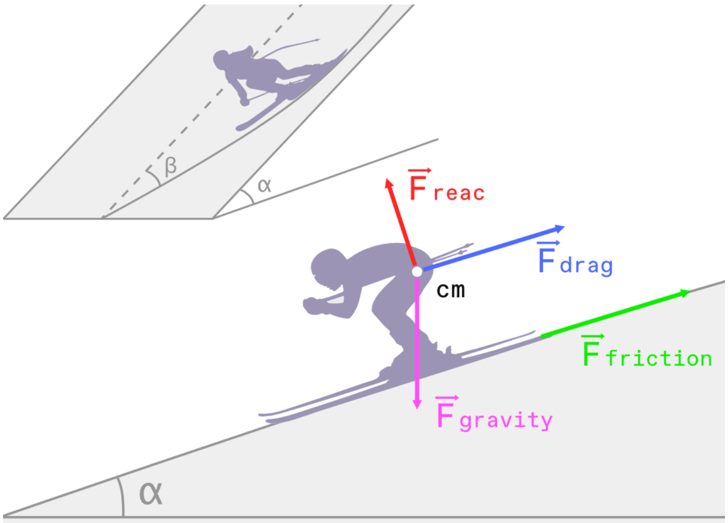

Figure 6: The physical model of the skier, depicting the acting forces on the centre of mass of the skier and the angles β and α.

Inputting a specific geometric trajectory on a given terrain topology the model evaluates the parameters α (the local **slope angle**) and β (the local **angle between the contour line and the skier's trajectory**) and simulates the physical evolution of the descent, returning the velocity profile and the dynamic stress experienced by the skier at any given location. By analysing these force distributions, we can identify critical points along the slope, specifically segments where the skier is subjected to extreme lateral accelerations or where the required friction forces exceed the physical grip of the snow, leading to potential loss of adhesion.

Although the simulation framework described above evaluates the physics of a given path, it leaves open the problem of identifying the optimal path. The generation of these trajectories is constrained by the physical boundaries of the slope and, in competitive scenarios like the giant slalom, by the obligatory passage through gates.

To address the challenge of trajectory identification, two distinct methodological approaches are considered.

1. *Numerical Optimization*: the first approach involves solving a mathematical optimization problem aimed at minimizing the total descent time, subject to the track boundaries and physical constraints. This method mathematically converges on an "ideal" trajectory. To create a robust dataset for analysis, this optimal path can be perturbed by applying noise to specific control points and interpolating the results to generate a spectrum of plausible, slightly sub-optimal trajectories. These variations provide a diverse set of inputs for the simulation engine.

2. *Reinforcement Learning (RL) Agent*: the second approach leverages machine learning, specifically an agent trained on a digital twin of the slope. In this context, a Reinforcement Learning algorithm is employed with the objective of minimizing the duration of descent. Constraints, such as staying within track limits or passing through gates, are enforced via a reward function that heavily penalizes violations.

While an RL agent may produce sub-optimal solutions compared to pure numerical optimization, the training process itself offers valuable insights. Areas where the agent struggles to converge, accumulating high negative rewards or requiring more training episodes, often correlate with the most technically difficult or dangerous sections of the slope. This allows for a predictive analysis of risk zones based on the agent's learning behaviour.

To overcome the computational intractability of continuous space in classical RL, the problem is discretized. Instead of continuous steering control, the decision space is reduced to a finite set of key interaction points, ideally located at the gates. The action space of the agent is defined by the lateral distance from the gate pole. By selecting these passage points and interpolating between them to form a continuous curve, the system generates a candidate trajectory which is then fed into the physics engine to be evaluated for time and stability.

4. Discussion

Here we discuss possible extensions of **snow analysis** (section 4.1), the planned work to implement **risk prediction** (section 4.2) and, finally, the limitations concerning **scalability** of our proposal (section 5).

4.1. Snow Modelling

Snow modelling is one of the most crucial steps in the project, integrating the digital surface model with the physical model of the skier and the interaction between the two. To this aim, it is essential to accurately model the behaviour of snow in all its properties. In recent decades, several commercial codes have been developed to model snow, including AMUNDSEN [22], Crocus [23] and SNOWPACK-/Alpine3D [24]. Created for different purposes (hydrogeological assessment and avalanche forecasting), these softwares allow the snowpack content to be represented, despite significant differences between them.

The feasibility of using ***Alpine3D*** to analyse and predict the snow's behaviour within the slope model was examined. Alpine3D is a three-dimensional, spatially distributed model that allows the dynamics of the snowpack on a mountainous topography to be predicted. It involves the use of a physical model based on mass and energy balance for a 1D soil/snow/canopy column. The meteorological conditions at the boundary of the DSM under analysis are applied to this, and through radiation, snowdrift and run-off balances, it allows the precise behaviour of the snowpack to be returned as output, together with its properties, for an appreciable period of time so that our model can be useful. The software would allow point-by-point mapping of key parameters for the output of the dynamic skier model, including the snow friction coefficient. Specifically, according to Wolfsperger et al. [25] the parameters needed to evaluate the latter are:

- Penetration resistance;
- Specific surface area;
- Snow density;
- Surface snow temperature;
- Snow depth;
- Liquid water content.

Despite the numerous advantages that Alpine3D possesses, among which its reliable results in several benchmarks [26] and being open source, the use requirements are often too elaborated for the final users of the system (e.g. the extensive slope would require the use of at least two weather stations, uphill and downhill, to interpolate the meteorological fields over the entire geometry), leading to high complexity of the measurements and increasing adoption resistance. As such, we have estimated the required variables to evaluate the friction coefficient relying upon data available in the literature. The use of the Alpine3D software is taken into account for future developments.

Similar constraints apply to the friction coefficient model; therefore, we have relied again on literature values during this initial development phase.

4.2. Risk Prediction

The data of the digital twin and the simulations must be elaborated to present a clear and concise representation of the risks. Through interview of the stakeholders (skiers, team trainers, facility owners and technicians of the sector), we discovered that the output mostly perceived as clear were heat maps (with colours associated with different risk levels) and explicit suggestions on where safety nets and escape routes are highly needed.

We propose a conceptual approach (yet to be implemented) to solve the following problems:

1. Identify the points of the track where **nets and escape routes are most needed**
2. Numerically **represent risk** on a predefined scale.

The modern approach to solving such problems would be the employment of supervised learning techniques to learn the desired risk values and safety devices. Unfortunately, the complete lack of data to create a learning dataset poses a threat, not only to the generalization capabilities of such an algorithm, but, most importantly, jeopardizes in principle the possibility of learning from data. This is why our proposed solution involves the exploration and comparison of different approaches.

4.2.1. Safety devices placement

To correctly identify the optimal placement areas for safety devices and to highlight the lack of escape routes, we suggest exploiting the simulations described in section 3.2. In particular, throughout statistical analysis, we propose to identify thresholds on the **lateral force** and orthogonal **load** that skiers can sustain. By running simulations on the gathered data, we can identify where these thresholds would be crossed, thus determining the points where athletes are more likely to lose adherence on the snow.

From these points, we can draw a set of possible trajectories that the skier, losing control, would go through and thus obtain the sides of the slope from which the skier is most likely to exit the track. Finally, exploiting geometrical analysis of the 3D model of the mountain, we can define if the subject would encounter a steep ravine, thus suggesting higher priority for safety nets.

4.2.2. Risk representation

Representing the risk with a scale is a non-trivial problem, since we incur in the risk of under-estimating or misrepresenting potentially fatal hazards. To prevent so we suggest to always operating, as in similar contexts, with the most preventive scenarios.

The aim of risk representation is thus to obtain a function $f_\vartheta : \mathcal{D} \to \mathcal{I}$ parametrized in ϑ, that maps from the set of the data $\mathcal{D}$, to an interval $\mathcal{I}$ subset of the real numbers (for instance the interval $[0, 1]$) or of the natural numbers (for instance a scale from 1 to 10).

The function must have inputs:

- The **weather** data gathered from forecasts, databases or on-site stations
- The **snow**'s physical properties
- The **3D geometry** of the slope and in particular its gradient, this will allow us to take into account areas of the slope where the descent is steeper and the zones where the track is less regular (we observe them as a high frequency varying gradient)
- The results of the **simulations** with the corresponding evolution of the forces, allowing to analyse points of higher stress for the athlete.

The function can be either computed as a (customizable) weighted average of scores assigned to the previous inputs or can be learned as a regression on a dataset of labelled samples from experts. We must notice that, to remove the human bias from the training, we suggest having a large and statistically relevant pool of ski technicians involved in the construction of this dataset.

5. Future research directions

The preliminary data collected during experimental trials on the *Kandahar* slope highlights the potentiality of the **SkiSlo** framework. While these results are promising, we anticipate that extended testing and improved data processing will eventually allow us to establish a standardized risk index. Successfully achieving this metric will mark a shift away from subjective assessment, offering a concrete method for accident prevention and substantially improving safety standards for skiers. To limit user resistance, taking into consideration scalability issues is of paramount importance. Three principal bottlenecks emerged from our analysis:

Data gathering: the collection of data might take time and resources. Ski facilities have the urge to gather data rapidly without closing the tracks for a long time; furthermore, given the rapidly changing nature of snow, data are considered available only for a short period. This is why we opted for using the minimum amount of data possible. Our gathering aims to be the least intrusive by adopting drones or already-implemented sensors on the snow groomers.

Data processing: post-processing of data can be computationally demanding. We thus suggest implementing the core of the software as an in-cloud solution, to also allow operations for users without exceptional computing power.

User presentation: interpretability of the results is a key objective of our work. Making the results understandable also to people with less familiarity with informatics tools is essential to stimulate their use and, consequently, obtain a tangible impact on ski safety.

The discussion on this regard is still open and ongoing, and further research on the topics is encouraged.

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Declaration on Generative AI

During the preparation of this work, the author(s) used Gemini and ChatGPT 4.0 exclusively to improve the readability and language quality of the manuscript. The tools were used for proofreading and stylistic polishing. The author(s) reviewed the output carefully and take full responsibility for the factual accuracy and final content of the work.

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