**The Influence of Weather Patterns on Snow Instability and Avalanche Frequency in Switzerland: A Comprehensive Analysis**

**Abstract:**  
This report investigates the relationship between meteorological conditions and snow instability in Switzerland, with the ultimate goal of forecasting avalanche risks. Using datasets containing snow instability profiles, avalanche accidents, and weather data retrieved from external APIs, we explore how past weather conditions affect snow stability and, by extension, avalanche probability. The report applies exploratory data analysis (EDA), correlation studies, and outlines a two-stage predictive modeling approach: first, forecasting snow instability indicators from weather and terrain variables, and second, inferring avalanche risk. Findings highlight the impact of snow accumulation, wind, and temperature on snowpack integrity. These insights aim to enhance avalanche forecasting models and support public safety strategies.

**1. Introduction**

Avalanches remain one of the most significant natural hazards in the alpine regions of Switzerland. With thousands of avalanche events recorded annually and substantial risks posed to both life and infrastructure, improving avalanche risk prediction is of paramount importance.

Traditionally, snow instability is evaluated through in-situ tests, among which the Rutschblock (RB) test is considered the most comprehensive. The RB test involves isolating a 2 × 1.5 meter column of snow on a slope and applying a sequence of increasing loads via a skier stepping or jumping on the column. The goal is to assess whether a weak layer within the snowpack fails and whether the failure propagates across the column. The outcome is assigned a score from 1 to 7, where lower scores indicate higher instability and a greater likelihood of skier-triggered avalanches. Scores of 1 to 3 suggest poor stability, while scores above 5 typically indicate stable conditions.

While the RB test provides direct insight into both strength and fracture propagation potential, it is limited by several factors. It is time-consuming, requires expert judgment for execution and interpretation, and is spatially constrained—capturing only the conditions at a single point on a slope. Moreover, RB scores are subject to variability due to local snowpack heterogeneity, and cannot be conducted safely or practically in many high-risk areas. These constraints highlight the need for data-driven models that can generalize risk estimation based on weather and terrain conditions without direct field testing.

This report proposes a data-driven approach leveraging meteorological and geographical data to predict snow instability and, consequently, avalanche probability. The primary objective is to explore whether historical weather patterns can reliably forecast instability, using a two-step model: first, predicting snow instability metrics, and second, inferring avalanche occurrence. This method aims to complement or replace manual testing with automated, scalable tools for real-time avalanche risk assessment.

**2. Data Characteristics**

The data used in this study originates from three primary sources. The snow instability data comprises field measurements collected by the Swiss Federal Institute for Snow and Avalanche Research (SLF), which include RB scores, grain sizes, and snowpack indices. Avalanche accident data consists of historical records of avalanche events in Switzerland from 1995 onwards. Weather data is sourced from the Open Meteo API, providing archived hourly and daily meteorological data for the 14-day period preceding each observation.

The datasets incorporate both cross-sectional and time-series characteristics. Snow instability profiles represent cross-sectional data, while weather data reflects temporal variation. The datasets are further enhanced with spatial information such as coordinates and elevation, enabling terrain-specific analysis.

One of the key snow instability indicators used is the Rutschblock score. This score ranges from 1 to 7, with each level representing the ease with which a weak layer fails under applied load. A score of 1 corresponds to failure upon gentle loading (such as approaching the block), while a score of 7 indicates that no failure occurred even under full dynamic loading. This score is thus a direct proxy for the likelihood of skier-triggered avalanches, and its inclusion in our modeling framework allows us to quantify mechanical instability as a function of terrain and weather conditions.

Snow grain size is another critical feature in snowpack analysis. Larger grains, especially when found in weak layers, indicate metamorphic processes such as faceting or depth hoar formation, both of which reduce cohesion and increase the risk of failure. Differences in grain size across adjacent layers can also create mechanical discontinuities that act as failure planes. Hence, grain size (both average and maximum) is a structural variable that signals instability potential and is frequently included in threshold-based models of snowpack failure.

Exploratory data analysis revealed several important insights. Univariate analysis examined key meteorological variables such as temperature, wind speed, snow depth, and sunshine duration using summary statistics and visualizations. Bivariate analysis, including correlation matrices, demonstrated strong associations between RB\_score, snowfall, and grain size. Multivariate analysis identified interaction effects, suggesting that combinations of weather conditions, such as snow and wind, jointly affect snow stability.

Several data processing challenges were encountered. The Swiss LV95 coordinate system required conversion to WGS84 for weather data retrieval through APIs. Additionally, temporal alignment between weather data and snow observations required precise date formatting and matching.

**3. Results and Interpretation**

The results underscore the importance of several weather variables in influencing snow instability. Variables such as RB\_score, SNPK\_Index, and Grain\_Size\_Diff showed significant sensitivity to cumulative snowfall, wind gusts, and sunshine duration observed over the prior days. Notably, high snowfall combined with elevated wind speeds substantially increased snow instability. Furthermore, the temporal lag of meteorological effects was evident, with recent snowfall within the past 24 hours exhibiting a stronger correlation with instability indicators than snowfall from earlier periods.

A supervised Generalized Linear Model (GLM) was applied to predict RB\_score using terrain features such as slope and aspect, along with four temporal weather intervals: 0–1, 1–3, 3–7, and 7–14 days. The preliminary model demonstrated a satisfactory explanatory power with an R-squared value exceeding 0.60. In addition, a secondary model was proposed to estimate avalanche risk. This model may either rely on deterministic thresholds informed by domain knowledge or utilize statistical correlation derived from historical avalanche accident data.

These results offer practical implications. Predicting RB\_score and SNPK\_Index from real-time weather inputs could substantially enhance decision-making for mountaineers and rescue operations. Moreover, the automation of such predictions diminishes the need for field-based snowpack testing, thereby reducing exposure to hazardous conditions.

**4. Summary and Concluding Remarks**

This study demonstrated the predictive value of weather variables in estimating snow instability metrics. It highlighted how interaction effects between weather elements and temporal lags play crucial roles in snowpack vulnerability. Furthermore, it introduced a reproducible analytical pipeline capable of delivering real-time avalanche risk assessments based on meteorological and geographical data.

Nevertheless, several limitations must be acknowledged. The reliability of predictions is contingent upon the accuracy of weather forecasts. The spatial distribution of snow profile measurements is uneven, which may introduce bias. Additionally, the models developed did not yet integrate machine learning methodologies, which could further enhance predictive performance.

Future work should explore the incorporation of machine learning algorithms to refine model precision. Expanding the input dataset to include additional terrain-specific variables such as curvature or vegetation could also improve accuracy. Finally, developing a web-based interface for real-time risk dissemination represents a promising direction to operationalize these findings.