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AUTOMATED AVALANCHE MONITORING: ENGINEERING AND SOFTWARE SOLUTIONS

Abstract: An autonomous avalanche hazard monitoring system has been developed and piloted in the East Kazakhstan Region to enable continuous, data-driven early detection and prediction of snow avalanches in mountainous environments. The system integrates a hardware–software ecosystem that overcomes the limitations of traditional manual observations by combining real-time data acquisition, transmission, and predictive analytics. The prototype includes base stations, autonomous snow-temperature measuring rails, meteorological sensors, and a secure web interface with an API for reliable data management.

Field deployments were conducted in three avalanche-prone areas with diverse terrain and climate conditions: Glubokoe district (Mountain Ulbinka), Altai district (Zubovsk), and Ulan district (Taynty river basin). The hardware, including 6-meter modular aluminum masts and sensor-equipped snow rails, was designed for extreme environments, operating reliably within a temperature range of –60 °C to +50 °C and withstanding strong winds and snow loads. The system supports autonomous operation in remote regions with minimal maintenance requirements.

The monitoring network collects high-resolution environmental data, including air temperature, humidity, wind parameters, atmospheric pressure, snow depth, and vertical snow temperature gradients. Data are transmitted every 15 minutes via LoRa, with LTE/Wi-Fi as backup, and stored in a centralized MySQL database. A dedicated software platform enables data visualization, processing, and integration with analytical modules, while a mobile application provides real-time monitoring and alerts.

Logistic regression models were applied to estimate avalanche probability based on meteorological and snowpack data, demonstrating the effectiveness of combining continuous monitoring with statistical forecasting. The system provides a scalable and adaptable framework for avalanche hazard assessment, early warning, and informed decision-making, contributing to improved safety in mountainous regions.

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Keywords: avalanche hazard; avalanche monitoring; software-hardware complex; sensor networks; automated detection; modular electronic system.

Introduction

The contribution of this study is primarily situated in the development, integration, and field validation of an autonomous avalanche monitoring system tailored to the climatic and geomorphological conditions of East Kazakhstan. Rather than introducing fundamentally new sensing principles or theoretical models, the work focuses on the systematic combination of established technologies such as modular hardware design, snow-temperature profiling, LoRa-based communication, and centralized data management into a coherent and operational framework suitable for harsh and infrastructure-limited mountain environments.

The key advancement lies in the engineering integration of heterogeneous components into a unified, autonomous monitoring platform capable of continuous real-time data acquisition, transmission, and processing. In contrast to many existing approaches that rely on single sensing modalities or fragmented system architectures, the proposed solution combines meteorological, snowpack, and contextual environmental data within a single digital infrastructure. This enables consistent data streams suitable for both operational monitoring and subsequent analytical modeling.

In addition, the study demonstrates the practical coupling of in-situ sensor networks with statistical forecasting methods, specifically logistic regression, to estimate avalanche occurrence probability based on observed environmental parameters. While the modeling approach itself is not novel, its implementation within a real-time monitoring pipeline and validation under field conditions represents an applied contribution to data-driven avalanche hazard assessment.

Accordingly, the novelty of the work should be understood as an applied systems-level contribution: the design, deployment, and evaluation of a scalable and adaptable monitoring architecture that bridges the gap between existing sensing technologies and their use in operational early-warning contexts. This includes addressing challenges of autonomous operation, energy efficiency, communication reliability, and environmental robustness in remote mountainous regions.

The study addresses the following key research and engineering tasks. First, it develops and deploys a modular hardware-software architecture capable of reliably collecting meteorological and snowpack parameters under extreme environmental conditions. Second, it implements a unified data infrastructure that integrates heterogeneous data sources into a centralized system for continuous monitoring and analysis. Third, it evaluates the feasibility of embedding statistical forecasting within an operational monitoring framework, thereby supporting data-driven decision-making for avalanche hazard assessment.

Avalanche events pose a significant threat to human life and infrastructure in mountainous regions, making timely monitoring and detection crucial for hazard mitigation. Recent advances in sensor technologies, embedded systems, and data processing algorithms have enabled the development of automated avalanche monitoring systems that combine real-time detection with predictive analytics. A variety of hardware and software solutions have been explored in recent years, ranging from ground-based sensor networks and remote sensing techniques to machine learning methods for analyzing avalanche-related data. Despite progress in this field, integrating modular electronic systems with efficient software frameworks remains a key challenge for achieving reliable and scalable avalanche monitoring.

The Sendai Framework for Disaster Risk Reduction midterm review emphasizes the growing importance of early warning systems, integrated risk assessment, and advanced monitoring technologies for mitigating natural hazards, including snow avalanches. The report highlights the need for improved data sharing and the adoption of modern technological solutions at national and regional levels. However, its contribution remains largely strategic and policy-oriented, without addressing the technical implementation of avalanche monitoring systems. In particular, it does not provide guidance on system architecture, sensor network design, autonomous data acquisition, or real-time data integration under harsh mountain conditions. This limitation reveals a clear research gap between high-level disaster risk management frameworks and their practical engineering realization. Unlike the conceptual recommendations presented in the Sendai Framework review, the present study develops and implements a fully integrated hardware–software system tailored for continuous, autonomous avalanche monitoring. It explicitly addresses challenges related to modular system architecture, field deployment in extreme environments, and real-time data transmission and processing. Thus, the contribution of this work lies in bridging the gap between policy-level recommendations and an operational, scalable monitoring solution capable of supporting data-driven avalanche forecasting in real-world conditions [1].

The Kazselezashchita report on regional safety and disaster prevention provides valuable empirical insights into avalanche activity and current risk management practices in Kazakhstan. It documents operational approaches such as expert-based hazard assessment, field observations, and controlled avalanche release, reflecting the established workflow of national safety services. However, the report primarily describes conventional, observation-driven methodologies and does not incorporate modern digital monitoring architectures or automated sensor networks. In contrast to emerging international trends toward real-time, data-driven hazard assessment, the approach outlined by Kazselezashchita remains largely dependent on manual data collection and expert interpretation, limiting temporal resolution and scalability. The absence of integrated hardware–software platforms, continuous data acquisition, and predictive analytics highlights a significant technological gap in the regional context. Addressing this limitation, the present study introduces an autonomous monitoring system that combines distributed sensor networks, real-time data transmission, and statistical forecasting methods. This positions the proposed solution as a direct advancement over existing practices by enabling continuous, objective, and scalable avalanche hazard assessment in Kazakhstan [2].

Despite the high level of avalanche activity, the national research landscape still lacks a comprehensive and systematically implemented framework for spatial avalanche forecasting based on modern digital technologies [3]. Existing approaches are largely grounded in expert judgment, empirical hazard mapping, and data from isolated monitoring stations, which constrain the transition toward continuous, real-time, and data-driven avalanche risk assessment.

The study by F.M. Bianchi, J. Grahn, M. Eckerstorfer, E. Malnes, and H. Vickers proposes a deep learning approach for snow avalanche segmentation in SAR images using Fully Convolutional Neural Networks [4]. The method enables automatic detection and mapping of avalanche-affected areas from satellite data, providing large-area coverage and independence from weather and lighting conditions. The study demonstrates the effectiveness of FCNNs for post-event avalanche mapping, while its main limitation is the focus on detection after the event rather than real-time forecasting and continuous monitoring.

The SensAlpin system demonstrates the effectiveness of automated meteorological monitoring networks for avalanche warning in alpine regions [5]. However, its architecture is tailored to well-developed infrastructure conditions, including stable power supply and dense communication networks. Consequently, it does not fully address the constraints of remote mountainous regions, where autonomous, energy-efficient, and communication-resilient monitoring systems are required.

Similarly, Campbell Scientific Alpine Automated Weather Instrumentation provides robust solutions for high-altitude meteorological data collection [6]. Nevertheless, these systems primarily function as environmental monitoring tools and lack tight integration with specialized snowpack sensing, unified data platforms, and embedded predictive models for avalanche hazard assessment.

Taken together, these studies highlight a fragmented landscape in which forecasting models, sensor technologies, and operational systems are often developed independently.

Therefore, the key research gap lies in the lack of an integrated, field-deployable architecture that combines autonomous sensor networks, real-time data transmission, and embedded predictive analytics under harsh environmental and infrastructural constraints. In contrast, the present study proposes and validates a unified hardware–software framework that explicitly addresses these challenges, enabling scalable and continuous avalanche monitoring and forecasting in remote regions of East Kazakhstan. In recent years, significant advances have been made in automated, remote-sensing-based approaches to monitoring avalanches in mountainous regions. Several studies demonstrate that modern technologies, ranging from satellite radars to fiberoptic systems, can substantially expand monitoring capabilities, overcoming the limitations of traditional field methods. The key approaches and their respective strengths and weaknesses are discussed below.

The study by M. Eckerstorfer, H. Vickers, E. Malnes, and J. Grahn presents a near-real-time avalanche monitoring system based on Sentinel-1 SAR data, enabling automated detection of avalanche polygons within minutes after satellite data acquisition [7]. In this work, the authors develop and validate an approach that leverages synthetic aperture radar (SAR) imagery to identify surface changes associated with avalanche events, even under conditions of cloud cover and limited visibility. The proposed system demonstrates the key advantages of satellite-based monitoring, including wide spatial coverage, regular data updates, and independence from weather and illumination conditions, making it particularly suitable for large and remote mountainous regions.

However, in contrast to in-situ monitoring systems, the reliability of SAR-based detection remains highly variable and dependent on snow type, surface conditions, and avalanche characteristics. The method shows limited sensitivity to small-scale avalanches and events with weak surface contrast, while relatively high false alarm rates reduce its suitability for operational early warning. Moreover, satellite-based approaches inherently lack continuous temporal resolution and do not provide direct measurements of internal snowpack properties, which are critical for predictive modeling.

These limitations highlight a key methodological gap between large-scale remote sensing approaches and ground-based, high-frequency monitoring systems required for real-time hazard assessment. Unlike the Sentinel-1-based framework, the present study focuses on a distributed in-situ sensor network that enables continuous measurement of meteorological and snowpack parameters, combined with real-time data transmission and statistical forecasting. This integrated approach enhances temporal resolution, improves reliability for operational use, and supports data-driven avalanche prediction under variable environmental conditions.

The study by A. Turquet, A. Wuestefeld, and co-authors presents an automatic avalanche detection system based on Distributed Acoustic Sensing (DAS), using fiber-optic cables to detect ground vibrations [8]. The system demonstrated high reliability, identifying all recorded avalanche events and enabling continuous real-time monitoring over distances up to 170 km, regardless of weather conditions.

Complementary research by Franz Kleine and colleagues shows that DAS data can capture characteristic frequency patterns of avalanche activity, including both major events and possible precursors [9]. However, both studies focus mainly on vibration-based detection and lack integration with meteorological or snowpack data, limiting their ability to assess the physical conditions of avalanche formation.

Despite these advantages, DAS-based systems are inherently constrained by their dependence on existing or newly installed fiber-optic infrastructure, which limits their applicability to specific linear corridors such as roads or pipelines. In addition, the sensitivity of DAS to environmental noise, including traffic-induced vibrations, necessitates complex signal processing and filtering, reducing robustness in heterogeneous operational environments. Furthermore, such systems primarily detect avalanche occurrence rather than providing continuous measurements of meteorological and snowpack conditions required for predictive modeling.

In comparison with satellite-based SAR methods, which offer large-scale coverage but limited temporal resolution and variable detection accuracy, DAS provides high-frequency, localized detection but lacks environmental context and deployment flexibility. These complementary limitations highlight a broader research gap: the absence of integrated monitoring frameworks that combine continuous environmental sensing, autonomous deployment, and embedded predictive capabilities without reliance on fixed infrastructure.

Addressing this gap, the present study proposes a distributed, autonomous sensor-based system that integrates meteorological and snowpack measurements with real-time data transmission and statistical forecasting. Unlike DAS systems, the proposed approach does not depend on linear infrastructure and enables flexible deployment across heterogeneous avalanche-prone terrains, while also supporting predictive hazard assessment rather than post-event detection alone.

A range of remote avalanche monitoring systems has been developed based on heterogeneous sensing technologies. For instance, the study by R. Bian, K. Huang, and co-authors compares avalanche radar and infrasound sensor configurations combined with ensemble machine learning methods for susceptibility assessment [10]. The authors demonstrate the effectiveness of these approaches under varying environmental conditions, highlighting the growing role of data-driven models in geohazard analysis. However, such systems are mainly focused on detecting avalanche occurrence rather than supporting continuous and comprehensive hazard assessment. Research by V. Blagoveshchenskiy, M. Myrzakhmetov, and E. Sadvakasov explores acoustic, infrasound, and video-based monitoring systems for transportation safety in mountainous regions such as the Ile Alatau [11]. Their work emphasizes practical deployment near infrastructure and confirms the effectiveness of these systems for real-time avalanche detection, although their functionality remains limited to event identification without deeper environmental monitoring or predictive integration. The study by S. Mayer, A. van Herwijnen, G. Ulivieri, and J. Schweizer evaluates an operational infrasound detection system in the Swiss Alps [12]. The authors show reliable detection of medium and large avalanches under all visibility conditions, while noting limitations such as sensitivity to small events, environmental noise interference, and challenges in precise localization. In parallel, studies by A. Aydin and R. Eker develop GIS-based avalanche hazard maps using digital terrain models in Turkey [13, 14]. Similarly, R.L. Soteres and colleagues combine GIS tools with field observations and historical data to assess avalanche susceptibility [15]. Recent works, including those by M. Rakhymberdina and N. Denissova, demonstrate the effectiveness of integrating remote sensing and GIS for avalanche detection and nationwide hazard mapping [16, 17]. The study by H.T. Larsen, J. Hendrikx, M.S. Slatten, and R.V. Engeset develops a nationwide framework for avalanche terrain mapping in Norway using GIS-based terrain analysis and digital elevation models [18]. The authors generate standardized avalanche terrain maps at a national scale, enabling consistent identification of potentially dangerous areas and supporting large-scale hazard assessment, land-use planning, and risk management. Furthermore, B. Choubin and co-authors highlight the application of machine learning methods for avalanche hazard prediction, emphasizing the importance of terrain and environmental factors [19]. Overall, these studies demonstrate significant progress in both detection and mapping approaches, yet most remain limited either to event detection or static hazard assessment, underscoring the need for integrated, real-time monitoring and predictive systems.

Across these approaches, a common limitation emerges: the separation between detection technologies, environmental sensing, and forecasting methodologies. Most existing systems are designed either for post-event identification or for localized hazard indication, without providing a unified framework that integrates multi-parameter observations, autonomous operation, and real-time predictive analytics.

This fragmentation defines a key research gap. In contrast to the above methods, the present study develops a modular and scalable hardware–software system that combines distributed sensor networks, continuous monitoring of meteorological and snowpack parameters, and embedded statistical forecasting. By integrating data acquisition, processing, and prediction within a single platform, the proposed approach extends beyond event detection toward proactive, data-driven avalanche hazard assessment in remote and infrastructure-limited regions.

Methods and Materials

2.1 Research area.

The East Kazakhstan region covers an area of approximately 97,800 km² and exhibits pronounced natural heterogeneity within a relatively compact territory. Climatic variability is substantial, extending from steppe and semi-desert zones in the south and southwest to complex mountain systems in the north and northeast. The region is characterized by extreme seasonal and diurnal temperature fluctuations, with long, cold, and snowy winters. The Saur–Tarbagatay, Kalba, and Altai mountain ranges play a decisive role in shaping the regional climate, while the presence of perennial glaciers contributes to highly localized microclimatic gradients. These conditions generate frequent and intensive snow accumulation processes, including wind redistribution, rapid snowpack metamorphism, and strong temperature contrasts. Taken together, these factors create a combination of topographic and climatic conditions that substantially elevate avalanche hazard across the mountainous areas of East Kazakhstan [20].

2.2. Automated Avalanche Monitoring System

The proposed automated avalanche monitoring system represents an integrated hardware–software complex designed to assess avalanche conditions and transmit real-time alerts. The development strategy involves the aggregation of historical, archival, and real-time datasets, including meteorological observations, slope condition and morphology parameters, remote sensing products, digital twin reconstructions, and records of spontaneous avalanche events. These datasets are processed using direct and inverse modeling approaches, supplemented by machine-learning techniques to enhance predictive accuracy.

2.3. Hardware Architecture

The hardware component of the system is centered on a base station constructed as a low-rise mast equipped with modular attachments. Station can be installed on or off a slope if installation on an avalanche slope is not possible. The base station operates in conjunction with a snow-depth and snow-temperature measuring rail installed at critical points of the terrain, such as avalanche initiation zones or areas subject to wind-driven snow transport.

2.4. Software Integration

All hardware modules are integrated through a dedicated software suite responsible for equipment synchronization, data transmission to the central server, long-term storage, and multistage processing. The software subsystem supports data visualization and implements a forecasting framework based on an ensemble of models.

In this regard, the research problem can be formulated as the task of estimating the probability of spontaneous avalanche occurrence based on a set of environmental variables obtained from an automated sensor network. The input data include meteorological and snowpack parameters (air temperature, humidity, wind speed, snow depth, and snow temperature gradient) collected at regular time intervals. The objective is to construct a predictive model that maps these variables to the probability of avalanche occurrence and integrates the result into an operational monitoring system.

Results

The authors have developed an avalanche hazard monitoring system for Eastern Kazakhstan. A prototype of an autonomous, automated avalanche hazard monitoring system was created with the possibility of early prediction and avalanche prevention. For real-world testing, the system's sensors were placed in avalanche-prone areas of Eastern Kazakhstan. In Glubokoe district of the East Kazakhstan region, near the village of Gona-ya Ulbinka (near the road) (Figure 1a). Placement coordinates: 49°57'30"N 82°58'32"E. In the Altai region, the village of Zubovsk (next to the school) (Figure 1b), coordinates of the location: N49°47'9.24" E84°16'23.04". In Ulan district, in the Taynty river basin (near the road) (Figure 1c), the coordinates of the location: N49°20'34.52" E83° 6'14.82".

a b c

Figure 1. Base stations in avalanche-prone areas of the East Kazakhstan region.

The main components of the avalanche monitoring system created within the framework of this project are (Figure 2):

- Base station;
- Snow-temperature measuring rail;
- API (application programming interface), a service for saving weather and climate parameters to a database;
- Web interface of the avalanche hazard monitoring system.

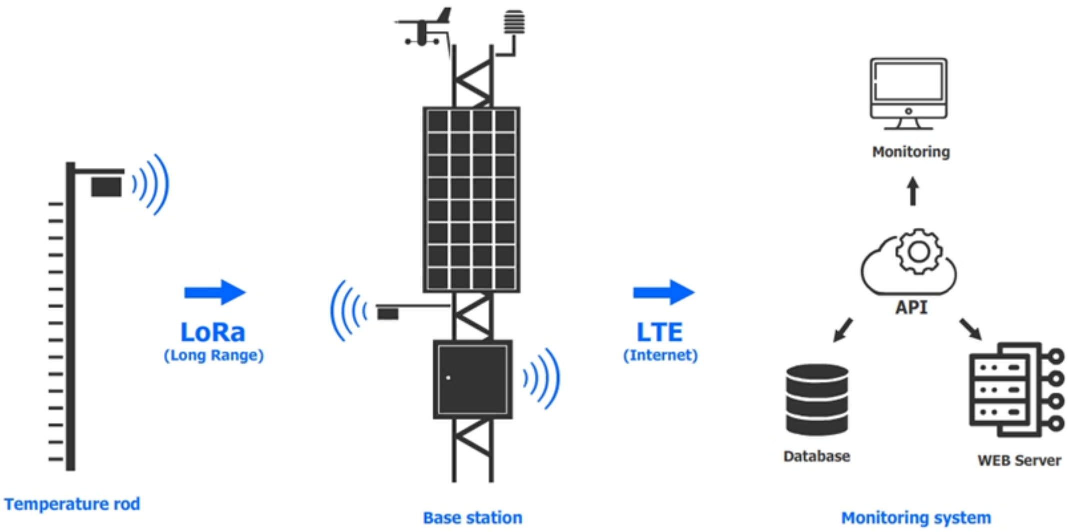


Figure 2. Avalanche hazard monitoring system diagram.

Among the climatic parameters, the negative temperature, which causes metal destruction, and humidity, which creates metal corrosion, have the greatest impact on the metal structure of the base station mast. To protect against corrosion, anti-corrosion coatings are applied to the metal. For the possibility of operating the mast at subzero temperatures, the appropriate steel grade is selected.

According to studies of the conditions for monitoring avalanche-prone areas in East Kazakhstan region, it was decided to install 6-meter-high aluminum masts, a triangular sectional structure with operating temperature limits from -60 °C to +50 °C, and a maximum load of 400 kg. The length of the section is 3 meters, length of the rib section is 400 mm. The mast has a block hoist for lifting the equipment. Three guy rods are installed in the corners of the triangular cross-section of the mast and are evenly spaced through 120°. The radius of the guy rods is 3.6 m.

The main reasons for choosing a truss:

1. Strength and stability: Truss structures are known for their durability and ability to withstand extreme weather conditions such as strong winds, snow loads, and temperature fluctuations, which are extremely important in mountainous conditions.

2. Ease of construction: trusses are usually lighter than solid poles, which makes them easier to transport and install in remote or hard-to-reach mountainous areas.

3. Modularity and adaptability: truss masts can be designed to be modular and easily adaptable to various types of monitoring equipment, including cameras, motion sensors, meteorological instruments, etc.

4. Cost-effectiveness: trusses are often more economical to manufacture and install compared to other types of matters, which makes their choice preferable, especially with a limited budget.

5. Good aerodynamics: trusses usually have less wind resistance, which reduces the risk of damage or tipping over during high winds or storms.

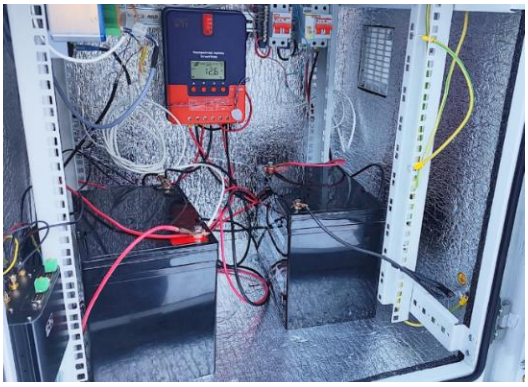
The snow avalanche base station (Figure 3) is a software and hardware complex consisting of sensors and equipment that collect information about key weather and climatic parameters to ensure effective monitoring and data transmission in real time. The list of received weather and climatic parameters includes: Wind speed; Wind direction; Air temperature; Relative humidity of the air; Atmospheric pressure; Snow cover height; The temperature gradient of the snow cover.

Figure 3. The type of construction of the snow avalanche base station.

The wind speed and direction data source is the DBM-6410 wind sensor. The temperature, humidity, and pressure sensor (Lambrecht THP[pro]) (Figure 4a), installed in the sensor housing, is used to measure temperature, humidity, and atmospheric pressure. The rest of the equipment is housed in a weather-proof outdoor cabinet (Figure 4b).)

Sensor readings are transmitted on the Ser[LOG] Plus data logger using the Modbus protocol. This logger supports the connection and operation of many different sensors, from temperature and humidity to more complex meteorological sensors such as barometers, anemometers, and other devices. The device supports various connection methods, including RS-232, RS-485, USB, and analog inputs. The registrar can collect data in real time, as well as support periodic or event-based data collection modes. It can store data in its memory or transfer it to an external server.

a



b

Figure 4. Placement of sensors and probes at the base station: a - Wind sensor and temperature, humidity, and pressure sensor; b - Outdoor all-weather cabinet equipment.

The Heltec LoRa 32 microcontroller, which is also equipped with a HI50 laser rangefinder, acts as a receiver at the base station. This allows the device to combine the functions of measuring the height of the snow cover and receiving data from snow-temperature measuring rails. The microcontroller aggregates data in its memory and transmits it to the AvaAPI API service with an interval of 15 minutes. Data is transmitted via a Wi-Fi connection between the Heltec LoRa 32 and the LTE/Wi-Fi router iRZ RL25w, which provides an Internet connection.

Below is the code executed on an LTE/Wi-Fi router that implements the functionality of a proxy server that accepts HTTP requests on a local host, changes the request header parameters, and forwards them to a remote API server using an SSL connection (Table 1, Appendix 1).

All sensor readings collected by the registrar are converted to JSON format (JavaScript Object Notation is a JavaScript-based text data exchange format), convenient for transmission, and sent every 15 minutes via HTTP protocol to AvaAPI (an API service developed as part of the current project). The AvaAPI server accepts the request, performs authorization, verifies the transmitted data, and stores it in a database for further analysis. The data transfer process between the registrar and the API service is carried out via an LTE Internet connection via the iRZ RL25w router. The system's autonomy is ensured using an OSDA Solar 380M ODA380-30-MH solar panel with a peak power of 380 watts, operating in combination with two 75 Ah batteries each. Battery charging is controlled using the SRNE SR-ML2420 MPPT controller, which optimizes the operation of the solar panel. The main equipment, except for sensors, is housed in a 12U weatherproof outdoor cabinet (Figure 4b), which protects the equipment from adverse weather conditions and maintains a preset temperature regime.

In addition to weather and climatic parameters, information about snow cover is important for monitoring and forecasting avalanche hazards. The collection of these parameters is provided by snow-temperature measuring rails, and a Heltec LoRa 32 microcontroller paired with a laser rangefinder installed directly on the base station, which is a receiver of data from snow-temperature measuring rails. The data transmission range of a LoRa signal depends on several factors, including frequency, terrain, environmental conditions, and signal strength. In conditions of good visibility and when using an optical antenna, the device can transmit data up to 30 km (in line-of-sight conditions).

Snow-temperature measuring rails are autonomous devices integrated into the monitoring system. Each rail is based on a CubeCell - AB01 Dev–Board (V2) microcontroller and is equipped with several key components (Figure 5) for data acquisition and transmission.

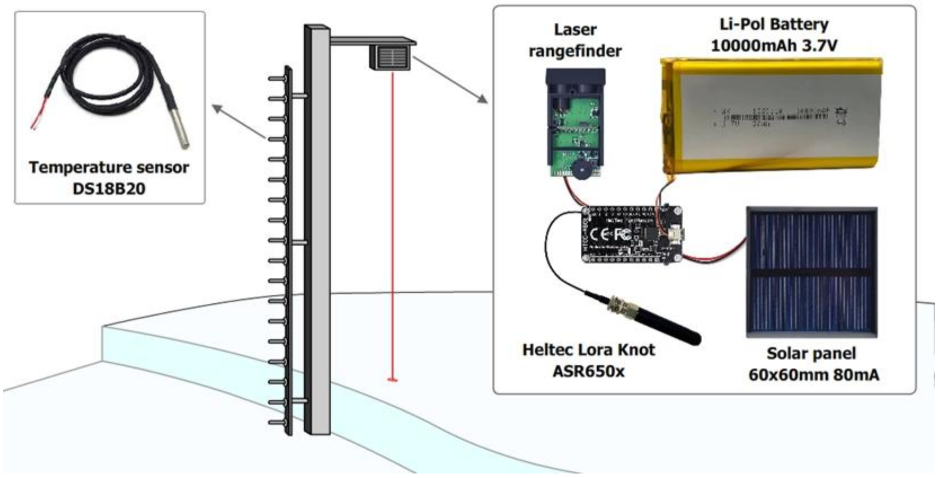
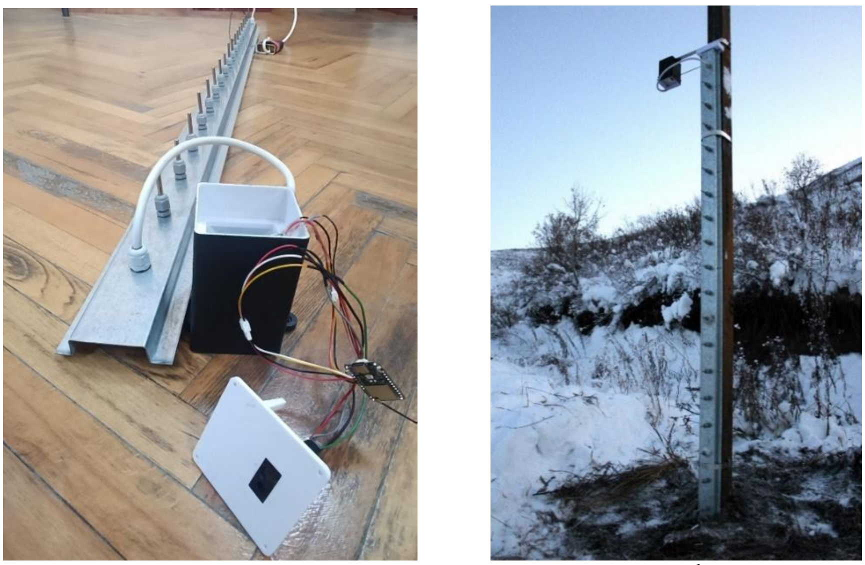


Figure 5. Temperature snow gauge.

A hat mounting profile has been selected for the manufacture of a snow-temperature measuring rail 50*20*2000 (OC-0.1-BC-1.2mm) and an L-shaped bracket 400mm*250mm*30mm (2 mm). For the layout of the electronic equipment, the cases are printed on a 3D printer and insulated with sealant (Figure 6).

The snow-temperature measuring rail includes: HI50 laser rangefinder designed for high-precision measurement of snow cover height; 18 DS18B20 temperature sensors mounted on a vertical rail in 10 cm increments; two lithium polymer batteries with a capacity of 10000 mAh, providing energy autonomy of the device; two solar panels measuring 60×60 mm with an output current 80 mA, which supports battery charging and extends the life of the device in offline mode.



a b

Figure 6. Snow-temperature measuring rail. a - structure and components; b - rail installed in an avalanche-prone area

The software code of a microcontroller on a rail for measuring snow temperature collects data from a laser rangefinder and a few temperature sensors and sends them via LoRaWAN (long-wave radio communication) to the base station receiver with a frequency of 15 minutes (Table 2, Table 1, Appendix 1).

Snow-temperature measuring rails collect data on snow height, temperature gradient of snow cover, and battery voltage. The collected data is transmitted every 15 minutes using the LoRa

(Long Range) wireless communication protocol at a frequency of 433MHz to a receiver located at the base snowfall station (Figure 7).

Figure 7. Receiver of data from a snow-temperature measuring rail.

The code executed on the snow-temperature measuring rail data receiver is shown below (Table 3, Appendix 1). When data arrives from the rail, the radio module reads the incoming data. Then a string of packets is generated, which includes information about the received data and the measured distance obtained using a laser rangefinder installed on the receiver. Next, a data packet is generated, encoded in base64, and sent to the target server over a Wi-Fi network using an HTTP POST request.

Information from all data sources is collected in a single digital database, based on which an algorithm for analyzing these parameters will be developed specifically for the East Kazakhstan region. Meteorological data are not the only important components of it. During the study of avalanche-prone areas of the East Kazakhstan region, the following information objects were identified: area, avalanche-prone area, avalanche collection, meteorological data, morphological type, type of slope exposure, type of vegetation, vegetation, degree of avalanche danger, device, observation parameters, observation data, preventive descents, spontaneous avalanche.

A database based on the MySQL database management system was created to store the collected data. Google Earth Pro was used to form the cartographic basis of the project.

To understand the interaction between previously identified information objects in the database, Figure 8 shows the logical schema of the database. The information objects selected for the study are shown, as well as the relationships between them and their attributive composition.

The data in the database created is collected from various data sources. For the specified database, data sources can be roughly divided into the following categories: Dictionary data - reference data of various types, records of avalanche-prone areas - information about avalanche-prone areas observed in the monitoring and forecasting system (operational logs of preventive descents and spontaneous avalanches of the State Institution Kazselezashchita); data from open sources — data from open sources (databases of the National Hydrometeorological Service of Kazakhstan Kazhydromet, etc.), which are necessary for predicting avalanches; observational data - data from various metering devices (stationary devices, unmanned aerial vehicles, etc.). Distribution of information objects of the database development process. The data sources are shown in Figure 9 for clarity.

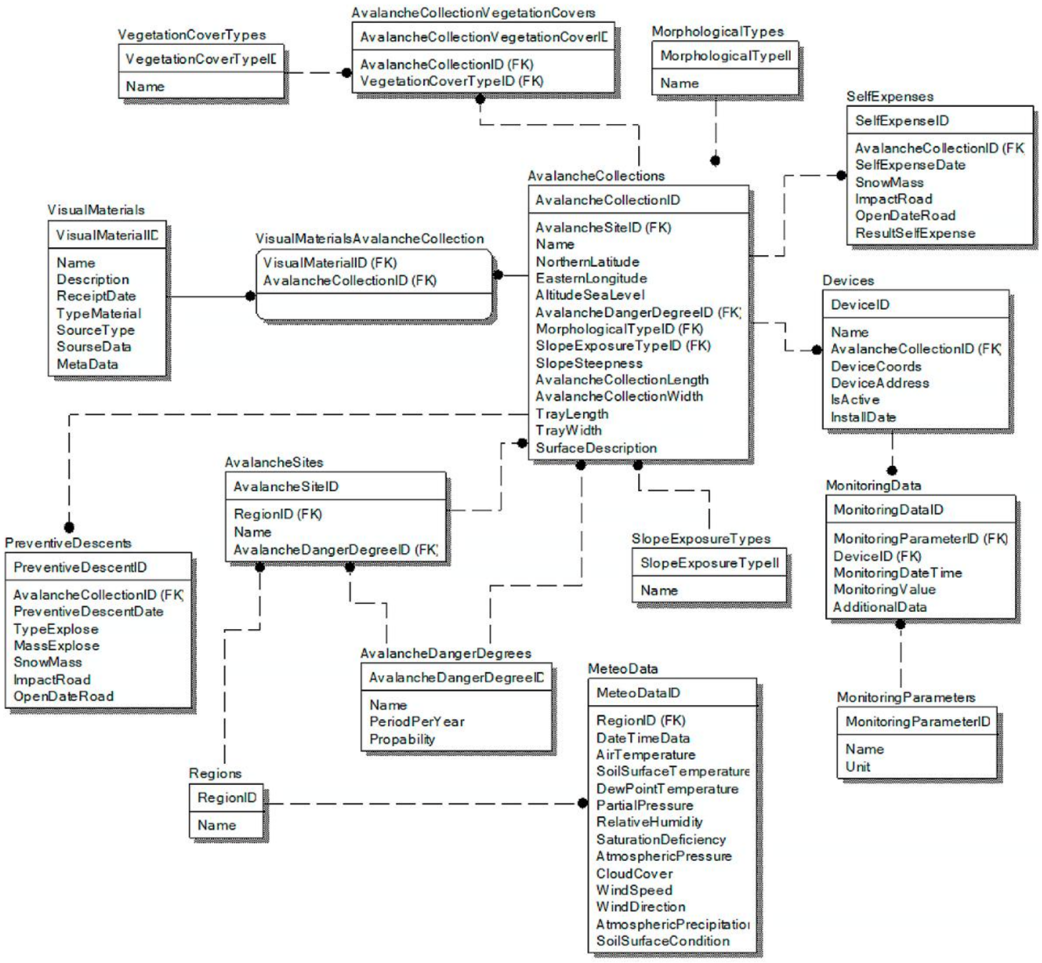


Figure 8. The logical schema of the database.

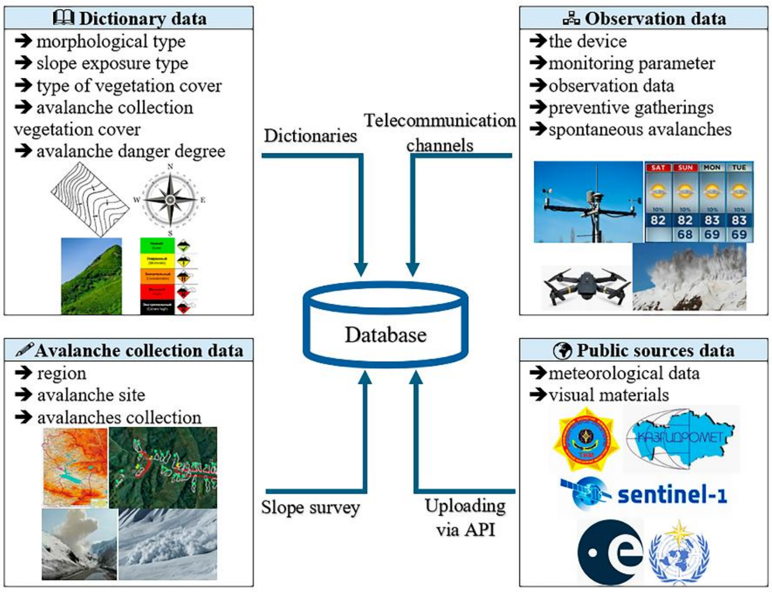


Figure 9. Distribution of database information objects by data sources.

The unified database created within the framework of this study for collecting data on avalanche-prone areas allows for operational monitoring of avalanche danger and, in addition, serves as a data source for predicting avalanche danger in the observed avalanche-prone areas.

In general, a software package has been developed for collecting and processing data on snow cover in avalanche-prone areas, which includes the following components:

- A mobile application that is used to collect data on avalanche-prone terrain (temperature, weather conditions, snow cover). This application was developed for the Android operating system, which allows it to be installed on many mobile devices running this operating system.
- MySQL database, which stores information collected in the mobile application.
- API interface for interaction between the database and the mobile application. Interaction with API data through REST requests (representation state transfer). To protect data transmission and credentials, the specified API uses the SSL/TLS (Secure Sockets Layer / Transport Layer Security) protocol.

The scheme of operation of the developed software package is shown in Figure 10.

Based on the collected data, it was proposed to predict spontaneous avalanches using regression analysis.

Regression analysis is one of the main statistical tools to determine the relationship between a set of input factors and a dependent variable. When constructing a regression, coefficients are determined for each input variable, which determines the degree of influence of each input factor on the value of the output variable.

When predicting spontaneous avalanches, we need to determine the probability of an avalanche during avalanche collection based on weather conditions, which in this case will act as input variables. Logistic regression is the most suitable tool for solving this problem.

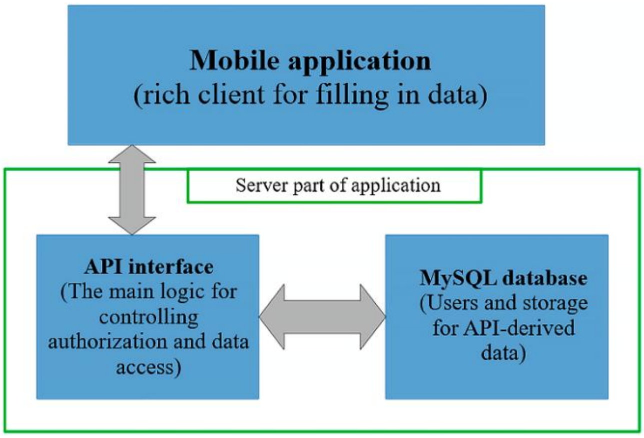


Figure 10. Operation diagram of the mobile application.

Logistic regression is used when there is an output variable obeying the binomial distribution law. Since the output value is binary, the specified regression type calculates the probability of assigning a regression value to one of the two possible values of the regression output variable.

To calculate the logistic regression for predicting spontaneous avalanches as part of the study, we defined the following set of input variables, shown in Table 4. The data shown in Table 4 for calculating logistic regression were obtained from the avalanche weather database developed as part of this study. In our case, the output variable will be the recorded spontaneous avalanches on a certain date in each avalanche array. To extract data from the database, we created views.

Table 4. Input variables for calculating logistic regression.

№	Variable	Explanation
1	avg_temperatures_day_1	average daytime temperature on the day of the avalanche
2	avg_temperatures_day_2	average daytime temperature the day before the avalanche

3	avg_temperatures_day_3	average daytime temperature 2 days before the avalanche
4	avg_temperatures_decade_1	average daytime temperature on the day of the avalanche
5	avg_temperatures_decade_2	average daytime temperature the day before the avalanche
6	avg_temperatures_decade_3	average daytime temperature 2 days before the avalanche;
7	rainfalls_value_1	the amount of precipitation on the day of the avalanche
8	rainfalls_value_2	the amount of precipitation the day before the avalanche
9	rainfalls_value_3	the amount of precipitation 2 days before the avalanche
10	snows7_average_1	average snow cover at 7:00 a.m. on the day of the avalanche
11	snows7_average_2	average snow cover at 7:00 a.m. the day before the avalanche
12	snows7_average_3	average snow cover at 7:00 a.m. 2 days before the avalanche
13	snows7_maximum_1	the maximum snow cover is at 7:00 a.m. on the day of the avalanche
14	snows7_maximum_2	the maximum snow cover is at 7:00 a.m. the day before the avalanche
15	snows7_maximum_3	the maximum snow cover is at 7:00 a.m. 2 days before the avalanche
16	snows19_average_1	average snow cover at 19:00 on the day of the avalanche
17	snows19_average_2	average snow cover at 19:00 the day before the avalanche
18	snows19_average_3	average snow cover at 19:00 2 days before the avalanche
19	snows19_maximum_1	the maximum amount of snow cover is at 19:00 on the day of the avalanche
20	snows19_maximum_2	the maximum amount of snow cover is at 19:00 the day before the avalanche
21	snows19_maximum_3	the maximum snow cover is at 19:00 2 days before the avalanche
22	temperatures7_value_1	temperature at 7:00 on the day of the avalanche
23	temperatures7_value_2	temperature at 7:00 the day before the avalanche
24	temperatures7_value_3	temperature at 7:00 2 days before the avalanche
25	temperatures19_value_1	temperature at 19:00 on the day of the avalanche
26	temperatures19_value_2	temperature at 19:00 the day before the avalanche
27	temperatures19_value_3	temperature at 19:00 2 days before the avalanche

We used the Loginom Community statistical software package to perform logistic regression calculations. In this software package, a script was created to calculate logical regression. The created package connects to the developed database, extracts data, and uses it to train logistic regression.

For a general understanding, Figure 11 shows a diagram of the interaction of the components of the system.

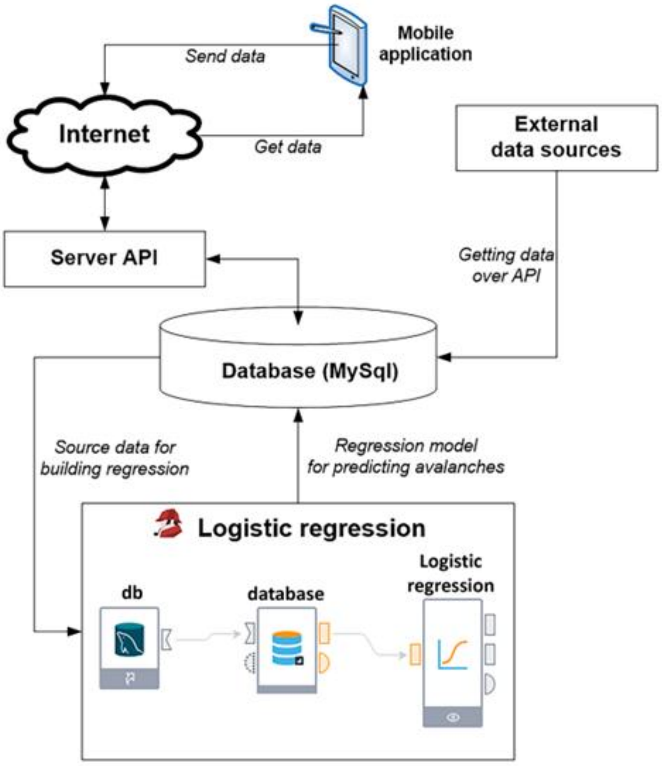


Figure 11. Component interaction diagram.

The avalanche hazard analysis and forecasting system based on logistic regression using the Loginom software platform is included in the created information system and operates using the MySQL database and the mobile application described above.

Discussion

To develop the logistic regression model, the available dataset was randomly divided into two subsets:

- Training set – 9,229 observations, used for model training.
- Test set – 6,152 observations, used for model evaluation.

After training the model, we obtained the regression coefficient, the value of which is shown in Table 5.

The trained logistic regression model produced a set of coefficients describing the influence of meteorological and snowpack variables on the probability of spontaneous avalanche occurrence. The values of the regression coefficients obtained during model training are presented in Table 5. Positive coefficients indicate that an increase in the corresponding parameter leads to a higher probability of avalanche formation, whereas negative coefficients reduce this probability. The results show that several temperature-related variables and snowpack indicators have a positive contribution to the predicted probability, while precipitation-related parameters demonstrate negative coefficients in the trained model. These coefficients form the basis of the probabilistic estimation used in the monitoring system and allow the model to quantify the influence of environmental conditions on avalanche hazard.

Table 6 presents the performance metrics of the constructed regression model, while Figure 12 shows the ROC curve for the model.

Table 5. The value of logistic regression coefficients.

№	Names of input fields	Regression coefficient
1	The constant	−2.6596
2	avg_temperatures_day_1	0.0397
3	avg_temperatures_day_2	0.3580
4	avg_temperatures_day_3	0.0271

5	avg_temperatures_decade_1	0.1441
6	avg_temperatures_decade_2	0.0778
7	avg_temperatures_decade_3	0.0879
8	rainfalls_value_1	−0.7986
9	rainfalls_value_2	−0.9923
10	rainfalls_value_3	−0.8184
11	snows7_average_1	−0.0794
12	snows7_average_2	−0.0289
13	snows7_average_3	0.0144
14	snows7_maximum_1	0.0256
15	snows7_maximum_2	0.0852
16	snows7_maximum_3	0.0041
17	snows19_average_1	0.0254
18	snows19_average_2	0.0247
19	snows19_average_3	0.0240
20	snows19_maximum_1	0.0169
21	snows19_maximum_2	−0.0595
22	snows19_maximum_3	−0.0789
23	temperatures7_value_1	0.1553
24	temperatures7_value_2	0.0886
25	temperatures7_value_3	0.1139
26	temperatures19_value_1	−0.0106
27	temperatures19_value_2	−0.1273
28	temperatures19_value_3	−0.0346

Table 6. Performance evaluation of the regression model.

Indicator	Training set	Testing set
Number of events	9229	6152
Number of events «Avalanche did not descend»	129	77
Number of events «Avalanche descended»	9100	9067
AUC ROC	0.9622	0.9505
Gini coefficient	0.9244	0.9009
True Positive Rate (TPR)	0.1163	0.1948
True Negative Rate (TNR)	0.9964	0.9949
False Positive Rate (FPR)	0.0036	0.0051
Positive Predictive Value (PPV)	0.2890	0.3261
F1 Score	0.1658	0.2439

Based on the results presented in Table 6 and Figure 12, it can be concluded that the developed regression model demonstrates high predictive performance. This is supported by the following indicators:

- High AUC-ROC values. The AUC exceeds 0.9 for both the training and test datasets, indicating strong predictive capability.
- High Gini coefficient values. The Gini coefficient is above 0.8 for both datasets, suggesting that the model has excellent discriminative power between classes.

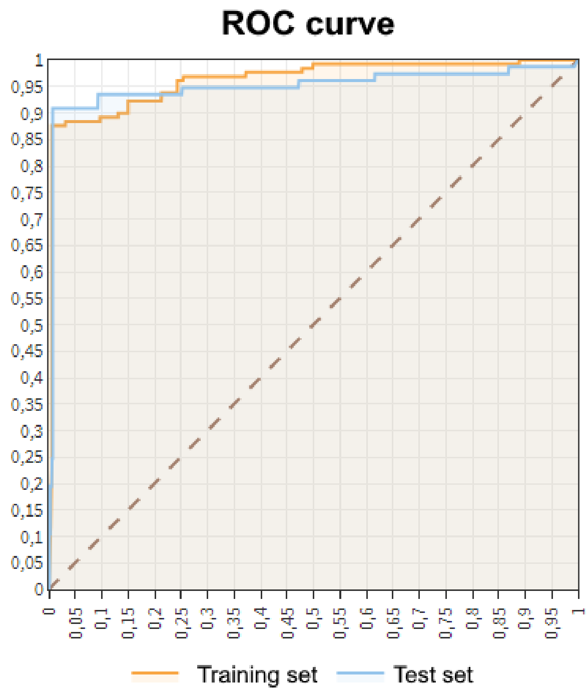


Figure 12. ROC curve for the logistic regression model.

Monitoring system is also a video surveillance of avalanche-prone slopes (Figure 13). The data received by the system can be presented in the form of tables and graphs (Figure 14).

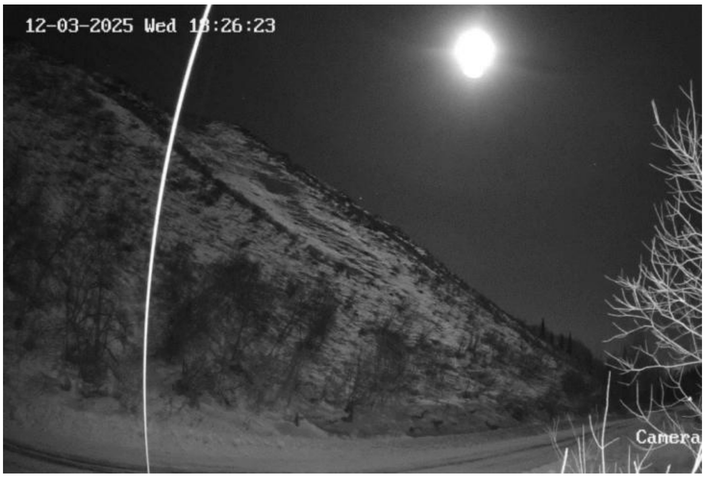


Figure 13. View of the avalanche-prone slope through the video camera of the base station.

Thus, based on the model description and its performance evaluation, it can be concluded that the developed logistic regression model can be effectively applied for predicting spontaneous avalanche occurrences using meteorological observations from avalanche-prone areas of the East Kazakhstan region.

Data from the base station, including key meteorological parameters such as air temperature, relative humidity, wind speed and direction, and atmospheric pressure, presented in a time-series format for real-time analysis (Figure 14.a). Data obtained from the snow-temperature measuring rail, showing temperature values recorded at different depths within the snowpack, enabling assessment of vertical thermal gradients (Figure 14.b). Visualization of temperature changes across snow layers based on the measuring rail data, illustrating the temporal evolution of temperature distribution within the snowpack and supporting the identification of potentially unstable layers associated with avalanche formation (Figure 14.c).

BS01 Base Station

BS01 | BS03 | Temperature rail 1 | Temperature rail 2 | BS. Snow Height | Power Consumption BS03

Date/Time	Humidity	Pressure	Pressure (mm.r.p.)	Temperature	Wind speed	Wind direction (degrees)	Wind direction
2025-12-08 00:39:41	80.5	961.3	721.04	-3.3	1.701	148.6	SE
2025-12-08 00:24:41	81.7	961.3	721.04	-3.4	1.371	152.7	SE
2025-12-08 00:09:41	80.3	961.6	721.26	-3.3	1.675	144.0	SE
2025-12-07 23:54:41	81.6	961.7	721.34	-3.4	1.376	147.1	SE
2025-12-07 23:39:41	81.2	961.8	721.41	-3.4	1.057	152.2	SE
2025-12-07 23:24:41	82.4	962.0	721.56	-3.5	1.492	151.9	SE
2025-12-07 23:09:41	83.2	962.1	721.64	-3.6	1.273	150.7	SE
2025-12-07 22:54:41	82.6	962.1	721.64	-3.5	1.159	139.4	SE
2025-12-07 22:39:41	81.3	962.1	721.64	-3.5	1.202	144.6	SE
2025-12-07 22:24:41	82.4	962.2	721.71	-3.6	1.371	146.3	SE
2025-12-07 22:09:41	81.3	962.2	721.71	-3.5	1.13	153.4	SE
2025-12-07 21:54:41	80.2	962.2	721.71	-3.4	1.415	151.8	SE
2025-12-07 21:39:41	80.2	962.3	721.79	-3.4	1.551	150.7	SE
2025-12-07 21:24:41	80.1	962.3	721.79	-3.4	1.732	151.0	SE

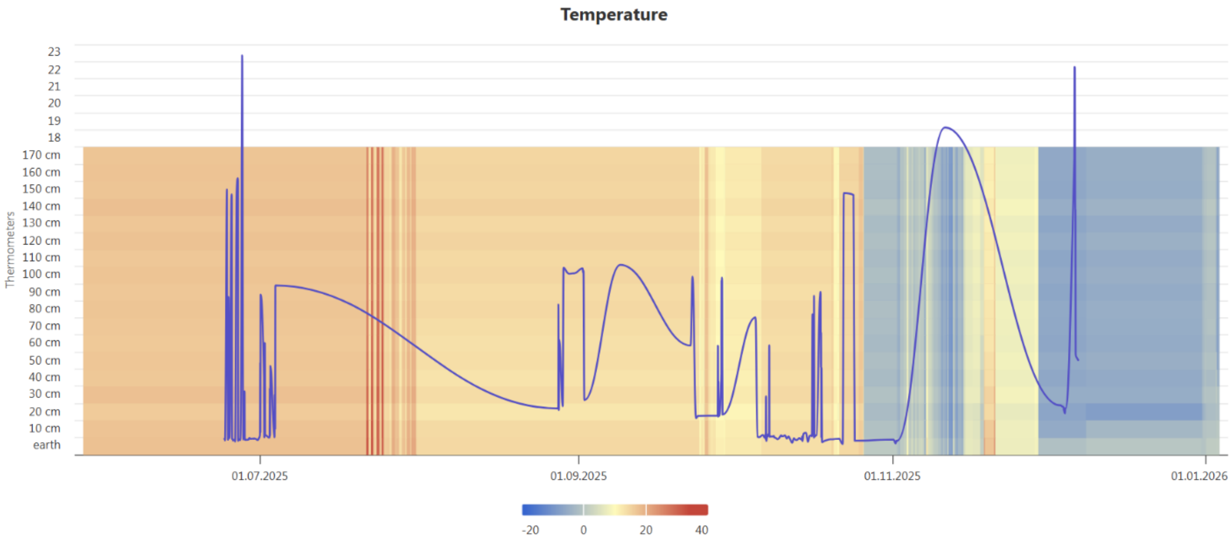
a

TG01 Temperature Rail

Base Station | BS. Snow Height | Temperature rail 2 | Temperature gradient

Date/Time	Voltage	Rangefinder readings	Snow Height	t(1)	t(2)	t(3)	t(4)	t(5)	t(6)	t(7)	t(8)	t(9)	t(10)	t(11)	t(12)	t(13)	t(14)	t(15)	t(16)	t(17)	t(18)
2025-12-07 03:26:09 [15 min]	2.8	2.202	0.503	0.88	0	-1.62	-1.06	-4.06	-4.94	-5.31	-5.06	-4.87	-5.31	-4.75	-5.5	-4.44	-4.44	-4	-5.25	-4.87	-4.94
2025-12-07 03:10:38 [15 min]	2.82	2.201	0.504	0.88	0	-1.62	-1.12	-3.94	-5	-5.37	-5.06	-4.94	-5.37	-4.75	-5.5	-4.44	-4.44	-4.06	-5.31	-5	-5
2025-12-07 02:55:08 [15 min]	2.85	2.2	0.505	0.88	0.06	-1.69	-1.12	-3.94	-4.94	-5.31	-5	-4.94	-5.37	-4.75	-5.5	-4.44	-4.44	-4.06	-5.31	-5	-4.94
2025-12-07 02:39:37 [15 min]	2.87	2.199	0.506	0.94	0	-1.69	-1.12	-3.87	-5	-5.31	-5	-4.87	-5.37	-4.69	-5.31	-4.37	-4.37	-4	-5.19	-4.94	-4.87
2025-12-07 02:24:06 [15 min]	2.89	2.2	0.505	0.88	-0.06	-1.62	-1.12	-3.94	-5	-5.44	-5.12	-5	-5.44	-4.87	-5.56	-4.56	-4.56	-4.12	-5.31	-5	-5.06

b



c

Figure 14. Visual representation of data: a- Data from the base station; b- Temperature rail data; c- Visualization of temperature changes by layers using a temperature rail

Conclusion

In this study, an autonomous modular system for avalanche hazard monitoring and early warning was developed, implemented, and tested under the climatic and geomorphological conditions of the East Kazakhstan region. Three pilot installations were deployed in avalanche-prone areas: Glubokoe district, the Altai district, and the Ulan district, allowing in-situ evaluation of sensor performance, data transmission stability, and system resilience under extreme environmental loads.

The hardware module of the system includes a base station equipped with meteorological and snowpack sensors, autonomous snow-temperature measuring rails operating via LoRa communication, and a resilient truss-type mast designed to withstand severe low temperatures, wind loads, and snow accumulation. The choice of an aluminum triangular truss ensured optimal stability, modularity, and cost-efficiency for remote mountain installations.

A comprehensive data acquisition pipeline was created, integrating a Ser[LOG] Plus data logger, Heltec LoRa 32 microcontrollers, an LTE/Wi-Fi router with a custom proxy server, and a solar-powered autonomous energy supply. All environmental and snowpack parameters, including wind speed and direction, air temperature, humidity, pressure, snow height, and temperature gradients, are transmitted at 15-minute intervals to a dedicated API service and stored in a unified MySQL database.

In parallel with hardware development, a digital information system was created to support operational monitoring and predictive analytics. It includes a structured database of avalanche-prone terrain, a mobile application for field data collection, and an API ensuring secure REST-based communication. Logistic regression was tested as a method for forecasting spontaneous avalanches based on meteorological and snowpack variables, demonstrating the feasibility of integrating statistical models into the monitoring framework.

Overall, the developed avalanche monitoring system provides a foundation for a scalable, data-driven early warning infrastructure in East Kazakhstan. The integration of autonomous sensors, unified data management, and predictive modeling enhances the region's capacity for timely avalanche hazard assessment and represents a significant step toward the transition from expert-based to instrument-based monitoring practices. Future work will involve expanding the sensor network, refining machine-learning models, and integrating real-time decision-support tools for regional emergency services.

The proposed automated avalanche monitoring system demonstrates the feasibility of integrating autonomous sensor networks, real-time data transmission, and statistical forecasting models for avalanche hazard assessment in mountainous regions. The field deployment confirmed the reliability of the hardware architecture and the stability of data transmission under harsh climatic conditions typical for East Kazakhstan. The integration of meteorological and snowpack observations into a unified database provides a valuable foundation for developing data-driven avalanche forecasting approaches.

At the same time, several limitations of the proposed system should be noted. First, the current monitoring network includes a limited number of observation points, which restricts the spatial representativeness of the collected data in complex mountainous terrain. Second, the forecasting component is currently based on logistic regression, which captures linear relationships between variables but may not fully reflect the nonlinear interactions typical of snowpack evolution and avalanche formation processes. Third, the accuracy of the predictive model depends on the availability and quality of historical avalanche records used for training. Finally, communication reliability in remote areas may be affected by terrain and weather conditions, which can influence the continuity of real-time data transmission.

Future work will focus on expanding the sensor network, increasing the volume of observational data, and exploring advanced machine-learning methods capable of modeling complex relationships between environmental variables and avalanche occurrence.

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Appendix 1

Table 1. The code for LTE/WiFi router.

```
import socket
import ssl
from struct import pack, unpack, unpack_from
def send_via_ssl_socket(packet : bytes):

   HOST, PORT = “ApiHost”, 0001
   sock = socket.socket(socket.AF_INET,
socket.SOCK_STREAM)
   sock.settimeout(10)
   sock.connect((HOST, PORT))
   sock.send(packet.encode(“utf-8”))
   sock.close()

ssock = socket.socket(socket.AF_INET,
socket.SOCK_STREAM)
ssock.bind((“0.0.0.0”, 5000))
ssock.listen()
try:
   while True:
       con, addr = ssock.accept()
       packet =
con.recv(1024).decode().replace(“Host:
192.168.1.11:5000”, “Host: ApiHost:0001”)
       con.send(
          “““HTTP/1.1 200 OK
          Server: Werkzeug/3.0.1 Python/3.10.12
          Date: Wed, 04 Dec 2024 07:00:46 GMT
          Content-Type: text/html; charset=utf-8
          Content-Length: 4
          Connection: close

          true”““
          .encode(“utf-8”)
       )
       send_via_ssl_socket(packet)
except KeyboardInterrupt:
   ssock.close()
```

Table 2. The software code of the microcontroller.

```
#include “LoRaWan_APP.h”
#include “Arduino.h”
#include “softSerial.h”
#include <OneWire.h>
#include <DallasTemperature.h>
#include <Regexp.h>
#define ONE_WIRE_BUS GPIO4

OneWire oneWire(ONE_WIRE_BUS);

DallasTemperature sensors(&oneWire);

int deviceCount = 0;
float tempC;
char txpacket[BUFFER_SIZE];
char rxpacket[BUFFER_SIZE];

static RadioEvents_t RadioEvents;

float txNumber;
bool lora_idle=true;
const String UID = “t1”;

softSerial ss(GPIO5, GPIO0);

String query_laser() {
  ss.begin(19200);
  String distance;

  while(true) {
    ss.write('D');
    distance = ss.readString();

    MatchState ms;
    char c_dist[50];
    distance.toCharArray(c_dist, sizeof(c_dist));
  return distance;
}
String ds18b20_query(){
  String result = ““;
  sensors.begin();
  deviceCount = sensors.getDeviceCount();

  if (deviceCount > 0){
    sensors.requestTemperatures();
    for (int i = 0; i < deviceCount; i++) {
      tempC = sensors.getTempCByIndex(i);
      result += (String)(i+1) + “:” + (String)tempC +
“;”;
    }
  }
  return result;
}

void loop()
{
  if(lora_idle == true)
  {
    digitalWrite(Vext, LOW);
    String temperatures = ds18b20_query();
    Serial.println(temperatures);
    txNumber += 0.01;
    String distance = query_laser();
    distance.trim();
    String voltage = (String)((float)getBatteryVoltage() /
1000.0);
    turnOnRGB(COLOR_SEND,0);
    Radio.Send( (uint8_t *)txpacket, strlen(txpacket) );
    lora_idle = false;
    delay(900000);
  }
}
```

```
  ms.Target(c_dist);

  if(ms.Match(“(([0-9]\.[0-9]+\m\,[0-9]+))”) > 0) {
   Serial.println(“Got normal reading”);
   Serial.println(distance);
   distance = distance.substring(distance.indexOf(' '),
distance.length() - 1);
   break;
  }
 }
ss.end();

void OnTxDone( void )
{
 turnOffRGB();
 lora_idle = true;
}

void OnTxTimeout( void )
{
 turnOffRGB();
 Radio.Sleep( );
 lora_idle = true;
}
```

Table 3. The code for data receiver.

```
#define HELTEC_POWER_BUTTON
#include <heltec_unofficial.h>
#include <WiFi.h>
#include <HTTPClient.h>
#include <SoftwareSerial.h>
#include <base64.h>

SoftwareSerial ss(41,);

String identifier    = “id”; // Change this for each new
base station
const char* ssid      = “net”;
const char* password  = “pass”;
String target_url     = “url”;
String api_key        = “apikey”;
volatile bool rxFlag = false;
long counter = 0;
uint64_t last_tx = 0;
uint64_t tx_time;
uint64_t minimum_pause;
String base64_output;

String query_laser() {
 ss.begin(19200);
 ss.write('D');
 String distance = ss.readString();
 ss.end();
 return distance;
}

void send_post_request(String packet) {
 if (WiFi.status() != WL_CONNECTED) {
   WiFi.disconnect();
   WiFi.reconnect();
 }
if(WiFi.status() == WL_CONNECTED) {
  WiFiClient client;
  HTTPClient http;
  http.begin(target_url);
  http.addHeader(“Content-Type”,
“application/json”);
  http.addHeader(“Api-Key”, api_key);
  int httpResponseCode =
http.POST(“{\”packet\”:\”“ +
(String)packet + “\”}”);
  http.end();
 }
}

void loop() {
 heltec_loop();
 String rxdata;
 if (rxFlag) {
  rxFlag = false;
  radio.readData(rxdata);
  if (_radiolib_status == RADIOLIB_ERR_NONE) {
   laser_data.trim();
   String packet = (String)”BEG “ + (String)”IB: “ +
(String)identifier + “;” +
     (String)rxdata + “BD:” +
     laser_data + “ END” ;
   base64_output = base64::encode(packet);
   send_post_request(base64_output);

  }
  RADIOLIB_OR_HALT(radio.startReceive
(RADIOLIB_SX126X_RX_TIMEOUT_INF));
 }
}

void rx() {
 rxFlag = true;
}
```