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Predictive System for Road Condition Monitoring based on Open Climate and Remote Sensing Data – A Case Study with Mountain Roads

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Abstract

Roads are a crucial component of a country's economic development. Therefore, monitoring and maintaining roads are primary tasks for transportation departments. This study proposes a cost-effective approach to reduce these expenses by introducing a predictive system. This system leverages openly accessible data sources, such as climate and remote sensing information. The foundational framework of this system relies on regression and neural network models, which have been trained using the aforementioned datasets, as well as data from on-site road inspections. These models assign varying weights to input parameters, elucidating the influence of both meteorological conditions and landscape characteristics on the road's overall condition. The resultant system offers forecasts for nine distinct attributes of road sections, each defined by their geographical coordinates. Furthermore, it categorizes the road's condition and provides a visual representation of this data on a geographical map. By exclusively utilizing openly accessible meteorological and remote sensing data, this system has the potential to serve dual purposes, facilitating remote diagnostics and aiding in road design support.

Keywords: Road maintenance; Road diagnostics; Open data; Remote sensing; Climate data; Meteorological data; Forecasting; predictive; Regression model; Neural network.
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1. Introduction

Mountainous regions present unique challenges for road infrastructure maintenance and safety. The intricate network of mountain roads is not only essential for regional connectivity and economic growth but also vital for ensuring the well-being of communities residing in these areas. However, the extreme terrain, harsh climatic conditions, and geological instability inherent to mountainous environments make the upkeep and assessment of road conditions a complex undertaking.[1,2]

Effective road condition monitoring in mountainous regions is paramount for mitigating the adverse impact of terrain-specific challenges.[3] Traditionally, road condition assessments have been reactive in nature, relying on periodic inspections or complaints from road users.[4] Such approaches are often inadequate, especially in mountainous areas where unpredictable weather events, landslides, and rapid road degradation are common occurrences.[5] To address these issues, a proactive approach that combines monitoring, prediction, and forecasting is crucial.[6]

This paper explores the development and implementation of a predictive system for road condition monitoring in mountainous regions. The emphasis here is on pre-diction and forecasting as essential components of road infrastructure management. Predictive systems utilize historical and real-time data to anticipate road conditions, enabling timely and cost-effective maintenance and significantly enhancing road safety.[7] In mountainous areas, where weather patterns and geological activity can lead to rapid road deterioration, predictive systems offer an innovative solution to address these challenges.[3,8]

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Recognizing the significance of predictive tools, several researchers have made notable advancements in this domain. They have pioneered sophisticated models that leverage data to forecast and assess the conditions of mountain roads.

Slope stability is of paramount importance in the context of mountain road conditioning and maintenance, and it is a primary cause of crack formation in road pavements. Cheng *et al*.[9] present SOFIL, an innovative slope collapse prediction model designed for mountain roads. Their research showcases significant performance enhancements compared to established methods, validated through comprehensive experimentation. The SOFIL model's core innovation is its combination of FKNN, an in-stance-based learning classifier, and FA, a swarm intelligence optimization technique. This fusion streamlines parameter tuning, reducing the reliance on human expertise, enhancing modeling simplicity, and improving accuracy.

In their respective works, Qi and Tang[10] and Wang *et al*.[11] emphasize the vital role of slope stability analysis in industrial engineering. Qi and Tang[10] highlight the significance of dataset collection and machine learning (ML) algorithms in advancing this field. Their research introduces and evaluates six integrated artificial intelligence (AI) approaches that combine metaheuristic and ML algorithms to predict slope stability. Utilizing the firefly algorithm (FA) for hyperparameter tuning, the models achieve excellent predictive performance, with AUC values ranging from 0.822 to 0.967. The support vector machine model emerges as the preferred choice. Mean-while, Wang *et al*.[11] propose a novel multi-dimensional connection cloud model to address the complexities of slope stability analysis. This model effectively handles un-certainties and distribution characteristics of indicators, capturing the randomness and fuzziness of measured index values concerning classification standards. It mitigates subjectivity by leveraging numerical characteristics derived from identical-discrepancy-contrary (IDC) relationships and unifies indicator correlations. Case studies and model comparisons demonstrate the model's effectiveness and reliability, offering a quicker and simpler alternative to traditional methods.

Similarly, to improve the spatial prediction of landslide susceptibility along mountain highways, Sun *et al*.[12] conducted a comprehensive study. They compared various machine learning algorithms, such as random forest (RF) and support vector machine (SVM), and examined different mapping units (grid and slope units). Their research focused on Chengkou, a mountainous county, and identified 334 landslides through field investigations, satellite imagery analysis, and historical records. After re-fining the initial set of twenty landslide conditioning factors and eliminating less significant ones, the study significantly enhanced forecast accuracy. The findings indicated that both RF and SVM models performed better when using the slope unit, with RF demonstrating superior performance. This research offers valuable insights for improving landslide susceptibility prediction along mountain highways.

Moreover, a road's primary degradation manifestations, applicable to any pavement type, encompass rutting and thermal cracking.[13] In the context of flexible materials, such as asphalt pavement, rutting is recognized as a prominent form of distress.[14] Primarily, rutting deformation is closely associated with heavily loaded vehicles and repetitive traffic loads. However, rutting is non-uniform on mountain roads, posing challenges for evaluation and necessitating accurate forecasting to enhance maintenance.[15] For instance, Majidifard *et al*.[16] developed a novel predictive model for asphalt mixture rutting depth using gene expression programming (GEP), a machine learning technique. They used a comprehensive Hamburg test database with 96 data points from various asphalt mixtures. The model considers key variables, including asphalt binder high-temperature performance grade (PG), mixture type, aggregate size, gradation, asphalt content, and total asphalt binder recycling content. Rigorous validation and sensitivity analyses were performed to assess the model's ac-curacy and variable influences. A comparative study confirmed the GEP model's ability to address mixture properties and test conditions. It is recommended for pre-design purposes and when laboratory testing for rut depth determination is unfeasible.

In addition to repeated loading, environmental effects, such as solar radiation, thermal fluctuations, and freeze-thaw cycles, also play a significant role in road pavement degradation. This has been emphasized by a group of researchers.[17-19] For instance, Trunzo *et al*.[17] applied Life Cycle Analysis (LCA) to assess the environ-mental impact of an Italian provincial road, considering both construction and usage processes. Their research focused on a mountainous road in central Italy with tunnels, viaducts, and low traffic volume (4.5 million passes over 60 years), adhering to European standards. The study evaluated seven impact categories, primarily emphasizing structural materials as major environmental contributors. Surprisingly, the "use" phase (maintenance, traffic, lighting) accounted for less than half of the overall impact. The research highlighted the challenge of selecting eco-friendly processes and recommended Multi-Criteria Decision Analysis (MCDA). Notably, high traffic volumes reduced the "until opening for traffic" phase's impact to 28%, underscoring the significance of design traffic in environmental sustainability. The study proposed the integration of environmental, social, and economic criteria for a comprehensive sustainability assessment of mountain roads. Moreover, in mountainous regions, the significant temperature fluctuations lead to a freezing-thawing cycle with larger temperature variations, causing moisture within the asphalt mixture to cyclically freeze and thaw during the winter and spring seasons. This process accelerates the detachment of the asphalt film and exacerbates water damage to the pavement.[19] In the study con-ducted by Abouelsaad and White,[20] the authors emphasized the significance of assessing the effects of ultraviolet irradiation on the resilient modulus and surface

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texture of asphalt and pavements. The results of this research underscore the importance of creating aging protocols that integrate heat, ultraviolet irradiation, and other environmental elements that can influence the aging characteristics of asphalt mixtures.

In addition to field tests that involve sampling asphalt and pavement from roads to assess their condition, researchers worldwide have been progressively exploring non-contact measurement methods for road pavement monitoring. Among cost-effective alternatives, the utilization of video recording equipment in combination with GPS sensors and remote sensing techniques are becoming increasingly common. In a recent study by Ruseruka *et al*.,[21] the authors emphasize the importance of cost-effective and real-time road condition monitoring (RCM) using a deep learning model based on the YOLOv5 algorithm. This model excels in categorizing flexible pavement distresses (FPD) with remarkable precision and recall, utilizing vehicle built-in cameras and GPS sensors to provide an efficient RCM approach, as demonstrated on campus roads and parking lots. In their research, Zhang *et al*.[22] address the challenges of extracting mountain roads from high-resolution remote sensing images (HRSIs) due to complex environments. They introduce the Road Datasets in Complex Mountain Environments (RDCME) dataset and a novel model, the Light Roadformer, which employs transformer and self-attention modules for accurate road edge extraction, resulting in significantly higher accuracy compared to previous models, with an intersection over union (IoU) of 89.5% on the validation set and 88.8% on the test set. Similarly, Chen *et al*.[23] present a framework for the automatic extraction of mountain road images from high-resolution remote sensing data using deep learning. This framework includes two sections: road scene classification and fine-road segmentation, improving the accuracy of extraction in challenging contexts. The study demonstrates the framework's effectiveness and suggests that the mountain road scene datasets created can serve as valuable benchmarks for similar research.

To establish a robust system for predicting mountain road conditions and maintenance, this study recommends the integration of remote sensing, climate data, and field data. Using a mountain road near Almaty, Kazakhstan, as an example for development and validation, data is sourced from various outlets. Notably, the authors have conducted extensive field research and remote sensing in the Almaty region, primarily drawing on data from the Ionosphere research institute. Subsequent sections will cover the datasets, predictive model, model performance results, discussions, concluding remarks, and future work on the developed predictive methods.

2. Materials and Methods

2.1 Data sets

Two sets of data have been utilized for training and validating the predictive model as shown in Fig. 1. The first set comprises climate and remote sensing data, while the second set involves field data obtained through sample studies conducted on the mountain road near the Almaty region. Let's consider the climate data, which encompasses meteorological factors of utmost importance. These factors include extreme high and low temperature values, the frequency of freezing and thawing cycles, solar irradiation, the intensity of precipitation (rainfall), snow cover depth, humidity, and irradiation for the specific area where the road section under investigation is situated.

Meteorological data for the region spanning several years is available through an open-access source, http://meteocenter.net. This platform serves as the primary repository for archival meteorological data, offering information at 3-hour intervals starting from March 2005. This data interval proves to be highly convenient for computational purposes. However, since it is unavailable from open sources, solar radiation data for the project is acquired through remote sensing, a method regularly conducted by the institute where the authors work, in collaboration with the national space research agency in the country. The data spans from January 2016 to December 2022 and is summarized in Table 1, which includes the key values for each year of the study, for the following parameters:

- Extreme high temperatures with 3-hour periods (exceeding 30 °C);
- Extreme low temperature with3-hour periods (below -15 °C);
- Number of highly intensive rainfalls (exceeding 30 mm) per year;
- Maximum rainfall/snow cover depth (measured in mm/cm);
- Number of freezing-thawing cycles.

Furthermore, from satellite images as a result of the remote sensing, the following parameters are chosen:

1. Vertical displacements with point coherence;
2. Slope exposure;
3. Dissections;
4. Topographic wetness index;
5. Aspect;
6. Solar radiation;
7. Vegetation index (SAVI);
8. Snow-covered zones.

The first five parameters depict landscape dynamics from different perspectives, while the topographic wetness index, solar radiation, vegetation index (SAVI), and snow-covered zones help detect additional environmental factors.

Processing 149 archive images from the Sentinel-1 satellite covering the period from 2017 to 2021 has produced geodynamical assessment maps of the automobile road area that is selected for the current study. Detailed information on the image processing methodology and tools can be found in Article.[24]

These parameters were collected not only for the precise road coordinates but also for the surrounding slopes, as these more distant factors can also impact road conditions. For further information on the remote sensing data, please refer to

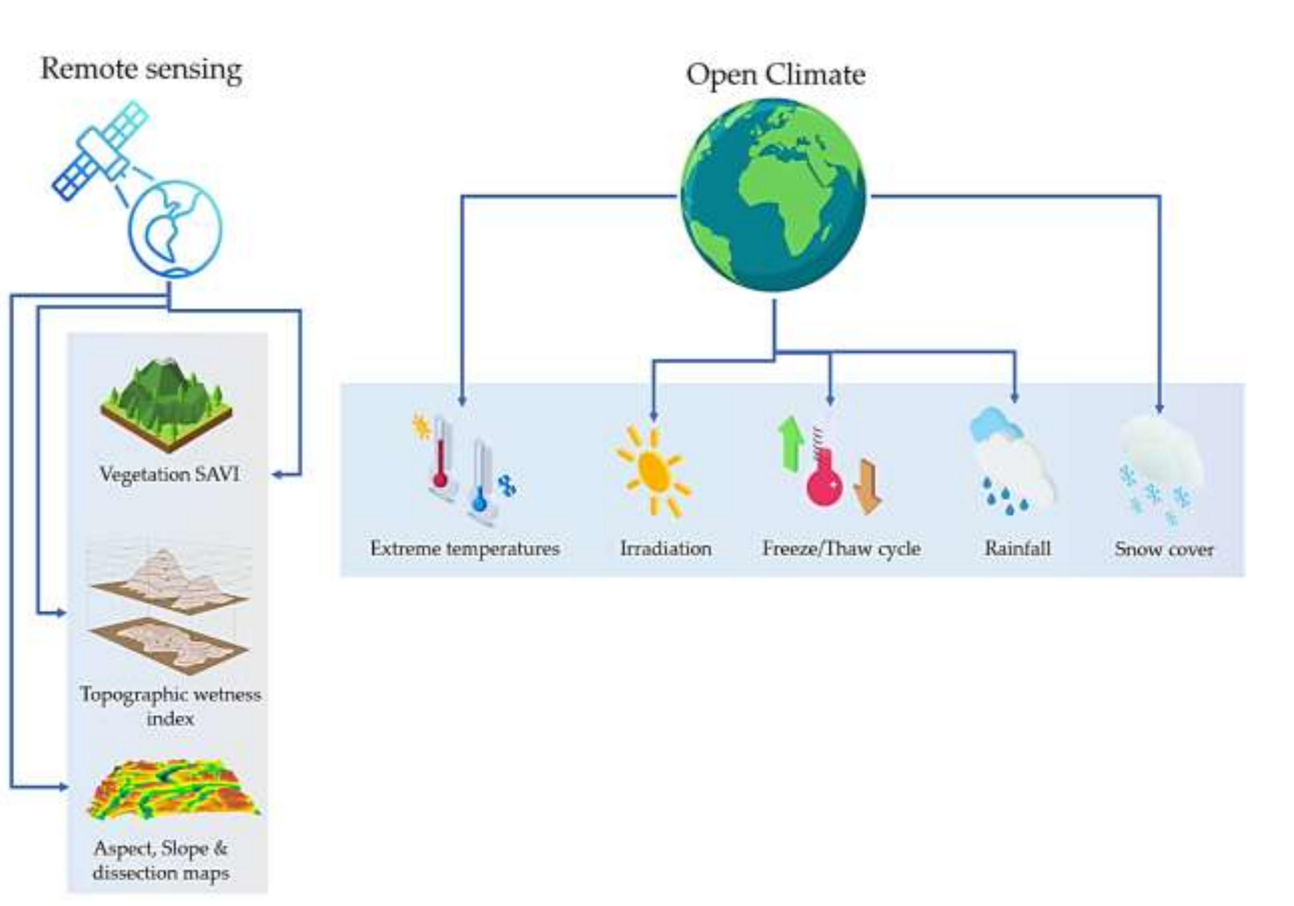

Fig. 1 Types of data used for the development of predictive models.

Table 1. Summary of the downloaded climate data from the open source.

Year	Extreme High Temperature (>30 °C), 3 h period	Extreme Low Temperature (<−15 °C), 3 h period	Freezing and Thawing Cycles	Highly Intensive Rainfall (>30 mm per 3 h), Number of Periods	Rainfall/Snow Cover Maximum Value, mm/cm
2016	62	1	102	10	43/42
2017	130	0	151	4	701/598
2018	107	60	93	0	26/25
2019	133	1	133	2	45/33
2020	76	0	105	3	320/598
2021	173	11	130	2	975/577
2022	118	0	113	1	792/315

a previous article.[25]

In the republic, decision-making regarding road management is based on road diagnostics, which are formalized by scores from regulatory documentation. Roads are categorized into three groups based on their condition:

I. Roadbed is solid, the transversal profile is preserved, and there are no deformations or defects in the road cover. Single cracks at intervals greater than 40 meters are permissible.

II. More than 5-30% of the road cover is deformed (specified for each cover type), showing inadequate strength of the roadbed. There may be occasional transversal pro-file distortions.

III. Severe deformations are evident, showing inadequate strength of the roadbed, with unstable holes in crack networks and occasional ruptures.

Group II is further subdivided into four subgroups:

Smooth cover with no deformations.

Smooth cover with occasional rare deformations that do not affect traffic conditions, speed, or safety.

Roads with small unevenness, widely-spaced cracks, and few other deformations.

Roads with significant unevenness, corrugations, raveling, and other deformations that affect traffic conditions and speed. Additionally, road cover edge failures are possible.

The results of the visual examination of the road section in the selected area, con-ducted on May 19, 2021, following the criteria outlined in, are presented in Table 2, organized by each kilometer of the road:

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Table 2. Results of visual examination of the road section in the selected mountain area.

The road's km	Road's width, m	Score according to	Details
1	9,5	I /1	No deformation registered
2	9,5	I /1	No deformation registered
3	9,5	I /1	No deformation registered
4	9,5	I /1	No deformation registered
5	8,0	I /1	No deformation registered
6	8,0	I/1	No deformation registered
7	8,0	I/1	No deformation registered
8	8,0	I/1	No deformation registered
9	7,5	I/3	Transverse cracks and unevenness
10	7,5	I/2-3	Transverse cracks and unevenness
11	7,5	I/2-3	Transverse cracks and unevenness
12	7,5	I/3-4	Transverse cracks and unevenness
13	7,5	I/4	Transverse cracks and unevenness
14	-	-	Construction works. No traffic
15	-	-	Construction works. No traffic
16	-	-	Construction works. No traffic
17	7,2	I/1-2	New roadbed. Some transverse cracks at 2-3 meter intervals
18	7,2	I/2	New roadbed. Some transverse cracks at 2-3 meter intervals
19	7,2	I/4	Clear longitudinal and transverse cracks. Occasional crack network. Washed out road's slope (WoS)
20	7,2	I/4	Clear longitudinal and transverse cracks. Occasional crack networks.
21	7,2	II	Clear longitudinal and transverse cracks. Occasional crack networks.

The results presented in Table 2 indicate that the road's cover is in excellent condition from the beginning of the section up to the 8th kilometer, with no significant defects. The width of the road varies between 8.5 and 9 meters in this section. However, starting from the 9th kilometer, the roadway narrows to 7.5 meters. Here, one can observe the occasional appearance of transverse and longitudinal cracks, small holes (SH), and small crack networks.

Construction works are ongoing from the 14th kilometer, covering a distance of 3 kilometers. This sector is nearly impassable for most traffic due to the construction activities. The last quarter of the road, beginning from the 17th kilometer and with a width of just 7.2 meters, has sustained the most damage. The height growth has led to the enlargement of both longitudinal and transverse cracks, forming extensive crack net-works. In this section, substantial roadbed destruction has also become apparent.

A more detailed diagnosis in accordance with state regulatory documentation should be obtained through field measurements of specific critical sections along the road. Therefore, for this type of diagnostics, five 50-meter testing sections on the 18th and 19th kilometers were selected. The results of the detailed diagnostics for each testing section are presented in Table 3.

The worst road condition is observed in the fourth section, which features a washed-out road slope and the highest number of almost every type of crack, except for central longitudinal cracks and the number of crack networks.[26] The

Table 3. Results of detailed diagnostics of the testing sections.

Testing section	Transversal crack by length						Longitudinal crack, m				Crack network	Details
	0-1 m	1-2 m	2-3 m	3-4 m	4-5 m	Total length, m	On a left side	In a center	On a right side	Total length, m		
1/1-2/1	6	3	1	-	-	15	∑11.5	∑16.9	∑12.1	41	2	-
3/2-4/2	8	3	2	-	-	20	∑8	∑17.04	∑13.9	39	5	-
5/3-6/3	7	6	3	2	-	36	∑17.8	∑19.25	∑7.4	44	3	-
7/4-8/4	11	6	3	3	1	49	∑34.8	∑3.3	∑22.2	60	2	Washed out road's slope (WoS)
9/5-10/5	5	4	2	1	1	28	∑6.8	∑18.1	∑15.6	41	2	Small holes (SH)

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third section exhibits a much better situation, both in terms of individual crack length and total length, although crack networks are slightly larger than those in the fourth section. The best condition for the total number of transversal and longitudinal cracks is found in sections one and two, although the second sector has the highest number of crack net-works. Surprisingly, the fifth sector, similar to the others in terms of longitudinal cracks and crack networks, features long transversal cracks and even small holes in its cover.

2.2 Structure of the predictive model

The development of forecasting models that achieve reasonable approximation levels typically involves a two-step process: model structure establishment and sub-sequent model training.[27]

In this research, basic regression models and feed-forward neural networks have been selected as initial models. The training process follows the approach outlined in Fig. 2, where a model processes both climate and remote sensing data to produce road state forecasts. These forecasts are then compared to factual data obtained from field research. If the resulting error exceeds an acceptable approximation threshold, it is used to fine-tune the forecasting model's parameters. This iterative process continues until the error aligns with the predefined acceptable threshold or the number of iterations reaches the specified limit. Ultimately, through this training, the models be-come skilled at generating forecasts with minimal error margins based on similar data.

In the context of forecasting and predicting road conditions, it's essential to con-sider long-term climate data because weather affects both short-term and long-term road states and landslide processes. In this research, climate data spanning five years leading up to the forecasted period is collected. However, due to limitations in the available weather archive, this data is sourced from a broader geographical area, specifically the Almaty region, where the selected region is a subset. The specific required data length, corresponding to the archive array, is determined empirically during the formation and training of forecasting models,[28] and in this study, a one-year period was found to be suitable.

To link the output data with the input data, remote sensing data plays a crucial role, as it is associated with both the measurement date and the selected road sections. This results in the creation of a three-dimensional data array, where the time axis aligns with the climatic data array, and the geographical axis connects it with field data (illustrated in Fig. 3).

Field data comprises information on the condition of the surveyed road, including several values such as the count of transversal cracks of specific lengths, the count of longitudinal cracks of specific lengths, and the count of crack networks, each varying in location. The forecasting models are specifically designed to yield values in a similar format, facilitating comparative studies.

3. Results

3.1 Comparison of the forecasting models

As previously mentioned, this research considered two fundamental types of forecasting models: regression models and feed-forward neural networks. These models form the basis for predicting road conditions using the available data in the current study.

Due to the varying performance of different forecasting models in predicting specific parameters, an individual forecasting error is computed for each parameter. This is achieved by calculating the arithmetic mean for each parameter, providing a comprehensive assessment of the models' performance for each specific parameter.

Each model has nine outputs, and errors are calculated separately as one model may excel in forecasting certain parameters while performing less effectively for others compared to the other model. Therefore, the arithmetic mean of errors is computed individually for each parameter. The testing dataset includes a set of values for each parameter, and the model forecasts the value, with the error between the forecasted and real value calculated as a percentage.[29] Consequently, there are a number of error percentages for each parameter, which are then averaged to assess the model's performance for that specific parameter.

To visualize the difference between forecasted and actual values, the error graph is applicable. In a similar fashion, for each output of a model, the arithmetic mean of all the actual values and the arithmetic mean of the forecasted values are calculated and visually compared.

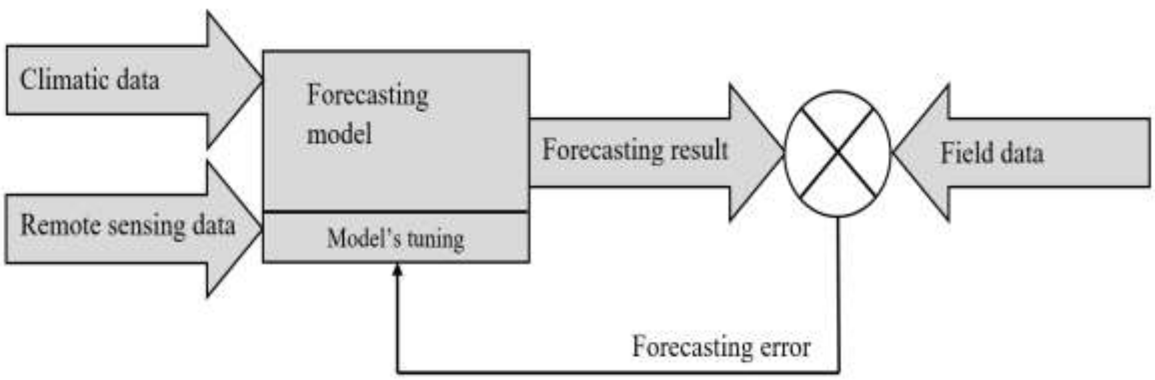

Fig. 2 Visualization of the data flow and its utilization in training forecasting models.

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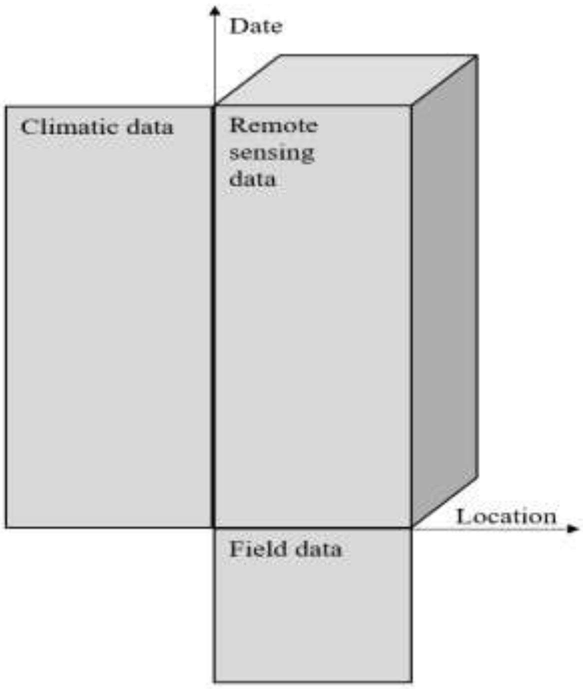

Fig. 3 Interconnection between the data.

The best-performing regression model, specifically the ordinary least squares model, demonstrated the following outcomes on the test dataset:
• The minimum arithmetic mean error was 6.45%;
• The maximum arithmetic mean error reached 297.26%;
• The average arithmetic mean error was 81.73%;
• The median value of arithmetic mean error was 44.83%.
These arithmetic mean values represent the differences between the forecasted and actual values for each parameter of the road's condition, as illustrated in Fig. 4.

The neural network model is the feed-forward neural network, which features two hidden layers, each containing 1000 neurons, and employs the gradient descent optimizer. This model produced the following results on the test dataset:
• The minimum arithmetic mean of error was 12.84%;
• The maximum arithmetic mean of error reached 101.39%;
• The average arithmetic mean of error was 51.55%;
• The median value of arithmetic mean of error was 45.12%.
These error values reflect the variation between the predicted and actual values for each parameter of the road's condition, as depicted in Fig. 5.

The performance of the feed-forward neural network model stands out for providing more accurate predictions on average. Nevertheless, it's essential to acknowledge that both the regression and neural network models yield acceptable forecasting errors. In specific scenarios, such as predicting the number of 4-5 meters long transversal cracks and longitudinal cracks on the right side, the regression model may outperform the neural network model.

Given these considerations, integrating both models as central components of the predictive system, operating concurrently, proves to be a prudent choice. This du-al-model approach enhances the system's robustness and adaptability, ensuring precise forecasts for a wide spectrum of parameters and road conditions.

3.2 Predictive system as GIS

The predictive system serves as a cost-effective alternative to traditional Geographic Information Systems (GIS) for forecasting and monitoring road conditions. Unlike GIS, which relies on expensive and time-consuming satellite

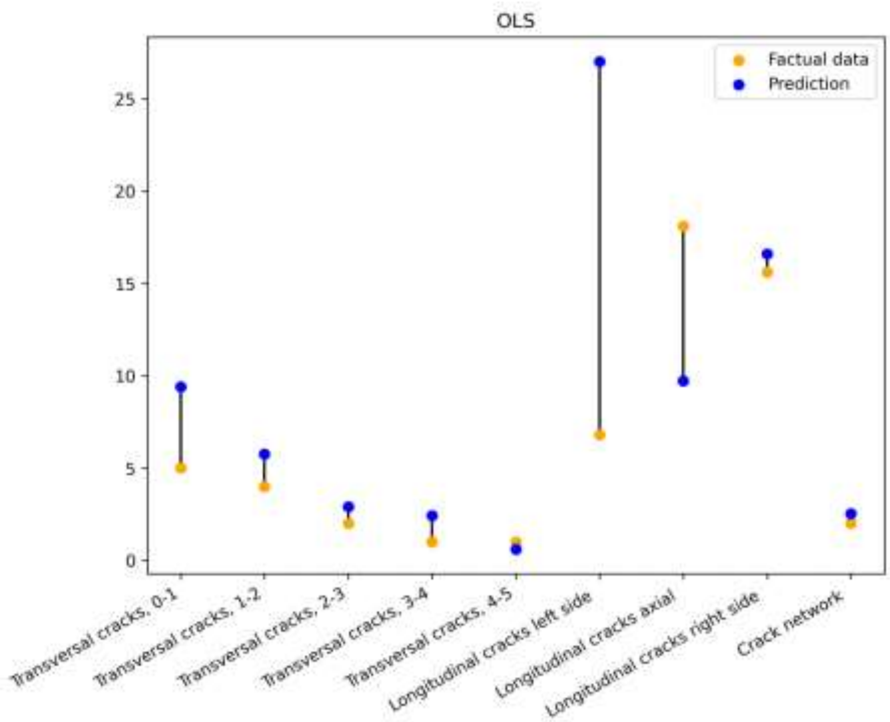

Fig. 4 Discrepancy between the arithmetic mean of forecasted and factual values for each parameter of the best regression model.

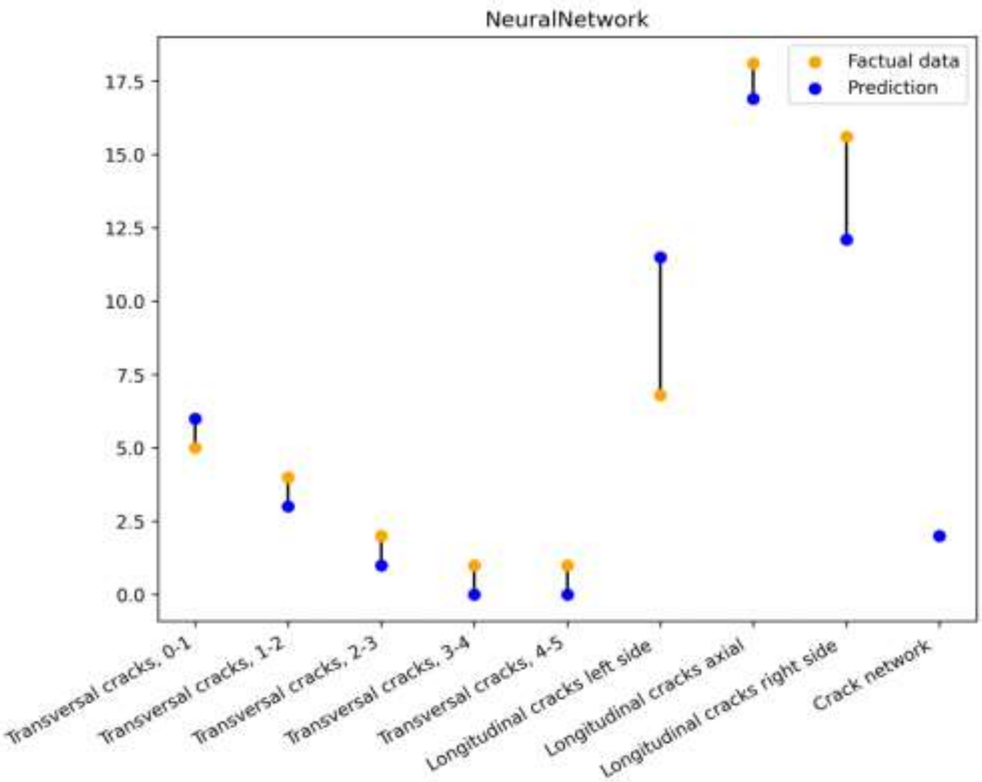

Fig. 5 Discrepancy between the arithmetic mean of forecasted and factual values for each parameter of the neural network selected in the current study.

imagery that requires periodic updates, our system leverages open climate and remote sensing data. This approach not only conserves valuable resources but also enhances efficiency by providing real-time or near-real-time road condition forecasts.[30] One of the key ad-vantages of our predictive system is its ability to continuously monitor road conditions without the need for frequent and costly satellite image acquisitions. By harnessing readily available climate and remote sensing data, it can quickly adapt to changing conditions and provide up-to-date assessments. This efficient approach minimizes both the time and financial investments required for maintaining accurate road condition information.

Additionally, our system can seamlessly integrate with existing GIS platforms, enhancing their capabilities by supplying real-time data and forecasts. This synergy between traditional GIS and our predictive system empowers decision-makers with comprehensive and timely insights, ultimately leading to more effective road maintenance and management strategies. Furthermore, the utilization of open data sources reduces the barriers to entry for organizations and agencies seeking to implement road condition monitoring systems. It allows for a broader adoption of these technologies, benefiting not only large-scale road networks but also smaller and less resource-rich regions.

Thus, it has the following features:

- Uploading New Climate Data: The system can directly use new climate data to ensure it remains up-to-date with the latest meteorological information. This data is sourced directly from the website http://meteocenter.net and is then converted into relevant parameters, including extremely high and low temperatures, freeze-thaw cycles, intense precipitation events, maximum precipitation, and snow cover.
- Downloading Remote Sensing Data: The system has the ability to download re-mote sensing data, which is collected in the form of separate Excel files. These data are then organized into a unified array, with coordinates serving as a key for reference. The system focuses on the data points closest to the specific road section being processed.
- Forecasting Road Surface Deformation: Using the available data, the system can forecast road surface deformation. This forecasting process is facilitated by the regression and neural network models developed during the research.
- Assessing Road Condition: Based on the forecasted deformation parameters, the system assesses the condition of the road. This assessment is typically conducted following a classification system accepted by road services.
- Visualizing Assessment on a Map: The system can visualize the assessment score in the form of a map, providing a clear and easily interpretable representation of the road condition.

For user convenience, the chosen implementation of the geo-information system is going to be designed as a web application. This web application can be deployed on existing websites or utilized as a mobile application,

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ensuring high accessibility and versatility.

To provide a more detailed description of the core computation process, all downloaded and processed data are input into the two selected forecasting models. These models generate forecasts and predictions for the condition of a specific road section in the form of 10 parameters, which are commonly used in the road sector to assess road conditions. From these forecasts, the highest values for each parameter are selected as the final result. After obtaining forecasts for each parameter, the system calculates the road's state category and subgroup according to the republican standard. The categories are defined as follows:

Category I: The roadbed is solid, and the transversal profile is preserved. There are no deformations or defects in the road cover. Single cracks at intervals of more than 40 meters are permissible. Category I is divided into four subgroups:

Subgroup 1 (I/1): Smooth cover with no deformations.

Subgroup 2 (I/2): Smooth cover with occasional rare deformations that do not affect traffic conditions, velocity, or safety.

Subgroup 3 (I/3): The road has small unevenness, widely spaced cracks, and an in-significant number of other deformations.

Subgroup 4 (I/4): The road has significant unevenness, corrugations, raveling, and other deformations that affect traffic conditions and velocity. Additionally, road cover edge failures are possible.

Category II: More than 5-30% of the cover is deformed (with specifications for each cover type), indicating inadequate roadbed strength, along with single transversal profile distortion.

Category III: Clear deformations that are significantly more severe, indicating in-adequate roadbed strength. This category includes unstable holes in crack networks and occasional ruptures.

The resulting assessment is visualized on a geographical map using road segments of different colors to represent the different categories:

- Category I/1 or 11 is indicated in green;
- Category I/2 or 12 is shown in light yellow;
- Category I/3 or 13 is represented in dark yellow;
- Category I/4 or 14 is displayed in orange;
- Category II or 20 is marked in red;
- Category III or 30 is represented in burgundy.

This visualization provides a clear and easily interpretable representation of the road segments' condition, enabling effective road management and maintenance decisions.

The system's forecasts can vary based on the specified time period. In this context, forecasts can be generated for a period of 1, 2, or 3 years after the construction or re-construction of the road. As an illustration, an example of a one-year forecast for the entire road is provided in Table 4 and is visually represented in Fig. 6.

The category is assessed by calculating the percentage of road deformation relative to the road section area. If it is less than 10%, it falls under Category I; in the range of 10-20%, it

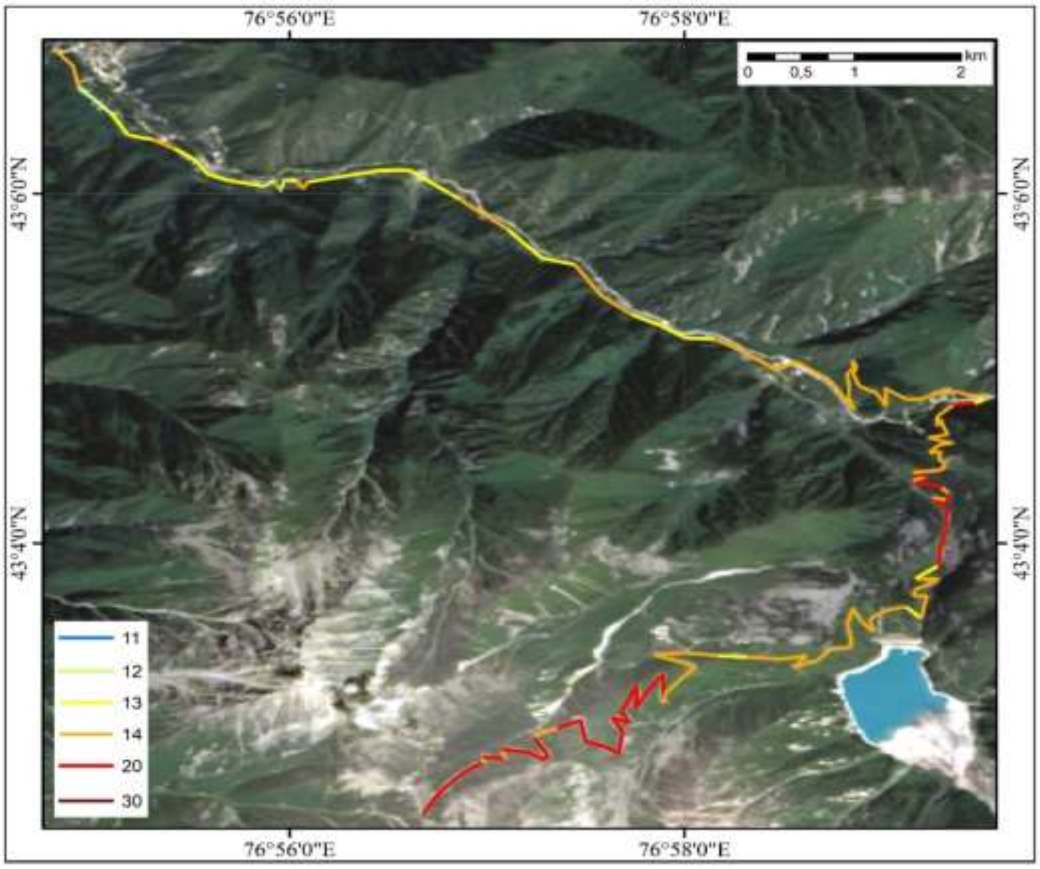

Fig. 6 The estimated category and subgroup of the road for first year after a reconstruction.

Table 4. The forecasted parameters and estimated category and subgroup for first year after a reconstruction.

Coordinates												
Starting	Ending	Number of trans-versal cracks, 0-1 m	Number of trans-versal cracks, 1-2 m	Number of trans-versal cracks, 2-3 m	Number of trans-versal cracks, 3-4 m	Number of trans-versal cracks, 4-5 m	Sum length of longi-tudinal cracks on left side, m	Sum length of longi-tudinal cracks, axial, m	Sum length of longi-tudinal cracks on right side, m	Crack network	Category	Subgroup
…	…	…	…	…	…	…	…	…	…	…	…	…
43.060272, 76.983738	43.060584, 76.985374	9,654	5,561	2,907	2,308	0,600	26,384	9,365	17,330	2,852	1	4
43.060584, 76.985374	43.059525, 76.986628	8,675	5,344	2,532	2,051	0,489	24,836	10,953	15,606	2,202	1	3
43.059501, 76.986622	43.061539, 76.987108	9,189	5,540	2,835	2,208	0,515	25,094	10,706	15,997	2,756	1	4
…	…	…	…	…	…	…	…	…	…	…	…	…

falls under Category II, and if it exceeds 20%, it falls under Category III. Similarly, the percentage of deformation is used for subgroup assessment: <1% corresponds to Subgroup 1, 1-5% to Subgroup 2, 5-8% to Subgroup 3, and 8-10% to Subgroup 4.

The provided figure illustrates variations in road state degradation along its length. More significant degradation is observed on the upper side of the road, which has steeper slope conditions, classified as Category II. In contrast, the lower side exhibits an acceptable condition, falling under Category I/2. It's important to note that the road shows signs of deformation even after just one year of operation. To further exemplify the system's forecasting capabilities, we present an example of a two-year forecast following reconstruction for the entire road in Table 5 and visually depict it in Fig. 7.

The forecast for the second year indicates a further deterioration in the condition of all road sections, with many of them reaching Category II and even Category III in the more exposed sections. To provide a longer-term perspective, we present an example of a three-year forecast following reconstruction for the entire road in Table 6 and visually represent it in Fig. 8.

The forecasted road state for the third year after reconstruction indicates a significant deterioration, reaching Category III, with only one section remaining in Category II on the lower side of the road. This forecast emphasizes the urgent need for reconstruction and repair, providing a clear visual representation of the necessity for such actions.

The final system is designed to perform preliminary diagnostics of the road condition for 1, 2, and 3 years ahead. It assesses the road's condition based on the standards adopted by the road industry of the Republic of Kazakhstan. Importantly, the forecasting relies on publicly available data, making the system cost-effective and accessible for implementation with minimal investment. This system offers a valuable tool for road authorities and services to proactively manage and maintain their road networks, ensuring road safety and functionality.

Table 5. The forecasted parameters and estimated category and subgroup for second year after a reconstruction.

Coordinates												
Starting	Ending	Number of trans-versal cracks, 0-1 m	Number of trans-versal cracks, 1-2 m	Number of trans-versal cracks, 2-3 m	Number of trans-versal cracks, 3-4 m	Number of trans-versal cracks, 4-5 m	Sum length of longi-tudinal cracks on left side, m	Sum length of longi-tudinal cracks, axial, m	Sum length of longi-tudinal cracks on right side, m	Crack network	Category	Subgroup
…	…	…	…	…	…	…	…	…	…	…	…	…
43.059501, 76.986622	43.061539, 76.987108	18,379	11,080	5,669	4,417	1,030	50,188	21,413	31,994	5,511	2	0
43.061539, 76.987108	43.061650, 76.986050	17,479	11,260	5,705	4,339	0,832	47,496	24,716	28,630	5,517	2	0
43.061650, 76.986050	43.062215, 76.986112	18,426	11,838	6,163	4,877	0,985	51,050	22,745	30,112	5,774	2	0
…	…	…	…	…	…	…	…	…	…	…	…	…

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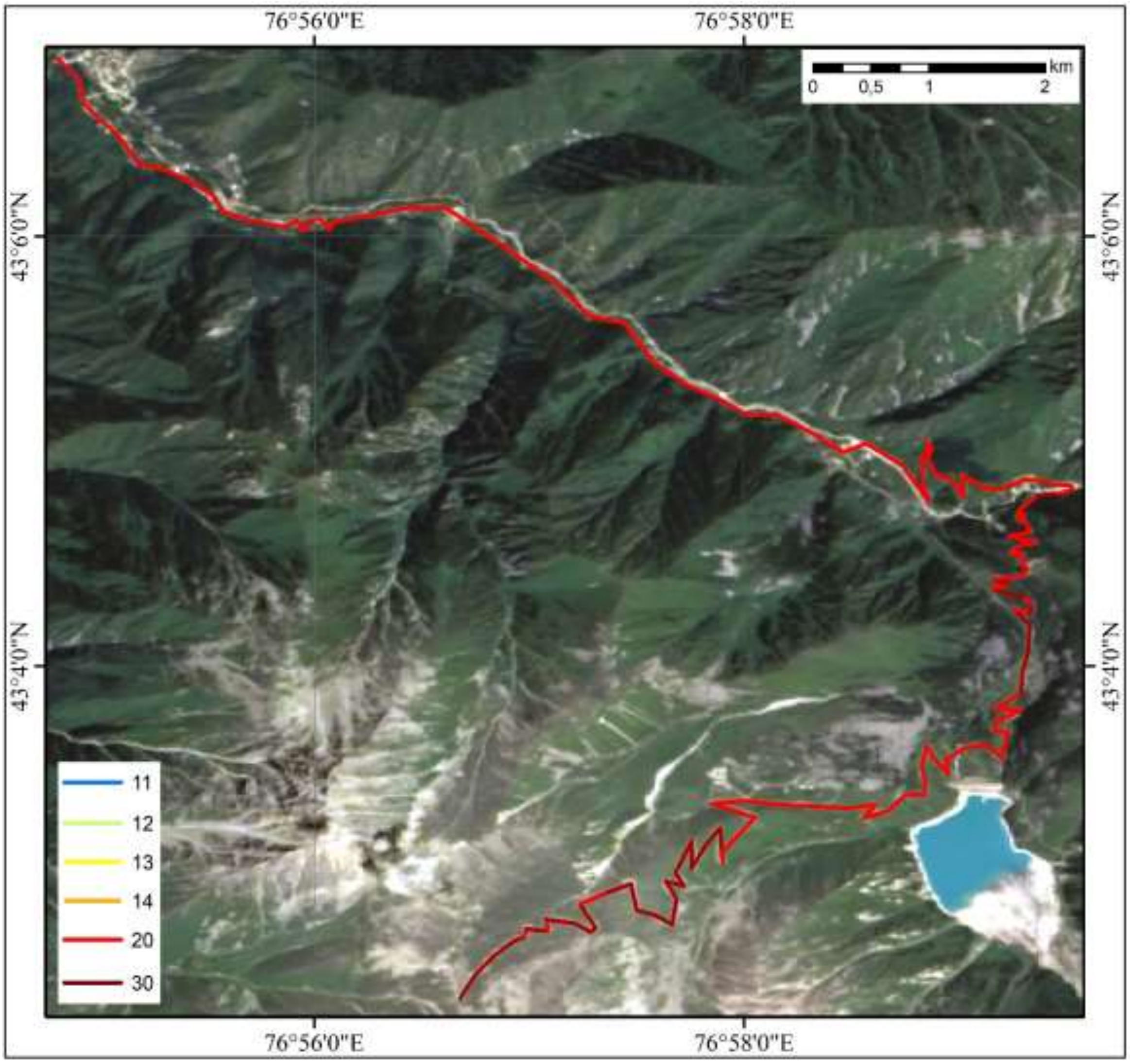

Fig. 7 The estimated category and subgroup of the road for second year after a reconstruction.

Table 6. The forecasted parameters and estimated category and subgroup for third year after a reconstruction.

Coordinates												
Starting	Ending	Number of trans-versal cracks, 0-1 m	Number of trans-versal cracks, 1-2 m	Number of trans-versal cracks, 2-3 m	Number of trans-versal cracks, 3-4 m	Number of trans-versal cracks, 4-5 m	Sum length of longi-tudinal cracks on left side, m	Sum length of longi-tudinal cracks, axial, m	Sum length of longi-tudinal cracks on right side, m	Crack network	Category	Subgroup
…	…	…	…	…	…	…	…	…	…	…	…	…
43.059501, 76.986622	43.061539, 76.987108	27,568	16,620	8,504	6,625	1,545	75,282	32,119	47,991	8,267	3	0
43.061539, 76.987108	43.061650, 76.986050	26,218	16,890	8,558	6,508	1,248	71,243	37,074	42,946	8,276	3	0
43.061650, 76.986050	43.062215, 76.986112	27,638	17,757	9,244	7,315	1,477	76,575	34,117	45,168	8,660	3	0
…	…	…	…	…	…	…	…	…	…	…	…	…

4. Discussion

4.1 Insights from weights of the predictive models

The previous article empirically justified that road deformation can be triggered by landscape factors with varying levels of impact. To further understand and quantify these impacts, the study compared the weights assigned to parameters in the predictive models. The sum of weights for each parameter in each model demonstrates the influence of those parameters on the forecasted output, allowing for a numerical assessment of each parameter's impact on road deformation.

The results of this empirical comparison, including the weights of the forecasting models (sum of weights between exact input and inner neurons for the neural network and sum

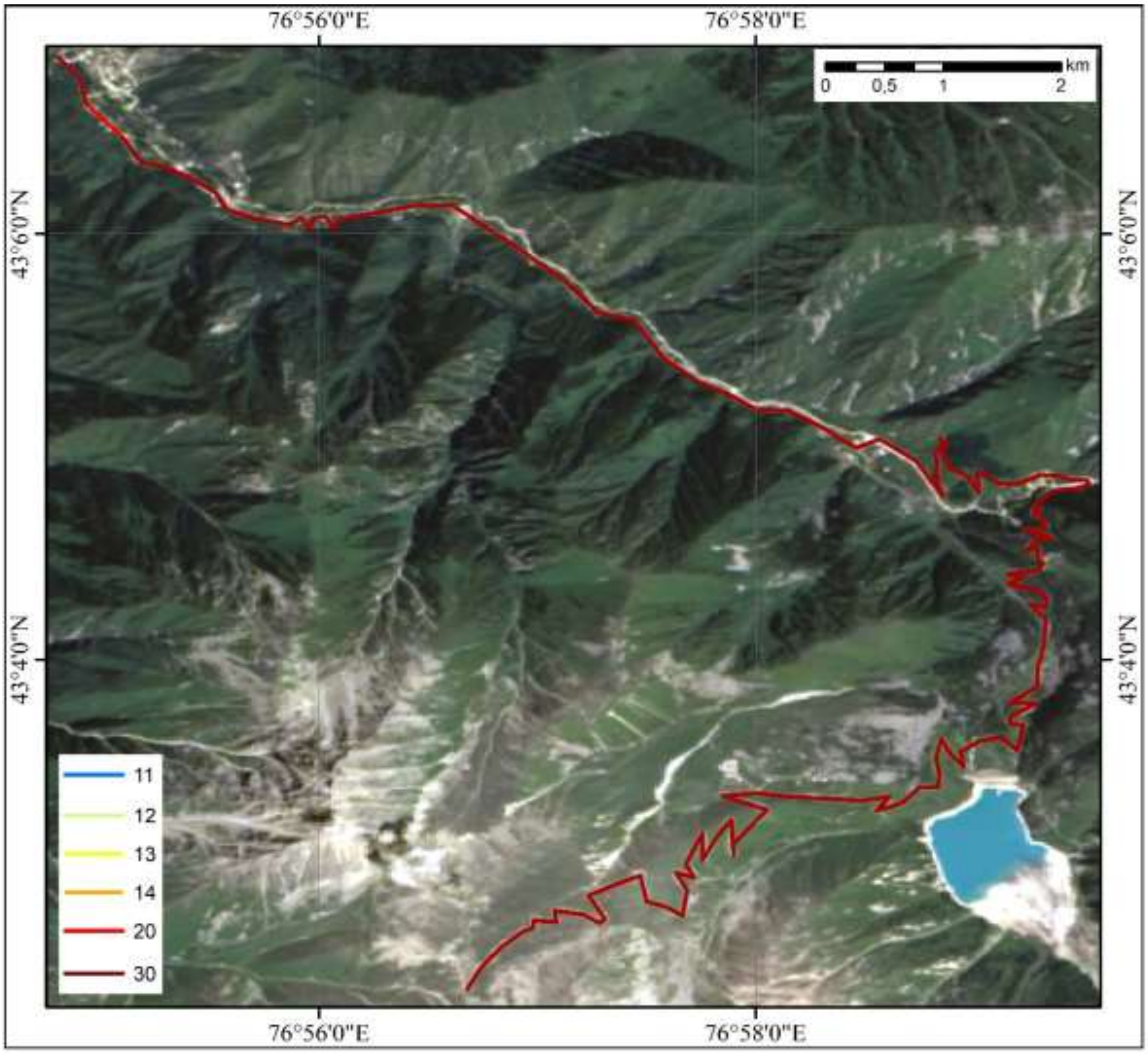

Fig. 8 The estimated category and subgroup of the road for third year after a reconstruction.

of coefficients beside exact input), are summarized in Table 7. This table pro-vides valuable insights into the quantitative impact of different parameters on road deformation, helping to prioritize and address factors that have a more significant effect on road conditions.

As illustrated in Table 7, the empirically observed impact of remotely sensed factors on roads exhibits significant variation, with some factors causing disruptions while others contribute to stability. Additionally, the degree of interference by these factors ranges from low to highly intensive. It is worth noting that the neural network model appears to assign relatively equal importance to all parameters, indicating a more balanced approach. In contrast, the regression model places greater emphasis on factors such as solar radiation and snow melting, which represent selective meteorological factors for specific coordinates. Parameters related to the surrounding land-scape are still considered but with less intensity.

Table 7. Impact of remotely sensed parameters on road's state.

Factor's impact	Vertical displacement velocity	Slope exposure	Dissections	Topographic wetness index	Aspect	Solar radiation	Vegetation index SAVI	Snow-melting
The empirical comparison								
Retaining	No	No	Yes	No	Yes	No	Yes	No
Disruptive	Yes	Yes	Highly	Yes	Yes	Yes	Yes	Highly
The weights' sum of the best forecasting models								
The regression model	6.12 e-11	1.87 e-9	1.14 e-13	3.60 e-10	1.50 e-8	7.13 e-5	1.27 e-11	1.04 e-7
The neural network	2503.509	2496.176	2499.623	2497.053	2493.089	2494.175	2493.980	2485.039

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Table 8. The sum of weights for meteorological input parameters.

Factor's impact by the best models	Extreme High Temperature (>30 °C)	Extreme Low Temperature (<−15 °C)	Freezing and Thawing Cycles	Highly Intensive Rainfall Values (> 30 mm un 3 h)	Rainfall	Snow Cover Maximum Value
The regression model	4.896 e-6	1.778 e-6	0	5.027 e-6	0	0
The neural network	25.343	24.696	24.811	24.947	25.092	25.112

An analysis of the weights assigned to meteorological parameters reveals a more substantial difference between the two model types, as shown in Table 8. This analysis underscores the distinct emphasis that each model places on meteorological factors, offering a clearer understanding of their respective forecasting approaches.

The analysis in Table 6 reveals that the neural network model assigns meteorological parameters relatively similar levels of importance, but they collectively carry significantly less weight compared to remote sensing data, approximately 100 times less. In contrast, the regression model emphasizes only half of the meteorological features, specifically extremely high and extremely low temperatures, as well as highly intensive rainfalls. Surprisingly, these meteorological parameters receive even higher consideration than landscape parameters. This observation suggests that while all factors contribute to road damage, meteorological impacts play a primary role in pavement deterioration. These findings underscore the critical importance of understanding and managing the effects of weather conditions on road conditions.

4.2 First step road diagnostic system's perspectives

The predictive system has been meticulously designed to offer preliminary road condition diagnostics for periods of 1, 2, and 3 years ahead. It adheres to the standards set by the road industry of the Republic of Kazakhstan for assessing road conditions. Importantly, the system's forecasting relies on publicly accessible data sources, making it a cost-effective and easily implementable solution with minimal financial investment required.

The system serves as a valuable and practical tool for road management authorities and services, enabling them to proactively address the maintenance and upkeep of their road networks in mountain areas. By providing reliable forecasts and assessments, it empowers decision-makers to ensure the safety and ongoing functionality of the road infrastructure.

Furthermore, the system incorporates data on the topography and condition of adjacent slopes, which is determined by the specified coordinates and the width of the road segment under evaluation. With some minor refinements to the system's inter-face, it can function not only as a predictive tool for assessing the condition of existing roads but also as a valuable consulting system for road design. This could involve determining the optimal route for the road along the terrain that experiences the least deformation and selecting the most suitable road width based on anticipated deformations, offering valuable insights for road construction and planning.

Furthermore, given the system's modular architecture, it provides the flexibility to accommodate advanced forecasting models in the future. This implies that as new and enhanced forecasting methods emerge, they can be smoothly integrated into the system, either as replacements for the existing models or in parallel with them. This adaptability guarantees that the system can remain current with the latest advancements in road condition forecasting, delivering continuous benefits for road management and maintenance.

5. Conclusions

Road maintenance and restoration in mountainous region, especially in countries like Kazakhstan, present unique challenges due to the country's climatic and economic conditions. To tackle these challenges and reduce the costs associated with road diagnostics in terms of both human and technical resources, the authors propose the development of a forecasting system that operates based on a training data using open climate and remote sensing data. This system relies on specially calibrated predictive models to achieve its objectives. However, the feasibility of this approach hinges on the ability of these models to provide accurate forecasts of mountain road conditions using publicly available data sources. This innovative solution has the potential to streamline road management and maintenance processes in Kazakhstan, optimizing resources and enhancing the efficiency of road infrastructure upkeep.

The design and training of the models involved the use of two datasets: the input dataset, which included preprocessed open climate data and remote sensing data, and the output dataset, which was based on the results of field research. These datasets were connected in a three-dimensional manner, with the time axis linking the remote sensing data with the climate data and the geographical axis connecting them with the field data. This integrated approach allowed for a comprehensive analysis and adjustment of the models, taking into account a wide range of factors that influence road conditions.

The resulting predictive models, including the selected regression model and the forward-feeding neural network, demonstrated an average error of 81.73% with a median value of 44.83% and an average error of 51.55% with a median value of 45.12%, respectively. The weights assigned to the models provide clear justification that both landscape and meteorological factors have a significant influence on road condition in mountainous area. These weights reflect the importance of various parameters in the forecasting models and highlight the multidimensional nature of the factors that impact road conditions.

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Thus, the predictive diagnostic system is designed as a GIS with several key features, including the ability to:

- directly can use meteorological data from archives;
- integrated usage of the remote sensing data from Excel files;
- forecast 9 parameters related to the condition of mountain roads;
- compute the road's category based on the standards established by the Republic of Kazakhstan;
- visualize the road's condition on a map.

This system offers a comprehensive platform for road condition assessment and management, incorporating both climate and remote sensing data to provide valuable insights for road maintenance and planning.

With some minor improvements to the system's interface, it can extend its role beyond predictive diagnostics for existing roads and become a valuable consulting tool for road design. This expanded functionality could involve tasks such as identifying the optimal route for a road along terrain that is less prone to deformation and selecting the most suitable road width based on anticipated deformations. Such insights would be highly beneficial for road construction and planning as well as for government bodies.

Moreover, the system's modular architecture ensures that it remains adaptable for future advancements in forecasting models. This flexibility enables the integration of more advanced models down the line, keeping the system up-to-date with the latest innovations in road condition forecasting. It represents a forward-looking approach to road management and maintenance.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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