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Web Application for Pipeline Hazard Assessment based on Google Earth Engine: Case Study of Ukrainian Carpathians

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SUMMARY

Pipelines are essential for energy supply stability. However, many of them face both natural and anthropogenic hazards. For pipeline hazard assessment, remote sensing provides regular, large-scale analysis, especially in hard-to-access areas. Cloud-based platforms like Google Earth Engine (GEE) enable efficient processing of large geospatial datasets. Also, GEE allows creating a web application with a custom GUI for specific thematic tasks. Thus, the aim of this study is to develop a GEE-based web application for automated pipeline hazard assessment utilizing multi-source remote sensing data. The proposed framework incorporates both natural and infrastructure parameter groups. The natural group includes terrain slope from SRTM V3, land surface temperature from MODIS, and accumulated precipitation from ERA5-Land. The infrastructure group consists of distance layers to roads, railways, and power transmission lines. Processing of this data implies normalization of input parameters and computing their weighted sum with expert-defined weighted coefficients. For the experiment, the developed application was tested on a section of the Urengoy–Pomary–Uzhgorod pipeline in the mountainous terrain of the Ukrainian Carpathians. As a result, the obtained pipeline hazard map indicates the following distribution of hazard classes: 13.93% low hazard, 49.11% medium hazard, 34.50% high hazard, and 2.46% very high hazard. For validation, the obtained map was overlaid with 198 documented landslides. The analysis demonstrated high consistency, since most landslides occurred within the high and very high hazard zones. Thus, the developed tool can support spatial decision-making for pipeline monitoring and hazard mitigation.

Keywords: Pipeline; Pipeline hazard assessment; Google Earth Engine; Remote sensing; Multi-criteria evaluation; Geospatial analysis; Landslide; Data fusion; Ukrainian Carpathians.

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Introduction

Pipeline systems are critical components of energy infrastructure, and their reliable operation is essential for energy supply stability (Silva et al., 2024). However, many pipelines are located in regions with challenging environmental conditions, where natural hazards such as landslides, erosion, and wildfires may affect their safe operation (Apostolov et al., 2021). Such environmental hazards are often closely linked to long-term processes of land degradation (Popov et al., 2021). In addition to natural hazards, pipeline safety may also be influenced by anthropogenic factors, including infrastructure-related elements such as roads, railways, and powerlines. Thus, the development of integrated approaches that combine various sources of pipeline hazards, including both natural and anthropogenic factors, has become an important task (Titarenko et al., 2026; Zhang et al., 2023).

Therefore, the development and implementation of effective monitoring of pipeline hazards is essential for ensuring environmental and economic safety (Mahmoud & Hasan, 2025). For this purpose, remote sensing tools are effective, as they provide large-scale and regular analysis, including in hard-to-access areas. These capabilities ensure continuous data collection and provide up-to-date information across the area of interest.

However, such monitoring requires processing of a large volume of remote sensing data, which must be updated and analyzed frequently. Under such conditions, this processing is best performed on cloud-based geospatial platforms such as Google Earth Engine (GEE) (Gorelick et al., 2017). This is because GEE does not require high-performance user computers and provides free access to a wide catalog of geospatial data. Also, GEE allows users to build web applications with a custom GUI, adapting them to specific research needs. Thus, the aim of this study is to develop a specialized GEE-based web application for automated pipeline hazard assessment utilizing multi-source remote sensing data.

Method and Theory

To enable an integrated pipeline hazard assessment, a cloud-based web application was developed using the Google Earth Engine (GEE) platform. This application is available at the following link: https://ee-artemaandreev.projects.earthengine.app/view/linear-infrastructure-hazard-assessment-tool.

The proposed framework incorporates both natural and infrastructure groups of parameters. The natural group consists of terrain slope, mean land surface temperature (LST), and mean accumulated precipitation, which were derived from SRTM V3 (Farr et al., 2007), MODIS (MOD11A2) (Wan et al., 2021), and ERA5-Land (Muñoz-Sabater, 2019) datasets from the GEE platform, respectively. The group of infrastructure parameters contains spatial layers of distance to roads, railways, and power transmission lines. These layers were generated by rasterization of the respective vector data through the calculation of the Euclidean distance from each pixel to the nearest infrastructure object.

The algorithm of the developed approach to pipeline hazard assessment is presented in the flowchart (Figure 1). The first step of the workflow implies the spatial standardization of each parameter by linear bounded normalization to overcome differences in physical units. This method rescales input values of the parameters into a dimensionless hazard score from 0 to 1 based on user-defined minimum and maximum thresholds. Under this logic, any input value equal to or below the minimum threshold is set to 0 (baseline safety), while any value equal to or exceeding the maximum threshold is set to 1 (maximum hazard saturation). Also, it should be noted that, unlike natural factors, infrastructure parameters follow inverted logic. This is because the hazard is highest near roads, railways, or power lines, and it decreases as the distance increases. Accordingly, the normalization procedure assigns a hazard score of 1 to the nearest locations and 0 to the most distant locations.

In the next step, all normalized layers are combined using the weighted sum. The weight coefficients for each parameter are set by an expert based on their impact on pipeline hazard. The sum of all weights must be equal to 1. Thus, the application calculates the Integrated Pipeline Hazard Index (IPHI) for each pixel using the following formula:

$$\boldsymbol{IPHI = \sum_{i=1}^{n} X_i * w_i} \quad (1)$$

where n is the number of input parameters, X_i is the normalized value of the i-th parameter, and w_i is the weight coefficient of the i-th parameter.

Since each input parameter was normalized, the values of the calculated index range from 0 to 1, where 0 indicates no hazard, 1 indicates the maximum hazard level, and intermediate values reflect varying degrees of pipeline hazard.

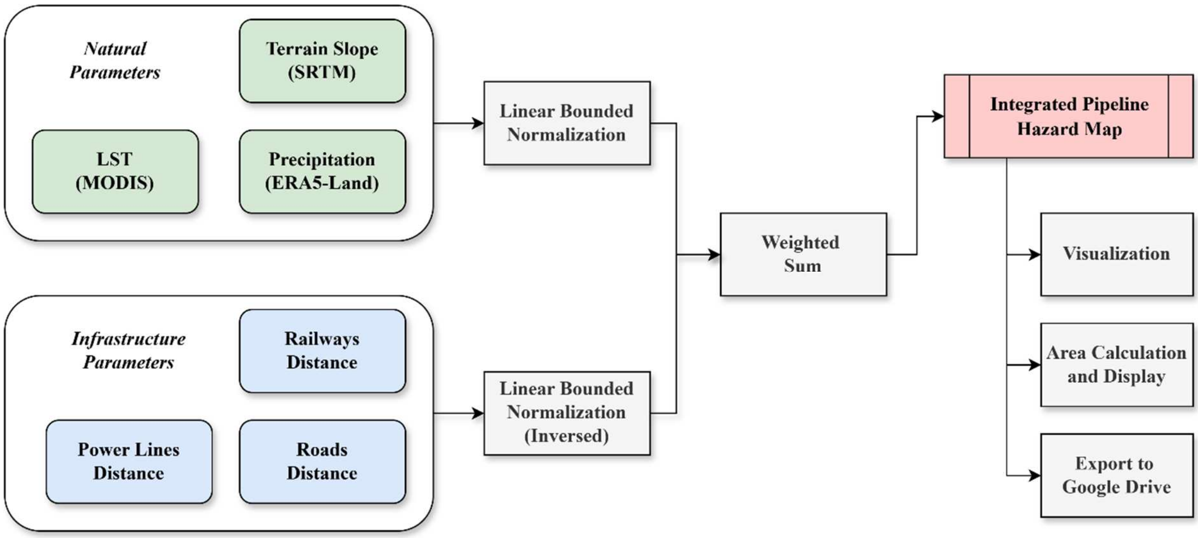

Figure 1. *Flowchart of the developed approach to pipeline hazard assessment*

As a result, the developed application generates the Integrated Pipeline Hazard Map. This is a geospatial raster layer that can be downloaded directly to the user's Google Drive for further analysis. However, it should be noted that data export to Google Drive is available only within the GEE Code Editor interface, while standalone GEE Apps do not support direct export. Additionally, the obtained map could be displayed on the interactive map, available in GEE. The application also generates class statistics within the GUI, showing the total area of each user-defined hazard class and its percentage of the entire study area.

Results

To evaluate the practical performance of the developed application, the experiment was conducted along the Urengoy–Pomary–Uzhgorod pipeline. The research area is located predominantly within the mountainous terrain of the Ukrainian Carpathians, focusing on the Dolyna–Volovets and Dolyna–Rososh sections. The lengths of these pipelines are 83.8 km and 130.27 km, respectively, with a total length of 214.07 km. The total area of the selected study area is 3371.91 km^2.

The study period was set to the summer of 2025, namely from June 1 to August 31. For the input parameters, we set minimum and maximum normalization limits as follows: terrain slope from 0 to 30°, LST from 250 to 320 K, precipitation from 0 to 20 mm, distance to railways from 0 to 300 m, distance to power lines from 0 to 300 m, and distance to roads from 0 to 300 m. The weight coefficients were assigned as 0.5 for terrain slope, 0.1 for LST, 0.2 for precipitation, 0.05 for distance to railways, 0.1 for distance to power lines, and 0.05 for distance to roads. The obtained hazard map was classified into 4 classes with the following ranges: 1) Low Hazard (0–0.2); 2) Medium Hazard (0.2–0.4); 3) High Hazard (0.4–0.6); 4) Very High Hazard (>0.6). The GUI of the developed application and the obtained hazard map are shown in Figure 2.

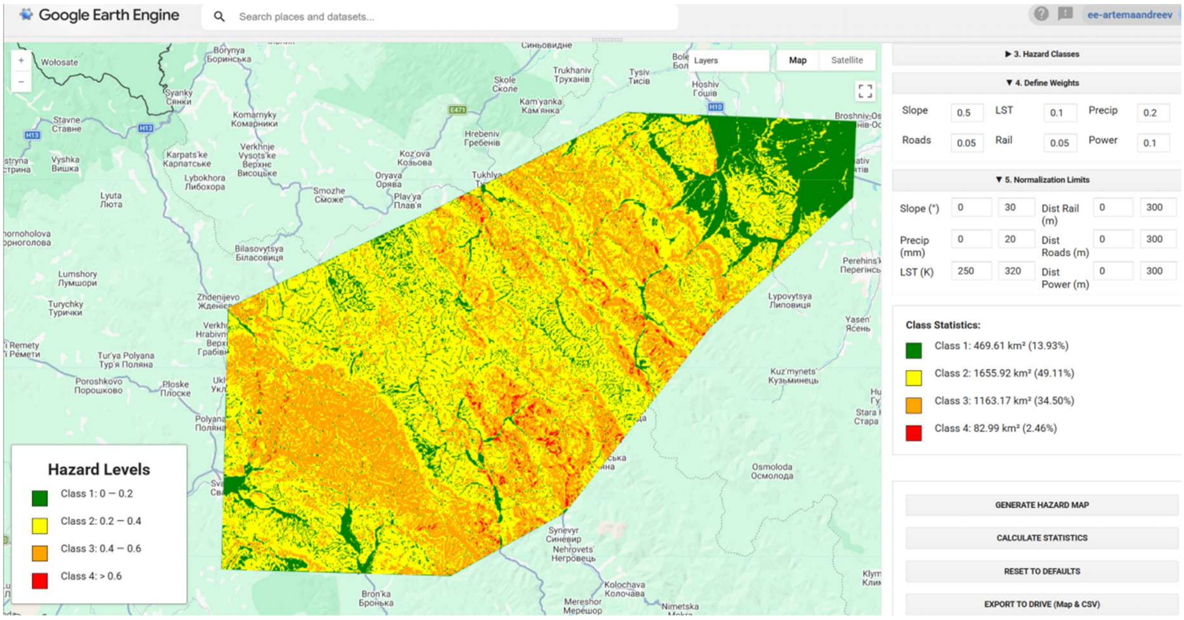

Figure 2. *GUI of the developed GEE web application displaying the pipeline hazard assessment map*

The spatial analysis of the study area revealed the following area distribution of hazard classes: 1) Low Hazard: 13.93% (469.61 km^2), 2) Medium Hazard: 49.11% (1655.92 km^2), 3) High Hazard: 34.50% (1163.17 km^2), and 4) Very High Hazard: 2.46% (82.99 km^2).

To validate the reliability of the obtained map of the pipeline hazard assessment, the data on documented landslides in the Transcarpathian region were used (Shtohryn et al., 2021). Since the study area is in mountainous terrain, landslide data are highly relevant to validating the pipeline hazard assessment. Thus, a raster layer containing 198 documented landslide locations was spatially overlaid onto the resulting pipeline hazard map. As a result, the obtained hazard assessment map demonstrated high consistency with these landslides, as the vast majority of them are concentrated within the high and very high hazard zones, whereas their occurrence is significantly lower in low-hazard areas.

Conclusions

This study presented an integrated geospatial approach for pipeline hazard assessment based on the multi-criteria evaluation of natural and infrastructure factors. The workflow of this approach implies two steps: 1) a linear bounded normalization applied to each input parameter to transform their values into standardized hazard scores from 0 to 1, and 2) a weighted sum where each parameter is multiplied by expert-defined weights indicating its specific impact on the total hazard.

Based on the presented approach, the web application for pipeline hazard assessment was developed using the GEE platform. This application provides a GUI that allows users to set input parameters, including the study area, study period, normalization bounds, and weight coefficients. As a result, the application visualizes the final map, calculates class statistics, and allows data export to Google Drive.

The application was tested within a 3371.91 km^2 study area along the Urengoy–Pomary–Uzhgorod pipeline in the Ukrainian Carpathians. The resulting hazard map revealed that a significant portion of the study area falls within the high and very high hazard classes (34.50% and 2.46%, respectively). To validate these results, the map was overlaid with 198 documented landslides, showing high consistency: most landslides fell within the high and very high hazard zones.

Future research may explore more advanced approaches to integrating multiple hazard-related parameters, including fuzzy logic, subjective logic, and other uncertainty-aware data fusion methods, to better account for uncertainty in heterogeneous geospatial datasets (Popov et al., 2020).

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