

Report

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SAFE HILLS - Dynamic Landslide Risk Forecasting Dashboard for Uttarakhand

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Section - I

Problem Definition

- Uttarakhand faces a big problem with landslides. The state has steep hills, heavy rains, and construction work that make the ground unstable. Every year, landslides destroy roads, buildings, and take lives. For example, in August 2025, a cloudburst in Uttarkashi caused a major landslide that washed away villages.
- Right now, there is no easy-to-use system that shows which areas are in danger before a landslide happens. Our project aims to solve this. We are building an online dashboard that maps landslide risk across Uttarakhand. This will help people prepare and stay safe.

Background

Uttarakhand is a hilly state. It has three main issues that cause landslides:

- Steep Slopes: The Himalayas have very steep mountains. This makes the ground naturally unstable.
- Heavy Rain: The monsoon season brings very heavy rainfall. This water seeps into the soil, makes it heavy, and can trigger landslides.
- Fragile Land: The rocks and soil in the Himalayas are young and broken. They can easily slip.

Because of these reasons, landslides are common. They damage roads, destroy villages, and kill people every year. This is the background situation that makes our project necessary.

Literature Review

We read research papers to learn how others have solved this problem. The papers showed us which factors are most important for predicting landslides, like slope steepness and rainfall. They also confirmed that using a computer model called Random Forest is a good method for this task.

Research papers used -

- <https://geoenvironmental-disasters.springeropen.com/articles/10.1186/s40677-024-00307-3#:~:text=2018%20%3B%20Chauhan%20et%20al,97>
- [At least four dead, dozens missing as flash floods hit north India village | Climate Crisis News | Al Jazeera](#)
- [Monsoon Season: Landslides Biggest Killer In Uttarakhand; Highest No. Of Casualties This Year | Dehradun News - Times of India](#)
- https://ndma.gov.in/sites/default/files/PDF/Reports/Detailed_report_UK_Disaster.pdf
- [A new random forest method for landslide susceptibility mapping using hyperparameter optimization and grid search techniques | International Journal of Environmental Science and Technology](#)
- https://www.journalijecc.com/index.php/IJECC/article/view/5011/10594?cf_chl_tk=1fPMZNWJuLpTsCFpqG3ufcw6P_9MlvsfhhtYB6Yprc-1761132797-1.0.1.1-9GJNGUCR_mBBL.rfgXZUyfviAZbamIEAKfzXCpXirzl

Section - II

Methodology

Our landslide risk assessment follows a clear 4-step process.

1) Data Collection Phase

2) Landslide Susceptibility Index (LSI)

- Slope steepness: 30% (most important)
- Rainfall amount: 22%
- NDVI: 18%
- Geology: 15%
- Drainage: 15%

We calculated a total risk score (0-1) for every point.

- Green colour - Low Risk (0-0.25)
- Yellow colour - Medium Risk (0.25-0.60)
- Red colour - High Risk (0.60-1.00)

$$\text{LSI} = (\text{Slope} \times 0.30) + (\text{Rainfall} \times 0.22) + (\text{NDVI} \times 0.18) + (\text{Geology} \times 0.15) + (\text{Drainage} \times 0.15)$$

3) Random Forest Classifier

- Training Process - We used 70% of our training data to teach the computer model. The model learned to recognize patterns between the physical features and landslide risk.
- Testing Process - We used the remaining 30% of data to test the model's accuracy. We calculated the Accuracy and Kappa coefficient of the model.
- Prediction Process - The trained model can then analyze any location in Uttarakhand and predict its landslide risk class.

4) Real-time Forecasting System

- When Forecast Data is available :
App integrates the Open-Metro API data.
- Generates 7-day risk predictions using real precipitation forecasts.
- When Forecast Data is not available:
It uses fallback mechanism, it applies 5% of monsoon rainfall with respect to Random Forest Classifier.
This is done to ensure that the app doesn't crash, due to data unavailability.

5) Results

- Statistics of affected areas.
- Map onclick Inspector of any particular location.
- Case study of Chamoli 2021 Landslides.
- Entire Uttarakhand ($53,483 \text{ km}^2$ mapped).

Datasets used

- **Study Area** - Our study area is the complete state of Uttarakhand in northern India. This Himalayan region is highly vulnerable to landslides due to its steep mountains, heavy monsoon rainfall.
- **Data Collection and Processing** - We used Google Earth Engine to collect and process all our data. The code we used to get the dataset- [Dataset Code](#)

(i) Topography - Elevation data was taken from SRTM (30m resolution) and Slope calculated from elevation.

(ii) Rainfall -

- Historical monsoon data (CHIRPS, June-Sept 2024).
- Real-time 7-day forecast (Open-Meteo API) - [API LINK](#)

(iii) Environmental Factors -

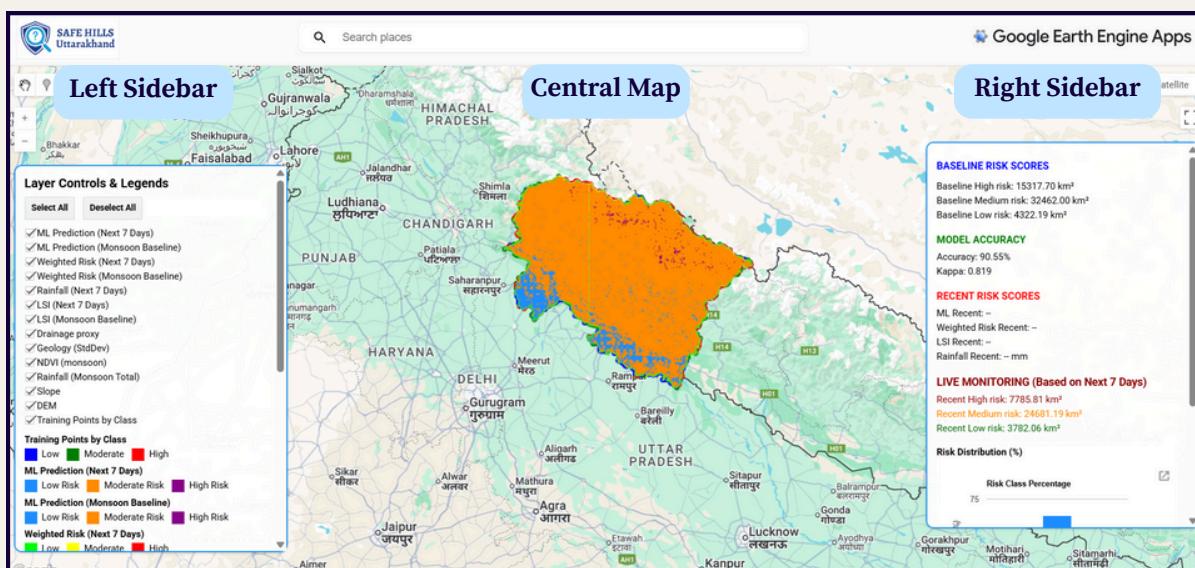
- Vegetation density (NDVI from Sentinel-2).
- Geology proxy from elevation roughness.
- Drainage capacity from slope.

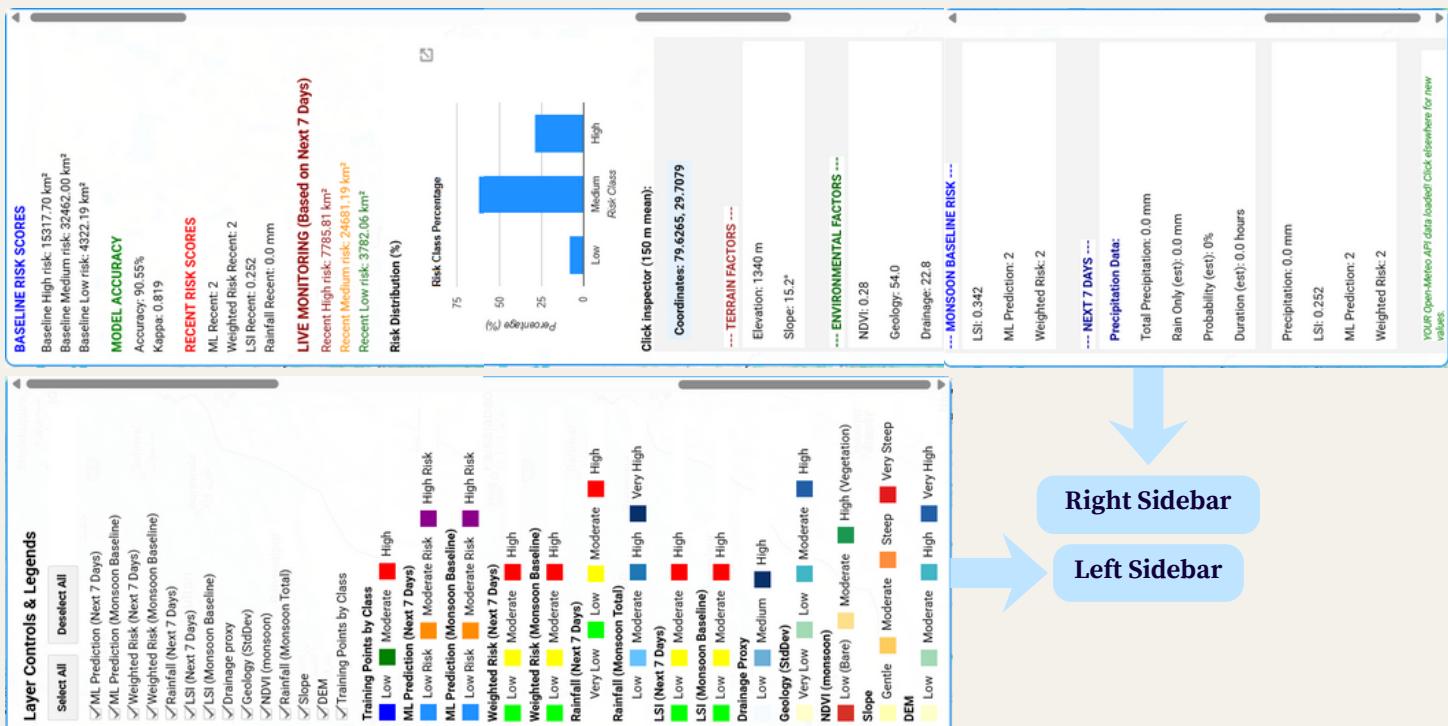
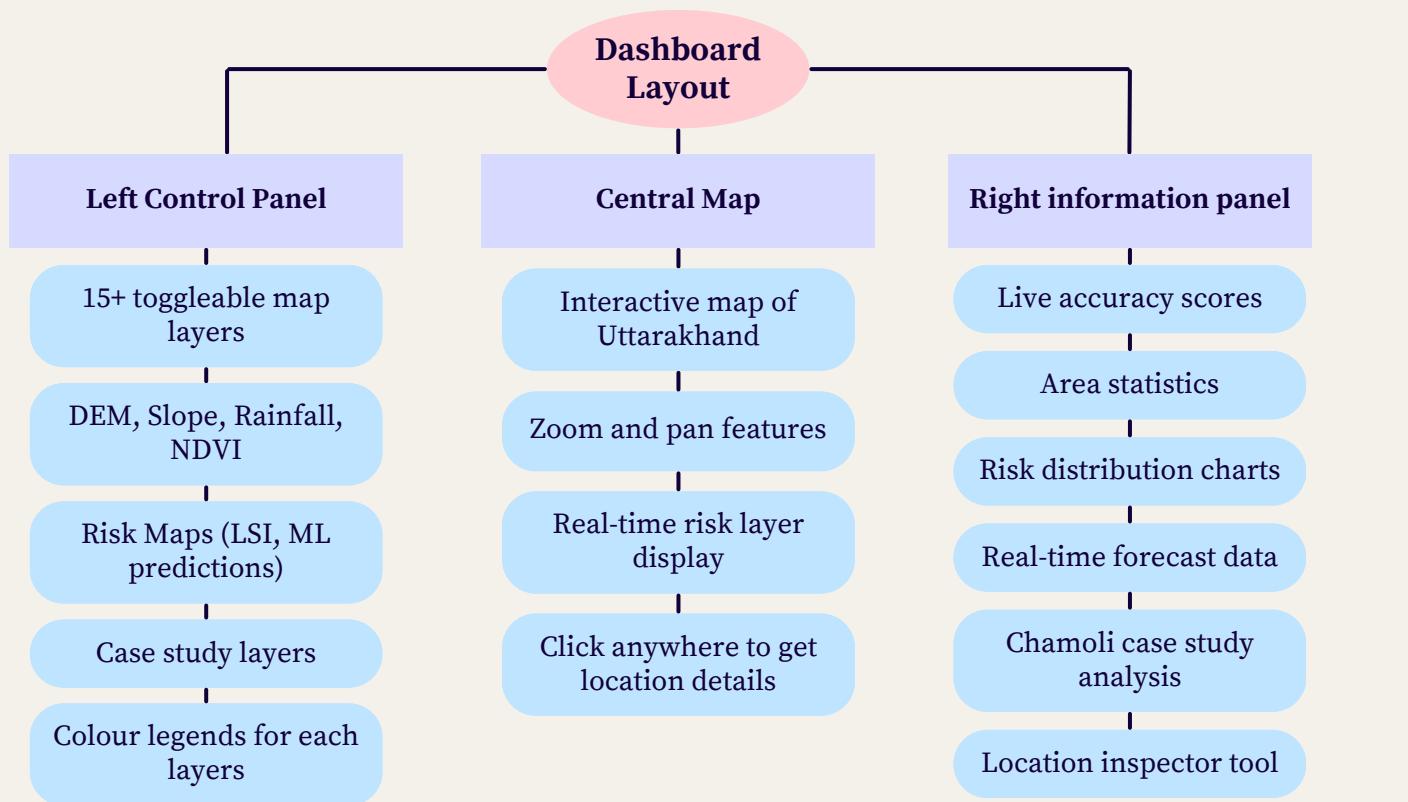
(iv) Training Data - The dataset downloaded from GEE : [Dataset](#)

- 7,881 pre-classified points across Uttarakhand. Classified in risk classes of Low, Medium and High. All the factors discussed above are part of the dataset.

Section - III

App design





Key features

- Dual risk system:
 - (i) Baseline risk: Long-term monsoon-based assessment
 - (ii) Recent risk: Next 7 days forecast-based assessment
- Smart Design:
 - (i) Colour-coded risks: Green (Low), Yellow (Medium), Red (High)
 - (ii) Instant layer switching
 - (iii) Real-time statistics updates
 - (iv) Works on all devices
- User-friendly tools:
 - (i) One-click layer visibility
 - (ii) Interactive risk charts
 - (iii) Location-specific data on click
 - (iv) Case study validation

Technical Highlights

- Cloud-powered:
 - (i) Runs on GEE
 - (ii) No software installation needed
 - (iii) Free access for all users
 - (iv) Fast processing of large datasets
- Reliable Performance:
 - (i) Handles missing forecast data gracefully
 - (ii) Quick response times
 - (iii) Works across all region of Uttarakhand
 - (iv) Minimal learning curves

Implementation

We used simple JavaScript code that runs in any modern browser.

Putting Together the Data Pipeline

STEP 1:

We connected multiple data sources:

- Height Data: From Nasa's SRTM (30m detail).
- Rainfall Records: CHIRPS daily rainfall data.
- Forest Cover: Sentinel-2 satellite images every 5 days.
- Landslide History: Our own database of 7881 verified locations.

STEP 2:

Cleaning and Preparing

- Made all data sets the same size and scale.
- Removed clouds and errors from satellite images.
- Converted everything to work with Uttarakhand's geography.

Building the Analysis Engine

Two Parallel Systems:

1. The simple Scoring Method

We created a straightforward weighted system:

- Steep Slope: 30%
- Heavy rainfall: 22%
- Bare land: 18%
- Weak rocks: 15%
- Poor drainage: 15%

This gives clear risk score from 1-3 that anyone can understand

2. The Smart AI method

- We trained a computer using real landslide data, using 70% of the dataset
- It learned patterns
- Tested it on 30% of the dataset to check accuracy
- It now predicts risk with 90% accuracy

Making It Live and Responsive

Real-time Features:

- We manually download forecast data from Open-Meteo, uploading the data as assets on GEE manually. The data stays static, until we manually update it again, no automatic updates.
- The 'recent risk' maps show risk based on our last manual data upload.
- Fallback: If our uploaded forecast data is missing or can't be found, The app uses a very basic calculation: 5% of total monsoon rainfall.

Performance Optimisations:

- Fast Loading: Shows basic maps immediately while calculating complex layers.
- Smart Zoom: Loads more detail only when you zoom in.
- Efficient Updates: Only recalculates what changed.

Designing for All Users

For Technical Users (Engineers, Planners):

- Full control over all data layers
- Detailed statistics and accuracy measures
- Export capabilities for reports

For General Users (Villagers, Students):

- Simple colour-coded maps (Green/Yellow/Red)
- One-click location checking
- Easy-to-understand risk levels

Simple feature we added:

- Click Inspection: Tap anywhere to see slope, rainfall, and risk for that exact spot.
- Compare Mode: See baseline risk vs current week's risk side-by-side.
- Case Studies: Learn from past landslides like the Chamoli 2021 event.

Section - IV

Impact assessment

Real Benefits Delivered

Technical Impact:

- Created Uttarakhand's free web-based landslide risk mapping tool
- Achieved 90% accuracy in identifying landslide-prone areas
- Processes 7881 data points to generate risk assessments
- Covers entire Uttarakhand (53483 km^2) with weekly risk updates

Practical Impact:

- Generates state-wise risk maps in 2 minutes
- Accessible on mobile phones with basic internet
- No cost for users-eliminates need for expensive software

Case Study Validation

Chamoli 2021 Analysis:

- Successfully identified the affected area as high-risk
- Detected all major contributing factors accurately
- Model predictions aligned with actual event platforms

Challenges

Implementation Challenges:

- Requires internet connectivity
- Needs basic digital literacy
- Lacks automatic alert system
- Limited by satellite data availability

Measurable Outcomes

Immediate Impact:

- Enhanced risk awareness among users
- Improved preliminary planning capabilities
- Better understanding of regional landslide patterns

Long-term Potential:

- Could guide development away from high-risk zones
- May contribute to reduced landslide impacts over time
- Supports educational initiatives on landslide safety

Honest Assessment

Our application serves as a practical decision-support tool rather than a prediction system. While it cannot prevent landslides, it empowers users with scientific data to make more informed choices about:

- Construction locations
- Infrastructure development
- Community planning
- Disaster preparedness

SDG Alignment

Primary Focus

SDG 11: Sustainable Cities and Communities

Our app helps achieve Target "By 2030, significantly reduce the number of deaths and people affected by disasters." We do this by:

- Identifying high-risk landslide zones where people should avoid building homes
- Helping disaster management teams plan evacuation routes
- Making sure schools and hospitals are built in safe location.

Secondary Focus

SDG 13: Climate Action

We support Target "Strengthen resilience and adaptive capacity to climate-related hazards." Through:

- Weekly landslide risk forecasts based on weather patterns
- Helping communities prepare for extreme rainfall events
- Building climate adaptation into local planning

SDG 15: Life on Land

We contribute to Target "Combat desertification, restore degraded land and soil." By:

- Identifying areas where landslides cause soil erosion
- Helping plan afforestation in vulnerable zones
- Preventing land degradation through better planning

Section - V

CHAMOLI - Case Study

Case Study Demonstration

This case study demonstrates the practical utility of the "Safe Hills" dashboard by simulating a real-world scenario faced by disaster management authorities in Uttarakhand. We will explore how this app can be used for proactive decision making during heavy rainfall events.

Scenario - Early Landslide Risk Assessment for Chamoli District

- Date - February 7, 2021
- Location - Chamoli District, Uttarakhand
- Actual Event - A massive rock and ice avalanche triggered a devastating flash flood in the Rishi Ganga and Dhauliganga rivers, causing widespread destruction and over 200 fatalities.

What if we look at this disastrous event from a Civil Engineering perspective?

Important Fact - While the exact trigger was complex, abnormal temperature patterns and potential rainfall contributed to slope instability in the preceding days.

Could a system like "Safe Hills" have detected the elevated landslide risk in the region before the catastrophic failure?

Step by Step Analysis using Dashboard -

["https://modis-lst-469710.projects.earthengine.app/view/casestudycad"](https://modis-lst-469710.projects.earthengine.app/view/casestudycad)

1) Visuals seen through the Case Study Layers

- First of all, the user will activate the case study layers from the left sidebar.
- Visual Output: Chamoli district is highlighted in yellow, with the exact landslide location marked in red. The visualisation shows the disaster occurred in an area of extremely challenging terrain.

2) Terrain Analysis at Landslide locations

Using the analysis from the dashboard -

PREDICTOR VALUES AT LANDSLIDE LOCATION:

- Elevation: 5600 m
- Slope: 45.8°
- Rainfall (Monsoon): 1850 mm
- NDVI: 0.15 (Sparse vegetation - high altitude)
- Geology (StdDev): 88.5 (Highly variable - fractured bedrock)
- Drainage: 68.7

3) Model Risk Assessment

MODEL ASSESSMENT FOR CHAMOLI:

- ML Prediction Class: 3 (High Risk)
- LSI Value: 0.616 (High Susceptibility)
- Weighted Risk Class: 3 (High Risk)

RISK INTERPRETATION:

- MODEL CORRECTLY IDENTIFIES HIGH RISK

HIGH TERRAIN RISK: Steep slope (34.7°) at high elevation (5291m)

4) Results -

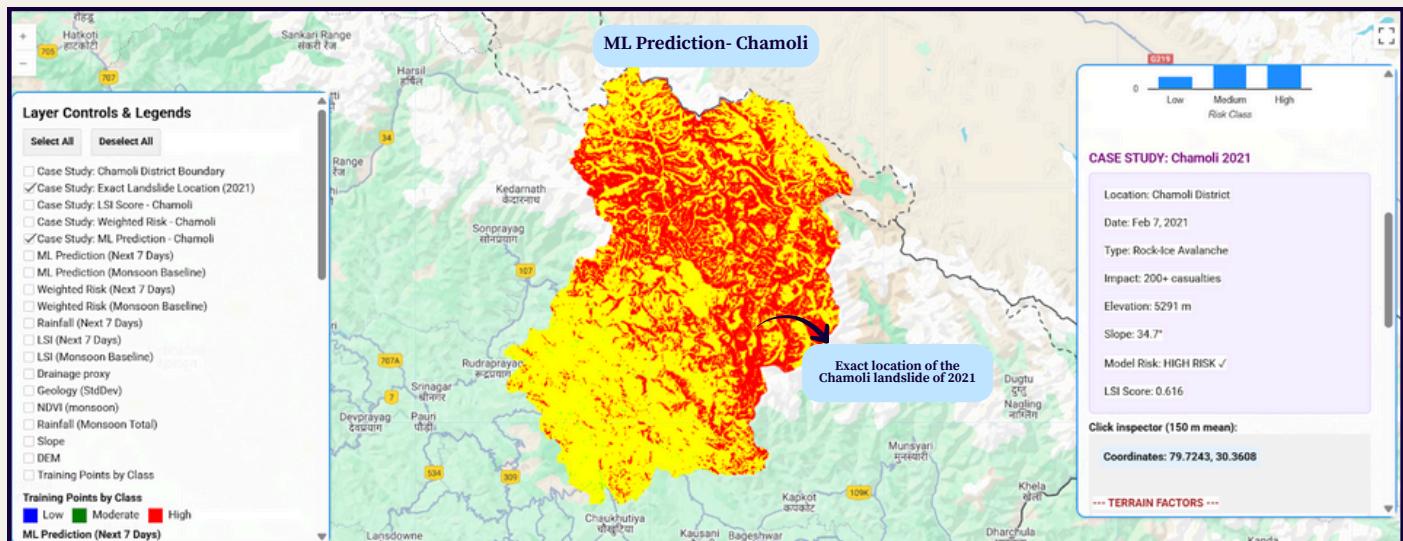
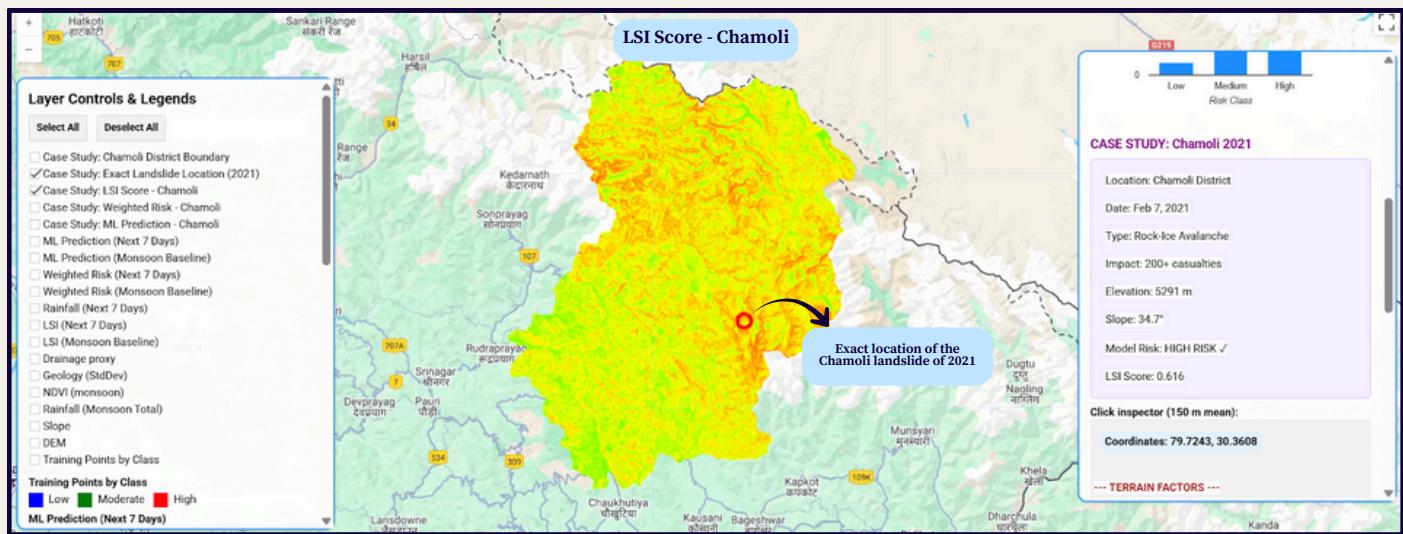
- Both Machine Learning (Random Forest) and Weighted Overlay (LSI) models classify the exact disaster location as High risk zone.
- The model successfully identifies the critical terrain and the environmental factors that lead to such a massive catastrophic failure.
- **Validation success** - The system demonstrates it would have flagged this area for priority monitoring before the disaster occurred.

PRACTICAL IMPLICATIONS AND “WHAT IF” SCENARIO...

If Safe Hills were operational in Feb 2021 -

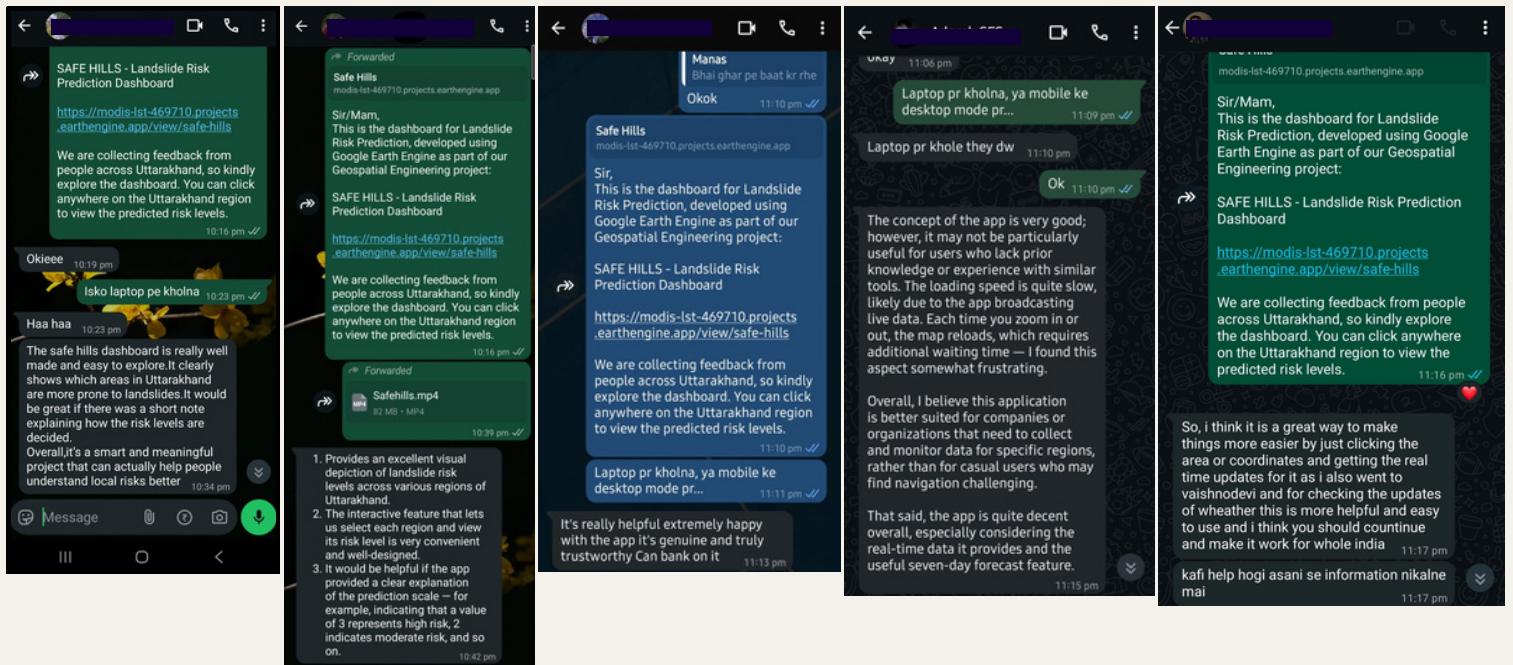
- Early Warning Generation- The system would have automatically flagged the Rishi Ganga valley as HIGH RISK based on terrain analysis.
- This early warning would help government/disaster prevention bodies to take preventive measures like Restricted access to the vulnerable valley area, Early alert to downstream hydropower projects etc..
- Timely evacuation of workers from hydropower sites could have significantly reduced casualties.

The accurate classification of the Chamoli disaster location as HIGH RISK by both models provides strong evidence that the integration of geospatial factors with real-time precipitation data creates a reliable tool for landslide risk management in Uttarakhand's challenging terrain.



Section - VI

User Feedbacks



Future scope

1. Use More Detailed Data: We can use higher-resolution satellite images. This would let us see the ground in more detail and find smaller, but still dangerous, landslide areas.
2. Add New Data Layers: We can add maps of soil type, how people use the land (like farming or buildings), and earthquake zones. This would make the risk prediction much stronger.
3. Build an Alert System: We can create a feature that automatically sends a text message or email to officials if a new "High Risk" zone appears in their area.
4. Make a Mobile App: We can create a simple version of the dashboard for mobile phones. This would help engineers and disaster managers check the risk map directly from the field.
5. Add a Time-Slider: We can add a feature that lets users see how the landslide risk has changed over the past weeks or months. This would help in understanding patterns.

Limitations

1. Map Detail: Our maps use 30-meter pixels. This is good for seeing big areas of risk, but it might miss very small landslides or small cracks in the land.
2. Training Data: Our computer model learned from a set of 7900 data points. If this data is not perfect, or doesn't cover all types of landslides, the model's predictions might not be perfect either.
3. Weather Forecast: Our "Next 7 Days" risk depends on a weather forecast from the internet. If this forecast is wrong, our landslide risk forecast will also be less accurate.
4. Missing Factors: We could not include some important data, like a detailed soil map or information about earthquakes, which can also trigger landslides. Adding these would make the model better.