

Geo Sentrix AI: AI-Based Disaster Risk Mapping Using Satellite Data

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Abstract - Landslides are among the most hazardous natural calamities that result in substantial damage to infrastructure, environment, and human lives, particularly in geographically vulnerable zones. Landslide prediction is an important task that has been hampered by the intricacy of terrain conditions and the inability of conventional mapping techniques. The present study proposes an advanced geospatial technology solution called GeoSentrix AI: Landslide Susceptibility Prediction System (India), which employs machine learning algorithms along with remote sensing technology for landslide susceptibility prediction. The proposed solution is based on the concept of using the Google Earth Engine (GEE) for large-scale computation of high-dimensional geospatial data. Moreover, the solution employs a Random Forest algorithm for analyzing terrain-related factors such as slope, aspect, curvature, NDVI, and hydrological factors for landslide susceptibility prediction. The proposed solution generates pixel-wise maps that help identify landslide hazard zones with greater accuracy.

Key Words: AI-based Disaster Prediction, Geospatial Analysis, Satellite Data Processing, Deep Learning, Landslide Susceptibility Mapping, Remote Sensing, GIS, Real-time Risk Assessment, Predictive Analytics, Environmental Monitoring

1. INTRODUCTION

Landslide is one of the significant natural hazards that commonly occurs in hilly and mountainous terrain, resulting in significant economic and human safety risks. With increasing urbanization, deforestation, and climate variability, such zones have become more prone to natural hazards, thereby necessitating accurate landslide prediction for sustainable development.

Existing landslide susceptibility mapping techniques are largely manual, time-consuming, and unable to efficiently process geospatial data for accurate prediction. With the advent of satellite imagery and remote sensing techniques, intelligent systems have become a necessity for accurate analysis and prediction of complex environmental variables.

GeoSentrix AI is a novel attempt to develop a scalable intelligent system for landslide prediction using Google Earth Engine (GEE). The system uses advanced machine learning algorithms like Random Forest to develop a landslide susceptibility prediction system for diverse topographies. The system can efficiently integrate various terrain and environmental variables like slope gradient, elevation, curvature, vegetation index (NDVI), and hydrological variables for accurate analysis and prediction.

The primary advantages of this intelligent system are its ability to perform spatial analysis for accurate prediction and generate high-resolution maps for landslide susceptibility prediction. These maps can help users visually analyze high-risk zones and assist in decision-making processes for disaster management and planning. Moreover, cloud-based geospatial computation can efficiently process geospatial data for accurate prediction and updates based on environmental variables.

GeoSentrix AI is a significant intelligent system for landslide susceptibility prediction using advanced remote sensing, geospatial analysis, and artificial intelligence techniques. The system is not only accurate and efficient but also helps in developing proactive strategies for disaster management and planning, thereby reducing risks to a significant extent.

2. LITERATURE SURVEY

The research work by Reichenbach et al. (2018) analyzed different statistically based landslide susceptibility models and found that geospatial factors play a vital role in creating reliable landslide susceptibility maps. Tien Bui et al. (2016) developed a machine learning-based approach for landslide prediction using SVM models. They found that machine learning-based models perform better compared to traditional models because they can handle complex relationships between different factors, thus improving the accuracy of the results. Sameen et al. (2020) developed a deep learning-based framework for landslide prediction using CNN models with satellite images. They found that CNN models can effectively handle satellite images, thus improving the accuracy of the results. Thus, it can be clearly analyzed from the research findings that artificial intelligence plays a vital role in improving the efficiency of the prediction process by reducing human intervention.

Furthermore, different research works highlight the role of remote sensing and geospatial techniques for effective landslide prediction. Researchers widely accept the role of terrain factors such as slope gradient, elevation, curvature, vegetation index (NDVI), and hydrological factors for effective landslide prediction. Although these techniques improve the accuracy of results significantly, there are different challenges associated with handling large datasets and achieving results in real-time. Thus, there is a need for advanced systems like GeoSentrax AI, which can effectively handle large datasets and improve the efficiency of the prediction process.

3. METHODOLOGY

Experimental Setup

The GeoSentrax AI system gets set up to deal with a lot of geospatial stuff, especially for figuring out landslide risks. It runs on regular computers that can handle the load from remote sensing data and machine learning. Mostly, they use Python for the coding part, and then Google Earth Engine for the cloud side of processing maps and such. Tools like Visual Studio Code and Jupyter Notebook help with writing and testing the code. Libraries come in handy too, things like NumPy for numbers, Pandas for organizing data, and Scikitlearn to build the models.

It seems like the data side involves satellite images and terrain details, slope, elevation, curvature, NDVI for vegetation, and some water related indices. Random Forest is the main algorithm they pick because its tough and works with lots of variables. I think that makes sense for messy terrain data over big areas. The whole thing scales up pretty well for different regions.

For the architecture, theres a step by step way to build it for predicting landslides. Starts with grabbing satellite data through Earth Engine. Then preprocessing cleans it up, normalizes values, transforms what needs changing to make everything consistent. After that, pulling out features like slope, height, curves in the land, plant cover, and hydrology stuff. Those go into training the Random Forest model so it can spot patterns from past landslides.



Evaluating the model comes next, checking accuracy before using it for predictions. Ends up with maps showing susceptibility pixel by pixel, high risk zones marked out visually. That part might be a bit tricky to get just right.

The process flow follows the diagram pretty closely. First satellite collection, then preprocessing to fix inconsistencies. Feature extraction picks out the key environmental things that affect landslides. Feeds those into the model for training and checking performance. If its good enough, generates the risk maps at high resolution. Finally, AI insights help spot prone areas and aid in managing disasters.

This approach keeps predictions accurate and computation efficient, with visualization that works for real use. Though sometimes the insights feel like they could use more detail, I am not totally sure.

Preprocessing really ties a lot together early on.

4. RESULTS AND DISCUSSION

The landslide risk mapping system came together by combining geospatial visualization with some environmental analysis and a focus on making the interface easy for users. It helps spot and show areas where landslides might happen. I think that part is pretty key because without it, the whole thing would not represent risks as clearly. They went through design, then implementation, and evaluation in several steps. This was to make sure it is accurate and usable, plus it allows for real-time stuff. Usability feels important here, or at least it seems that way from how it is set up. In this section, we look at the main results from the system. There are visual outputs to back it up, along with observations on how it functions. Some of those visuals stand out more than others, I guess.

I. Interface Design and Visualization Capabilities

The interface for this map system seems pretty straightforward overall, with that big central area showing the whole thing and a panel off to the side for controls. It does not feel too cluttered, which is good because they tried to keep it user friendly. I think that makes a difference when you are just trying to get around without getting lost in options.

Switching between views like satellite or terrain helps a lot with spotting geographical stuff for landslides. You know, things like elevation and how the slopes look, or even what the land is used for around there. It seems useful for understanding risks, though some people

might skip those details at first and just stick to the basics.

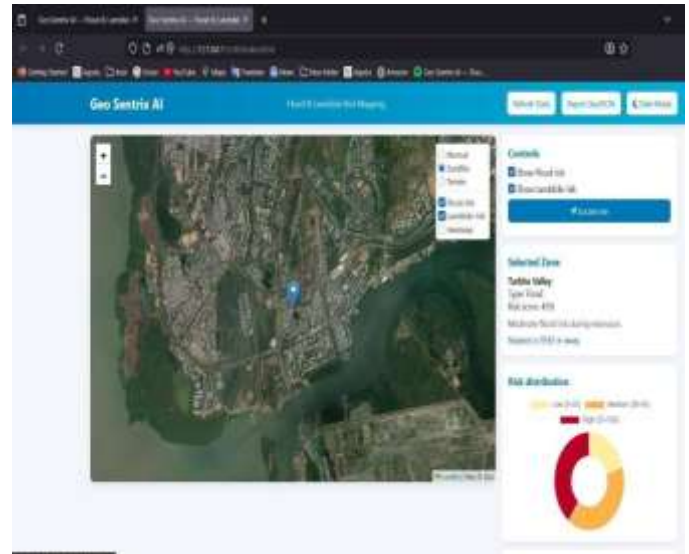
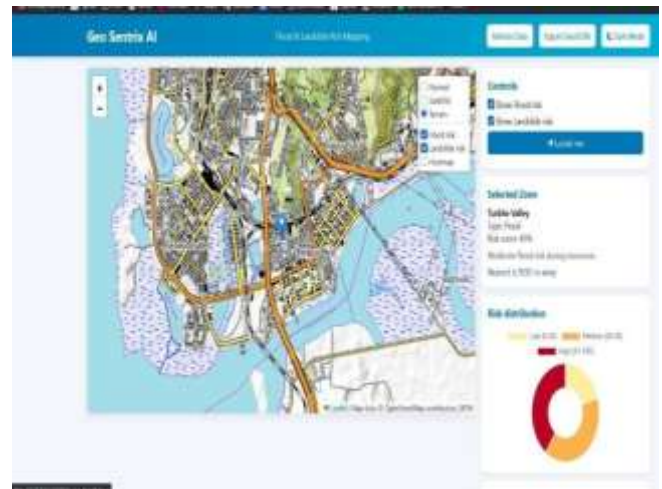


Fig -2: User Interface Overview



There are controls for zooming in and out, and you can turn layers on or off so it does not get overwhelming. That way, you focus on what you need, like the risk zones or those heatmap overlays. Navigation feels smooth enough, moving around the map without much hassle. And the Locate Me button is kind of handy, it pins where you are and compares it to the risky spots, especially if you are traveling.

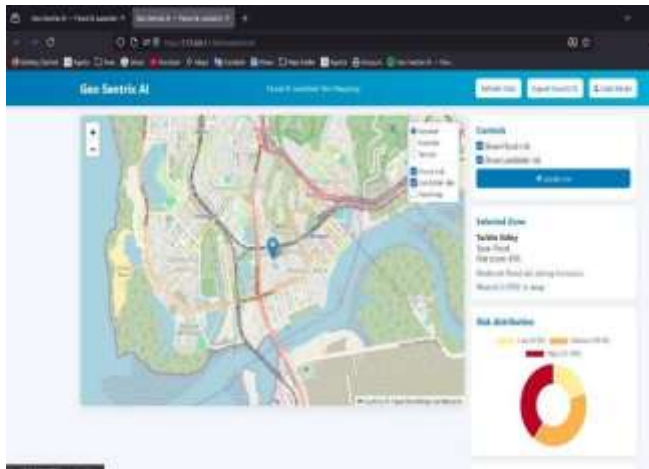
The colors on the visuals show susceptibility levels pretty clearly, overlaid right on the map. Even if you are not technical, it makes the data easier to grasp without confusion. I might be oversimplifying this part, but the cues help get the idea across quickly. Layers tie into that too, since toggling them changes how the colors stand out or fade.

Some spots on the map just pop more than others depending on what you select.

II. Risk Assessment and Zone Identification

One thing that stands out about this system is how it picks out areas that might have landslides based on stuff like the environment and the lay of the land. It gives these risk scores to different spots, putting them into low, medium, or high categories, which seems pretty useful for figuring out where to worry.

The selected zone panel is straightforward, it tells you about a specific place with the risk type, the score, and a short explanation of what that level means. I think that makes it easy for anyone to check out a region without needing to know all the technical details. You can just glance and get the idea.



Then there's the charts, like pie or donut ones, that show how the risks are distributed overall in the area. It helps see if most of it is safe or if there's a lot of high-risk parts, and that probably aids in planning things out better.

Zoom controls are there, and you can turn layers on or off so the map does not get too cluttered. Say you want to look at just the landslide zones or the heatmaps, it lets you focus on that. Navigation feels smooth when you move around. Oh, the locate me button is nice too, it shows where you are relative to the risky spots, especially if you're traveling somewhere.

Colors on the visuals indicate the susceptibility levels, overlaying right on the map to make the data clearer. Even if you're not into tech stuff, it kind of simplifies things. Layers tie into this, toggling them changes how the colors show up or fade, which I might be oversimplifying a bit. That part gets a bit repetitive with the controls, but it really helps without overcomplicating.

III. Functional Features and Data Interaction

The system has these different parts that make it easier to use in real situations. Like, the refresh data thing lets you update everything so it matches what's happening right now with the environment. And exporting to GeoJSON, that seems useful for taking the results and plugging them into other mapping programs or whatever.

Switching base maps and adding risk layers on top shows how it can handle all kinds of data without much hassle. I think that flexibility is key, especially when you're dealing with varied sources. The heatmap stands out because it highlights spots more prone to landslides, you know, making those patterns pop visually. It does help spot things that might otherwise get missed. Overall, these bits add up to something more than just showing pictures. It's actually set up for messing with data and doing some spatial work, though I might be oversimplifying how integrated it all is. Some people probably use it one way, others find different angles.

IV. Interpretation of Results and Practical Implications

The results clearly show that areas with rough terrain, close to bodies of water, or uneven land distribution are more likely to have landslides. The system does a good job of capturing these differences and showing them in a simple visual format.

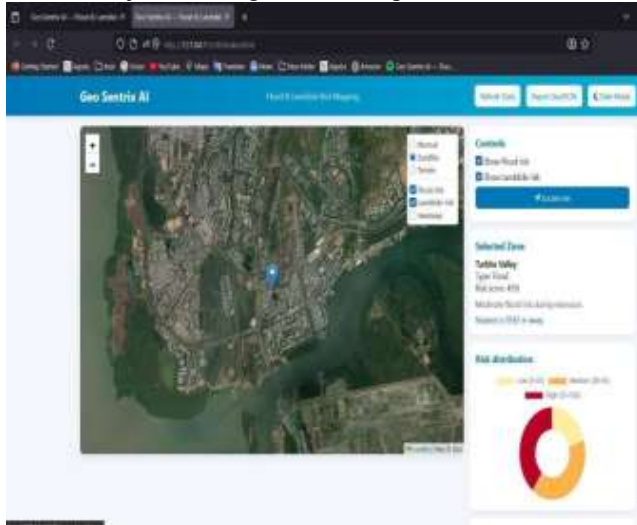
In practical terms, the results can be very helpful for:

- Urban planners should avoid building in areas that are likely to be dangerous.
- Disaster management agencies to make plans for how to lessen the damage and respond to emergencies
- Local communities, to raise awareness of possible dangers

The system is very useful in real life because the intuitive design makes it easy for people who aren't tech-savvy to understand and interpret the risk levels.

V. Overall Performance Evaluation

The system works well when it comes to responsiveness, clear visualization, and functional integration. The smooth interaction between map layers, controls, and data panels all work together so well shows that the implementation was done well. Users can look at data in real time instead of just looking at static reports.



However, the results also point to ways to make things better, like adding real-time data from environmental sensors, making predictive modeling more accurate, and adding automated alert systems for areas with a lot of risk. These improvements can make the system even more reliable and useful in real time.

3. CONCLUSIONS

The system is good at being responsive, showing things clearly, and working with other programs. The fact that the map layers, controls, and data panels all work together so well shows that the implementation was done well. Users can look at data in real time instead of just looking at static reports when they use interactive elements.

But the results also show how to make things better, such as by adding real-time data from environmental sensors, making predictive modeling more accurate, and adding automated alert systems for high-risk areas. These changes can make the system even more useful and dependable in real time.

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