

A Site Classification Approach for the Implementation of Multi-Temporal SAR for Geohazard Initiation Potential on the Railway Right of Way

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Statement of Significance (Relevance of Research): Railway transportation has been the backbone of national economies worldwide. When geohazards occur and damage the network they will impact railway operations, resulting in delays and detrimental economic effects. A potential tool for monitoring the vast network for geohazards is satellite radars. The authors have reported on implementation of Multi-Temporal InSAR (MTInSAR) techniques and developed post processing techniques that monitor the railway right of way (ROW) for identifying critical locations that show high risk for geohazard initiation before an event takes place. This paper discusses implementation issues of the employed techniques and presents a comprehensive site characterization and classification system of the area of interest.

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INTRODUCTION

Railway transportation has been the backbone of national economies worldwide with well-established benefits compared to other modes [1]. The extensive railroad network, frequently traversing rugged terrain, encounters several geological risks, including landslides, collapses, debris flows, and earthquakes [2]. Geohazard failures along the railway right of way (ROW) frequently cause damages that impact railway operations and safety, potentially with detrimental economic and social effects [3].

Satellite radars have been explored as potential tools for rail network geohazard monitoring. Interferometric Synthetic Aperture Radar (InSAR) is a signal processing approach that has shown potential to investigate various geohazards, including slope failures [4] [5] [6] and has been commonly employed for the mapping and monitoring of landslides globally [7] [8]. Limitations in conventional InSAR techniques stemming from atmospheric effects, site conditions and terrain characteristics have spurred the development of the Multi-Temporal InSAR (MTInSAR) techniques that reduce errors in the displacement measurements and enabled tracking changes over time. Although no single technique can solve all SAR limitations, selecting the appropriate technique based on limitations can increase the efficiency of SAR implementations in recognizing geohazards [9].

The authors have reported on one implementation of MTInSAR techniques that monitors the railway ROW for identifying critical locations that show high risk for geohazard initiation [10] [11]. Persistent Scatterer Interferometry (PSInSAR) and Small Baseline and Subset (SBAS) are suitable for site mobilization monitoring, within the “Multi-Temporal Threshold Stacking” (MTTS) and “Multi-Temporal Timeline Analysis” (MTTA) workflow introduced in [10] [11]. On the other hand, Coherence Change Detection (CCD) is suitable for monitoring and detecting changes in soil moisture content in the track and the ROW [10] [12] [13].

Recognizing the crucial role of site conditions in determining the quality of satellite data for the selection of the most effective MTInSAR, this presentation introduces a site characterization and classification approach of the area of interest. The concept is designed to effectively characterize regions based on site conditions in view of satellite monitoring process, classifies sites with respect to effects of site conditions on the quality and availability of radar data, and is a valuable tool for selecting the appropriate SAR method in monitoring and detection tasks. The next section discusses and quantifies the site characteristics that affect the quality of the radar data in view of the proposed MTInSAR-based workflow for critical geohazard locations, followed by the introduction of the classification system. The discussion concludes with the implementation of different SAR techniques according to the classification system and their ability to identify geohazard potential.

METHODOLOGY

The development of the technique that monitors the railway ROW for identifying critical locations exhibiting high-risk for geohazard initiation is based on the study of nineteen sites with a history of geohazard events, and/or availability of soil moisture measurements, listed in **TABLE 1**. The sites are studied for a period of at least twelve months before an event using both archived and current satellite SAR data. The MTInSAR processing techniques and the MTTS and MMTA post-processing approach reported by the authors [10] are implemented and the findings are assessed in view of the data availability and site characteristics and guided the development of the proposed site classification concept. A site characterization and classification process is desired to guide the selection of the appropriate tools for monitoring the railway ROW. The proposed concept accounts for the predominant factors affecting the quality of results as identified in this study in view of the availability of satellite SAR data for the site. Four distinct categories, A, B, C and D (good to bad) are established to classify sites based on their potential for facilitating successful studies. These categories are developed based on SAR Data Availability and Site Parameters.

TABLE 1 List of study sites with history of geohazard occurrence and soil moisture data records

ID	Site location	Coordinates (Lat/long)	Event	Event Date	Site Class
1	Lincoln, NE	40.70, -96.53	Derailment	6/25/2021	B
2	Birmingham, AL	33.47, -86.95	Stability Monitor	Continuous	B
3	Maupin, OR	45.17, -121.10	Rockfall	5/7/2020	A
4	Atlanta, GA	33.83, -84.30	Sinkhole	12/2021	C
5	Burlington, ND	48.25, -101.46	Derailment	5/1/2022	A
6	Shiner, TX	29.43, -97.18	Derailment	6/3/2022	A
7	Yellowstone, MT	43.64, -111.36	Landslides	6/16/2022	A
8	Santa Clemente, CA	33.25, -117.37	Soil Erosion	10/1/2022	A
9	Sandstone WV	37.76, -80.89	Rockfall/Derailment	4/9/2023	C
10	Raymond, MN	45.01, -95.23	Derailment	4/30/2023	B
11	Blackville, SC	33.36, -81.33	Moisture Data	Continuous	B
12	Yosemite, CA	37.76, -119.82	Moisture Data	Continuous	A
13	Bodega, CA	38.32, 123.07	Moisture Data	Continuous	A
14	Santa Barbara, CA	34.41, -119.88	Moisture Data	Continuous	A
15	Cortez, CO	37.26, -108.50	Moisture Data	Continuous	A
16	Chatham, MI	46.33, -86.92	Moisture Data	Continuous	B
17	Sandstone, MN	46.11, -92.99	Moisture Data	Continuous	B
18	Stonehaven, Scotland	56.95, -2.32	Mudslides/Derailment	8/12/2020	C
19	Pikeville, KY	37.34, -82.39	Landslide/Derailment	2/13/2020	D

SAR Data Availability: Sites should have access to extensive stacks of satellite data (over 12 months) to effectively monitor the region. Regions with less than 7 months of data are automatically classified as “C” class due to the inability to perform multi-temporal SAR analysis. If the region is covered by multiple satellites, the classification process is applied for each satellite, and the highest classification is chosen as the site classification, since visibility may improve when viewed from an alternate angle or through an additional satellite.

Site Parameters: The site parameters directly influencing the proposed site classification in order of priority are: (i) slope grade, (ii) slope alignment, (iii) vegetation, (iv) surface roughness, and (v) surface wetness. The classification process is captured in a flowchart shown in **Figure 1**. The classification begins by identifying the slope grade and potential slope alignment. These are prioritized because the sensor covers a large area (250 km x 250 km), and topographic features are the most significant influences on the classification. Next, the process considers surface parameters that can affect classification on a more regional level.

Slope grade: The slope grade is classified into three categories based on the incidence angle of the observing satellite. Regions with slope values more than 50 have a higher chance of geometric distortions like layover, shadowing, and overlaying effects. Flat terrain has additional influences like surface wetness, which do not influence regions with slopes [14].

Slope alignment: The slope alignment is classified into two categories: (i) slope aligned with the line of sight, and (ii) slope directly faces the satellite, i.e. perpendicular to LOS. Large-scale deformations are still detected in case (ii), and conventional InSAR can still be used for monitoring and early warning systems. Finally, regions with large slopes not facing the satellite cannot be monitored due to the shadowing effect.

Vegetation: - After slope alignment, the radar signal first interacts with vegetation before it interacts with the surface. Two cases are considered: (i) Low vegetation (<12 cm) and (ii) medium vegetation (12-45 cm). The proposed system does not consider data from sites with large vegetation(>45cm) as no

backscatter is available from these conditions and the site should be classified as D.

Surface roughness: In view of the wave backscattering and surface roughness of the region, the process distinguishes between smooth and rough. Regions with slope in the look direction of the SAR sensor require surface roughness for backscattering. When the region is smooth, the signal gets reflected away; this signal loss leads to a classification of D. The presence of vegetation helps in some smooth terrains where the radar signal gets reflected due to the vegetation acting like a rough surface. In conditions where the surface is facing toward the sensor, the surface roughness does not influence to the degree as it would other terrain conditions.

Surface wetness: - Surface wetness causes the surface roughness of the region to be converted to a smooth surface, causing the specular reflection to the radar signal, i.e., the signal gets reflected away. The only conditions where the surface wetness can improve the results would be when additional elements like vegetation or man-made structures cause the reflected radar signal to go back to the sensor [15].

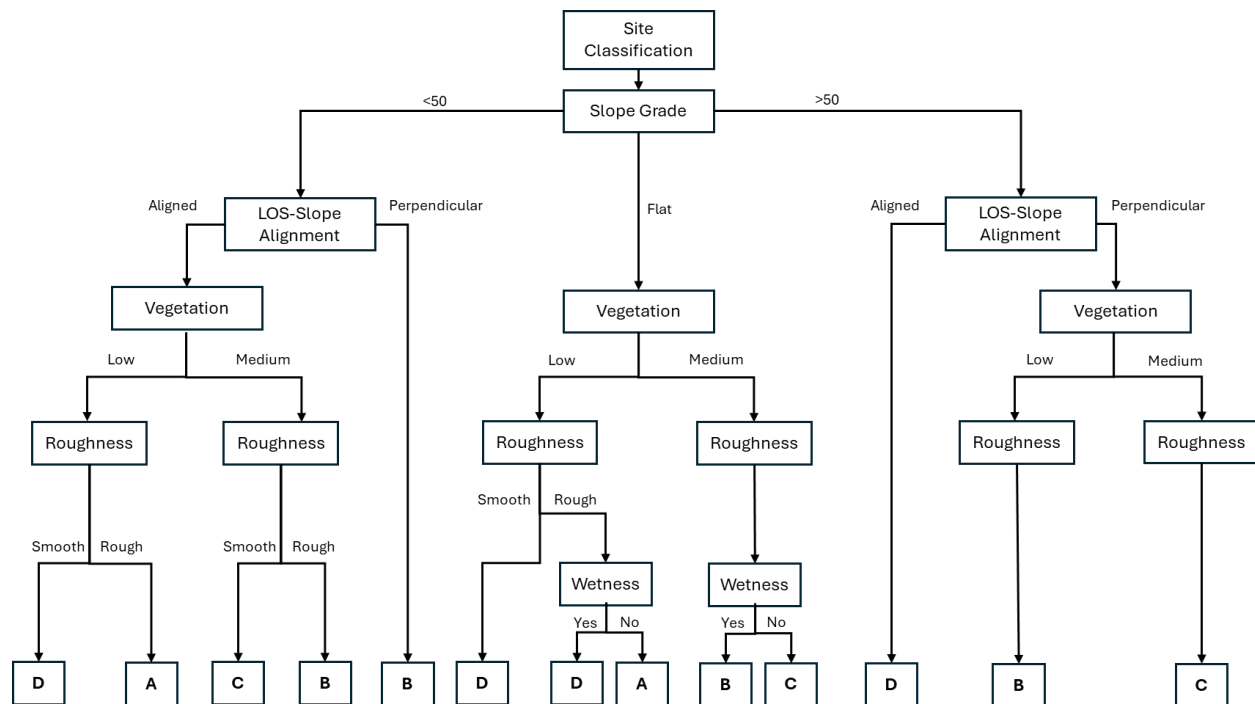


Figure 1 Site Classification Concept

A descriptive characterization of each site class is presented next:

Class A – Ideal: Examples include flat terrain and hilly/mountainous terrain (when slopes follow the satellite line of sight), minimal vegetation coverage without significant seasonal variation, multiple satellites and/or orbits, and at least 24-month satellite historical data are available with multiple orbit directions.

Class B – Normal: Examples include open terrain, rolling hills, short escarpments, minimal vegetation coverage without significant seasonal variation, and at least 12-month satellite historical data available.

Class C – Noisy: Examples include hilly/mountainous terrain (when slopes face away from satellite line of sight) with medium to dense and tall vegetation with significant seasonal variation, escarpments, less than 12-month satellite historical data available, or intermittent data availability.

Class D – Dark: These are sites that are not visible to the satellite, and there is no line of sight. Examples include mountainous terrains, gorges with dense and tall vegetation, tall escarpments, and dense vegetation coverage without significant seasonal variation.

After a site has been classified, the most appropriate method can be selected from **TABLE 2**

TABLE 2 Method selection based on site class

Method	Site Class			
	A	B	C	D
PSInSAR	Yes	Yes ¹	No	No
SBAS	Yes ³	Yes	No	No
CCD	Yes ³	Yes	Yes ²	No
/w MTSS	Yes ³	Yes	Yes	No
/w MTTA	Yes	Yes	Yes	No

¹ no presence of seasonal vegetation
² coherence change measured from the surrounding region
³ PSInSAR can provide more reliable results than other methods

FINDINGS

The proposed classification concept is applied to the sites listed in **TABLE 1** and one case is presented here. In Sandstone, West Virginia, a freight train experienced derailment after colliding with a rockfall blocking the track, injuring three crew members and the subsequent release of diesel gasoline into the adjacent river. The occurrence transpired during the early hours of Wednesday, March 8, 2023, approximately one mile from the town. Locomotive video footage shows the rock blocking the track right before the collision. This region has high vegetation on one side of the railway line and a river on the other side. Due to these site conditions, this region is classified as C. In view of **TABLE 2**, the preferred method of analysis is PSInSAR with MTSS. **Figure 2(a)** shows an aerial image of rockfall event where two failure areas 100 m apart are clearly identified. Archived SAR images for a period of 15 months before the event were analyzed PSInSAR with and without MTSS post processing and the deformation maps are shown in **Figure 2(b)** and **(c)**, respectively. It is evident that, despite the low classification of the site, the PSInSAR with MTSS successfully identified the high-risk areas at least a month before the event took place.



Figure 2 Implementation Example Site 9, Class C, 15 month monitoring before the event: (a) Aerial image of rockfall showing two failure areas 100 m apart; (b) PSInSAR without MTSS deformation map fails to identify potential for failure initiation; (c) PSInSAR with MTSS deformation map clearly identifies potential for failure initiation in two areas 100 m apart at least one month before the event.

CONCLUSIONS

This paper introduces a site classification concept based on site characteristics for choosing the most appropriate site-specific SAR approach for critical location identification susceptible to geohazard failure. The proposed methodology, which was validated through implementation examples on different sites, highlight the practical implementation of this system as well as the benefits it offers in terms of improving the efficiency and effectiveness of geohazard monitoring. PSInSAR are better suited for monitoring site class A regions. The displacement data effectively identified locations experiencing higher formation

rates compared to the surroundings, indicating higher risk of geohazard failure. SBAS analysis, on the other hand, can be used in monitoring site class B regions. The Multi-Temporal Threshold Stacking” (MTTS) and “Multi-Temporal Timeline Analysis” (MTTA) postprocessing workflow introduced by the authors, when used with PSInSAR deformation data, can identify geohazard potential in sites classified as B, and when used with SBAS data, geohazard potential in sites classified as C can be identified. For future works, the site classification can be improved further by adding soil type and soil moisture.

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