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SGAM – Smart Geotechnical Asset Management: Enhancing predictive maintenance with data-driven insights and Earth Observation technologies

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ABSTRACT: Natural hazards such as landslides, subsidence, and liquefaction represent growing threats to critical infrastructure. Building upon the methodological foundation presented in the SGAM project, this work introduces enhancements to the Smart Geotechnical Asset Management (SGAM) framework, with particular emphasis on its hazard assessment component. The SGAM system integrates geotechnical monitoring, Earth Observation (EO) data, and machine learning techniques to support predictive maintenance of linear infrastructure. In this paper, we present methodological refinements, expanded geohazard integration, and new insights from recent applications. A synthesis geospatial layer supports proactive risk mitigation by highlighting high-priority intervention zones. These developments aim to improve data-driven infrastructure management.

KEY WORDS: Infrastructure resilience, geohazards, EO data, AI algorithms

1 INTRODUCTION

Infrastructure systems worldwide are increasingly vulnerable to natural hazards, including seismic events and landslides, resulting in significant economic and social impacts. Prior studies estimate that around 0.5% of global assets are exposed to such hazards annually [1]. These threats often disrupt vital services such as transport and logistics, emphasizing the need for resilient infrastructure planning.

In the literature, several frameworks have been developed to support multi-hazard risk management, particularly in relation to linear assets. These approaches are generally developed for integrated and quantitative frameworks capable of modelling multi-hazard scenarios, infrastructure vulnerability, and resilience. This type of analysis is inherently multidisciplinary and typically requires high-resolution input data, including detailed fragility curves and comprehensive ancillary datasets [2][3]. To overcome the challenges associated with data availability, other studies [4][5] adopted index-based methodologies, offering a more qualitative approach that emphasizes the exposure and vulnerability components of risk rather than detailed hazard modelling. In this context, SGAM (Smart Geotechnical Asset Management) framework was introduced as a semi-automated decision support system integrating EO data, geotechnical monitoring, and data fusion algorithms [6]. The original SGAM methodology, laid the groundwork for a multi-hazard approach to infrastructure risk analysis.

This paper advances that framework by expanding the hazard models, improving the integration of InSAR-derived movement data with hazard assessments, and streamlining the generation of prioritized summary layers.

2 METHODOLOGY

The present study builds upon the SGAM framework previously introduced in [6], refining its methodology for the hazard assessment of linear infrastructure. SGAM remains a semi-automated decision support system that leverages satellite Earth Observation (EO) data, machine learning techniques, and geological knowledge to support asset management and predictive maintenance. In this paper, we present methodological advancements with specific focus on the characterization of landslide, subsidence, and liquefaction hazards.

This version includes a development for individual hazard types, aiming to improve interpretability and accuracy at the asset level. While the geodatabase architecture and structure have already been described in detail in [6], here it is referenced as a resource for hazard data management.

SGAM employs a multi-hazard workflow, integrating ground motion data from satellite InSAR with thematic layers (e.g., topography, geology, land use) through supervised learning algorithms. The spatialized outputs are then segmented and intersected with infrastructure elements to enable the classification of asset segments into risk levels. Key enhancements include differentiated processing for slow and fast landslides, velocity-based subsidence scoring, and refined soil classification for liquefaction susceptibility.

In addition, this study introduces a summary geospatial layer, which was not present in the earlier framework. This integrative product consolidates hazard-specific outputs into a unified decision-support layer, providing a risk-informed prioritization of intervention areas along the infrastructure network.

2.1 Hazard assessment

The SGAM project is instrumental in identifying geohazards, which are of paramount importance for ensuring infrastructure safety, as already mentioned in [6]. The framework was tested in a pilot area encompassing a 110 km-long highway located in northern Italy. As a preliminary step in the hazard analysis, the

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available ancillary data were compiled and organized, as summarized in Table 1.

Input Data	Dataset
Topography	DTM (Tinitaly 10 m) for slope, curvature, and roughness
Geology	National Lithological Map 1:100.000
Land Use	Regional databases
Seismicity	PGA and Vs30 for liquefaction analysis
InSAR (PS)	EGMS Ortho Dataset (EW and UD)

Table 1: Input data for SGAM application in the pilot area

These datasets represent the foundational layers from which each hazard-specific analysis is developed, as illustrated schematically in Figure 1.

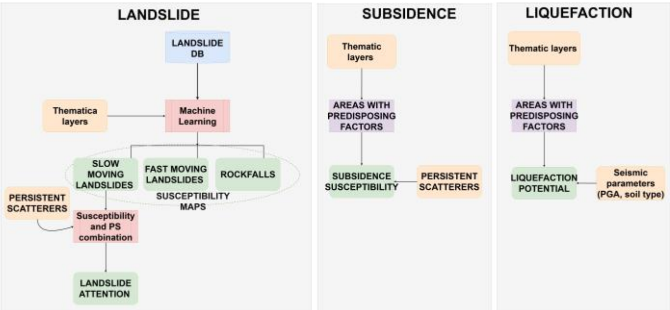

Figure 1: Workflow of SGAM application

2.1.1 Landslides

Building on the susceptibility analysis presented in [2], this study introduces a more detailed approach to characterize landslide hazards affecting linear infrastructure. The methodology refines both the input data structure and the classification logic, with particular attention to the kinematic behaviour of slope movements.

Susceptibility is evaluated as the intrinsic propensity of terrain to generate landslides, based on factors such as slope angle, lithology, land use, and morphometry. As in [2], machine learning algorithms trained on available inventories are employed to model landslide density and generate susceptibility maps.

Persistent Scatterers (PS) from satellite InSAR data are incorporated more systematically than in [2], serving as a proxy for activity status. These data support the validation and enhancement of susceptibility outputs by highlighting zones with active deformation. The improved pipeline also includes a Landslide Attention Index, which scores infrastructure segments based on hazard level and PS data velocities.

Figure 2 represents the combination of susceptibility classes and PS velocities, considering a threshold of 2.5 mm/years.

	No PS	V<|2.5|mm/yr	V>|2.5|mm/yr
Hazard class 1	Low	Low	Medium - high
Hazard class 2	Medium - Low	Low	Medium - high
Hazard class 3	Medium	Low	High
Hazard class 4	Medium	Medium - Low	High
Hazard class 5	Medium - high	Medium	High

Figure 2: Landslide attention matrix

2.1.2 Subsidence

The assessment of ground subsidence hazards in this study builds upon the foundations described in [6], introducing a more robust integration of vertical ground motion data with thematic geological and topographic layers. Subsidence is defined as the slow downward movement of the ground surface due to natural or anthropogenic causes, such as compaction or groundwater withdrawal.

This analysis integrates lithological characterization, slope thresholds, and PS InSAR measurements to identify and classify regions affected by subsidence.

While [6] included initial mapping efforts, the current approach incorporates a classification along the infrastructure into hazard classes based on maximum vertical velocities and contextual geomorphological settings. This classification allows infrastructure managers to identify critical zones where maintenance or reinforcement actions may be needed.

2.1.3 Liquefaction

The liquefaction hazard model presented here extends the susceptibility mapping approach introduced in [6], offering a more detailed evaluation of geotechnical and seismic parameters. Liquefaction occurs when saturated soils lose cohesion during seismic shaking, compromising ground stability.

The new model introduces a segmentation-based hazard index that aligns with infrastructure elements. In contrast to the more generalized susceptibility zoning described in [6], this version includes quantitative thresholds for seismic acceleration and susceptibility reclassification, enabling improved spatial resolution.

Additionally, the workflow supports continuous refinement as new geophysical or seismic datasets become available, facilitating dynamic hazard re-evaluation over time.

2.2 Summary layer

A key innovation introduced in this study—absent from the framework outlined in [6]—is the development of a summary geospatial layer that consolidates the outputs of the hazard-specific models into a decision-support product. This synthesis layer serves as a comprehensive tool for identifying high-hazard zones along linear infrastructure, prioritizing them for monitoring, maintenance, or intervention.

The summary layer integrates the results from landslide susceptibility (including activity-based scoring from PS data), subsidence hazard classification (based on vertical deformation velocity), and liquefaction potential (based on seismic-geotechnical analysis) (Figure 3). These individual assessments are spatially combined through a rule-based approach to assign a composite risk score to each infrastructure segment.

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The results are made available within a GIS environment, enabling interactive visualization of the hazard assessments for each segment of the infrastructure network. By visualizing hazard in a single layer, decision-makers can easily identify critical areas where multiple hazards converge or where the severity of a single hazard justifies immediate action. This tool enhances operational readiness and resource allocation, offering a practical output directly usable by infrastructure managers and planners.
The introduction of this summary layer represents a major step forward in the SGAM methodology, improving its usability, interpretability, and impact in real-world applications.

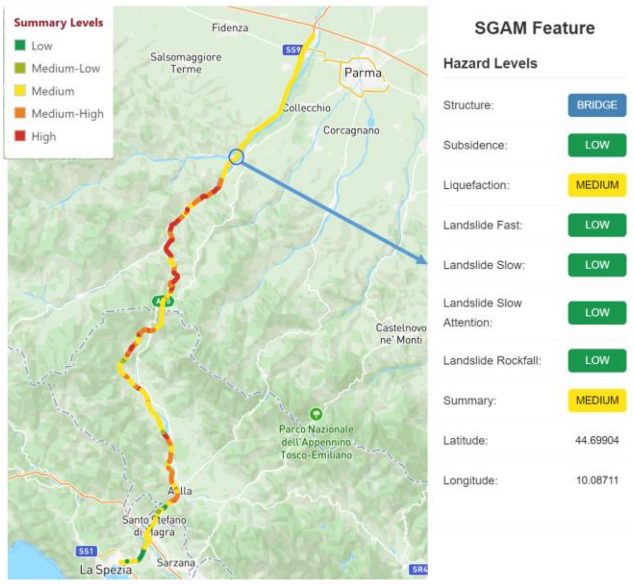

Figure 3: Example of SGAM result on linear infrastructure.

3 CONCLUSIONS AND FUTURE OUTLOOK

This study expands upon the foundational SGAM methodology presented in [6], delivering key enhancements in hazard modeling, data integration, and operational usability. While the previous version laid out the general framework for a semi-automated, EO-based geohazard assessment system, the current work provides a more refined and implementable approach by detailing the modeling procedures for landslides, subsidence, and liquefaction.

One of the most significant contributions of this study is the introduction of a summary geospatial layer, which enables an integrated and view of infrastructure vulnerability. This addition makes SGAM not only a robust analytical framework but also a decision-ready platform for operational use in infrastructure management and planning.

Future developments will aim to expand the temporal and spatial scope of SGAM through the integration of multi-temporal EO datasets, including LiDAR and drone-based surveys, and the adoption of automated change detection techniques. Additionally, work will continue incorporating vulnerability and exposure metrics to complement hazard-based assessments, building a more comprehensive picture of infrastructure resilience.
The SGAM system, as further developed in this work, offers a scalable and adaptable solution, capable of supporting infrastructure managers in making informed decisions in the face of complex and evolving natural hazards.

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