Towards a Digital Twin infrastructure for landslides: users and data requirements

Federica Gaspari[1], Marco Gentile[1], Daniela Carrion[1], Riccardo Barzaghi[1], Lorenzo Panzeri[1], Laura Longoni[1]

[1] Dept. of Civil and Environmental Engineering (DICA), Politecnico di Milano, Milan, Italy – (federica.gaspari, marco.gentile, daniela.carrion, riccardo.barzaghi, lorenzo.panzeri, laura.longoni)@polimi.it

Keywords: digital twin, landslides, hazard management, data integration, requirement analysis

Abstract

The increasing frequency and magnitude of landslides necessitates a fundamental shift from reactive mitigation to proactive, predictive risk governance. To define the necessary tools for this transition, this study conducts a systematic literature review and operational analysis of current Digital Twin (DT) implementations in the geosciences. Through this review, we identify four primary target user groups (emergency responders, technical experts, public administrators, and citizens) and map their specific 4D data requirements and interaction logics. Our findings highlight that most existing systems function as "Digital Shadows" characterised by unidirectional data flows and a topography gap, where dynamic sensor data is superimposed onto static, outdated 3D meshes. Based on these requirements, we propose a theoretical layered architectural framework for a Data Hub designed to bridge these gaps. The conceptual architecture is structured into three interconnected tiers: an Acquisition Layer for multi-scale data ingestion; a Modelling and Processing Layer for AI and physics-based stability assessment; and an Application and Service Layer for translating complex data into actionable intelligence. Finally, this work investigates a possible implementation path for landslides DT projects by outlining technical recommendations. This includes the adoption of cloud-native formats (e.g., Cloud Optimized GeoTIFF, Zarr) and unified interoperability standards (e.g., OGC SensorThings API) to evaluate the feasibility of transitioning towards a true bi-directional cyber-physical system for landslide risk management.

1. Introduction

Landslides and mass movements, particularly rockfalls and debris flows, pose critical risks to infrastructure and community safety. In complex environments such as the Prealpine regions in Italy, the increasing frequency and magnitude of these events amplified by climate change necessitates a fundamental paradigm shift from reactive mitigation to proactive, predictive risk governance (Arosio et al., 2018; Maimour et al., 2024). Digital Twins (DTs) are emerging as a powerful framework to address this challenge, offering a virtual, real-time representation of physical assets and processes with evolving interdisciplinary applications in the environmental domain ranging from river basins and lakes to mountainous regions and glaciers (Blair, 2021; Yang et al., 2024; Biraghi et al., 2022; Chioni et al., 2024; Gaspari et al., 2025).
However, the application of DT technology in geosciences is currently characterized by significant terminological confusion, often being applied to diverse systems ranging from static 3D models to advanced cyber-physical systems. Most reviewed implementations are more accurately classified as "high-fidelity Digital Shadows" rather than true twins. According to the classification framework by Kritzinger et al. (2018), these systems typically utilize a one-way data flow where sensor data informs a digital model for visualization and analysis, but the model does not exert automated, command-driven control over the physical environment.
Current state-of-the-art frameworks rely on high-resolution Geomatics for data acquisition, including UAV/aerial photogrammetry (Santangelo et al., 2019; Ahmad et al., 2021), InSAR (Handwerger et al., 2025; Huntley et al., 2019; Pagano et al., 2023), and Terrestrial Laser Scanning (Reid et al., 2021; Janeras et al., 2017). These topographic foundations are increasingly coupled with data-driven AI models (Chen et al., 2023b; Piciullo et al., 2025) or physics-based simulation engines (Ju et al., 2025; Xu et al., 2025) to evaluate slope stability and Factor of Safety.
Despite these technical advancements, designing an effective digital twin for complex geological systems in practice corresponds to an information management and system design problem. A major challenge in geomatics is the discrepancy between real-time environmental updates, such as rainfall, and 3D terrain models that are outdated. Without a dynamic way to update topography, the system cannot reach its full potential. In the framework of the TWINFALL project, this work presents a requirements analysis for a landslide digital twin (LDT) to ensure that the infrastructure is explicitly designed to serve the operational needs of its end users. By defining the characteristics of a multi-tier Data Hub, this study aims to link multiscale surveying and modelling techniques with decision-making workflows, moving beyond passive observation towards the active, autonomous control required for true cyber-physical systems (Chen et al., 2015).

2. Conceptual framework of landslide Digital Twins

While the concept of a DT is widely established in Industry 4.0 and Smart Cities, its application to natural hazards and specifically landslides requires a paradigm shift in definition. In industrial contexts, a DT is typically a virtual replica of a man-made, deterministic asset with known geometry and integrated sensors. In contrast, a LDT must represent a complex, stochastic, and evolving natural system where the design is not human made but dictated by geological and geomorphological processes.
We define the LDT as a dynamic, bi-directional virtual replica of a physical slope, continuously updated through a multi-tier data hub. Different from a static 3D model, the LDT is characterised by three core characteristics: subsurface uncertainty, multi-physics interaction logic, and spatio-temporal continuity.

2.1 Subsurface uncertainty

Unlike a machine with a known bill of materials or a building whose floor plan designs and materials are available, a landslide’s internal geometry is often hidden. The LDT must reconcile fragmented data from historical drilling and boreholes (Xu et al., 2025), sensor networks (Maesano et al., 2025) , and remote sensing and in-situ geomatics (Huntley et al., 2019; Themistocleous, 2025) to simulate a reality that is fundamentally stochastic and probabilistic (Santangelo et al., 2019) (Figure 1).

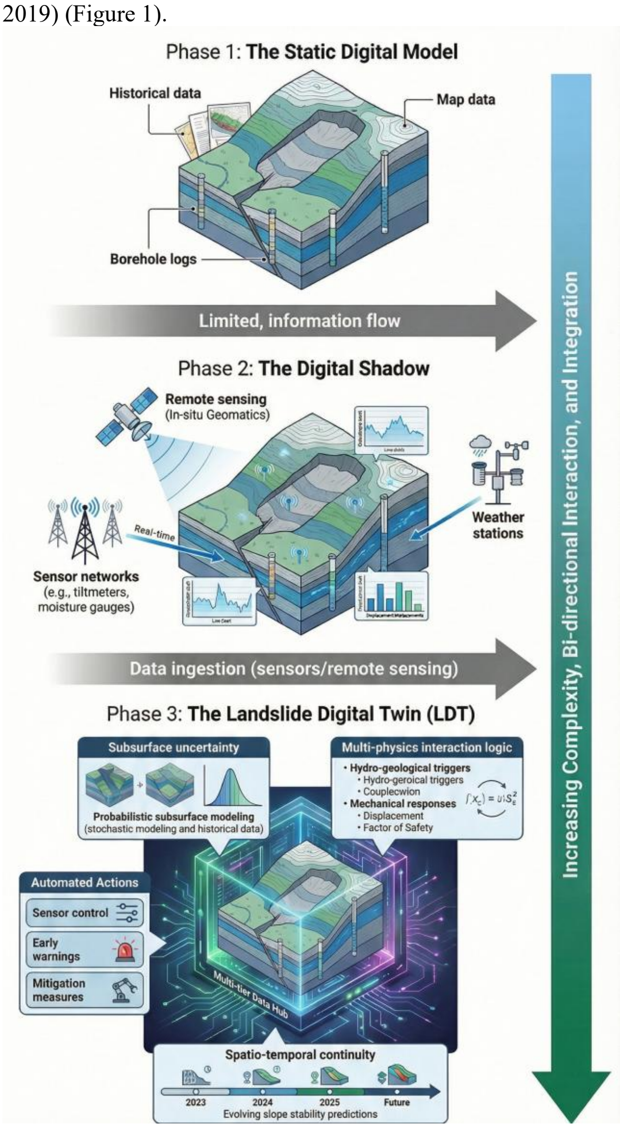

Figure 1. Evolution of Landslide monitoring system maturity. This diagram illustrates the progression from Phase 1 - Static Digital Model and Phase 2 - Digital Shadow with one-way data flow to Phase 3 - Landslide Digital Twin, which achieves full complexity through bi-directional interaction and real-time integration. Image generated by Google NotebookLM (Gemini model) based on author-provided prompts.

2.2 Multi-physics interaction logic

The LDT should model the coupling between hydro-geological triggers, such as rainfall and pore water pressure (Liu et al., 2022), and mechanical responses, including displacement and factor of safety (FoS) (Chen et al., 2023b). The bi-directional link traditionally considered as the core element for DT status is achieved when the digital model can automatically trigger actions in the physical world, such as remotely altering sensor collection status and operational parameters via web-enabled control (Chen et al., 2015), or issuing automated early warnings based on predicted evolution (Piciullo et al., 2025).

2.3 Spatio-temporal continuity

While an industrial twin focuses on a lifecycle of design-build-maintain, the LDT focuses on monitor-predict-mitigate. It must manage information about long past periods through historical remote sensing archives (Handwerger et al., 2025) as well as real-time event-driven monitoring using high-frequency physics engines (Ju et al., 2025). This integration within a single data hub provides the necessary actionable insights for long-term risk estimation and urgent operational response (Du et al., 2025).

By satisfying three core conditions, the LDT moves beyond a simple visualisation tool or digital shadow, becoming a proactive infrastructure for risk management that accounts for the inherent unpredictability of the natural world.

3. Methodology

The methodology for identifying the requirements of a LDT follows a systematic, evidence-based approach centred on documented implementations in recent literature. This process is structured into three primary phases: literature review, maturity and operational analysis, and theoretical design of the data hub.

3.1 Systematic literature review

To establish a solid foundation for the technique and data reviewing stage, a systematic search was conducted in Scopus and Web of Science for the period January 2016 – December 2025. The search combined hazard terms (e.g., "landslide", "rockfall") with technical maturity terms ("Digital Twin", "Virtual Replica") and dynamic geomatics indicators ("4D", "IoT", "Real-time"). Out of 543 identified records, 143 papers were selected for full analysis. In particular, the selected papers were required to illustrate a prototyped or operational dynamic system integrating time-dependent numerical, 2D, or 3D data. Static models and standalone remote sensing papers without integration were excluded to focus on integrated platforms.

3.2 Maturity and operational analysis

Following the identification of relevant literature, the identified systems were evaluated against a categorical framework to distinguish their functional capabilities. Systems were classified into three levels of maturity (Digital Model, Digital Shadow, and Digital Twin) based on the direction and automation of data flow between the physical and virtual domains (Kritzinger et al., 2018).

This classification allows for the mapping of technical solutions to specific user needs, distinguishing between systems designed for long-term risk estimation (often relying on satellite data) and those required for operational early warning (requiring real-time, in-situ sensor feeds).

3.3 Theoretical design of the LDT Data Hub

The final stage involves the conceptual design of a LDT Data Layer architecture. This Data Hub serves as the integrated base for: the data acquisition layer, managing the flow from multi-sensor streams, including UAVs, InSAR, and IoT networks; the modelling layer, reconciling the subsurface uncertainty of geological processes with physics-based and data-driven simulation engines; the application layer, translating complex 4D datasets into actionable insights through immersive visualization platforms like WebGIS or game engines.

4. User and data requirements

The utility of a LDT is defined by its ability to transform 4D data from heterogeneous sources, scales, and timelines into actionable insights for diverse user groups, each requiring a specific interaction logic with the system. Based on the insights of the operational analysis of the reviewed literature, four main groups of targets users’ groups have been identified.

Primarily, emergency responders and command centres operate under a real-time emergency response logic, using 3D systems that integrate the live health and location data of rescue workers to facilitate seamless coordination and collaboration between frontline teams and command centres during disaster events (Yang et al., 2023). This immediate operational focus contrasts with the proactive risk management logic required by geologists, modelists and technical experts, who rely on daily automated value forecasts and high-frequency monitoring of hydrological variables, such as pore water pressure, to assess slope stability before a failure occurs (Piciullo et al., 2025; Maesano et al., 2025).

Furthermore, public administrators and infrastructure managers adopt a long-term planning and prevention logic, leveraging consistent, wide-area satellite coverage and historical archives to establish baseline conditions, map regional hazards, and manage risk for critical transportation corridors (Aati et al., 2020; Huntley et al., 2019; Handwerger et al., 2025). Finally, modern LDT frameworks increasingly incorporate a crowdsourcing logic where citizens and the general people act as human sensors (Goodchild, 2007), using mobile applications to upload geotagged photographs that bridge observational gaps and update the site's digital replica following extreme weather events (Themistocleous, 2025).

To move from a passive Digital Shadow to a functional LDT, the system must consume data across multiple scales and dimensions, transitioning from simple 3D snapshots to a continuous 4D stream. This consumption is structured as a multi-scale hierarchy where high-resolution topographic foundations are integrated with high-frequency environmental triggers and deep-time historical archives.

Table 1 synthesizes the primary data streams identified in the literature as essential for feeding an integrated LDT framework.

Data typology	**Primary technologies and sources**	**Functional role**
Topographic data (3D geometry)	UAV/Aerial Photogrammetry, Terrestrial Laser Scanning, and Airborne Laser Scanning.	Defines the physical boundary and provides the mesh for run-out and mobility simulations
Kinematic data (displacement)	InSAR/Persistent Scatterer Interferometry, Ground Based - InSAR, and GNSS time-series.	Track surface deformation rates and identify the transition from slow-moving to rapid failure.
Environmental data (triggers)	In-situ IoT networks monitoring Volumetric Water Content, Pore Water Pressure, and rainfall.	Provides the real-time engine that drives stability forecasting and automated alerts.
Subsurface data (internal state)	Electrical Resistivity Tomography, borehole drilling data, and IRT (InfraRed Thermography) for fracture detection.	Resolves internal uncertainty by correlating surface movement with deep hydrological fluctuations.
Predictive data (forecasts)	API-based meteorological services and weather station feed.	Enables the "what-if" capability of the twin by simulating slope response to incoming storm events.

Table 1. Primary data streams and functional roles categorising the multi-scale data required for an LDT, including topographic, kinematic, environmental, subsurface, and predictive inputs necessary to drive real-time stability simulations.

The data requirements documented in the literature highlight a fundamental shift from single-sensor analysis to a multi-sensor integration strategy. Researchers increasingly integrate the high temporal resolution of satellite radar (InSAR) with the high spatial resolution of UAV photogrammetry or Terrestrial Laser Scanning to overcome inherent sensor limitations, such as line-of-sight restrictions or vegetation occlusion (Donati et al., 2023; Teo et al., 2023).

However, the consumption of this data reveals a significant technical friction point: temporal heterogeneity. While IoT sensors and satellite feeds provide near continuous or periodic updates (ranging from minutes to weeks), the high-fidelity 3D topography often remains a static reference epoch due to the logistical costs of frequent rescanning (Anders et al., 2022; Siafali et al., 2024). This creates a geomatics bottleneck where dynamic semantic data (like a rainfall spike) is superimposed onto an outdated physical mesh, potentially leading to inaccurate post-failure simulations.

Furthermore, the lack of standardised data exchange protocols means that geotechnical time-series and geospatial point clouds often reside in data silos.

Resolving this fragmentation is essential: for an LDT to be mature, it must not only consume these data streams but also fuse them into a unified 4D environment where sensor intelligence is fully contextualized within the evolving 3D geometry and geospatial contexts.

5. Theoretical design of the Data Hub

The proposed LDT Data Hub is conceived as a multi-tier, integrated "central brain" designed to overcome the technical fragmentation and data silos currently prevalent in landslide monitoring. Rather than acting as a simple passive repository, this architecture functions as a unified infrastructure that bridges the gap between Geomatics, geotechnical engineering, and the specific operational requirements of end-users. It is explicitly designed to manage the flow of information from raw data acquisition to high-level decision support, ensuring that high-frequency sensor intelligence is no longer isolated but is instead properly contextualized within an evolving 3D spatial model. By centralising these heterogeneous streams, the Data Hub provides the solid foundation necessary for the modelling and application layers to function as a synchronized, near-real-time environment.

5.1 Acquisition layer

The acquisition layer represents the primary interface with the physical environment, responsible for the multi-scale consumption of heterogeneous data streams that vary significantly in both spatial resolution and update frequency. At its foundational level, this layer integrates high-resolution 3D topographic data from photogrammetry and laser scanning to establish the physical geometry and provide the mesh required for mobility simulations (Frauenfelder et al., 2025). This geometric base is continuously enriched by high-frequency monitoring streams from in-situ IoT networks, tracking parameters such as volumetric water content, pore water pressure, and tilt (Piciullo et al., 2025; Maesano et al., 2025; Romdhane et al., 2017), as well as satellite InSAR displacement vectors, which provide the wide-area kinematic context necessary to identify transitions from slow-moving to rapid failure (Handwerger et al., 2025; Huntley et al., 2019) . Finally, the layer ingests dynamic external triggers, such as live rainfall feeds and API-based meteorological forecasts, to provide the real-time inputs essential for proactive stability forecasting and automated early warning protocols (Xu et al., 2025; Barrile et al., 2023).

5.2 Modelling and processing layer

The modelling and processing layer functions as the analytical core of the hub, where raw data is transformed into geo-mechanical intelligence through advanced simulations of physical mechanics and material behaviour (Gatti et al., 2023; Fois et al., 2024). To overcome the trade-off between high-fidelity representation and computational latency, this layer increasingly employs surrogate or hybrid modelling approaches. These methods employ machine learning algorithms such as Convolutional Neural Networks (CNN) or Artificial Neural Networks (ANN) trained on massive datasets generated from physics-based Finite Element Method (FEM) simulations to deliver near-instantaneous stability predictions (Chen et al., 2023b; Lin et al., 2024; Xu et al., 2025). Furthermore, this layer is responsible for developing automated, event-triggered workflows and 4D modelling processes capable of updating digital topography in near-real-time following geomorphological changes. By coupling physical models with Bayesian back-analysis or probabilistic assessments, the processing engine can account for subsurface uncertainty and predict the time-variant factor of safety driven by real-time hydrological data (Liu et al., 2022; Ju et al., 2025).

5.3 Application and service layer

The application and service layer serves as the final interface, translating complex numerical simulations and 4D datasets into the specific interaction logic required by diverse end-users. Current visualisation strategies are divided between traditional WebGIS platforms, such as the CesiumJS-based platforms used for 3D emergency response and progressive modelling (Yang et al., 2023; Barrile et al., 2023), and immersive game engines like Unreal Engine, which provide real-time interactive simulations and pixel streaming for remote access (Maesano et al., 2025) . Beyond mere visualisation, this layer facilitates the transition to a mature cyber-physical system through a service-oriented architecture designed for active remote control. By adopting a Sensor Planning Service (SPS) and middleware programs, the digital system can transmit control commands back to the physical hardware, remotely and automatically altering a sensor's operational parameters based on the digital model's requirements (Chen et al., 2015). This closed feedback loop is the defining characteristic that elevates the system from a passive monitoring tool to a proactive infrastructure for autonomous risk management.

5.4 Interaction and flows between layers

The different layers and their interaction logics for target user groups are mapped in Figure 2.

The conceptual architecture is structured as a vertical stack where the acquisition layer serves as the foundational entry point for multi-scale consumption. This layer must manage the ingestion of heterogeneous data, reconciling the long-term perspective of historical satellite archives with the real-time urgency of in-situ sensor networks. Consequently, a flexible data model is required to encode and manage the recording and filtering of a large number of observations and property metadata. In this way, it provides a unified documented spatial and temporal context, ensuring that sensor intelligence is integrated within a 4D environment rather than remaining isolated. This foundation feeds directly into the processing layer, acting as an engine room where the raw data is transformed into a practical understanding of phenomena through the implementation of modelling and simulation algorithms. The bidirectional link required for the LDT maturity is represented here as a bridge: data previously collected in situ by specialists or contributed by citizen scientists is used to calculate risk parameters or predict future scenarios, while simulation parameters defined by public administrators or decision makers in the interfaces of the uppermost application and service layer are used to recalibrate different scenarios and update the variables inside calculation modules previously defined by technical experts in hydrology, geology, and other relevant disciplines.

Finally, the uppermost tier is the service and application layer, which functions as the primary interface for user interaction. This layer is responsible for broadcasting the system's results through specialised platforms to satisfy the unique requirements of different end-users. For instance, emergency responders from civil protection agencies interact with this layer through real-time 3D environments that track personnel and visualise hazard propagation during a crisis. For public administrators, the architecture provides simplified, wide-area risk maps for long-term land-use planning. Finally, the layer supports a bi-directional flow for citizens and the general public, who can contribute crowdsourced data back into the system to help bridge observational gaps in remote or sensitive regions, while also accessing communication platforms to view the current status of the site.

6. Implementation requirements

To successfully transition the LDT from a conceptual architecture to an operational, bi-directional cyber-physical system, specific technical requirements must be met. A fundamental barrier to achieving a "True Digital Twin" in geosciences is the presence of data silos caused by the fragmented landscape of hardware interfaces and the lack of standardized software protocols. Addressing the interoperability gap requires rigorous implementation strategies focused on scalable data formats, established exchange standards, and flexible, semantically integrated database models. Table 2 provides an overview of the formats and standards currently adopted by the latest DTs implementations, aligned to the data needs of landslides.

The acquisition and processing layers of the LDT must manage high-frequency, multi-dimensional data ranging from IoT sensor feeds to extensive 3D topographic models.

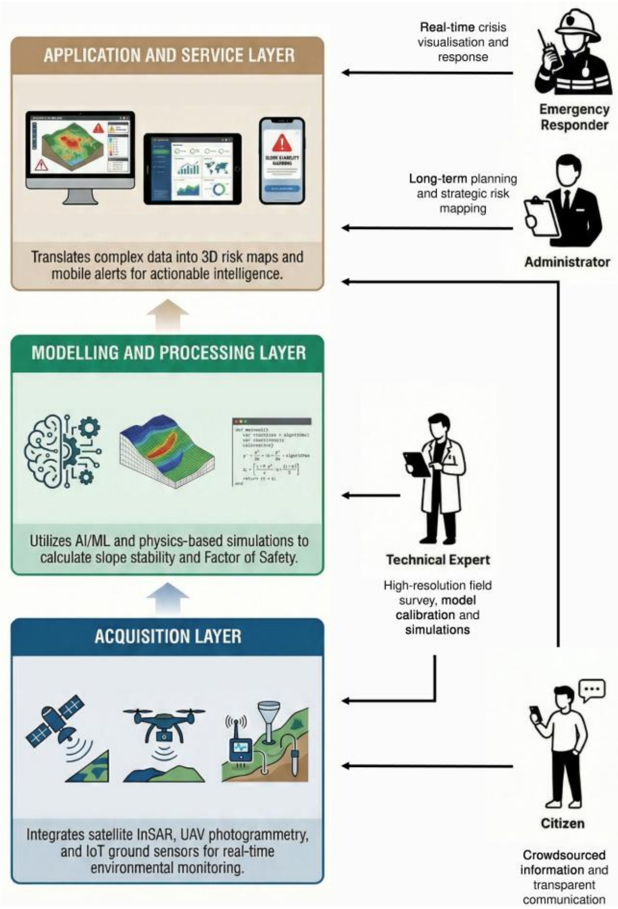

Figure 2. Conceptual layered architecture of the LDT Data Hub, mapping the interaction between the three functional tiers of Data Acquisition, Modelling, and Application and specific user groups, illustrating how information flows from multi-scale sensing to decision-maker and respondent support. Image generated by Google NotebookLM (Gemini model) based on author-provided prompts.

To ensure scalability and computational efficiency, the LDT infrastructure should transition towards cloud-native and highly scalable data formats such as Cloud Optimized GeoTIFF (COG) (OGC, 2023), Zarr (OGC, 2022), GeoParquet, NetCDF (OGC, 2015), and HDF (OGC, 2019). These modern formats support the storage and retrieval of massive multidimensional arrays and point clouds, enabling de-facto harmonized access and knowledge representation without the overhead of heavy, vendor-specific APIs.
Furthermore, time-series data and coverage models should be encoded using lightweight formats like CovJSON to facilitate rapid integration into web-based visualization platforms and game engine applications.
The LDT implementation must be deeply rooted in the FAIR (Findable, Accessible, Interoperable, or Repeatable, Wilkinson et al., 2016) data principles to overcome the historical fragmentation of environmental monitoring data. Resolving the incompatibility between geotechnical time-series sensors and 3D geospatial datasets requires the adoption of unified bi-directional communication standards.
To achieve this, the architecture should leverage Open Geospatial Consortium (OGC) standards, integrating models such as Observation & Measurements and the OGC SensorThings API to automatically generate harmonized interfaces for diverse in-situ IoT data. Access harmonization mechanisms, such as Kerchunk and broad OGC APIs, are necessary to overlay base queries and seamlessly fuse data across heterogeneous sources. Additionally, managing the metadata for dynamic 4D models, capacity requirements, and workflows should be formalised using SpatioTemporal Asset Catalogs (STAC) extensions and OGC API Records, ensuring that both data provenance and simulation lineage are transparent and easily interoperable.

Layer	Formats	Standards and protocols
Acquisition Layer	Cloud-native, scalable formats for multidimensional arrays and point clouds: COG, Zarr, GeoParquet, NetCDF, and HDF. Lightweight formats like CovJSON for time-series data.	OGC standards, Observation & Measurements, and OGC SensorThings API to harmonize IoT data. Kerchunk and broad OGC APIs for data access and fusion.
Modelling and Processing Layer	Zarr, NetCDF, HDF to handle the storage and retrieval of massive multidimensional arrays generated by simulations.	STAC extensions and OGC API Records for managing metadata, capacity requirements, and ensuring transparent simulation lineage and data provenance.
Application and Service Layer	CovJSON to facilitate rapid, lightweight integration of time-series and coverage models into web-based platforms and game engines.	Leverages unified bi-directional communication standards and OGC APIs for seamless system-to-sensor integration.

Table 2. A summary of the technical requirements to resolve data silos, highlighting the use of cloud-native formats (e.g., COG, Zarr), OGC interoperability standards, and FAIR data principles.

7. Conclusions

The transition towards a functional DT for landslide risk management represents a complex, multi-scale challenge that must be driven by a user-centric approach. This study's main contribution is the development of a layered architectural framework for a Landslide Digital Twin, grounded in a rigorous requirement analysis that maps the specific operational needs of diverse end-users, ranging from emergency responders and technical experts to public administrators and citizens, against state-of-the-art surveying and modelling techniques.
By systematically reviewing recent literature and current implementations, this research shows that most existing systems function merely as passive Digital Shadows, limited by unidirectional data flows. We identified a topography gap, the superimposition of dynamic, high-frequency environmental sensor data onto a static, outdated 3D topographic mesh, and data interoperability as the primary technical bottlenecks preventing the realization of a true bi-directional cyber-physical system. To resolve this fragmentation, we conceptualised a multi-tier Data Hub encompassing acquisition, modelling, and application layers. This hub is designed to synthesise stochastic subsurface uncertainty, multi-physics interaction logic, and spatio-temporal continuity into a unified 4D environment. Furthermore, this work outlines a potential implementation path for the TWINFALL project by investigating the feasibility of cloud-native formats and OGC interoperability standards.

Moving forward, evaluating the practical integration of the identified formats and protocols. On the roadmap to develop LDT applications, possible future works focus on:

- Overcoming the topography gap through the development of automated, event-triggered 4D workflows capable of continuously updating the digital physical mesh in near-real-time following geomorphological changes.
- Enforcing data standardisation to break down existing data silos, adopting flexible, service-oriented platforms that facilitate the unified exchange of both geotechnical time-series and geospatial point clouds.
- Implementing active bi-directional control to elevate the LDT from a monitoring tool to an autonomous risk management infrastructure, enabling the system to remotely alter physical sensor parameters and issue automated early warnings based on AI and physics-based stability forecasts.

Ultimately, prioritising these integrated, standardised approaches is essential to transform complex, multi-scale geoscientific data into the actionable intelligence required for proactive and sustainable risk governance in the face of a changing climate.

Acknowledgements

This research is part of TWINFALL project, grant number 2024–3408, which has been funded in 2025 by Fondazione CARIPLO.

References

Aati, S., Avouac, J. P., 2020: Optimization of optical image geometric modeling, application to topography extraction and topographic change measurements using PlanetScope and SkySat imagery. *Remote Sensing*, *12*(20), 3418.

Ahmad, N., Shafique, M., Hussain, M. L., 2021: Landslide assessment by using multi-temporal UAV datasets: a case study in northern Pakistan. *Arabian Journal of Geosciences*, 14(18), 1855.

Anders, K., Winiwarter, L., Schröder, D., Höfle, B., 2022: Integration of Kalman Filtering of Near-Continuous Surface Change Time Series into the Extraction of 4D Objects-by-Change. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, *43*, 973-980.

Arosio, D., Longoni, L., Papini, M., Boccolari, M., Zanzi, L., 2018: Analysis of microseismic signals collected on an unstable rock face in the Italian Prealps. *Geophysical Journal International*, 213(1), 475-488.

Barrile, V., Cotroneo, F., Genovese, E., 2023: Platform Prototype for the Prediction of Landslide Susceptibility Through a 4D WebGIS Equipped with Cellular Automata and Neural Networks. In *Italian Conference on Geomatics and Geospatial Technologies* (pp. 81-95). Cham: Springer Nature Switzerland.

Biraghi, C. A., Carrion, D., Brovelli, M. A., 2022: Citizen science impact on environmental monitoring towards SDGs indicators: the CASE of SIMILE project. *Sustainability*, 14(13), 8107.

Blair, G. S., 2021: Digital twins of the natural environment. *Patterns*, *2*(10).

Chen, N., Xiao, C., Pu, F., Wang, X., Wang, C., Wang, Z., Gong, J., 2015: Cyber-physical geographical information service-enabled control of diverse in-situ sensors. *Sensors*, 15(2), 2565-2592.

Chen, G., Kang, X., Lin, M., Teng, S., Liu, Z., 2023: Stability prediction of soil slopes based on digital twinning and deep learning. *Applied Sciences*, *13*(11), 6470.

Chioni, C., Pezzica, C., Favargiotti, S., 2024: Territorial Digital Twins: A key for increasing the community resilience of fragile mountain inner territories? *Sustainable Development*, *32*(2), 1548-1563.

Donati, D., Stead, D., Rabus, B., Engelbrecht, J., Clague, J. J., Newman, S. D., Francioni, M., 2023: Characterization of the Fels Landslide (Alaska) Using Combined Terrestrial, Aerial, and Satellite Remote Sensing Data. *Remote Sensing*, *16*(1), 117.

Du, W., Fu, X., Sheng, Q., Chen, J., Zhou, Y., Zheng, S., 2025: Physics-based and data-driven long-term evolution of a landslide: From inversion to prediction. *Engineering Geology*, 108252.

Fois, M., Makarim Katili, A., De Falco, C, Larese, A., Formaggia, L., 2024: Landslide run-out simulations with depth-averaged models and integration with 3D impact analysis using the Material Point Method. In *16th World Congress on Computational Mechanics and 4th Pan American Congress on Computational Mechanics* (pp. 1-12).

Frauenfelder, R., Salazar, S. E., Paulsen, E. M., Reutz, E. H., Steinholt, I. H., Rødvand, L. A., Paniagua, P., L'Heureux, J. S., 2025: Erosion detection and monitoring in quick clay areas by repeat UAV-borne LiDAR surveys: Two case studies from Norway. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1523, No. 1, p. 012039). IOP Publishing.

Gaspari, F., Barbieri, F., Fascia, R., Ioli, F., Pinto, L. Migliaccio, F., 2025: Strategies for Glacier Retreat Communication with 3D Geovisualization and Open Data Sharing. *ISPRS International Journal of Geo-Information*, *14*(2), 75.

Gatti, F., Fois, M., de Falco, C., Perotto, S., Formaggia, L., 2023: Parallel simulations for fast-moving landslides: Space-time mesh adaptation and sharp tracking of the wetting front. *Inter-national Journal for Numerical Methods in Fluids*, 95(8), 1286-1309.

Goodchild, M. F., 2007: Citizens as sensors: the world of volunteered geography. *GeoJournal*, *69*(4), 211-221.

Handwerger, A. L., Lacroix, P., Bell, A. F., Booth, A. M., Huang, M. H., Mudd, S. M., Bürgmann, R., Fielding, E. J., 2025: Multi-sensor remote sensing captures geometry and slow-to-fast sliding transition of the 2017 Mud Creek landslide. *Scientific Reports*, *15*(1), 29831.

Huntley, D., Bobrowsky, P., Hendry, M., Macciotta, R., Elwood, D., Sattler, K., Best, M., Chambers, J., Meldrum, P., 2019. Application of multi-dimensional electrical resistivity tomography datasets to investigate a very slow-moving landslide near Ashcroft, British Columbia, Canada. *Landslides*, *16*(5), 1033-1042

Janeras, M., Jara, J. A., Royan, M. J., Vilaplana, J. M., Aguasca, A., Fabregas, X., Gili, J.A., Buxó, P., 2017: Multi-technique approach to rockfall monitoring in the Montserrat massif (Catalonia, NE Spain). *Engineering Geology*, 219, 4-20.

Ju, L. Y., Xiao, T., He, J., Xu, W. F., Xiao, S. H., Zhang, L. M., 2025: A simulation-enabled slope digital twin for real-time assessment of rain-induced landslides. *Engineering Geology*, 108116.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W., 2018: Digital Twin in manufacturing: A categorical literature review and classification. *Ifac-PapersOnline*, *51*(11), 1016-1022.

Lin, M., Chen, X., Chen, G., Zhao, Z., Bassir, D., 2025: Stability prediction of multi-material complex slopes based on self-attention convolutional neural networks. *Stochastic Environmental Research and Risk Assessment*, *39*(10), 4679-4695.

Liu, X., Wang, Y., Koo, R. C., Kwan, J. S., 2022: Development of a slope digital twin for predicting temporal variation of rainfall-induced slope instability using past slope performance records and monitoring data. *Engineering Geology*, *308*, 106825.

Maesano, C., Genovese, E., Calluso, S., Manti, M. P., Barrile, V., 2025: Sensor-based slope stability prediction using a digital twin and AI-driven stability forecasting. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *48*, 183-188.

Maimour, M., Ahmed, A., Rondeau, E., 2024: Survey on digital twins for natural environments: A communication network perspective. *Internet of Things*, 25, 101070.

OGC, 2015. *OGC CF-netCDF 3.0 encoding using GML Coverage Application Schema*, Version 2.0. Edited by B. Domenico and S. Nativi. OGC 14-100r2. Available at: https://docs.ogc.org/is/14-100r2/14-100r2.html (27 March 2026).

OGC, 2019. *OGC Hierarchical Data Format Version 5 (HDF5®) Core Standard*, Version 1.0. Edited by A. Jelenak, T. Habermann, and G. Heber. OGC 18-043r3. Available at: https://docs.ogc.org/is/18-043r3/18-043r3.html (Accessed: 27 March 2026).

OGC, 2022. *Zarr Storage Specification 2.0 Community Standard*, Version 2.0. OGC 21-050r1. Available at: https://portal.ogc.org/files/100727 (27 March 2026).

OGC, 2023. *OGC Cloud Optimized GeoTIFF Standard*, Version 1.0. Edited by Joan Maso. OGC 21-026. Available at: https://docs.ogc.org/is/21-026/21-026.html (27 March 2026).

Pagano, N., Sonnessa, A., Cotecchia, F., Tarantino, E., 2023: Integrated Use of Geomatic Methodologies for Monitoring an Instability Phenomenon. In *International Conference on Computational Science and Its Applications* (pp. 217-233). Cham: Springer Nature Switzerland.

Piciullo, L., Abraham, M. T., Drøsdal, I. N., Paulsen, E. S., 2025: An operational IoT-based slope stability forecast using a digital twin. *Environmental Modelling & Software*, 183, 106228

Reid, M. E., Godt, J. W., LaHusen, R. G., Slaughter, S. L., Badger, T. C., Collins, B. D., Schulz, W. H., Baum, R. L., Coe, J. A., Harp, E. L., Schmidt, K. M., Iverson, R. M., Smith, J. B., Haugerud, R. A., George, D. L., 2021: When hazard avoidance is not an option: lessons learned from monitoring the postdisaster Oso landslide, USA. *Landslides*, *18*(9), 2993-3009.

Romdhane, R. F., Lami, Y., Genon-Catalot, D., Fourty, N., Lagrèze, A., Jongmans, D., & Baillet, L., 2017. Wireless sensors network for landslides prevention. In *2017 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)* (pp. 222-227). IEEE.

Santangelo, M., Alvioli, M., Baldo, M., Cardinali, M., Giordan, D., Guzzetti, F., Marchesini, I., Reichenbach, P., 2019: Brief communication: Remotely piloted aircraft systems for rapid emergency response: road exposure to rockfall in Villanova di Accumoli (central Italy). *Natural Hazards and Earth System Sciences*, 19(2), 325-335.

Siafali, E., Tsioras, P. A., 2024: An innovative approach to surface deformation estimation in forest road and trail networks using unmanned aerial vehicle real-time kinematic-derived data for monitoring and maintenance. *Forests*, *15*(1), 212.

Teo, T. A., Fu, Y. J., Li, K. W., Weng, M. C., Yang, C. M., 2023: Comparison between image-and surface-derived displacement fields for landslide monitoring using an unmanned aerial vehicle. *International journal of applied earth observation and geoinformation*, *116*, 103164.

Themistocleous, K., 2025: Innovative methods for safeguarding cultural heritage. *Italian journal of engineering geology and environment*, 123-132.

Wilkinson, M. D., et al., 2016 : The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data*, *3*, 160018

Xu, J., Zhang, Y., 2025: AI-Powered Digital Twin Technology for Highway System Slope Stability Risk Monitoring. *Geotechnics*, *5*(1), 19.

Yang, Z., Li, J., Hyyppä, J., Gong, J., Liu, J., Yang, B., 2023: A comprehensive and up-to-date web-based interactive 3D emergency response and visualization system using Cesium Digital Earth: taking landslide disaster as an example. *Big Earth Data*, *7*(4), 1058-1080.

Yang, Y., Xie, C., Fan, Z., Xu, Z., Melville, B. W., Liu, G., Hong, L., 2024: Digital twinning of river basins towards full-scale, sustainable and equitable water management and disaster mitigation. npj *Natural Hazards*, 1(1), 43.