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OGC CLIMATE DISASTER AND RESILIENCE PILOT: LANDSLIDE DEMONSTRATORS REPORT

ENGINEERING REPORT

PUBLISHED

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I EXECUTIVE SUMMARY

Landslides pose a significant threat, often triggered by extreme weather events like heavy rainfall or earthquakes, leading to extensive damage and loss of life. Traditional methods for detecting and measuring landslides are typically time-consuming and lack accuracy. This report introduces Landslideflow, a workflow based on the Common Workflow Language (CWL) designed to improve the detection and measurement of landslides. Utilizing remote sensing data, such as satellite images and digital elevation models, Landslideflow generates precise landslide displacement maps. The workflow is scalable and cloud-optimized, enabling it to handle large data volumes efficiently. Moreover, Landslideflow leverages advanced computer vision and machine learning techniques to enhance accuracy, offering a robust solution that is easy to deploy on cloud platforms. As an open-source tool, Landslideflow is freely accessible, providing a valuable resource for researchers and practitioners in the field. Landslideflow is a powerful tool for detecting and measuring landslides. It is accurate, scalable, cloud-optimized, and open source. Landslideflow can be used by scientists, engineers, and policymakers to better understand and mitigate the risks associated with landslides.

II KEYWORDS

The following are keywords to be used by search engines and document catalogues.

hackathon, application-to-the-cloud, testbed, docker, web service, climate resilience, data conflation

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IV OVERVIEW

The OGC Climate Disaster and Resilience Pilot — D131 report introduces Landslideflow, a Common Workflow Language (CWL) based workflow for detecting and measuring landslides. Landslides are a major natural hazard that can cause widespread damage and loss of life. Traditional methods of detecting and measuring landslides are often time-consuming and inaccurate. Landslideflow addresses these challenges by leveraging advanced computer vision and machine learning techniques to generate accurate landslide displacement maps. The workflow is designed to be scalable, cloud-optimized, and open source. It is based on the STAC and STAC API standards and utilizes OGC APIs and OGC Standards. The report highlights the benefits of Landslideflow, including its accuracy, scalability, cloud-optimization, and open-source nature. It concludes by emphasizing the potential of Landslideflow as a powerful tool for scientists, engineers, and policymakers to better understand and mitigate the risks associated with landslides.

V FUTURE OUTLOOK

The Landslideflow platform's future development will focus on enhancing detection accuracy by transitioning from an optical flow-based approach to a data-driven deep learning model. Integrating soil and moisture readings into the model will further improve detection precision.

To ensure reproducibility and ease of use, the containerization of the platform will be improved, enabling deployment across diverse computing environments. Comprehensive documentation will guide the translation of code into Common Workflow Language (CWL), with strategies for handling proprietary models where public release is not desirable.

Additionally, services will be developed to convert models into the ONNX format, supported by an interface using NETRON for model preview. The integration with Training Data Markup Language (TDML) will be assessed and refined to enhance platform functionality and user experience. These advancements will make the platform more robust, versatile, and accessible to the scientific community.

VI VALUE PROPOSITION

Landslideflow offers several compelling advantages over traditional methods of landslide detection and measurement: - Accuracy: Landslideflow capitalizes on advanced computer vision and machine learning techniques to create accurate landslide displacement maps. - Scalability: Landslideflow's scalability makes it apt for processing large volumes of data. - Cloud Optimization: Landslideflow is designed for cloud environments, streamlining deployment and execution. - Open Source: The open-source nature of Landslideflow ensures free availability and accessibility.

These features position Landslideflow as a valuable tool for scientists, engineers, and policymakers, empowering them to better understand and mitigate landslide risks.

1

INTRODUCTION

1 INTRODUCTION

As the effects of climate change become more pronounced, the frequency of extreme weather events has escalated. These severe occurrences often culminate in catastrophes, as documented in the Intergovernmental Panel on Climate Change (IPCC) report.

Such events manifest in various forms, including floods, hurricanes, and wildfires. This report highlights the contribution of our proposed platform for detecting landslide displacement as a Common Workflow Language (CWL) workflow named, Landslideflow. The platform is based on STAC and STAC API, which are in process of being OGC Community Standards. The platform is also using OGC API Standards: OGC API Processes Part 1: Core, OGC API Processes Part 2: Deploy, Replace and Undeploy, and "OGC EOAPI". With the newly developed eoAPI by development seed, we also offer OGC API — Tiles using the "raster" endpoint. The detection algorithm is based on the Optical Flow method which is a prominent computer vision approach for estimating accurate displacement between subsequent images in time of a same region. The platform developed as a part of this pilot is available here: https://cdrp-02.geolabs.fr/ogc-api/api.html.

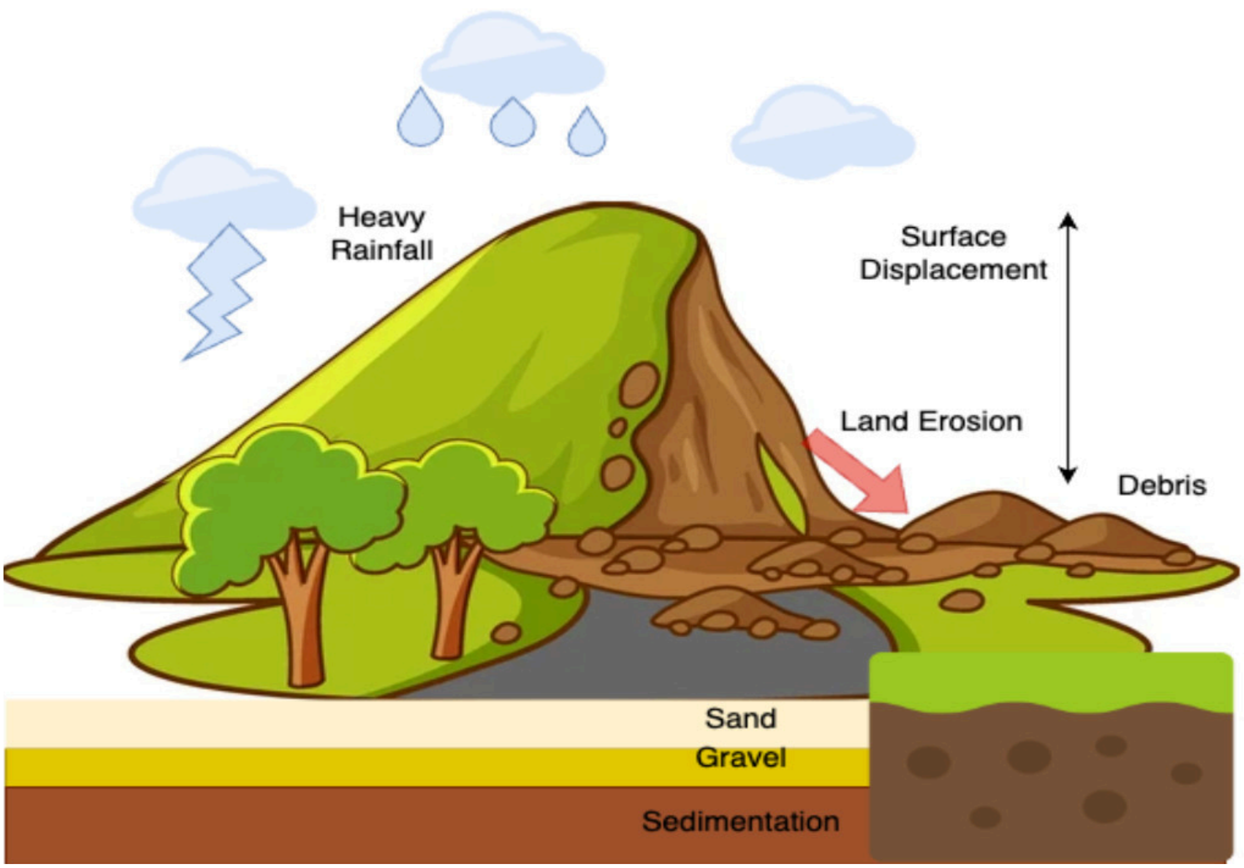


Figure 1 — Illustration of the conceptual diagram for the landslide detection and displacement prediction task.

Landslides are one of the most pervasive natural hazards, with the potential to cause catastrophic impacts on both human life and infrastructure. Occurring in various forms, from rock falls to debris flows, landslides are often triggered by a combination of factors, including geological conditions, intense rainfall, earthquakes, and human activities such as deforestation and unregulated construction. The consequences of landslides are often devastating, leading to loss of life, displacement of communities, and significant economic losses.

The ability to detect and monitor landslides in near real-time is crucial for disaster risk reduction and response efforts. Remote sensing technologies, such as satellite imagery, have proven to be effective tools for landslide detection and monitoring. By analyzing changes in land surface features over time, such as ground deformation and slope movement, satellite-based methods can provide valuable insights into landslide activity and behavior.

The Landslideflow platform aims to leverage the power of satellite imagery and machine learning algorithms to detect and monitor landslide displacement in near real-time. By processing and analyzing satellite data using advanced computer vision techniques, the platform can identify areas at risk of landslides and provide early warning alerts to relevant stakeholders. The Landslideflow platform is designed to be scalable, flexible, and user-friendly, making it accessible to a wide range of users, including disaster management agencies, researchers, and policymakers.

The Landslideflow platform is part of the OGC Climate Disaster and Resilience Pilot, which aims to develop innovative solutions for disaster risk reduction and climate change adaptation. By harnessing the collective expertise of the OGC community, the pilot seeks to address key challenges related to climate disasters and resilience, such as data interoperability, information sharing, and decision support. The Landslideflow platform is a testament to the power of collaboration and innovation in addressing complex global challenges.

The following sections provide an overview of the Landslideflow platform, including its key features, architecture, and functionality. The platform is currently in the prototype stage and is being tested in various landslide-prone regions around the world. The Landslideflow team welcomes feedback and input from the OGC community to further enhance the platform and maximize its impact on disaster risk reduction and resilience efforts.

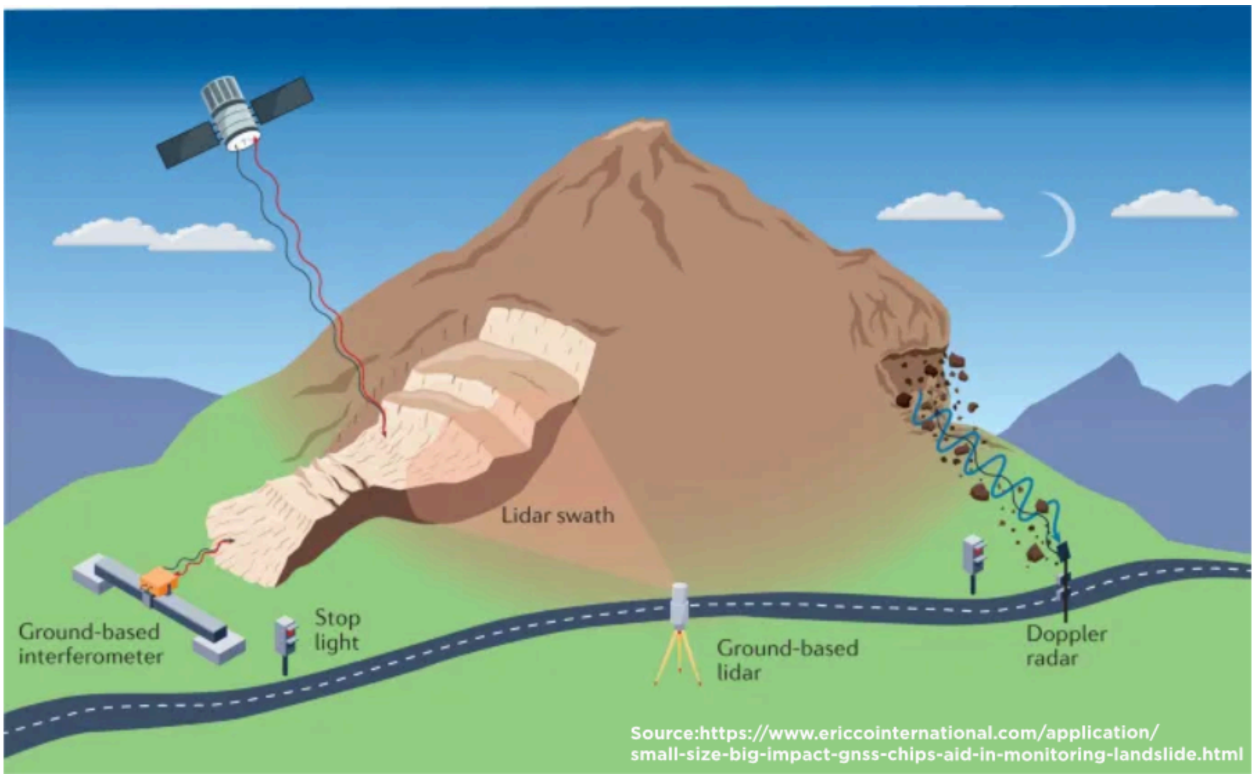
2

TOPICS

2 TOPICS

2.1. Remote Sensing for Landslide Analysis

A landslide is a substantial displacement of earth, rock, or debris down an inclined surface. It is a form of "mass wasting," which is caused by the downward movement of soil and rock due to the direct influence of gravity. Typically, landslides have multiple contributing factors. They can occur due to unstable slopes or reduced strength in the underlying materials. Various factors can initiate landslides in slopes already predisposed to movement, including rainfall, snowmelt, changes in water levels, stream erosion, fluctuations in groundwater levels, earthquakes, volcanic activity, human-induced disturbances, or a combination of these elements. Seismic activity and other external forces can also trigger landslides underwater, referred to as submarine landslides. These submarine landslides have the potential to generate tsunamis, which can cause significant damage to coastal regions.



In the context of geological phenomena, landslides are frequently initiated by external factors such as precipitation or seismic activity. Furthermore, the occurrence of landslides is influenced by various proxies, including soil moisture content, topographical characteristics, and the geological composition of the soil. To mitigate the catastrophic impact of landslides, timely detection and estimation of land displacement are crucial. Remote sensing data plays a pivotal role in this regard, enabling the analysis of landslide detection and displacement. However, the challenge lies in the requirement for extensive data processing of satellite imagery and in situ observations, which can be computationally demanding.

To address this challenge, automated analysis approaches that incorporate computer vision and machine learning techniques have been proposed. However, these approaches often lack scalability and do not support cloud-optimized development. In this work, we present Landslideflow, a Common Workflow Language (CWL) based workflow designed to generate landslide displacement maps as output, given multi-modal remote sensing datasets including satellite images (MSI), digital elevation models (DEMs), derived slope, and aspect maps as inputs. The proposed Landslideflow is based on ZOO-Project and ZOO-Services.

2.2. ZOO-Project and ZOO-Services

The ZOO-Project is an Open-Source Processing Engine and an OSGeo Project that adheres to the OGC Standards, commencing with WPS 1.0.0 and then 2.0.0. It serves as a Reference Implementation of the OGC API — Processes — Part 1: Core. The ZOO-Project is built upon the ZOO-Kernel, which is capable of managing the execution of local processes implemented in various programming languages, including C/C++, Java, C\#, Python, PHP, Perl, Ruby, Fortran, R, and JavaScript (limozjs or Node.js). Furthermore, it supports existing processing applications such as OrfeoToolBox (OTB) and SAGA-GIS, automatically transforming them into standard OGC Web Services or API..

The primary focus of the ZOO-Project is the utilization of the MapServer for on-demand publication of Open Geospatial Consortium (OGC) Web Services (WMS, WFS, and WCS). To ensure the successful publication of a resultant dataset through MapServer, modification of solely the process's metadata is necessary. This eliminates the requirement for alterations to the process code. The ZOO-Project inherently supports flexibility and facilitates seamless integration with a diverse range of other open-source libraries, including GDAL, CGAL, GRASS GIS, OrfeoToolbox, SAGA GIS, and many more. It is designed to utilize existing geospatial algorithms through the standardized Web Processing Service (WPS) and offers numerous notable examples to assist in the construction of customized solutions.

The ZOO-Project has been used in various projects including the GeoSUD and Phidias-HPC project. These projects have facilitated the implementation of remote task execution on High-Performance Computing (HPC) systems, utilising the Secure Shell (SSH) protocol for connectivity purposes, as well as the SLURM workload manager for scheduling and monitoring tasks. Initially, applications from the OrfeoToolBox (OTB) were employed, which were later supplemented with workflows encapsulated in Singularity containers. This implementation was based on the WPS 2.0.0 Standard and leveraged the inner outputs to provide the URLs to the OGC Web Services (WMS+WFS or WMS+WCS) associated with the result.

Within the context of OGC Testbed19, the ZOO-Project was employed to facilitate the deployment of singularity containers encompassing workflows or individual applications, subsequently executing them on a remote high-performance computing (HPC) infrastructure. This framework leverages the Open Geospatial Consortium (OGC) API — Processes — Part 2: Deploy, Replace, and Undeploy (DRU) draft specification for deployment purposes, whereas Part 1: Core is utilised for process execution invocation. Drawing upon the OGC Best Practice for Earth Observation Application Package, the ZOO-Project was integrated into the Earth Observation European Platform for Cloud and Analytics (EOEPCA) project to support the Common Workflow Language (CWL) conformance class outlined in the OGC API — Processes — Part 2: DRU draft. Furthermore, the ZOO-Project-DRU Helm chart simplifies the deployment of the ZOO-Project, encompassing both DRU and CWL support.

During the Testbed19, the ZOO-Project prototyped an implementation for deploying OpenEO User-Defined Processes utilising the OGC API-Processes Part 2: DRU draft specification, enabling their execution. Furthermore, this activity showcased a prototype platform that facilitates the coexistence of both eoAPI and the ZOO-Project, with the latter providing a unified OpenAPI for accessing both services. The combination of Processing and STAC API capabilities through a unified API presents novel opportunities. The implementation of DRU capabilities necessitates the fulfilment of specific security requirements. It is impossible to restrict the use of specific endpoints internally if the ZOO-Project passes request headers to the secured services. In this context, it is essential to acknowledge that the ZOO-Project's OpenAPI enables user authentication via Basic Authentication or OpenID Connect. In the Open Geospatial Consortium (OGC) CDRP 2024, the functionality developed during the Testbed-19 is extended as Landslideflow to support a scientific use case. This use case involves deploying Landslideflow for remote process execution of a landslide displacement approach as a Common Workflow Language (CWL) workflow.

2.3. Methodology

This section describes the methodology for the proposed Landslideflow platform.

2.3.1. Brief Understanding of Service Architecture

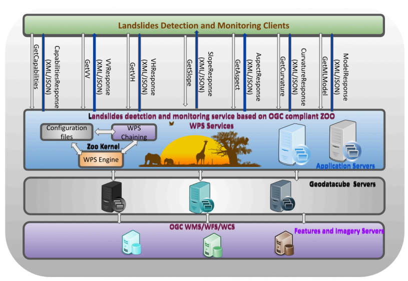


Figure 2 — Illustration of an architecture comprising of OGC web services for a sample landslide detection and monitoring client

Traditionally, a Landslide detection and monitoring client would necessitate interaction with Open Geospatial Consortium (OGC) Web Processing Service (WPS) services and OGC APIs (refer to the figure above). This interaction entails web services interfacing with the Features and imagery databases in the form of Geodatacubes based on predetermined bounding boxes, thereby adhering to the initial defined work for OGC GeoDataCube. The standards for GeoDataCube are still in development.. These web services facilitate data (both raw and derived) access as Request-Response, enabling standardized and interoperable remote processing for a specified geographical region.

2.3.2. Inference-as-a-service based on OGC API Processes

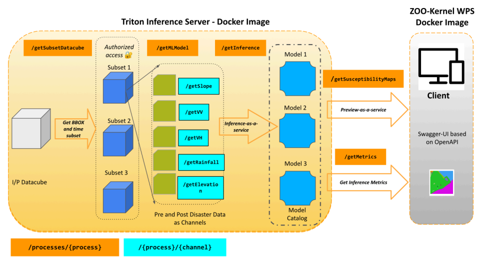


Figure 3 — Illustration of the inference-as-a-service based on OGC API - Processes

The retrieved data is passed to the inference-as-a-service (See above figure) for generating the displacement maps based on the inference generated from the optical flow model. The output is then visualised in a Swagger-Ui client based on the OpenAPI. Some of the processes used in this processing are as shown below.

- Get Subset based on provided BBOX and Time range
  - `/processes/{getSubsetDatacube}`
- Retreive ML model parameters from the Subsetted Datacube
  - `/processes/{getMLModel}`
    - `Parameters: {getVV, getVH, getSlope, getCurvature, getAspect, getElevation, getRainfall}`
- Generate Inference from the deep learning model using inference-as-a-service
  - `/processes/{getInference}`
- Generate output landslide susceptibility maps and evaluation metrics
  - `/processes/{getSusceptibilityMap, getMetrics}`

Figure 4 — Illustration of the processes used in the Landslideflow platform

2.3.3. LandslideFlow: ML Inferencing as a CWL Workflow

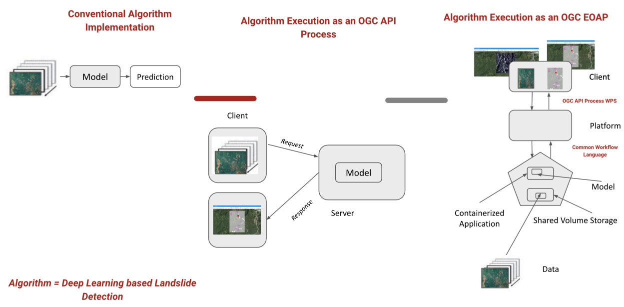


Figure 5 — Execution mechanisms for Earth observation algorithms

However, this model-data interaction can be abstracted in a containerised platform for deploying the end-to-end analysis using CWL workflow. The OGC EOAP facilitates this development by enabling algorithm execution as an OGC EO Application Package

2.3.4. Algorithm: Optical Flow based Landslide Displacement Analysis

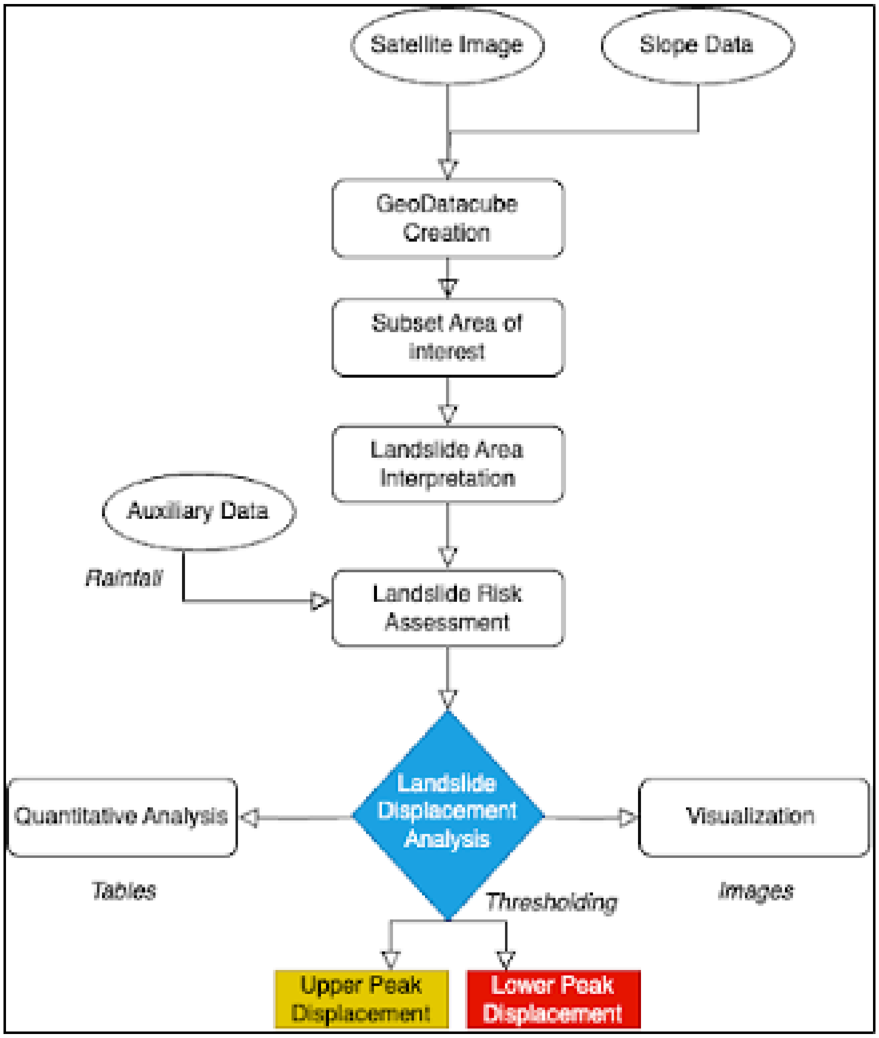


Figure 6 — Illustration of high-level framework for generating landslide displacement maps.

We tested the proposed Landslideflow for two use-cases based on different types of data used for processing.

1. Based on using Sentinel 1 — SAR data comprising of VV and VH polarisation for earthquake induced landslide of Hokkaido, Japan [2] (Source: https://zenodo.org/records/7248056)

2. Based on Sentinel 2 data for rainfall triggered landslides in Taiwan. We used sentinel-2 data made available on AWS by Element84. (Source : https://registry.opendata.aws/sentinel-2-l2a-cogs)

2.3.4.1. Case-study 1: Hokkaido landslide

2.3.4.1.1. Study Area

On 6th September 2018 Hokkiado was impacted by an earthquake of magnitude 6.7 causing more than 6000 landslides. The study area spans over Hokkaido, Japan having the temporal range from 7th July, 2018 to to 4th Nov, 2018 and spatial extent covering latitude range from 42°31'31.658" to 43°0'52.7" and longitude from 141°42'35.899" to 142°14'23.546".

2.3.4.1.2. Dataset Description

The dataset comprises Sentinel-1 acquired imagery. These images are Radiometrically and Terrain Corrected (RTC) images derived from the "Ground Range Detected". The RTC images are stacked for VH and VV polarization channels and time. Additionally, the dataset incorporates topography-based data, specifically Digital Elevation Model (DEM), and derived products utilizing DEM such as slope, aspect, and curvature. Furthermore, a label layer is integrated into the dataset.

The dataset is structured with dimensions of time, y-axis, and x-axis. The resultant dataset is a data cube comprising various data variables. In addition to polarimetric information, the dataset also contains interferometric data, including phase and coherence components. However, these components have not been utilised for analysis. We used the data provided by Vanessa et. al. (source: https://zenodo.org/records/7248056)

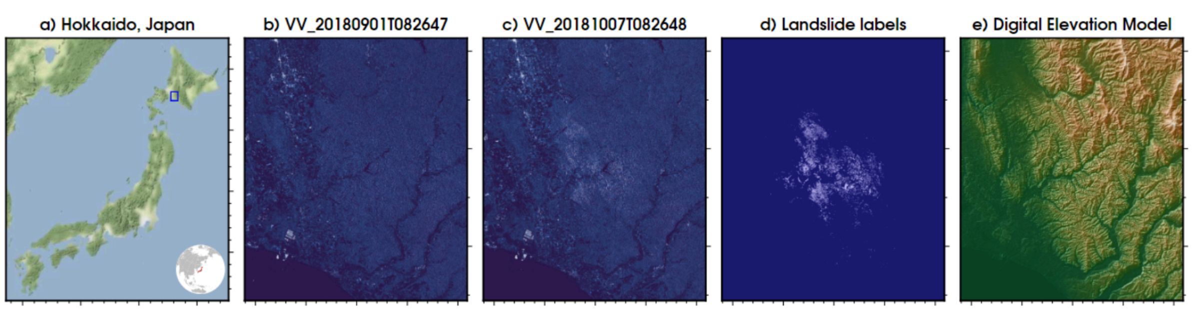


Figure 7 — Study area and components of the generated data cube. (Source: https://arxiv.org/pdf/2211.02869)

2.3.4.2. Case-study 2: Taiwan Landslide

2.3.4.2.1. Study Area

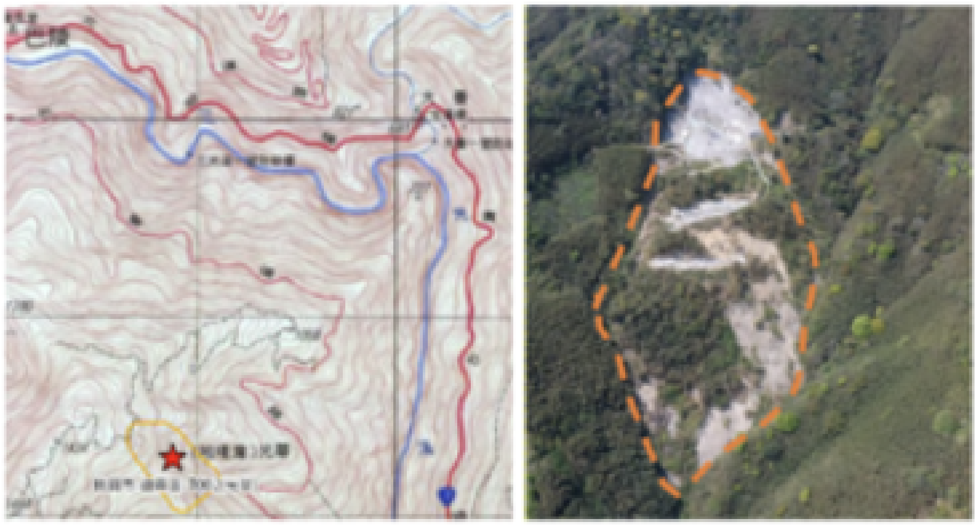


Figure 8 — Taoyuan City-Fuxing district large-scale collapse location and aerial photo. (Courtesy: Agency of Rural Development and Soil and Water Conservation, ARDSWC, MOA, Taiwan)

2.3.4.2.2. Dataset Description

Although we did not use the entire provided data, the dataset comprised of data as described in below table along with their sources.

Table 1 — Available datasets

DATASET NAME	TYPE OF DATA	SOURCE	IF USED FOR MODELING
Surface extensometer Readings	Observational	ARDSWC	x
Electronic water pressure gauge	Observational	ARDSWC	x
Geologic Data	Observational	ARDSWC	x
UAV images	Images	ARDSWC	✓
Rain Gauge measurements	Observational	ARDSWC	x

DATASET NAME	TYPE OF DATA	SOURCE	IF USED FOR MODELING
GNSS measurements	Observational	ARDSWC	x
Satellite images	Images	Copernicus Sentinel Data access	✓
Digital Elevation Model	Images	ARDSWC	✓
Slope Map	Images	Derived	✓
Aspect Map	Images	Derived	✓

2.3.4.3. Implementation

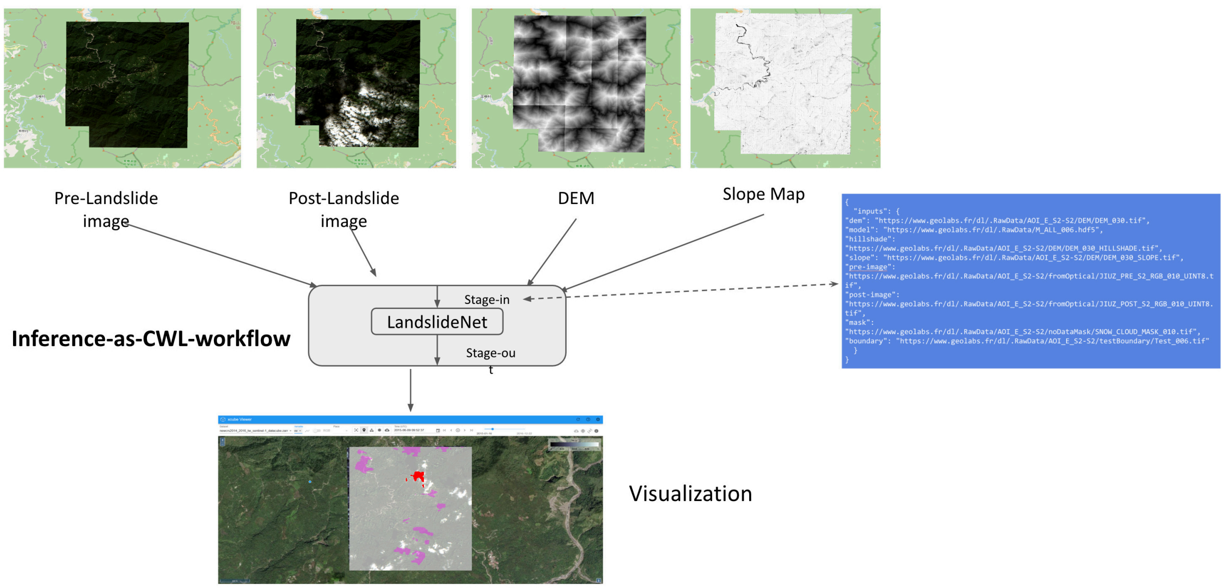


Figure 9 — Illustration of the Landslideflow platform for the Taiwan Landslide case study

2.3.5. ML inference-as-a-CWL Workflow

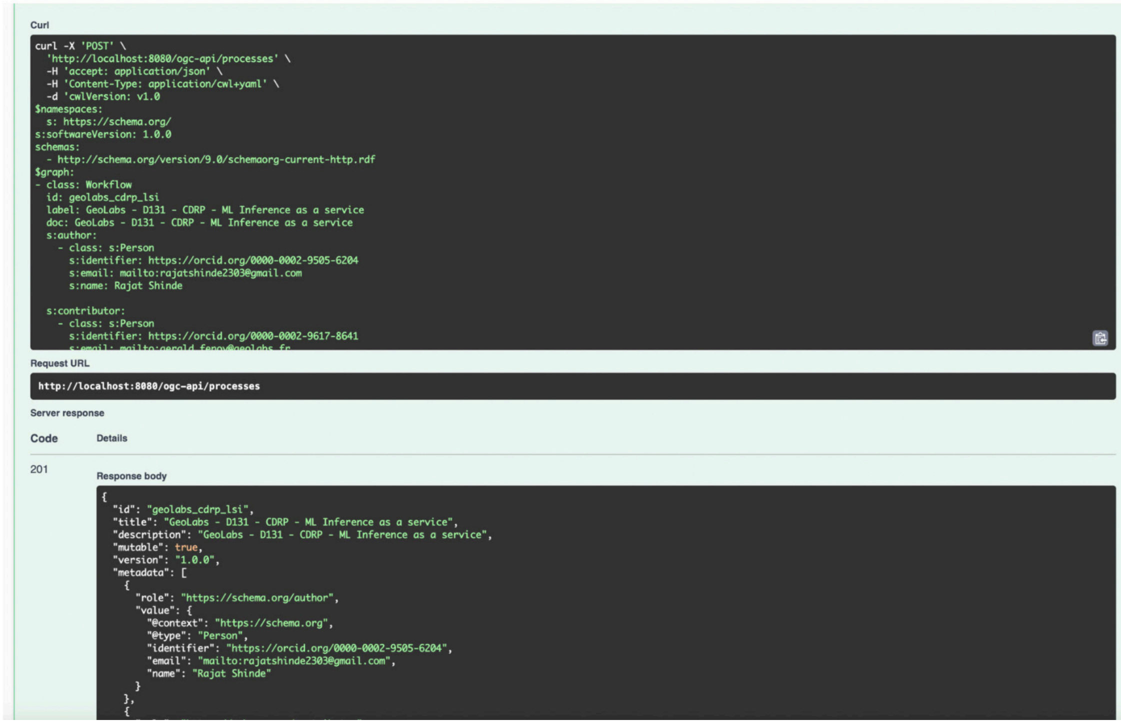


Figure 10 — Deploy inference

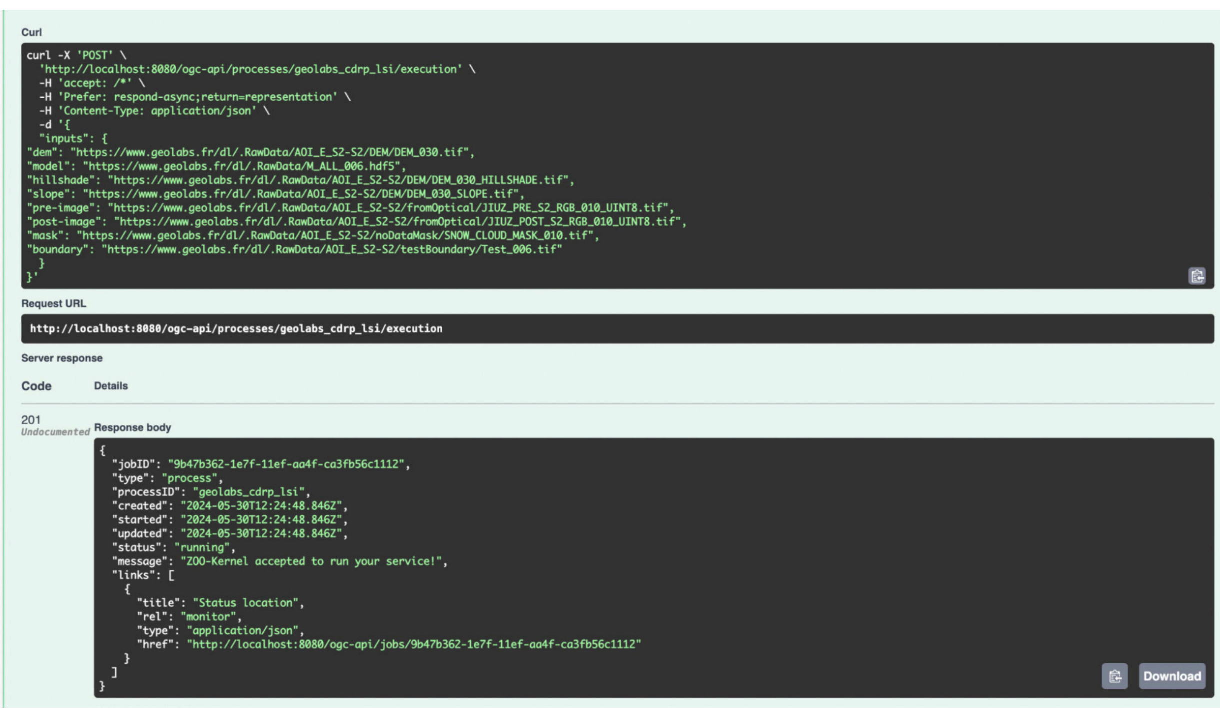


Figure 11 — Run inference

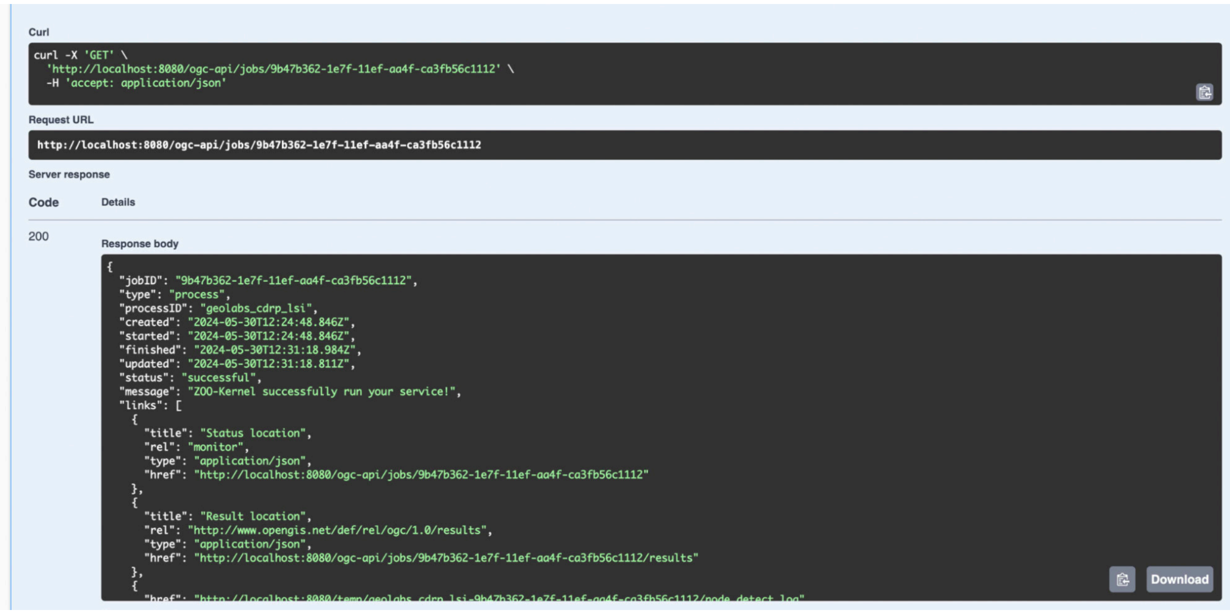


Figure 12 — Access results

2.4. Broad Impact

This proposed prototype is targeted to provide multiple advantages and create broad impact as follows:

- **Standardised implementation**: All the components of the proposed prototype are based on OGC standards and OGC APIs and are plug-and-play in nature, making it a fully automated standardised workflow.
- **Improved disaster response**: The deep learning model will be able to identify landslides quickly and accurately, which will help improve disaster response efforts.
- **Increased efficiency**: The CWL output allows to share the project with a wider audience and reproduce the results, increasing efficiency. Additionally, multiple instances of the proposed prototype can be implemented and deployed in scale for different disasters.
- **Support System for disaster response**: The project will help us to make decisions for responding quickly.
- **Inference from already existing ML model server :** The workflow allows us to make inferences using already developed existing models which are not added yet to the CWL workflow, making the solution versatile, following the best practices for Earth Observation Application Package (Source:https://docs.ogc.org/bp/20-089r1.html)

2.5. Future Directions

1. Enhance landslide detection by transitioning from an optical flow-based detection approach to a data-driven deep learning-based approach.
2. Integrate soil and moisture readings as variables into the deep learning model to improve detection accuracy.
3. Containerize the developed landslide detection platform to ensure reproducibility and facilitate usage within the scientific community.
4. The creation of a formal documentation that outlines the process of translating various types of code into Common Workflow Language (CWL). Additionally, this documentation should address the alternative handling of models in scenarios where the requirement to make the model publicly available online is undesirable, particularly in cases involving proprietary models.
5. Additionally, we would have the capacity to integrate services for converting any (supported) model into ONNX. This would enable the provision of an interface utilizing NETRON for the purpose of previewing the model. Furthermore, an assessment of the integration with TDML would be conducted to determine the extent to which it requires refinement.

2.6. Conclusion

The work provides a standardised implementation for detection of landslides using imagery as source for two example cases, which will in turn help to improve the detection and decrease the detection time. The decreased detection will further impact the overall response time and support early relief and planning the response. The overall process is standardised and adapts CWL, making it available to users, authorities and government task forces, without involving much technical details.

2.7. Acknowledgements

We formally acknowledge the Agency of Rural Development and Soil and Water Conservation, ARDSWC, MOA, Taiwan for providing us with the Taiwan Landslide data. Additionally, we recognize and express our gratitude to the scientific community for making the code and data related to this research publicly accessible.

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