Bernard Hakizimana, 2023, 11:6
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Towards an Intelligent and Adapted Small Scale Landslides Monitoring System in East Africa: Shyira Landslide Monitoring Using Sentinel - 1 SAR Data on Google Earth Engine Cloud Computing

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Abstract- Rainfall-induced landslides pose significant threats in Rwanda's North-Western provinces, contributing to major disasters. This paper addresses technological challenges in disaster response, specifically focusing on soil displacement quantification. The study centers around the Mukungwa River at a local scale, utilizing remote sensing techniques and community science. The methodology employs In SAR polarization and phase measurements, with a specific focus on Shyira Landslide Monitoring using Google Earth Engine Cloud Computing.

A citizen science approach is seamlessly integrated into the study's framework. The landslide detection methodology involves carefully selecting an Area of Interest (AOI) and distinct time periods Before Event (B Event) and After Event (A Event), corresponding to the landslide occurrence. To comprehensively represent ground surface properties pre- and post-landslide, SAR image stacks are generated. These stacks, calculated as temporal medians of SAR data, are constructed for ascending data, descending data, and a combination of both. Landslide detection entails assessing changes in the backscatter coefficient using the standard SAR intensity log ratio approach.

The classification process categorizes changes into three classes: stable, subsidence/decrease, and increase/uplift. To deepen insights, a CSV file is generated for statistical analysis, providing a quantitative examination of landslide event dynamics. The study conducts comprehensive statistical analysis and derives meaningful recommendations. This research significantly contributes to understanding landslide monitoring through a robust methodology that combines remote sensing technologies, community engagement, and statistical analysis. Findings include the impact and damages of the landslide; out of the 5,000 surveyed buildings, 96 were completely destroyed, 231 suffered extensive damage, and 1,150 were moderately affected. The derived recommendations have implications for disaster response strategies and underscore the importance of technological advancements in addressing the challenges posed by landslides.

Keywords- Landslides, Sentinel-1 SAR, Google Earth Engine, Citizen Science.

I. INTRODUCTION

Frequent rainfall-induced landslides and flooding pose formidable challenges in Rwanda and the broader African Great Lakes region, resulting in devastating consequences for communities. The tragic events of May 2023 claimed approximately 130 lives in the Northern and Western provinces of Rwanda, causing substantial damage to infrastructure and homes around the Mukungwa River according to BBC News. (2023, May 3rd). Prodromou's (2023) study highlighted landslides as a significant geohazard, causing human losses and impacting the global economy. To address this critical issue, there is a pressing need for advanced techniques in landslide monitoring with a specific focus on quantifying soil displacement.

Despite efforts to address landslides, existing real-time kinematic sensor solutions encounter challenges related to topologies, costs, and power consumption. This research embarks on planning the deployment of wireless sensor networks using innovative remote sensing technologies, notably InSAR techniques, and incorporates community science in participative mapping involving youth. The primary objective is to revolutionize early landslide detection at a small scale, emphasizing precise soil displacement quantification at the centimeter level.

While initiatives like the National Disaster Management Policy (2012), the National Risk Atlas of Rwanda (2015), and the Volcanoes Community Resilient Project (2023) have been undertaken, the study acknowledges existing gaps and aims to address them. The focus is on leveraging Earth Observation and freely available Copernicus datasets, such as Sentinel-1 and Sentinel-2 satellite images, for systematic landslide monitoring. The proposed methodology seeks to overcome limitations associated with current in situ measurements.

Aligned with the Nationally Determined Contributions to climate change mitigation and adaptation (Rwanda, NDC Updated, 2020), this research represents an innovative approach that integrates artificial intelligence and machine learning. These technologies are positioned at the forefront of adapted solutions being developed and deployed globally. The study emphasizes configuring wireless sensor networks tailored to the specific nature of landslides, effectively mitigating power consumption and cost factors in deployed solutions. Given the vulnerability of Rwanda to climate change impacts, especially in hilly or mountainous areas with small plot cultivation, the study addresses the heightened risks of increased runoff and landslides. The research aims to significantly contribute to enhancing the country's resilience to these climate-related challenges.
Research Objectives:

1. To quantify the precise displacement of rainfall-induced landslides in the Western and Northern provinces of Rwanda within the African Great Lakes region.
2. Conduct a comprehensive study of the specified area utilizing advanced remote sensing techniques, specifically In SAR, facilitated by the Google Earth Engine cloud computing platform.
3. To pioneer an innovative community science approach aimed at engaging youth participation in landslide monitoring efforts.

II. LITERATURE REVIEW

Landslides in the Africa Great Lakes region, particularly in Rwanda, Eastern DRC, and Western Uganda, have significant socio-economic implications and pose challenges for existing early warning systems (MIDIMAR, 2013; MINEMA Contingency Plan, 2018). While initiatives like the National Disaster Management Policy (2012) and the National Risk Atlas of Rwanda (2015) have been introduced, they often lack effectiveness at the village level, relying on national systems without contextualized design and network setup (National Risk Atlas, 2015).

In addressing the deficiencies of current systems, recent advancements in wireless network designs for landslide response have shown progress but still fall short in positioning as the primary indicator of soil displacement or stability (De, D., Mukherjee, et al., 2020). Specifically focusing on Rwanda as a case study, policy efforts and risk atlases have been implemented, but there is a need for adapted technological solutions at the local level to respond efficiently.

The Africa Great Lakes region, experiencing an increase in casualties, especially in the Western province of Rwanda, Eastern DRC, and Western Uganda, calls for tailored technological solutions (Muhire, KT Press, 2023). Current early warning systems lack responsiveness to specific village-level needs and have not been calibrated based on vegetation and terrain characteristics (Syafiq Bin Samsuddin, 2013). The existing topologies fail to address the sophisticated nature of disasters, creating a gap in measuring the velocity and timing of landslides (García-Hernando, et al., 2008).

Moreover, current sensors primarily quantify parameters other than soil displacement, highlighting the need for evaluating and innovating machine learning models for a more efficient disaster response (Prodromou et al., 2023). The potential of Google Earth Engine (GEE) as a platform for rapid mapping and integrating satellite data for landslide monitoring is recognized in the literature (Prodromou et al., 2023).

Several studies have demonstrated the effectiveness of SAR data from Sentinel-1 on the Google Earth Engine platform. Powell et al. (2023) integrated passive and active satellite data for rapid landslide mapping, utilizing GRD Sentinel-1 and multispectral Sentinel-2 data. Meena et al. (2023) explored SAR data for automatic landslide mapping using deep learning segmentation models. Li et al. (2023) applied the SBAS time series strategy to monitor landslide movement, correlating it with precipitation. Chaturvedi (2022) evaluated Sentinel-1 SAR images for rapid landslide detection.

Mayuga et al. (2022) mapped the 2018 Naga landslide area in the Philippines using Sentinel-1 data. Hand werger et al. (2022) used Google Earth Engine for generating landslide density heat maps, showcasing effective results.

1. The Study Area

In Studies conducted across Rwanda, the relationship between landslide factors and inventory map was calculated using the Spatial Multi-Criteria Evaluation (Jean Baptiste et al, 2018). The results revealed that susceptibility is spatially distributed countrywide with 42.3% of the region classified from moderate to very high susceptibility, and this is inhabited by 49.3% of the total population. In addition, Provinces with high to very high susceptibility are West, North and South (40.4%, 22.8% and 21.5%, respectively).

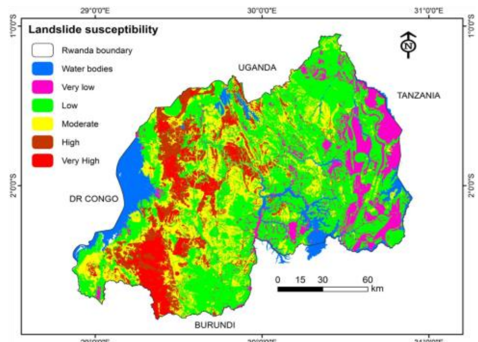

Figure.1 Landslide susceptibility- Source: Jean Baptiste et al (2018)

The study area exhibits a profound contextual connection to the Volcano region catchment, situated within the expansive Congo and Nile basins. This catchment, characterized by its north-to-south orientation, occupies the western expanse of Rwanda, nestled around the Congo Nile ridge. Notably, several gullies, including Susa, Rwebeya, Muhe, and Cyuve, originate from the majestic Volcano Mountains, converging as they traverse the landscape.

The intricate network of these gullies converges into the Mukungwa River, a vital watercourse that ultimately feeds into the Nyabarongo River. The convergence point, situated within the Vunga corridor, experiences a significant influx of water volume, establishing a dynamic and interconnected hydrological system. For the purpose of this study, exclusive focus is directed towards the Mukungwa sub-catchment, allowing for a detailed examination of its unique characteristics and hydrological dynamics. The interconnectedness of these catchments, coupled with their susceptibility to the merging water bodies in the Vunga corridor, underscores the importance of understanding their hydrological intricacies and environmental influences.

The Study Area is located between long and Lat ["29° 32.10'E","2° 16.22'S”] and ["29° 39.80'E","2° 26.88'S"]

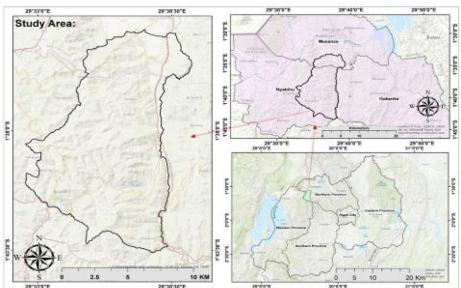

Figure.2 Study Area Map

III. MATERIALS AND METHOD

1. Citizen Science Approach

Citizen science serves as a transformative methodology, harnessing the collective power of public volunteers to actively engage in data collection and classification, thereby augmenting the scientific community's capabilities (Kullenberg et al., 2016). This collaborative approach not only empowers individuals to contribute meaningfully to scientific endeavors but also fosters a sense of shared responsibility in advancing knowledge.

Participation in citizen science projects extends beyond data collection, acting as a powerful educational tool that demystifies the scientific process for the public. Through hands-on involvement, volunteers gain valuable insights into research methodologies and develop a deeper understanding of various scientific subjects. This dual-purpose approach not only enhances scientific literacy but also cultivates a broader awareness of diverse topics.

The impact of citizen science reverberates through its dual role as both a knowledge-building engine and an educational catalyst. By embracing this methodology, the scientific community not only benefits from expanded data resources but also plays a pivotal role in nurturing a scientifically informed and engaged citizenry. This symbiotic relationship highlights the enduring value of citizen science in fostering collaboration, knowledge dissemination, and public empowerment.

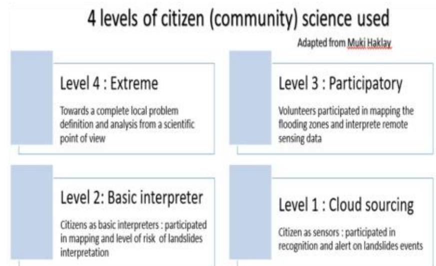

Figure.3 Source: Haklay, M. (2012)

2. Google Earth Engine Cloud Computing Platform

The adoption of the Google Earth Engine (GEE) as a cloud-based computing platform stems from its increasing popularity in big data and time series analyses, as evidenced by a comprehensive systematic review (Qiang Zhao et al., 2021). Also, a notable application in the aftermath of the 2008 Wenchuan earthquake by Yang et al. (2020), evaluating co-seismic landslide recovery using Landsat-derived vegetation data, further underscored the effectiveness of GEE. The platform was chosen for its user-friendly interface and efficient handling of extensive datasets.

Dongxin's (2020) proposal introduces an intelligent landslide monitoring and early warning system based on a micro services architecture. Leveraging the Spring Boot framework and My Batis for database integration, the system offers seamless data management services, emphasizing functionalities such as data manipulation and monitoring. This approach highlights the significance of intelligent monitoring and early warning systems in landslide management.

Addressing the need for comprehensive monitoring systems in urban areas, Svalova (2015) delves into the intricacies of deep block landslides in Moscow. The study analyzes the mechanisms and engineering geological conditions contributing to landslides, offering insights into the preparation process and the overall dynamics of deformations. The findings underscore the importance of monitoring systems in ensuring the stable functioning of city infrastructure. Canavesi et al.'s (2020) work employs a random forest model to evaluate landslide susceptibility, utilizing a set of 12 independent variables. The inclusion of both categorical (e.g., land use, soil type) and numerical variables (e.g., slope gradient, elevation) showcases a comprehensive approach to landslide assessment. This methodology emphasizes the critical role of data selection and analysis methods in addressing complex issues such as landslides.

The Google Earth Cloud Computing Platform has demonstrated its prowess in gathering, integrating, processing, analyzing, distributing, and visualizing data through the Google Earth API and Google Earth Engine. Its quick and reusable cloud computing capabilities provide enhanced methods for emergency assessments, ongoing monitoring, and the development of efficient early warning systems. This synthesis emphasizes the multifaceted benefits of leveraging advanced technologies, such as Google Earth Engine and intelligent monitoring systems, in addressing landslide-related challenges. The increasing role of cloud computing platforms is pivotal for quick, scalable, and impactful solutions in emergency situations and ongoing environmental monitoring.

IV. METHOD

1. Google Earth Engine (Gee) Cloud Computing Platform

The primary objectives of leveraging the Google Earth Engine (GEE) cloud computing platform revolve around furnishing accessible tools within GEE. These tools empower users to harness freely available Synthetic Aperture Radar (SAR) data for the swift detection of areas likely to have undergone landslides. The essence lies in facilitating a rapid and efficient process through open-access capabilities.

This methodology is intricately woven into the fabric of Google Earth Engine, employing the JavaScript application programming interface (API). This interface serves as a versatile conduit for coding, mapping/visualization, documentation, and beyond. Notably, the flexibility of this platform allows for the seamless export of products, enabling offline analyses with ease which Handwerger et al. (2022) demonstrated.

2. Landslide Detection Approach

The study's methodology for landslide detection involved the careful selection of an area of Interest (AOI) and distinct time periods, namely Before Event (B Event) and After Event (A Event), corresponding to the event of interest (EOI), which, in this case, is the landslide occurrence.

To refine the dataset, a filter was applied, excluding all pixels with values $\leq -30\,\text{dB}$, aligning with recommendations from the GEE S1 Data Catalog. This step was crucial to mitigate the impact of poor-quality data and reduce noise.

For a comprehensive representation of pre- and post-event ground surface properties, SAR image stacks were generated. These stacks, calculated as temporal medians of SAR data before and after the event, were constructed separately for ascending data, descending data, and a combination of ascending and descending data. The combined data stack was derived as the mean of the ascending and descending stacks.

Landslide detection was achieved by assessing changes in the backscatter coefficient, employing the standard SAR intensity log ratio approach, as demonstrated by Jung and Yun (2020). The classification process involved categorizing changes between pre-event and post-event conditions into three classes: stable, subsidence/decrease, and increase/uplift.

To gain deeper insights, a CSV file was generated for statistical analysis. This allowed for a more thorough understanding of the landslide event dynamics through quantitative examination of the data.

3. Data

Sentinel 1 SAR Data.

The Sentinel-1 mission delivers timely and comprehensive data leveraging a stateof-the-art dual-polarization C-band Synthetic Aperture Radar (SAR) instrument. This dataset encompasses Ground

Range Detected (GRD) scenes characterized by diverse resolutions, band combinations, and instrument modes. Each scene is equipped with one or two polarization bands, complemented by an additional 'angle' band that furnishes essential incidence angle information.

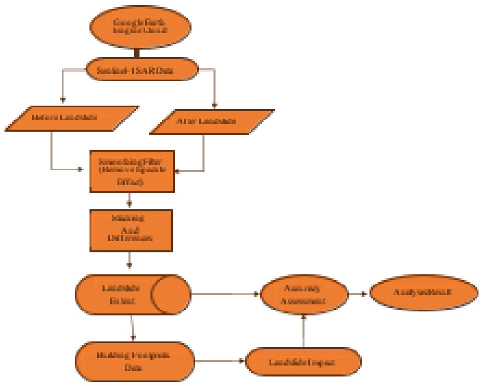

Figure.4 Flow chart that shows the from Google earth engine cloud computing to Analysis and results

4. Impact of the Landslide

The Shyira landslide has had profound and devastating impacts on the affected community. Tragically, according to BBC News. (2023, May 3rd), it resulted in the loss of 130 lives, inflicted injuries on many, and forced the displacement of numerous individuals. The repercussions extend to agriculture, with vast agricultural lands bearing the brunt of the landslide, leading to the destruction of crops and farmland. This, in turn, is expected to significantly hinder food production, contributing to potential food shortages.

The aftermath is marked by the arduous task of rebuilding, as the community grapples with the daunting challenge of reconstructing homes and livelihoods. The physical landscape itself has undergone transformation, with visible deformations in the land surface, indicating the substantial geological impact of the landslide. Beyond the tangible consequences, there are profound effects on both the physical and psychological well-being of the affected population.

V. ACCURACY ASSESSMENT

In the evaluation aimed at validating the correlation between Google Earth Engine Cloud computation and the accuracy of Sentinel SAR data for landslide monitoring, a robust relationship was observed between the computed and actual results. Out of the 5,000 surveyed buildings for accuracy assessment, 96 were found to be completely destroyed, 231 suffered extensive damage, and 1,150 were in a moderately affected state. These findings strongly align with areas indicating a decrease or subsidence, as highlighted by the computation. It is crucial to emphasize the significance of this correlation, enhancing the reliability of Google Earth Engine Cloud computation for effective landslide monitoring.

1. Citizen Science Approach and Impact Assessment

The utilization of the Citizen Science approach played a pivotal role in assessing accuracy. Twenty members of the community were trained in the Citizen Science data collection approach, emphasizing integration and how to identify landslide occurrences. They were equipped with tools developed to alert other community members about potential landslide areas. This approach not only fostered community understanding of landslide monitoring but also empowered them with the knowledge and tools to report landslide incidents effectively.

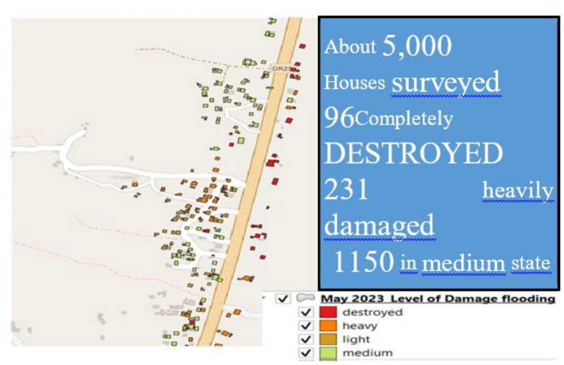

Figure.5 Showing the Field Assessment Validation

The Citizen Science initiative not only contributed to accuracy assessment but also had tangible impacts on community engagement and preparedness. By involving community members directly in the monitoring process, a sense of shared responsibility was fostered. This proactive engagement empowered the community to take preventive measures and respond swiftly to potential landslide threats.

The impact of the Citizen Science approach extends beyond the quantitative assessment, emphasizing its role in building resilience and fostering a community-driven approach to disaster response.

VI. RESULT

In the aftermath of the landslide, the post-landslide map is classified into three distinct categories, providing a comprehensive overview of the dynamic changes in the affected terrain:

1. Stable Areas (Blue Colors)
Designates regions that have remained unchanged or exhibited remarkable stability following the landslide event. The blue hues on the map delineate areas where the topography and ground characteristics have sustained minimal alteration.

2. Uplift/Increase Areas
Highlighting zones characterized by uplift or discernible increase, often originating from regions that experienced subsidence during the landslide occurrence. These areas, visually represented on the map, signify notable alterations in the landscape marked by elevation changes or heightened ground features.

3. Decrease/Subsidence Areas
Clearly identifies regions manifesting a decrease or subsidence in the aftermath of the landslide. Displayed prominently on the map, these areas depict ground-level changes, showcasing the impact of the landslide event on the local terrain.

This comprehensive classification provides a visual narrative of the post-landslide landscape, aiding in a nuanced understanding of the varied responses of different areas to the geological event.

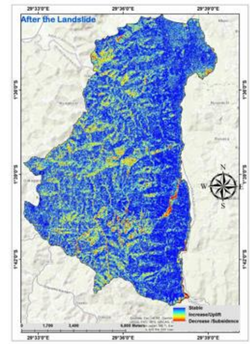

Figure.6 After landslide Map

VII. ANALYSIS

The study leveraged a CSV file containing 885,632 points generated within the study area, using Python script code. This dataset was utilized to create a pair plot, effectively visualizing the before-event and after-event data.

The pair plot serves as a powerful analytical tool, providing a comprehensive overview of the relationships between different variables. In study, it visually represents the differences between conditions before and after the landslide event. Each point in the plot corresponds to a specific observation, allowing for a side-by side comparison of various parameters.

Through the pair plot analysis, the study aimed to uncover patterns, trends, and potential correlations within the dataset. The pair plot served as a valuable exploratory tool, facilitating a detailed examination of the dataset and offering insights into the nature and extent of changes associated with the landslide event.

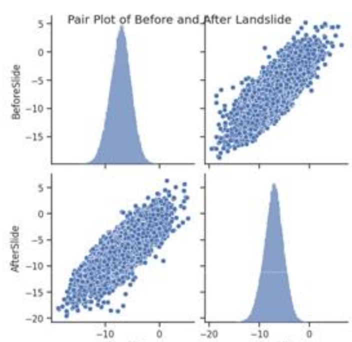

Figure.7 Pair Plot before the landslide and after

The scatter plot, an essential component of the pair plot analysis, was enriched by incorporating regression lines, enhancing the visualization of relationships between variables before and after the landslide event.

The scatter plot with regression lines serves as a dynamic representation of the correlation between paired observations. By fitting regression lines to the scatterplots of before and after-event data, the study aimed to capture the overall trend and direction of the relationship between variables. The regression lines provide a statistical depiction of the association, offering insights into the potential linear patterns in the data.

This approach enables a more nuanced interpretation of the dataset. Not only observe the general changes illustrated by the scatter plot but also discern the degree and direction of correlation between specific variables. The regression lines contribute to a more comprehensive understanding of how changes in one variable may be linked to changes in another.

The inclusion of regression lines in the scatter plot enhances the analytical depth of the visual representation. It allows for a more nuanced interpretation of the dataset, facilitating a deeper exploration of the relationships and dynamics between variables before and after the landslide event.

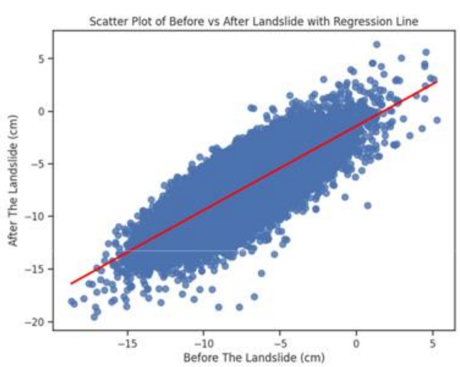

Figure.8 Pair Plot before the landslide and after

The study employed the Empirical Cumulative Distribution Function (ECDF) to analyze the statistical distribution of data before and after a landslide event. This technique provides a visual representation of cumulative probabilities for each condition, allowing for a comparative assessment of their distributions. By examining the ECDF plots, an insight into the cumulative behavior of variables, enhancing the understanding of how the landslide influenced the dataset's overall distribution could be accessed. This approach contributes to a comprehensive exploration of the dataset's statistical characteristics in the context of the landslide event.

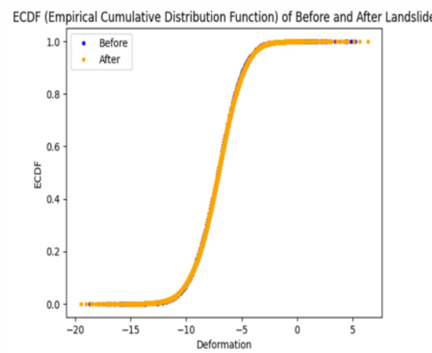

Figure.9 Pair Plot before the landslide and after

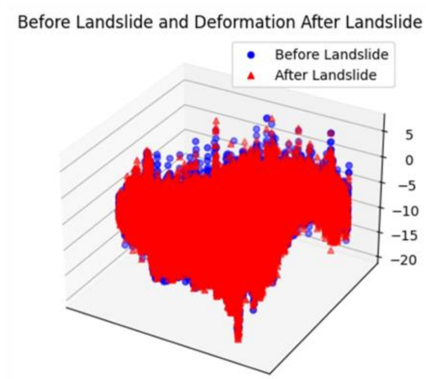

Figure.10 Pair Plot before the landslide and after

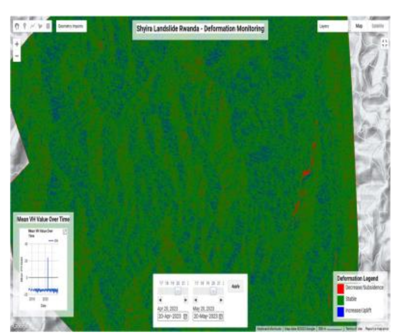

Figure.11 Google Earth Engine Cloud Computing - (Source: Author

VIII. CONCLUSION

In conclusion, our study establishes a robust correlation between Google Earth Engine Cloud computation and the accuracy of Sentinel SAR data for landslide monitoring. The assessment of 5,000 surveyed buildings underscores the effectiveness of this approach, revealing clear indications of areas experiencing a decrease or subsidence. Google Earth Engine's capabilities in processing and analyzing extensive datasets contribute to its reliability in assessing landslide-related changes. The integration of Citizen Science proves crucial, enhancing accuracy and community involvement. The training of community members in data collection and the provision of tools for identifying and reporting landslide incidents have proven effective. This community engagement is essential for creating a more comprehensive and real-time understanding of landslide occurrences.

The successful integration of Google Earth Engine, Sentinel SAR data, and Citizen Science sets a precedent for future landslide monitoring initiatives. This holistic approach, combining advanced technology and community engagement, can serve as a model for similar environmental monitoring projects. The synergy of technology and community-driven efforts demonstrates a potent strategy for accurate and efficient landslide monitoring, with broader implications for the future of environmental monitoring and community engagement initiatives.

Recommendations

1. Enhancement of Data Resolution

Investing in higher spatial and temporal resolution data is essential to significantly improve the accuracy of landslide detection and monitoring.

2. Optimizing Google Earth Engine (GEE)

While GEE provides powerful capabilities for large-scale data analysis, further optimization is recommended to handle increased processing loads, address user limits, and overcome computational memory constraints.

Integration of Multi-sensor and Multisensory Data: Enhance the accuracy and comprehensiveness of landslide monitoring by integrating diverse sensor data, including rainfall patterns, geological information, soil composition, Vegetation Index, slope characteristics, and elevation data.

3. Machine Learning Integration

Leverage machine learning platforms to process and analyze integrated data, contributing to the development of an effective early warning system for landslide-prone areas.

4. Consideration of Human Factors

Recognize the role of human activities in landslide occurrences by incorporating socio-economic and human behavior data to better understand and mitigate the impact of human activities on landslide risk.

5. Comprehensive Early Warning System

Advocate for the development of a comprehensive early warning system that not only focuses on landslide detection but also considers factors such as human activities, enabling timely and effective evacuation strategies.

6. Community Engagement

Emphasize the importance of community engagement in the early warning system, educating and involving local communities in understanding risks, interpreting warnings, and actively participating in evacuation procedures.

7. Holistic Approach

Stress the need for a holistic approach that considers both natural and human-induced factors in landslide monitoring and management. Collaboration between environmental scientists, data scientists, local communities, and policymakers is essential for a comprehensive and effective strategy.

8. Continuous Monitoring and Research

Encourage ongoing research and monitoring efforts to adapt to evolving technologies and address emerging challenges. Staying abreast of advancements in remote sensing, data analytics, and machine learning is crucial to continually improve landslide monitoring systems.

Implementing these recommendations will advance the effectiveness of landslide monitoring, early warning systems, and community resilience, ultimately minimizing the impact of landslides and saving lives.

REFERENCES

1. Bai, D., Tang, J., Lu, G., Zhu, Z., Liu, T., & Fang, J. (2020). The design and application of landslide monitoring and early warning system based on micro service architecture. Geomatics, Natural Hazards and Risk, 11(1), 928-948. DOI:10.1080/19475705.2020.1766580
2. BBC News. (2023, May 3rd). Rwanda landslide: Dozens killed and homes destroyed. BBC News. https://www.bbc.com/news/world-africa-65469374
3. Canavesi, V., Segoni, S., Rosi, A., Xiao, T., Nery, T. D., Catani, F., & Casagli, N. (2020, June 5). Different Approaches to Use Morphometric Attributes in Landslide Susceptibility Mapping Based on Meso-Scale Spatial Units: A Case Study in Rio de Janeiro (Brazil). Remote Sensing; Multidisciplinary Digital Publishing Institute. https:// doi.org/ 10.3390/ rs12111826
4. Chaturvedi, S. K. (2022, September 1). Landslide Assessment Using Sentinel-I SAR-C Interferometry Technique. Nature Environment and Pollution Technology. https://doi.org/10.46488/nept.2022.v21i03.025
5. Dongxin Bai, Jingtian Tang, Guangyin Lu, Ziqiang Zhu, Taoying Liu & Ji Fang. (2020). The design and application of landslide monitoring and early warning system based on micro service architecture. Geomatics, Natural Hazards and Risk, 11(1), 928-948. DOI: 10.1080/19475705.2020.1766580
6. Dou, J., Bui, D. T., Yunus, A. P., Jia, K., Song, X., Revhaug, I., Xia, H., & Zhu, Z. (2015, July 27). Optimization of Causative Factors for Landslide Susceptibility Evaluation Using Remote Sensing and GIS Data in Parts of Niigata, Japan. PLOS ONE; Public Library of Science. https://doi.org/10.1371/journal.pone.0133262
7. EGU General Assembly 2023, Vienna, Austria, 23–28 Apr2023,EGU2312618,https://doi.org/10.5194/egusphere-egu23-12618, 2023.
8. European Union/ESA/Copernicus. (August 2023). Sentinel-1 SAR GRD: C-band Synthetic Aperture Radar Ground Range Detected, log scaling. Google EarthEngine.https://developers.google.com/earthengine/datasets/catalog/COPERNICUS_S1_GRD#band
9. Funk, Chris, Pete Peterson, Martin Lands feld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, James Rowland, Laura Harrison, Andrew Hoell & Joel Michaelsen. "The climate hazards infrared precipitation with stations-a new environmental record for monitoring extremes". Scientific Data 2, 150066. doi:10.1038/sdata.2015.66 2015.
10. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R.: Google Earth Engine: Planetary-scale geospatial analysis for everyone, RemoteSens.Environ.,202,1827,https://doi.org/10.1016/j.rse.2017.06.031, 2017.
11. Haklay, M. (2012). Citizen Science and Volunteered Geographic Information: Overview and Typology of Participation.CrowdsourcingGeographicKnowledge,105122.DOI:10.1371/journal.pone.0147152
12. Hand werger, A. L., Huang, M. H., Jones, S. Y., Amatya, P., Kerner, H., & Kirschbaum, D. (2022, March 9). Generating landslide density heatmaps for rapid detection using open-access satellite radar data in Google Earth Engine. Natural Hazards and Earth System Sciences; Copernicus Publications. https://doi.org/10.5194/nhess-22-753-2022
13. Kullen berg, el al 14 (January 2016). "What Is Citizen Science? – A Sciento metric Meta-Analysis". PLOS ONE.11(1):e0147152.Bibcode:2016PLoSO..1147152K.doi:10.1371/journal.pone.0147152. ISSN 1932-6203.
14. Li, B., Jiang, W., Li, Y., Luo, Y., Jiao, Q., & Zhang, Q. (2023, September 1). Monitoring and analysis of Woda landslide (China) using InSAR and Sentinel-1 data. Advances in Space Research; Elsevier BV.https://doi.org/10.1016/j.asr.2023.04.055

15. Mayuga, P. J., Tiongson, S. F., Abao, J. J., Mendoza, J. M., Pernez, G. A., & Ramirez, R. (2022). Landslide Area Mapping Using Synthetic Aperture Radar (SAR) Data: the Case of The 2018 Naga Landslide. IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia. DOI:10.1109/IGARSS46834.2022.9884207
16. Meena, S. R., Nava, L., Bhuyan, K., Monserrat, O., & Catani, F. (2023, May 15). Sentinel-1 and Deep Learning for rapid landslide mapping. https://doi.org/10.5194/egusphere-egu23-16249
17. Prodromou, M., Theocharidis, C., Fotiou, K., Argyriou, A.,Polydorou, T., Hadjimitsis, D., & Tzouvaras, M. (2023). Fusion of Sentinel-1 and Sentinel-2 satellite imagery to rapidly detect landslides through Google Earth Engine. EGU General Assembly 2023. DOI: 10.5194/egusphere-egu23-12618
18. P. J. Mayuga, S. F. Tiongson, J. J. Abao, J. M. Mendoza, G.A.Pernez and R. Ramirez, "Landslide Area Mapping Using Synthetic Aperture Radar (SAR) Data: the Case of The 2018 Naga Landslide," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia, 2022, pp. 7883-7886,doi:10.1109/IGARSS46834.2022.9884207.
19. Qiang Zhao et al , 2021 , Progress and Trends in the Application of Google Earth and Google Earth Engine Remote Sens. 2021, 13(18), 3778;https://doi.org/10.3390/rs13183778
20. Svalova, V. (2015, January 1). Modeling and monitoring for landslide processes. Research Gate.https://www.researchgate.net/publication/298091306_Modeling_and_monitoring_for_landslide_processes
21. Yang, W., Qi, W., & Fang, J. (2020, December 29). Using Google Earth Engine to monitor co-seismic landslide recovery after the 2008 Wenchuan earthquake. https://doi.org/10.5194/esurf-2020-106