Proceedings of ISERME 2025
19-20 September 2025
https://doi.org/10.31705/ISERME.2025.10

Post-Landslide Vegetation Recovery Assessment in Dumbarawatta, Sri Lanka Using S2DR3 Model - Based Downscaling of Sentinel-2 Imagery

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Abstract

Landslides are among the most destructive natural hazards, causing significant damage to infrastructure, ecosystems, and human settlements. Monitoring vegetation recovery after such events is critical for ecological restoration and effective hazard management. Given the challenges of conducting field surveys and UAV-based monitoring in inaccessible terrain, remote sensing approaches can be an efficient alternative. Sentinel-2 optical imagery, with a native spatial resolution of 10 meters and minimal cloud interference, provides a valuable resource for monitoring vegetation dynamics. However, to obtain more detailed and accurate spatial information, alternative approaches such as downscaling are required. In this study, the Sentinel-2 Deep Resolution 3.0 model (S2DR3) is used to downscale imagery from 10m to 1m resolution. Leveraging this enhanced resolution, the Normalized Difference Vegetation Index (NDVI) is applied to monitor vegetation disturbance and regrowth over time following a rainfall-induced landslide that occurred on 4 June 2021 in Dumbarawatta, Sri Lanka. The analysis is conducted using the Google Earth Engine platform, offering a scalable and cost-effective methodology for post-landslide environmental monitoring. This approach supports informed decision-making in landscape recovery and land management, particularly in complex and mountainous terrains. The S2DR3 downscaled product detected up to 5% more vegetation cover than Sentinel-2, enhancing accuracy in post-landslide recovery assessments.

Keywords: Google Earth Engine, Land Slide Recovery, NDVI, S2DR3 Model

1 Introduction

Landslides are among the most frequent and devastating natural hazards globally, resulting in significant socio-economic losses, ecological damage, and human casualties. They are typically triggered by intense or prolonged rainfall, seismic activity, or anthropogenic interventions [1]. On 4th June 2021, a major landslide occurred in Dumbarawatta, Dumbara Grama Niladhari Division in the Ayagama Divisional Secretariat Division, Sri Lanka, around 6:30 a.m. This event was triggered by over 300 mm of cumulative rainfall over 48 hours, illustrating the vulnerability of steep, saturated slopes in the region.

Globally, the assessment of post-landslide vegetation recovery is critical for understanding the long-term stability of the affected area and the success of natural or artificial restoration interventions [2]. While field measurements and UAV-based monitoring have been widely used, they often prove infeasible in remote or inaccessible terrains. Recent advances in satellite remote sensing and cloud-based platforms such as Google Earth Engine (GEE) have enabled researchers to analyze vegetation recovery using large-scale, high-temporal-resolution satellite datasets [3].

Among various remote sensing indices, the Normalized Difference Vegetation Index (NDVI) is extensively used to assess vegetation density, health, and regrowth patterns [4]. NDVI values derived from Sentinel-2 imagery have shown promising results in identifying both the extent of landslide damage and subsequent vegetative recovery [5]. However, the 10 m spatial resolution of Sentinel-2 may be insufficient for detailed recovery assessments in small or heterogeneous landscapes.

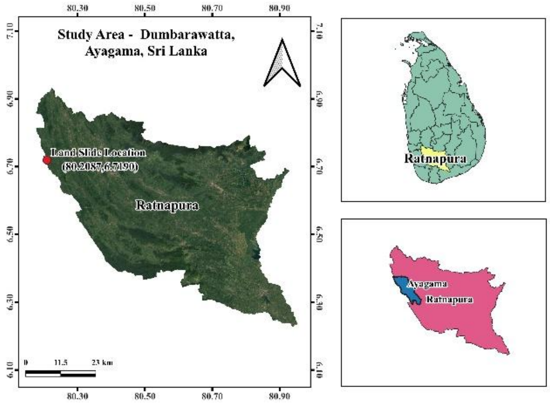
To address this limitation, this study employs the Sentinel 2 Deep Resolution 3. 0 (S2DR3) model , a significant advancement in super-resolution modeling specifically designed to upscale all 12 spectral bands of Sentinel-2 Level-2A imagery from their native 10 m, 20 m, and 60 m spatial resolutions to a uniform 1 m resolution [6]. Unlike earlier methods, which often compromised spectral integrity, S2DR3 is optimized to preserve subtle spectral variations across bands particularly important for detecting changes in vegetation and soil conditions. The model is capable of accurately reconstructing fine spatial features down to approximately 3 meters, greatly enhancing the clarity and reliability of vegetation assessments in fragmented or steep terrains [6]. This enhancement allows for finer-scale analysis of post-landslide vegetation dynamics, providing unprecedented insight into micro-scale regrowth patterns that are crucial for understanding the effectiveness of natural regeneration and slope stabilization interventions.

Previous studies have demonstrated the utility of NDVI for tracking landslide recovery over multi-year timescales [7] but few have leveraged deep learning-enhanced satellite imagery for high-resolution vegetation monitoring. This research fills that gap by integrating NDVI analysis with deep super-resolution techniques in a cloud-computing environment to evaluate vegetation recovery in Dumbarawatta from 2021 to 2024. This combination of tools and datasets offers a novel and scalable approach for post-disaster environmental monitoring in Sri Lanka and beyond.

2 Methodology

2.1 Study Area

Study area located in the Dumbara Grama Niladhari Division of the Ayagama Divisional Secretariat in the Ratnapura District of Sri Lanka, the selected area features steep slopes, thick vegetation, and frequent rainfall conditions commonly associated with landslide susceptibility. Figure 1 illustrates the study area.

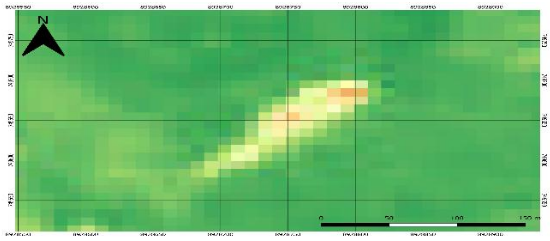


(a)

Figure 1: Study Area- Dumbarawatta, Sri Lanka.

2.2 Data Acquisition and Preprocessing

Satellite imagery obtained from the Copernicus Open Access Hub, chosen for its low cloud coverage, was enhanced using the S2DR3 super-resolution model to increase the spatial resolution. The resulting high-resolution GeoTIFF files were subsequently uploaded to Google Earth Engine, where they were clipped spatially and prepared for time-series analysis of the study region.



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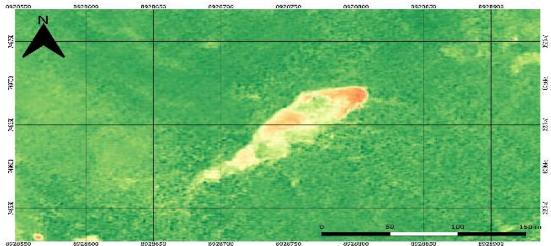


(b)

Figure 2: (a) Raw Sentinel-2A Scene (NDVI Pseudo Color). (b) Downscaled Image Using S2DR3 Model.

2.3 NDVI Based Classification

Normalized Difference Vegetation Index (NDVI) was applied to the downscaled product using following formula.

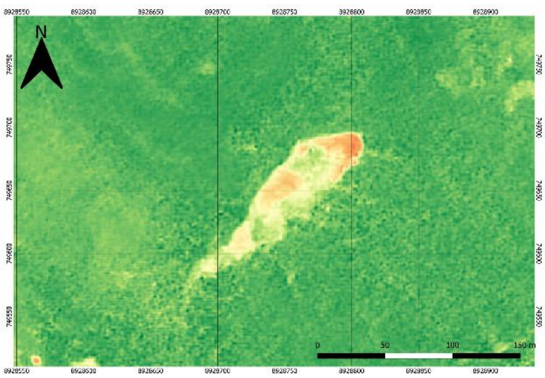
$$NDVI = \frac{B8-B4}{B8+B4} \tag{1}$$

Pre and post event NDVI values were compared to identify changes in vegetative cover. Areas showing significant Lower NDVI were considered landslide affected zones.

A Random Forest classifier was applied to classify land cover into forest, landslide, and other categories using the NDVI. Training samples were manually delineated, and classification accuracy was assessed through a confusion matrix as shown in the Table 1.

Table 1: Classification accuracy of Images.

Date of Image	Overall Accuracy	Kappa Coefficient
2021/07/29	0.921875	0.880104
2021/12/21	0.892307	0.831730
2022/08/18	0.915254	0.870840
2022/12/21	0.912280	0.864672
2023/08/03	0.838709	0.744855
2023/12/21	0.921877	0.881261
2024/08/27	0.790322	0.678371
2024/12/30	0.870967	0.801758



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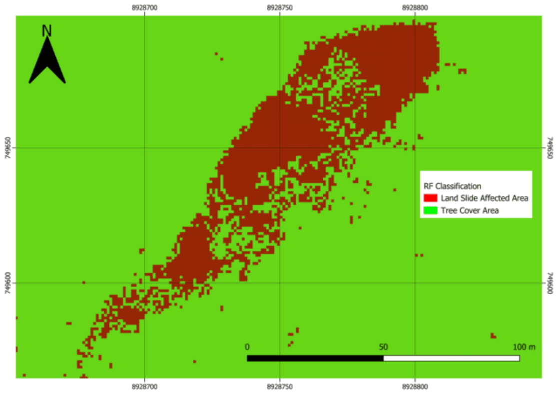


(b)

Figure 3: (a) NDVI Image of downscaled image. (b) Classified Image after Random Forest Classifier.

2.4 Analysis of Land Slide Area

Sentinel-2 imagery Downscaled product of Sentinel 2 imagery from 2021 to 2024 was analyzed with 2 cloud free scenes included for the seasonal consistency and reduce data gaps as shown in the Table 2.

Table 2: Analyzed Images in Sentinel 2.

Year	Data Points
2021	2
2022	2
2023	2
2024	2

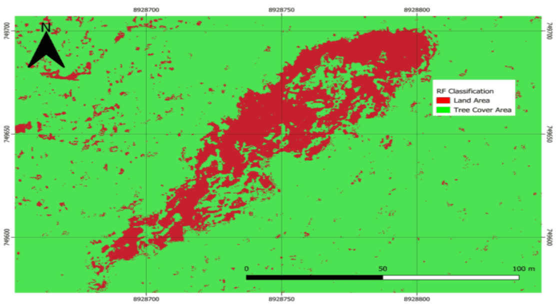
All images were classified into land cover classes such as vegetation, bare land, and built-up areas. For each classified image, the area of each land cover class was calculated to observe temporal changes. By comparing class areas across the selected images, trends in reforestation and land cover transformation were identified.

2.5 Ground Truth Validation

To assess the accuracy of the downscaled Sentinel-2 imagery, a high-resolution Google Earth image (0.3m/pixel) from January 2022 (Figure 4 (a)) used as a reference dataset. An independent land cover classification of this image (Figure 4 (b)) established a ground truth map, considered suitable despite a one-month temporal difference. The classification showed an overall accuracy of 0.709 and a Kappa coefficient of 0.413, indicating fair consistency.

The close match between the classified area likely to confirm the reliability of downscaling process. The tree cover (36295.14m2) and landslide area (4256.02m2) from the Google Earth image closely corresponded to the areas derived from the downscaled image (36853.86m2 and 3681.00m2).

(a)



(b)

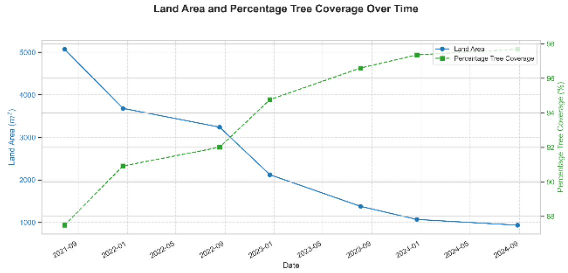
Figure 4: (a) Geo referenced high resolution imagery by google satellite (2022 Jan). (b) Classified high resolution image.

3 Results and Discussion

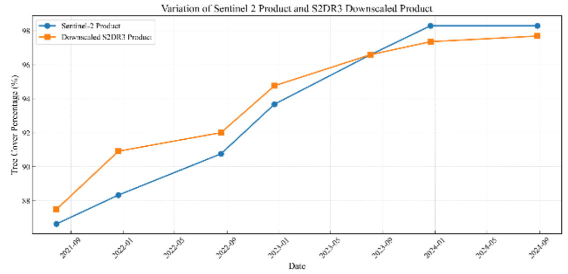
3.1 Vegetation Regrowth Assessment

The regrowth of vegetation following the 2021 Dumbarawatta landslide was assessed using percentage vegetation cover, calculated as the ratio of tree-covered area to total land area within the affected zone. This approach provided a quantifiable measure of ecological recovery over time. NDVI values derived from multi-temporal Sentinel-2 imagery was processed to delineate vegetated and non-vegetated regions, allowing for the estimation of tree cover at discrete intervals from 2021 to 2024.

Figure 5(a) presents the temporal trend of vegetation regrowth, expressed as a percentage of land area. Vegetated areas were identified by applying a threshold NDVI value indicative of healthy canopy cover, and total coverage was computed for each time step. The results reveal a gradual and consistent increase in vegetation cover throughout the study period.



(a)



(b)

Figure 5: (a) Change of land area and the percentage of tree coverage over time. (b) Variation of the tree coverage in Sentinel 2 product and S2DR3 downscaled product.

Immediately following the landslide in mid-2021, vegetation cover within the impacted region dropped significantly, with initial estimates indicating only 87.49% coverage compared to pre-event levels. By mid-2022, a partial recovery was observed, with vegetation cover increasing to approximately 92.01%, reflecting early stages of natural regrowth and possible intervention-based replanting. The trend continued through 2023 and into 2024, with vegetation cover reaching 97.69%, approaching pre-landslide conditions in some sections.

This pattern suggests a positive trajectory of ecological restoration, particularly in areas where slope stability allowed for natural recolonization. However, heterogeneity in regrowth was evident across the site, likely influenced by factors such as soil retention, slope gradient, and prior land use. The use of vegetation percentage rather than absolute NDVI values enabled clearer communication of recovery status and facilitated spatial comparison across time steps.

Figure 5(b) demonstrates the superior performance of the S2DR3 downscaled product for NDVI-based vegetation detection when compared to the original Sentinel-2 imagery. The super-resolved data consistently reported 5% enhancement in the tree cover percentages, particularly in early regrowth stages, by effectively differentiating fragmented vegetation patches often missed at the native 10 m resolution. Consequently, the original Sentinel-2 imagery tended to misclassify these partially vegetated areas as barren, leading to an overestimation of the landslide-affected zones. This highlights the distinct advantage of utilizing super-resolved imagery in post-disaster assessments, where the accurate characterization of fine spatial details within heterogeneous landscapes is critical for reliable analysis.

The increasing vegetation cover demonstrates the resilience of the local ecosystem and provides a basis for evaluating the effectiveness of both natural and artificial mitigation strategies.

3.2 Assessment of Vegetation Recovery Using Downscaled S2DR3 Product

Monitoring vegetation recovery after landslide events has traditionally depended on ground-based surveys [8], UAV imaging, or medium-resolution satellite data [9]. Field-based methods, although precise, are often limited by logistical challenges such as difficult terrain, high costs, and time-consuming data collection. Likewise, satellite imagery from platforms like Landsat, with spatial resolutions of 30 meters, lacks the granularity needed to detect subtle or small-scale vegetation changes particularly in complex, heterogeneous post-landslide environments. These constraints reduce the reliability of long-term recovery assessments and hinder the evaluation of localized restoration efforts.

The use of the S2DR3 super-resolution model, applied to Sentinel-2 imagery, represents a significant advancement by enhancing the spatial resolution from 10 meters to 1 meter while preserving the spectral fidelity across all 12 multispectral bands [6]. This enhancement enables the detection of micro-scale vegetative dynamics, including early-stage regrowth along slope edges, narrow gullies, and fragmented patches. When integrated with Google Earth Engine, this approach facilitates scalable and efficient time-series analysis with high spatial accuracy. Compared to traditional methods, this technique not only improves visual and analytical clarity but also enhances the accuracy of land cover classification, making it particularly well-suited for post-disaster vegetation monitoring and long-term ecological planning.

Figures 6 illustrate the recovery progression in the Land Slide achieved from 2021- 2024.

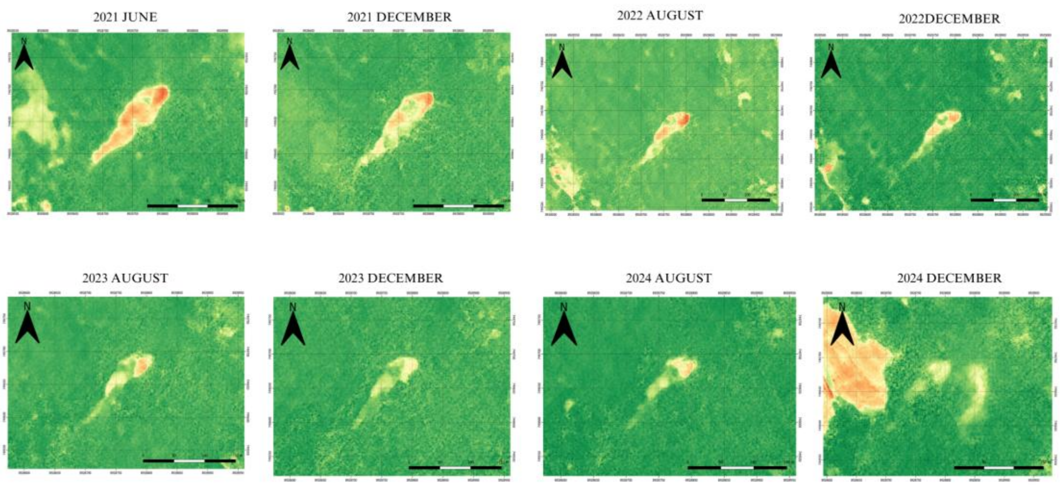


Figure 6: (a) Temporal Variation of the LandSlide Recovery Progression from 2021 to 2024.

4 Conclusion

This study assessed post-landslide vegetation recovery in the Dumbarawatta area of Sri Lanka following the major landslide event on 4th June 2021, triggered by intense rainfall. Utilizing deep learning based super-resolution satellite imagery (S2DR3 model) applied to Sentinel-2 data, combined with NDVI-based vegetation indices within the Google Earth Engine platform, we were able to monitor vegetation regrowth at an unprecedented 1-meter spatial resolution from 2021 to 2024.

The findings revealed a clear trajectory of vegetation recovery, with percentage vegetation cover increasing from approximately 87.49% immediately post-landslide to 97.69% by mid-

2024, nearing pre-event levels in many areas. This gradual regrowth highlights the resilience of the local ecosystem and the effectiveness of natural regeneration alongside mitigation efforts. The study also demonstrated that the S2DR3 super-resolution model significantly improves detection of fine-scale vegetative dynamics in complex, heterogeneous terrain, overcoming limitations of conventional medium-resolution satellite data.

These results underscore the value of integrating advanced remote sensing techniques and cloud-based computing platforms for scalable, accurate monitoring of post-disaster ecological recovery, especially in challenging or inaccessible environments. The approach presented here can support ongoing environmental management, restoration planning, and hazard mitigation strategies.

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