

A regional-scale landslide mapping following extreme rainfall using freely available remote sensing data

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Abstract

The 2022 extreme flood event triggered widespread rainfall-induced landslides and infrastructure damage across the Wilsons River catchment, New South Wales, Australia. Accurate post-event landslide inventories are essential for hazard and risk assessment, yet manual mapping remains time-consuming and often impractical over large areas. This study developed a semi-automated workflow for regional landslide inventory mapping using multi-temporal Sentinel-2 Normalized Difference Vegetation Index (NDVI) differencing combined with sequential terrain-based filtering and manual validation. Candidate landslides identified using an NDVI change threshold were progressively refined through river buffer, elevation, slope and minimum mapping unit filters, each selected through systematic evaluation against independent reference data. The final inventory comprised 3,689 landslide polygons covering 6.91 km² within a 1,871 km² study area. Field validation confirmed correct identification of all visited landslides, and comparison with local council remediation records further supported the inventory's reliability. The workflow effectively reduced commission errors associated with riverbank erosion and floodplain vegetation loss while preserving genuine landslide features. Relying exclusively on freely available imagery and standard GIS techniques, the approach offers a practical, reproducible and transferable framework for rapid post-event inventory generation in forested, subtropical catchments, supporting susceptibility modelling, catchment management and disaster recovery planning.

1 Introduction

Rainfall-induced landslides are major geomorphic processes that contribute to hillslope erosion, delivery of sediment to waterways, and influence landscape evolution in steep and highly weathered environments (Sidle and Ochiai, 2006). Extreme rainfall events can trigger widespread slope failures by increasing soil moisture and pore-water pressures, resulting in the rapid mobilisation of soil and organic material downslope (Amarasinghe et al., 2024). These processes alter sediment transport and can have significant environmental and socio-economic consequences, including impacts on infrastructure, agricultural land, terrestrial and aquatic ecosystems (Gomi et al., 2002; Johnston et al., 2015; Sidle and Ochiai, 2006). With the increasing frequency and intensity of extreme rainfall events predicted under a changing climate, understanding the spatial distribution of landslides has become increasingly important for hazard assessment and catchment management (Masson-Delmotte et al., 2021).

Landslide inventories provide the basis for susceptibility analyses, hazard assessments, and investigations of post-disturbance landscape responses (Guzzetti et al., 2012; Malamud et al., 2004). Traditionally, inventories have been compiled through field surveys and aerial photograph interpretation; however, these approaches are often time-consuming, costly, and impractical over large or inaccessible regions (Van Den Eeckhaut et al., 2012).

Advances in remote sensing have substantially improved the ability to detect and map landslides at regional scales. In particular, optical satellite imagery combined with vegetation indices has been widely used to identify landslide scars through changes in vegetation cover following disturbance (Pawar and Sharma, 2025). Multi-temporal Normalized Difference Vegetation Index (NDVI) differencing has proven effective for detecting vegetation loss associated with landslide activity in a variety of environments (Dias et al., 2023; Jeong et al., 2024; Wen and Teo, 2022). The increasing availability of freely accessible satellite imagery, including Sentinel-2, has further expanded opportunities for developing semi-automated landslide inventories over broad spatial extents (Drusch et al., 2012).

Despite these advantages, NDVI-based approaches present several challenges. Vegetation loss caused by agricultural activities, forestry operations, infrastructure development, and seasonal rainfall variability may produce spectral responses similar to those associated with landslides, leading to false positives (Mondini et al., 2011b). Furthermore, flood-induced channel adjustments, riverbank erosion and floodplain sediment deposition can generate spectral features that are difficult to distinguish from hillslope failures using optical imagery alone. Dense vegetation and complex terrain further complicate automated classifications, reducing the reliability of methods based solely on spectral information (Zhong et al., 2020). Previous studies have shown that incorporating topographic and geomorphic constraints can improve mapping accuracy and reduce misclassification, particularly in densely vegetated landscapes (Zhong et al., 2020). However, the selection of suitable filtering criteria remains highly dependent on local environmental conditions (Reichenbach et al., 2018).

In eastern Australia, extreme rainfall events have triggered numerous landslides, yet comprehensive landslide inventories remain scarce – particularly in subtropical environments characterised by dense vegetation and complex topography (Brooks et al., 2025). Existing Australian landslide inventory and susceptibility work has focused primarily on the Sydney Basin (Palamakumbure et al., 2015), with subtropical catchments such as the Northern Rivers region of NSW comparatively understudied.

During February and March 2022, prolonged and intense rainfall associated with successive low-pressure systems produced one of the most severe recorded flood events in the Northern Rivers region of New South Wales (Bureau of Meteorology, 2022). The event triggered widespread slope failures across the Wilsons River catchment, particularly in the elevated areas surrounding Lismore, Nimbin, and Dunoon (Brooks et al., 2025). In addition to the immediate impacts of flooding, rainfall-induced landslides caused prolonged disruption to critical transport infrastructure throughout the region. Major landslides damaged key access routes, isolating rural communities and requiring extensive reconstruction works that continued for more than two years after the event (Lismore City Council, 2023, 2025; Transport for NSW, 2024). Although the impacts of flooding have been extensively documented, the spatial extent and distribution of landslides generated by this event remain poorly quantified. Existing information is largely limited to local observations and isolated assessments, and no comprehensive catchment-scale inventory currently exists for the Wilsons River catchment. Developing robust and reproducible inventories is essential for improving understanding of post-event landscape responses and supporting future susceptibility assessments and hazard management (Reichenbach et al., 2018).

This study addresses this knowledge gap by developing a semi-automated approach for mapping post-flood landslides within the Wilsons River catchment using freely available Sentinel-2 imagery combined with terrain constraints and spatial filtering techniques. By integrating NDVI differencing with elevation thresholds, river-buffer masking, and manual validation, the approach aims to reduce misclassification associated with non-landslide disturbances and

improve inventory accuracy in densely vegetated subtropical landscapes. The resulting inventory represents the first catchment-scale assessment of landslide distribution following the 2022 flood event in the Wilsons River catchment and provides a simple and reproducible framework that can be applied to similar data-limited regions.

The objectives of this study were to: (i) develop a spatially explicit inventory of landslides triggered by the 2022 flood event; (ii) evaluate the effectiveness and limitations of combining NDVI differencing with terrain-based constraints in a subtropical catchment; and (iii) analyse the spatial distribution of landslide occurrence across sub-catchments within the study area.

2 Materials and methods

2.1 Study area

The study area is located within the Wilsons River catchment in the Northern Rivers region of New South Wales (NSW), Australia, covering approximately 1,871 km² (Fig. 1). The catchment forms part of the upper Richmond River system and includes the towns of Lismore, Nimbin, Dunoon, and Clunes. During the February–March 2022 extreme rainfall event, these areas experienced widespread flooding and numerous slope failures. The region is characterised by steep upland terrain in the headwaters and lower-gradient floodplains downstream, resulting in strong topographic variability across the catchment (Fig. 1c).

The landscape is strongly influenced by the remnants of the Tweed Shield Volcano complex, with geology dominated by Cenozoic mafic volcanic rocks and smaller areas of Jurassic sedimentary rocks (Sidle and Ochiai, 2006). Long-term weathering of these materials has produced deep clay-rich soils that are highly susceptible to saturation during prolonged rainfall (Highland and Bobrowsky, 2008). The catchment is characterised by narrow ridgelines, steep hillslopes, and deeply incised valleys, particularly within the elevated northern and northwestern areas of the catchment (Fig. 1). These geomorphic characteristics favour the occurrence of shallow landslides and debris movements during periods of intense rainfall (Amarasinghe et al., 2024).

The region experiences a humid subtropical climate, with mean annual rainfall generally exceeding 1,500 mm and strong interannual variability associated with the El Niño–Southern Oscillation (Bureau of Meteorology, 2022). Land use within the catchment comprises a mixture of native forest, grazing land, horticulture, cropping and rural residential development. Historical vegetation clearing and agricultural activities have modified runoff conditions and contributed to erosion and degradation of geomorphic and riparian conditions within the Richmond River catchment (Beardmore et al., 2019). The combination of steep topography, highly weathered soils, dense vegetation, and extreme rainfall makes the Wilsons River catchment particularly suitable for investigating landslide occurrence in subtropical environments (Isbell, 2016).

In February and March 2022, intense rainfall associated with successive low-pressure systems generated one of the most severe flood events recorded in eastern Australia (Bureau of Meteorology, 2022). Prior to the catastrophic flood event, prolonged La Niña conditions had already heavily saturated the Wilsons River catchment. This antecedent saturation was compounded by an extraordinary meteorological event, during which multi-day catchment totals exceeded 1,000 mm in several locations, featuring extreme 24-hour localized rainfall peaks of up to 775 mm in upstream sub-catchments. The event caused widespread extreme flooding throughout the Northern Rivers region and triggered thousands of landslides across the upper Richmond River catchment (Lismore City Council, 2025).

2.2 Datasets

The landslide inventory was developed using freely available satellite imagery, topographic data, and vector datasets within a Geographic Information System (GIS) environment. These datasets were selected to identify vegetation disturbances associated with the 2022 flood event, constrain potential landslide locations using topographic characteristics, and quantify the spatial distribution of mapped landslides across the study area.

Sentinel-2 Level-2A multispectral imagery was used to detect vegetation change associated with landslide activity. Sentinel-2 provides optical imagery at spatial resolutions of 10, 20, and 60 m across 13 spectral bands and has been widely applied for environmental monitoring and natural hazard assessment due to its high spatial resolution, frequent revisit time, and free accessibility (Drusch et al., 2012; European Space Agency, 2015). Cloud-free Sentinel-2 imagery representing pre- and post-event conditions was acquired for May 2021 and May 2022, respectively, and processed within a Geographic Information System (GIS) environment. The red and near-infrared bands, both available at a spatial resolution of 10 m, were used to calculate the Normalized Difference Vegetation Index (NDVI) for each period.

Topographic information was derived from a 1 m resolution Digital Elevation Model (DEM) generated from airborne LiDAR data acquired as part of the CSIRO–National Emergency Management Agency (NEMA) Northern Rivers Resilience Initiative (NRRI). The DEM was used to derive elevation and slope rasters for terrain analysis. Elevation and slope are among the most influential terrain variables controlling landslide occurrence and are commonly incorporated into landslide mapping studies to reduce false detections and improve inventory accuracy (Guzzetti et al., 2012; Reichenbach et al., 2018). The DEM was also used to define the spatial extent of terrain-based constraints applied during the mapping workflow.

The NSW Hydrology Geofabric river network was used to identify major drainage lines within the study area. River corridors frequently exhibit substantial vegetation change following flood events due to erosion, sediment deposition, and channel migration (Bureau of Meteorology, 2022). These processes can produce reductions in NDVI that are unrelated to hillslope failures, increasing the likelihood of false-positive landslide detections when optical imagery is used alone (Behling et al., 2014). Consequently, the river network was used to evaluate a series of buffer distances designed to minimise false positives while preserving genuine landslide features.

Sub-catchment boundaries were obtained from the NSW Spatial Services database and used to investigate the spatial distribution of landslides across the study area. Following the development and validation of the final landslide inventory, each mapped landslide polygon was assigned to its corresponding sub-

catchment, and landslide density was calculated as the number of mapped landslides per square kilometre. Table 1 summarises the datasets used in this study.

Table 1
Summary of the datasets used in this study.

Dataset	Source	Resolution	Purpose
Sentinel-2 Level-2A	Copernicus ESA	10 m	NDVI calculation and change detection
LiDAR-derived Digital Elevation Model (DEM)	CSIRO–NEMA Northern Rivers Resilience Initiative	1 m	Elevation and slope derivation
NSW Hydrology Geofabric	NSW Spatial Services	Vector	River buffer analysis

2.3 Landslide mapping workflow

The landslide inventory was developed using a semi-automated workflow that combined satellite-derived vegetation change detection with terrain-based constraints and manual validation (Fig. 2). The methodology comprised five sequential stages: (i) image pre-processing and calculation of the Normalized Difference Vegetation Index (NDVI); (ii) identification of candidate landslide polygons through NDVI differencing; (iii) evaluation of multiple threshold values and terrain constraints to minimise false positives while retaining genuine landslide features; (iv) post-processing and manual validation of the mapped polygons; and (v) spatial analysis of the final inventory at the sub-catchment scale. The workflow was designed to provide a reproducible approach for rapid post-event landslide mapping using freely available datasets and standard GIS techniques.

A complete summary of all threshold combinations and candidate filtering scenarios evaluated during the workflow development is provided in Table A1.

2.3.1 Image pre-processing and NDVI calculation

Cloud-free Sentinel-2 Level-2A multispectral satellite imagery acquired in May 2021 (pre-event) and May 2022 (post-event) was used to detect vegetation changes associated with the February–March 2022 flood event. The use of imagery from the same month in consecutive years helped minimise the influence of seasonal vegetation variability, allowing observed differences in vegetation condition to be more reliably attributed to disturbance caused by landslides rather than phenological changes (Jeong et al., 2024; Wen and Teo, 2022).

The imagery was processed within a Geographic Information System (GIS) environment using ArcGIS Pro. Each image was clipped to the study area boundary prior to analysis to ensure spatial consistency between the two observation periods. The Normalized Difference Vegetation Index (NDVI) was calculated for both dates using the Near-Infrared (Band 8) and Red (Band 4) spectral bands, each with a spatial resolution of 10 m. NDVI is one of the most widely used spectral indices for assessing vegetation condition because it exploits the strong reflectance of healthy vegetation in the near-infrared region and its absorption in the red portion of the electromagnetic spectrum (Jeong et al., 2024). NDVI values were calculated using Eq. (1):

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

1

where *NIR* represents the reflectance of Sentinel-2 Band 8 and *Red* represents the reflectance of Band 4.

Following NDVI calculation, an NDVI difference raster was generated by subtracting the pre-event NDVI raster from the post-event NDVI raster. Negative values indicate a reduction in vegetation cover between May 2021 and May 2022, while positive values represent an increase in vegetation greenness. Because shallow landslides typically remove or severely disturb vegetation, areas exhibiting substantial decreases in NDVI were considered potential landslide candidates and were subsequently evaluated using a series of threshold values and terrain constraints described in the following sections (Behling et al., 2014; Mondini et al., 2011b).

2.3.2 Sensitivity analysis and threshold selection

Following the generation of the Δ NDVI raster, a sequential sensitivity analysis was undertaken to identify the combination of vegetation change thresholds and terrain constraints that most effectively distinguished landslide-related vegetation loss from other forms of landscape disturbance. Rather than adopting threshold values reported in previous studies, multiple parameter values were systematically evaluated to determine the combination that maximised the detection of genuine landslides while minimising false-positive classifications within the study area. Similar sensitivity-based approaches have been recommended for semi-automated landslide mapping because optimal parameter values are influenced by local topography, vegetation characteristics, image resolution, and the magnitude of the triggering event (Malamud et al., 2004; Mondini et al., 2011b).

The sensitivity analysis was performed sequentially, with the optimal parameter selected at each stage serving as the input for the subsequent stage (Fig. 2). Initially, five Δ NDVI threshold values (< -0.05 , < -0.10 , < -0.15 , < -0.20 , and < -0.25) were evaluated to identify the threshold that best captured vegetation loss associated with landslides while limiting the inclusion of unrelated vegetation disturbances. Candidate landslide polygons generated from the selected Δ NDVI threshold were then subjected to a series of terrain-based constraints.

River buffer distances of 0, 25, 50, 75 and 100 m were assessed to reduce false detections associated with riverbank erosion, sediment deposition, and channel migration following the flood event (Freihardt and Frey, 2023). Because these processes can produce substantial reductions in vegetation cover that

are unrelated to hillslope failures, excluding areas immediately adjacent to drainage lines has been shown to improve the reliability of remotely sensed landslide inventories (Behling et al., 2014).

Following river buffer assessment, elevation thresholds of 25, 50, 75, 100 and 125 m above sea level were evaluated. Areas at lower elevations were expected to contain a greater proportion of floodplain vegetation change and flood-related disturbances unrelated to landslide activity. Subsequently, slope thresholds of 2°, 5°, 7.5° and 10° were examined to remove areas unlikely to experience slope failure, recognising that shallow landslides predominantly occur on steeper terrain (Guzzetti et al., 2012).

Finally, a minimum mapping unit (MMU) was applied to remove isolated polygons likely to represent image noise or minor vegetation disturbances rather than landslides. Five MMU thresholds (200, 400, 500, 600 and 800 m²) were evaluated. For each stage of the sensitivity analysis, the resulting inventories were visually compared with high-resolution aerial imagery. Parameter selection was based on the ability to maximise the identification of genuine landslides while minimising obvious false-positive detections.

2.3.3 Post-processing and manual validation

The optimal combination of NDVI and terrain-based thresholds identified through the sensitivity analysis was applied to generate the preliminary landslide inventory. Candidate landslide pixels were converted to vector polygons using the Raster to Polygon tool in ArcGIS Pro.

To improve inventory accuracy, all candidate polygons were manually validated through visual interpretation of aerial imagery, following standard practice in remote sensing-based landslide inventory mapping (Behling et al., 2014; Santangelo et al., 2010). Each polygon was assessed individually to determine whether its spectral and morphological characteristics were consistent with landslide activity. Polygons representing other forms of vegetation disturbance, including riverbank erosion, flood-related sediment deposition, agricultural land clearing, forestry operations, road corridors, and image artefacts, were removed from the inventory. Manual interpretation also considered the shape, size, topographic position, and spatial context of individual polygons to distinguish genuine landslides from unrelated landscape changes.

3 Results

3.1 Sensitivity analysis

The sequential sensitivity analysis progressively reduced the number of candidate landslide polygons through the application of increasingly restrictive vegetation and terrain-based filters (Table A1, Table 2). The least restrictive Δ NDVI threshold (< -0.05) generated 329,844 candidate polygons covering 189.71 km² of the study area. Increasing the threshold progressively reduced both the number and total area of candidate polygons. Visual comparison with high-resolution aerial imagery showed that < -0.10 provided the best balance between capturing identifiable landslides and limiting non-landslide vegetation disturbance, whereas more restrictive thresholds (< -0.15 to < -0.25) increasingly excluded genuine landslide features. Consequently, < -0.10 was selected for subsequent analyses.

Table 2
Summary of the sequential sensitivity analysis used to determine the optimal parameter combination for landslide mapping.

Filtering stage	Parameter tested	Candidate polygons	Area (km²)	Decision
NDVI threshold	< -0.10	124,932	72.97	Selected
River buffer	50 m	110,965	62.51	Selected
Elevation	> 100 m	66,731	25.31	Selected
Slope	$> 5^\circ$	63,086	20.76	Selected
Minimum mapping unit	600 m²	4,597	11.91	Selected
Final inventory	Manual validation	3,689	6.91	Final

Application of a 50 m river buffer reduced the inventory to 110,965 polygons (62.51 km²) by removing vegetation disturbances associated with riverbank erosion and channel adjustment. Increasing the exclusion distance to 100 m further reduced the mapped area; however, visual assessment indicated that genuine landslides located adjacent to drainage lines were also removed. Therefore, the 50 m river buffer provided the most appropriate balance between reducing false-positive detections and preserving landslide features.

Applying an elevation threshold of > 100 m further reduced the inventory to 66,731 polygons (25.31 km²) by excluding low-lying areas predominantly affected by floodplain vegetation change and sediment deposition. Subsequent application of a minimum slope threshold of 5° decreased the inventory to 63,086 polygons (20.76 km²), whereas increasing the threshold to 10° removed a substantial number of genuine landslides observed on moderately inclined hillslopes. Accordingly, the 5° slope threshold was retained.

Finally, application of the 600 m² minimum mapping unit reduced the inventory to 4,597 polygons covering 11.91 km². Subsequent manual validation removed false-positive detections that remained after the automated filtering process, resulting in a final inventory of 3,689 landslide polygons covering 6.91 km² (Table 2). The majority of false positives were associated with extensive plateau surfaces and large areas exhibiting substantial changes in vegetation colour between the two image acquisition dates. These areas were not excluded by the selected terrain constraints because they satisfied the slope and

elevation criteria, yet the observed reductions in NDVI reflected vegetation senescence, land-use practices, or other non-landslide disturbances rather than hillslope failures. Their removal during manual interpretation substantially improved the reliability of the final landslide inventory.

3.2 Final landslide inventory

Application of the complete mapping workflow, including NDVI differencing, terrain-based filtering and manual validation, produced a final inventory comprising 3,689 landslide polygons, covering a total area of 6.91 km² (Table 2). The mapped landslides were concentrated predominantly within the steep, elevated northern portion of the catchment, particularly in the vicinity of Nimbin and the upper Richmond River headwaters, with fewer landslides identified across the lower-elevation southern areas (Fig. 3). Representative examples of the mapped inventory are presented in Fig. 4, illustrating the successful discrimination of landslides from flood-related vegetation disturbance and riverbank erosion. Field investigations conducted at representative locations throughout the study area confirmed that all visited landslides were successfully retained in the final inventory (Fig. 5).

Comparison between the initial NDVI-derived candidate polygons and the final inventory demonstrates the effectiveness of the filtering and validation procedure. Although NDVI differencing successfully identified widespread landslide-related vegetation disturbance, numerous candidate polygons were associated with flood-related vegetation disturbance rather than hillslope failure. The rejected candidate polygons (blue) were concentrated primarily along river corridors, floodplains and other low-elevation areas, where riverbank erosion, sediment deposition and vegetation damage caused substantial reductions in NDVI following the 2022 flood event (Fig. 3). These disturbances exhibited spectral responses similar to landslides but lacked the geomorphic characteristics of slope failures during visual interpretation.

Representative examples of the final inventory illustrate how the proposed workflow retained coherent landslide scars while removing extensive false positives associated with floodplain processes and riverbank erosion (Fig. 4). Manual validation further eliminated isolated misclassifications that persisted after the automated filtering steps, including large plateau areas that exhibited significant post-flood vegetation change but were unrelated to landslide activity. Importantly, all landslides visited during field investigations were preserved throughout the filtering process (Fig. 5), providing qualitative evidence that the workflow effectively removed non-landslide disturbances without excluding independently verified landslides. The resulting inventory provides a spatially consistent and reproducible dataset suitable for subsequent analyses of landslide distribution and density across the study area.

3.3 Sub-catchment-scale landslide distribution

The final landslide inventory revealed substantial spatial variability in landslide density among the seven sub-catchments (Fig. 6). Landslide density ranged from 0.41 to 3.30 landslides km⁻², with the highest densities occurring in the northern and north-western sub-catchments surrounding Nimbin and The Channon. These areas are characterised by steep dissected terrain and correspond to the most severely affected regions by the 2022 rainfall-induced landslides.

The highest landslide densities were recorded in the Leycester Creek (3.30 landslides km⁻²) and Goolmangar Creek (3.09 landslides km⁻²) sub-catchments, followed by Terania Creek (2.37 landslides km⁻²) and Coopers Creek (1.87 landslides km⁻²). In contrast, the Wilsons River at Wyrallah Rd sub-catchment exhibited the lowest landslide density (0.41 landslides km⁻²), reflecting its predominantly low-relief floodplain environment where hillslope failures are uncommon. Although Goolmangar Creek contained the greatest number of mapped landslides (843), normalising by sub-catchment area showed that Leycester Creek exhibited the highest landslide density, highlighting the importance of accounting for differences in sub-catchment size when comparing landslide occurrence (Table 3).

Because a small number of landslide polygons intersected sub-catchment boundaries, these polygons were assigned to each intersecting sub-catchment during the spatial analysis. Consequently, the summed landslide count across all sub-catchments is slightly greater than the total number of mapped landslides.

Table 3
Landslide distribution across sub-catchments, showing the number of mapped landslides, sub-catchment area and landslide density.

Sub-catchment	Number of Landslides	Sub-catchment Area (km ²)	Landslide Density (landslides km ⁻²)
Back Creek	492	275.08	1.79
Leycester Creek	816	247.06	3.30
Terania Creek	575	242.50	2.37
Goolmangar Creek	843	272.73	3.09
Coopers Creek	476	253.90	1.87
Wilsons River at Eltham	401	331.81	1.21
Wilsons River at Wyrallah Rd	100	244.12	0.41

Overall, the spatial distribution of landslide density closely reflects the geomorphological characteristics of the Wilsons River catchment, with landslides spatially concentrated within the steep upland sub-catchments and becoming progressively less frequent across lower-elevation terrain.

4 Discussion

4.1 Effectiveness of the NDVI-based workflow

The proposed workflow successfully produced a catchment-scale landslide inventory using freely available Sentinel-2 imagery combined with simple terrain-based constraints and manual validation. A total of 3,689 landslides were identified following the 2022 flood event, demonstrating that multi-temporal NDVI differencing provides an effective first-stage approach for detecting widespread vegetation disturbance associated with rainfall-induced landslides, while substantially reducing the time required for inventory generation compared with conventional manual mapping. This is consistent with previous investigations demonstrating the suitability of NDVI differencing for rapid, regional-scale landslide detection following extreme rainfall events (Ferrario and Livio, 2023; Jeong et al., 2024; Mondini et al., 2011a; Notti et al., 2023). However, consistent with these studies, the results also confirmed that spectral information alone is insufficient to reliably distinguish landslides from other forms of vegetation disturbance following extreme flood events (Jeong et al., 2024; Reichenbach et al., 2018).

Previous studies have shown that the incorporation of topographic information substantially improves landslide mapping by reducing false positives associated with river corridors, low-relief terrain and other non-landslide disturbances (Zhong et al., 2020). The present study supports these findings, demonstrating that the sequential application of river buffers, elevation and slope constraints progressively reduced commission errors while preserving the majority of genuine landslides. Unlike many previous studies, however, each terrain constraint was systematically evaluated using multiple threshold values before selection, providing an objective basis for the adopted workflow rather than relying solely on thresholds reported in the literature.

The spatial distribution of landslides was also consistent with established geomorphological controls on rainfall-induced slope failures. Landslide density was greatest within the steep upland sub-catchments surrounding Nimbin and The Channon, whereas the Wilsons River at Wyrallah Rd sub-catchment exhibited the lowest density owing to its predominantly low-relief floodplain setting. This pattern agrees with previous studies that identify slope gradient, elevation and terrain morphology as the principal controls governing landslide occurrence following intense rainfall events (Sidle and Ochiai, 2006).

Because no independent regional landslide inventory exists for the study area, the final inventory was evaluated qualitatively against field-visited landslides and against government records documenting the impacts of the 2022 flood event across the Northern Rivers region. The highest landslide densities identified within the Leycester Creek, Goolmangar Creek and Terania Creek sub-catchments correspond closely with locations where widespread landslides caused prolonged road closures and substantial damage to transport infrastructure (Lismore City Council, 2023; Transport for NSW, 2024), and the major landslides currently undergoing remediation under the Lismore City Council Flood Restoration Portfolio are represented within the final inventory. Although these government datasets were not developed as comprehensive landslide inventories and were therefore used only as qualitative evidence, their strong spatial agreement with the mapped landslides, together with the successful identification of all field-visited landslides, provides additional confidence that the proposed workflow captured the principal landslides triggered by the 2022 flood event while minimising non-landslide disturbances.

4.2 Limitations

Despite the successful application of the proposed workflow, several limitations should be acknowledged. First, the use of Sentinel-2 imagery limits the minimum detectable landslide size due to its 10 m spatial resolution (Drusch et al., 2012). Small or narrow failures occurring beneath dense vegetation may therefore remain undetected, while mixed pixels along landslide margins can reduce the precision of mapped boundaries (Mondini et al., 2011b).

Second, although terrain-based filtering substantially reduced false positives, manual validation remained an important final component of the workflow. Several large plateau areas exhibited significant post-flood reductions in vegetation cover that produced NDVI responses comparable to landslides but were unrelated to mass movement. Similarly, flood-related vegetation disturbance, riverbank erosion and sediment deposition generated spectral signatures that could not be reliably distinguished using spectral information alone. Visual interpretation was therefore required to remove these residual commission errors and produce a reliable final inventory, consistent with observations reported in previous landslide inventory studies (Santangelo et al., 2010).

Finally, the inventory was evaluated qualitatively through comparison with field-visited landslides and independently identified landslide remediation sites rather than through a formal quantitative accuracy assessment. Although these comparisons provided confidence in the overall performance of the workflow, future studies would benefit from comprehensive independent validation datasets or high-resolution post-event LiDAR to enable quantitative assessment of mapping accuracy and omission errors.

4.3 Implications for regional landslide mapping

The proposed workflow provides a practical and reproducible approach for developing regional landslide inventories using freely available satellite imagery and commonly available GIS datasets. Because the methodology relies primarily on Sentinel-2 imagery, digital elevation models and publicly accessible hydrological data, it can be readily implemented in regions where high-resolution airborne surveys or extensive field mapping are unavailable or economically impractical.

The systematic evaluation of NDVI thresholds and terrain constraints presented in this study also provides a transparent framework for adapting the methodology to other catchments. Rather than adopting threshold values directly from previous studies, the results demonstrate the importance of evaluating filtering parameters according to local geomorphological conditions, vegetation characteristics and flood impacts. This approach increases the transferability of the workflow while maintaining flexibility for different environmental settings.

Beyond inventory generation, the resulting landslide dataset provides an important foundation for future research and hazard management. Regional inventories are fundamental for landslide susceptibility modelling, sediment connectivity analyses and catchment-scale assessments of post-disturbance landscape evolution (Guzzetti et al., 1999; Guzzetti et al., 2012). In addition, rapidly generated inventories can assist local governments and emergency agencies in prioritising field inspections, planning recovery works and identifying areas requiring ongoing slope monitoring following extreme rainfall events.

The workflow presented here therefore offers a practical framework for supporting post-disaster landslide assessment in subtropical catchments affected by future extreme rainfall events.

5 Conclusion

This study developed a semi-automated workflow for post-event landslide inventory mapping in the Wilsons River catchment, Australia, using multi-temporal Sentinel-2 NDVI differencing combined with sequential terrain-based filtering and manual validation. The workflow successfully reduced commission errors associated with vegetation loss unrelated to landsliding while retaining representative landslide features. The final inventory comprised 3,689 landslide total area of 6.91 km², providing the first systematic regional-scale landslide inventory for the study area following the 2022 flood event.

The sequential evaluation of NDVI thresholds, river buffer distances, elevation, slope and minimum mapping unit demonstrated the importance of systematically optimising each filtering step rather than relying on arbitrary parameter selection. The selected workflow effectively excluded false positives associated with riverbank erosion and floodplain environments while successfully identifying all landslides visited during field validation.

The proposed workflow relies exclusively on freely available Sentinel-2 imagery and standard GIS techniques, making it readily transferable to other forested and subtropical catchments affected by rainfall-induced landslides. Although manual validation remains necessary to remove residual false positives, the approach substantially reduces interpretation time compared with fully manual mapping while maintaining a high level of inventory quality.

The resulting inventory provides a valuable baseline dataset for future investigations of landslide susceptibility, sediment connectivity, erosion processes and catchment management within the Wilsons River catchment. More broadly, the workflow offers a practical and reproducible framework for rapidly generating post-event landslide inventories that can support emergency response, infrastructure recovery and long-term landscape management following extreme rainfall events.

Declarations

Competing interests

The authors declare that they have no conflict of interest.

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Author Contribution

A.L.S.C. developed the methodology, conducted the formal analysis and investigation, performed the GIS and software-based analyses, and wrote the original manuscript draft. D.M. contributed to the investigation, supervised the research, and reviewed and edited the manuscript. S.J. supervised the research and reviewed and edited the manuscript. All authors contributed to and approved the final version of the manuscript.

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Data Availability

The final landslide inventory generated in this study is available through Zenodo at <https://doi.org/10.5281/zenodo.22105157>. The dataset is provided in ESRI shapefile format. Sentinel-2 imagery used in the analysis is freely available through the Copernicus Data Space Ecosystem (<https://dataspace.copernicus.eu/> , last access: 25 August 2026).

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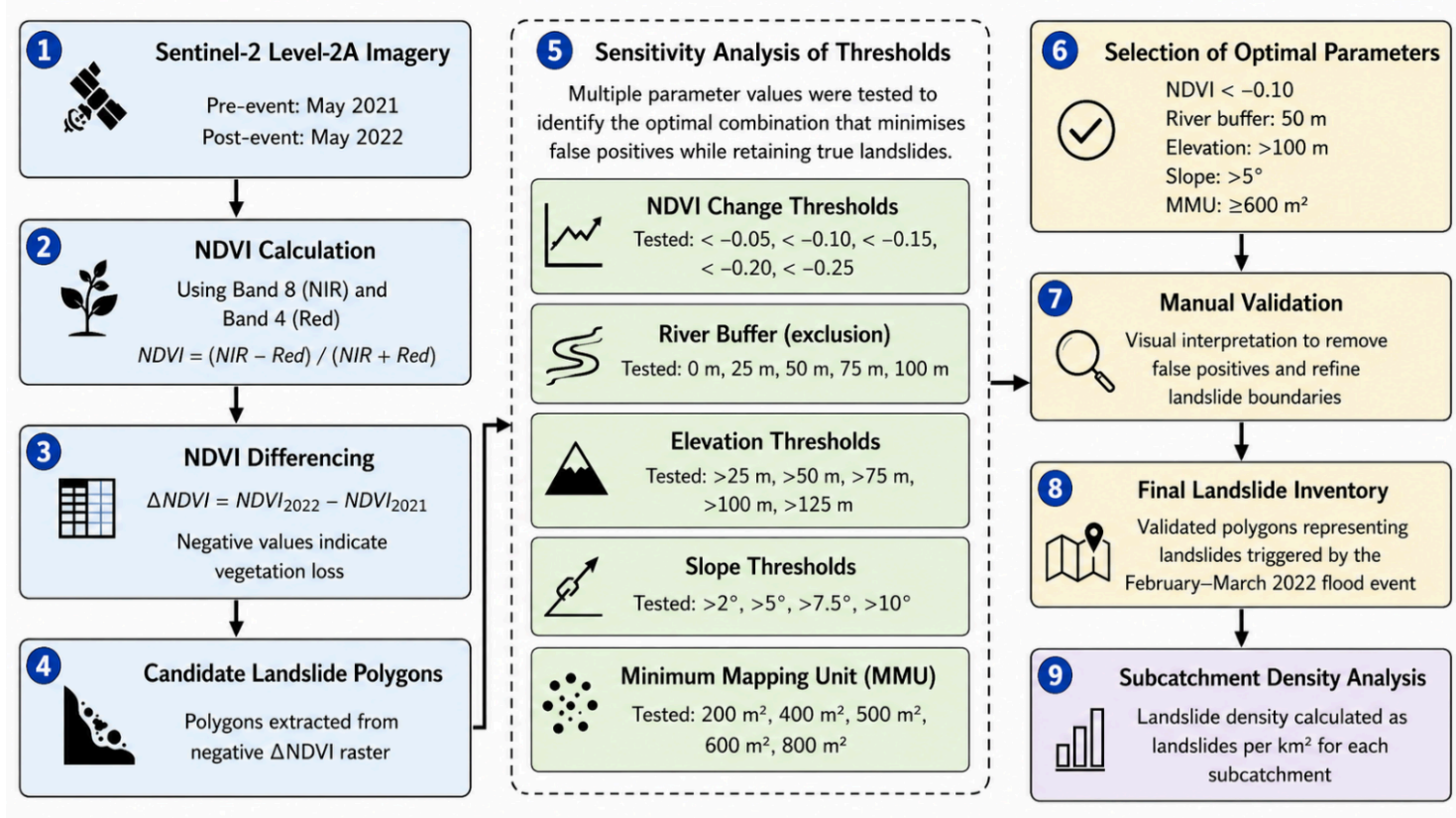


Figure 2

Overview of the workflow used to generate the post-flood landslide inventory from Sentinel-2 imagery.

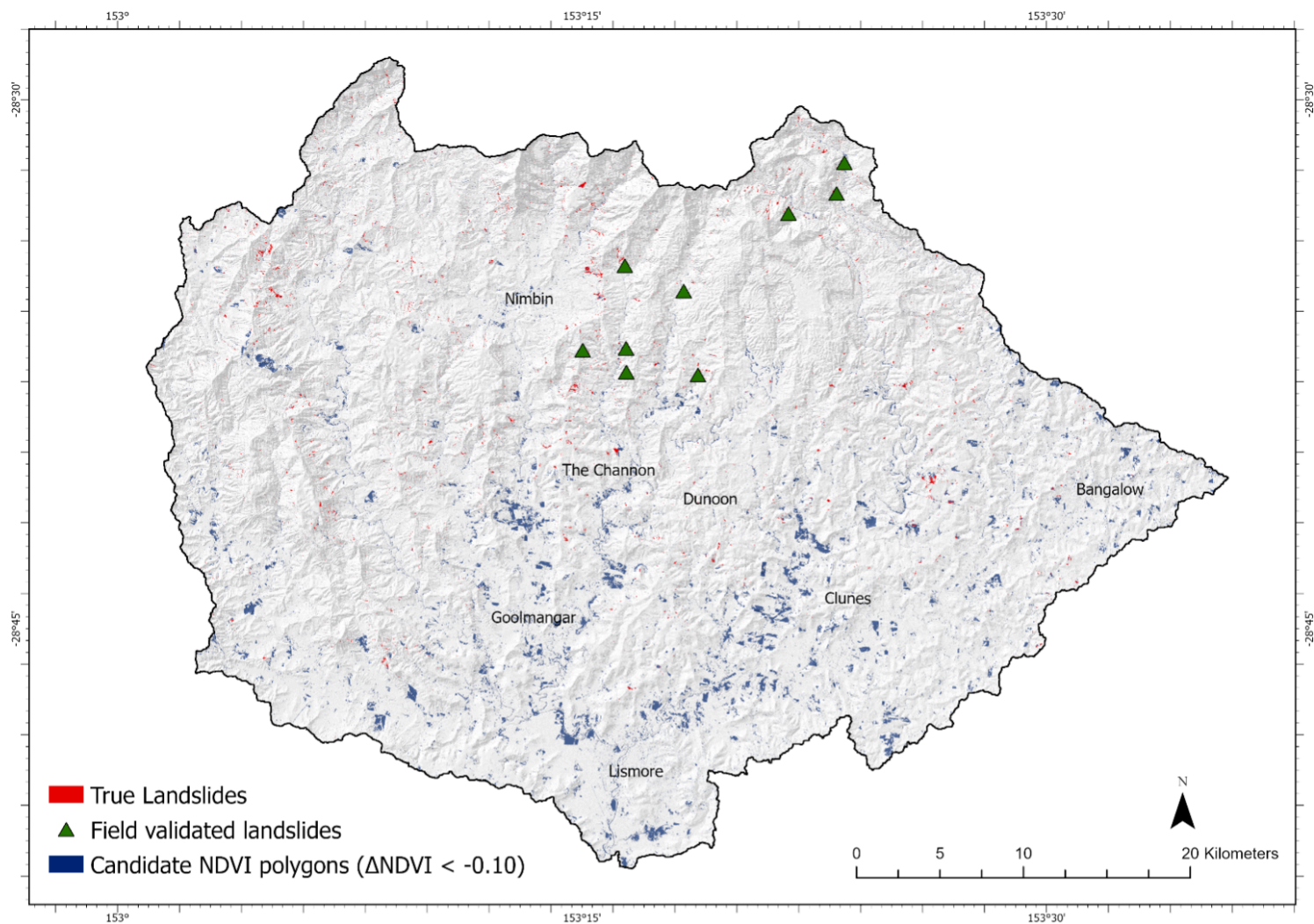


Figure 3

Final landslide inventory for the study area following application of the complete mapping workflow. Red polygons represent the manually validated landslide inventory, blue polygons indicate NDVI-derived candidate polygons that were rejected.

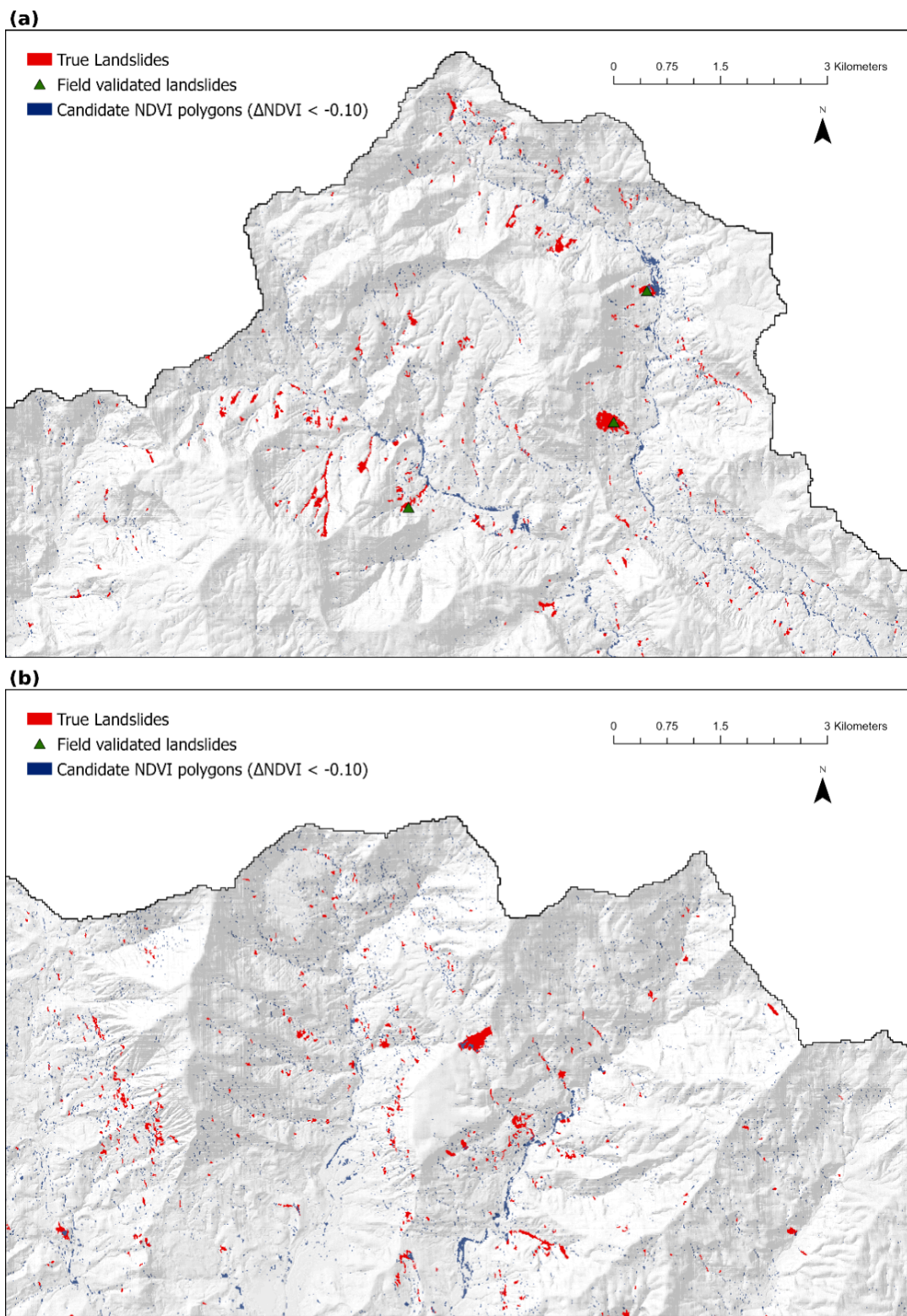


Figure 4

Representative examples of the final landslide inventory, illustrating successful discrimination between landslides and riverbank erosion or floodplain disturbance: (a) large landslide complexes with co-located field-visited (ground-truthed) landslides; (b) preservation of large landslide complexes with successful discrimination from riverbank erosion.

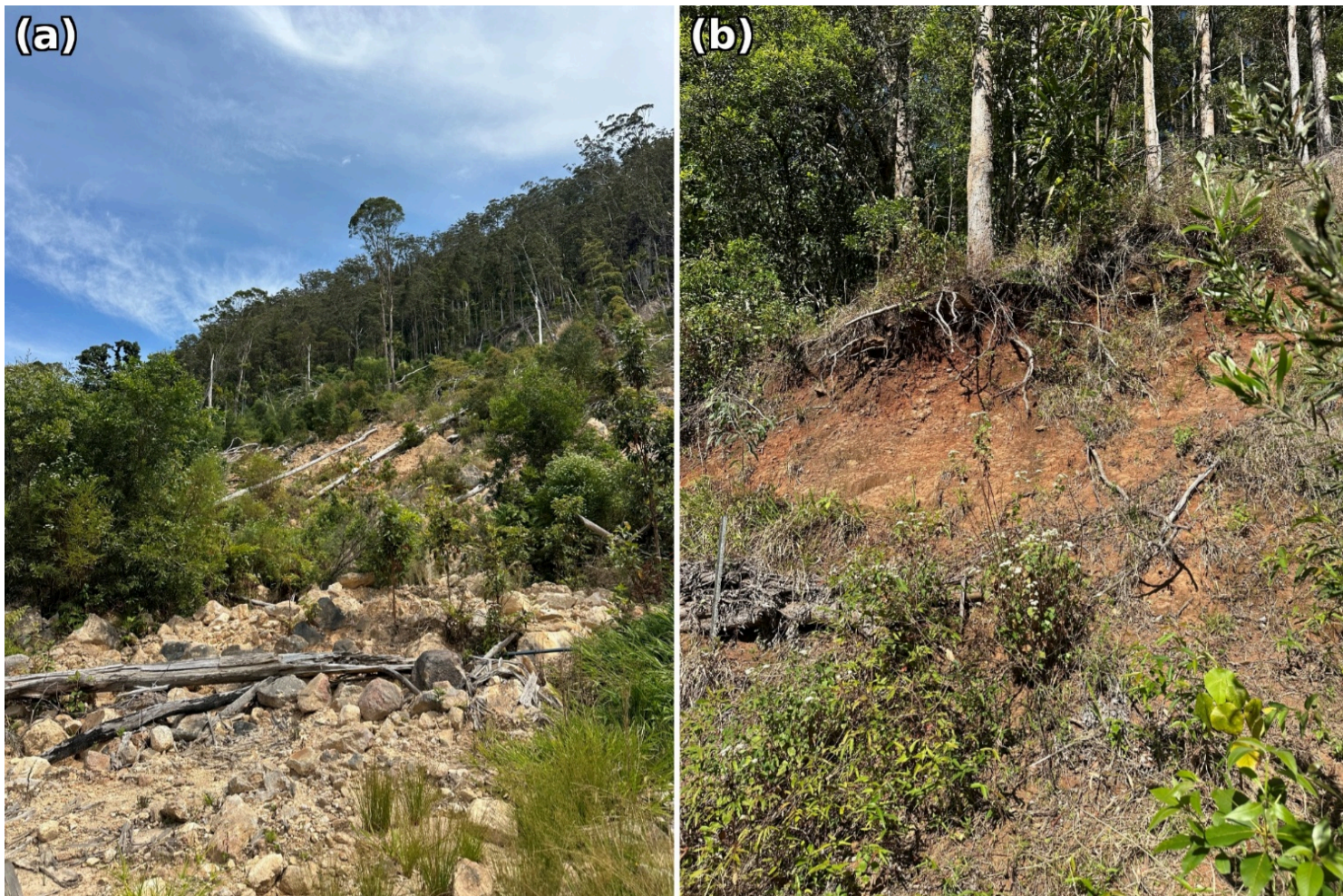


Figure 5

Representative landslides visited during field validation. (a) Large landslide with extensive debris accumulation along Upper Wilsons Creek Road. (b) Shallow landslide located at Tuntable Creek. Both landslides were successfully identified by the final mapping workflow.

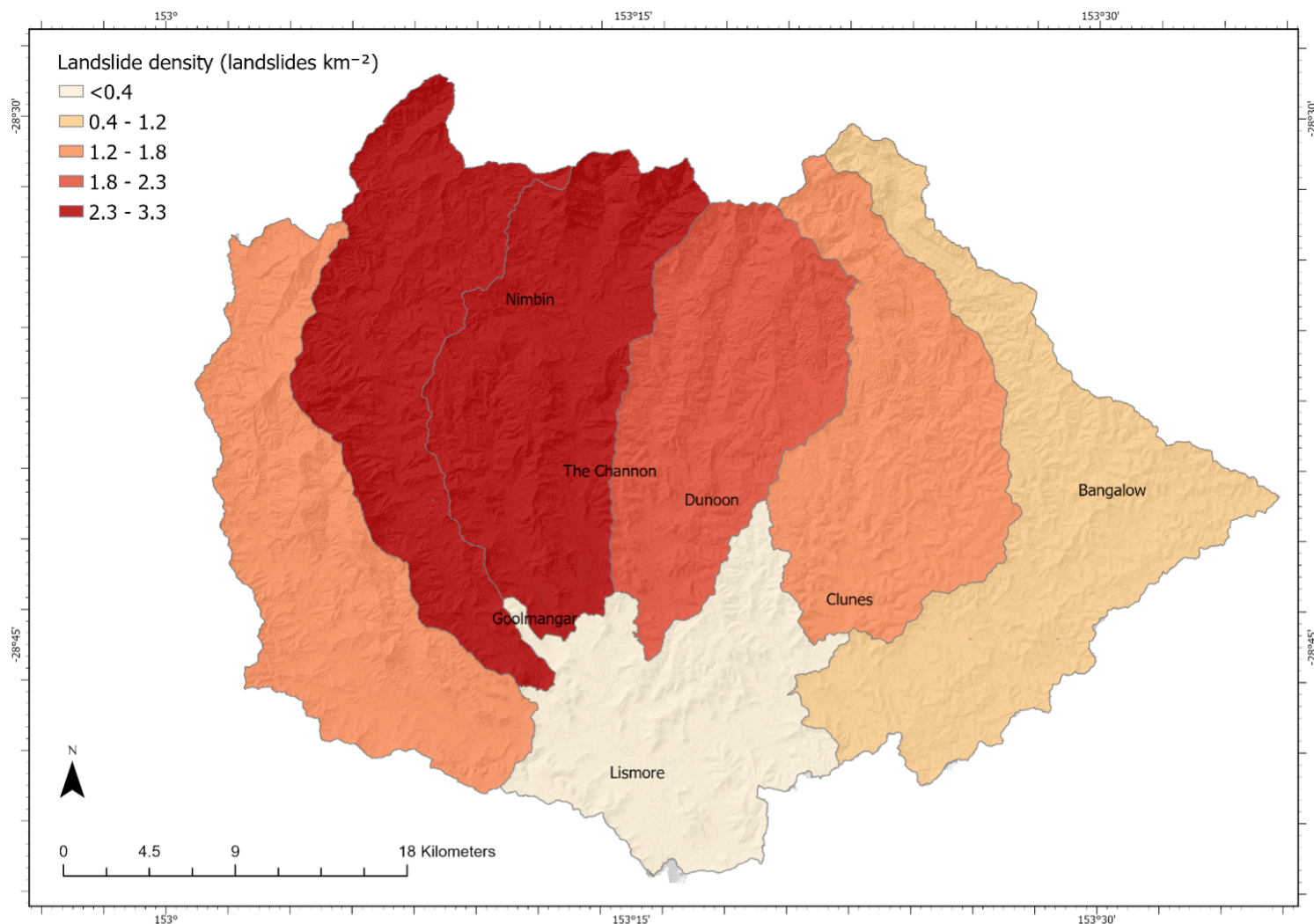


Figure 6

Spatial distribution of landslide density across the seven sub-catchments of the Wilsons River catchment following the 2022 extreme rainfall event. Landslide density is expressed as the number of mapped landslides per square kilometre.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Appendix.docx](#)