

From Efficient Geomorphological Mapping to Semi-Automated Landslide Detection

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Summary

This PhD dissertation investigates **geomorphological mapping and landslide detection in Central-upland Germany** using high-resolution digital terrain models (DTMs), remote sensing data, and advanced object-based methods. Landslides are key drivers of landscape evolution and present significant natural hazards, yet detecting both active and forest-covered landslides consistently remains challenging.

At the **local scale**, the study focuses on the Jena region ($\sim 44 \text{ km}^2$), where LiDAR-derived DTMs were combined with thematic spatial datasets to produce a highly detailed geomorphological map at 1:5000 scale. This work demonstrates the usefulness of high-resolution terrain data for capturing subtle geomorphological features, enabling precise mapping of landslide-prone areas and supporting broader landscape analysis. Building on this foundation, a **semi-automatic approach** was developed to map **forested landslides** within a larger study area ($\sim 150 \text{ km}^2$), effectively detecting older and less visible landslides beneath dense forest cover. The results highlight the potential of Geographic Object-Based Image Analysis (GEOBIA) for improving landslide detection in areas where conventional field mapping is limited.

At the **regional scale**, the dissertation evaluates the **transferability of the developed GEOBIA workflow** to the Swabian Alb ($\sim 356 \text{ km}^2$), mid-mountainous region in western Germany characterized by cuesta-related landscapes and rotational landslides. Using DTMs acquired in 2003 and 2023, the study examines the performance of the model under different environmental and land-cover conditions. The analysis demonstrates that high-resolution DTMs enable accurate mapping of forested landslides, while the method remains robust but slightly less precise in open or mixed land-cover areas. Comparisons between the two acquisition periods show that updated terrain data improve detection of newly activated or reactivated landslides, emphasizing the importance of up-to-date inventories for hazard assessment.

Overall, this dissertation establishes a workflow integrating LiDAR DTMs, GIS, and GEOBIA for creating **high-resolution, geomorphological map and transferable landslide inventories**. The approach successfully captures both forest-covered and open landslides across local and regional scales, supporting hazard assessment, susceptibility mapping, and long-term landscape monitoring. These findings demonstrate the innovation and practical value of combining high-resolution terrain data with semi-automatic object-based mapping in mid-mountainous regions, advancing the understanding of landslide processes under complex environmental conditions.

Keywords: Geomorphological mapping, forested landslides, inventory mapping, Remote sensing, LiDAR-derived DTMs, Geographic Object-Based Image Analysis (GEOBIA), Semi-automatic mapping, Swabian Alb, Jena region, Central German uplands.

Zusammenfassung

Diese Dissertation untersucht die geomorphologische Kartierung und die Erkennung von Hangrutschungen in den **Mitteldeutschen Mittelgebirgen** mithilfe hochauflösender digitaler Geländemodelle (DGM), Fernerkundungsdaten und fortgeschrittener objektbasierter Analysemethoden. Hangrutschungen sind zentrale Prozesse der Landschaftsentwicklung und stellen zugleich eine bedeutende Naturgefahr dar. Die konsistente Erfassung sowohl aktiver als auch bewaldeter (d. h. unter Vegetationsbedeckung liegender) Hangrutschungen bleibt jedoch aufgrund komplexer Reliefstrukturen, eingeschränkter Geländezugänglichkeit und der Überprägung durch Landnutzung methodisch herausfordernd.

Auf **lokaler** Ebene liegt der Fokus auf der Region Jena (ca. 44 km²). Hier wurden aus LiDAR-Daten abgeleitete DGMs mit thematischen Geodaten (u. a. Orthophotos, topographische und geologische Karten) kombiniert, um eine hochdetaillierte geomorphologische Karte im Maßstab 1:5000 zu erstellen. Die Ergebnisse zeigen, dass hochauflösende Geländedaten die Erfassung subtiler geomorphologischer Formen und Prozessgrenzen deutlich verbessern und damit eine präzise Abgrenzung hangrutschungsrelevanter Bereiche sowie eine umfassendere landschaftsgeomorphologische Interpretation ermöglichen. Aufbauend darauf wurde ein halbautomatischer Ansatz zur Inventarisierung bewaldeter Hangrutschungen in einem größeren Untersuchungsraum (ca. 150 km²) entwickelt, der insbesondere ältere und morphologisch weniger ausgeprägte Hangrutschungen unter dichter Waldbedeckung erfassen kann. Damit wird das Potenzial der Geographischen Objektbasierten Bildanalyse (GEOBIA) verdeutlicht, die Hangrutschungserkennung dort zu verbessern, wo eine konventionelle feldbasierte Kartierung nur eingeschränkt möglich ist.

Auf **regionaler Ebene** bewertet die Dissertation die **Übertragbarkeit des entwickelten GEOBIA-Workflows** auf die Schwäbische Alb (ca. 356 km²), eine Mittelgebirgsregion, die durch Schichtstufen-Landschaften und überwiegend rotationsartige Massenbewegungen geprägt ist. Auf Basis von DGMs aus den Jahren 2003 und 2023 werden die Modellergebnisse unter unterschiedlichen Umwelt- und Landbedeckungsbedingungen verglichen. Die Analysen zeigen, dass hochauflösende DGMs eine zuverlässige Detektion bewaldeter Hangrutschungen ermöglichen, während die Methode in offenen oder heterogen genutzten Landschaftsausschnitten weiterhin robuste Ergebnisse liefert, jedoch tendenziell mit geringerer Präzision. Der Vergleich der beiden DGM-Zeitstände verdeutlicht zudem, dass aktuelle Geländedaten die Erkennung neu aktivierter oder reaktivierter Hangrutschungen verbessern und damit die Bedeutung zeitnaher, konsistenter Hangrutschungsinventare für Gefahren- und Risikoanalysen unterstreichen.

Insgesamt entwickelt diese Dissertation einen integrierten Arbeitsablauf, der LiDAR-basierte DGMs, GIS-Analysen und GEOBIA-Methoden zur Erstellung **hochauflösender geomorphologischer Karten und übertragbarer Hangrutschungsinventare kombiniert**. Der Ansatz ermöglicht die Erfassung sowohl bewaldeter als auch offener Hangrutschungen auf lokaler und regionaler Skala und liefert damit eine belastbare Grundlage für Gefahrenbewertung, Suszeptibilitätsanalysen und die langfristige Beobachtung geomorphologischer Prozesse. Die Ergebnisse belegen den wissenschaftlichen und praktischen Mehrwert der Kombination hochauflösender Geländedaten mit

halbautomatischen objektbasierten Kartierungsverfahren und tragen zu einem vertieften Verständnis von Hangrutschungsprozessen in komplexen Mittelgebirgslandschaften bei.

Schlüsselwörter: Geomorphologische Kartierung; bewaldete Hangrutschungen; Hangrutschungsinventarisierung; Fernerkundung; LiDAR-basierte digitale Geländemodelle (DGM); Geographische Objektbasierte Bildanalyse (GEOBIA); halbautomatische Kartierung; Schwäbische Alb; Region Jena; Mitteldeutsche Mittelgebirge.

List of Publications

Paper 1: Zangana, I., Otto, J. C., Mäusbacher, R., & Schrott, L. (2023). Efficient geomorphological mapping based on geographic information systems and remote sensing data: an example from Jena, Germany. *Journal of Maps*, 19(1), 1–13. DOI: [10.1080/17445647.2023.2172468](https://doi.org/10.1080/17445647.2023.2172468)

- The open access published, peer-reviewed article is reproduced in Chapter 6 of the dissertation. It is accompanied by the following dataset publication:

Zangana, I., Otto, J. C., Mäusbacher, R., and Schrott, L. (2023). Dataset: Detailed geomorphological mapping based on geographic information systems and remote sensing data of Jena and surrounds, Germany, RADAR. DOI: [10.22000/798](https://doi.org/10.22000/798)

Paper 2: Zangana, I., Bell, R., Drăguț, L., Sîrbu, F., & Schrott, L. (2025). Mapping forest-covered landslides using Geographic Object-Based Image Analysis (GEGEOBIA), Jena region, Germany. *Nat. Hazards Earth Syst. Sci.*, 25(12), 4787–4806. DOI: [10.5194/nhess-25-4787-2025](https://doi.org/10.5194/nhess-25-4787-2025)

- The open access published, peer-reviewed article is reproduced in Chapter 7 of the dissertation.

Paper 3: Zangana, I., Bell, R., Drăguț, L., & Schrott, L. (2026). Transferability of Semi-automated Landslide Mapping Based on High-Resolution DTMs, Swabian Alb, Germany. *Geomorphology*. *Submitted*.

- The submitted manuscript is reproduced in Chapter 8 of the dissertation.

The three papers are embedded within synthesized chapters describing the study context as well as the data and methods applied. The papers in their original published or submitted format, including all supplementary/appendices materials, are provided in full at the end of the dissertation.

Own Contributions to the Publications

This dissertation comprehends two published peer-reviewed papers and one submitted manuscript as listed on page XII. In the following, I detail my own contributions for each of the papers. All of the papers include author contribution statements to further detail the contributions of the different co-authors.

My contributions to the paper **“Efficient geomorphological mapping based on geographic information systems and remote sensing data: an example from Jena, Germany (Paper 1)”** include conceptualization, data acquisition and preparation, methodological development, geomorphological mapping, field validation, investigation, writing of the initial draft and writing – review and editing, with a particular emphasis on the production of the high-resolution geomorphological map as the central outcome.

I conceptualized the study and designed the geomorphological mapping framework. I conducted a comprehensive literature review covering the evolution from traditional field-based mapping to digital and on-screen geomorphological mapping approaches. I acquired, processed, and integrated all relevant datasets, including high-resolution DTMs, orthophotos, and auxiliary geospatial data. I developed a systematic GIS-based workflow to extract geomorphological information and interpret landform genesis through a combination of terrain derivatives and multi-source datasets. I carried out the complete geomorphological mapping through on-screen digitizing in ArcGIS and converted all outputs into vector-based datasets in ArcGIS Pro. I conducted field campaigns (before and after mapping) using DGPS measurements to validate the mapped geomorphological features at multiple locations across the study area.

I performed the geomorphological interpretation and spatial analysis and produced the final high-resolution geomorphological map at a scale of 1:5,000, which represents the central outcome of the publication. I prepared all figures, map layouts, and supplementary materials. I generated and organized metadata and coordinated the publication of the datasets through the RADAR repository to ensure public accessibility. I wrote the initial manuscript draft and the first version of the main geomorphological map. I revised both the manuscript and the main map based on co-author input and reviewer comments. I managed communication with the journal editors and reviewers, prepared the revised manuscript, and coordinated the responses to reviewer comments. I handled the submission process and obtained APC funding from the University of Bonn.

My contributions to the paper **“Mapping forest-covered landslides using Geographic Object-Based Image Analysis (GEOBIA), Jena region, Germany (Paper 2)”** include conceptualization, methodological development, data processing, workflow implementation, validation, analysis investigation, writing of the initial draft and writing – review and editing.

I conceptualized and designed the GEOBIA-based methodology for semi-automatic landslide detection. I conducted a targeted literature review of existing GEOBIA workflows focused on forested environments and DTM-based landslide mapping to guide the methodological

development. I prepared and processed all LiDAR-derived DTM datasets and derived land surface variables (LSVs). I developed the complete GEOBIA workflow in eCognition Developer, including multi-resolution segmentation (MRS), supervised classification of Support Vector Machine (SVM), feature selection for training the algorithm, and expert-based refinements. I designed and refined the ruleset through iterative testing and evaluation, integrating morphometric, geometric, and contextual criteria. I co-developed the moving-window optimization concept for LSV scaling and independently applied and executed the optimization procedures.

I conducted all model runs, parameter tuning, and result evaluations within eCognition and exported the classification outputs to GIS for further spatial analysis. I prepared the reference landslide inventory through manual on-screen digitizing from high-resolution DTM derivatives and partially validated it in the field; this inventory served as the basis for the model accuracy assessment. I conducted all accuracy assessments in R software, including partially custom-developed scripts for performance evaluation. I produced all maps, figures, and analytical outputs and organized all datasets to ensure reproducibility of the workflow. I wrote the full manuscript draft and managed revisions, communicated with journal editors and reviewers, prepared revised versions of the manuscript, and responded to reviewer comments. I coordinated submission procedures and secured APC funding from the University of Bonn.

My contributions to the paper “**Transferability of Semi-automated Landslide Mapping Based on High-Resolution DTMs, Swabian Alb, Germany (Paper 3)**” include leading the study design, methodological transfer and implementation, data processing, analysis, investigation, writing of the initial draft and writing – review and editing.

I conceptualized the study and designed the transferability assessment framework to evaluate the GEOBIA workflow developed in Paper 2 in a geomorphologically distinct region. I co-collected and prepared multi-epoch DTM datasets (2003 and 2023) and land use data, organized all spatial datasets within a GIS environment, and prepared all LSVs required for the analysis. I created the landslide inventory map (i.e. reference map) for the Swabian Alb through manual on-screen digitizing from the high-resolution DTM hillshades in QGIS, distinguishing landslide scarps and bodies separately, and validated it in collaboration with co-authors.

I implemented the GEOBIA workflow in eCognition, applying our developed ruleset. I independently conducted MRS and classification for each DTM epoch and for different landslide components and performed all model runs, parameter applications, and result evaluations. I exported all results to GIS for further spatial analysis and produced the final maps, figures, and quantitative outputs. I conducted all accuracy assessments and compiled the statistical results. I independently drafted the manuscript, figure and maps, coordinated co-authors' feedback, and prepared for submission. I managed the submission process and prepared all required documentation for the journal.

List of Abbreviations

AA	Accuracy Assessment
DGPS	Differential Global Positioning System
DEM	Digital Elevation Model
DOPs	Digital Orthophotos
DoD	DEM of Difference / Differential Elevation Model
DLM	Digital Land use Map
DTM	Digital Terrain Model
FP	False Positive
FPr	False Positive rate
FN	False Negative
FNr	False Negative rate
GEOBIA	Geographic Object-Based Image Analysis
GIS	Geographic Information Systems
GMK	Geomorphologische Karte (German mapping system)
ha	Hectare
HCDP	Human Capacity Development Program
LGL-BW	State Office for Geoinformation (Baden-Württemberg)
LiDAR	Light Detection and Ranging
LSP	Land Surface Parameter
LSV	Land Surface Variable
LULC	Land Use / Land Cover
MI / MII	Model I / Model II (Default / Optimized)
MRS	Multi-resolution Segmentation
m a.s.l.	Meters above sea level

OBIA	Object-Based Image Analysis
RADAR	Radio Detection and Ranging
SAR	Synthetic Aperture Radar
RGB	Red, Green and Blue (Image channels)
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machine
TPI	Topographic Position Index
TLBG	Thuringian State Office (Soil Management)
TLUBN	Thuringian State Office (Environment)
TO	Topographic Openness
TRI	Terrain Roughness Index
TP	True Positive
TPr	True Positive rate
UAV	Unmanned Aerial Vehicle

Statement on the Use of Place Names

In this dissertation, original German place names are used wherever possible to maintain consistency with local usage and official maps. Special German characters (ä, ö, ü, ß) are retained unless technical or publishing constraints require otherwise. For well-known locations that have widely recognized international equivalents—such as “Cologne” for “Köln”—the international form is used to enhance readability for an international audience. This approach preserves the accuracy and cultural significance of local names while ensuring clarity for readers.

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1. Introduction

Understanding landform evolution and geomorphological processes requires reliable spatial information on terrain characteristics and process-related landforms. Geomorphological maps provide a fundamental and widely used framework for representing landforms, surface processes, and near-surface materials, and they play an important role in hazard assessment, land management, and spatial planning (Smith et al., 2011; Dramis et al., 2011; Parry, 2011; Schrott et al., 2012; Otto and Smith, 2013). Traditionally, geomorphological mapping has relied heavily on field surveys, which are time-consuming and often limited in steep, complex, or inaccessible terrain (Otto & Dikau, 2004; Seijmonsbergen, 2013). The increasing availability of high-resolution remote-sensing data, particularly LiDAR-derived digital terrain models (DTMs), has significantly improved terrain visualization and enabled more efficient and accurate digital geomorphological mapping (Smith and Clark, 2005; Gustavsson et al., 2006; Hengl and Reuter, 2008; Schneevoigt et al., 2008; Knight et al., 2011; Martin et al., 2011; Smith et al., 2011a; Schneevoigt, 2012; Schrott et al., 2013; McDowell, 2013; Frodella et al., 2014; Tzvetkov, 2018).

In parallel, landslides represent key geomorphic processes shaping landscapes worldwide and constitute significant natural hazards to infrastructure and settlements (Guzzetti et al., 1999, 2012). Reliable landslide inventories are therefore essential for hazard assessment, yet the identification of older or forest-covered landslides remains challenging using traditional mapping approaches due to vegetation cover, erosion, and anthropogenic modifications (Van Den Eeckhaut et al., 2005; Santangelo et al., 2010; Bell et al., 2012; Goetz et al., 2014; Li et al., 2015). Semi-automated mapping approaches based on Geographic Object-Based Image Analysis (GEOBIA) have become increasingly important in addressing these challenges, especially when combined with high-resolution DTMs (Drăguț and Blaschke, 2006; Blaschke et al., 2008; Blaschke, 2010). However, mapping performance strongly depends on methodological choices such as segmentation strategies and the selection of appropriate window sizes for land surface parameters (LSP; Drăguț and Eisank, 2011; Seijmonsbergen et al., 2011; Drăguț et al., 2014).

Building upon these developments, this dissertation integrates high-resolution LiDAR-based geomorphological mapping, semi-automated detection of forest-covered landslides, and the evaluation of methodological transferability across regions. Using study areas in the Jena region and the Swabian Alb in Germany, the work combines manual and semi-automated approaches to improve geomorphological and landslide mapping and to assess the robustness of semi-automated workflows under varying environmental and data conditions.

1.1. Motivation and Relevance

Geomorphological mapping and landslide inventory analysis are essential for understanding landscape evolution, assessing natural hazards, and supporting land-use planning and risk mitigation (Dramis et al., 2011; Parry, 2011). Geomorphological maps not only have scientific value but also support the visualization and communication of landscape characteristics for education, tourism, and land management (Dramis et al., 2011; Luca et al., 2011; Bollati et al., 2017; Devoto et al., 2012). Traditionally, these maps are produced through labor-intensive fieldwork, which is time-consuming, requires significant experience, and may be constrained by accessibility or steep terrain (Otto et al., 2011; Schrott et al., 2013; Seijmonsbergen, 2013). Field mapping can also be subject to interpretation uncertainty and limited spatial coverage, especially in steep and complex terrain (Beckenbach et al., 2014b; Gustavsson et al., 2004).

Remote sensing has increasingly been used to support both manual and semi-automatic geomorphological mapping. High-resolution digital elevation models (DEMs), LiDAR, and stereophotogrammetric methods allow detailed characterization and analysis of the Earth's surface and the detection of landforms and processes (e.g. Hengl and Reuter, 2008; Mcdowell, 2013; Smith and Pain, 2009). Semi-automatic approaches, such as those based on geographic object-based image analysis (GEOBIA) or rule-based classification, facilitate the extraction of landforms, geomorphic processes, and landslide inventories from digital datasets (e.g. Van Den Eeckhaut et al., 2006; Schneevoigt et al., 2008; Blaschke, 2010; Drăguț and Eisank, 2012; Eisank, 2013; Anders, 2013; Hölbling et al., 2012, 2017; Piloyan and Konečný, 2017; Rajbhandari et al., 2017; Feizizadeh et al., 2017; Chen et al., 2018; Knevels et al., 2019; Robson et al., 2020; Dias et al., 2023). While these approaches improve efficiency, their accuracy often depends on the specific landform or process considered and generally requires expert validation (Hillier, Sofia, & Conway, 2015; Otto & Smith, 2013).

Landslides, in particular, represent a significant natural hazard, with older or forested landslides often remaining underrepresented in inventories due to detection difficulties in the field (Guzzetti et al., 1999, 2012; Bell et al., 2006; Santangelo et al., 2010; Petschko et al., 2016). High-resolution LiDAR and DTMs enable more precise mapping, even beneath forest cover, by providing detailed topographic information and allowing the calculation of land surface variables (LSVs) such as slope, curvature, and hillshade (Anders, Seijmonsbergen, & Bouten, 2015; Anders, Seijmonsbergen, Bouten, & Smith, 2011; Napieralski, Barr, Kamp, & Kervyn, 2013; L. Schrott et al., 2013; Zangana et al., 2023). The integration of GEOBIA with land surface variables (LSVs) further enhances semi-automatic detection of landslide scarps and bodies, supporting more comprehensive and reproducible landslide inventories (Drăguț and Blaschke, 2006; Martha et al., 2012; Van Den Eeckhaut et al., 2012; Knevels et al., 2019; Hölbling et al., 2017; Karantanellis et al., 2020; Dias et al., 2023b, 2025).

Despite these advancements, several challenges remain. Optimal parameterization of LSVs, such as the selection of moving-window sizes, strongly influences mapping accuracy but is often not systematically addressed (Anders et al., 2009; Drăguț and Eisank, 2011; Pawluszek et al., 2018; Knevels et al., 2019; Sîrbu et al., 2019). Additionally, the transferability of semi-automatic approaches to different environmental contexts or DTM qualities is still limited, constraining their wider application in regional hazard assessment and landscape analysis (Seijmonsbergen et al., 2011; Zangana et al., 2025).

This dissertation is motivated by the need to overcome limitations in geomorphological and landslide mapping by integrating high-resolution LiDAR DTMs, multiscale LSVs, visualization techniques, and semi-automated GEOBIA-based workflows. By bridging traditional field methods and automated approaches, the research improves accuracy, efficiency, and transferability in mapping landforms and landslides. Together, the three studies advance manual on-screen mapping, develop semi-automatic detection methods, and evaluate their applicability across regions, providing robust and reproducible approaches for hazard assessment, landscape analysis, and geomorphological research (Zangana et al., 2023, 2025; Zangana et al., submitted).

1.2 Objectives and Research Questions

Recent advances in high-resolution terrain data, particularly LiDAR-derived DTMs, have significantly improved the possibilities for geomorphological mapping and landslide detection. Nevertheless, several gaps remain. Manual geomorphological mapping is still time-consuming and difficult to standardize across regions, while semi-automatic approaches often struggle in forested terrain where landslides remain hidden beneath vegetation. Moreover, workflows developed for one study region frequently show limited transferability when applied to different geomorphological settings or terrain datasets. Consequently, there is still a need for robust and transferable approaches that combine expert geomorphological knowledge with automated analysis methods while ensuring reliable application across regions and data conditions.

The motivation of this dissertation is therefore to improve digital geomorphological mapping and landslide inventory generation by integrating high-resolution terrain analysis, semi-automatic mapping approaches, and transferability testing across regions. The work aims to bridge the gap between detailed manual geomorphological interpretation and scalable semi-automatic terrain analysis methods suitable for hazard assessment and landscape studies.

To address these challenges, the dissertation pursues the following research objectives:

Research Objectives

1. To improve geomorphological mapping quality and efficiency through the integration of high-resolution LiDAR-derived DTMs, visualization techniques, and supporting thematic datasets (*Paper 1*)
2. To develop and evaluate semi-automatic landslide detection methods capable of identifying forest-covered landslides using optimized terrain parameters and object-based image analysis techniques (*Paper 2*)
3. To evaluate how parameter selection and segmentation strategies influence landslide detection performance, particularly in forested middle-mountain terrains (*Paper 2*)
4. To assess the transferability of semi-automatic landslide mapping workflows when applied to regions with different geomorphological and environmental conditions (*Paper 2 & Paper 3*)
5. To evaluate how differences in terrain datasets and acquisition periods influence landslide detection results, including the effect of DTM quality and temporal differences (*Paper 3*)
6. To investigate how additional datasets, such as land-use or land-cover information, can support improved landform mapping and landslide detection, particularly in vegetated areas (*Paper 1 & Paper 3*)

Together, these objectives provide the basis for addressing the following research questions examined in the three papers forming this dissertation.

Research Questions

1. How can high-resolution terrain data and complementary spatial datasets improve geomorphological mapping and landslide identification in middle-mountain regions? (*Paper 1 & Paper 2*)
2. How effectively can semi-automatic, GEOBIA-based approaches detect landslides, particularly those obscured by forest cover, compared to traditional mapping approaches? (*Paper 2 & Paper 3*)
3. How do parameter choices and terrain analysis settings influence landslide detection performance in forested environments? (*Paper 2*)

4. To what extent are semi-automatic landslide detection methods transferable between regions with differing geomorphological conditions? (*Paper 2 & Paper 3*)
5. How do differences in (terrain) data quality and acquisition timing affect landforms and geomorphological processes mapping results? (*paper 1 & Paper 3*)
6. How can integrating additional spatial datasets improve the robustness of landform mapping and landslide detection workflows in complex terrain? (*Paper 1 & Paper 3*)

1.3. Outline and Conceptual Framework

Based on the motivation and objectives in Chapter 1, Chapter 2 presents the conceptual foundations of geomorphological mapping, including the transition from traditional field-based approaches to remote sensing and digital terrain analysis, as well as semi-automated mapping approaches. Chapter 3 focuses on landslide mapping, covering inventory mapping, mapping approaches and data sources, and semi-automated detection using GEOBIA, including challenges in complex and forested terrain. Chapters 4 and 5 introduce the study areas, datasets, and methodological procedures that form the framework for this dissertation.

The three papers comprising this dissertation are presented in Chapters 6 to 8 and build sequentially upon one another in terms of methodological development, spatial application, and validation scope.

This dissertation investigates digital geomorphological mapping and landslide inventory generation within a cumulative methodological framework that integrates high-resolution terrain representation, object-based classification, and transferability assessment. The work is motivated by the need to advance reproducible geomorphological analysis in environments where landform expression may be obscured by vegetation cover and complex terrain structure.

Geomorphological mapping has traditionally been grounded in field-based observation and stereoscopic aerial photograph interpretation for the delineation of landforms and process domains, reflecting the long-standing interpretative tradition of geomorphology (Dramis et al., 2011; Otto et al., 2011; Devoto et al., 2012; Seijmonsbergen, 2013). While field mapping remains fundamental for process understanding, it is often constrained by accessibility limitations, spatial coverage, and observer subjectivity.

The increasing availability of high-resolution LiDAR-derived DTMs has significantly transformed geomorphological mapping practice. LiDAR technology enables the detailed representation of bare-earth morphology beneath vegetation canopies and provides morphometric information at sub-meter spatial resolution (Hengl & Reuter, 2008; Smith et al., 2011; Schrott et al., 2013). Derived land surface parameters, including slope, curvature, and composite terrain visualizations, allow geomorphic structures to be quantified and analysed systematically.

Within this context, the first paper of this dissertation establishes a structured digital geomorphological mapping framework based on high-resolution LiDAR terrain data. The study integrates GIS-based terrain derivatives with multi-visualisation techniques to support systematic identification and delineation of geomorphic units. Rather than pursuing fully automated mapping, the workflow formalises expert geomorphological knowledge into

transparent analytical procedures, thereby improving mapping reproducibility and reducing interpretative uncertainty.

Building upon this methodological foundation, the second paper extends the framework toward process-oriented semi-automatic mapping using GEOBIA. GEOBIA provides a means of translating continuous raster terrain information into spatially coherent objects that can be classified based on morphometric, spatial, and contextual attributes (Drăguț & Blaschke, 2006; Blaschke, 2010). Landslides are conceptualised as discrete geomorphic entities characterised by structural and morphological signatures.

The study employs multiresolution segmentation combined with machine learning classification to develop a semi-automatic landslide inventory mapping approach for forest-covered rotational landslides. A key methodological contribution lies in addressing scale dependency in geomorphometric analysis. The calculation of land surface variables was optimised using separate window sizes for landslide scarps and bodies, recognising that different landform components exhibit different spatial expressions (Drăguț et al., 2011; Drăguț & Eisank, 2011). Validation against expert-derived inventories demonstrated improved detection performance and reduced false-positive mapping.

Despite methodological advances, semi-automatic mapping approaches often remain context-sensitive. Models calibrated in specific geomorphological settings may require substantial re-parameterization when transferred to regions with different lithological, morphological, or land-use characteristics. This sensitivity limits operational scalability and motivates systematic evaluation of model robustness.

Accordingly, the third paper evaluates the transferability of the GEOBIA-based mapping framework by applying it to a geomorphologically distinct escarpment landscape in the Swabian Alb. The model is tested without fundamental re-optimisation of segmentation and classification parameters in order to assess methodological stability across environmental contexts. The study further examines the influence of land-use integration on forest-covered landslide detection and compares mapping performance using Digital Terrain Models from 2003 and 2023 to evaluate the influence of terrain representation and data quality.

The dissertation therefore follows a cumulative conceptual progression from structured digital geomorphological mapping, to semi-automatic object-based landslide detection, and finally to cross-regional methodological validation. This progression reflects a shift from methodological structuring toward robustness assessment and generalisation of digital geomorphological workflows.

The conceptual and methodological structure of the dissertation is summarised in Figure 1, which illustrates the relationship between high-resolution terrain data, digital terrain analysis, object-based classification, and the sequential development of the three papers.

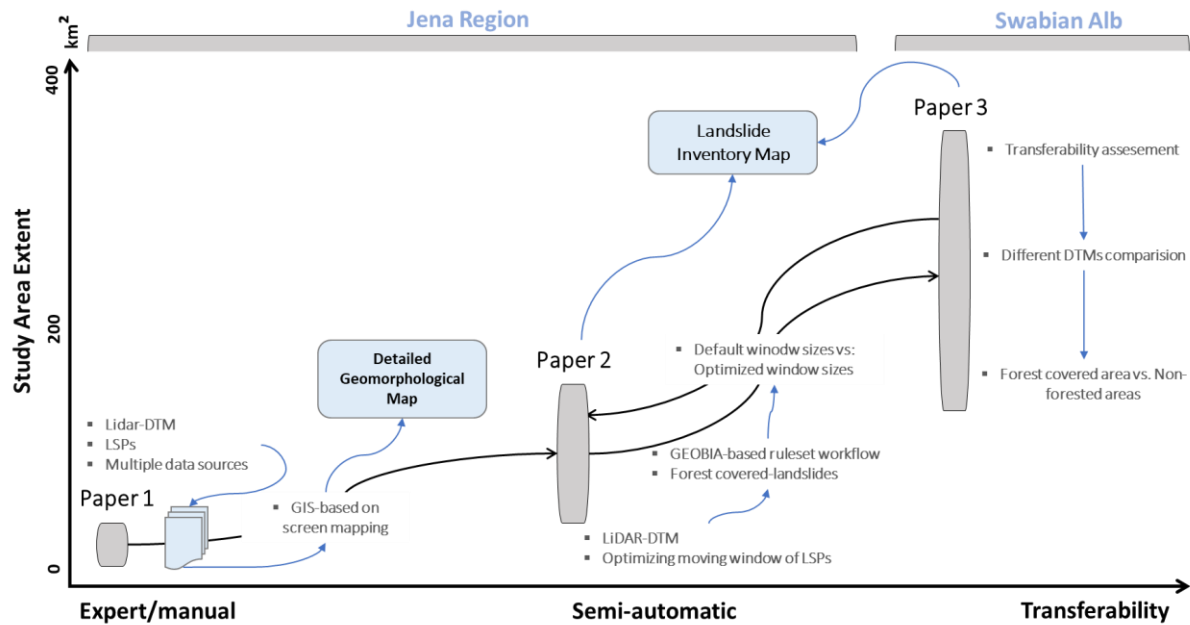


Figure 1 Conceptual and methodological framework of the dissertation. The figure illustrates the progression of geomorphological mapping and landslide detection across multiple methodological stages. High-resolution LiDAR-based terrain analysis, combined with multiple data sources, enables detailed digital geomorphological mapping at local scale in the Jena region (Paper 1). Building on this foundation, GEOBIA-based semi-automated landslide detection is developed and applied in forested terrain of Jena using high-resolution DTM derivatives (Paper 2). The transferability of this workflow is subsequently evaluated in the geomorphologically distinct Swabian Alb, allowing assessment across varying terrain conditions and spatial configurations (Paper 3).

In summary, this dissertation contributes to the advancement of digital geomorphological mapping and semi-automatic landslide detection by integrating morphometric terrain analysis with object-based classification and robustness evaluation. By linking terrain structure to analytical representation and systematically assessing methodological stability across spatial contexts, the work supports the development of reproducible and transferable workflows for detailed geomorphological feature delineation and landslide inventory mapping.

2. Geomorphological mapping

Geomorphological mapping provides a structured representation of landforms and processes, linking surface morphology to geomorphic dynamics and forming a basis for subsequent methodological developments in terrain analysis and interpretation (Dramis et al., 2011; Seijmonsbergen, 2013).

2.1. Conceptual Foundations of Geomorphological Mapping

Geomorphological mapping represents one of the most fundamental approaches for analysing and understanding Earth surface processes. It provides a spatially explicit representation of landforms, surface materials, and geomorphic processes, thereby enabling the interpretation of landscape evolution and environmental dynamics (Dramis et al., 2011; Parry, 2011; Knight et al., 2011; Otto and Smith, 2013b). Beyond its descriptive function, geomorphological mapping constitutes an interpretative framework in which morphological evidence is translated into process-based understanding, linking present-day surface expressions to past and ongoing geomorphic activity (Seijmonsbergen, 2013; Otto et al., 2011).

Geomorphological maps serve multiple scientific and applied purposes. They are widely used in hazard and risk assessment, particularly in identifying areas susceptible to landslides, erosion, and flooding (Parry, 2011; Guzzetti et al., 2012). Furthermore, they provide essential input for land-use planning, environmental management, and geoconservation (Bollati et al., 2017; Devoto et al., 2012). In addition, geomorphological maps are increasingly utilised in interdisciplinary contexts, including ecology, forestry, and soil science, where terrain characteristics strongly influence ecosystem processes (Gustavsson et al., 2008; Seijmonsbergen, 2013; De Muro et al., 2015; Kooijman et al., 2017).

A defining characteristic of geomorphological mapping is its inherently interpretative nature. Unlike purely measurement-based disciplines, geomorphological mapping requires the integration of observational data with expert knowledge to infer process–form relationships (Otto and Dikau, 2004; Knight et al., 2011). This interpretative component introduces both strength and complexity: while it enables a rich understanding of landscape dynamics, it also makes mapping outcomes dependent on the experience and methodological choices of the investigator.

In this context, geomorphological maps should not be understood as static representations, but rather as conceptual models of landscape organisation. They reflect both the available data and the methodological framework through which these data are interpreted. Consequently, developments in data acquisition and analytical techniques have continuously reshaped the practice of geomorphological mapping.

2.2 From Field-Based Mapping to Digital Terrain Analysis

Geomorphological mapping approaches have evolved considerably in response to advances in data availability and analytical techniques, ranging from traditional field-based methods to digitally supported terrain analysis and interpretation (Smith & Pain, 2009; Hengl & Reuter, 2008; Seijmonsbergen, 2013).

2.2.1. Traditional Field-Based Mapping

Historically, geomorphological mapping has been grounded in detailed field observations, supported by topographic maps and the interpretation of aerial photographs (Seijmonsbergen, 1992; Otto & Dikau, 2004; Gustavsson et al., 2008). Field-based mapping enables the direct assessment of landforms, sediments, and geomorphic process indicators, providing a level of detail and interpretative depth that remains difficult to achieve from remote approaches alone (Knight et al., 2011; Otto & Smith, 2013; Seijmonsbergen, 2013).

A key strength of field mapping lies in its capacity to identify subtle geomorphic features and internal landform characteristics, including stratigraphy, material composition, and small-scale morphological variations. Such detailed observations are essential for reconstructing geomorphic processes and for distinguishing between landforms that may appear morphologically similar but differ in origin (Knight et al., 2011).

Despite these advantages, field-based mapping is subject to several practical limitations. Accessibility, complex terrain, and dense vegetation can significantly constrain observations, particularly in steep or forested environments (Santangelo et al., 2010; Beckenbach et al., 2014a; Bell et al., 2012). Moreover, the approach is time-intensive, with typical mapping rates of only a few square kilometres per day (Smith, 2011). As a result, spatial coverage is often limited, and the reproducibility of mapping outcomes may vary among investigators due to differences in expertise and interpretation (Jones et al., 2007; Hillier et al., 2015a).

In addition, traditional manual mapping often involves the integration of multiple layers of information and a wide range of symbols, which can reduce map readability and complicate interpretation (Smith et al., 2011). This issue is evident, for example, in the GMK project in Germany (e.g. Barsch and Mäusbacher, 1979; Barsch and Stäblein, 1989; Garleff, 1985), highlighting the need for simplification (see Figure 2).

2.2.2. Remote Sensing and Digital Mapping Approaches

The increasing availability of remote sensing data since the mid-twentieth century has fundamentally transformed geomorphological mapping (Smith & Pain, 2009; Schrott et al., 2013). Early applications relied on aerial photography, which enabled broader spatial coverage but still depended on manual interpretation (James et al., 2012; Smith et al., 2011c; Smith et al., 2013). The transition to digital mapping was accelerated by the development of Geographic Information Systems (GIS; Otto et al., 2017) and the widespread availability of Digital Elevation Models (DEMs) (see Hengl and Reuter (2008) for extensive review of techniques and application of geomorphometry in geomorphology).

A major breakthrough in this evolution has been the introduction of high-resolution LiDAR-derived Digital Terrain Models (DTMs), which provide detailed representations of the bare-earth surface (van Asselen and Seijmonsbergen, 2006; ; Smith et al., 2006; James et al., 2012; Seijmonsbergen, 2013; Hofierka et al., 2018), even in densely vegetated areas (Booth, Roering, & Perron, 2009; Chen et al., 2015; Haneberg, Cole, & Kasali, 2009; Hölbling et al., 2016; Knevels et al., 2019; Li et al., 2015; Piloyan & Konečný, 2017; Pradhan, 2017; Van Den Eeckhaut et al., 2005). These datasets enable the detection of subtle geomorphic features that are often invisible in traditional field surveys or optical imagery (Schulz, 2004; Beckenbach et al., 2014b).

These limitations have driven the development of complementary approaches based on remote sensing and digital data, which extend mapping capabilities beyond the constraints of direct field observation.

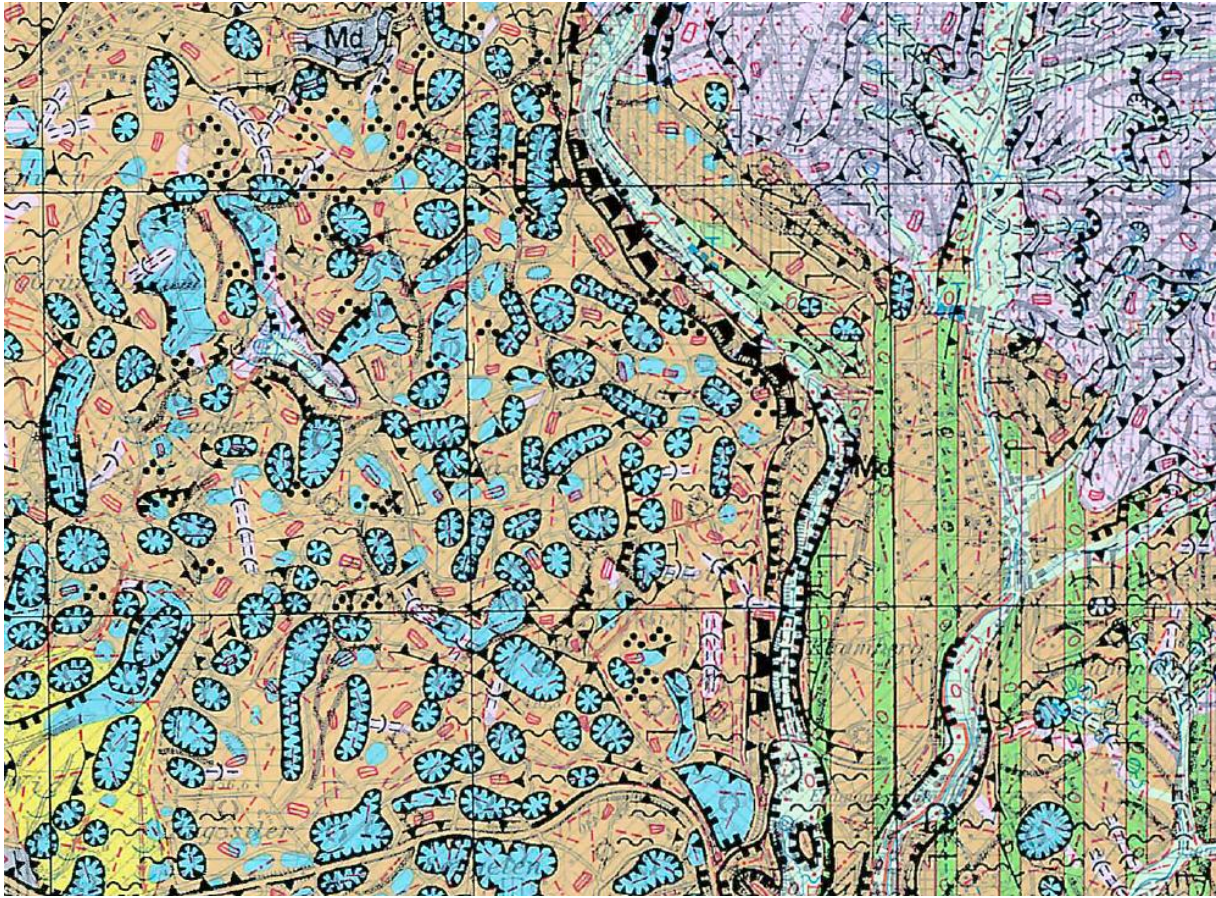


Figure 2 Geomorphological map of the Wehr area (Sheet 8313) demonstrating the GMK25 mapping system (D. Barsch & Mäusbacher, 1979a) and its thematic detail and information density.

Legend: Coloured polygons represent geomorphic domains—brown: denudational; yellow: aeolian; lilac: glacial; pink: cryogenic; green: fluvial; blue: karstic. Black dots indicate floats/rock fragments. Black linear symbols with perpendicular ticks illustrate slope breaks and escarpments, where tick size/type and spacing reflect step height and width. Blue lines represent rivers and streams; red symbols indicate bedrock or subsurface materials.

Digital terrain analysis builds upon these datasets through the derivation of land surface parameters (LSPs), such as slope, curvature, aspect, and topographic indices (MacMillan & Shary, 2009). These parameters quantify terrain characteristics and provide objective metrics for identifying and classifying landforms (Miliaresis, 2001; Hengl and Reuter, 2008; Drăguț and Eisank, 2011, 2012).

Visualization techniques further enhance the interpretability of digital terrain data (refer to Smith et al. (2013) for more details of visualization techniques in geomorphological mapping). Methods such as multidirectional hillshading, local relief models, and openness analysis improve the visibility of geomorphic structures and reduce directional bias in terrain representation (Doneus, 2013; Nagi, 2014; Hillier et al., 2015a; Tzvetkov, 2018). The integration of multiple visualization layers allows for a more comprehensive interpretation of complex landscapes.

Compared to traditional methods, digital mapping approaches significantly increase efficiency and spatial coverage (Seijmonsbergen, 2013). The extent of mapping can reach tens to hundreds of square kilometres per day, depending on data availability and resolution (Smith, 2011; Otto & Smith, 2013). At the same time, digital workflows improve reproducibility by providing explicit and transferable analytical procedures (see Otto and Smith (2013) for detailed review of geomorphological mapping approaches).

Despite these advances, digital geomorphological mapping remains closely tied to expert interpretation. The selection of appropriate datasets, parameters, and visualization techniques requires a deep understanding of geomorphic processes and their expression in terrain data.

2.3. Semi-Automated Mapping and Emerging Paradigms

The increasing availability of high-resolution terrain data has led to the development of semi-automated and automated mapping approaches. These methods aim to reduce subjectivity and improve efficiency by applying computational algorithms to identify and classify landforms directly from digital datasets (Drăguț & Blaschke, 2006; Blaschke, 2010; Seijmonsbergen et al., 2011).

A common workflow involves the calculation of LSPs, followed by segmentation and classification. Segmentation groups pixels into homogeneous objects, while classification assigns these objects to geomorphological classes based on their attributes (Baatz & Schäpe, 2000; Drăguț et al., 2010). Both unsupervised and supervised classification techniques are used, ranging from statistical clustering to knowledge-based rule sets and machine learning approaches (Hengl and MacMillan, 2009; Eisank, 2013; Anders et al., 2015; Jorge and Brennand, 2017; Chen et al., 2018; Nalepa and Kawulok, 2019).

Among these approaches, Geographic Object-Based Image Analysis (GEOBIA; see Section 3.3 for more detail) has gained particular importance. By shifting the unit of analysis from pixels to objects, GEOBIA allows the incorporation of spatial context, geometry, and topological relationships, thereby improving the representation of complex landforms (e.g. Hay et al., 2005; Hay and Castilla, 2008; ; Schneevoigt et al., 2010; Blaschke, 2010; Kim et al., 2011; D'Oleire-Oltmanns et al., 2012; Anders, 2013; Eisank, 2013; Chen et al., 2018)

The effectiveness of semi-automated approaches is highly sensitive to parameter configuration and environmental conditions. Complex or degraded landforms, along with landscapes exhibiting overlapping geomorphometric signatures from distinct processes, present substantial challenges for reliable automated detection (Hillier, et al., 2015b; Otto & Smith, 2013). Furthermore, the scale at which terrain parameters are derived critically influences the detectability of geomorphic features. These limitations indicate that automated methods do not replace geomorphological expertise, but instead reframe it toward the design, calibration, and validation of analytical workflows (Seijmonsbergen, 2013).

2.4. Synthesis and Link to Paper 1

The methodological evolution outlined above demonstrates that geomorphological mapping has transitioned from a predominantly field-based practice to a data-rich and digitally supported discipline. Field-based, expert-driven digital, and semi-automated approaches each

contribute distinct strengths, but also introduce specific challenges related to efficiency, interpretability, and reproducibility (Otto & Smith, 2013).

A recurring theme across these approaches is the importance of scale, data integration, and methodological transparency. The interpretation of landforms depends not only on the quality of input data but also on how these data are processed and visualised. In this context, the combination of multiple datasets and visualization techniques has emerged as a key strategy for improving mapping quality (e.g. Hiller and Smith, 2008; Kennelly, 2008; Bishop, 2013; Bishop et al., 2012; Doneus, 2013; Anders et al., 2015; Zangana et al., 2023).

Within this context, Paper 1 presents a structured framework for manual digital geomorphological mapping. The approach integrates high-resolution LiDAR-derived DTMs with multiple LSPs, orthophotos, geological maps, and topographic data within a systematic workflow. By explicitly organising the mapping process, it enhances consistency, transparency, and interpretability while maintaining the advantages of expert-driven analysis.

The framework presented in Paper 1 positions manual digital mapping as a central methodological step that bridges traditional geomorphological expertise and emerging automated approaches. It establishes a reproducible foundation for subsequent developments in semi-automated landform detection addressed in later chapters.

Overall, geomorphological mapping has evolved into a multi-faceted discipline integrating field observation, remote sensing, and digital terrain analysis. While high-resolution data and computational methods have expanded mapping capabilities, the interpretation of geomorphic features remains strongly dependent on expert knowledge and methodological decisions.

Paper 1 contributes to this development by establishing a structured manual digital on-screen mapping framework that enhances consistency and transparency. This framework forms the methodological foundation for the subsequent transition toward semi-automated approaches developed in this dissertation.

3. Semi-Automated Landslide Detection

Landslides represent one of the most widespread and geomorphologically significant mass movement processes shaping slopes across a wide range of climatic and geological environments. As gravity-driven displacements of rock, debris, or soil, they contribute fundamentally to landscape evolution, sediment redistribution, and slope system dynamics (Cruden & Varnes, 1996; Guzzetti et al., 2012). Their occurrence is controlled by a combination of predisposing factors, including lithology, slope geometry, and hydrological conditions, as well as triggering mechanisms such as intense rainfall, seismic activity, or anthropogenic disturbance (Corominas et al., 2014; Guzzetti et al., 1999, 2021).

From a geomorphological perspective, landslides produce diagnostic morphological signatures, including head scarps, tension cracks, displaced masses, and depositional lobes, which can persist in the landscape long after activity has ceased (Cruden and Varnes, 1996; Bell et al., 2012). The identification and mapping of these features form the basis of landslide inventory mapping, which is essential for hazard assessment, susceptibility modelling, and the reconstruction of landscape evolution (Guzzetti et al., 1999; van Westen et al., 2008)

3.1. Landslide Inventory Mapping

Landslide inventory maps provide a spatially explicit record of slope failures, documenting their location, extent, type, and, where possible, temporal occurrence (Guzzetti et al., 1999; Guzzetti et al., 2012). These inventories constitute a fundamental dataset for quantitative landslide hazard and risk assessment and are widely used in susceptibility modelling, frequency analysis, and process-based studies (Guzzetti et al., 2012; Reichenbach et al., 2018)

The preparation of landslide inventories is grounded in several core geomorphological assumptions. First, landslides are assumed to leave identifiable morphological signatures that can be detected through field observation or remote sensing (Napieralski et al., 2013; Zhong et al., 2019). Second, the principle of uniformitarianism suggests that past landslide occurrences provide insight into future slope instability under similar environmental conditions (Guzzetti et al., 1999). Third, specific morphological features are interpreted as indicators of distinct movement types and failure mechanisms (Cruden & Varnes, 1996).

Inventories are commonly classified based on their temporal and spatial characteristics. Event-based inventories document landslides triggered by a specific event, such as an earthquake or rainfall episode, whereas multi-temporal or historical inventories integrate landslides over longer time periods (Ghosh et al., 2012; Guzzetti et al., 2012). Geomorphological inventories, which aim to delineate the full extent of landslide features, typically provide the highest level of detail but require substantial interpretative effort (Santangelo et al., 2010).

The quality of landslide inventories depends on both positional accuracy and thematic completeness. Errors may arise from limitations in data resolution, environmental conditions such as vegetation cover, and the subjective interpretation of the investigator (Guzzetti et al., 1999, 2012; Santangelo et al., 2010). Consequently, the development of consistent and reproducible mapping approaches remains a central objective in landslide research.

3.2. Mapping Approaches and Data Sources

The methods used for landslide mapping closely parallel those employed in general geomorphological mapping (Chapter 2), but are adapted to the specific morphological and process-related characteristics of slope failures. Traditionally, landslide inventories have been derived from field surveys and the visual interpretation of aerial photographs (Malamud et al., 2004; Guzzetti et al., 2012). Field mapping allows for the direct observation of geomorphic features and materials and is often considered the most reliable approach for detailed investigations. It enables the identification of subtle features such as tension cracks, minor scarps, and internal deformation structures that may not be visible in remotely sensed data (Guzzetti et al., 2012).

However, field-based mapping is limited in spatial extent and is often constrained by accessibility, cost, and time requirements. These limitations are particularly pronounced in mountainous or densely vegetated regions, where large areas remain difficult to survey comprehensively (Santangelo et al., 2010; Zhong et al., 2019).

The interpretation of aerial photographs has historically provided a means of extending mapping efforts to larger areas. Using stereoscopic visualization, investigators can identify landslides based on characteristic morphological features and terrain patterns (Guzzetti et al., 2012). Nevertheless, this approach is influenced by image quality, scale, and environmental conditions, such as vegetation cover and shadowing, which may obscure critical features (Carrara et al., 1995; Guzzetti et al., 1999, 2012)

The advent of high-resolution remote sensing data, particularly LiDAR-derived digital terrain models, has significantly enhanced landslide mapping capabilities. LiDAR enables the generation of high-resolution bare-earth models that reveal subtle topographic features beneath vegetation, providing a major advantage in forested environments (Schulz, 2004; Tarolli, 2014; Van Den Eeckhaut et al., 2005; Li et al., 2015; Zhong et al., 2019). This has led to a substantial increase in the detection of previously unrecognized or relict landslides (Hölbling et al., 2017; Van Den Eeckhaut et al., 2012)

In addition to LiDAR, other remote sensing techniques, such as synthetic aperture radar (SAR) and differential interferometry (DInSAR), enable the monitoring of ground deformation and the detection of active landslides (Tofani et al., 2013; Hölbling et al., 2016). Optical satellite imagery and UAV-based photogrammetry further contribute to landslide mapping by providing high-resolution surface information and multi-temporal datasets (Karantanellis et al., 2021; Piralilou et al., 2019). A simplified workflow illustrating the data sources and methodological steps used in landslide inventory mapping based on remote sensing is presented in Figure 3.

3.3. Semi-Automated and Geographic Object-Based Image Analysis (GEOBIA) Approaches

The increasing availability of high-resolution terrain data has facilitated the development of semi-automated approaches for landslide detection (Martha et al., 2013; Tarolli, 2014). These methods aim to reduce the subjectivity and time requirements associated with manual mapping by applying computational algorithms to identify landslide features based on their

morphological characteristics (Feizizadeh & Blaschke, 2013; Martha et al., 2010; S. d'Oleire-Oltmanns et al., 2012).

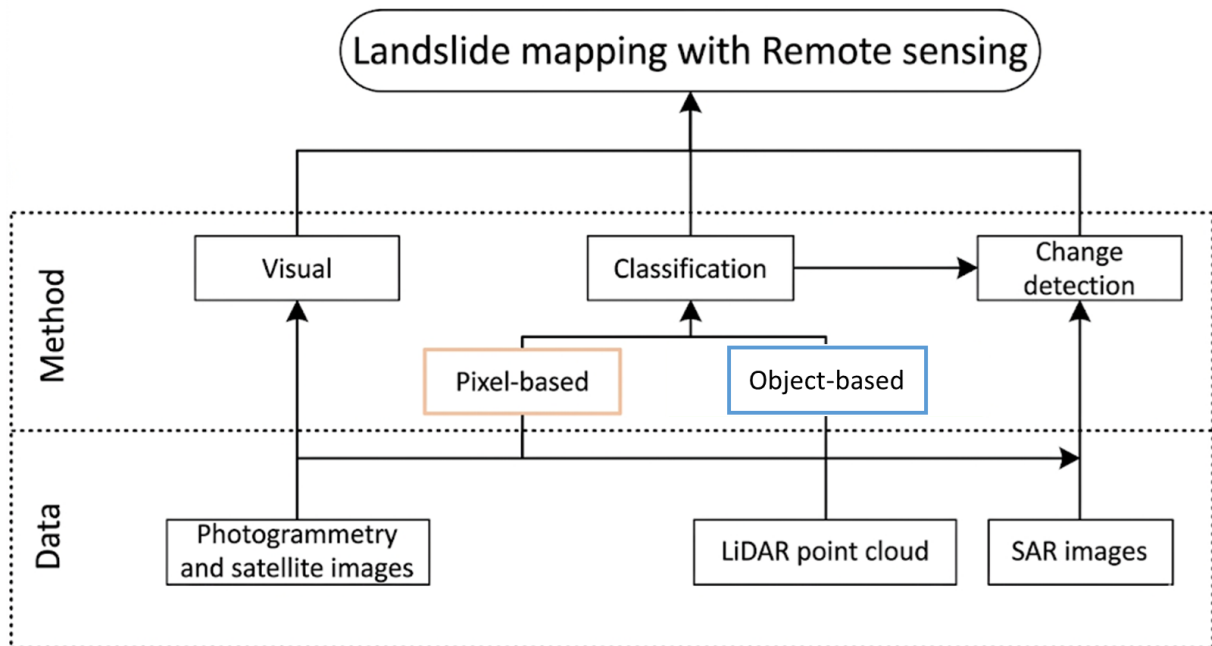


Figure 3 General workflow for landslide mapping from remote sensing data. Modified after Zhong et al. (2019).

Early approaches to automated landslide detection relied on pixel-based classification methods, which analyse the spectral or topographic properties of individual pixels (Keyport et al., 2018). However, such methods often struggle to represent the spatial complexity of geomorphic features, particularly in high-resolution datasets where within-class variability may exceed between-class variability (Blaschke, 2010a).

Geographic Object-Based Image Analysis (GEOBIA) addresses these limitations by shifting the unit of analysis from pixels to meaningful spatial objects (Blaschke, 2010; Hay & Castilla, 2008). In this framework, terrain data are segmented into homogeneous regions based on spectral, topographic, and spatial criteria, and these segments are subsequently classified using a combination of attributes, including shape, texture, and contextual relationships (Drăguț & Blaschke, 2006; Eisank et al., 2014). The general workflow of a GEOBIA-based approach is illustrated in Figure 4.

A key advantage of GEOBIA is its ability to incorporate spatial context and hierarchical relationships, which are essential for representing geomorphological features. Landslides, for example, consist of multiple components, such as scarps, bodies, and deposits, which are spatially related and occur at different scales. Object-based approaches allow these relationships to be explicitly modelled, improving classification accuracy and interpretability (Blaschke et al., 2014; Höbling et al., 2017; Dias et al., 2023b).

Furthermore, GEOBIA supports knowledge-driven classification, where expert knowledge is encoded in rule sets that define the relationships between terrain attributes and geomorphic features (Anders et al., 2015; Karantanellis et al., 2020; Dias et al., 2025). This enables the integration of geomorphological reasoning into semi-automated workflows, bridging the gap between manual interpretation and automated analysis.

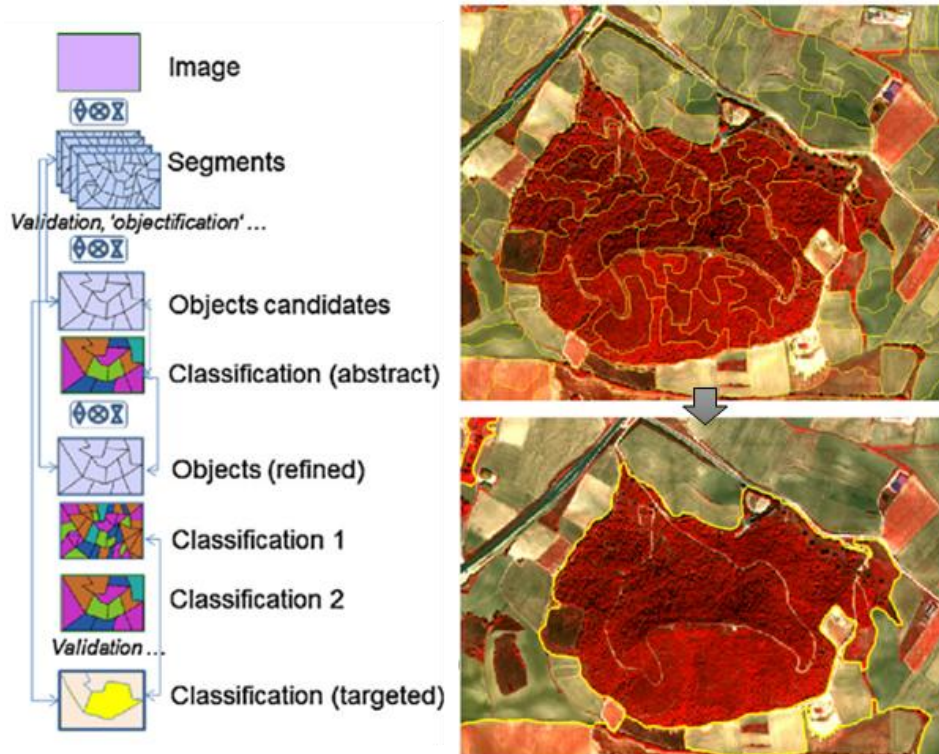


Figure 4 Conceptual workflow of GEOBIA. Modified after Blaschke et al. (2014).

3.4. Landslide Detection in Complex and Forested Terrain

Landslide inventory mapping underpins hazard assessment and spatial probability modelling, as it defines the spatial distribution and characteristics of slope failures (Guzzetti et al., 1999, 2021). Traditional inventories derived from field mapping, aerial photograph interpretation, and historical records remain methodologically fundamental but are constrained in forested and geomorphologically complex terrain due to vegetation cover, surface degradation, and limited accessibility (Van Den Eeckhaut et al., 2005; Bell et al., 2012; Santangelo et al., 2010). These constraints are particularly pronounced for relict landslides, where diagnostic morphologies are progressively attenuated.

High-resolution LiDAR-derived DTMs provide a methodological advance by enabling bare-earth terrain representation beneath vegetation cover, thereby improving the detectability of subtle landslide morphology such as degraded scarps, hummocky deposits, and internal deformation structures (Guzzetti et al., 2012; Tarolli, 2014). Nevertheless, the interpretability of LiDAR-based terrain analysis is contingent on parameterization of LSVs, particularly window size selection in moving-window operations (Anders et al., 2011b; Prasicek et al., 2014; Goetz et al., 2014; Wei et al., 2017; Pawluszek et al., 2018; Sîrbu et al., 2019).

Landslides exhibit inherently multi-scale morphology, comprising nested structures ranging from kilometer-scale landslide bodies to meter-scale scarps and internal deformation features. These components are characterized by distinct spatial frequencies and therefore require scale-specific analytical treatment (Anders et al., 2011; Knevels et al., 2019; Sîrbu et al., 2019; Zangana et al., 2025). Fixed-scale parameterization of LSVs introduces systematic limitations by either over-smoothing diagnostic features or amplifying terrain noise, particularly in heterogeneous forested environments (Tarolli, 2014; Pawluszek et al., 2018).

A further challenge in landslide detection arises from equifinality, whereby distinct geomorphic processes result in similar landforms. This overlap makes it difficult for automated systems to accurately distinguish between distinct feature classes (Smith et al., 2011b; Napieralski et al., 2013). Morphological degradation in forested terrain additionally reduces feature distinctiveness over time due to erosion, soil development, and vegetation succession, thereby increasing reliance on terrain derivatives rather than optical data (Bell et al., 2012; Goetz et al., 2014; Van Den Eeckhaut et al., 2012).

Recent GEOBIA-based landslide mapping approaches have consistently demonstrated superior performance in forested terrain. However, they remain constrained by inconsistent or default parameterization of LSV window sizes and limited treatment of scale variability in landslides components (Pawluszek et al., 2018; Knevels et al., 2019). Although multi-scale optimization has been shown to improve feature detection (Seijmonsbergen et al., 2011; Sîrbu et al., 2019), no standardized operational framework for scale-adaptive LSV configuration is established; a detailed review of scale-related issues is available in Drăguț and Eisank (2011) and Drăguț et al., (2011).

3.5. Synthesis and Link to Paper 2 and Paper 3

To address this limitation, this dissertation develops a scale-optimised GEOBIA framework for the semi-automated mapping of deep-seated rotational landslides in forested mid-mountain environments (Jena, Germany). The approach integrates LiDAR-derived DTMs with systematically optimised LSV window sizes at object-specific scales, enabling a differentiated representation of landslide components within a hierarchical object structure (Paper 2; Paper 3). Further details on the optimised moving-window sizes of LSVs applied in the modelling approach (Paper 2) are provided in Section 7.1.1.

This framework extends conventional GEOBIA workflows by explicitly coupling segmentation scale, terrain-derivative scale, and geomorphic object scale. Comparative analysis against default parameter settings indicates improved consistency and robustness of landslide delineation in structurally complex forested terrain (Chapter 7). The resulting workflow strengthens methodological reproducibility by embedding scale sensitivity directly into object-based classification logic, thereby enhancing transferability across heterogeneous geomorphic settings (Chapter 8).

Collectively, these investigations establish the conceptual and operational basis for the rule-set architecture presented in the Paper 2 appendices, supporting reproducible semi-automated landslide mapping in densely vegetated landscapes.

4. Study Area: The Middle-Mountain Regions of Germany

This chapter delineates the environmental and geomorphological characteristics of the study areas selected for this dissertation, providing the necessary context for the investigations presented in the subsequent research papers. The research focuses on two representative middle-mountain (German: Mittelgebirgen) settings in Germany (Figure 5): (i) the Jena region in eastern Thuringia (Central German uplands), which served as the primary site for geomorphological mapping and model development (Paper 1 and Paper 2), and (ii) the Swabian Alb escarpment in Baden-Württemberg (southwestern Germany), evaluating the cross-regional transferability of the semi-automated landslide detection workflows (Paper 3).

Both regions are characterized by cuesta-related landscapes, the South German Scarplands and the Thuringian Basin margin, defined by pronounced lithological contrasts and steep hillslopes (for a review of the landscapes and landforms of Germany, see Lehmkuhl et al., 2025). In these settings, the alternation of permeable and impermeable strata creates a high predisposition for gravitational mass movements, particularly rotational landslides. These processes are not only fundamental drivers of long-term landscape evolution but also constitute a significant hazard in these land-use-intensive regions (Guzzetti et al., 1999; Guzzetti et al., 2012).

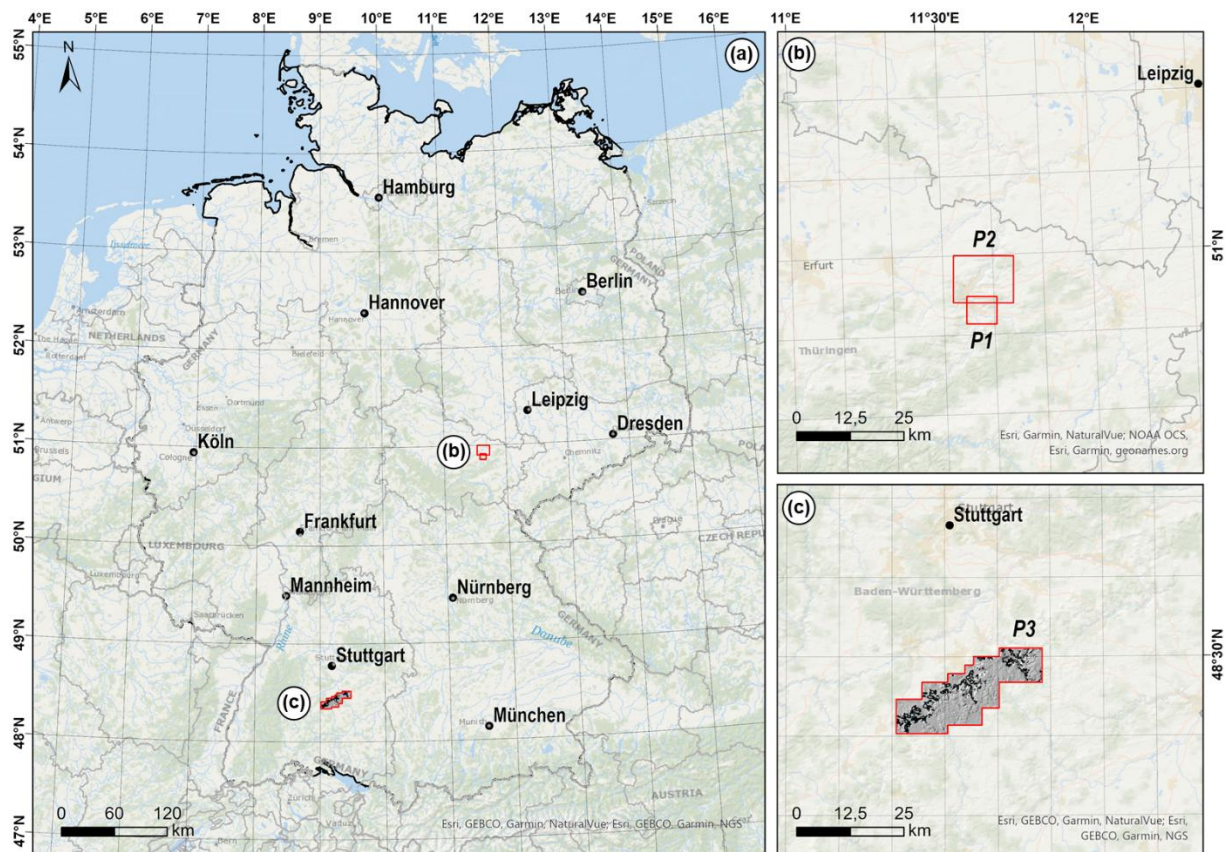


Figure 5 The study areas of this thesis. (a) Location of the study areas in Germany. (b) Jena region efficient geomorphological mapping and semi-automated landslide detection approaches in Papers 1 and 2 respectively. (c) Swabian Alb region, used in the study to investigate the transferability of the method developed in Paper 2 (Paper 3). The specific sites analysed in the individual papers (P1, P2, and P3) are indicated in the respective subsets.

4.1. The Jena Region (Thuringia, Central Germany Uplands)

This dissertation investigates geomorphological mapping and landslide detection methods in two representative middle-mountain (Mittelgebirge) settings in Germany: the Jena region in eastern Thuringia (Central German Uplands), and the Swabian Alb escarpment in Baden-Württemberg (Southwestern Germany). Both areas exhibit classic "Schichtstufenland" (cuesta landscape) topography, a rich Mesozoic stratigraphy, and are recognized as model sites for landslide research in Central Europe (Wilde & Terhorst, 2025).

4.1.1. Geological and Geomorphological Setting

The Jena region is situated on the southeastern margin of the Thuringian Basin, which forms a broad syncline within the Central European Triassic system and is structurally bounded by the uplifted blocks of the Harz, Thuringian Forest, and Schiefergebirge (Lehmkuhl et al., 2025; Malz & Kley, 2012; Seidel, 1992). The local stratigraphy follows the characteristic Triassic succession, consisting of the Buntsandstein (Lower-Middle Triassic) forms the principal thickness of fluvial sandstones, siltstones, and marly red beds, passing upwards (via the evaporite- and clay-rich Röt/Salinarröt interval) into the marine carbonates and marls of the Muschelkalk, and capped locally by Keuper and Jurassic units (Bachmann et al., 2005; Götz, 2000; Malz & Kley, 2012; Puff & Klein, 2011; Seidel, 1992).

The layering and mechanical contrast between the ductile, gypsiferous marls and clays of the Röt Formation and the overlying, more stable Muschelkalk limestones create a predisposition for slope instability and mass movement along the escarpments (Achilles et al., 2016; Bachmann et al., 2005). This predisposition is further enhanced by hydro-mechanical interactions at the Muschelkalk–Röt interface, where permeable limestone units overlie low-permeability clay and gypsum layers. During periods of increased moisture availability, water infiltrates through the fractured Muschelkalk and accumulates at this boundary, leading to elevated pore water pressure in the underlying Röt units and a consequent reduction in shear strength (Schmidt & Beyer, 2002). The regional geology is further complicated by halokinetic processes and salt tectonics, represented by both thick evaporite sequences and prominent fault zones such as the Finne Fault Zone (Malz & Kley, 2012). These structures are reflected in frequent relief inversion, tectonic scarps, and accelerated basin-margin subsidence (Meynen et al., 1959).

Karst and subsidence phenomena are particularly marked in the Upper Buntsandstein (Salinarröt), where thick gypsum and clay sequences undergo subsurface dissolution, leading to the development of sinkholes, solution pipes, and widespread subsidence dolines, notably in the Gembdental area (Achilles et al., 2016b; Meynen et al., 1959; Kempe, 1996; Siefert et al., 2006). In addition, the dissolution of gypsum within the Röt formation contributes to structural weakening and local collapse processes, which may initiate or accelerate slope instability and mass movement development (Schmidt & Beyer, 2002; Siefert et al., 2006). Such processes further promote slope weakening and local groundwater anomalies, which combined with the mechanical instability of gypsiferous and marly units, favor the frequent occurrence of landslides and complex mass movements (Achilles et al., 2016a; Bachmann et al., 2005;

Kohlhepp et al., 2016; Siefert et al., 2006). This lithological contrast represents a key preconditioning factor controlling landslide initiation and morphology in the study area.

Geomorphologically, the Jena landscape is defined by a striking relief: the deeply incised Saale valley and its tributaries are flanked by steep Muschelkalk escarpments, tabular plateaus (e.g., Hausberg, Jenzig, Wöllmisse), and dissected by numerous dry valleys and karstic depressions (Eissmann, 2002; Lehmkuhl et al., 2025; Meynen et al., 1959). The relief between valley floors and plateau margins is often greater than 100–200 metres, creating strong local environmental gradients and pronounced slope–valley coupling (Meynen et al., 1959). Characteristic landforms include stepped escarpments, extensive colluvial fans, fluvial terraces, and the legacy of anthropogenic landscape alteration such as historical quarrying, vineyard terracing, and forest management (Günter et al., 2011; Puff & Klein, 2011)

Overall, the interplay of Triassic lithostratigraphy, tectonic segmentation, salt/gypsum dissolution, river incision, and Quaternary surface processes has produced one of the most geologically and geomorphologically varied landscapes in Central Germany. The geomorphological structure and spatial distribution of major landform units in the Jena region are synthesised in the “Main Map”, which represents a key outcome of the mapping framework developed in Paper 1 (Figure 8; see Supplementary Material of Paper 1 in the Appendix for a high-resolution version).

4.1.2. Hydrological Setting

The Jena region’s hydrological system is characterized by the Saale River, which traverses the southeastern Thuringian Basin in a deeply incised main valley accompanied by numerous tributaries—such as the Roda, Leutra, and Pennickental streams—each contributing to the drainage and geomorphic diversification of the landscape (Götz, 2000; Zangana et al., 2023b). Quaternary fluvial terraces are well developed along the Saale, forming both active and relict floodplains with complex alluvial architecture (Lehmkuhl et al., 2025; Seidel, 1992)

Karstification and subrosion are especially active at key geological boundaries: extensive gypsum- and salt-bearing horizons in the Upper Buntsandstein and Lower Muschelkalk are undergo intense dissolution, forming subsurface conduits, sinkholes, solution pipes, and large dolines as seen in the Gembdental and Rollborn spring localities (Achilles et al., 2016b; Siefert et al., 2006). These processes disrupt typical drainage patterns, feeding a dense network of springs, seeps, and, in some areas, supporting the precipitation of travertine or the formation of perched aquifers. Karstification processes significantly modify the regional hydrological system by promoting subsurface drainage pathways and localized spring discharge, thereby altering groundwater flow patterns and slope water balance (Siefert et al., 2006). Anthropogenic impacts, such as urban encroachment and channel engineering, have locally altered stream pathways; particularly in areas like the Pennickental, streambeds have been straightened, partially infilled, or blocked, leading to intermittent flow and disruption of natural hydrological connectivity (Eissmann, 2002; Stadt Jena, 2016). More broadly, landslide occurrence in the region is closely linked to long-term hydrological conditions rather than

isolated rainfall events. Empirical evidence indicates that a sustained level of antecedent moisture input into slope systems is a critical precondition for large-scale mass movements, while short-duration high-intensity rainfall primarily acts as a triggering mechanism once this threshold is exceeded (Schmidt & Beyer, 2002). The southern part of the region is characterised by wide, box- or saucer-shaped valleys formed by Buntsandstein, while the northern part, which is dominated by limestone, has narrower, V-shaped valleys (Zangana et al., 2023b). Numerous small lakes—natural, artificial, or quarry-related—occur along floodplains, further increasing hydrological and ecological diversity (Figure 8; see Supplementary Material of Paper 1 in the Appendix for the high-resolution version).

4.1.3. Land Use and Anthropogenic Influence

Land use in the Jena region closely reflects its geomorphology and bedrock. Urban, industrial, and infrastructural development predominates on the easily accessible valley floors and lower terraces flanking the Saale and its main tributaries; meanwhile, the steep escarpments and plateaus of Muschelkalk and Buntsandstein remain predominantly forested (TLUBN, 2022; Zangana et al., 2023b). The valley's fertile Holocene to Pleistocene alluvium supports intensive agriculture, while grasslands and pastures, and orchard remnants lead to a more fragmented land cover on the northern and higher plateaus (Rau et al., 2000; TLUBN, 2022). Soil-landscape feedback is evident: shallow rendzinas and steppe soils characterize the limestone crestlines and plateaus, pararendzinas and Cambisols dominate the colluvial and marly-sandy slopes, and deep Gleysols and Vega soils occupy the alluvial floodplains (Rau et al., 2000).

Anthropogenic process domains are extensively distributed—including anthropogenic terraces, artificial embankments, landfill and quarry infill, and historical paramilitary or industrial modifications. The Mönchsberg area was significantly reshaped by limestone quarrying (Chapter 6.1.1), creating an artificial plateau and a prominent break of slope approximately 30 m in height with an area of 400 × 600 m (cf. Figure 11; Günter et al., 2011). Agricultural terraces, vineyard steps, and river embankments are additional legacies of centuries of land management. Ultimately, urban sealing, altered runoff, and cumulative soil disturbance all contribute to a highly modified landscape intricately layered onto the inherited Triassic relief (Zangana et al., 2023).

4.1.4. Landslide Setting

The unique lithostratigraphic structure and tectonic history of the Jena region create highly favorable conditions for landslides and mass movement processes, particularly along the escarpments of the Thuringian Triassic “Schichtstufenland” (Lehmkuhl et al., 2025; Puff & Klein, 2011; Schmidt & Beyer, 2002). The most landslide-prone zones occur at the contacts where the competent Lower Muschelkalk carbonates overlie the mechanically weak, gypsiferous, and marly clays of the Upper Buntsandstein (Röt/Salinarröt) (Achilles et al., 2016a; Bachmann et al., 2005; Schmidt & Beyer, 2002). Here, the loss of shear strength in water-saturated marls and the presence of evaporites—often affected by subsidence—promote sliding, block topple, and complex compound landslide morphologies (Achilles et al., 2016b; Puff & Klein, 2011; Schmidt & Beyer, 2002). These processes are characteristic of bipartite

cuesta slopes, where a resistant caprock overlies weaker, clay-rich strata, resulting in a two-part slope morphology consisting of a steep upper escarpment and a gentler, deformable lower slope (Schmidt & Bayer, 2002).

For example, Gemündental, east of the Jena city, represents a key reference locality where extensive mass movement features, deep-seated rotational and translational landslides have produced pronounced step scarps, rotated Muschelkalk blocks, “nackentäler” (neck valleys), hummocky and irregular surfaces, and associated colluvial and flow deposits, stated by Achilles et al. (2016a). Many landslide bodies show clear evidence for multiple phases of reactivation and downslope migration, as well as superposed secondary failures and antithetic back-rotations. Ongoing subsidence of underlying gypsum- and salt-bearing units often creates or preserves slope depressions and contributes to slope failure by altering groundwater pathways (Achilles et al., 2016b; Meynen et al., 1959). Furthermore, the susceptibility of slopes is strongly influenced by morphometric and climatic factors, particularly slope aspect. North- to west-facing slopes, which receive higher moisture input due to prevailing wind directions and reduced evapotranspiration, exhibit increased landslide activity compared to drier, leeward slopes (Schmidt & Bayer, 2002).

The main triggers for landslides in the region include prolonged or intense precipitation events, rapid snowmelt, anthropogenic alteration (e.g., quarrying or slope cuts), and groundwater fluctuations due to karst or subsidence processes (Achilles et al., 2016a). Local destabilization may also occur due to undercutting processes, such as river incision at the slope base or excavation activities, which reduce support and promote failure initiation (Schmidt 2002).

Overall, landslide occurrence in the region reflects a combination of internal controls (lithology, structure, slope geometry) and external triggers (rainfall, hydrological changes), with hydrological preconditioning playing a decisive role in determining slope stability (Schmidt 2002). Slopes mantled by forest often preserve relict landslide geomorphology, making the Jena hillslopes a particularly instructive natural laboratory for landslide research and mapping.

4.2. The Swabian Alb Escarpment (Baden-Württemberg, SW Germany)

4.2.1. Geological and Geomorphological Setting

The Swabian Alb (in German: Schwäbische Alb) represents a classical cuesta landscape (i.e. scarpland) in Central Europe, extending approximately 220 km in a NE–SW direction across southwestern Germany, with a maximum width of about 70 km (Bell, 2007). The region is characterised by a pronounced escarpment morphology, with the Albtrauf forming a steep northwestern-facing cuesta front rising approximately 200–400 m above the adjacent foreland (Bell et al., 2012; Schaller et al., 2025; Wilde & Terhorst, 2025). This distinct topographic contrast reflects the structural control exerted by gently dipping to near-horizontal sedimentary strata.

Geologically, the Swabian Alb is dominated by a sequence of Mesozoic sedimentary rocks, with resistant Upper Jurassic (Malm) limestones forming the plateau surface, underlain by less competent Middle and Lower Jurassic marls and clay-rich units. These, in turn, overlie Triassic formations (Keuper and Muschelkalk), with the pre-Mesozoic basement at depth (Terhorst & Kreja, 2009; Wilde & Terhorst, 2025). The resulting lithostratigraphic configuration creates a strong mechanical contrast between permeable carbonate rocks and underlying impermeable or weakly permeable marls and clays. This lithological contrast is a key factor controlling slope instability, particularly along the Albtrauf, where resistant limestone caps overlie mechanically weak substrates. Such conditions favour the development of large-scale rotational and complex landslides, often associated with deep-seated slip surfaces located within marl or clay horizons (Goetz et al., 2014; Wilde & Terhorst, 2025).

In addition to structural controls, karstification plays a fundamental role in shaping the geomorphology of the Swabian Alb. The extensive dissolution of limestone has resulted in well-developed karst systems, including caves, sinkholes, dry valleys, and karst springs (Goldscheider, 2005). These features influence both surface and subsurface drainage patterns, contributing to spatial variability in slope hydrology and stability (Goldscheider, 2005; Terhorst, 2007; Wilde & Terhorst, 2025).

The long-term geomorphic evolution of the region is closely linked to escarpment retreat and drainage reorganisation since the Neogene. Differential incision between the Danube and Neckar catchments, combined with river capture processes, has contributed to the present-day relief structure and the spatial distribution of mass (Schaller et al., 2025; Wilde & Terhorst, 2025).

4.2.2. Hydrological Setting

The hydrological regime of the Swabian Alb is fundamentally governed by its status as part of the largest coherent karst landscape in Germany. The plateau is characterized by high infiltration rates and a notable absence of surface drainage, as the river network has a low density due to the Upper Jurassic limestones being heavily karstified. This leads to the formation of dry valleys on the plateau while precipitation is directed almost entirely into subterranean networks. According to Goldscheider (2005), this system is best understood through an origin-pathway-target model, where the epikarst—the uppermost, intensively fractured layer of the carbonate aquifer—acts as a critical zone that concentrates infiltrating water and directs it rapidly into vertical shafts.

At the escarpment, these hydrological conditions play a critical role in both the initiation and reactivation of landslides. Groundwater flow is concentrated at lithological boundaries, particularly where the permeable Oxfordian limestones overlie the impermeable marls or clays of the Middle Jurassic. These impermeable zones act as aquicludes, promoting the development of perched water tables. Goldscheider (2005) highlights that in areas where low-permeability layers like the Kimmeridgian marls are present, lateral subsurface flow is generated and often focused into swallow holes, completely bypassing the soil's protective filtration. This "bypassing" mechanism facilitates a rapid increase in pore water pressure at the

limestone-marl interface, which reduces effective stress and triggers slope failure (Bell et al., 2012; Terhorst & Kreja, 2009).

The extreme connectivity and anisotropy of this karst network are further demonstrated by the Danube-Aach system, where groundwater can reach flow velocities as high as 250 m/h through wide, open conduits. Such high-velocity subterranean flow implies that hydrostatic pressure can rise significantly and unpredictably in specific slope sectors during recharge events. Karst processes thus contribute to highly complex and locally variable groundwater regimes, creating unpredictable localized zones of instability that enhance the overall susceptibility of the Albtrauf (Goldscheider, 2005; Terhorst & Kreja, 2009).

Climatic factors, including intense rainfall and rapid snowmelt, further modulate this karst-driven hydrology. Periods of prolonged precipitation are particularly critical as they lead to substantial groundwater recharge through karst fissures. Wilde and Terhorst (2025) note that catastrophic events are often preceded by extreme moisture levels, such as the nearly 250 mm of rainfall prior to the 1983 Mössingen landslide or the 160 mm recorded in just three days before the 2013 Landhaussiedlung activation. These intense events overwhelm the karst pathways, elevating pore pressure to the threshold of failure and serving as the primary external triggers for mass movements in the region (Neuhäuser & Terhorst, 2007; Schaller et al., 2025).

4.2.3. Land Use and Anthropogenic Influence

Soil development in the Swabian Alb is a dynamic process governed by the "cuesta" topography and the underlying lithology. On the plateau, shallow and stony Rendzinas (Leptosols) predominate, formed from the weathering of the resistant Oxfordian limestones. In contrast, the steeper escarpment slopes are characterized by deeper, clay-rich Cambisols derived from Middle Jurassic marls. The soil profiles are not static; rather, they are part of a high-magnitude denudation system where anthropogenic disturbances and slope instability accelerate the movement of soil material from the escarpment into footslope positions (Schaller et al., 2025). These footslopes often contain thick packages of colluvial material, which Wilde and Terhorst (2025) identify as critical archives of past landslide activity and human-induced erosion cycles.

The landscape has undergone profound transformations, shifting from a "natural" state to a deeply cultural one. Historical patterns, rooted as far back as the Hallstatt culture, involved extensive forest clearing to facilitate grazing and marginal agriculture. Over the last century, this has evolved into a more heterogeneous system characterized by the abandonment of marginal grasslands, significant reforestation on steep slopes, and the intensification of agriculture in the more accessible foreland areas (Bell et al., 2012; Bieling, Plieninger, & Schaich, 2013; Plieninger et al., 2013). These shifts directly influence slope hydrology; the transition from traditional vineyard management (viticulture) or open sheep-grazing to modern forest cover alters infiltration rates, which in turn affects the infiltration conditions that governs landslide triggering (Goldscheider, 2005).

Forested areas, which now dominate the steep slopes along the Albtrauf, generally contribute to slope stabilization through root reinforcement and reduced surface runoff. However, Bell et al. (2012) emphasize that dense forest cover also serves to mask relict landslide features, making them nearly invisible without the use of high-resolution LiDAR data. In contrast, the urbanized and agricultural areas in the foreland face increasing instability due to infrastructure development and modified drainage systems (Terhorst & Kreja, 2009). The socio-economic impact of this instability is significant; Blöchl & Braun (2005) note that while landslides in remote forests may have low economic consequences, movements near residential settlements—such as the "Landhaussiedlung" in Mössingen—result in substantial financial loss and necessitate complex technical mitigation.

Ultimately, the persistence and visibility of landslides in the Swabian Alb are products of both natural decay and human intervention. While farming activities like planation can erase the geomorphic signatures of historical landslides, modern infrastructure and land-use changes often act as the primary triggers for their reactivation (Bell et al., 2012; Schaller et al., 2025). This long-term anthropogenic pressure has created a "temporal mosaic" where contemporary landslide susceptibility is inextricably linked to the legacy of historical land management.

4.2.4. Landslide Setting

The Swabian Alb, and specifically the Albtrauf (the Jurassic escarpment), is widely recognised as one of the most landslide-prone regions in Germany (Neuhäuser & Terhorst, 2007; Terhorst & Kreja, 2009). Landslides are predominantly rotational and complex in type, reflecting the region's specific geological (Chapter 4.2.1) and hydrological (Chapter 4.2.4) conditions. According to Wilde and Terhorst (2025), the structural geomorphology of the "Schichtstufenland" is the primary driver of these processes. The presence of alternating permeable Oxfordian limestone and impermeable Callovian marl and clay (e.g., Ornatenton) layers creates favourable conditions for the development of glide horizons, along which slope failure is initiated (Neuhäuser & Terhorst, 2007; Terhorst & Kreja, 2009).

Typical landslide morphologies include distinct head scarps, displaced main blocks, intermediate depressions (e.g., "Nackentäler"), and hummocky depositional zones. Many of these features persist over long timescales and can be clearly identified in high-resolution terrain data (see Chapter 5.2.2, for the manual inventory mapping using DTM-data). Both relict (Pleistocene–Holocene) and active landslides are present. Research by Bell et al. (2012) suggests that the landslide inventory of the Swabian Alb represents a temporal mosaic; relict landslides—often dating back to the Late Pleistocene or Early Holocene—frequently form the foundational structure for contemporary slope morphology.

A well-documented example is the 1983 Mössingen landslide at the Hirschkopf, which involved approximately 6 million m³ of displaced material and illustrates the potential magnitude of slope failures in the region (Bell, 2007; Bell et al., 2012). This event remains a benchmark in regional geomorphology, demonstrating that catastrophic failures can occur even on slopes previously considered stable (Wilde & Terhorst, 2025).

Beyond the Mössingen event, the Albtrauf is characterized by various significant mass movements. The Pfullingen landslide exemplifies the classic block-sliding nature of the escarpment, while the Reutlingen area has experienced notable historical events, including the 1922 and 1999 landslides at the Achalm (Wilde & Terhorst, 2025). In the nearby Tübingen district, the Talheim landslide (2013) serves as a critical example of how extreme precipitation can trigger the reactivation of dormant slide masses. Similarly, the 2013 activation at the "Landhaussiedlung" in Mössingen area underscores the persistent hazard these processes pose to residential infrastructure and urban development (Wilde & Terhorst, 2025). Crucially, many contemporary landslides represent the reactivation of prehistoric or relict slide debris (Wilde & Terhorst, 2025). Bell et al. (2012) emphasize that human impact—including historical viticulture, forest clearing, and infrastructure development—has significantly influenced the persistence and visibility of these features. Anthropogenic disturbances often mask older landslides or, conversely, act as the primary trigger for the reactivation of long-term unstable slopes.

Together, the Jena region and the Swabian Alb provide a complementary framework for methodological development and transferability assessment. Jena represents a controlled environment for detailed geomorphological mapping and the detection of predominantly relict, forest-covered landslides, whereas the Swabian Alb introduces greater variability in landslide type, activity, and environmental conditions. This contrast enables evaluation of the robustness of morphometric signatures across settings with differing lithological and hydrogeological controls, while highlighting the need for context-specific parameterisation. The combined use of both areas therefore directly supports the development of transferable geomorphological mapping and landslide detection approaches. Consequently, the next chapter outlines the data sources (5.1) and methodological workflows (5.2) used for detailed geomorphological mapping and GEOBIA-based landslide detection.

5. Data and Methods

The geomorphological complexity of the study areas and the partial inaccessibility of the terrain require a data-intensive approach based primarily on LiDAR-derived datasets, complemented by remote sensing data and additional ancillary information. This chapter describes the data sources and methodological approaches applied in this dissertation. The presented methods are based on the three papers included in this thesis and combine expert-based high-resolution detailed geomorphological mapping with semi-automated landslide detection approaches.

5.1. Data sources

5.1.1. LiDAR-Derived Digital Terrain Models (Paper 1, 2 and 3)

Airborne LiDAR-derived DTMs form the core dataset across all components of this dissertation because they provide a high-resolution representation of terrain morphology and enable the identification of geomorphic features even under forest canopy (Van Den Eeckhaut et al., 2012; Hofierka et al., 2018; Knevels et al., 2019).

For the detailed geomorphological mapping in Jena (Paper 1), the analysis is based on a LiDAR-derived DTM with 2 m resolution provided by the Thuringian State Office for Soil Management and Geoinformation (TLUBN, 2019a; Zangana et al., 2023a).

For semi-automated landslide mapping in the Jena region (Paper 2), a higher-resolution LiDAR-derived DTM with 1 m grid resolution is used as the primary elevation dataset for deriving LSVs and for compiling the reference landslide inventory.

The study, Swabian Alb, (Paper 3), utilized LiDAR-DTMs from 2003 and 2023 (1 m x 1 m) provided by the State Office for Geoinformation and Land Development (Landesamt für Geoinformation und Landentwicklung Baden-Württemberg (LGL-BW, <http://www.lgl-bw.de>, last access: 20.04.2026). These DTMs served as the foundational dataset for both the manual reference inventory and the semi-automatic model runs. A set of terrain-based LSVs were derived from the original DTM, including: slope, plan and profile curvature, Topographic Openness (TO), Terrain Roughness Index (TRI), and Topographic Position Index (TPI). All DTMs were stored and processed in ETRS89/UTM zone 32N (EPSG:25832); any inputs delivered in other CRSs were reprojected on import.

5.1.2. Remote Sensing and Ancillary Data (Paper 1 and Paper 3)

To strengthen interpretations of landform genesis and to place geomorphological boundaries more robustly than is possible from the DTM-based alone, the mapping workflow integrates several complementary ancillary datasets, consistent with multi-source geomorphological mapping practice (Otto & Smith, 2013; Smith & Pain, 2009). While the LiDAR-derived terrain products provide the primary basis for recognizing relief, breaks-of-slope, and subtle topographic signatures, ancillary data add information on surface texture, material, and

human modification that is not directly encoded in elevation data and can therefore reduce ambiguity in landform classification.

High-resolution digital orthophotos (DOPs; ~0.2 m) and Google Earth imagery are used to support visual interpretation of landform expression and to provide contextual signals such as vegetation patterns, soil/rock exposure, drainage traces, and anthropogenic structures; Google Earth additionally offers 3D visualization that helps assess relative position and continuity of features across slopes and valley bottoms in Paper 1. A digital topographic base map (DTK10; 1:10,000; TLBG, 2019) is used to cross-check mapped elements against established cartographic information (e.g., hydrography, infrastructure) and to ensure consistent delineation and naming within the local mapping framework. Geological maps at multiple scales (e.g., GK25 at 1:25,000 and GK200 at 1:200,000; TLUBN, 2019b) are consulted to support lithological interpretation, to evaluate whether mapped landforms are plausible given substrate properties, and to verify landform–material relations (e.g., contrasts between resistant and weak lithologies that may control scarp formation or valley morphology).

Targeted field investigations are conducted where remote-sensing interpretation remains uncertain (e.g., under dense canopy, in areas with complex anthropogenic overprint, or where multiple genetic interpretations are possible) and to validate a selection of mapped features through ground-truthing. These checks focus on confirming diagnostic criteria (e.g., sediment/rock type, evidence of mass movement, degree of weathering, or channel characteristics) and help calibrate interpretation rules applied during on-screen mapping. As shown in Table 1, the datasets are described in terms of their source, resolution or map scale, role in mapping, as well as their main strengths and limitations for detailed geomorphological mapping (Paper 1).

In Paper 3, a digital land use/land cover dataset (DLM25; 1:25,000; for 2003), was acquired from the relevant Baden-Württemberg state authority (LGL-BW, <https://www.lgl-bw.de/Produkte/Landschaftsmodelle/Basis-DLM/index.html>; Bell, 2007), is additionally used to stratify evaluation by land cover type and to assess performance differences under contrasting conditions, particularly in forested areas where terrain visibility and feature detectability can be reduced even with field support.

All ancillary layers (orthophotos, DTK10, geological maps, and land use data) were reprojected to ETRS89/UTM zone 32N (EPSG:25832), if not already in that CRS, to ensure consistent metric measurements.

5.1.3. Terrain Derivatives and Morphometric Variables (Paper 1, 2 and 3)

DTM-derived terrain derivatives (computed in EPSG:25832) support both manual geomorphological interpretation and semi-automatic classification because they enhance diagnostic morphometric signatures that are often difficult to recognize in elevation data alone (Hengl & Reuter, 2008; Smith, 2011). In this thesis, a suite of LSPs is calculated from the LiDAR DTM in QGIS and ArcGIS to improve the delineation of landforms elements (e.g., ridges, valley bottoms, breaks-of-slope) and the detection of process-related features (e.g., incisions, terrace

edges, landslide scarps and deposits) (Doneus, 2013; Smith & Clark, 2005). Standard visualizations include hillshade (including multi-directional hillshade), slope, and curvature, which each emphasize different aspects of relief and therefore provide complementary evidence during the detailed geomorphological mapping (Paper 1).

Multi-directional hillshade is preferred for interpretation because it reduces the illumination bias inherent to single-azimuth hillshades and improves the visibility of subtle microtopography, particularly on slopes facing away from the chosen illumination direction (Nagi, 2014; Smith & Clark, 2005). Slope maps highlight abrupt transitions in gradient that commonly correspond to geomorphic boundaries (e.g., scarps, terrace risers, channel banks), whereas curvature measures support the identification of convex and concave forms that can indicate ridges, hollows, incisions, and mass-movement morphology.

To further improve contrast between landforms and surrounding terrain, topographic openness (TO) is used as an openness-based visualization that captures the degree of enclosure/exposure of each location and thereby emphasizes both elevated and depressed features (Daxer, 2020; Doneus, 2013). Following Anders, et al. (2011), TO is combined with slope to create a composite visualization that improves the separation of landform elements from adjacent terrain and supports more consistent boundary placement, especially in areas where single derivatives provide ambiguous signals. These derivative and composite maps are interpreted alongside ancillary datasets (Section 5.1.2; e.g., orthophotos, topographic and geological maps) to cross-check geomorphic signatures against surface appearance and lithological context.

For the GEOBIA-based landslide mapping component (Papers 2 and 3), a consistent set of morphometric predictor variables is derived to represent complementary descriptors of local relief, convexity/concavity, roughness, and relative position. The variables include slope, plan curvature, profile curvature, TO, terrain roughness index (TRI), and topographic position index (TPI), which together capture key characteristics of landslide source and deposit zones and enable segmentation- and object-based classification (Dias et al., 2023; Feizizadeh & Blaschke, 2013; Karantanellis et al., 2020; Knevels et al., 2019; Sîrbu et al., 2019; Miet Van Den Eeckhaut et al., 2012).

Table 1 Data sources for geomorphological mapping—resolution/scale, application, weaknesses, strengths/improvements. (CRS: ETRS89/UTM 32N, EPSG:25832). Adapted from Paper 1.

DATA SOURCES	RESOLUTION /SCALE	REQUIREMENT	APPLICATION	WEAKNESS	STRENGTH/IMPROVEMENT
Hillshade and multidirectional hillshade	2 m	QGIS /ArcGIS online, which computes hillshade from six different directions as opposed to the single direction of a default hillshade	To provide • a quick indication of the terrain • on-screen surveys analyzing landforms as a substitute for the field survey • a background for other layers to better visualize landforms	Traditional hillshades are made by illuminating light from the northwest. This frequently results in overexposure of the illuminated sides and obscuration of details in the terrain on non-illuminated sides	• Promotes the balance between over-exposed and non-illuminated areas, resulting in a more accurate representation of the landscape • Can develop on-screen mapping accuracy (Nagi, 2014 & Tzvetkov, 2018)
Simple LSPs: 1. Slope	2 m	ArcGIS/QGIS (default algorithm)	• To provide valuable knowledge to interpret and digitize breaks in slopes on-screen manually • To determine the boundaries of landforms	A single classification interval alone does not provide the necessary information needed for precise interpretation of landforms, because of the morphological difference in landform types and the range of landform sizes (e.g., steps, depressions, and knolls)	Mapping from • a range of classification intervals instead of a single group (see Jones et al., 2007)

Continued

DATA SOURCES	RESOLUTION /SCALE	REQUIREMENT	APPLICATION	WEAKNESS	STRENGTH/IMPROVEMENT
2. Curvature	10 m	ArcGIS and QGIS (default algorithm)	To provide a valuable source for manual landform delineation (e.g., ridges, crests, stream networks, and drainage ways/adjustments)	A correct landform investigation might be difficult due to the high-resolution of the original DTMs (e.g., 2 m resolution)	To obtain a reasonable raster • Focal Statistical toolbox processed (e.g., 5 × 5 to 9 × 9 moving window instead of the default 3 × 3) • extract the curvature from a resampled DTM of 10 m
3. Topographic openness (TO)	25 × 25 m, 50 × 50 m, 250 × 250 m	QGIS (for steps see Daxer, 2020)	• To manually correct landforms that are created based on other parameters • To better define landforms boundary	-	Consider both the highest and lowest parts of landforms (Daxer et al., 2020 & Meng et al, 2018))
Composite LSPs (slope & TO)	Slope 3 × 3 m with TO25 × 25 m and TO250 × 250 m	Can be obtained by • QGIS > Plugin > Semiautomatic Classification > RGB • ArcGIS > Toolbox > Data Management > Composite Bands • Arc Pro > Toolboxes > Data Management > Raster Processing > Composite Bands	When applying it, • the detection of landforms boundaries is improved in comparison to single LSPs • it provides us with greater accuracy and presents the landscape better than those on a single LSP (see Smith et al., 2013)	-	• A clear distinction between the landform character and its surrounding features • Both the highest and lowest parts of the landform are much better detected (Doneus, 2013) in comparison to other data sources (Figure 9)

Continued

Tabel 1 Continued.

DATA SOURCES	RESOLUTION /SCALE	REQUIREMENT	APPLICATION	WEAKNESS	STRENGTH/IMPROVEMENT
Geological map	1:25,000 and 1:200,000	In a digital format such as GK25 or at a better and more detailed scale	It provides valuable information - by overlaying on other data sources, it can manually define the boundaries of landforms and their geomorphic processes - to obtain the genesis of landforms	When a geological map at a scale of 1:200,000 is required to delineate a detailed map (e.g., at scales of 1:5,000–1:10,000)	When draped over the DTM data and LSPs, manual mapping of landforms and their geomorphological processes boundaries are modified and enhanced
Topographic map	1:10,000	An appropriate scale (e.g., < 1:10,000) and a digital format	Provides preliminary data for - manually delineating landforms/processes - manually modifying the hydrology layer elements	If the scale of the topographic map is smaller than that of the targeted map	Scale variation issue improves by modifying the boundaries of landforms and genesis from overlying it over a DTM and DTM derivatives and by field examination, then considering the objectives of the map
Orthophoto/Google earth images	0.20 m	A reasonable resolution of about <20 cm	- Visualize the landscape in 3D and 2D - Combine it with other data sources to characterize the feature and its genesis - As a substitute for field mapping and to become familiar with the area prior the field checking	When: - The resolution of the images is coarser than the scale of the map - Wherever the image quality is insufficient (e.g., >20 cm) to examine the landforms of interest	By field examination and by comparison with other data sources

5.2. Methodological Approach

5.2.1. Manual Geomorphological Mapping (Paper 1)

Manual geomorphological mapping is carried out by systematic on-screen digitisation in a GIS software using LiDAR-DTM visualizations in combination with ancillary datasets, following established concepts (Dramis et al., 2011; Otto et al., 2011). For Jena, a 2 m LiDAR DTM forms the base, supported by orthophotos, topographic and geological maps, and targeted field observations. Digitisation is performed at a working scale of $\sim 1:1,000$ to capture subtle forms; the final map is compiled at 1:5,000 in ETRS89/UTM zone 32N (EPSG:25832), with cartographic generalisation as required (simplification, merging, and point-symbol substitution) applied where necessary for an A0 layout (Otto et al., 2011).

The workflow follows two stages (Figure 6). In **Stage I**, expert-driven interpretation (i) infers landform genesis and dominant processes and (ii) delineates geomorphological process domains by iteratively cross-checking DTM evidence with ancillary datasets (Otto & Smith, 2013). Interpretation uses multi-directional hillshade and openness-based/composite visualizations (e.g., slope + topographic openness) to enhance microtopography and support consistent boundary placement (Anders et al., 2011; Doneus, 2013; Nagi, 2014). For consistent representation, the geomorphological symbol set proposed by Otto (2008) is adopted.

Feature extraction combines visual interpretation with targeted GIS measurements. Crests and ridges are supported by curvature-based focal statistics with varying neighbourhood sizes (Smith & Clark, 2005; Wood, 1996). Steps and breaks-of-slope are digitised from slope patterns and then characterised (e.g., width classes) using *Measure* and *3D Analyst* tools in ArcGIS. Hillslope processes and deposits (e.g., landslides, debris flows, incision-related forms, alluvial-fan signatures) are delineated from the combined evidence; where polygon boundaries are not defensible, features are represented as points to avoid false precision. Hydrology is mapped as lines/points/polygons: streamlines are derived from the topographic map and corrected in the field; stream types (perennial vs intermittent) are assigned based on field evidence. Lakes are pre-selected from the DEM (areas $>20 \text{ m}^2$ with slope $<0.5^\circ$) and edited using the topographic map, while sources, seepage and waterlogging areas—undetectable from LiDAR alone—are compiled from topographic maps, orthophotos, and field checks. Valley/pathway types are classified following the GMK concept (Barsch & Liedtke, 1985) by identifying narrow valleys (e.g., $<25 \text{ m}$ width) and examining cross-profiles with the DEM profile tool (*3D Analyst*), supported by expert interpretation.

Process domains are delineated with a “default-and-replace” logic (Figure 6; STAGE I, lower panel). The entire area is first set as a denudational domain and then iteratively replaced where other processes dominate (e.g., fluvial where incisions, erosional rims, channels and floodplains are present; anthropogenic where maps/orthophotos indicate modification; karstic where Muschelkalk units coincide with depressions and undulating topography). Refinement continues until full coverage and internal consistency are achieved.

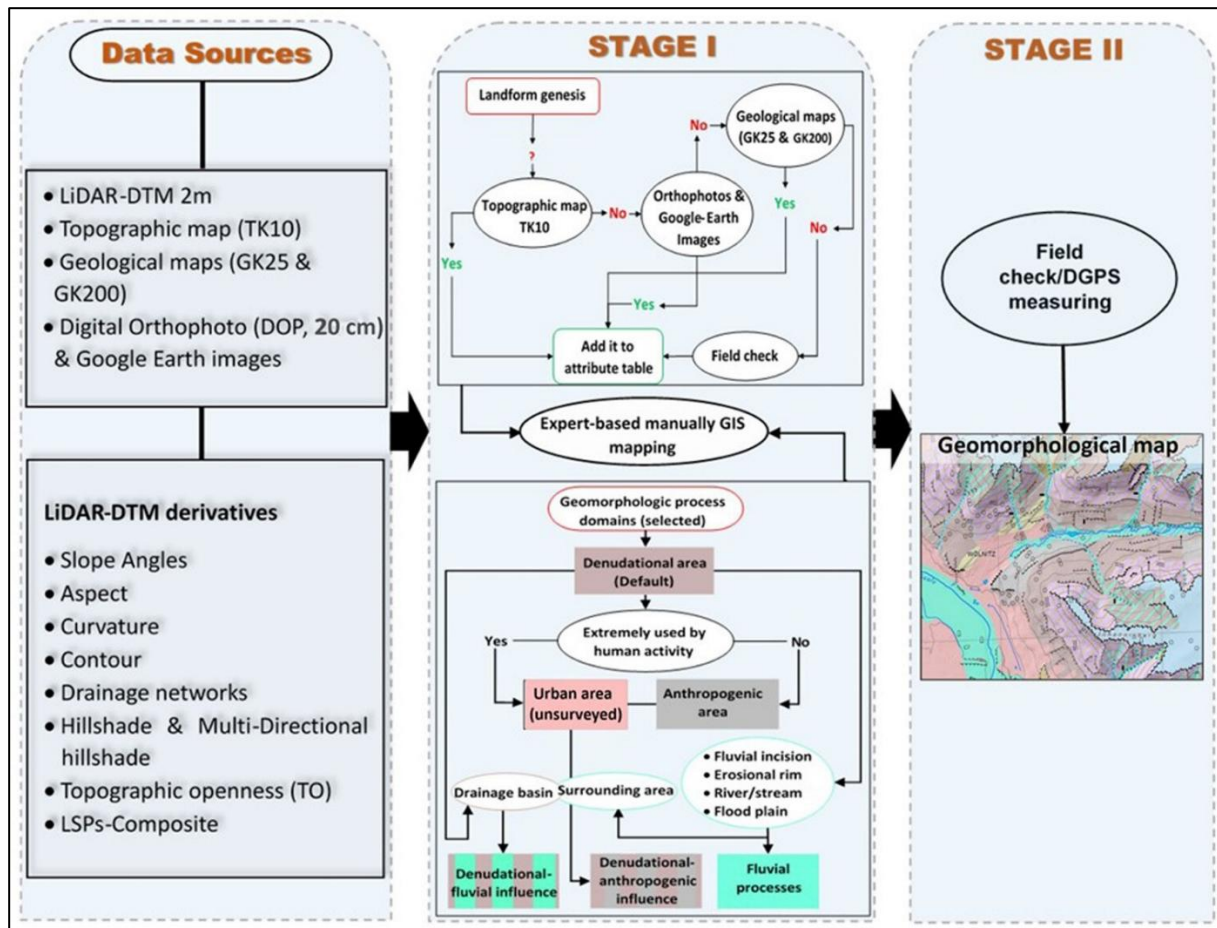


Figure 6 Flowchart of the methodology used for detailed geomorphological mapping (adapted from Paper 1, Figure 2).

Stage II (field verification and map finalisation) comprises two targeted surveys supported by DGPS: a pre-mapping reconnaissance to calibrate interpretation rules and a post-mapping validation to check selected features, refine boundaries/attributes, and confirm process-domain assignments. DGPS points/transects are linked to mapped features in GIS, and resulting corrections are fed back into the geodatabase; an example of the spatial linkage between LiDAR visualizations, mapped elements, and DGPS checks is shown in Figure 11 (adapted from Paper 1, Fig. 5). Further details on validation and the quantitative assessment framework for GEOBIA outputs are provided in Chapter 5.2.6.

5.2.2. Manual Landslide Inventory Mapping (Reference Data; Paper 2 and 3)

Reliable reference inventories are essential for training and validating semi-automatic landslide mapping workflows and for subsequent susceptibility or hazard applications (Guzzetti et al., 2012). In this thesis, reference inventories are compiled through expert visual interpretation and systematic on-screen digitisation of LiDAR-derived visualizations—primarily hillshade—supported by complementary terrain derivatives, consistent with LiDAR-based landslide mapping practice (Schulz, 2004), and the general principle that inventories document the spatial distribution of observed landslides (Guzzetti et al., 1999). Mapping is carried out at fine interpretation scales (typically in the range of ~1:1,000 to 1:200, depending on feature

size and terrain complexity) to capture the shape and internal structure of landslide features as accurately as defensible from the data.

Where possible, landslide scarps and bodies are delineated as separate components because they often show different morphometric signatures and may respond differently in object-based modelling and subsequent performance assessment. This component-wise inventory structure also supports the development of dedicated GEOBIA rulesets for each entity and reduces the likelihood that mixed objects blur the class definition during segmentation and classification. In the Jena area, inventory compilation is guided by hillshade interpretation but is systematically cross-checked using multiple derivatives (e.g., slope, curvature, topographic openness (TO), topographic position index (TPI), and terrain roughness index (TRI)) where hillshade or slope alone is insufficient for robust boundary placement, particularly in complex terrain or where anthropogenic modification obscures diagnostic forms. In the Swabian Alb case, reference mapping follows the same hillshade-guided logic (Schulz, 2004), again supported by derivatives, and is subsequently intersected with land use/land cover information to derive a forest-only subset used for targeted evaluation under canopy conditions.

Thesis pointer: In the method section, briefly report the chosen interpretation scales and any minimum mapping unit (if defined). Summary statistics of the resulting inventories (e.g., number of scarps/bodies, total mapped area) are best reported in a short inventory table placed in the Study Area and/or Results chapter(s), while this section focuses on the compilation procedure.

5.2.3. Moving-Window Scaling and Optimisation of LSVs

Many morphometric predictors are scale-dependent; therefore, the moving-window (neighbourhood) size used for derivative computation is treated as a key parameter rather than a fixed default (Drăguț et al., 2011; Drăguț & Eisank, 2011). Instead of applying a single window to all variables, we optimise neighbourhood sizes to maximise separability between landslide and non-landslide terrain, acknowledging that different features—and even different parts of the same feature—are best expressed at different scales (Seijmonsbergen et al., 2011). Optimisation is implemented separately for landslide scarps and bodies to reflect their distinct geometry and topographic expression, building on the automatic selection logic of Sîrbu et al. (2019). The selected sizes are then fixed for final LSV computation used throughout the GEOBIA workflow, which also facilitates transferability testing across epochs and study areas by holding parameters constant and interpreting performance differences as data- or environment-driven.

Operationally, two configurations are used: Model I (MI) and Model II (MII). In MI, LSVs are computed in ArcGIS 10.7 using default moving-window settings based on standard raster practice; in MII, window sizes are optimised per LSV and landslide component using R 4.3.2 following Sîrbu et al. (2019). Both MI and MII are evaluated in Jena region, whereas only MII (the optimised-LSVs approach) is applied in the Swabian Alb; the resulting moving window sizes for both approach are summarised in Table 2.

Table 2 LSVs and corresponding window sizes per model/landslide components. Adapted from Paper 2.

Models/LSVs		Slope	C_plan	C_profile	TO	TRI	TPI
I *	Scarp & Body	3x3	3x3	-	3x3 & 25x25	3x3	33x33
	Scarp	11x11	7x7	5x5	5x5	7x7	11x11
II **							
	Body	11x11	5x5	7x7	7x7	9x9	13x13

* Default window size, ** optimal window size

5.2.4. GEOBIA-Based Semi-Automated Landslide Mapping

Semi-automated landslide detection is implemented following GEOBIA principles, in which raster predictor layers are segmented into meaningful image objects and subsequently classified into thematic classes, enabling the integration of morphometric information with object geometry and spatial context (Blaschke, 2010). Segmentation is performed using Multi-Resolution Segmentation (MRS) (Baatz & Schäpe, 2000), with parameter selection guided by iterative testing and, where applicable, scale-parameter support tools (Drăguț et al., 2011; Drăguț et al., 2010). Because landslide scarps and bodies represent different geomorphic entities and frequently differ in size, shape, and textural expression, segmentation and classification are implemented in separate workflows (or rulesets) for each component to reduce mixed objects and improve thematic coherence. All predictor raster, segmentation and classification steps were executed in EPSG:25832. The overall methodological framework, consisting of three main stages, is illustrated in Figure 7.

Classification is conducted using supervised Support Vector Machines (SVM), which has proven robust in GEOBIA and landslide-mapping contexts (Hong et al., 2017; Tzotsos & Argialas, 2008). Training samples are derived from the manual reference inventory and are refined iteratively by comparing preliminary classification outputs against inventory polygons and adjusting samples until results stabilise, which is consistent with common GEOBIA calibration practice. The resulting outputs provide initial candidate landslide objects that are subsequently improved through GEOBIA-based refinements (Section 5.2.5).

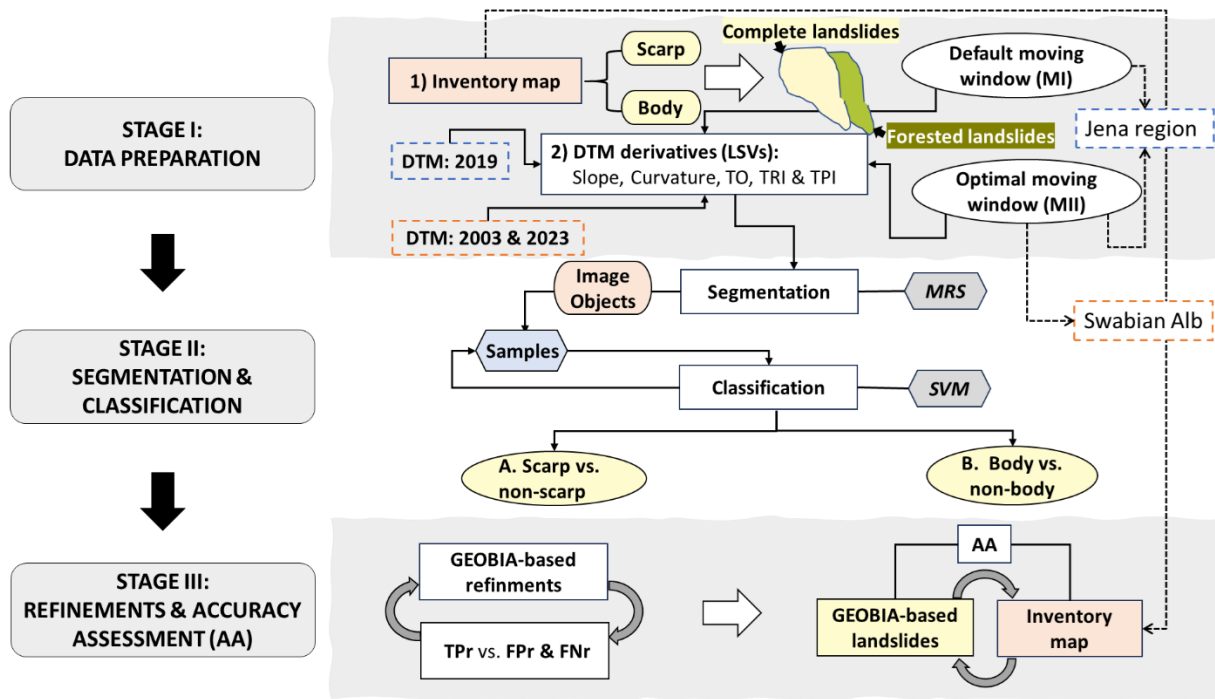


Figure 7 Flowchart of the GEOBIA-based semi-automated landslide mapping methodology applied in the Jena region and the Swabian Alb, adapted from Paper 2 and Paper 3.

5.2.5. GEOBIA-Based Refinements (Paper 2 and 3)

Following the supervised classification (Figure 7, Stage II), a dedicated Stage III refinement is implemented in eCognition as an expert-rule set to address commission and omission errors where non-landslide terrain mimics landslide morphology. This hybrid strategy—machine learning followed by object-based, rule-driven constraints—has been shown to improve thematic mapping quality (Eisank et al., 2014; Johnson & Xie, 2011; Robson et al., 2020; Zylshal, Sulma, Yulianto, Nugroho, & Sofan, 2016). The refinement aims to increase the true positive rate while reducing both false positives and false negatives by evaluating object-level features spanning (i) morphometric attributes (e.g., slope, curvature, TO, TRI, TPI), (ii) geometric descriptors (e.g., area, shape index, length-to-width ratio), and (iii) contextual relations (e.g., distance to landslide-related objects, adjacency, and the “relative border to neighbour” metric). The latter quantifies how much of an object’s boundary is shared with a reference class (value 1 = fully enclosed), which supports targeted reclassification; for instance, objects sharing > 80% of their border with TP landslide objects (scarps or bodies) or being fully surrounded by them are candidates for merging, whereas expansion into clearly stable terrain is explicitly disallowed (for a further and comprehensive overview of the ruleset developed, see Appenix/Paper 2, Tables A1–B2 in the Appendices).

Refinement proceeds iteratively using eCognition’s interactive tools: objects are filtered and inspected, candidate merges/expansions are applied, and results are checked against the reference inventory using both number- and area-based accuracy metrics; iterations stop when no further improvements are observed. Landslide scarps and landslide bodies are refined in separate passes with tailored criteria to reflect their distinct geometry and context.

5.2.6. Validation (Paper 1) and Accuracy Assessment (Paper 2 and 3)

Validation is implemented using two complementary strategies reflecting the different mapping approaches applied in this thesis. For the manual geomorphological mapping (Paper 1), validation is based on targeted field verification to confirm landform interpretations and to resolve ambiguous boundaries that cannot be decided confidently from LiDAR-derived visualizations and ancillary datasets alone. Two field surveys were conducted with the support of differential GPS (DGPS): a pre-mapping reconnaissance survey to obtain an overview of dominant landforms and processes, followed by a post-mapping survey to validate selected mapped elements and evaluate the effectiveness of the multi-source mapping workflow. The link between screen-based interpretation and in situ checking is illustrated by the validation example (Chapter 6.2, Figure 11), which contrasts LiDAR visualizations (e.g., openness-/composite-based and hillshade) with the mapped geomorphological features and shows the distribution of DGPS validation points used for verification.

For the GEOBIA-based semi-automatic landslide mapping (Paper 2 and 3), validation is implemented as a quantitative accuracy assessment against the manual landslide reference inventory. Complementary metrics are reported because object counts alone can mask large area errors, whereas area-only measures can hide systematic fragmentation or merging of mapped objects (Cai et al., 2018). Object-based accuracy evaluates correspondence between detected and reference polygons using an overlap criterion (commonly >50%) to define correct detections (Van Den Eeckhaut et al., 2012; Knevels et al., 2019), while area-based accuracy quantifies true-positive, false-negative, and false-positive landslide areas via GIS overlay (Cai et al., 2018). In addition, segmentation quality is diagnosed using dedicated measures (e.g., area fit index, over-/under-segmentation, precision, recall and F-measure) to distinguish segmentation-driven from classification-driven errors (Simoes et al., 2023). In transferability testing, in Paper 3 accuracy reporting is stratified by relevant subsets (notably forest-covered areas) and, where applicable, by DTM epoch to assess robustness to land cover and input data quality differences (Van Den Eeckhaut et al., 2012).

In summary, the investigations in this dissertation are primarily based on LiDAR-derived DTMs, complemented by orthophotos/imagery, topographic and geological maps, and land use/land cover information. These datasets underpin both the detailed geomorphological mapping and the compilation of reference data for semi-automated landslide detection. Methodologically, this chapter combines expert-driven, multi-source manual mapping (Paper 1) with semi-automatic landslide mapping workflows based on GEOBIA and supervised machine learning (Paper 2 and 3), including scale-optimised predictor derivation and structured validation. Together, these approaches provide a consistent framework for analysing geomorphological features and processes and for testing transferability across contrasting study areas and DTM conditions, which is evaluated in the following chapters.

6. Efficient geomorphological mapping based on geographic information systems and remote sensing data: an example from Jena, Germany (Paper 1)

This chapter is based on the publication that contributes to the foundational geomorphological framework of this dissertation. It addresses research questions 1, 5 and 6.

Zangana, I., Otto, J. C., Mäusbacher, R., and Schrott, L., 2023. Efficient geomorphological mapping based on geographic information systems and remote sensing data: an example from Jena, Germany. Journal of Maps, 19(1). DOI: 10.1080/17445647.2023.2172468

While traditional geomorphological mapping relies heavily on time-consuming fieldwork, modern high-resolution data offers a pathway to more efficient, yet structurally rigorous, digital mapping. This paper explores the synergy between classical geomorphological expertise and advanced visualization techniques to evaluate how the combination of LiDAR-derived products improves the accuracy of manual landform delineation in complex middle-mountainous terrain.

The methodology introduces a systematic two-stage workflow. In Stage I, high-resolution (2 m) LiDAR-DTMs were used alongside advanced visualization techniques, such as Topographic Openness (TO) and Composite LSPs, to delineate landform boundaries like crests and slope breaks that are typically obscured in standard models. In Stage II, digitally mapped features and ambiguous landforms were verified through targeted field surveys and ground-truthing using Differential GPS (DGPS) to ensure genetic and spatial accuracy.

The chapter continues to outline the findings' geomorphological relevance by developing a process domain approach. Rather than mapping isolated features, the research systematically delineates geomorphological process domains to ensure that the interaction between different geomorphic agents is captured spatially. The resulting geomorphological map ("Main Map") represents a primary output of the mapping framework developed in Paper 1; this 1:5,000-scale benchmark is presented as Figure 8, and the high-resolution version can be found as Supplementary Material of Paper 1 in the Appendix. This result demonstrates that digital workflows can match the spatial precision of traditional field-based approaches while significantly increasing efficiency.

To summarize, the chapter's research objectives are the generation and comparison of a detailed geomorphological map using a combination of high-resolution LiDAR-DTM data, LSPs, and orthophotos. The research presented in this chapter is a proof of concept for a structured manual-digital mapping workflow, establishing the foundational geomorphological

understanding required for the larger-scale semi-automated investigations in the subsequent chapters of this dissertation.

6.1. Results

Different geological formations have diverse and significant impacts on the landscapes of the Jena region. For instance, the northern part of the study area is dominated by limestone, which is characterized by escarpments, slopes, landslides, and V-shaped valleys. However, the southern part, dominated by sandstone, features several boxes and saucer-shaped valleys, flood plains, and terraces.

Some landforms were generalized or have been omitted for the final map to consider relevant landform visibility and improve readability. The final map is divided into four main classes/layers: geomorphological processes domains, hydrological features & pathways, hillslope processes & deposits, and topography & structural landforms.

6.1.1. Geomorphologic process domains

The northeastern part, the plateau, and the western part of the map edges, i.e. the high altitudes, are mostly dominated by karstic processes; however, rare karst features were also detected.

The northern and southern parts of the study area are dominated by the gravitational processes. The Kernberge, Johannisberg, Gräfenberg, and Einsiedlerberg mountain slopes are compatible with landslides, rock falls, creeps, and debris flows. The northeastern, central, and southern parts of the study area are dominated by denudational processes where other dynamic processes were not observed. The low-altitude zone and the valley slope areas are mostly characterized by fluvial processes, specifically along the Saale River and its tributaries. Fluvial–anthropogenic domains occur in the northwestern part, termed the Obere Aue area, and near Lobeda in the center of the map; i.e. the flood plain was modified by anthropogenic activities such as construction, and in the northeastern part of the area, the Pennickental river bed was influenced by mining activities.

Anthropogenic process domains are distributed all over the map. For instance, a part of Mönchsberg, the southwestern part of the area, was significantly altered by anthropogenic activity associated with the Steinbruch quarry, cf. Figure 11. As a result, a break in slope of approximately 30 m and a plateau of approximately 400 × 600 m was created.

The aeolian processes (loess accumulations) are not active in the area and ‘since loess in Europe was mainly accumulated during the cold stages of the Quaternary’ (Lehmkuhl et al., 2018) a clear distinction of the local extent of this class is not well defined in our area. It is presented on the map within sub-classes as it has been influenced by other processes. We identified loess accumulations on the eastern side of the Roda River, the western side of the Saale River, over the Spitzenberg Mountain slopes toward the Saale, and on the slopes toward the Ilmnitz, specifically between the contour lines of 175 and 225 m.

Periglacial processes are inactive in the study area and illustrated via the combination with other processes. It is mostly distributed along the hilly-mountain slope in the northern and southwestern parts of the map, where mainly dominated by the gravitation processes. The fluvial terraces occur along both flanks of the Saale and Roda channels, between 175 and 200 m asl. These terraces mostly undergo alteration by denudational and fluvial processes (see Figure 8/Main Map, legend 1, for corresponding classes).

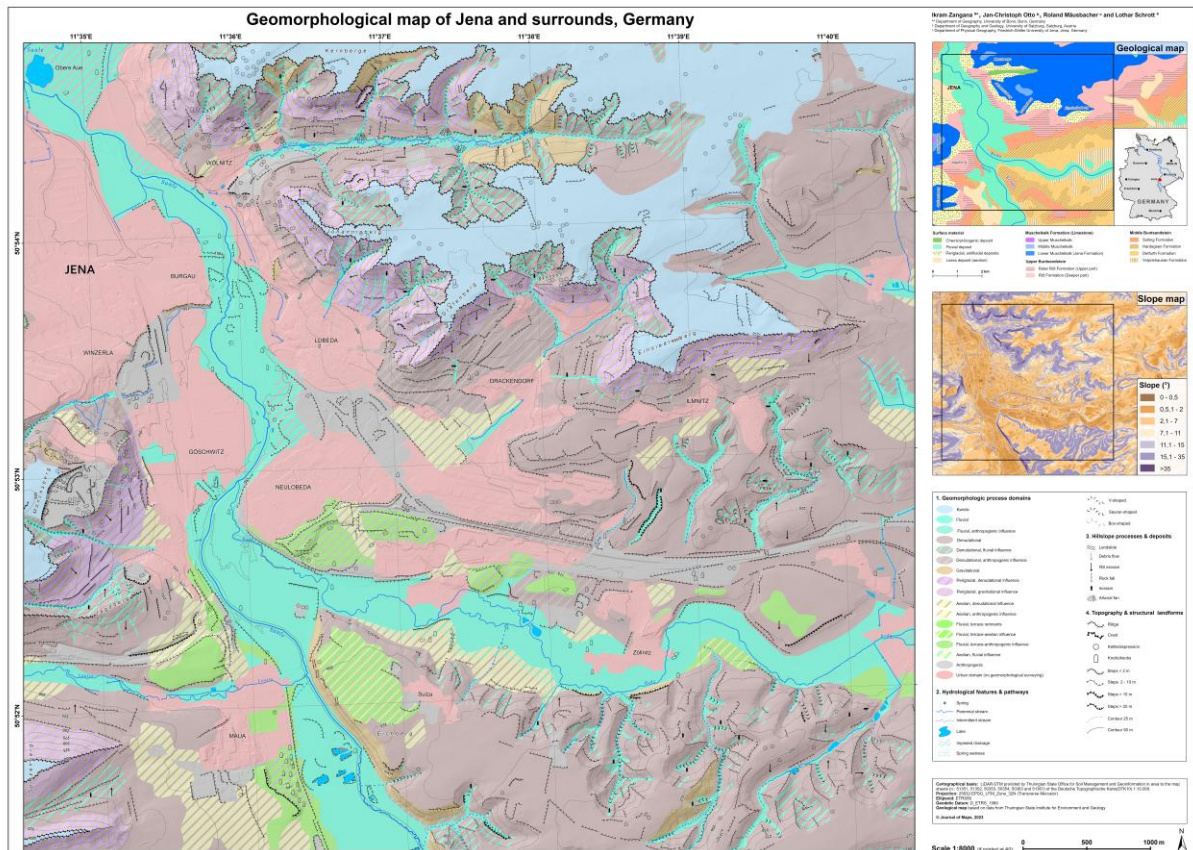


Figure 8 Geomorphological map of the study area. This map corresponds to the “**Main Map**” published with Paper 1. A high-resolution digital version is provided in the Supplementary Material of Paper 1 and included in the Appendix; the printed version is presented in A3 format for readability (adapted from Paper 1).

6.1.2. Hydrological features and pathways

The investigation area is mostly characterized by the Saale River valley and its tributaries. Perennial streams (e.g. Roda, Leutra, and Pennikental) and intermittent streams also contribute to terrain modification. In the northern part of the map, the Pennickental stream bed mostly undergoes alteration by anthropogenic activities (Section 6.1.1.). Thus, the water is hampered to flow persistently and partially covers both stream flanks (Figure 8/Main Map, legend 2).

Various lakes with a range of sizes are distributed along the river and stream channels. For example, despite the trace of the Saale meander and the ridges of the old lakes, several lakes occur on the Saale active fluvial plain, near the southwestern corner of the map. The southern

part of the study area is mostly covered by the sandstone formations dominated by saucer- and box-shaped valleys, whereas the northern part is controlled by limestone formations, where v-shaped valleys have mainly been investigated (see the Main Map/Figure 8, legend 2).

6.1.3. Hillslope processes and deposits

The central and northern parts of the study area are dominated by hills (e.g. Kernberge, Johannisberg, Gräfenberg, and Einsiedlerberg). The hill crests, which follow a west–east trend, are characterized by numerous incisions, and geomorphological evidence of rill erosion, rock falls and debris flows, especially in the slopes toward the Pennickental (e.g. Diebeskrippe landslide), the slopes toward the Saale, and the Einsiedlerberg slopes toward the south (see Section 6.1.1.). In addition, on the southwestern part of the map, the mountain slopes of Mönchsberg, Jagdberg, and Spitzenberg to the Saale are dominated by a range of incisions, rill erosions, and rockfalls (Main Map/Figure 8, legend 3). Generally, the incision and rill erosion occur throughout the mapped area at a range of scales. Small alluvial fans occur at the mouth of the tributaries of Pennickental, in the northern part of the investigation area, and are mostly altered by shallow mass movements and anthropogenic activities.

6.1.4. Topography and structural landforms

The depressions are mainly distributed across the tops of the plateau landscape, located in the northern portion of the map; however, more specifically, they occur on the slopes of the Kernberge and Johanniseberg toward Wöllnitz, at the top of Mönchsberg (also Steinbruch), and its slopes toward the Winzerla, and on the slopes around Gräfenberg and Georgstein. Knoll/knob features (Figure 8/legend 4) mostly dominated the low-altitude (i.e. flat) areas along the Saale valley. Most exhibit a range of anthropogenic origins (see the Figure 8/Main Map, legend 1) and are mostly modified by fluvial and denudational processes. Furthermore, steps and breaks in slope features occur throughout the mapped area; however, the northern portions of the map are extensively covered with mountainous areas, where the terrain is more complex than the southern part of the area.

Finally, most of the landforms and geomorphic process boundaries of the study area (e.g. plateau, mountains, valleys, catchments, terraces, and landslides) are controlled by crests, ridges, and breaks of slopes.

6.2. Discussion

This investigation supports evidence from previous observations (e.g. Jones et al., 2007; Roering et al., 2013) that reveal the accuracy of LiDAR data, showing that it is valuable for accelerated geomorphological mapping (Figure 9). Owing to the complex interactions between geomorphological processes in nature, a clear distinction between landforms solely from the remote sensing data was impossible. Therefore, Figure 6/Stage I illustrates our proposed approach as a step toward detecting landform geneses and geomorphological process domains by combining all data sources from on-screen mapping. Nonetheless, further developments could increase the extent of applicability of such pursuits, for instance, (1) by applying it to different environments and (2) by developing a novel approach to delineate and

classify landform genesis automatically using DEMs based on LSPs (Seijmonsbergen et al., 2011).

We observed some discrepancies when overlaying different data sources, such as the topographic map and DOP with the DTMs. This occurs because of variations in scale as well as the date of data collection. For instance, anthropogenic activities such as roads, buildings, or construction may be represented only in some of the data, owing to different times of acquisition. Hence, utilizing data sources with the same scale and similar acquisition time is recommended (Otto & Smith, 2013). However, if the existing data sources do not fit to each other, which is hard to achieve, relying on the most recent data or conducting ground-truthing to illustrate current processes is more reliable.

The geological map enhanced on-screen mapping by providing adequate information to detect landform genesis, such as landslides with gravitational processes and terraces with fluvial processes (Figure 10). Nevertheless, a detailed boundary distinctions of landforms cannot be extracted from geological maps in contrast to their recognition from LSP composites and hillshade maps. This disagreement may reflect the lower scale of the geological map in comparison to the produced map. This research corroborates the ideas of Anders et al. (2011, 2015), Doneus (2013), Meng et al. (2018), and Daxer (2020), who suggested that TO and LSP composite maps are valuable for geomorphological mapping.

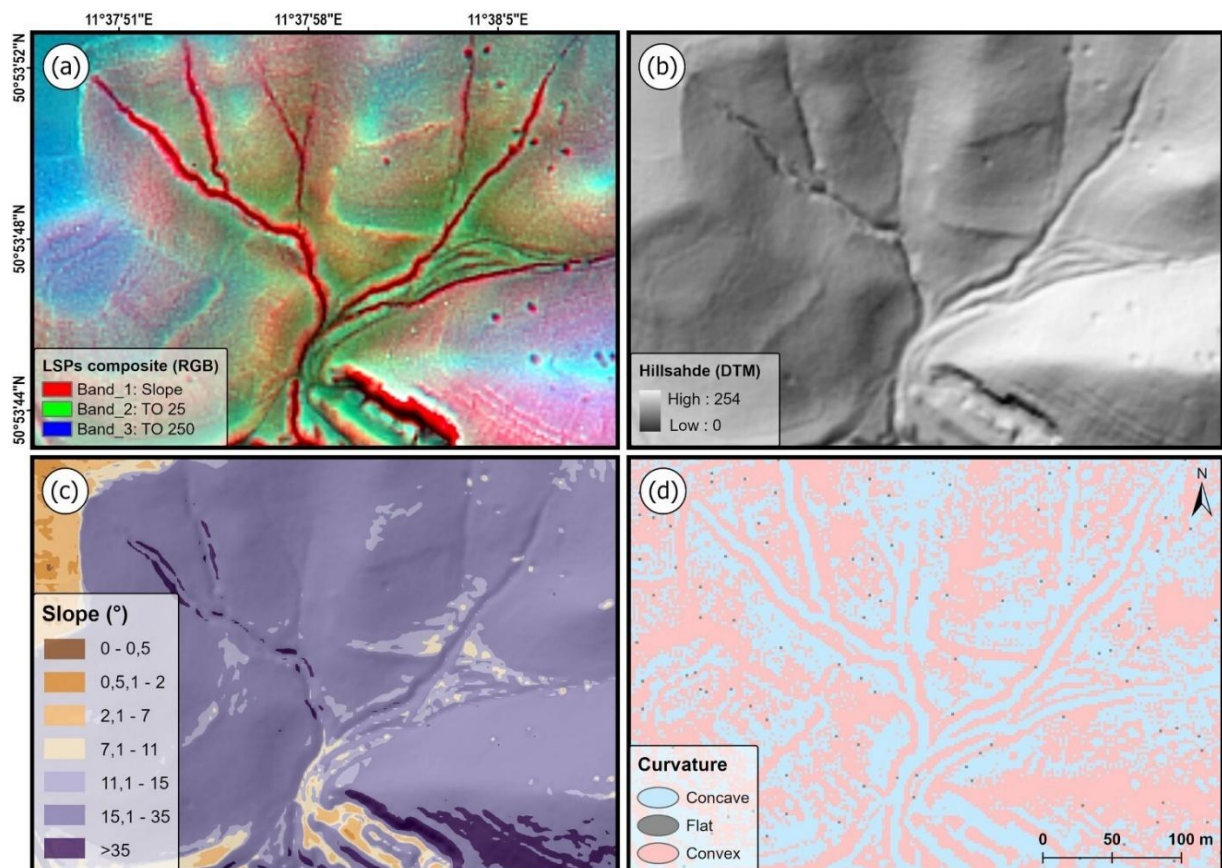


Figure 9 (a) LSPs composite map clearly defines landforms (bomb craters, queries, erosional rim...etc.) and their boundaries compared to DTM data and its derivatives, such as (b) hillshade, (c) slope, and (d) curvature.

This effort can be counted as an experiment toward an extension of the efficiency of that concept for manual mapping. In contrast, the slope map, which was classified based on the GMK25 legend (Main Map/Figure 8), is less suitable for a comprehensive representation of landforms. For example, Figure 9(c) indicates that most of the steps, incisions, bomb craters, and ridges are not fully represented based on this legend since the GMK25 legend was designed for a 1: 25,000 scale map; however, not for a detailed scale such as 1:5000. Different classification intervals of slope angles were experienced in the initial steps when considering the general ideas of Jones et al. (2007), but further investigation is still needed, taking the map scale into account. In contrast to the traditional hillshade map, multidirectional hillshades promote the balance between over-exposed and non-illuminated areas of the map, resulting in a more realistic representation of the terrain (Nagi, 2014), and can further develop the accuracy of on-desktop mapping.

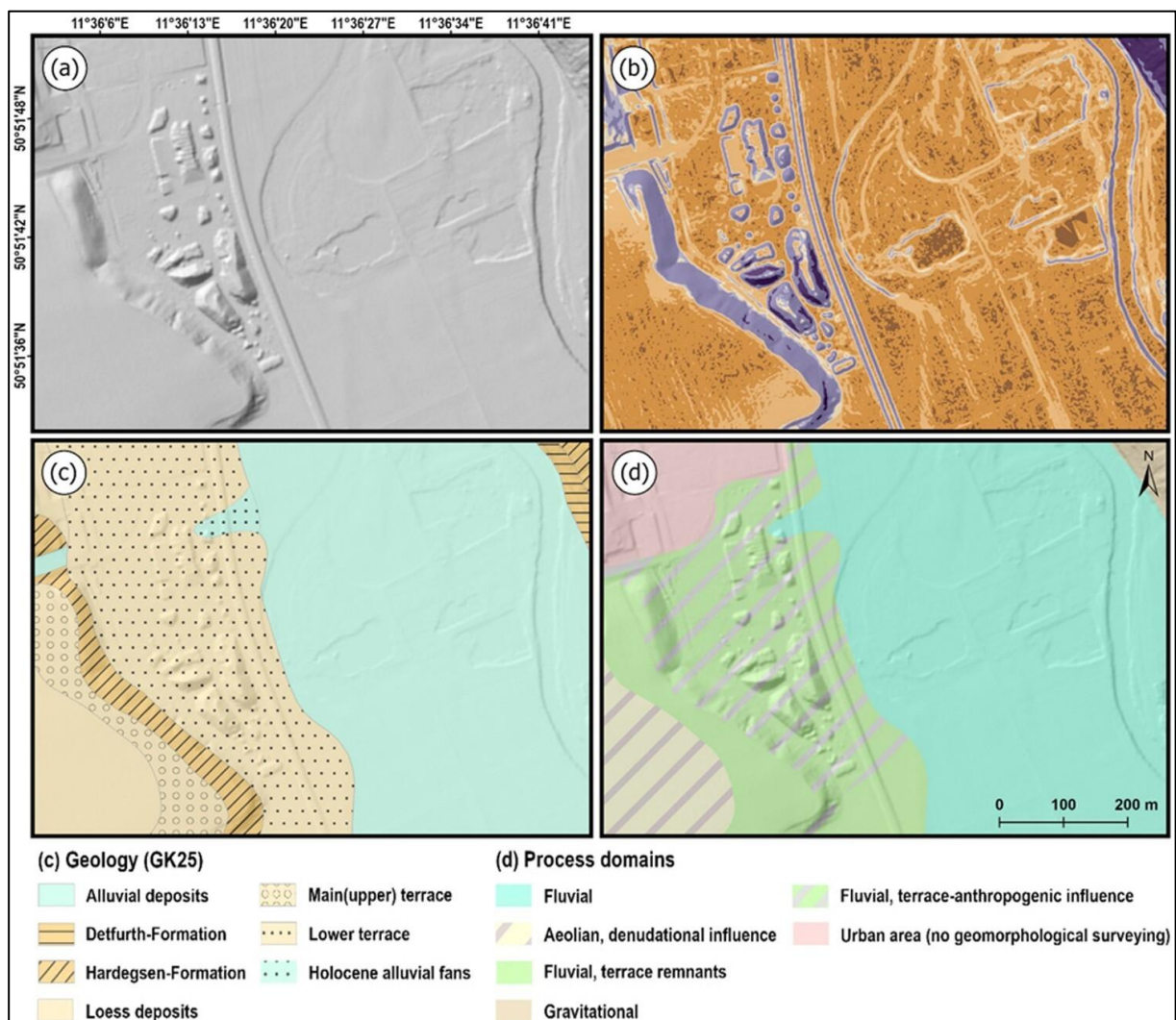


Figure 10 Example of process domain delineation (fluvial process): (a) Hillshade (for legend, see Paper 1 Fig. 3(b)). (b) slope (for legend, see Appendix II). (c) geological map-GK25 and (d) the geomorphologic process domains. Adapted from Paper 1.

We validated the DTM-based GIS map with DGPS measurements in the field. Figure 11 indicates a good agreement between screen-based landforms and field checks related to the

high resolution of digital base data for mapping. We observed an accuracy between a few millimeters (in most cases) to a meter or more (in seldom cases). However, mismatches between both approaches were observed. For example, in areas mostly covered by forest or vegetation, DGPS measuring was impossible. Some landforms were detected in the field but unidentifiable in LiDAR data. For example, hollows, knolls, and active processes such as sheet erosion or debris flows were not identified solely from the remotely sensed data. This can be due to the resolution of the DTM and the offset between acquisition times of digital and field data.

Therefore, the resolution of digital data should be considered when a geomorphological map with higher precision and detailed scale is required. Therefore, the results presented here show that LiDAR data can quickly create a detailed geomorphological map of the middle-mountain environment but should not be considered a complete replacement for traditional methods.

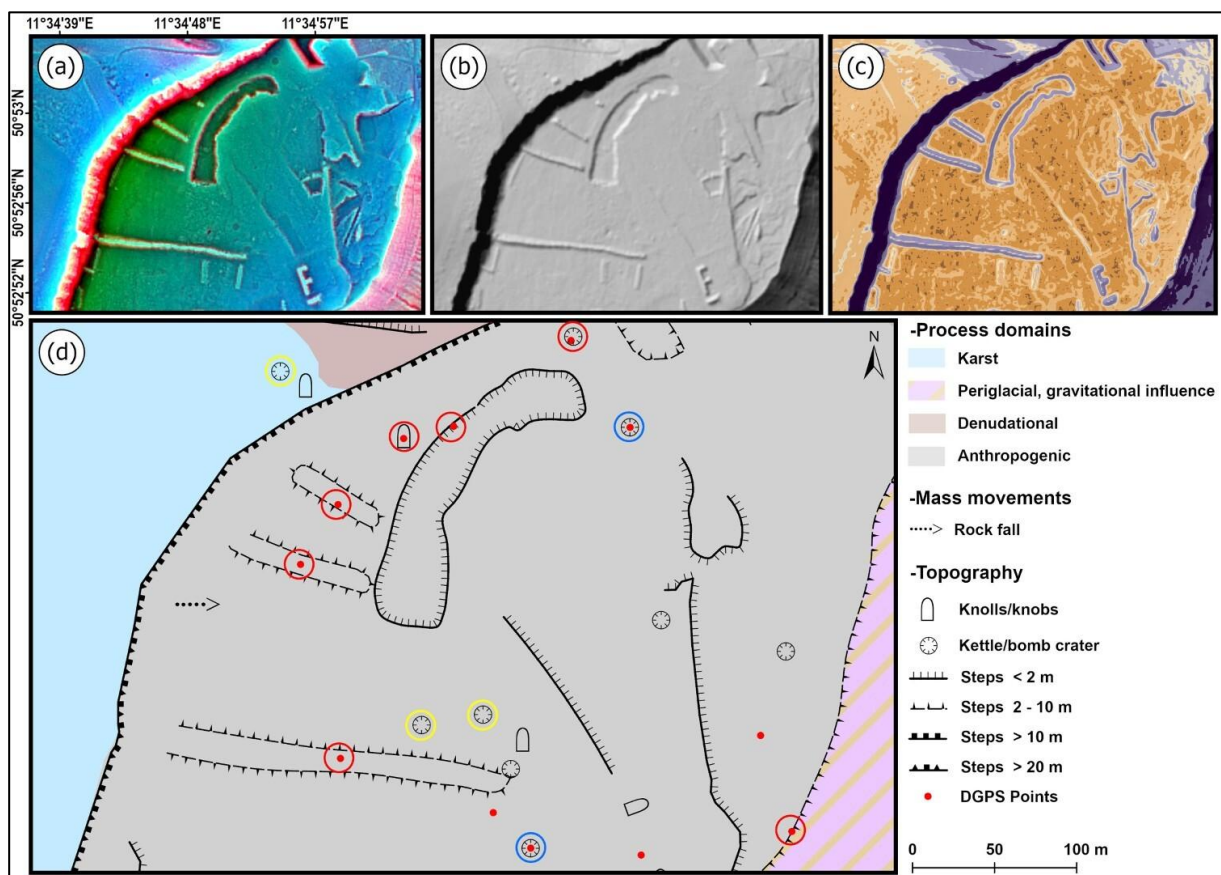


Figure 11 (a) LSPs-composite map, (b) hillshade, (c) the slope map of the Steinbruch quarry area, (d) an overview of the field/DGPS survey (red points). Red circles show that these landforms fit the DGPS measurements, and yellow circles present features that were not found in the field due to dense vegetation. Blue circles present landforms that could not be mapped by LiDAR-DTM-based on-screen analyses (see Fig. 3 for the legends of (a, b, and c) and Fig.1 for the location of this area). Adapted from Paper 1.

6.3. Conclusion

This paper introduced a manual geomorphological map at a scale of 1:5000, based on ArcGIS tools and combining DTM, DTM derivatives, and LSPs-composite maps. Other inputs such as

topographic maps, Google Earth images, DOPs, geological maps, and field examination were used to improve the mapping. This map can be used as a substitute approach geomorphological information from classical field-based maps.

Our approach provides high-accuracy layers of information. Moreover, the results obtained show that incorporating relevant LSPs, such as slope, curvature, elevation, multidirectional hillshade maps, and other derivatives such as TO and LSPs composite maps, provide valuable means of improving manually constructed digital geomorphological maps. Our proposed approach presents most geomorphological map layers and their properties at high quality; however, combining new layers of information or additional and better datasets might optimize the map.

We conclude that a combination of different data types, together with TO and LSPs, significantly enhances digital geomorphological mapping. Nevertheless, a field check of remotely sensed information still provides the best guarantee of producing accurate and updated high-resolution maps.

Google Earth images and DOP datasets with a resolution of approximately <20 cm are highly recommended for comprehensive mapping in flat and non-vegetated areas. The geological map can provide further improvement and flexible fine-tuning considering the genesis of some landforms (e.g. landslides and terraces). It is also valuable to determine the boundary of some geomorphological process domains (e.g. gravitational and fluvial processes). Notwithstanding, since the scale of the geological map is relatively smaller than that of the target map, uncertainties concerning the genesis of some landforms and their boundaries arose. Hence, geomorphological mapping can be enhanced when complemented with an equivalent resolution of geological data.

This approach is valuable for creating high-quality base data prior to or instead of field mapping, or when field survey time is limited. Furthermore, it provides a step forward in substituting traditional geomorphological mapping approaches with on-screen digitized mapping, thereby presenting data sources for future studies in this area, despite its utility as a training sample for semiautomatic landform classification of typical landforms.

Our proposed approach can be applied in different environments to enhance the usability of geomorphological landforms and process domains.

7. Mapping forest-covered landslides using Geographic Object-Based Image Analysis (GEOBIA), Jena region, Germany (Paper 2)

This chapter is derived from the second publication included in this dissertation and focuses on research questions 1, 2, 3 and 4.

Zangana, I., Bell, R., Drăguț, L., Sîrbu, F., and Schrott, L., 2025. Mapping forest-covered landslides using Geographic Object-Based Image Analysis (GEOBIA), Jena region, Germany. Nat. Hazards Earth Syst. Sci., 25, 4787–4806. DOI: 10.5194/nhess-25-4787-2025

Detecting landslides in densely forested terrain is challenging because traditional pixel-based approaches often fail to accurately delineate scarps and landslide bodies. This study develops and evaluates a semi-automated Geographic Object-Based Image Analysis (GEOBIA) workflow to improve detection and spatial delineation, while providing a robust assessment of mapping accuracy.

The workflow combined multiscale image segmentation with iterative object refinement. Candidate landslide objects were visually inspected, filtered using attribute thresholds, and compared against a reference inventory. Ambiguous features were merged, expanded, or reclassified based on spatial rules such as adjacency to true positives, boundary overlap exceeding 80%, or full enclosure within known landslide zones, while strictly avoiding non-landslide terrain. Scarps and landslide bodies were processed separately, allowing parameter adjustment to capture their distinct geomorphological characteristics.

Accuracy assessment employed both number- and area-based metrics to quantify true positives, false negatives, and false positives. Additional segmentation metrics, including area fit index, over- and under-segmentation, F-measure, recall, and precision, were calculated using custom R scripts to evaluate spatial fidelity and reproducibility across models. This combination of thematic and spatial assessment ensured a comprehensive evaluation of the GEOBIA workflow.

The results demonstrate that GEOBIA can reliably identify landslide features in complex, forested landscapes. Iterative refinement, component-specific parameters, and context-aware rules significantly improved detection accuracy. The research objectives were to develop a transferable semi-automatic workflow, evaluate segmentation and refinement strategies, quantify thematic and spatial accuracy, and provide a methodological framework supporting both local hazard assessment and broader geomorphological studies. This chapter illustrates the potential of GEOBIA to complement traditional field-based inventories and to enable effective mapping of landslide-prone landscapes.

7.1. Results

This chapter presents the main results of this study, specifically the optimisation results of window sizes for LSVs in MII, the results of GEOBIA-based landslide detection and the model performance evaluation results from different AA approaches.

7.1.1. Optimisation of window sizes for LSVs in MII

Figure 12 shows the variation in the optimal window size for each LSV across multiple runs, highlighting noticeable differences between landslide scarps and bodies. Some LSVs (e.g. TO, plan curvature and profile curvature) have consistent window sizes, whereas others (e.g. slope and TRI) show greater variability. Figure 12 and Table 3 show the final window sizes used in the analysis for both landslide components in MII, along with the default values used in MI for comparison. The optimal window sizes differ not only between LSVs but also between scarps and bodies within the same LSV. Hence, separate rule sets were developed in eCognition for each landslide component. Segmentation, classification, refinement and AA were then performed independently for the scarps and bodies.

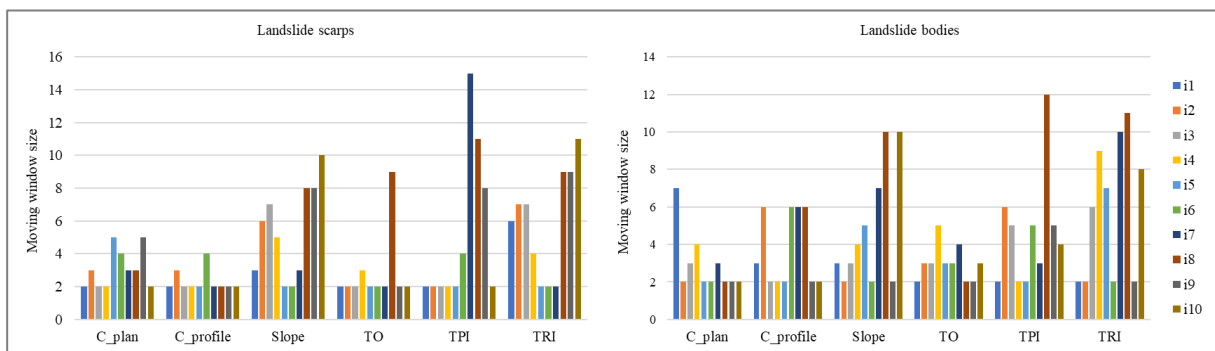


Figure 12 Optimal window sizes for each LSV in predicting landslide scarps and bodies. Note: i1, i2, ..., i10: number of iterations; C: curvature; TO: topographic openness; TRI: terrain roughness index; TPI: terrain position index.

Table 3 LSVs and corresponding window sizes per model.

Models/LSVs		Slope	C_plan	C_profile	TO	TRI	TPI
I *	Scarp & Body	3x3	3x3	-	3x3 & 25x25	3x3	33x33
	Scarp	11x11	7x7	5x5	5x5	7x7	11x11
II **	Body	11x11	5x5	7x7	7x7	9x9	13x13

* Default window size, ** optimal window size

7.1.2. GEOBIA-based landslide modelling results

The GEOBIA-based landslide modelling results, specifically those of landslide scarps and bodies for both models (MI and MII), were compared with the inventory map to assess their spatial correspondence (Figures 13 and 14). Figure 13(a) shows the MI results (default window sizes).

The brown and yellow polygons represent the model-detected landslide scarps and bodies, and the blue and pink polygons indicate the landslide scarps and bodies in the reference map for comparison. Figure 14(a) shows the same area but illustrates the MII results. In both figures, the polygons within the black-dashed-line regions are further discussed in Chapter 7.2. A visual inspection of these maps shows that MI covers a larger portion of the landslide body areas compared with MII, but MII performs better in detecting scarp zones. However, on-screen analysis shows that MII is more precise than MI for each landslide component, as indicated by the brown and yellow polygons (GEOBIA-based results) and the blue-(scarps) and pink (bodies) polygons (reference map). This is particularly evident when considering the accuracy of landslide size and FPr. These results are assessed more thoroughly in Figures 15 and 16 and Chapter 7.2.1.

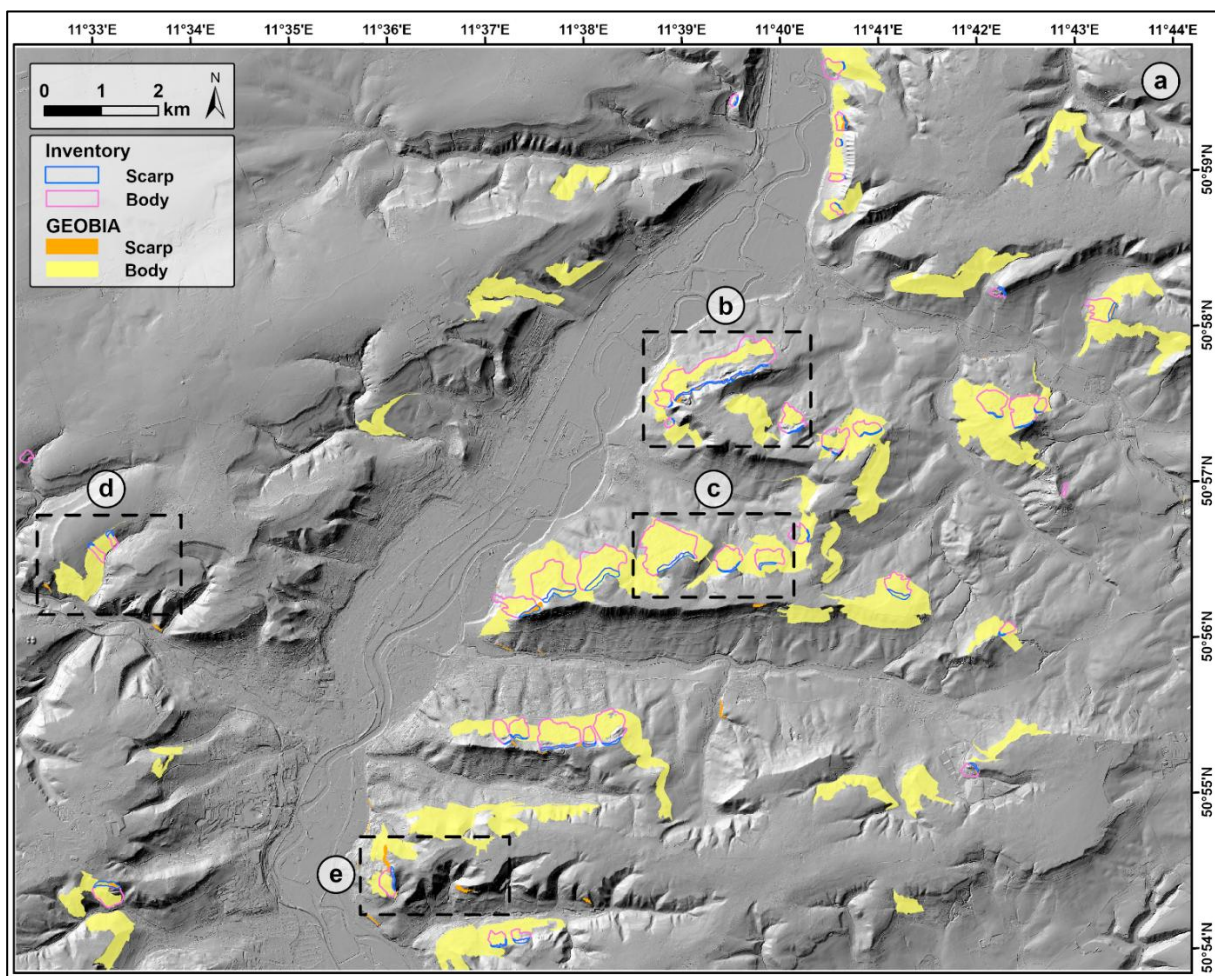


Figure 13 Final map of semi-automatic landslide detection using MI, displayed over hillshade DTM (TLUBN, 2019) throughout study area. Detected landslides are shown as coloured polygons (brown: scarps; yellow: bodies), while the inventory map is also displayed for comparison. The insets outlined by black dotted lines are magnified and analysed in Figure 15.

The morphological characteristics of the landslides (scarps and bodies) in the Jena region highlight notable distinctions between these components, as summarized in Tables 4 and 5. The results show that scarps have slope mean values of 48° and 40.5° in MI and MII, respectively, whereas bodies maintain a consistent slope mean value of approximately 20°

across both models. This suggests that scarp areas are more sensitive to the optimized approach applied in MII, while body areas remain relatively unchanged. Scarps exhibit positive values for plan curvature (C_{plan}), while bodies show lower values. Similarly, for profile curvature ($C_{profile}$), scarps display positive values, whereas bodies exhibit negative values, further emphasizing their distinct morphological characteristics. The TRI mean values further differentiate scarps and bodies, with scarps showing significantly higher values (3.73 and 5.09 for MI and MII, respectively) compared to bodies (0.95 and 1.93 for MI and MII, respectively). Additionally, TPI values for scarp areas are higher in MII than in MI, while for body areas, the TPI values are notably lower in MII compared to MI.

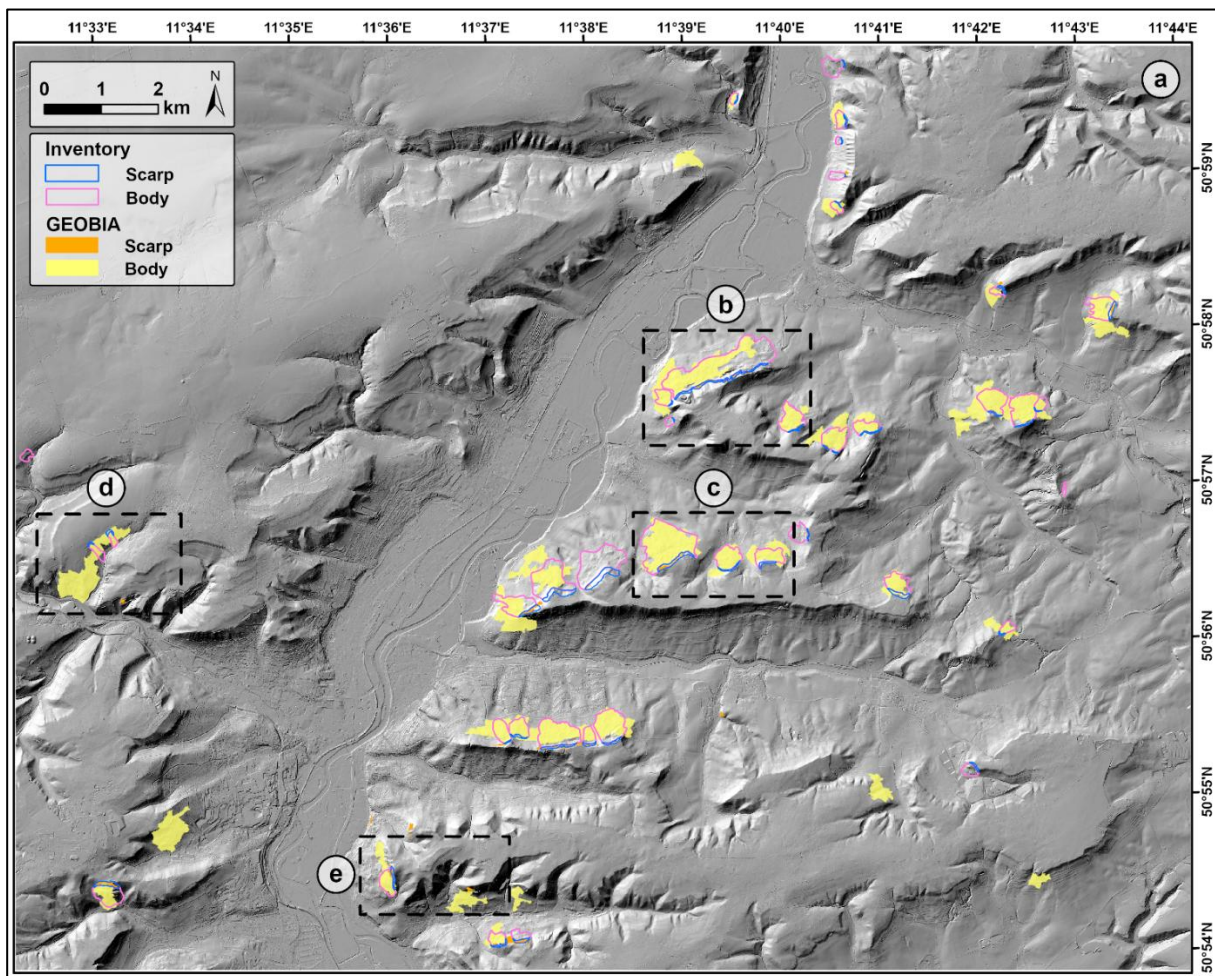


Figure 14 Final map of semi-automatic landslide detection using MII, displayed over hillshade DTM (TLUBN, 2019) throughout study area. Detected landslides are shown as coloured polygons (brown: scarps; yellow: bodies), while the inventory map is also displayed for comparison. The insets outlined by black dotted lines are magnified and analysed in Figure 8.

Table 4 The morphological characteristics of landslides (scarps and bodies) in Jena region as detected by GEOBIA, Model I.

LSVs/value	Scarp			Body		
	min	max	mean	min	max	mean
Slope (°)	34.9	61.5	48.2	14.88	25.69	20.28
C_plan	-1.04	12.19	5.57	-0.032	0.128	0.048
TO3x3	-0.003	0.029	0.013	-0.00085	0.00051	-0.00017
TO25x25	-0.001	0.099	0.049	-0.00201	0.00373	0.00086
TRI	1.82	5.64	3.73	0.68	1.22	0.95
TPI	0.1	2.8	1.4	-0.07	0.05	-0.01

Table 5 The morphological characteristics of landslides (scarps and bodies) in Jena region as detected by GEOBIA, Model II.

LSVs/value	Scarp			Body		
	min	max	mean	min	max	mean
Slope (°)	33.4	47.7	40.5	15.9	27.9	21.9
C_plan	0.0001	0.0205	0.0107	-0.0044	0.0014	-0.0015
C_profile	-0.0028	0.0040	0.0006	-0.0014	-0.0001	-0.0012
TO	-0.0014	0.0086	0.0036	-0.00186	0.00003	-0.00091
TRI	3.77	6.42	5.09	1.32	2.54	1.93
TPI	1.59	13.24	7.41	-3.83	0.11	-1.86

7.1.3. Accuracy assessment results

7.1.3.1. Thematic accuracy assessment

The thematic accuracy assessment is conducted using two complementary approaches: object-based (number-based) and area-based accuracy metrics. First, the number-based AA results (Table 6) show a significant improvement in the scarp zones for MII, with a higher TPr and significant reductions in both FPs and FNs. In the landslide body areas, the FPs were also significantly reduced, indicating an overall improvement in classification accuracy under the optimised window size. Next, the area-based AA results are summarised in Table 7, with MII showing significant improvements over MI. As for scarp detection, MII increases the TP area from 6.3 ha to 9.1 ha and reduces the FNs accordingly, demonstrating better detection performance than MI. Although the FPs remain relatively high, they moderately decrease under MII. As for landslide body detection, MII significantly reduces the FPs from over 760 ha in MI to approximately 155 ha, indicating a significant improvement in mapping accuracy. However, a trade-off is observed, with the FNs increasing slightly. These trends are also

noticeable in Figures 15 and 16, which shows a significantly lower FP in MII (red polygons in Figure 16) than in MI (Figure 15).

Table 6 Number-based comparison of True Positives (TPs), False Positives (FPs) and False Negatives (FNs) in landslides detection per model.

Landslide	Model	TP	(%)	FP	(%)	FN	(%)
Scarps	I	21	55.2	24	53.3	17	44.8
	II	25	65.8	5	16.6	13	34.2
Bodies	I	17	42.5	21	52.5	23	57.5
	II	21	52.5	8	20.0	19	47.5
Inventory		38 (scarps) / 40 (bodies)					

Table 7 Comparison of True Positives (TPs), False Positives (FPs) and False Negatives (FNs) in landslides detection per model (area in hectares).

Landslide	Model	TP	%	FP	%	FN	%
Scarps	I	6.3	30.6	9.3	59.6	14.3	69.3
	II	9.1	43.8	8.0	47.0	11.6	56.2
Bodies	I	191.2	78.7	769.2	80.0	51.8	21.3
	II	161.9	66.6	155.8	49.0	81.0	33.3
Inventory		20.7 (scarps)/243 (bodies)					

7.1.3.2. Segmentation metrics

The US values for both models are below 0.50 in landslide scarp detection. Specifically, the US value drops from 0.84 in MI to 0.60 in MII, demonstrating that the use of the optimal window size in MII significantly improves the results (Table 8). Likewise, the OS value for scarps decreases from 0.53 in MI to 0.33 in MII. Additionally, the precision value improves in MII, confirming the effectiveness of the optimised approach.

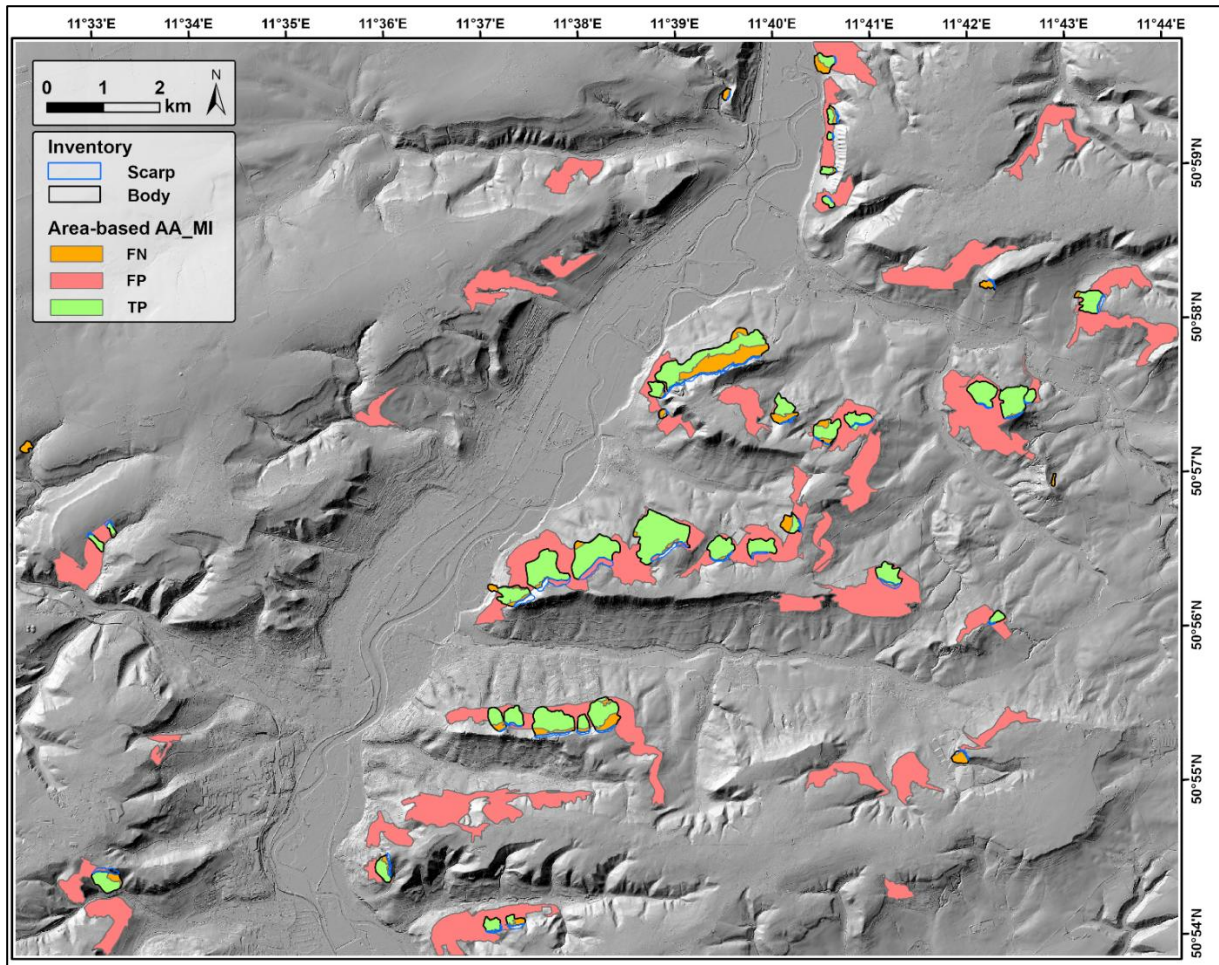


Figure 15 Area-based accuracy assessment of landslide body mapping using GEOBIA in Model I (True Positives (TP), False Positives (FP), and False Negatives (FN)), displayed over hillshade DTM (TLUBN, 2019).

7.2. Discussion

This study highlights the efficacy of integrating GEOBIA with high-resolution DTM data for the inventory mapping of forest-covered old landslides in middle-mountain regions. The implementation of the optimal window size (MII) substantially enhances landslide detection accuracy while significantly reducing both the number and total area of FPs relative to the use of the default window size (MI). These results align with those of Sîrbu et al. (2019), who demonstrated window size variability across different LSVs for landslide scarps. Our study broadens this understanding by analysing both scarp and landslide body areas, revealing that window sizes differ not only across LSVs but also between landslide scarp and body areas within the same LSVs (Figure 12, Table 3). Consequently, landslide scarps and bodies should be detected separately within the model for an accurate analysis of each landslide component.

In our study area, large forest-covered landslides (>0.5 ha) are more successfully detected than smaller landslides, as they mostly show a strong geomorphological signature (Figure 17(b)). This is similar to previous findings (Knevels et al., 2019; Dias et al., 2023). However, MII has a lower proportion of misclassified areas within the same inset (Section 7.1.3, Figure 17), highlighting its ability to delineate landslide features accurately throughout the study area. Additionally, some automatically delineated landslide polygons extend beyond the boundaries

of the inventoried actual landslide areas (Figures 13 and 14). These deviations can be attributed to limitations in the segmentation and classification algorithms, which may produce irregular or overly coarse objects, or potential misclassifications or errors in object merging due to the use of a low threshold for object characteristics during refinement and the final layout.

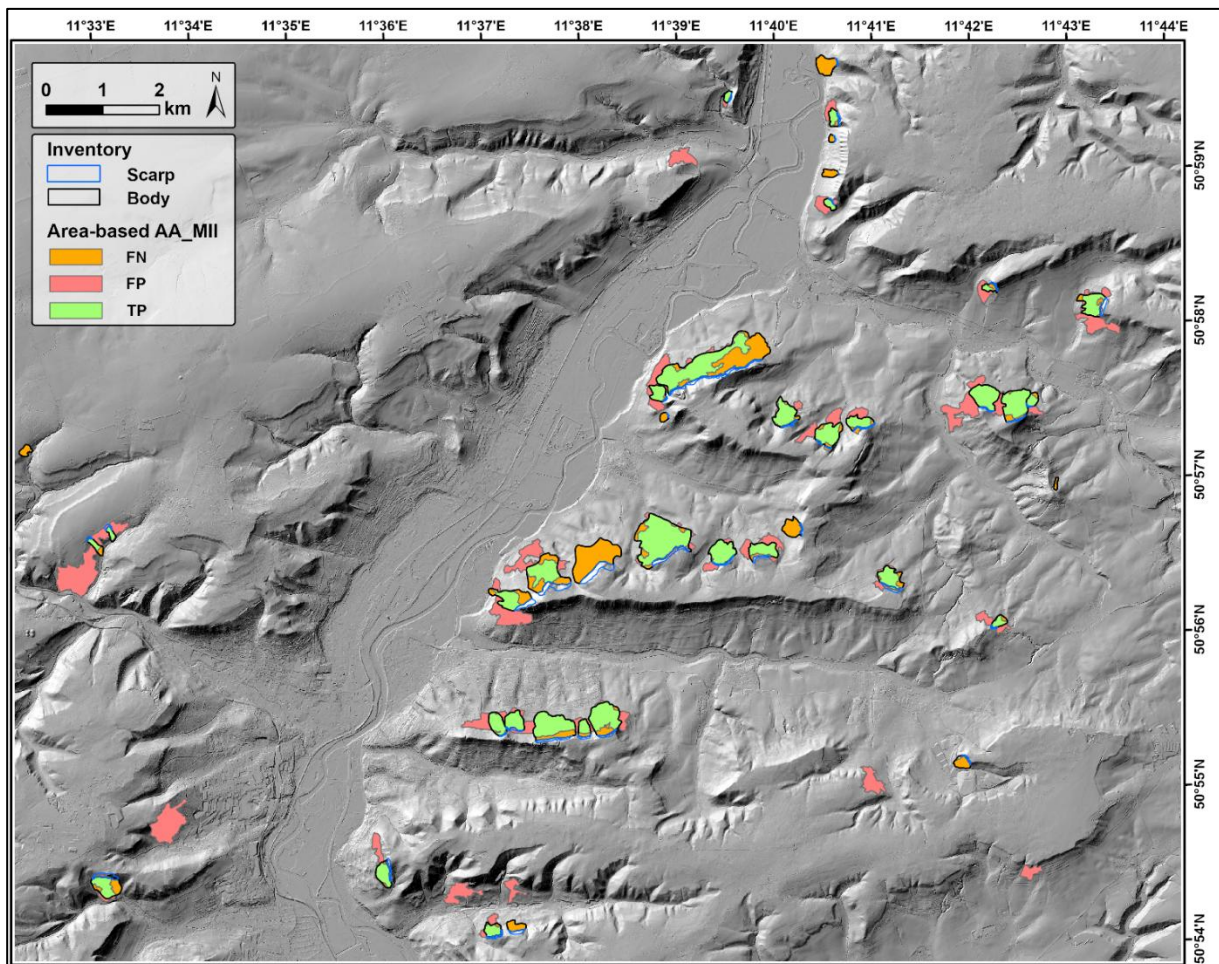


Figure 16 Area-based accuracy assessment of landslide body mapping using GEOBIA in Model II (True Positives (TP), False Positives (FP), and False Negatives (FN)), displayed over hillshade DTM (TLUBN, 2019).

We should acknowledge that in one instance (see Figure 17(b)), a large mapped landslide may in fact consist of multiple individual events. Due to uncertainty regarding the precise boundaries between these possible landslides, we decided to map the area as a single, large landslide in the inventory map. However, this issue is partially addressed through the area-based accuracy assessment presented in Section 7.1.3, which minimizes the impact of such limitations on model validation. Future studies could improve the accuracy further by labelling such ambiguous cases as "uncertain" or separating them from clearly defined landslides in the inventory. This would help to better assess model performance and transferability.

Other misclassifications occur in areas where the geomorphological signature or roughness resembles the characteristics of landslide body or scarp candidates defined by the developed rule set. Both models incorrectly detect a scarp in the same inset/window in Figure 17(d) but

in different locations. The parameters in these areas are similar to those of actual landslide scarps, so distinguishing them solely based on DTM data is difficult. The misclassified area is actually rock outcrops, which are common in this region due to its local-scale variations in lithology, where different layers and materials respond differently to weathering and erosion (see the geological map of the region in Zangana et al., 2023). Most landslide scarp FPs in our study can be attributed to this issue. In addition, both models misclassify landslide scarps as landslide bodies for two landslides from the inventory map in the same location in Figure 17(d).

Thus, the scarp and landslide body areas in these cases landslides from the inventory map in the same location in Figure 17(d). Thus, the scarp and landslide body areas in these cases are highly similar, possibly due to landslide type/age and human activity, so the rule set cannot easily differentiate them from the rest of the study area. However, the landslides are successfully mapped, highlighting the need for detecting different landslides separately. This shortcoming of our approach is similar to those reported in previous studies on forest-covered landslides (Li et al., 2015; Pawłuszek et al., 2019), demonstrating the challenges of performing inventory mapping without FPs using DTM data alone (Eeckhaut et al., 2012; Bell et al., 2012; Goetz et al., 2014; Knevels et al., 2019).

Furthermore, both models identify the same location in Figure 17(e) as a landslide candidate (as a landslide scarp or a landslide body). The right-hand part of Figure 17(e) in MII shows a landslide that is excluded from the initial inventory due to its dissimilarity with the other landslides and its small size. In MII, the body area of this landslide is incorrectly mapped over cropland, grassland and built-up areas. On the left-hand side of the same window (Figure 17(e), MI), the landslide body is wider

than the inventory map area that may correspond to the inventory map but is excluded from the initial inventory due to the insufficiency of the available information for it to be classified as a large landslide. In the MI image in Figure 16(d), the FP area extends over a wide region, particularly into forested areas and erosional rims, demonstrating that this model has lower landslide detection precision than MII. Therefore, landslide size should be addressed in future studies. Detecting landslides of different types and sizes at various levels can enhance detection rates and further reduce the FPr.

An analysis of the AA results reveals that MII outperforms MI in detecting landslide components (bodies and scarps) in terms of correctly identified areas and FP reduction. For instance, MII reduces the FPr by approximately 30% and 20% for landslide scarps and landslide bodies, respectively (Table 6). MII slightly underestimates the landslide body areas; the TPr for landslide body detection decreases, offset by an increase in the TPr for scarp areas. Although MI yields a higher TPr for landslide body areas, its FPr is approximately 30% higher than that of MII, highlighting the importance of considering the FPr alongside the TPr and FNR for a comprehensive evaluation of model performance. MII has considerable potential, effectively reducing the FPr while maintaining a strong TPr. However, further research is needed to enhance the applicability of this approach across various environments and datasets.

Table 8 Metrics used per landslide component per model.

	Scarp		Body	
Metric	M I	M II	M I	M II
AFI	-0.37	-1.25	-10.21	-3.89
OS	0.53	0.33	0.18	0.18
F_measure	0.42	0.50	0.28	0.57
US	0.30	0.43	0.84	0.60
recall	0.36	0.48	0.80	0.77
precision	0.50	0.52	0.17	0.45

Our TPr is comparable to that of Eeckhaut et al. (2012), who investigated the semi-automatic detection of landslides using lidar data and identified 71% of landslides using object-based detection. In comparison, MII achieves TPr values of 65.8% and 72.5% for landslide scarps and landslide bodies, respectively. However, our approach demonstrates significantly better accuracy through minimising of FPs. Eeckhaut et al. (2012) identified 18 FP landslides in an area affected by 38 deep-seated landslides (47%), and Martha et al. (2010) reported 73 FP landslides for 55 expert-identified landslides (132%). As shown in Tables 2 and 3, our study identifies only 5 FP landslide scarps (20% relative to the TPs) and 7 FP landslide bodies (24% relative to the TPs). Therefore, MII detects landslides more efficiently than MI and the abovementioned approaches. However, some studies (Martha et al., 2010; Eeckhaut et al., 2012; Knevels et al., 2019) do not provide the number or total area of FPs or only present them numerically, hindering a comprehensive comparison of methods. Conversely, our evaluation is more detailed, enabling a systematic assessment of model precision in identifying a specific number of TPs while minimising FPs.

Misclassification also occurs in areas with degraded geomorphological signatures (Figure 17(d, e)). Landslide scarps are often misidentified in regions with features resembling those of scarp candidates. These errors may be attributed to human-made structures, such as roads, pits, ridges and rock toes. Similar false detections are observed in areas with partially eroded or weathered limestone formations, particularly in areas where they overlay sandstone. This misclassification pattern aligns with commonly reported results (Eeckhaut et al., 2012; Hölbling et al., 2017; Knevels et al., 2019; Dias et al., 2023).

Selecting the appropriate window sizes for the LSVs is challenging (Figure 12, Table 3). The results show considerable variability across the 10 runs, with the optimal window sizes often being larger for scarp zones than for body areas. For example, the TPI and TRI significantly deviate between the optimal and default window sizes, highlighting the need to fine-tune window sizes based on the specific geomorphometric characteristics of each landslide feature. By contrast, the default window sizes used in MI often result in under- or over-segmentation,

especially in scarp zones, compromising detection accuracy. These results highlight the complexity of adjusting window sizes for accurate scarp and body detection and emphasise the advantages of the tailored approach of MII in overcoming these limitations.

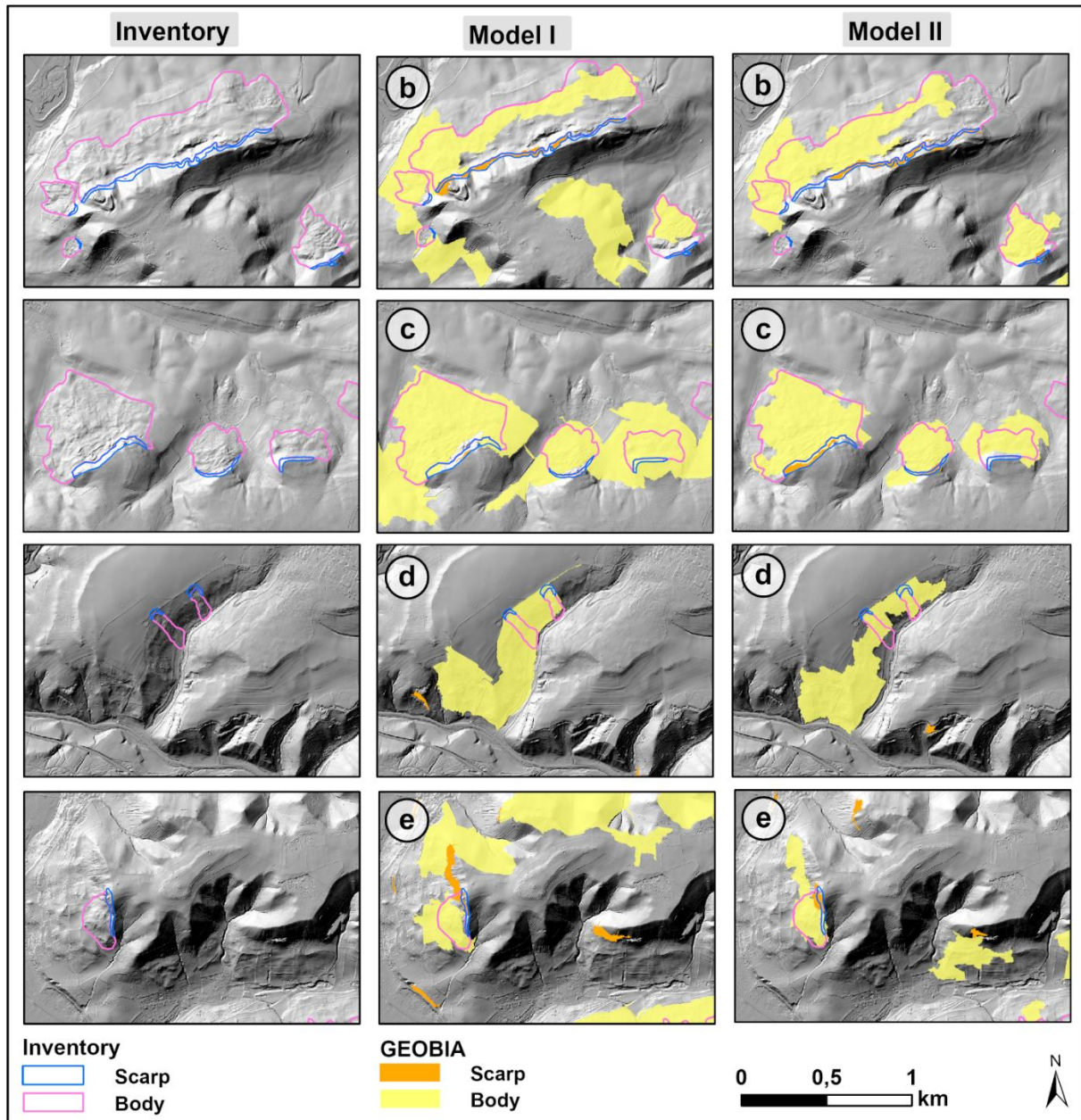


Figure 17 Detailed results of Model I (MI) and Model II (MII) for selected areas. The left column shows the landslide inventory overlaid on the hillshade DTM (TLUBN, 2019). The middle and right columns display MI and MII results, respectively, corresponding to the inset areas b–e shown in Figures. 12 and 13. These zoomed-in views highlight differences in model performance within representative subregions.

Compared with MI, MII is more effective in detecting individual landslides as distinct polygons and separating them from neighbouring landslides. Additionally, MII significantly reduces the FP number and area, as shown in the model comparison in Figure 17. This highlights the robustness of the optimal window size approach of MII, which is more effective for landslide detection than default or manually selected window sizes, which have been commonly used in many studies for decades. Overall, this approach is a valuable advancement in improving

semi-automatic landslide inventory mapping, particularly in forested areas, where the limited availability of optical data often hampers complete inventory mapping (Eeckhaut et al., 2012; Li et al., 2015; Knevels et al., 2019). Although Stage III was first developed in the Jena region, the framework and rulesets can be applied to other areas where landslides are well expressed in hillshade and distinct from their surroundings. This condition is often met for forest-covered landslides of varying ages, and may also apply to younger landslides, with no or limited human impact. While some refinement parameters may need local adjustment, the method is not restricted to a specific landslide type or setting, and its broader applicability should be further evaluated in future studies

7.3. Conclusion

A GEOBIA-based approach is developed and used for the semi-automatic mapping of landslide inventories in the forested areas of the middle-mountain regions of Jena, Germany. The proposed method effectively maps forest-covered landslides, with a particular focus on medium and large landslides (greater than 0.5 ha), but does not detect smaller landslides. MII, which uses the optimal window size, maps landslide scarps with higher accuracy than MI, which relies on default window sizes. MII shows a significant (15%) improvement in scarp detection during number-based AA while reducing the FPr by 30%. However, this FPr reduction entails a trade-off, as the FNr increases by approximately 15%. Nonetheless, MII remains highly effective for semi-automatic landslide mapping in forest-covered areas.

High-resolution DTM derivatives serve as the base data for landslide mapping using GEOBIA, which incorporates an optimal window size to detect forest-covered old landslides in middle-mountain regions. Our analysis shows that this approach may significantly improve the accuracy of landslide mapping in areas with sparse or no vegetation and in regions where landslides are newly formed or have recently altered the terrain. This is due to the superior ability of DTM data to show recent landslide features compared with historical ones.

This study emphasises the importance of calculating window sizes separately for different landslide components, as landslide scarps and bodies require distinct window sizes for accurate detection. This factor should be considered thoroughly before any calculation or modelling process involving landforms of interest. As landform detection depends on the defined window size, our automated objective approach is highly suited for future research and semi-automatic landform modelling. However, further evaluation is required to ascertain the transferability of this method to other regions; nonetheless, this method should be globally applicable to the detection of landslides with well-defined geomorphological features using high-resolution DTM data. As the pioneering use of GEOBIA for landslide inventory mapping in the Jena area, this study serves as a foundation for future research on landslides in this region. Furthermore, it can be used as a base map for hazard and risk assessments, especially as climate change may reactivate old landslides, as has occurred in many areas across Germany and around the world.

8. Transferability of Semi-automated Landslide Mapping Based on High-Resolution DTMs, Swabian Alb, Germany (Paper 3)

This chapter is based on the publication that evaluates the technical robustness and cross-regional applicability of the semi-automated workflows developed in this dissertation (Paper 2). It directly addresses research questions 2, 4, 5 and 6.

Zangana, I., Bell, R., Drăguț, L., and Schrott, L., 2026. Transferability of Semi-automated Landslide Mapping Based on High-Resolution DTMs, Swabian Alb, Germany. (Submitted/In Preparation).

While previous chapters focused on workflow development in the Jena region, this paper addresses the "transferability gap" by applying the optimized Geographic Object-Based Image Analysis (GEOBIA) framework to the Swabian Alb escarpment. The study evaluates whether a model designed for one cuesta landscape (Paper 2) can be effectively transposed to another with different environmental conditions and data qualities.

The methodology follows a three-stage validation framework. Stage I utilizes pre-determined optimal moving window sizes for Land Surface Variables (LSVs)—including Topographic Openness (TO) and Terrain Roughness Index (TRI)—applied to 1 m LiDAR-DTMs from 2003 and 2023. Stage II implements a Multi-Resolution Segmentation (MRS) and Support Vector Machine (SVM) workflow, maintaining original parameters to test model stability. Stage III performs a dual-layer Accuracy Assessment (AA) against a complete manual inventory and a forest-restricted subset to isolate the influence of land cover.

Results demonstrate high transferability, with detection rates increasing from 75% (2003 DTM) to 86% (2023 DTM), highlighting the impact of data quality on resolving geomorphic signatures. Notably, forested areas showed a 15% higher true-positive rate than non-forested zones, suggesting that forest cover protects the landslide "morphological fingerprint" from human modification. Area-based accuracy was 30% higher than in the Jena study, confirming the robustness of the ruleset for cuesta-related rotational slides.

In summary, this chapter validates the scalability of the dissertation's methodological framework was developed in Paper 2. By proving the model remains effective across different regions and land-use patterns, this research establishes the workflow as an operational tool for regional landslide inventorying and natural hazard management.

8.1. Results

This chapter presents the key results of the study, including the outcomes of the GEOBIA-based landslide mapping, and the model performance evaluation derived from different accuracy assessment approaches.

8.1.1. GEOBIA-based landslide mapping results

8.1.1.1 Landslide Mapping Results for the Entire Study Area

The GEOBIA-based modelling results for landslide scarps and bodies were compared with the manual inventory map (i.e. the reference map) to evaluate their spatial correspondence (Figures 18 and 19). These figures illustrate the detected landslide features: dark-yellow polygons represent correctly mapped True Positives (TP), open-yellow polygons indicate False Negatives (FN), and pink polygons represent areas incorrectly classified as landslides, referred to as False Positives (FP), for both model-detected scarps and bodies. Black and blue polygons

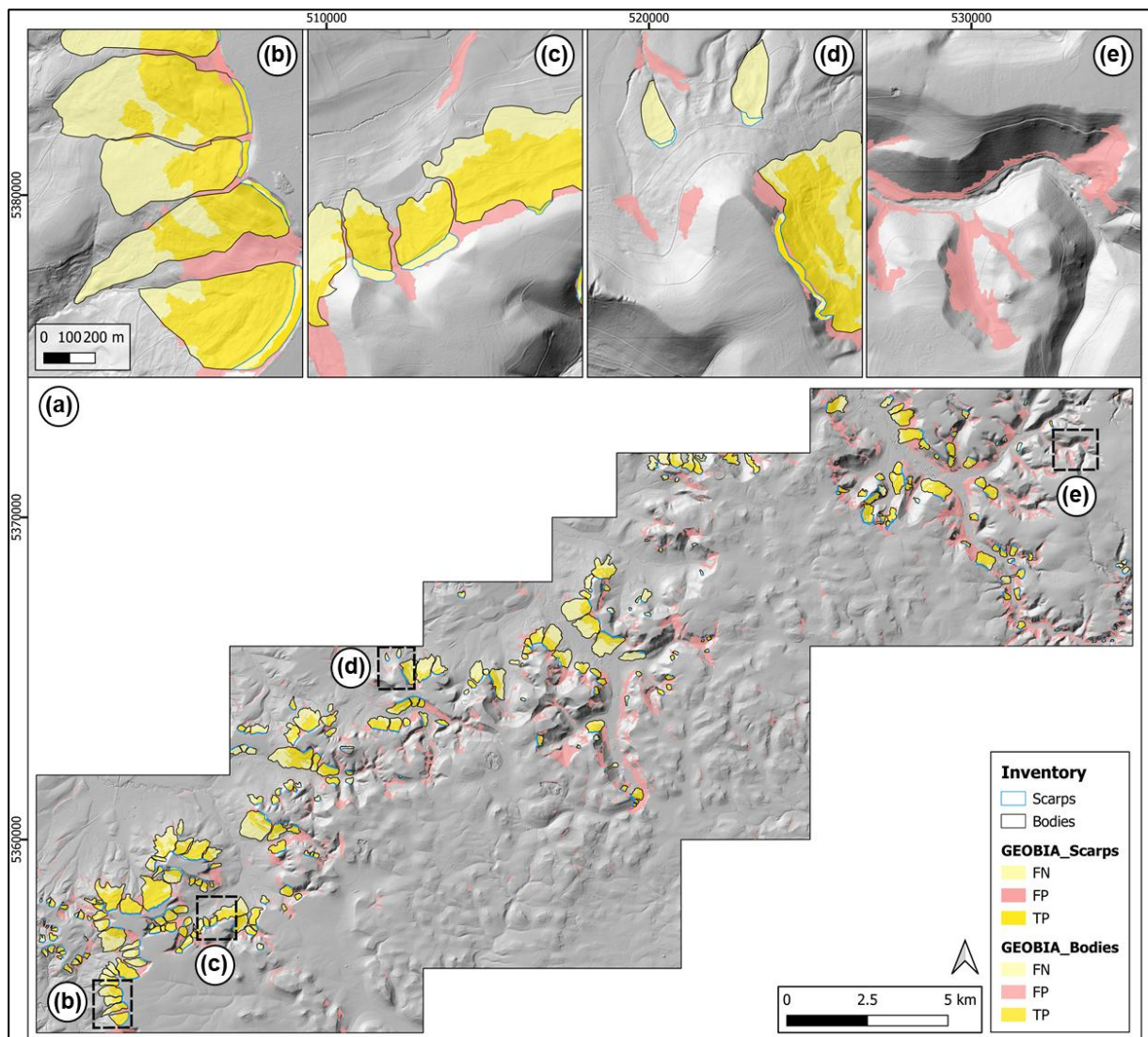


Figure 18 Final map of semi-automatic landslide detection based on the 2003 dataset, displayed over a hillshade DTM (Source: © LGL, www.lgl-bw.de) for the entire study area (a). Detected landslides are shown as coloured polygons (dark yellow: True Positives, TP; pink: False Positives, FP; yellow: False Negatives, FN), while the reference inventory map is also displayed for comparison. Insets (b-e) provide detailed views of selected sites.

show the corresponding landslide features from the reference inventory. Areas outlined by black dashed boxes are discussed in greater detail in Chapter 8.2.

Visual and on-screen analyses demonstrate that the model accurately captures individual landslide components and shows strong spatial agreement with the reference inventory. This accuracy is particularly evident in the precise delineation of landslide extents and the low False Positive rate (FPr) especially in the forested areas. A more comprehensive quantitative evaluation of the results is provided in Tables 9 and 10 in Section 8.2.1.

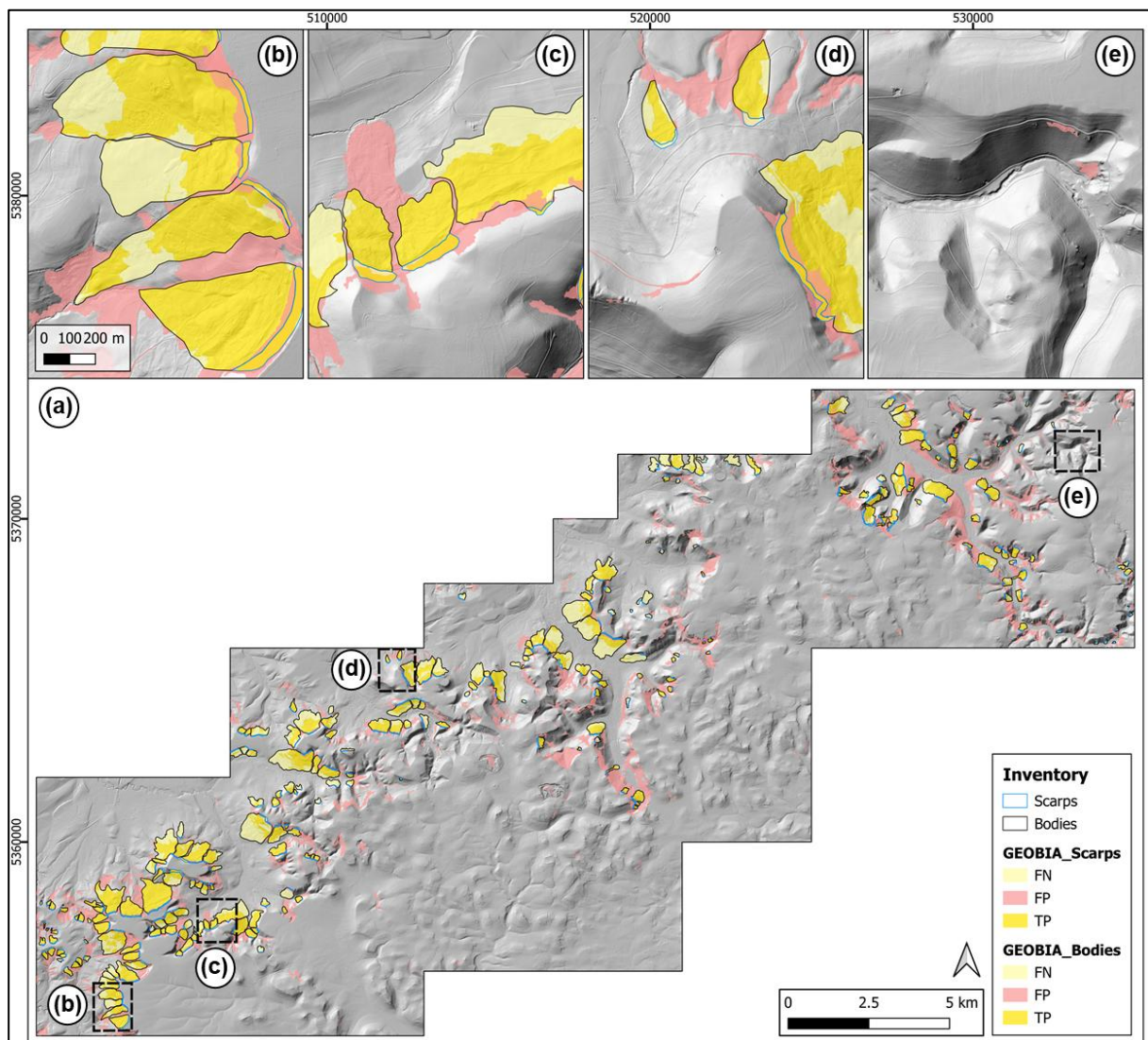


Figure 19 Final map of semi-automatic landslide detection based on the 2023 dataset, displayed over a hillshade DTM (Source: © LGL, www.lgl-bw.de) for the entire study area (a). Detected landslides are shown as coloured polygons (dark yellow: True Positives, TP; pink: False Positives, FP; yellow: False Negatives, FN), while the reference inventory map is also displayed for comparison. Insets (b-e) provide detailed views of selected sites.

8.1.1.2. Landslide Mapping Results for Forest-Covered Areas

Figures 20 and 21 present the model results restricted to forested areas, where landslide bodies are located beneath forest cover. Landslides occurring outside forested regions across the study area were excluded from this evaluation. The green dotted polygons represent the

forest-only landslide inventory, which was derived by intersecting the original inventory with the forest land use layer.

This filtered inventory therefore includes only landslides within forested areas and serves as the reference dataset for this assessment. Model outputs derived from the 2003 and 2023 DTMs were compared exclusively against this forest-based inventory. Detailed mathematical interpretations can be found in the subsequent section and are summarized in Tables 9 and 10 in Section 8.2.1.

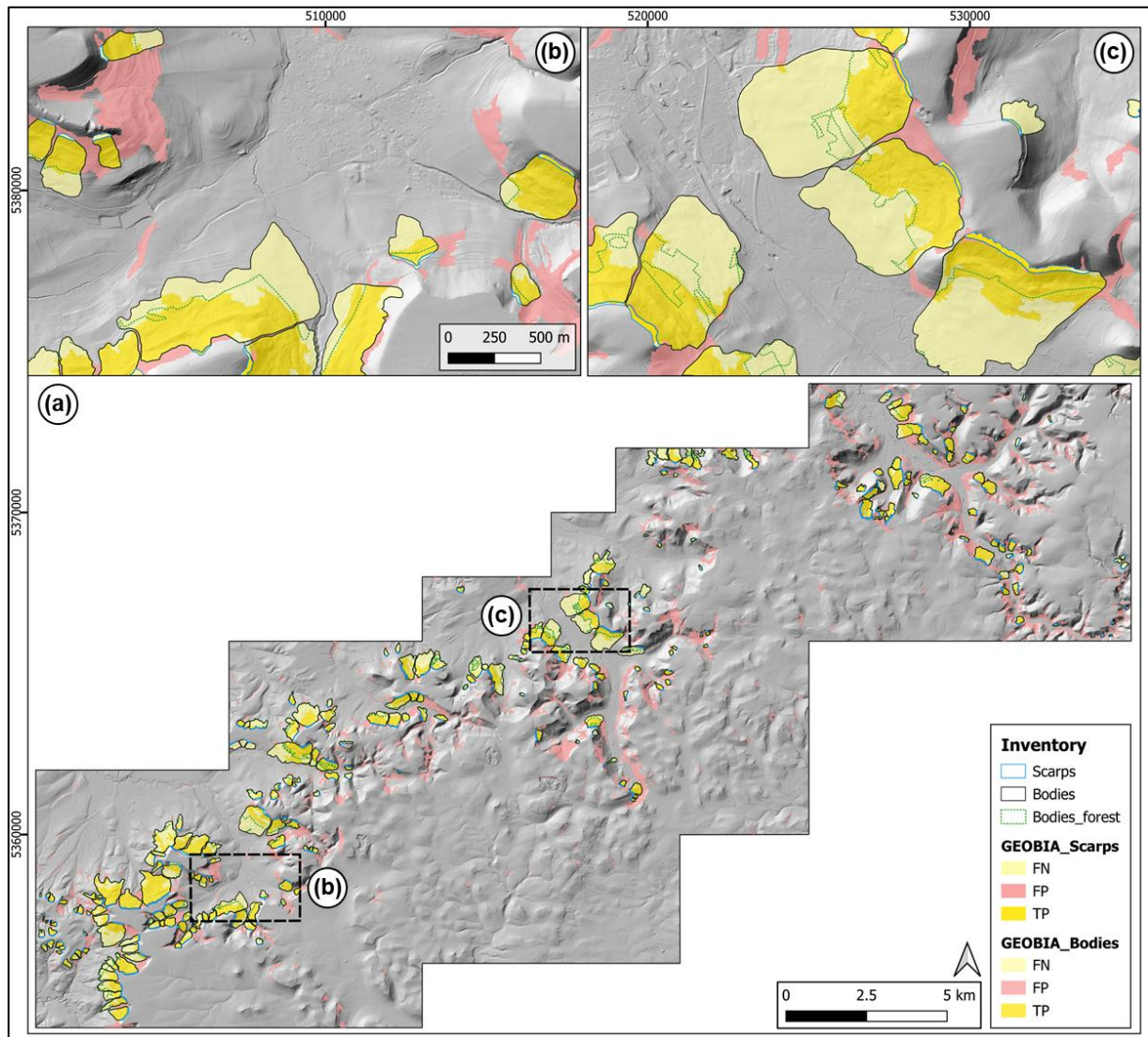


Figure 20 Final map of semi-automatic landslide detection based on the 2003 dataset within forested areas (a), displayed over a hillshade DTM (Source: © LGL, www.lgl-bw.de). Detected landslide bodies are shown as coloured polygons (dark yellow: True Positives, TP; pink: False Positives, FP; yellow: False Negatives, FN), while the reference inventory map is shown for comparison. Insets (b) and (c) provide detailed views of selected forested sites.

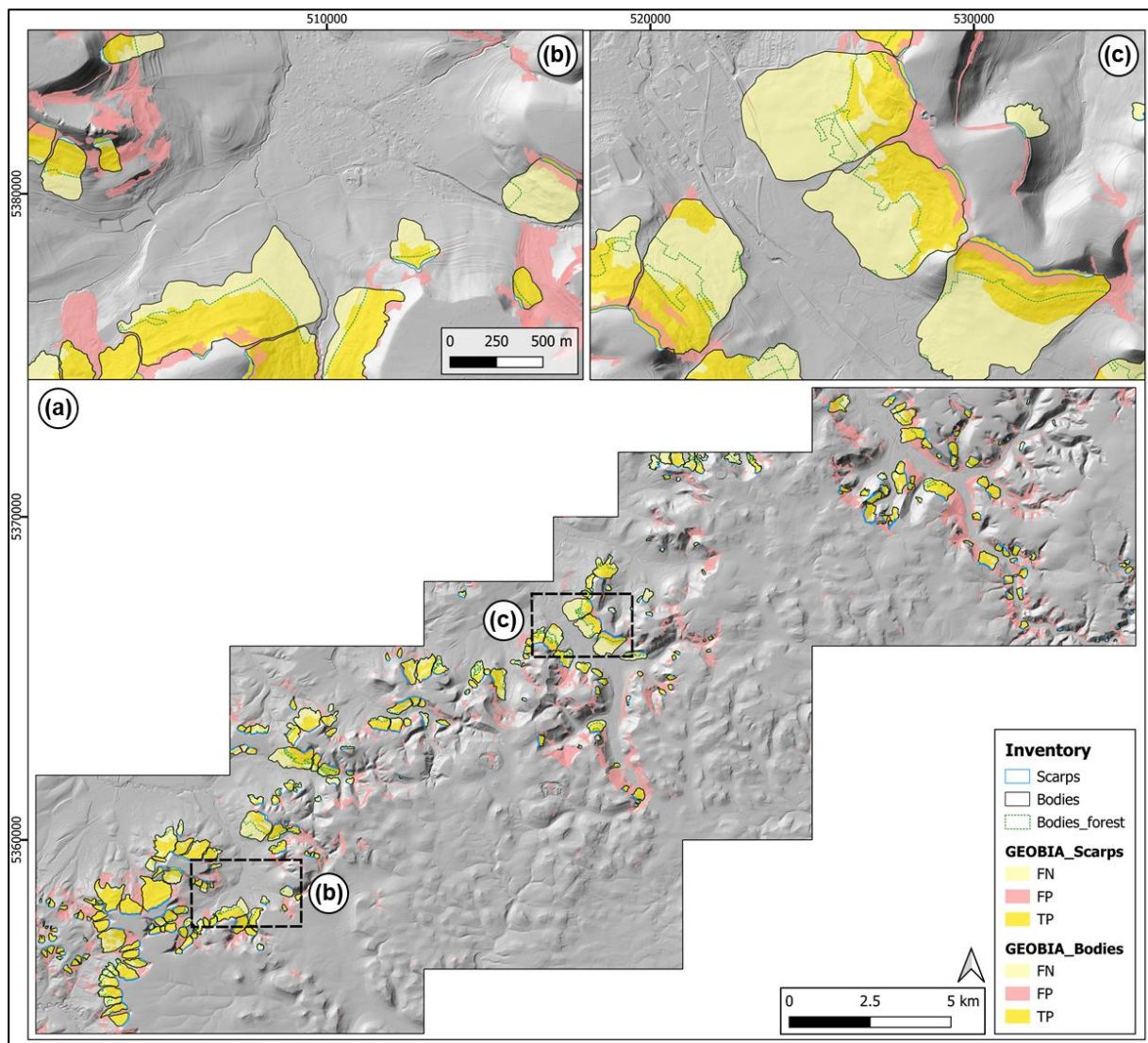


Figure 21 Final map of semi-automatic landslide detection based on the 2023 dataset within forested areas (a), displayed over a hillshade DTM (Source: © LGL, www.lgl-bw.de). Detected landslide bodies are shown as coloured polygons (dark yellow: True Positives, TP; pink: False Positives, FP; yellow: False Negatives, FN), while the reference inventory map is shown for comparison. Insets (b) and (c) provide detailed views of selected forested sites.

8.1.2. Accuracy assessment results

8.1.2.1 Thematic accuracy assessment

The thematic accuracy assessment was conducted using two complementary approaches: object-based (number-based) and area-based accuracy metrics, applied to the 2003 and 2023 datasets for both the entire study area and the forested area only.

Entire study area: The object-based accuracy assessment (Table 9) shows a slight increase in correctly mapped landslide bodies from 198 (75.3%) in 2003 to 203 (77.2%) in 2023, with unmapped bodies decreasing from 42 (15.9%) to 39 (14.8%). For scarp zones, the number of correctly mapped features increased from 84 (29.8%) to 104 (36.9%), while unmapped scarps decreased from 186 (66.0%) to 168 (59.8%). The area-based accuracy assessment (Table 10) indicates higher True Positive (TP) areas in 2023 for both landslide bodies and scarps. TP areas

for landslide bodies increased from 1,282 ha (57.7%) to 1,387ha (62.4%), accompanied by a reduction in False Negative (FN) areas from 939.5 ha (42.3%) to 835ha (37.6%). In the scarp zones, TP areas increased from 42.7 ha (44.6%) to 51.7 ha (54.1%), while FN areas decreased from 52.9 ha (55.4%) to 43.9 ha (45.9%).

Forested area: Within forested landslide bodies (we analysed only the body areas as the scarps were too small to be evaluate the model performance, specifically for the area-based assessment), the number-based assessment (Table 11) shows an increase in correctly mapped features from 207 (82.1%) in 2003 to 219 (86.9%) in 2023, with unmapped features decreasing from 27 (10.7%) to 21 (8.3%). The area-based assessment (Table 12) shows that TP areas increased from 1,195.5 ha (66.7%) in 2003 to 1,300.2 ha (72.5%) in 2023, while FN areas decreased from 598.1 ha (33.3%) to 493.5 ha (27.5%).

Table 9 Object-based accuracy assessment of GEOBIA landslide detection for the entire study area (2003 and 2023).

Landslide	Model/Year	Correctly mapped*		Almost mapped**		Not mapped***	
		Count	(%)	Count	(%)	Count	(%)
Bodies (Inventory: 263)	2003	198	75.3	23	8.8	42	15.9
	2023	203	77.2	21	8	39	14.8
Scarps (Inventory: 282)	2003	84	29.8	12	4.26	186	66
	2023	104	36.9	10	3.6	168	59.8

Note: * area: ≥50%; ** area: 40–49%; *** area: <40%

Table 10 Area-based accuracy assessment of GEOBIA landslide detection for the entire study area (2003 and 2023).

Landslide	Model/Year	TP (ha)		FP (ha)		FN (h)	
		Area	(%)	Area	(%)	Area	(%)
Bodies (Inventory: 2221.8 ha)	2003	1282.3	57.7	1852.8	59	939.5	42.3
	2023	1386.7	62.4	1864.5	57.3	835	37.6
Scarps (Inventory: 95.6 ha)	2003	42.7	44.6	66.9	61	52.9	55.4
	2023	51.7	54	273.3	84	43.9	45.9

Table 11 Object-based accuracy assessment of GEOBIA-based landslide body detection in forested areas (2003 and 2023).

Landslide	Model/Year	Correctly mapped		Almost mapped		Not mapped	
		Count	(%)	Count	(%)	Count	(%)
Bodies in forest (Inventory: 252)	2003	207	82	18	7	27	10.7
	2023	219	86.9	12	4.8	21	8.3

Table 12 Area-based accuracy assessment of GEOBIA-based landslide body detection in forested areas (2003 and 2023).

Landslide	Model/Year	TP (ha)		FP (ha)		FN (h)	
		Area	(%)	Area	(%)	Area	(%)
Bodies in forest	2003	1195.5	66.7	1939.5	61.9	598	33.3
(Inventory: 1793.6 ha)	2023	1300.2	72.5	1951	60	493.5	27.5

8.2. Discussion

8.2.1 Transferability of semi-automatic landslide-based mapping

The results demonstrate that the semi-automatic GEOBIA-based landslide mapping approach can be successfully transferred to the Swabian Alb, achieving overall high detection performance across different land-cover types. Landslide bodies with strong geomorphological signatures are consistently identified, with particularly high accuracy in forested environments. Using the 2023 DTM, landslide body detection in forested areas reaches approximately 87% (Table 11), representing an improvement of about 35% compared to the Jena region results (original model) reported by Zangana *et al.* (2025). Furthermore, across the entire study area (i.e.: bodies inside and outside forested area), the detection reached 77.2% using 2023 data, representing a substantial 24.7% improvement over the 52.5% reported for the Jena region (Figure 23). This higher success rate in the Swabian Alb demonstrates that the transferred GEOBIA model is highly effective at identifying the region's distinct geomorphological signatures, even when applied across diverse land-cover types. These findings demonstrate that the core model logic remains robust when transferred to a different geomorphological and geological setting, and that higher-resolution DTMs substantially improve the detection of both newly activated and reactivated landslides. The role of data resolution and other influencing factors is discussed in the following subchapters.

8.2.2. Influence of DTM quality on GEOBIA-based landslide detection: comparison of 2003 and 2023 results

The comparison between the 2003 and 2023 datasets demonstrates that higher-quality DTM data improve GEOBIA-based landslide detection, particularly for scarps. Object-based accuracy metrics (Table 13) show a slight increase in correctly mapped landslide bodies from 198 (75.3%) to 203 (77.2%), with unmapped bodies decreasing from 42 (15.9%) to 39 (14.8%), while improvements are more pronounced for scarps, where correctly mapped features increase from 84 (29.8%) to 104 (36.9%) and unmapped scarps decrease from 186 (66.0%) to 168 (59.8%). Area-based results (Table 14) support these trends, indicating reductions in False Negative areas of approximately 100 ha for landslide bodies and 10 ha for scarps in the 2023 dataset. These improvements are also evident spatially, as shown in Figure 19(d–e), where additional landslides are detected and previously misclassified areas are correctly mapped as True Positives compared with the 2003 results (Figure 18). Compared with the Jena region, scarp detection remains higher in Jena, whereas landslide body detection improves in the 2023

dataset in the Swabian Alb, reflecting differences in geomorphological settings rather than model behaviour.

Table 13 Object-based comparison of GEOBIA-based landslide detection results (2003 and 2023, with Jena region).

Landslide	Model/Year	Correctly mapped		Almost mapped		Not mapped	
		Count	(%)	Count	(%)	Count	(%)
Bodies	2003	198	75.3	23	8.8	42	15.9
	2023	203	77.2	21	8.0	39	14.8
	Jena	21	52.5	0	0	19	47.5
Scarps	2003	84	29.8	12	4.26	186	66.0
	2023	104	36.9	10	3.6	168	59.8
	Jena	25	65.8	0	0.0	13	34.2

Table 14 Area-based comparison of GEOBIA-based landslide detection results (2003 and 2023, with Jena region).

Landslide	Model/Year	TP (ha)		FP (ha)		FN (ha)	
		Area	(%)	Area	(%)	Area	(%)
Bodies	2003	1282.3	57.7	1852.8	59.1	939.5	42.3
	2023	1386.7	62.4	1864.5	57.3	835.0	37.6
	Jena	161.9	66.6	155.8	49	81	33.3
Scarps	2003	42.7	44.6	66.9	61.1	52.9	55.4
	2023	51.7	54.1	273.3	84.1	43.9	45.9
	Jena	9.1	43.8	8	47	11.6	56.2

8.2.3. Performance of GEOBIA-based landslide mapping: Forested areas vs. Entire study area

The model performs best in forested areas, consistent with its original development for forest-covered landslides in the Jena region by Zangana *et al.* (2025). In Figure 19(c) (GEOBIA-based 2023 DTM), landslides with pronounced geomorphological signatures—including fresh or recently reactivated landslides—are effectively detected. However, a proportion of landslide bodies in this subset are classified as FN when compared with the reference inventory. This does not indicate model failure but reflects that the inventory was derived from the 2003 DTM and therefore does not include landslides activated or expanded after 2003 (Figure 18-c). Updating the inventory with the 2023 data would improve accuracy assessment outcomes. This aligns with findings by Dias *et al.* (2025), who noted that the reliability and type of input inventory directly impact the accuracy of the resulting landslide map.

Number- and area-based results (Tables 8 and 9) show improved performance in forested areas between 2003 and 2023. Correctly mapped landslide bodies increased from 207 (82.1%) to 219 (86.9%), while unmapped features decreased from 27 (10.7%) to 21 (8.3%). Similarly, the True Positive area increased from 1,195.5 ha (66.7%) to 1,300.2 ha (72.5%), accompanied by a reduction in False Negative area from 598.1 ha (33.3%) to 493.5 ha (27.5%).

Compared with the entire study area in 2003, forested areas mapped using the 2023 dataset show substantially higher detection rates, with correctly mapped landslide bodies increasing

from 75.3% to 86.9% and True Positive areas increasing from 57.7% to 72.5% (Table 9 and Figure 22). These results demonstrate improved detection sensitivity when the model is applied to forested environments using higher-quality DTM data.

Table 15 Object-based comparison of GEOBIA landslide body detection performance (Swabian Alb and Jena region).

Landslide	Model/Year	Correctly mapped		Almost mapped		Not mapped	
		Count	(%)	Count	(%)	Count	(%)
	Swabian Alb						
Bodies	2003	198	75.3	23	8.8	42	15.9
(Inventory: 263)	2023	203	77.2	21	8.0	39	14.8
Bodies in forest	2003	207	82.1	18	7.1	27	10.7
(Inventory: 252)	2023	219	86.9	12	4.8	21	8.3
	Jena	21	52.5	-	-	19	47.5

Table 16 Area-based comparison of GEOBIA landslide body detection performance (Swabian Alb and Jena region).

Landslide	Model/Year	TP (ha)		FP (ha)		FN (ha)	
		Count	(%)	Count	(%)	Count	(%)
	Swabian Alb						
Bodies	2003	1282.3	57.7	1852.8	59	939.5	42.3
(Inventory: 2221.8 ha)	2023	1386.7	62.4	1864.5	57.3	835.0	37.6
Bodies in forest	2003	1195.5	66.7	1939.5	61.9	598.1	33.3
(Inventory: 1793.6 ha)	2023	1300.2	72.5	1951.0	60	493.5	27.5
	Jena	161.9	66.6	155.8	49	81	33.3

8.2.3 Limitations and challenges

Despite the strong overall performance, some limitations typical of GEOBIA-based landslide mapping remain evident. In this study, FP rates are approximately 10% higher than those reported for the Jena region (Table 9). This is primarily related to the dense spatial clustering of landslides in the Swabian Alb, where adjacent or overlapping landslide bodies are difficult to delineate as separate objects without sacrificing TP detection (Figures 18 and 19, inset b). In addition, complex reactivation patterns—where younger movements partially overprint older landslide bodies—introduce internal boundary noise, further increasing FP rates (Figure 19, insets b–e). Similar behaviour has been widely reported in previous GEOBIA-based studies and reflects the inherent challenge of mapping compound and overlapping landslides (Dias et al., 2023; Martha et al., 2010; Van Den Eeckhaut et al., 2012; Zangana et al., 2024; Zangana et al., 2025). Importantly, despite the elevated FP rates relative to the Jena region, the commission errors observed in the Swabian Alb remain comparable to—or lower than—those reported in earlier studies, such as Martha *et al.* (2010), where FP counts exceeded expert-mapped inventories.

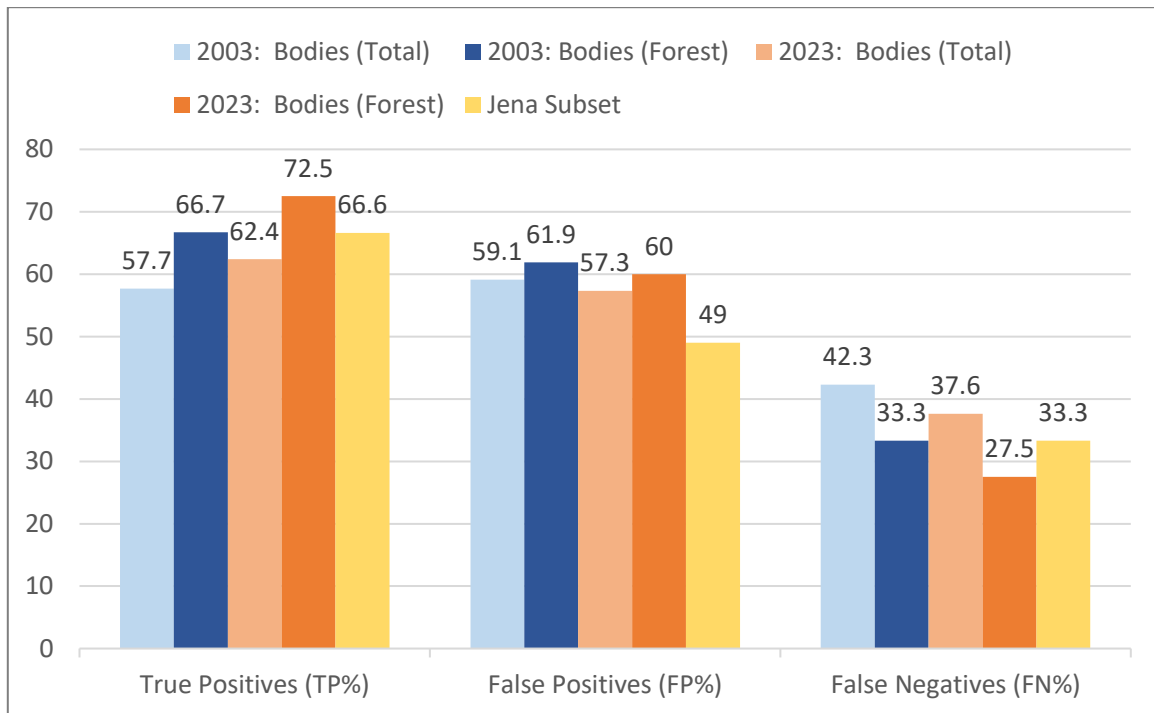


Figure 22 Comparative performance analysis of landslide body detection for total study area vs. forested terrain (Area-based).

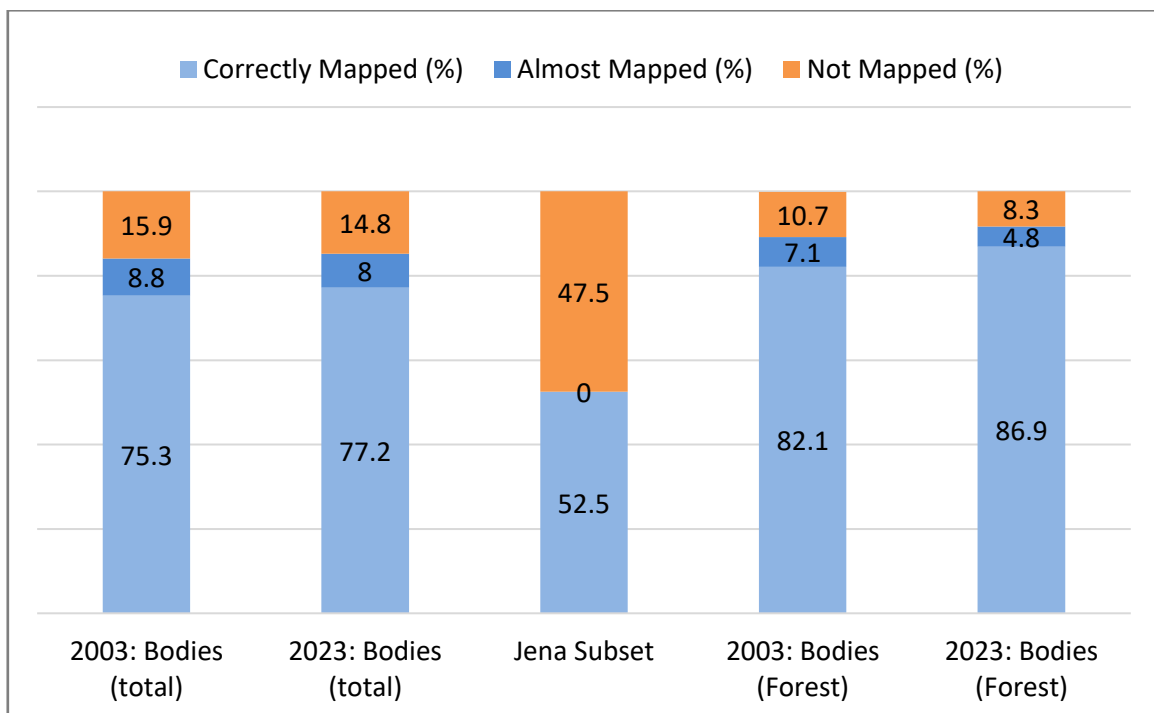


Figure 23 Comparative performance analysis of landslide body detection for total study area vs. forested terrain and Jena region (object-based).

Landslide scarp detection represents a further challenge, with lower accuracy compared to the Jena region. This is primarily attributed to the strong geomorphological similarity between

landslide scarps and rock outcrops in the Swabian Alb, particularly within steep limestone terrains and areas affected by anthropogenic modification. Similar misclassification patterns were also observed in the Jena region and others, indicating that scarp delineation is sensitive to lithological context and slope morphology (Van Den Eeckhaut et al., 2012; Knevels et al., 2019; Zangana et al., 2025). Future refinements of the original ruleset, aimed at improving scarp detection and minimizing FP from landslide bodies, are therefore needed to reduce commission errors and enhance model performance in complex terrains further.

8.3. Conclusion

This study demonstrates that the semi-automated, GEOBIA-based landslide mapping framework, which was originally developed for the Jena region by Zangana *et al.* (2025), can be successfully transferred to the cuesta landscapes of the Swabian Alb in Germany without any modification to the original rule set. Using high-resolution terrain data, landslide body detection reached 77.2% across the entire study area and approximately 87% in forested terrain, exceeding detection rates previously reported for the original study region. These results confirm that the geomorphological signatures of landslides can be robustly captured across different geological and land-cover settings when suitable terrain data is available.

Comparison of the 2003 and 2023 models indicates that differences in detection results partly reflect landslides that became visible in the newer dataset but are not represented in the older one, underlining the value of using recent high-resolution DTMs for landslide mapping. While landslide bodies are reliably detected, challenges remain in scarp delineation and in separating spatially clustered or overlapping landslides, particularly in steep limestone terrain where morphological similarities with rock outcrops and anthropogenic features lead to increased commission errors. Future developments should therefore focus on improved segmentation strategies and classification refinements, as well as on distinguishing between active and stable landslides, in order to better identify zones of elevated hazard.

Overall, the demonstrated transferability and performance of the GEOBIA workflow suggest that it can be applied to other regions with only slight modifications. The resulting high-resolution landslide inventories are important for future susceptibility and risk assessments, as well as for regional land-use planning and hazard mitigation. Furthermore, the results confirm that the method performs particularly well in forested areas and is particularly effective at detecting landslides with clear geomorphological signatures in high-resolution DTMs. More broadly, this study highlights the value of object-based terrain analysis for large-scale geomorphological mapping, as well as for improving our understanding of landslide processes in complex landscapes.

9. Synthesis and Outlook

This chapter synthesizes the three papers highlighting their findings to provide comprehensive responses to the research questions (see Chapter 1.2). It concludes with an outlook on potential future research and a discusses of the transferability of the methods and insights presented in this dissertation.

9.1. Summary of the included papers

Paper 1 establishes a detailed geomorphological mapping of the Jena region by combining high-resolution LiDAR hillshades, LSPs, LSP-composite map, topographic maps, orthophotos, and geological maps to classify the landscape into major geomorphic process domains and landform categories. The resulting map delineates four main layers: geomorphological process domains, hydrological networks, hillslope features, and topographic/structural forms. Key findings include the strong influence of bedrock: northern limestone areas feature steep escarpments, V-shaped valleys, and landslide complexes, whereas southern sandstone regions display broad box- and saucer-shaped valleys with extensive floodplains and terraces. The map also identifies widespread gravitational processes (landslides, rock falls, debris flows) on prominent ridges (e.g. Kernberge, Johannisberg) and fluvial-dominated zones along the Saale River and tributaries, along with localized anthropogenic modifications (e.g. quarry-induced scarps and plateau at Mönchsberg). Aeolian (loess) and periglacial signatures were minimal or relic, appearing only as subordinate features. The discussion emphasizes that LiDAR-enhanced data greatly improve feature detection and mapping speed, but notes that geomorphic interpretation still relies on integrating multiple data sources. It highlights challenges such as mismatches between datasets of different scale or vintage, and suggests best practices (e.g. using consistent data sources, on-site validation, multidirectional hillshading). Overall, Paper 1 demonstrates that LiDAR-DTM based on-screen mapping can rapidly produce a high-resolution geomorphological map of a complex middle-mountain terrain, while acknowledging that remote sensing complements rather than fully replaces traditional field observations.

Paper 2 builds on this framework to develop a semi-automated landslide inventory using object-based image analysis (GEOBIA) on the same study area. A rule-based workflow was developed and implemented in eCognition software. The approach first optimizes moving-window sizes for various terrain variables (slope, curvature, roughness, topographic position index, etc.) separately for landslide scarps and bodies, finding that optimal window parameters differ significantly between the landslide components. Custom rule sets and classification workflows were then applied to detect scarps and bodies independently. Comparing the optimized model (MII) to a baseline default model (MI) shows that MII yields substantially higher mapping precision: for example, in MII the true positive area for scarps increases (from 6.3 to 9.1 ha) and false positives drop markedly, especially for landslide bodies (from over 760 ha to ~155 ha). In essence, MII produces far fewer commission errors while maintaining a high detection rate for genuine landslides. Landform analysis further confirms that scarps tend to have steeper slopes, higher surface roughness, and positive curvature values, whereas

bodies are gentler and smoother – distinctions that the optimized model captures effectively. The discussion highlights that larger, well-formed landslides are most reliably mapped, while misclassifications mainly occur in areas where terrain roughness imitate landslide features (e.g. rock outcrops or excavation sites). Overall, Paper 2 demonstrates that carefully tuning object-based model parameters to the specific morphology of scarps versus bodies significantly improves the accuracy of semi-automated landslide mapping in forest-covered, mid-mountain terrain.

Paper 3 tests the transferability of the GEOBIA-based landslide mapping approach developed in Paper 2, originally applied to forested landslides, to a new region—the Swabian Alb—where landslides occur across both forested and other land-use types, and evaluates the influence of data quality on detection performance. The semi-automatic GEOBIA model is applied to both a 2003 and a more recent (2023) high-resolution DTM for the entire study area. Results show that the transferred model achieves high detection rates under diverse conditions: for example, using the 2023 DTM, roughly 77 % of landslide bodies are correctly identified over the whole area (up from 75 % with the 2003 data) and approximately 87 % in forested zones. Scarp detection also improves with the newer data (true-positive area rising from 57 % to 62 % for scarps), indicating that higher-quality elevation data markedly increase mapping accuracy. The analysis confirms that forested areas yield the best results (due to strong geomorphic signatures), while some remaining omissions reflect inventory differences (new or reactivated landslides since 2003) or the inherent difficulty of separating closely overlapping slide bodies. Comparing to the original Jena model, the Swabian Alb application shows similarly robust performance and a substantial reduction in false positives under the optimized settings. Overall, Paper 3 demonstrates that the object-based landslide mapping approach is transferable across different landscapes and benefits strongly from up-to-date, high-resolution data. It provides an effective method for catchment-scale inventory generation and underscores the crucial role of data resolution and contemporary reference data in achieving high accuracy.

9.2. Answers to the research questions

Middle-mountain geomorphological systems are shaped by complex lithological and climatic interactions, creating heterogeneous landscapes. In these settings, gravitational mass movements—particularly landslides—are dominant processes and significant natural hazards, especially on steep, land-use-intensive slopes (Guzzetti et al., 2012; Bell et al., 2012). Precise mapping is therefore vital for both geomorphological theory and practical hazard assessment.

Traditional mapping relies on expert field surveys and analogue data, which are insightful but often time-intensive and subject to the bias of the interpreter (Smith et al., 2013; Gustavsson et al., 2006). However, high-resolution LiDAR-derived DTMs have transformed this analysis, enabling the detection of subtle morphometric features even under dense vegetation, thereby enhancing mapping accuracy and completeness (Tarolli, 2014; Doneus, 2013).

Recent geospatial advances have facilitated semi-automated landform classification. Geographic Object-Based Image Analysis (GEOBIA), combined with machine learning like Support Vector Machines (SVM), allows for systematic feature extraction based on morphometric and contextual data (Blaschke, 2010; Martha et al., 2010). These approaches are especially effective in forested or inaccessible terrains where traditional mapping typically struggles.

Despite progress, challenges remain regarding parameter sensitivity, data resolution impacts, and the transferability of methods across differing geomorphological settings (Stumpf & Kerle, 2011; Van Den Eeckhaut et al., 2012). Furthermore, integrating multiple data sources—including geology and land-use—remains essential to complement purely topographic analyses and ensure robust landscape interpretation.

Consequently, this dissertation integrates expert-based mapping with semi-automated landslide detection. Utilizing LiDAR and complementary datasets, the three included papers address key questions regarding (i) geomorphological mapping workflows, (ii) semi-automated landslide detection performance and sensitivity, (iii) transferability between regions, and (iv) the effects of data quality, timing, and multi-source integration in complex terrain. The following section synthesizes the results to answer the research questions defined in Chapter 1.2.

Research Question 1: How can high-resolution terrain data and complementary spatial datasets improve geomorphological mapping and landslide identification in middle-mountain regions? (Paper 1 & Paper 2)

The results of this dissertation demonstrate that high-resolution LiDAR-derived DTMs, when combined with complementary spatial datasets, substantially enhance geomorphological mapping and landslide identification in complex middle-mountain environments (Doneus, 2013; Tarolli, 2014). Paper 1 establishes a high-resolution geomorphological map of the Jena region by integrating a LiDAR-derived DTM (2 m resolution) with orthophotos, topographic maps, geological maps, and field verification, thereby improving the delineation of landforms and process domains compared with traditional mapping approaches, cf. Figure 8/Main Map, the high-resolution version can be found as Supplementary Material of Paper 1 in the Appendix (Gustavsson et al., 2006; Smith et al., 2013). A central methodological contribution lies in the combined use of multidirectional hillshading and LSPs/LSVs, including slope, curvature, and topographic openness (TO), because composite LSP products (e.g., TO–slope composites, cf. Figure 9) increase the visual interpretability of landform boundaries and internal structures beyond what single-parameter layers typically provide (e.g. Anders et al., 2011; Doneus, 2013; Smith et al., 2013; Daxer, 2020).

The integration of complementary datasets further strengthens mapping reliability, cf. Figure 6/STAGE I upper Panel: geological information constrains lithological controls and supports interpretation of landform genesis, (cf. Figure 10c and d), while orthophotos and topographic

maps assist in recognizing hydrological features and anthropogenic modifications (Dramis et al., 2011; Otto and Smith, 2013).

Paper 2 confirms that high-resolution terrain data (1 m LiDAR-DTM) are fundamental for landslide detection, particularly in forested environments, because landslide morphology can remain preserved under canopy even when optical imagery is limited (Van Den Eeckhaut et al., 2012; Stumpf and Kerle, 2011). Using LiDAR-derived morphometric variables (e.g., slope, curvature, TO, TRI, TPI) within a GEOBIA framework (MRS segmentation, SVM classification, and rule-based refinements), Paper 2 shows that landslide morphology can be characterised and delineated systematically when supported by an expert-based reference inventory for training and validation, cf. Figure 7.

In summary, high-resolution LiDAR-DTMs improve geomorphological mapping and landslide detection by enhancing the detectability and boundary precision of geomorphic features, while complementary datasets (geology, orthophotos, topographic maps, and field checks) increase interpretive robustness by constraining genesis and process-domain assignment (Dramis et al., 2011; Otto and Smith, 2013).

Research Question 2: How effectively can semi-automatic, GEOBIA-based approaches detect landslides, particularly those obscured by forest cover, compared to traditional mapping approaches? (Paper 2 & Paper 3)

The semi-automatic GEOBIA-based approach applied in this dissertation is effective for detecting landslides in forested terrain, where traditional field mapping and optical interpretation are commonly constrained by limited visibility and accessibility (Van Den Eeckhaut et al., 2012; Stumpf and Kerle, 2011). Paper 2 demonstrates that combining multi-resolution segmentation (MRS) with SVM classification in an object-based framework enables systematic extraction of landslide scarps and bodies from LiDAR-derivative data, cf. Chapter 7.1.2, consistent with the broader development of GEOBIA methods for geomorphic feature mapping, (Blaschke, 2010; Martha et al., 2010).

Quantitatively, the optimized model (MII), cf. Chapter 7.1.1, substantially reduces commission errors compared to the baseline model, including a strong reduction in false positives for landslide bodies (from 80% to 49%) and improved true-positive mapping of scarp areas (from 30.6% to 43.8%), demonstrating that semi-automated GEOBIA-based optimized moving windows sizes of LSVs (i.e. MII) applied in Paper 2 can produce inventories with high practical usefulness when compared to expert mapping (cf. Tables 6 and 7).

Paper 3 confirms that detection performance remains high when the approach is applied in a different middle-mountain region (Swabian Alb), including forested and open terrain, indicating that GEOBIA can support rapid, scalable mapping beyond what is feasible with manual mapping alone (cf. Tables 15 and 16, Figures 20 and 21). At the same time, both Paper 2 and Paper 3 show that misclassifications persist where non-landslide terrain has morphometric similarity to landslide candidates (e.g., rock outcrops or anthropogenic

features), reflecting a known limitation of automated geomorphic classification based primarily on topographic signatures (Martha et al., 2010; Stumpf and Kerle, 2011).

In summary, GEOBIA-based mapping provides a powerful complement to traditional approaches by enabling reproducible and area-efficient landslide detection in forested terrain, while still requiring expert validation to minimize confusion with morphometrically similar non-landslide features (Van Den Eeckhaut et al., 2012; Blaschke, 2010).

Research Question 3: How do parameter choices and terrain analysis settings influence landslide detection performance in forested environments? (Paper 2)

Paper 2 demonstrates that GEOBIA-based landslide detection is sensitive to parameter selection, particularly segmentation scale, rule-set thresholds, and the moving-window sizes used to compute terrain derivatives, which is consistent with the well-established scale-dependence of landform representation in geomorphometry (Drăguț et al., 2011; Drăguț and Blaschke, 2006; Stumpf and Kerle, 2011). A key outcome is that landslide scarps and bodies exhibit distinct morphometric characteristics and therefore require separate parameterization, cf. Tables 4 and 5: scarps are associated with steep slopes, sharper curvature patterns, and higher roughness, whereas landslide bodies tend to show smoother and more gradual morphometry (Van Den Eeckhaut et al., 2012).

Accordingly, optimized window sizes differ between scarps and bodies, see Figure 12 and Table 3, and this component-specific scaling improves classification quality; the optimized model reduces false positives substantially and improves scarp detection relative to default settings (i.e. default moving windows sizes), demonstrating that “default” parameter choices can materially bias inventory outcomes (cf. Figure 15, which shows the mapping result using default moving-window settings from the Jena region).

In addition, rule-based post-classification refinement (cf. Appendix, Paper 1 / Appendices A–B) reduces commission errors in areas where rough terrain (e.g., rock outcrops, excavation sites) imitates landslide morphology, illustrating that classification performance depends not only on derivative selection but also on object shape and contextual constraints (Blaschke, 2010; Martha et al., 2010; Knevels et al., 2019).

In summary, Paper 2 shows that reliable GEOBIA-based landslide detection in forested terrain requires feature-specific parameterisation (e.g. landslide scarps versus landslide bodies), systematic scaling of DTM derivatives (see Sîrbu et al., 2019), including moving-window sizes tailored to landform components, and iterative refinement using morphometric and contextual object rules (D’Oleire-Oltmannsa et al., 2012; L. Drăguț et al., 2014; Lucian Drăguț & Eisank, 2012). Without such tuning, false positives increase and landslide components are more frequently omitted, leading to reduced inventory reliability (Martha et al., 2010; Van Den Eeckhaut et al., 2012).

Research Question 4: To what extent are semi-automatic landslide detection methods transferable between regions with differing geomorphological conditions? (Paper 2 & Paper 3)

The transferability of the GEOBIA-based landslide detection approach is first established in Paper 2 through the development of a semi-automated, ruleset-based framework implemented in eCognition and calibrated for the forested landscapes of the Jena region (cf. Figure 8). The approach achieves robust detection performance by explicitly distinguishing between landslide scarps and bodies and by integrating morphometric, geometric, and contextual criteria within an object-based framework (cf. Section 5.2.4). This includes the use of LSVs such as slope, curvature, TPI, and TRI in both the optimised and default configurations (see Chapter 7.1.1), combined with MRS, supervised classification using SVM, and expert-based refinement (cf. Section 5.2.5), following established GEOBIA methodologies (e.g. Anders et al., 2011; T. Blaschke, 2010b; Blaschke et al., 2014; Dias et al., 2023; Drăguț & Blaschke, 2006; Drăguț & Eisank, 2012; Eisank et al., 2011; Hölbling et al., 2012; Karantanellis et al., 2021; Knevels et al., 2019; Robson et al., 2020)

Building on this framework, Paper 3 evaluates the transferability of the method through its application to the Swabian Alb, Chapter 8.2.1, a geomorphologically distinct region characterised by different lithological conditions, land-use patterns, and terrain configurations. In contrast to the Jena region, the Swabian Alb exhibits more heterogeneous land cover and varying slope morphologies, providing a suitable test case for assessing model generalization, cf. Chapter 4.2. The transferability assessment is further supported by the use of two-epoch LiDAR-DMT datasets (2003 and 2023), which allow evaluation of both methodological robustness and the influence of data quality, cf. 8.2.2. In this context, the direct transfer of segmentation and classification rules from Paper 2 to the Swabian Alb enables a systematic test of model robustness without recalibration. The results show that detection performance remained consistently high under this transfer scenario. In particular, landslide body detection reached 77% across the entire study area and approximately 87% in forested terrain. cf. Table 15, exceeding detection rates previously reported for the original study region, cf. Figure 23, demonstrating that improvements in data quality and resolution directly enhance detection performance (cf. Chapter 8.2.2 and 8.2.3).

The results further demonstrate that the methodological framework is largely transferable across regions with differing geomorphological characteristics. Detection rates achieved in the Swabian Alb are comparable to those obtained in the Jena region, indicating that the fundamental morphometric signatures of landslides—such as slope gradients, curvature patterns, and surface roughness—are sufficiently consistent to enable cross-regional application (Hölbling et al., 2017; Knevels et al., 2019; Stumpf & Kerle, 2011; Van Den Eeckhaut et al., 2006). This is particularly evident for landslide bodies, which show stable and reliable detection performance in both study areas, despite differences in terrain structure, lithology, and vegetation cover (Figures 22 and 23).

At the same time, the analysis reveals that regional factors such as lithology, land use, and geomorphological process regimes influence the expression and detectability of landslide features. In particular, variations in vegetation cover and anthropogenic land use introduce additional complexity, which can affect classification performance and lead to localised misclassifications, see Table 16/FP. For example, areas with exposed rock outcrops or anthropogenic modifications may exhibit morphometric characteristics similar to landslide features, thereby increasing commission errors, cf. Chapter 8.2.3. As shown in Chapter 8.1 (Paper 3), these effects are most pronounced in non-forested areas and in zones where geomorphic signatures are less distinct or more heterogeneous, cf. Figures 18/b-e.

Furthermore, the results indicate that while the general rule set and workflow structure can be transferred, certain parameter settings—particularly those related to segmentation scale, object heterogeneity thresholds, and classification rules—may require adjustment to account for regional variability. This finding is consistent with previous studies highlighting the sensitivity of GEOBIA approaches to scale and parameter selection (e.g. Drăguț et al., 2011; Drăguț & Blaschke, 2006; Blaschke, 2010; Dias et al., 2025; Hölbling et al., 2017; Knevels et al., 2019; Stumpf & Kerle, 2011; Van Den Eeckhaut et al., 2006; Zangana et al., 2024, 2025).

Despite these limitations, the successful application of the model in the Swabian Alb demonstrates that the approach can be transferred with only minor modifications, cf. Chapter 8.2.3. The use of predefined parameter sets, combined with a consistent GEOBIA workflow and feature-specific classification rules, ensures methodological robustness, reproducibility, and scalability. In particular, the explicit separation of landslide components (scarps vs. bodies) and the integration of contextual information contribute to the stability of the model across different geomorphological settings.

Overall, the findings confirm that semi-automated, object-based landslide detection represents a transferable and adaptable methodological framework for geomorphological analysis. While local calibration may be required to optimise performance, the core approach demonstrates strong potential for application across different regions, supporting large-scale and comparative geomorphological studies.

Research Question 5: How do differences in (terrain) data quality and acquisition timing affect landforms and geomorphological processes mapping results? (Paper 1 & Paper 3)

Differences in terrain-data quality and acquisition timing exert a first-order control on geomorphological mapping outcomes because they influence (i) how clearly landforms and process signatures are expressed in DTMs and derivatives and (ii) how reliably mapped results can be validated against reference datasets, consistent with broader evidence that high-quality topographic data improve geomorphological interpretation (e.g. Doneus, 2013; Tarolli, 2014). Paper 1 shows that a LiDAR-DTM with 2 m resolution supports detailed geomorphological mapping, but the detectability of small or weakly expressed features is still constrained by resolution, vegetation, and scale-dependent derivative behaviour, cf. Table 1, which can require generalization in the final cartographic product (Otto et al., 2011).

A key implication from Paper 1 is that terrain derivatives are not equally informative at all scales: slope, curvature, and hillshade can highlight different feature types, yet their usefulness depends on parameterization and map scale, so some fine features (e.g., small depressions/knolls or subtle slope breaks) may be simplified or substituted by point symbols in the final map layout, c.f. Chapter 6.2 and Figure 8/Main Map. Paper 1 also documents that mismatches between datasets can arise because topographic maps, orthophotos, and DTMs may differ in acquisition date and scale, particularly in anthropogenically modified areas, reinforcing that temporal inconsistency can directly affect boundary placement and interpretation of active vs relict processes (see Table 1).

Paper 3 extends these findings by explicitly comparing two-epoch terrain datasets (2003 vs 2023 DTMs) and demonstrates that higher-quality (i.e. more recent DTMs), improve semi-automatic landslide detection performance, particularly by increasing true positives and reducing false negatives (especially for sharp features such as scarps), see Chapter 8.2.2 and Table 14. Crucially, Paper 3 shows that acquisition timing affects not only mapping but also *evaluation*: when a model output derived from a newer DTM is assessed against an older inventory (i.e., mapped based on the 2003 hillshade-derived DTM), real landslide reactivations after the inventory date, cf. Chapter 4.2.4, may be counted as false positives, cf. Figures 18c and 19c, thereby underestimating model performance and potentially misleading geomorphological interpretation (Guzzetti et al., 2012).

In summary, Papers 1 and 3 demonstrate that both terrain-data quality (resolution and derivative representation) and acquisition timing (currency of DTM, imagery, and reference inventories) control mapping reliability: improved DTMs enhance detectability and delineation, whereas temporally inconsistent validation datasets can bias accuracy assessment and process interpretation (Doneus, 2013; Guzzetti et al., 2012; Zangana et al., 2025).

Research Question 6: How can integrating additional spatial datasets improve the robustness of landform mapping and landslide detection workflows in complex terrain? (Paper 1 & Paper 3)

Integrating complementary spatial datasets alongside LiDAR-derived DTMs improves robustness in complex terrain because it reduces equifinality in morphometric interpretation—i.e., similar topographic signatures can reflect different processes—and therefore strengthens both boundary delineation and genetic/process interpretation (Dramis et al., 2011; Otto and Smith, 2013). In Paper 1, robustness is increased by combining the LiDAR-DTM and its derivatives with topographic maps, geological maps, orthophotos/Google Earth imagery, and targeted field checks, providing independent evidence for interpreting landform genesis when LiDAR morphology alone is ambiguous, cf. Chapter 5.2.1.

A concrete robustness gain is process-domain delineation: the workflow uses geology and diagnostic morphometric signatures to separate domains such as fluvial, gravitational, karstic, denudational, and anthropogenic, rather than relying only on topography, which is crucial where process boundaries are transitional or overprinted by human modification, cf. Figure 6.

Paper 1 further shows that certain features cannot be extracted reliably from LiDAR alone (e.g., seepages, sources, and waterlogging), so integrating topographic maps, orthophotos, and field surveys is necessary to improve completeness of the hydrological layer and thus the interpretation of coupled hillslope–fluvial processes, cf. Chapter 6.1.2.

In addition, composite visualization products (e.g., TO–slope composites, cf. Figure 9) increase robustness by sharpening landform boundaries and improving discrimination of subtle features compared with single-parameter layers, supporting openness-based visualization concepts (Doneus, 2013) and multi-parameter mapping approaches (Table 1; Anders et al., 2011; Smith et al., 2013). Finally, Paper 1 emphasizes that integrating multiple datasets is also a quality-control mechanism: mismatches between DTM-derived layers and topographic/orthophoto products often reflect differences in acquisition date and scale (e.g., anthropogenic change), so cross-checking against the most recent sources and field validation improves reliability (cf. Tabel 1; see Otto and Smith, 2013).

Paper 3 demonstrates a complementary robustness gain through explicit integration of LULC information (DLM25, scale of 1:2500; LGL-BW, <https://www.lgl-bw.de/Produkte/Landschaftsmodelle/Basis-DLM/index.html>; Bell, 2007) to stratify modelling evaluation and interpretation. By separating forested from non-forested terrain, Paper 3 shows that landslide detection performance is highest in forests, where geomorphic signatures are preserved and less affected by agricultural planation or construction, cf. Figures 20 and 21., whereas open terrain introduces additional confounders and boundary ambiguities, cf. Chapters 8.1.1 and 8.2.3. This land-cover stratification therefore functions as a diagnostic layer: it helps explain where false positives and false negatives are most likely, improving transparency of model limitations and strengthening the logic of regional transferability and performance reporting (Guzzetti et al., 2012). Paper 3 also shows that robustness depends on temporal consistency between terrain data and reference inventories: when models derived from a newer DTM are validated against an older inventory, newly reactivated landslides, see Figure 19c, may be counted as false positives even though they represent real change, implying that multi-temporal terrain analysis and inventory updating are essential for robust validation in dynamic landscapes.

In summary, Papers 1 and 3 show that integrating complementary datasets (geology, topographic maps, orthophotos, field evidence, land cover, and multi-temporal terrain products) improves robustness by constraining landform genesis, increasing completeness where LiDAR-only mapping is insufficient, reducing boundary ambiguity through enhanced visualization, and enabling context-specific evaluation of semi-automated landslide detection—provided that scale and acquisition-time consistency are explicitly considered (Dramis et al., 2011; Otto and Smith, 2013). The main methodological benefits and limitations identified across Papers 1–3 are synthesised in Table 17; for a detailed overview of the limitations and advantages of the methodology and data sources applied in Paper 1, see Table 1.

Table 17 Benefits and limitations of the data types and mapping approaches used in this dissertation for detailed geomorphological mapping and semi-automated landslide detection in the middle-mountain terrain of Germany.

Component	Benefits	Limitations
LiDAR-DTM based mapping	Detailed, systematic delineation of landforms/process domains; supports forest-terrain interpretation.	Genesis/process ambiguity remains; expert validation needed.
Visualization (multidirectional hillshade; TO/LSP composites)	Reduces hillshade bias; improves boundary visibility and landform contrast beyond single layers.	Scale/parameter choices strongly affect what becomes visible.
Complementary datasets (geology, topographic maps, orthophotos, field checks)	Constrains genesis and anthropogenic influence; improves completeness for features poorly captured by LiDAR alone.	Scale/acquisition-date mismatches can introduce inconsistencies.
GEOBIA-based landslide detection (LiDAR derivatives)	Reproducible, scalable mapping of forest-covered landslides; scarp/body handled separately.	Best for medium/large landslides; confusion with rough non-landslide terrain.
Parameterization (window sizes, segmentation, refinements)	Optimized settings improve detection and reduce false positives scarp/body vs default settings.	Tuning-sensitive; poor settings raise FP/FN and confuse rough non-landslide terrain.
Multi-temporal DTMs & transferability	Newer DTMs improve detection due to higher resolution and more recent/reactivated landslides; workflow transferable to comparable settings (best in forests).	Outdated inventories bias validation; regional geomorphic/land use differences require adjustments

9.3. Future research directions and transferability

A central outcome of this dissertation is that transferability is not only discussed conceptually but explicitly tested: Paper 3 evaluates the transferability of the GEOBIA-based landslide-mapping framework developed for the Jena region (Paper 2) by applying it to the Swabian Alb cuesta escarpment, thereby providing direct evidence that the workflow is transferrable across regions with differing geomorphological and land-use conditions (Chapter 8.2.1). The results show that the model performs effectively in the new region, particularly in forested terrain and when higher-quality DTM data are used, cf. Table 11, indicating that the core geomorphometric signatures targeted by the ruleset (e.g., scarp steepness/roughness and body morphology) remain sufficiently consistent to support cross-regional application.

At the same time, Paper 3 demonstrates that transferability must be interpreted together with validation conditions: model skill can be underestimated if the reference inventory does not represent the same temporal state of the terrain as the DTM used for modelling, cf. Chapter 8.2.2. A key future direction is therefore to strengthen transferability assessment by incorporating temporal alignment and multi-epoch inventories. Paper 3 illustrates that landslides reactivated after the reference-inventory date may be counted as false positives when model outputs from a newer DTM are compared with an older inventory, even though these detections may reflect real geomorphic change, cf. Figures 18c and 19c. Future studies should compile reference inventories derived consistently from each DTM epoch (or implement formal inventory-updating prior to accuracy assessment), which would improve the interpretability of performance metrics and reduce temporally induced commission errors. This aligns with findings by Dias et al. (2025), who noted that the reliability and type of input inventory directly impact the accuracy of the resulting landslide map (cf., Guzzetti et al., 2012).

In addition, a promising future avenue is to extend the GEOBIA workflow from single-epoch inventory mapping toward explicit multi-temporal landslide change detection and inventory updating. While Paper 3 compares two DTMs (2003 vs 2023) primarily to evaluate transferability and the influence of terrain-data quality, the same framework could be applied independently to each available DTM epoch and then compared across epochs to identify new initiations, partial reactivations, and boundary expansion/contraction. Such GEOBIA-based post-classification comparison would improve the completeness of inventories in regions with repeated reactivation and help distinguish “true” model commission errors from real post-inventory change, which is essential given the long-recognized need for regularly updated, temporally consistent landslide inventories in hazard assessment (Ardizzone et al., 2023; Bell et al., 2012; Gazibara et al., 2019; Guzzetti et al., 2012; Santo et al., 2016; Santangelo et al., 2010).

A second line of future work concerns transferability across contrasting land-cover settings. Paper 3 indicates that detection performance improves when analysis is restricted to forested areas, cf. Table 15, suggesting that land-cover stratification is not only a reporting tool but also a pathway to developing specialized, transferable model variants for forested versus non-

forested terrain, see also Figures 18, 19, 20, and 21. Future studies should therefore refine the Paper 2 ruleset into two branches—forest-focused and non-forest-focused—and test both across multiple regions, because non-forested landscapes introduce confounders such as anthropogenic relief and land-use-driven smoothing that can weaken landslide signatures and increase misclassification, cf. Figures 20c and 21c. However, this behaviour has been documented in previous studies (e.g., Dias et al., 2023; Goetz et al., 2014; Knevels et al., 2019; Schmaltz et al., 2016; Van Den Eeckhaut et al., 2012).

Third, broader transferability requires addressing data resolution and availability. Paper 3 shows that improved DTM quality enhances detection (e.g., higher true positives and/or reduced false negatives in the newer dataset), but high-resolution LiDAR DTMs remain unevenly available globally. Future work should test performance on coarser DTMs (e.g., 5–30 m) and quantify how segmentation scales, derivative window sizes, and thresholds must be adapted, consistent with known scale effects in geomorphometry and object-based representation (Drăguț et al., 2011; Drăguț & Eisank, 2012; Goetz et al., 2014; Pawluszek et al., 2018; Prasicek et al., 2014; Sîrbu et al., 2019; Zangana et al., 2025). This would enable the development of a resolution-dependent transfer framework and facilitate application in regions lacking high-resolution LiDAR data.

Finally, Paper 1 highlights that transferability and robustness are also influenced by multi-source consistency: mismatches between topographic maps, orthophotos, and DTMs can arise due to differences in acquisition date and scale, especially in anthropogenically modified and very active and complex terrain (cf. Chapter 6.2). Future applications should therefore prioritize harmonized datasets (where possible) and targeted field validation, while clearly documenting uncertainty sources during transfer to new regions (Otto and Smith, 2013). In addition, the integration of GEOBIA-based approaches offers potential to enhance detailed geomorphological mapping across diverse landforms, increasing objectivity and supporting semi-automated analysis (e.g., Anders, 2013; Drăguț & Blaschke, 2006; Drăguț & Eisank, 2012; Janowski, Wroblewski et al., 2022; S. d'Oleire-Oltmanns et al., 2012; Verhagen & Drăguț, 2012).

In summary, Paper 3 provides direct proof-of-concept that the GEOBIA framework is transferable between two German cuesta landscapes, but it also shows that robust transferability assessment depends on (i) temporally consistent reference inventories and multi-epoch validation, (ii) land-cover-stratified evaluation and potentially specialized rulesets, and (iii) systematic testing across DTM resolutions and acquisition conditions.

10. Overall conclusion

The integration of high-resolution terrain data with complementary geospatial datasets and semi-automated, object-based analysis establishes a consistent and scalable framework for geomorphological mapping and landslide detection in complex middle-mountain environments, as demonstrated in the structurally controlled cuesta landscapes of the Jena region and the Swabian Alb. By integrating detailed terrain analysis with methodological development and cross-regional validation, the results advance both the methodological foundation and the practical implementation of geomorphological mapping and semi-automated landslide detection across diverse environmental settings.

At the foundational level, the study confirms that high-resolution LiDAR-derived Digital Terrain Models (DTMs) significantly enhance the identification and interpretation of geomorphological landforms and processes. The integration of Land Surface Variables (LSVs), such as slope, curvature, and terrain roughness, enables the qualitative and quantitative characterization of geomorphic processes and supports detailed mapping at scales up to 1:5,000. As initially conceptualized in the mapping paradigm evolution (Chapter 2), the results from the Jena region show that combining visual interpretation of terrain derivatives with field validation provides a reliable reference dataset and highlights the importance of expert knowledge in geomorphological analysis. In particular, the differentiation of geomorphic process domains enables for a structured understanding of landscape dynamics and provides the conceptual basis for further subsequent semi-automated approaches.

Based on this foundation, the dissertation demonstrates that GEOBIA-based methodologies constitute a robust framework for semi-automated landslide detection. By integrating multi-resolution segmentation with machine learning and expert-informed rulesets, the workflow enables the systematic extraction of landslide features from high-resolution DTM data. A primary contribution is the optimization of scale-dependent analysis, which yielded a 15% increase in scarp detection accuracy and a 30% reduction in false positives. While this reduction in commission errors entails a 15% increase in false negatives, the workflow maintains high consistency with expert-derived inventories, marking a significant advancement toward efficient, reproducible regional-scale mapping.

Furthermore, the dissertation evaluates model transferability and data dependency, revealing that while the framework is architecturally flexible, performance is influenced by regional geomorphological contexts and data characteristics. When applied to the Swabian Alb, it achieved an overall detection rate of 77%, which increased to 87% in forested terrain. Although the parameters from the initial study were applied without recalibration, the results indicate that cross-regional accuracy can be further optimized through local training-data adaptation and parameter tuning. Additionally, the enhanced performance observed with higher-resolution contemporary DTMs underscores the critical necessity of data quality and temporal consistency for robust model transfer.

Beyond methodological transferability, the results highlight land use and land cover (LULC) as a key control on detectability. Forested environments consistently yield higher detection rates owing to the preservation of geomorphological signatures within LiDAR-derived terrain models, whereas non-forested and anthropogenically modified areas introduce greater variability in surface expression. This emphasizes the added value of LiDAR-based DTMs over optical data and supports the integration of contextual spatial information into semi-automated classification workflows.

Despite these methodological advancements, the dissertation rigorously identifies persistent uncertainties inherent in automated detection processes. These include the morphometric resemblance between landslides and geomorphologically unrelated terrain features, as well as pronounced sensitivity of segmentation outcomes to parameter selection. Such challenges are evidenced by a well-documented trade-off between precision and completeness: while substantial reductions in commission errors were attained, these gains were accompanied by a slight increase in omission errors. Collectively, these findings underscore the indispensable role of expert validation, thereby situating semi-automated methodologies as sophisticated decision-based instruments rather than as substitutes for conventional geomorphological mapping.

In summary, this dissertation confirms that the synergy of high-resolution terrain data and GEOBIA-based frameworks significantly advances mapping capabilities in complex landscapes. By achieving high consistency with expert-derived inventories across varying terrain conditions, the developed workflow bridges the gap between expert-led geomorphological analysis and computational efficiency. By enabling the generation of consistent, reproducible inventories at regional scales, this work underlines the critical interdependence of data quality, methodological adaptation, and expert knowledge.

Future research projects involving the integration of multi-temporal datasets and advanced machine learning hold considerable potential for improving these approaches into dynamic monitoring systems. Expanding this framework to incorporate temporal change detection will offer deeper insights into landscape evolution and facilitate application in data-scarce regions. Ultimately, by demonstrating how methodological innovation addresses complex environmental challenges, this dissertation provides a vital foundation for the ongoing evolution of digital geomorphology and the enhancement of hazard assessment frameworks.

From a broader geomorphological perspective, this dissertation advances the field of digital geomorphology by synthesizing methodological innovation with high-resolution topographic data to address non-linear environmental challenges. By streamlining the transition from knowledge-based geomorphological mapping to semi-automated detection, the framework presented herein enhances both the thematic precision of landform characterization and the reliability of hazard assessment protocols. Ultimately, this work establishes a rigorous, scalable foundation for future research and practical landscape management, providing the necessary tools for more resilient risk-mitigation strategies in an era of increasing terrain instability.

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Appendix

Paper 1: Zangana, I., Otto, J. C., Mäusbacher, R., & Schrott, L. (2023). Efficient geomorphological mapping based on geographic information systems and remote sensing data: an example from Jena, Germany. *Journal of Maps*, 19(1), 1–13. DOI: [10.1080/17445647.2023.2172468](https://doi.org/10.1080/17445647.2023.2172468)

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Efficient geomorphological mapping based on geographic information systems and remote sensing data: an example from Jena, Germany

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ABSTRACT

We present a detailed geomorphological map (1:5000-scale) of a middle mountainous area in Jena, Germany. To overcome limitations and to extend the possibility of manually digital mapping in a structural way, we propose an approach using geographic information systems (GIS) and high-resolution digital data. The geomorphological map features were extracted by manually interpreting and analyzing the combination of different data sources using light detection and ranging (LiDAR) data. A combination of topographic and geological maps, digital orthophotos (DOPs), Google Earth images, field investigations, and derivatives from digital terrain models (DTMs) revealed that it is possible to generate the geomorphologic features involved in classical mapping approaches. LiDAR-DTM and land surface parameters (LSPs) can provide better results when incorporating the visual interpretation of multidirectional hillshade and LSP composite maps. Findings enabled us to systematically delineate landforms and geomorphological process domains. We suggest that further use of digital data should be undertaken to support analysis and applications.

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1. Introduction

Geomorphological maps are among the best tools for understanding the physical context of features at the Earth's surface. They provide a conventional description of landforms, processes, and near-surface materials (Dramis et al., 2011). In addition to their scientific value, geomorphological maps play a significant role in hazard assessment (Parry, 2011), the visualization of landscape characteristics for education and tourism (Bollati et al., 2017), and land management and planning (Devoto et al., 2012).

Geomorphological maps are traditionally based on manual fieldwork, which can be time-consuming, require significant experience and could provide some pitfalls during the mapping and layout process (e.g. Seijmonsbergen, 2013; Otto et al., 2011). Geomorphological maps can also be purely based on remote-sensing data, like digital elevation models or digital imagery. Field mapping can be less accurate to remotely mapped data, especially in steep and complex terrain, owing to problems of accessibility (Otto & Dikau, 2004; Gustavsson et al., 2008; Beckenbach et al., 2014). Additionally, semi-automatic approaches (e.g. Blaschke, 2010; Drăguț & Eisank, 2012; MacMillan & Shary, 2009; Schneevoigt et al., 2008; Wu et al., 2016; Piloyan & Konečný, 2017; Chen et al., 2018) have been developed to facilitate the generation of

geomorphological information, such as detection and classification of landforms, processes, or geomorphic process units, directly from remote sensing data (e.g. aerial photographs, LiDAR and RADAR [both airborne or satellite-based]). However, accuracy and reliability of semi-automated approaches are often below field and remote mapping approaches and are mostly restricted to selected landforms and processes (Otto & Smith, 2013; Hillier et al., 2015). In addition, Skentos (2018) indicated that despite attempts to generalize the derived algorithms, not all automated procedures are adequate for landform classification under all circumstances.

Remotely sensed data sources have become more extensively available since the middle of the twentieth century (Smith & Pain, 2009). In the late 1990s, high-resolution data including light detection and ranging (LiDAR) has become accessible (Mcdowell, 2013). LiDAR data have improved the description and analysis of Earth's surface processes and landforms (see Hengl & Reuter, 2008; Smith et al., 2011) and provides a sophisticated approach for overcoming some of the issues inherent to classical-based methods, such as time required and quality of data (Beckenbach et al., 2014; Jones et al., 2007). Smith (2011) found that ~2 km² can be mapped per day by an experienced geomorphologist using a traditional field-based

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method in comparison to $\sim 10\text{--}100\text{ km}^2$ per day for remote digital mapping. According to Schrott et al. (2013), high-resolution remote sensing data, such as LiDAR, has augmented the visualization of terrain. Consequently, geomorphological maps based on remote sensing data, especially high-resolution digital elevation models (DEMs), have increased in the last few decades (Chandler et al., 2018; Garcia & Grohmann, 2019; Gehrmann & Harding, 2018; Gustavsson et al., 2006, 2008; Jones et al., 2007; Lambiel et al., 2016; Magliulo & Valente, 2020; Otto et al., 2017; Seijmonsbergen et al., 2011; Seijmonsbergen, 2013). The application of high-resolution data can improve the quality of the product, is less time-consuming, and requires less cost and risk involved in field campaigns (Napieralski et al., 2013).

Visualization techniques provide vital support for manual mapping based on remote sensing and DEM data to enhance the interpretation of landforms and processes (Doneus, 2013; Otto & Smith, 2013; Nagi, 2014; Daxer, 2020). For example, selected land surface parameters (LSPs), including slope (slope gradient, the first derivative of elevation), hillshade, curvature (profile and plan curves, the second derivative of elevation), and composite maps of LSPs, can present valuable visualization techniques to detect the distribution and boundaries of landforms (Anders et al., 2011, 2015). Further research is required to extend the capabilities of visualization techniques and high-resolution data for the generation of geomorphological maps and to improve manual digital mapping approaches in a structured way.

Herein, we present an approach to manual mapping using a combination of high-resolution LiDAR-DTM data, LSPs, topographical maps, geologic maps, digital orthophotos (DOPs), and a set of visualization techniques applied to a low-range mountain area in central Germany. We developed a systematic workflow that can be transferred and implemented to different terrains.

Our study aims to assess the effect of combining various data sources and visualization techniques on the quality and accuracy of the resulting geomorphological map and thereby evaluate the efficacy of such data sources to extract the genesis of geomorphologic processes and landforms.

The map presents geomorphological landscape elements and processes from the Saale valley near Jena and its surrounding slopes and hills at a 1:8000 scale. The high-resolution map provides a key tool for further geomorphological research in the area.

2. Study area

The area is located in the eastern part of Thuringia State, near the city of Jena, in Germany (Figure 1). It is approximately 44 km^2 in size spreading across two different elevation zones. One is a low-elevation area

that includes most of the Saale River valley and parts of the Roda River catchment. The lowest point in this area is about 140 m asl. The other is an elevated zone consisting of a plateau, low mountains, and the adjacent slopes at elevations up to 400 m asl. As part of the Thuringia basin, the study area dominated by two major geological formations. The Muschelkalk formation (limestone) covers the majority of the high-altitude areas, while the Buntsandstein formation (red sandstone) covers the low-altitude areas (Föhlisch, 2002; Seidel, 1992).

The city of Jena, in the northwestern part of the study area, demonstrates how human impact on the environment can cause extensive changes in the character of the landscape.

Specifically, most of the flood plain along both the eastern and western sides of the Saale River have been modified by human activities (e.g. buildings, road construction and so on).

The annual mean temperature is between 9°C and 11°C . Summer mean temperature are around 16° and 18° , winter means between 0° and 2° . The mean annual rainfall is between 600 and 800 mm (TMUEN, 2017). Land use is dominated by residences, industries, and infrastructures in the valley floors and some parts of the gentle slopes. The forests are strongly concentrated on the steepest slopes and top of the plateau. Farmlands are mostly distributed along with the Saale River flood plains and its tributaries. However, to a smaller extent, grasslands/pastures are scattered in the northern half of the study area (TLUBN, 2022). According to the 'Soil-Geological concept map' of Thuringia, 1:100,000 (Rau et al., 2000), the soil types in this area include Rendzinas (Leptosols) formed on Muschelkalk formations mainly on the plateau area. Pararendzinas (Pelosols) formed in the Buntsandstein area and on the slopes. However, the Holocene floodplain and flat areas of the region are covered by the Gley-vega soil types (Gleysols). The Braunerde/Braun soils (Cambisols) cover areas where sandstone, sandstone/siltstone, and claystone sequences of the lower and middle Buntsandstein are dominated. Podzols (Podzols) covered some southern parts of the study area.

3. Materials and methods

A LiDAR-DTM with a 2 m cell size was provided by the Thuringian State Office for Soil Management and Geoinformation and used as the base for mapping (TLBG, 2019a). Other data sources used for geomorphological mapping include high-resolution satellite imagery (Google Earth images), DOPs (20 cm cell size) (TLBG, 2019b), a digital topographic map of Thuringia at 1:10,000 scale (DTK10) (TLBG, 2019c), and geologic maps of Thuringia at 1:25,000 and 1:200,000 scales (GK25 & GK200) (TLUBN, 2019).

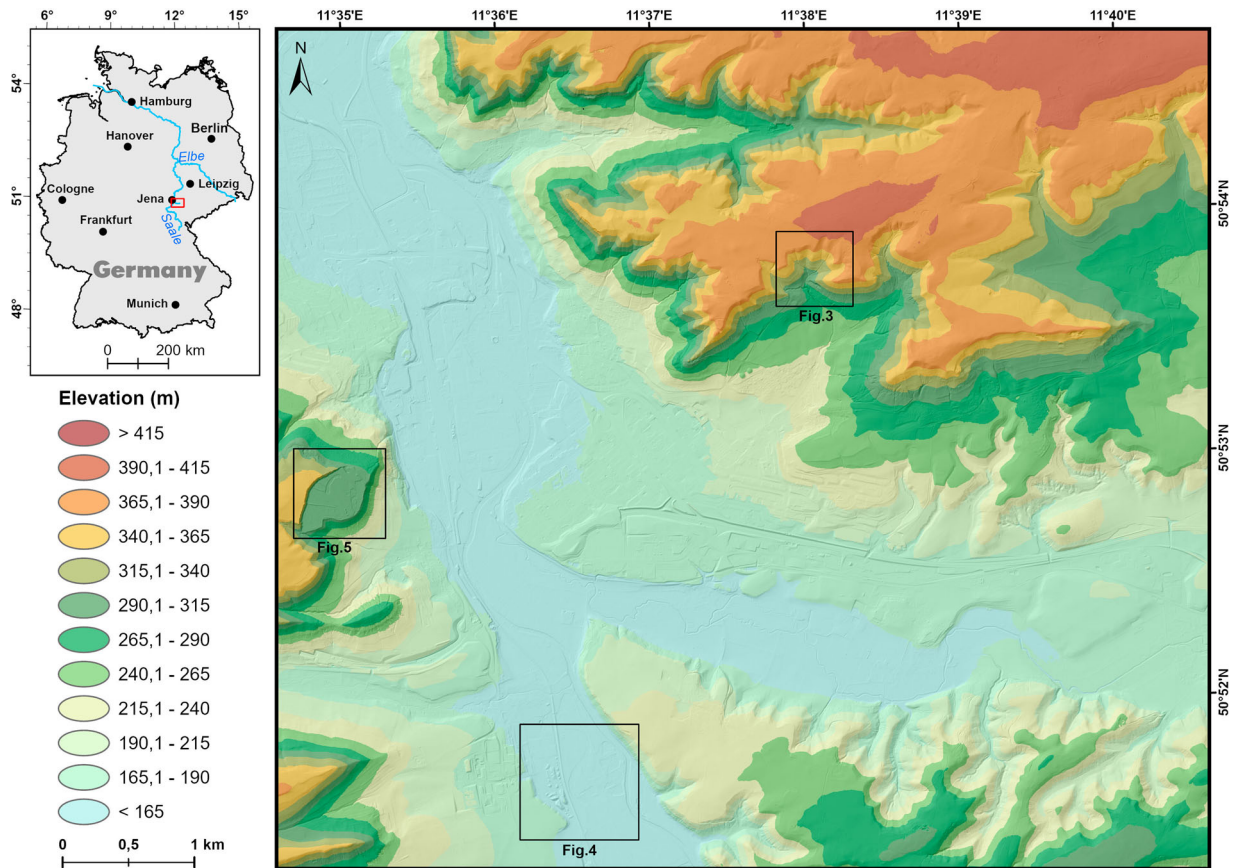


Figure 1. Location of the study area, black squares show the approximate locations of the frames in figures 3, 4 and 5.

Various LSPs were calculated based on DTM using QGIS and ArcGIS (Table 1 and Figure 2). We generated a composite LSP by combining the topographic openness (TO; for more see Daxer, 2020) with slope following the methods of Anders et al. (2011) (refer to Figure 3). In combination with other data sources (e.g. geology, topographic maps and DOPs), DEM derivatives and LSPs were applied to enhance the visualization and detectability of landforms and surface features, especially landforms related to variation across a spatial scale. The TO and LSP composite maps provided a clear distinction between the character of the landform and the surrounding features, also highlighting the highest and lowest parts of landforms (Doneus, 2013), again in comparison to other data sources (Figure 3 and Table 1). In addition, multidirectional hillshade maps are valuable for the visualization of LiDAR-DTMs required for manually analyzing landforms. This raster is created, for example, using ArcGIS Pro by the ‘*Raster Function*’ toolboxes from the ‘*Imagery*’ tool. For visualization, we employed the symbols for geomorphological mapping used by Otto (2008).

Mapping was performed as part of a two-stage procedure (Figure 2). Following the compilation and preparation of the source data, an approach was adopted to generate a geomorphological map in Stage I. Table 1 presents the different data sources and their application in this study. Additionally,

comments on potential limitations of the data to landform detection are listed. Mapping was performed at a high-resolution scale of 1:1000 to obtain greater detail of information (Otto & Smith, 2013).

Stage I comprised two main parts: identifying the genesis of landforms/processes and extracting geomorphologic process domains. Stage I, or the upper part, presents our proposed approach to systematically identify landform genesis. This was conducted *via* evaluation of available data sources and field surveys. For example, if the genesis of a landform were ambiguous, the topographic map needed to be analyzed. In addition, orthophotos was proceeded in some cases. As a last option/solution, a field check could then be required.

In order to identify crests and ridges, we applied focal statistics analyses with varying moving window sizes using the curvature raster as input data (Smith & Clark, 2005; Wood, 1996). Steps and slope breaks were generated manually after visual inspection of the slope layers and classified by calculating the width of the slope breaks based on GIS-DTM data, using ‘*Measure*’ and ‘*3D Analyst*’ toolboxes in ArcMap, for instance, steps class of 2–10 m (for more see Main Map, legend 4). Alluvial fans were mapped from the combination of topographic data and the aid of geologic maps. Since it is impossible to precisely outline an area symbol from the DTM, a point symbol feature was used instead. The hillslope processes &

Table 1. Detailed description of data sources, resolution, the required procedure/application, limitations, and the advantages or improvements for constructing geomorphologic maps.

Data sources	Resolution/ scale	Requirement	Application	Weakness	Strength/improvement
Hillshade and multidirectional hillshade	2 m cell size	QGIS /ArcGIS online (ArcPro), which computes hillshade from six different directions as opposed to the single direction of a default hillshade	To provide - a quick indication of the terrain - on-screen surveys analyzing landforms as a substitute for the field survey - a background for other layers to better visualize landforms	Traditional hillshades are made by illuminating light from the northwest. This frequently results in overexposure of the illuminated sides and obscuration of details in the terrain on non-illuminated sides	- Promotes the balance between over-exposed and non-illuminated areas, resulting in a more accurate representation of the landscape - Can develop on-screen mapping accuracy (Nagi, 2014, Tzvetkov, 2018)
Simple LSPs: 1. Slope	2 m cell size	ArcGIS/QGIS (default algorithm)	- To provide valuable knowledge to interpret and digitize breaks in slopes on-screen manually - To determine the boundaries of landforms	A single classification interval alone does not provide the necessary information needed for precise interpretation of landforms, because of the morphological difference in landform types and the range of landform sizes (e.g. steps, depressions, and knolls)	Mapping from a range of classification intervals instead of a single group (see Jones et al., 2007)
2. Curvature	10 m cell size	ArcGIS and QGIS (default algorithm)	To provide a valuable source for manual landform delineation (e.g. ridges, crests, stream networks, and drainage ways/ adjustments)	A correct landform investigation might be difficult due to the high-resolution of the original DTMs (e.g. 2 m resolution)	To obtain a reasonable raster - Focal Statistical toolbox processed (e.g. 5×5–9×9 moving window instead of the default 3×3) - extract the curvature from a resampled DTM of 10 m
3. Topographic openness (TO)	25×25 m, 50×50 m, 250×250 m	QGIS (for steps see Daxer, 2020)	- To manually correct landforms that are created based on other parameters - To better define landforms boundary	–	Consider both the highest and lowest parts of landforms (Daxer, 2020 & Meng et al., 2018)
Composite LSPs (slope & TO)	Slope 3×3 m with $TO_{25} \times 25$ m and $TO_{250} \times 250$ m	Can be obtained by - QGIS > Plugin > Semiautomatic Classification > RGB - ArcGIS > Toolbox > Data Management > Composite Bands - Arc Pro > Toolboxes > Data Management > Raster Processing > Composite Bands	When applying it, the detection of landforms boundaries is improved in comparison to single LSPs it provides us with greater accuracy and presents the landscape better than those on a single LSP (see Smith et al., 2013)	–	A clear distinction between the landform character and its surrounding features Both the highest and lowest parts of the landform are much better detected (Doneus, 2013) in comparison to other data sources (Figure 5)
Geological map	1:25,000 and 1:200,000	In a digital format such as GK25 or at a better and more detailed scale	It provides valuable information by overlaying on other data sources, it can manually define the boundaries of landforms and their geomorphic processes to obtain the genesis of landforms	When a geological map at a scale of 1:200,000 is required to delineate a detailed map (e.g. at scales of 1:5,000–1:10,000)	When draped over the DTM data and LSPs, manual mapping of landforms and their geomorphological processes boundaries are modified and enhanced

(Continued)

Table 1. Continued.

Data sources	Resolution/ scale	Requirement	Application	Weakness	Strength/improvement
Topographic map	1:10,000	An appropriate scale (e.g. < 1:10,000) and a digital format	Provides preliminary data for - manually delineating landforms/ processes - manually modifying the hydrology layer elements	If the scale of the topographic map is smaller than that of the targeted map	Scale variation issue improves by modifying the boundaries of landforms and genesis from overlying it over a DTM and DTM derivatives and by field examination, then considering the objectives of the map
Orthophoto/ Google earth images	0.20 m cell size	A reasonable resolution of about <20 cm	- Visualize the landscape in 3D and 2D - Combine it with other data sources to characterize the feature and its genesis As a substitute for field mapping and to become familiar with the area prior the field checking	When: The resolution of the images is coarser than the scale of the map Wherever the image quality is insufficient (e.g. > 20 cm) to examine the landforms of interest	By field examination and by comparison with other data sources

deposits layer including, for example, landslide, debris flow, incision, and alluvial fan (see the Main Map, legend 3), was manually delineated based on the relevant data sources and field check, using a point-based feature.

The hydrological features were digitized using blue color (lines, points, and polygons). Streamlines were extracted from the topographic map and manually corrected based on field observations. Stream types were differentiated between perennial and intermittent based on field surveys. Lakes were extracted by selecting areas bigger than 20 m² where slope values were lesser than 0.5° from the DEM and modified manually using the topographic map. The extraction of sources, waterlogging, and seepages was impossible using LiDAR data only. Hence, we obtained these characteristics from the combination of topographic maps, orthophotos, and field surveys. In contrast, to define and classify pathways, we followed the geomorphological map of Germany (GMK) concept (Barsch & Liedtke, 1985), using different techniques. In the initial step, each valley with a width of <25 m on the ground was identified. In the second step, valley profiles were examined manually using DEM data and the *profile graph* tool (using *3D Analyst* toolbox, ArcMap). Different valley types were classified based on the visual inspection of the cross-profiles designed using our experience.

We employed an approach to determine the predominant landforms and processes in the middle-mountain regions during the early stages of mapping to ensure that irrelevant landforms/processes were not processed (see Figure 2, Stage I/lower part).

In the initial step, a single polygon (color fill) was drawn to cover the entire study area and defined as

a denudational domain by default. This was done by considering the yes/no criteria *via* comparison with other typical characters of occurring geomorphic processes. However, any part of the initial polygon (denudational process domain) was removed, and subsequently substituting it with an active type of a geomorphic process in that domain. For example, the signature of denudation area was replaced with a fluvial process domain wherever fluvial incisions, erosional rims, rivers/streams, and flood plains were identified. Likewise, the topographic map and DOP were analyzed to separate anthropogenic areas (gray polygons) from urban domains (rose-quartz color fill). In other words, anthropogenic activity areas can be divided into two parts: (1) zones that were slightly altered by human activities, which are classified as anthropogenic process domains (see the Main Map, legend 1), and (2) zones that were strongly modified by anthropogenic activities; these were not surveyed and represented by a rose-quartz color-fill polygon. Following a similar procedure, karstic domains were delineated if the area (1) was dominated by the lower Muschelkalk formation (Jena Formation; see the inset geologic map in the Main Map) and (2) was characterized by depressions and undulating topography consistent with gentle slopes. In this way, the loop was continued until the entire study area had been classified. As a result, this layer has been divided into six classes of main geomorphological processes, ten sub-classes of interactive processes domain, and one class for unsurvey areas.

During Stage II (Figure 1), various parts of the study area were checked in the field. Two field checks were carried out with the support of a differential GPS (DGPS). Field surveys were prepared by accessing

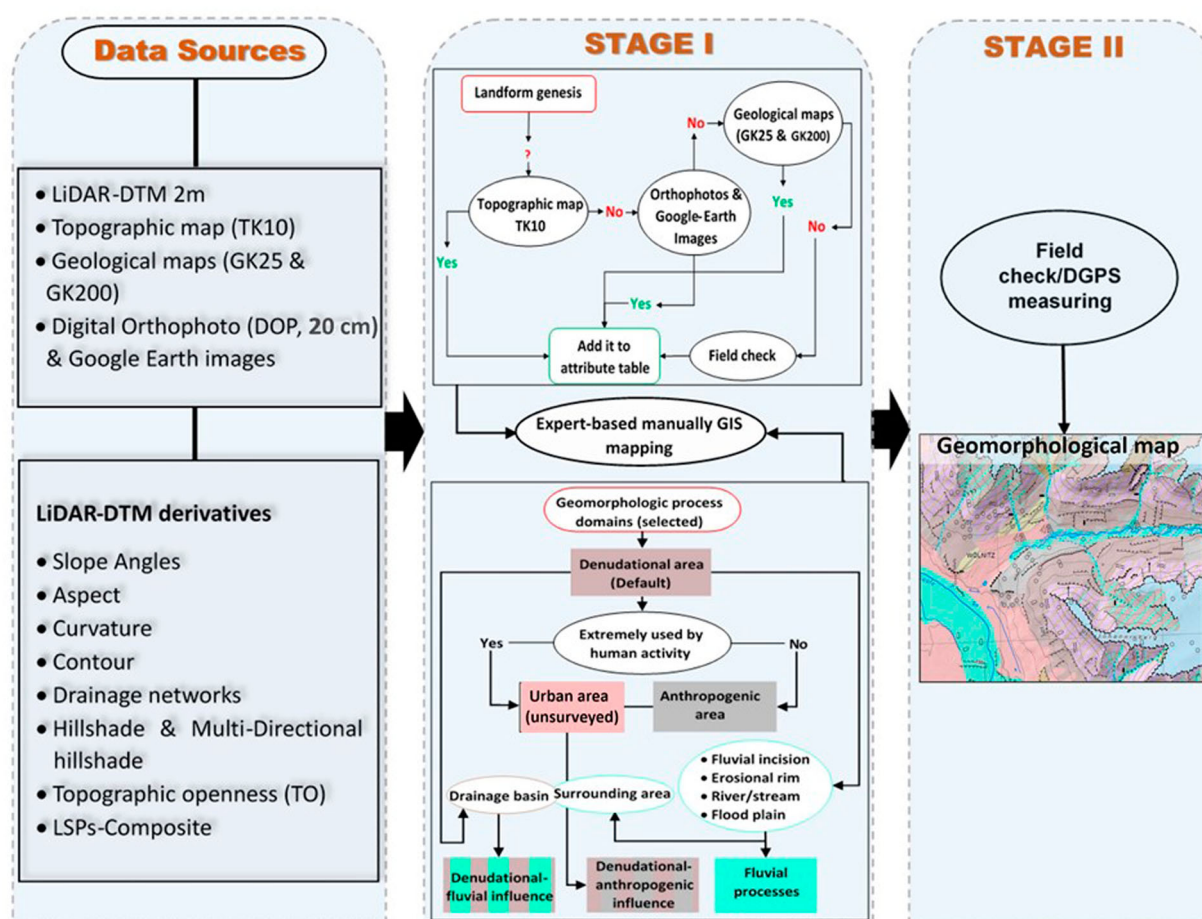


Figure 2. Flowchart showing the methodology used in this study.

existing scientific publications on the study area. The first field survey/pre-mapping was conducted at the beginning of the study to obtain a general overview of the landscapes, geomorphic processes, and landforms and to take some notes. The second survey was after the GIS-based/post-mapping to validate some features in the field with the aid of DGPS and to compare the efficacy of our method, using the combination of different data sources and the field-based mapping (refer to Figure 5). The Main Map was produced in ArcGIS 10.7 at a scale of 1:5000 with a Universal Transverse Mercator projection (Zone 32). The final map layout was chosen to fit an A0 format, requiring some degree of generalization (see Otto et al., 2011). For instance, many depressions and knoll-like landforms were substituted with point symbols instead of line symbols or were removed; however, any geomorphic domains that were too small to present on the final layout had to be replaced with the neighboring area or merged with the adjacent polygon. As an example, fluvial and denudational processes were merged into a single class by being denoted as of fluvial influence, in order to indicate the interaction between processes in a domain.

In addition, any delineated geomorphic processes (polygon features) at smaller scales were grouped or reproduced by their neighbor classes (Dramis et al.,

2011). This was manually executed; however, it is similar to the general concept of region-growing algorithms (Drăguț & Eisank, 2012). Furthermore, because of size and density of landforms, many steps and breaks in slope lines were subsequently removed or replaced with point symbols; for example, instead of presenting the steps of the incision by a line symbol, we employed a point symbol (Main Map, legend 3).

4. Results

Different geological formations have diverse and significant impacts on the landscapes of the Jena region. For instance, the northern part of the study area is dominated by limestone, which is characterized by escarpments, slopes, landslides, and v-shaped valleys. However, the southern part, dominated by sandstone, features several boxes and saucer-shaped valleys, flood plains, and terraces.

Some landforms were generalized or have been omitted for the final map to consider relevant landform visibility and improve readability. The final map is divided into four main classes/layers: geomorphological processes domains, hydrological features & pathways, hillslope processes & deposits, and topography & structural landforms.

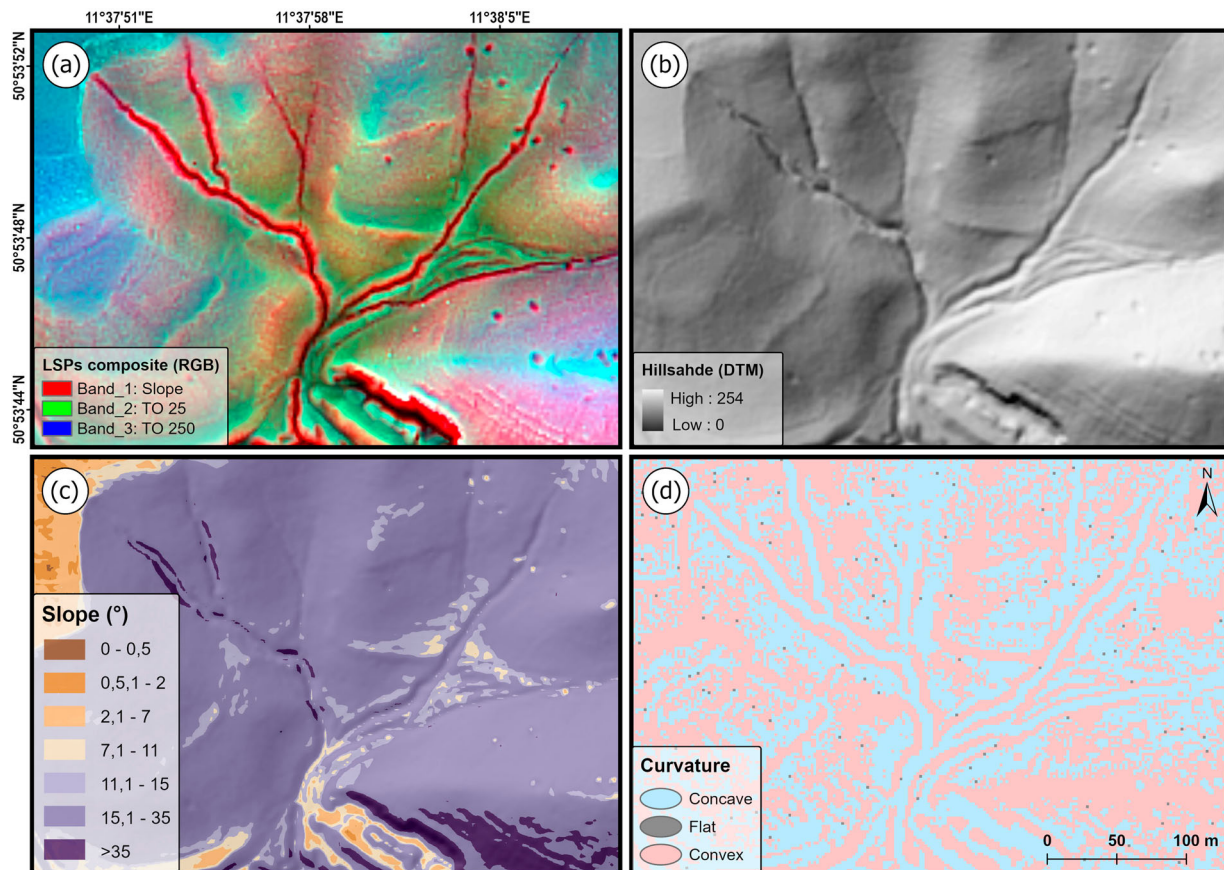


Figure 3. (a) LSPs composite map clearly defines landforms (bomb craters, queries, erosional rim...etc.) and their boundaries compared to DTM data and its derivatives, such as (b) hillshade, (c) slope, and (d) curvature.

4.1. Geomorphologic process domains

The northeastern part, the plateau, and the western part of the map edges, i.e. the high altitudes, are mostly dominated by karstic processes; however, rare karst features were also detected.

The northern and southern parts of the study area are dominated by the gravitational processes. The Kernberge, Johannisberg, Gräfenberg, and Einsiedlerberg mountain slopes are compatible with landslides, rock falls, creeps, and debris flows. The northeastern, central, and southern parts of the study area are dominated by denudational processes where other dynamic processes were not observed. The low-altitude zone and the valley slope areas are mostly characterized by fluvial processes, specifically along the Saale River and its tributaries. Fluvial–anthropogenic domains occur in the northwestern part, termed the Obere Aue area, and near Lobeda in the center of the map; i.e. the flood plain was modified by anthropogenic activities such as construction, and in the northeastern part of the area, the Pennickental river bed was influenced by mining activities.

Anthropogenic process domains are distributed all over the map. For instance, a part of Mönchsberg, the southwestern part of the area, was significantly altered by anthropogenic activity associated with the

Steinbruch quarry. As a result, a break in slope of approximately 30 m and a plateau of approximately 400 × 600 m was created.

The aeolian processes (loess accumulations) are not active in the area and ‘since loess in Europe was mainly accumulated during the cold stages of the Quaternary’ (Lehmkuhl et al., 2018), a clear distinction of the local extent of this class is not well defined in our area. It is presented on the map within sub-classes as it has been influenced by other processes. We identified loess accumulations on the eastern side of the Roda River, the western side of the Saale River, over the Spitzenberg Mountain slopes toward the Saale, and on the slopes toward the Ilmnitz, specifically between the contour lines of 175 and 225 m.

Periglacial processes are inactive in the study area and illustrated *via* the combination with other processes. It is mostly distributed along the hilly-mountain slope in the northern and southwestern parts of the map, where mainly dominated by the gravitation processes. The fluvial terraces occur along both flanks of the Saale and Roda channels, between 175 and 200 m asl. These terraces mostly undergo alteration by denudational and fluvial processes (see the Main Map, legend 1, for corresponding classes).

4.2. Hydrological features and pathways

The investigation area is mostly characterized by the Saale River valley and its tributaries. Perennial streams (e.g. Roda, Leutra, and Pennickental) and intermittent streams also contribute to terrain modification. In the northern part of the map, the Pennickental stream bed mostly undergoes alteration by anthropogenic activities (Section 4.1). Thus, the water is hampered to flow persistently and partially covers both stream flanks (Main Map, legend 2).

Various lakes with a range of sizes are distributed along the river and stream channels. For example, despite the trace of the Saale meander and the ridges of the old lakes, several lakes occur on the Saale active fluvial plain, near the southwestern corner of the map. The southern part of the study area is mostly covered by the sandstone formations dominated by saucer- and box-shaped valleys, whereas the northern part is controlled by limestone formations, where v-shaped valleys have mainly been investigated (see the Main Map, legend 2).

4.3. Hillslope processes and deposits

The central and northern parts of the study area are dominated by hills (e.g. Kernberge, Johannisberg, Gräfenberg, and Einsiedlerberg). The hill crests, which follow a west–east trend, are characterized by numerous incisions, and geomorphological evidence of rill erosion, rock falls and debris flows, especially in the slopes toward the Pennickental (e.g. Diebeskrippe landslide), the slopes toward the Saale, and the Einsiedlerberg slopes toward the south (see Section 4.1). In addition, on the southwestern part of the map, the mountain slopes of Mönchsberg, Jagdberg, and Spitzenberg to the Saale are dominated by a range of incisions, rill erosions, and rockfalls (Main Map, legend 3). Generally, the incision and rill erosion occur throughout the mapped area at a range of scales. Small alluvial fans occur at the mouth of the tributaries of Pennickental, in the northern part of the investigation area, and are mostly altered by shallow mass movements and anthropogenic activities.

4.4. Topography and structural landforms

The depressions are mainly distributed across the tops of the plateau landscape, located in the northern portion of the map; however, more specifically, they occur on the slopes of the Kernberge and Johanniseberg toward Wöllnitz, at the top of Mönchsberg (also Steinbruch), and its slopes toward the Winzerla, and on the slopes around Gräfenberg and Georgstein. Knoll/knob features (legend 4) mostly dominated the low-altitude (i.e. flat) areas along the Saale valley. Most exhibit a range of anthropogenic origins (see the Main Map,

legend 1) and are mostly modified by fluvial and denudational processes. Furthermore, steps and breaks in slope features occur throughout the mapped area; however, the northern portions of the map are extensively covered with mountainous areas, where the terrain is more complex than the southern part of the area.

Finally, most of the landforms and geomorphic process boundaries of the study area (e.g. plateau, mountains, valleys, catchments, terraces, and landslides) are controlled by crests, ridges, and breaks of slopes.

5. Discussion

This investigation supports evidence from previous observations (e.g. Jones et al., 2007; Roering et al., 2013) that reveal the accuracy of LiDAR data, showing that it is valuable for accelerated geomorphological mapping (Figure 5). Owing to the complex interactions between geomorphological processes in nature, a clear distinction between landforms solely from the remote sensing data was impossible. Therefore, Figure 1/Stage I illustrates our proposed approach as a step toward detecting landform geneses and geomorphological process domains by combining all data sources from on-screen mapping. Nonetheless, further developments could increase the extent of applicability of such pursuits, for instance, (1) by applying it to different environments and (2) by developing a novel approach to delineate and classify landform genesis automatically using DEMs based on LSPs (Seijmonsbergen et al., 2011).

We observed some discrepancies when overlaying different data sources, such as the topographic map and DOP with the DTMs. This occurs because of variations in scale as well as the date of data collection. For instance, anthropogenic activities such as roads, buildings, or construction may be represented only in some of the data, owing to different times of acquisition. Hence, utilizing data sources with the same scale and similar acquisition time is recommended (Otto & Smith, 2013). However, if the existing data sources do not fit to each other, which is hard to achieve, relying on the most recent data or conducting ground-truthing to illustrate current processes is more reliable.

The geological map enhanced on-screen mapping by providing adequate information to detect landform geneses, such as landslides with gravitational processes and terraces with fluvial processes (Figure 4). Nevertheless, a detailed boundary distinctions of landforms cannot be extracted from geological maps in contrast to their recognition from LSP composites and hillshade maps. This disagreement may reflect the lower scale of the geological map in comparison to the produced map. This research corroborates the ideas of Anders et al. (2011, 2015), Doneus (2013), Meng et al. (2018),

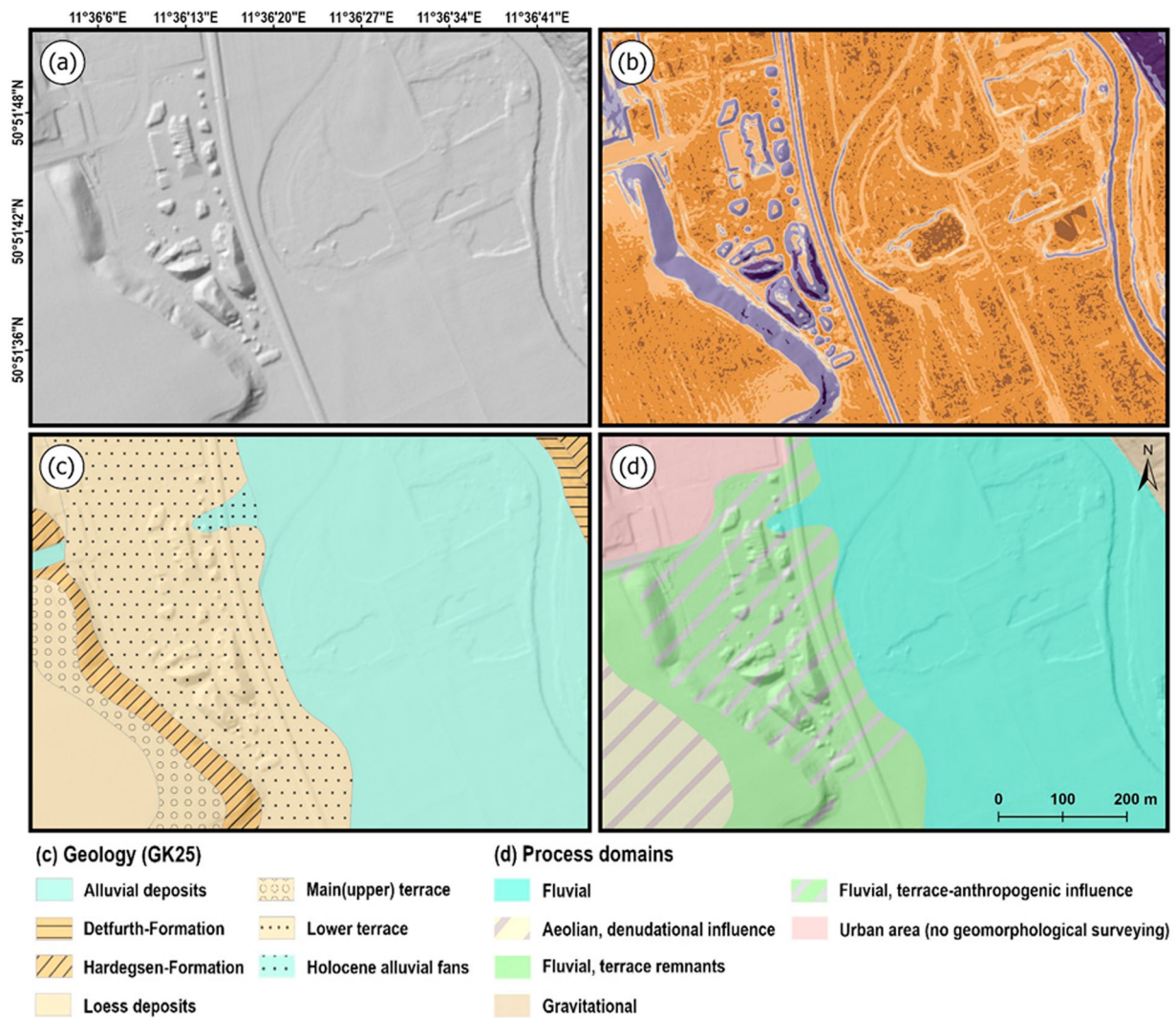


Figure 4. Example of process domain delineation (fluvial process): (a) Hillshade (for legend, see Fig. 3(b)). (b) slope, (for legend, see Fig. 3(c)). (c) geological map-GK25 and (d) the geomorphologic process domains.

and Daxer (2020), who suggested that TO and LSP composite maps are valuable for geomorphological mapping. This effort can be counted as an experiment toward an extension of the efficiency of that concept for manual mapping. In contrast, the slope map, which was classified based on the GMK25 legend (Main Map), is less suitable for a comprehensive representation of landforms. For example, Figure 3(c) indicates that most of the steps, incisions, bomb craters, and ridges are not fully represented based on this legend since the GMK25 legend was designed for a 1:25,000 scale map; however, not for a detailed scale such as 1:5000. Different classification intervals of slope angles were experienced in the initial steps when considering the general ideas of Jones et al. (2007), but further investigation is still needed, taking the map scale into account. In contrast to the traditional hillshade map, multidirectional hillshades promote the balance between over-exposed and non-illuminated areas of the map, resulting in a more realistic representation of the terrain (Nagi, 2014), and can further develop the accuracy of on-desktop mapping.

We validated the DTM-based GIS map with DGPS measurements in the field. Figure 5 indicates a good agreement between screen-based landforms and field checks related to the high resolution of digital base data for mapping. We observed an accuracy between a few millimeters (in most cases) to a meter or more (in seldom cases). However, mismatches between both approaches were observed. For example, in areas mostly covered by forest or vegetation, DGPS measuring was impossible. Some landforms were detected in the field but unidentifiable in LiDAR data. For example, hollows, knolls, and active processes such as sheet erosion or debris flows were not identified solely from the remotely sensed data. This can be due to the resolution of the DTM and the offset between acquisition times of digital and field data. Therefore, the resolution of digital data should be considered when a geomorphological map with higher precision and detailed scale is required. Therefore, the results presented here show that LiDAR data can quickly create a detailed geomorphological map of the middle-mountain environment but should not be

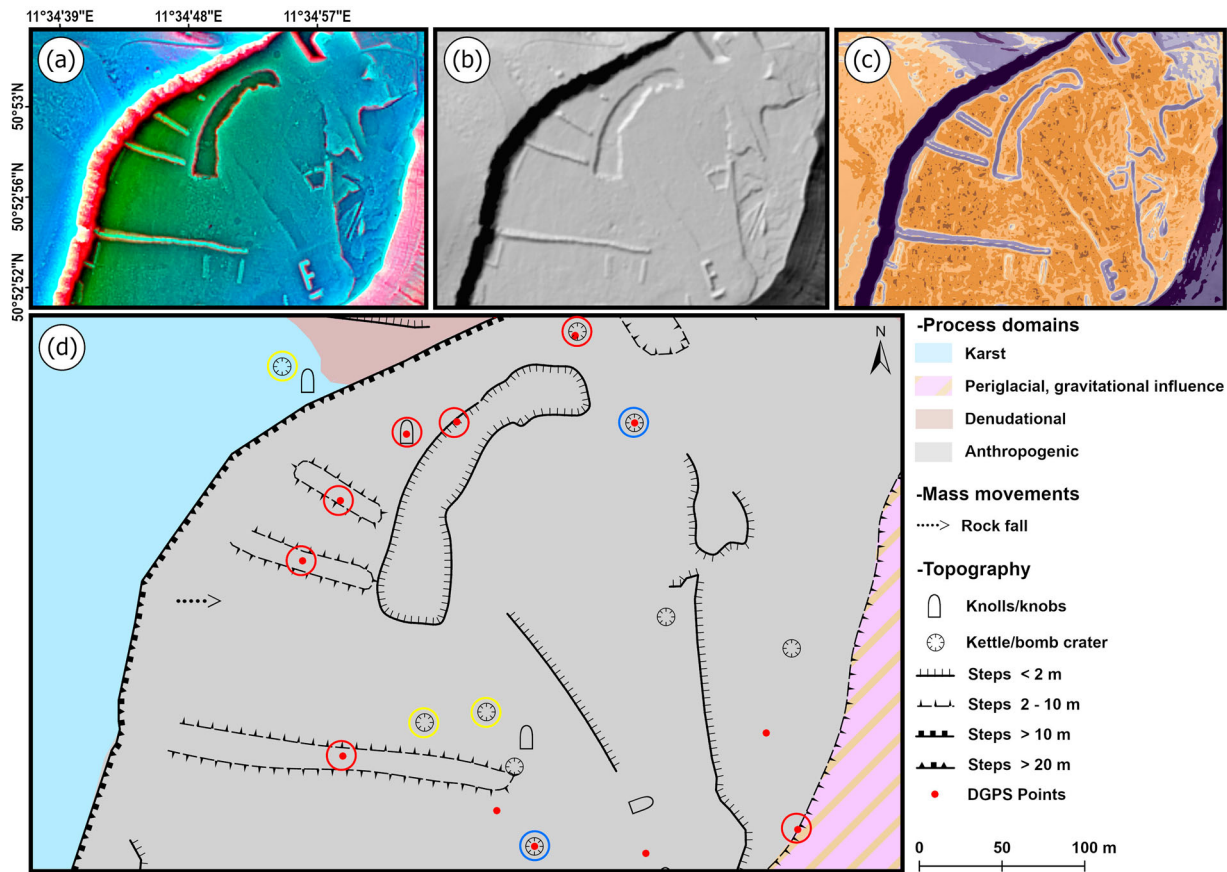


Figure 5. (a) LSPs-composite map, (b) hillshade, (c) the slope map of the Steinbruch quarry area, (d) an overview of the field/DGPS survey (red points). Red circles show that these landforms fit the DGPS measurements, and yellow circles present features that were not found in the field due to dense vegetation. Blue circles present landforms that could not be mapped by LiDAR-DTM-based on-screen analyses (see Fig. 3 for the legends of (a, b, and c) and Fig.1 for the location of this area).

considered a complete replacement for traditional methods.

6. Conclusion

This paper introduced a manual geomorphological map at a scale of 1:5000, based on ArcGIS tools and combining DTM, DTM derivatives, and LSPs-composite maps. Other inputs such as topographic maps, Google Earth images, DOPs, geological maps, and field examination were used to improve the mapping. This map can be used as a substitute approach geomorphological information from classical field-based maps.

Our approach provides high-accuracy layers of information. Moreover, the results obtained show that incorporating relevant LSPs, such as slope, curvature, elevation, multidirectional hillshade maps, and other derivatives such as TO and LSPs composite maps, provide valuable means of improving manually constructed digital geomorphological maps. Our proposed approach presents most geomorphological map layers and their properties at high quality; however, combining new layers of information or additional and better datasets might optimize the map.

We conclude that a combination of different data types, together with TO and LSPs, significantly enhances digital geomorphological mapping. Nevertheless, a field check of remotely sensed information still provides the best guarantee of producing accurate and updated high-resolution maps.

Google Earth images and DOP datasets with a resolution of approximately <20 cm are highly recommended for comprehensive mapping in flat and non-vegetated areas. The geological map can provide further improvement and flexible fine-tuning considering the genesis of some landforms (e.g. landslides and terraces). It is also valuable to determine the boundary of some geomorphological process domains (e.g. gravitational and fluvial processes). Notwithstanding, since the scale of the geological map is relatively smaller than that of the target map, uncertainties concerning the genesis of some landforms and their boundaries arose. Hence, geomorphological mapping can be enhanced when complemented with an equivalent resolution of geological data.

This approach is valuable for creating high-quality base data prior to or instead of field mapping, or when field survey time is limited. Furthermore, it provides a step forward in substituting traditional geomorphological

mapping approaches with on-screen digitized mapping, thereby presenting data sources for future studies in this area, despite its utility as a training sample for semi-automatic landform classification of typical landforms.

Our proposed approach can be applied in different environments to enhance the usability of geomorphological landforms and process domains.

Software

The dataset of the geomorphological map, including the morphometric analysis and the symbols of the map legend, has been digitized and managed, and the final design was obtained using ESRI ArcGIS 10.7, QGIS 3.16.3, ArcGIS Pro 2.6.2.

Open Scholarship



This article has earned the Center for Open Science badge for Open Data. The data are openly accessible at <https://doi.org/10.22000/798>.

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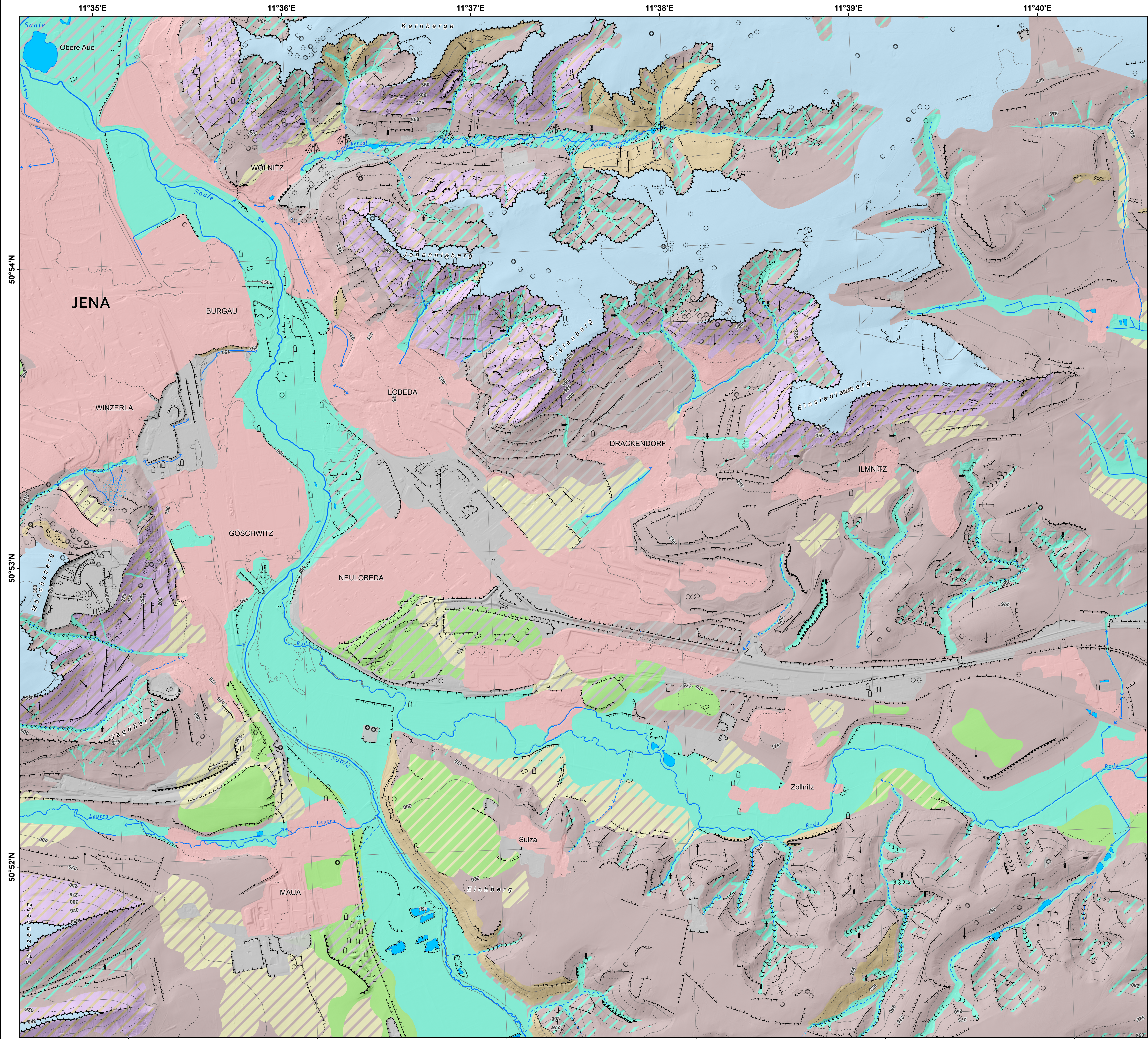
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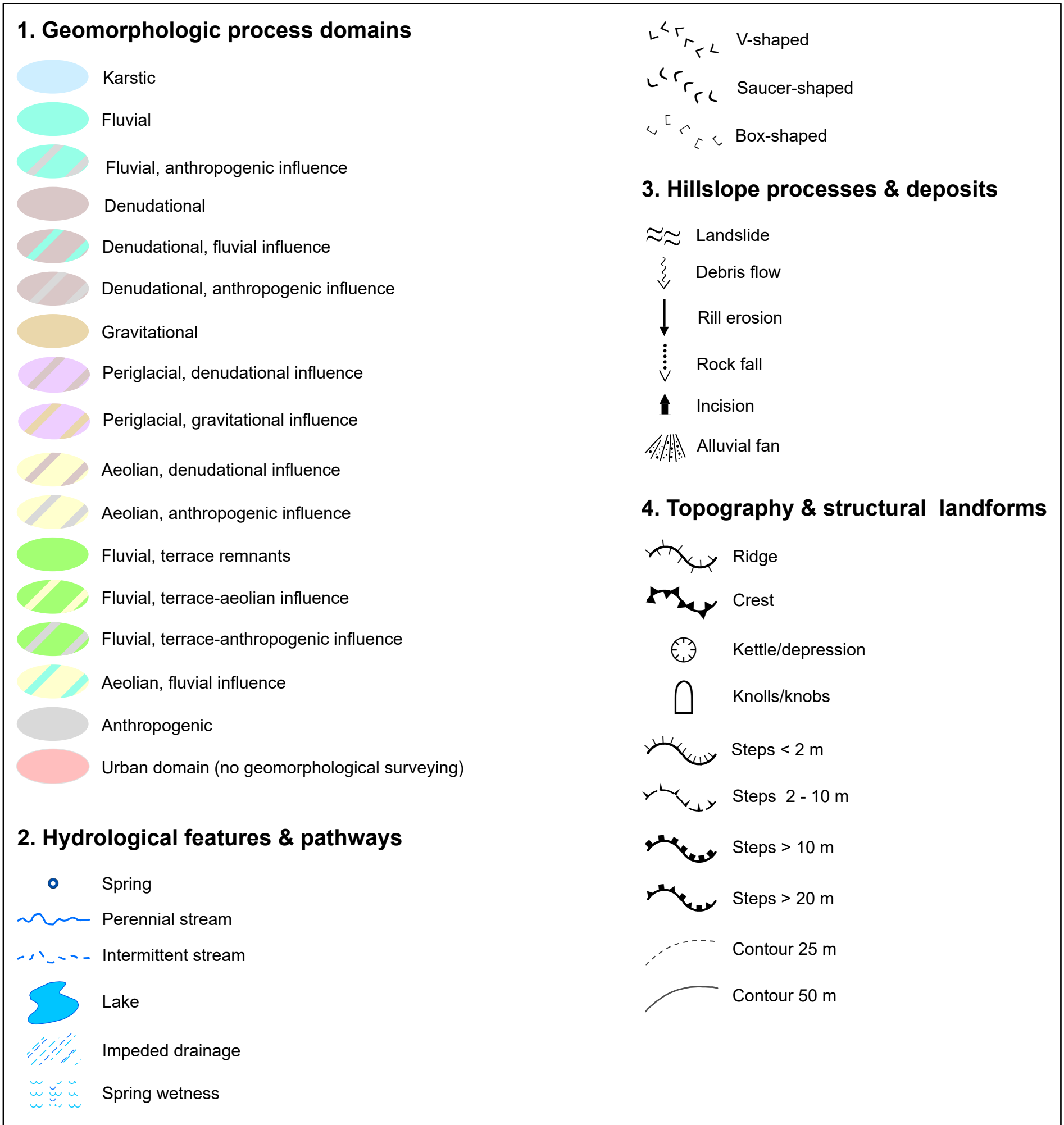
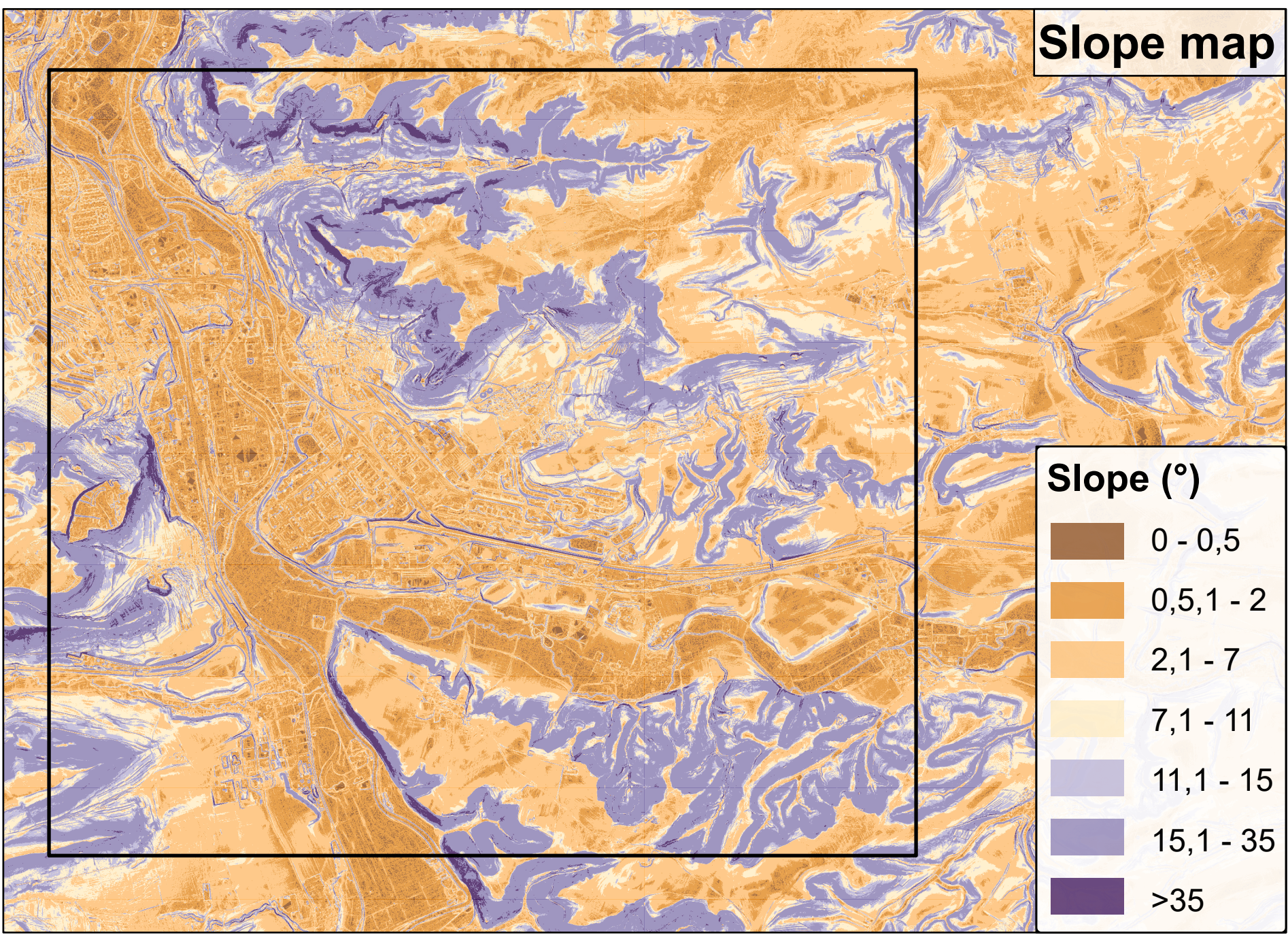
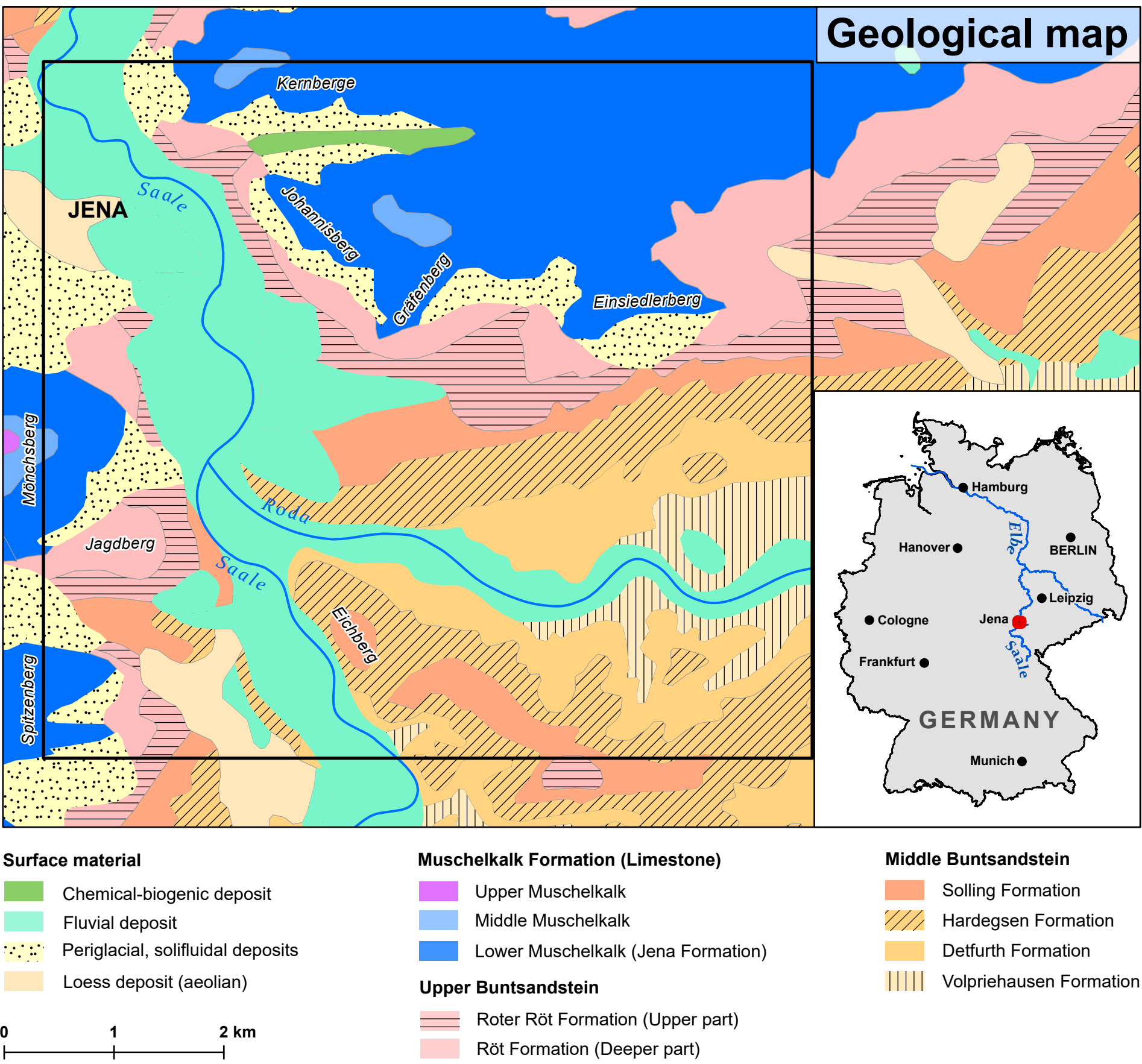
Supplemental material: **Main Map**

Geomorphological map of Jena and surrounds, Germany



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Cartographical basis: LIDAR-DTM provided by Thuringian State Office for Soil Management and Geoinformation in area to the map sheets (n.: 51351, 51352, 50353, 50354, 50363 and 51361) of the Deutsche Topographische Karte (DTK10) 1:10.000.
Projection: 25832-EPGSG_UTM_Zone_32N (Transverse Mercator)
Ellipsoid: ETRS89
Geodetic Datum: D, ETRS 1989
Geological map based on data from Thuringian State Institute for Environment and Geology
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Mapping forest-covered landslides using Geographic Object-Based Image Analysis (GEOBIA), Jena region, Germany

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Abstract. Landslide inventories are crucial for the assessment of landslide susceptibility and hazard. An analysis of old landslides can reveal periods of intensified landslide activity, but the features of these landslides may have diminished over time, particularly in the context of human impact. However, landslide features are often preserved well under forest cover and are thus valuable for compiling or updating landslide inventories. However, the mapping of these features remains challenging. Light detection and ranging (lidar) analysis and its derivatives are essential in landslide research, particularly in landslide identification and mapping. Unlike the expert-based analysis of lidar derivatives, the use of object-based approaches to map landslides from lidar data (semi)automatically requires further studies. This study adopts geographic-object-based image analysis based solely on lidar derivatives for the inventory mapping of forest-covered old landslides within a middle-mountain region in Jena, Germany, and surrounding areas. A manually prepared expert-based inventory map was used for model training and validation. Lidar derivative data were processed using (a) a default moving-window size (3×3 ; model I) and (b) an optimal window size (model II). Multi-resolution segmentation and support vector machine classification with distinct rule sets were implemented for each model, followed by refinement and accuracy assessment against the inventory map for model performance evaluation. The proposed approach achieved a 70 % detection of existing landslides compared with the inventory. Model II outperforms model I in accuracy, as indicated by its superior performance in scarp area detection (15 % improvement) and significantly lower false positives (30 % reduction). However, although this method excel-

lently identifies and maps forest-covered old landslides, its applicability is currently limited to large and medium landslides (area > 0.5 ha). Overall, our findings suggest that landslides worldwide with clear geomorphological signatures in lidar data can be identified using this approach.

1 Introduction

Landslides are significant in landform evolution, and numerous regions worldwide have considerable landslide hazard. In certain areas, landslides frequently cause greater mortality and economic loss than other natural hazards, such as earthquakes, volcanic eruptions and floods (Guzzetti et al., 1999, 2021; Aksoy and Ercanoglu, 2012). Landslide hazard is the probability of a landslide of a specific magnitude occurring in a particular area within a defined time frame (Guzzetti et al., 1999). Landslide hazard assessment necessitates the creation of detailed landslide maps, with landslide inventory maps specifically recording the geographic distribution of documented landslides based on their detection and delineation (Guzzetti et al., 1999). Such inventories are traditionally developed through analyses of aerial photographs, supplemented by fieldwork and collection of historical data (Guzzetti et al., 1999, 2012; Santangelo et al., 2010). Albeit a standard geomorphological practice, the field mapping of landslides, particularly older ones, is hindered by factors such as landslide size, limitations in field perspectives, forest cover or erosion and anthropogenic modifications. Compared with traditional field techniques, remote methods using aerial photographs and high-resolution digi-

tal elevation models (DEMs) provide more comprehensive and accurate data, increasing mapping precision (Santangelo et al., 2010; Guzzetti et al., 2012; Bell et al., 2012; Crawford, 2014; Schmaltz et al., 2016; Petschko et al., 2016; Bernat Gazibara et al., 2019).

In recent decades, geographic-object-based image analysis (GEOBIA) has emerged as a powerful method for semi- or fully automated landform mapping (e.g. Drăguț and Blaschke, 2006; Blaschke, 2010a; Schneevoigt et al., 2010; Seijmonsbergen et al., 2011; Anders et al., 2011, 2013; Draguț and Eisank, 2012; Zylshal et al., 2013; Eisank et al., 2014; Robb et al., 2015; Pedersen, 2016; Guilbert and Moulin, 2017; Hossain and Chen, 2019). The integration of GEOBIA into semi-automatic landslide mapping is a significant development in this field. Lahousse et al. (2011) developed a multiscale GEOBIA technique for landslide mapping, but it is limited to specific areas and landslide types. Aksoy and Ercanoglu (2012) proposed a semi-automatic inventory mapping method that uses fuzzy logic based on thematic data and spectral information. Feizizadeh and Blaschke (2013) developed a rule-based classification approach utilising satellite data. Hölbling et al. (2016) identified spatiotemporal landslide hotspots by analysing historical and recent aerial photographs. Hölbling et al. (2017) compared GEOBIA and manual mapping approaches and concluded that GEOBIA-based semi-automatic mapping encounters difficulties in areas where landslides are covered by vegetation. Karantanellis et al. (2020, 2021) stated that landslide modelling based on unmanned aerial vehicles (UAVs) enables detailed, automated landslide characterisation, with high adaptability to specific sites. They also found that UAVs enable time- and cost-efficient data collection, whereas machine learning algorithms are effective for local-scale sub-zone landslide mapping when integrated into GEOBIA. Dias et al. (2023) showed that applying GEOBIA-based methods to high-resolution satellite imagery can successfully identify shallow landslides and debris flows with over 70 % accuracy. Karantanellis and Hölbling (2025) further emphasised the utility of high-resolution digital data, in combination with GEOBIA-based methods, for improving landslide mapping and assessment accuracy.

Limited studies have explored the use of GEOBIA for landslide mapping in forested regions, particularly in the underexamined context of old landslide inventories. Plank and Martinis (2016) used an object-based and change detection approach with DEM and synthetic-aperture radar (SAR) imagery to map landslides in vegetated areas by integrating pre-event optical and post-event very-high-resolution polarimetric SAR data. However, their study focused only on fresh landslides, not old landslides under forest cover. Comprehensive inventory mapping is required to address this limitation. Eeckhaut et al. (2006, 2012) studied landslides occurring beneath forest cover, achieving a detection rate of approximately 70 % using lidar data alone. Their investigation encompassed multiple levels, but the moving-window

size of land surface variables (LSVs) for landslide components (e.g. landslide scarp and body) were not adequately addressed; both components were treated using the same window size. Knevels et al. (2019) used open-source software to map forest landslides using GEOBIA. Using high-resolution lidar data, they attained a 69 % detection rate relative to manual mapping. Despite using default window sizes, the authors acknowledged the potential of identifying the optimal window size for different landslide portions, possibly enhancing model performance. In summary, previous researchers used default window sizes to calculate LSVs, underscoring the need to explore optimal moving-window approaches to enhance landslide mapping.

Determining the optimal window sizes for different LSVs relative to specific landforms is critical in semi-automatic landform detection using digital data; a detailed review of scale-related issues is available in Draguț and Eisank (2011). Seijmonsbergen et al. (2011) demonstrated that using multiple window sizes for LSVs can enhance semi-automatic landform detection. They found that different landscape features are best detected using different window sizes, but they manually selected these sizes to compare with expert-based mapped features. Pawluszek et al. (2018) investigated the impact of scaling window sizes on the automatic detection of landslides using digital terrain model (DTM) data. After DTM rescaling, the landslide modelling accuracy improved relative to that of the original (non-rescaled) DTM. Sîrbu et al. (2019) developed an automated approach to selecting the optimal window size of each LSV relative to landslide scarps, significantly improving detection accuracy in two study sites in comparison with that under the default selection of window sizes. However, landslide bodies were not examined in this study. No standard or operational method has been developed to achieve this goal despite the considerable progress in automated landslide mapping.

This study investigates the potential of using GEOBIA and high-resolution DTM data for the semi-automatic mapping of forest-covered old landslides (mainly focus on the deep-seated “rotational” landslides) in middle-mountain regions in Jena, Germany. Specifically, the effectiveness of using lidar data and their derivatives for the semi-automated inventory mapping of forest-covered landslides is assessed, particularly the role of optimised window sizes. The central research question is as follows: How can DTM derivatives and optimised window sizes enhance the reliability of GEOBIA-based semi-automatic landslide mapping in forested environments? Thus, the influence of optimal window sizes for LSVs on the accuracy of semi-automatic landslide mapping is first determined. This is then compared with results achieved using default window sizes. By addressing these aspects, this study seeks to advance the understanding of, and improve practices in, landslide mapping within forested environments.

2 Study area

The study area is in the eastern part of Thuringia, near the city of Jena, Germany (Fig. 1). It is approximately 150 km² in size and encompasses two elevation zones. The first zone is a low-elevation area that includes most of the Saale River valley and parts of the Roda River catchment. The other is an elevated zone consisting of a plateau, low mountains and adjacent slopes at elevations reaching 400 m above sea level (m a.s.l.) (Zangana et al., 2023a). Moreover, the study area is situated within the Thuringian Basin and has two predominant geological formations. The Muschelkalk Formation (limestone) predominates in the higher-altitude regions, whereas the Buntsandstein Formation (red sandstone) dominates in the lower-altitude areas (Föhlisch, 2002; Seidel, 1992).

The preconditioning factors influencing landslide occurrence in the study area are geological and structural characteristics, particularly the stratigraphic contact between limestone and underlying sandstone. This lithological configuration, when combined with the steep slope geometry of the cuesta escarpments, plays a pivotal role in the slope instability. Such structural settings are known to favour rotational landslides, particularly in cuesta landscapes, where differential weathering and erosion of layered sedimentary rocks promote mass movement. According to Achilles et al. (2016), the landslides may have been triggered during the Holocene, likely beginning at the end of the Weichselian glaciation, due to increased precipitation, glacial meltwater infiltration, and associated hydrological changes. While the exact age of these landslides remains uncertain, especially when relying solely on LiDAR-derived DTMs, the widespread presence of dense forest cover over many large landslide bodies suggests limited recent activity and supports the possibility of an older origin (Zangana et al., 2024). Most of the mapped landslides occur on hillslopes in the eastern part of the Saale River basin, predominantly facing north and northwest. However, to the best of our knowledge, there are no recent studies or official records documenting damage or economic losses correlated with older deep-seated landslides in the region.

The annual mean temperature is 9–11 °C, the summer mean is approximately 16–18 °C and the winter mean is 0–2 °C. The mean annual rainfall is 600–800 mm (TMUEN, 2017). Land use is dominated by residences, industries and infrastructure in the valley floors and some gentle slopes. Forests cover steep slopes and high plateaus. Farmlands are primarily located along the floodplains of the Saale River and its tributaries, whereas grasslands and pastures are more sparsely distributed, mainly in the northern portion of the study area (Landnutzung). The soil types in this area include rendzinas (Leptosols), which are on the Muschelkalk Formation, predominantly within the plateau area, and pararendzinas (Pelosols), which are in the Buntsandstein area and on the slopes. However, the Holocene floodplain and flat areas of the region are covered by gley–Vega soil types (Gleysols).

Cambisols are found in areas dominated by sandstone, sandstone/siltstone and claystone sequences of the lower and middle Buntsandstein, while podzols (Podzols) are present in some southern parts of the study area (Rau et al., 2000; Zangana et al., 2023b).

3 Methodology

3.1 Data

Landslide mapping is based on lidar–DTM data with a 1 m × 1 m resolution provided by the Thuringian State Office for Soil Management and Geoinformation (TLUBN, 2019; Zangana et al., 2023a). Different LSVs, namely, slope, topographic openness (TO), curvature (plan and profile), terrain roughness index (TRI) and topographic position index (TPI), were generated using an original DTM. A landslide inventory map (reference map) was created using manual on-screen mapping in ArcMap 10.7. Traditional and multi-directional hillshade were used as the primary visual base, following the method described by Schulz (2004). Hillshades and slope maps were visually evaluated for landslide features such as scarps and bodies by systematically panning through the imagery at scales ranging from 1 : 1000 to 1 : 200 and mapped accordingly at this scale to ensure the correct delineation of landslide boundaries. However, additional LSVs (e.g. curvature, TO, TPI, and TRI) were employed as supplementary layers to facilitate interpretation and boundary delineation, particularly in regions where hillshade and slope alone were inadequate for fully resolving the geomorphic manifestation of landslides. Furthermore, as in the method applied by Zangana et al. (2023b), we incorporated a LSVs-composite map visualisation that improved the detection of morphological features of landslides. Scarps and bodies were mapped separately wherever they could be clearly distinguished. In a few instances, scarp features could not be identified with confidence from the available data. Approximately 10 % of the mapped landslides were validated in the field. The inventory primarily includes deep-seated (rotational) landslides (34 landslides), along with a few shallow landslides (6 landslides).

3.2 GEOBIA-based landslide inventory mapping

We used the software eCognition 10.3 and developed a structured workflow to design a rule set for semi-automatic landslide mapping. This workflow enabled landslide identification using two distinct models. Model I (MI) used the default window size to calculate the LSVs as a pre-processing step for segmentation and classification, whereas model II (MII) used the optimal window size. The final results were exported as shapefiles to ArcGIS 10.7. The overall methodological framework, consisting of three main stages, is illustrated in Fig. 2.

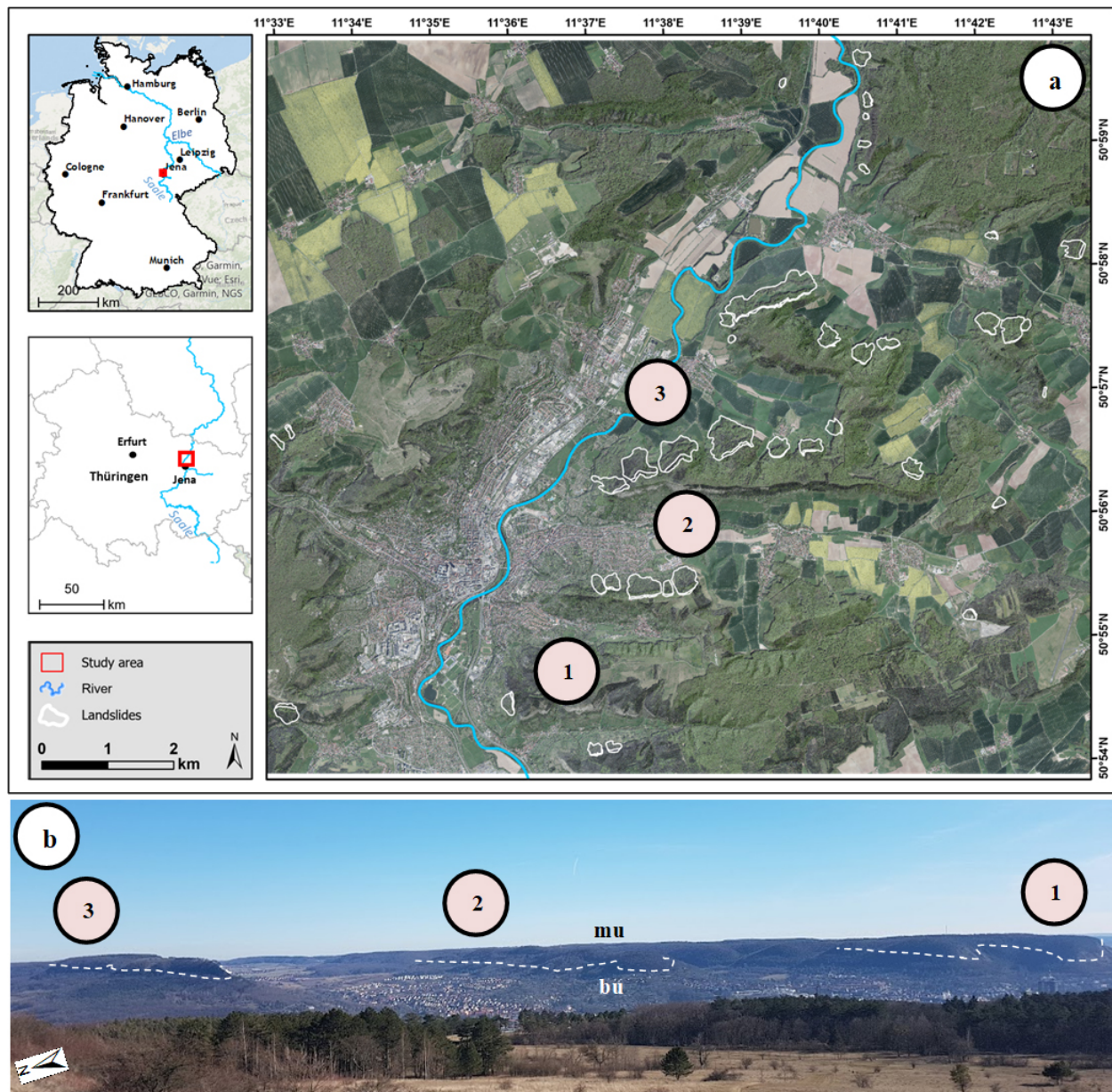


Figure 1. Study area. (a) Map: An orthophoto of the study area is overlaid on a hillshade DTM, with the landslide inventories delineated by white polygons. (b) Photo (taken by Ikram Zangana on 24 February 2019): The photo faces the southeast direction, showing the hillslopes of Kerenberge, Hausberg and Jenzig, along with a forested area and part of Jena City. Key locations are marked (1, 2 and 3), and the white dashed lines indicate the lithological boundaries, with Muschelkalk (mu) limestone above and Buntsandstein (bu) sandstone below. The orthophoto and the hillshade-DTM in (a) were obtained from TLUBN (2019) and other datasets are sourced from Esri (2017).

3.2.1 STAGE I: Data preparation

This stage was divided into two main steps. Step 1: A landslide inventory map was manually prepared using DTM hillshade data and a visual analysis of all relevant LSVs. This inventory map served as a reference for model development and as a baseline with which the final GEOBIA results were compared for accuracy assessment (AA). Step 2: ArcGIS 10.7 and R 4.3.2 were used to generate LSVs using differ-

ent window sizes. For MI, the default window sizes in ArcGIS were applied based on standard raster calculation methods and commonly published values. For MII, we adopted an advanced approach involving the automatic detection of optimal window sizes for each LSV for alignment between landslide-prone and non-landslide areas (Sîrbu et al., 2019).

For model training samples were collected from landslide scarps (MI: 6.09 ha; MII: 1.32), landslide bodies (MI: 36.20 ha; MII: 27.2 ha) non-scarp areas (MI: 9.42 ha; MII:

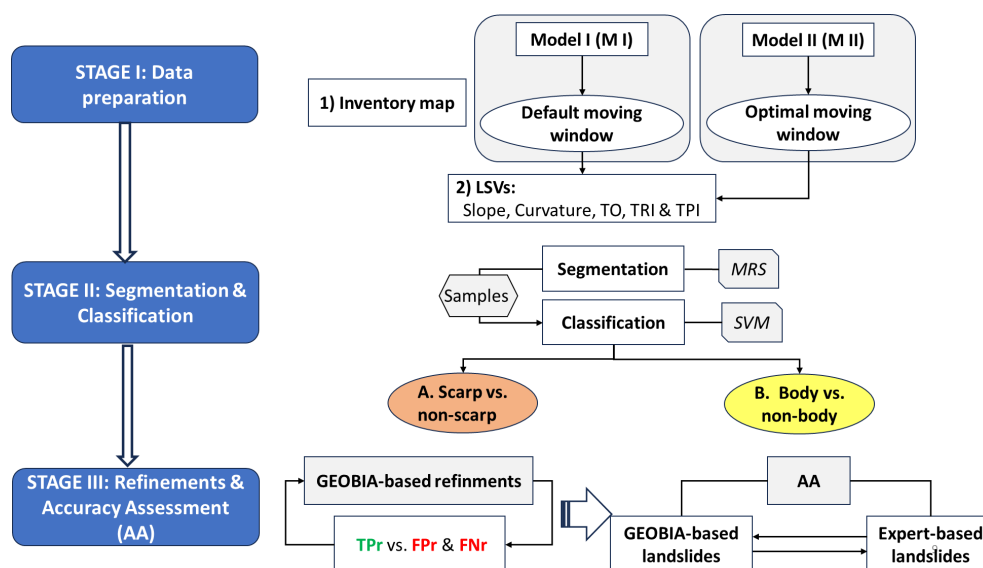


Figure 2. Flowchart of method used for mapping of landslide scarps and bodies. First, data are prepared using default and optimal window sizes. Then, segmentation and classification are conducted via MRS and SVM. Finally, refinement and accuracy assessment (AA) are performed by comparing the reference map with the GEOBIA results.

4.07 ha), non-body areas (MI: 53.95 ha; MII: 41.21 ha). These values represent the total sampled area used for each model (MI and MII). Classification was then performed using unsupervised methods and support vector machines (SVMs; for further details, see Tzotsos and Argialas, 2008; Hong et al., 2017). An algorithm was trained using these samples and then used to classify the data accordingly. For optimal results, this stage was repeated multiple times while adjusting the training samples iteratively to enhance accuracy in comparison with the inventory map.

3.2.2 STAGE II: Segmentation and classification

Segmentation and classification were performed using eCognition at two hierarchical levels. Segmentation was conducted using multi-resolution segmentation (MRS; Baatz and Schäpe, 2000) after trial-and-error across different scales (Draguț et al., 2010; Li et al., 2015) for distinct landslide components (landslide scarps and bodies). Specifically, landslide scarps and bodies were segmented and identified using separate projects and rule sets. MRS with scale parameters of 50 and 20 for landslide scarps using shape of 0.1 and compactness of 0.5 and MRS with scale parameters of 70 and 30 for landslide bodies using shape of 0.1 and compactness of 0.5 achieved the best fit and were thus applied to MI and MII, respectively.

3.2.3 STAGE III: Refinement and accuracy assessment (AA)

This stage consisted of two main steps: GEOBIA-based refinement and accuracy assessment (AA). The first, a

GEOBIA-based refinement aimed to enhance the initial SVM classification from Stage II by incorporating additional object-based rules. Based on the outcomes of Stage II, an additional stage (Stage III) was developed using expert knowledge and implemented as a rule set within the eCognition framework. This GEOBIA-based refinement leverages expert-driven interpretation in combination with object-level spatial and contextual information to enhance classification accuracy. Previous studies have demonstrated the value of combining machine learning with rule-based approaches for improving thematic mapping quality (Johnson and Xie, 2011; Eisank et al., 2014; Zylshal et al., 2016; Robson et al., 2020).

The refinement process focused on iteratively improving the true positive rate (TPR) while reducing both the false positive rate (FPR) and false negative rate (FNR). This was achieved by assessing a comprehensive set of object-based features derived from morphometric (e.g., slope, curvature, TPI), geometric (e.g., area, shape index, length-to-width ratio), and contextual attributes (e.g., distance to landslide-related objects, and the relative border to neighbor metric). The latter measures the proportion of an object's boundary shared with a predefined class, helping to identify embedded or adjacent features for reclassification. For example, a relative border value of 1 indicates complete enclosure by a reference class, while lower values suggest partial adjacency (for a further and comprehensive overview of the ruleset developed, see Tables A1–B2 in the Appendices).

Refinements were conducted using eCognition's interactive visualization tools, enabling semi-automated object filtering and targeted adjustments based on spatial inconsisten-

cies. Objects were assessed through iterative cycles of visual inspection, attribute filtering, and validation against the reference inventory using both number- and area-based accuracy metrics. Key decisions included merging or expanding TP-classified regions and reclassifying ambiguous objects based on rules such as (1) adjacency to existing TP objects, (2) sharing $> 80\%$ boundary with TPs, and (3) being fully surrounded by TP zones. Importantly, no expansion was allowed into areas clearly identified as non-landslide terrain. This process was repeated until no further improvements were observed. The landslide scarps and bodies were analysed separately, so different criteria and parameters were applied to each of them during the development of the rule set in eCognition. In other words, the landslide scarp area was treated separately from the landslide body area.

The second step, called AA, involved comparing the final result of GEOBIA-based refinement (stage III, part 1) with expert-based landslide data (i.e. the inventory map). This comparison helped assess the efficacy of each model (MI and MII) against the reference map. For a comprehensive investigation, AA was conducted separately for landslide scarps and bodies. As seen in Sect. 3.3, number-based AA, area-based AA and calculation of additional metrics were adopted (Cai et al., 2018; Simoes et al., 2023).

3.3 Accuracy assessment

Various metrics were used to evaluate the congruence between the GEOBIA mapping outcomes and the reference map quantitatively. These comparisons were conducted independently per model and per landslide component: landslides scarps and bodies.

3.3.1 Thematic accuracy assessment

We assessed the results through number-based and area-based accuracy assessment. First, following Cai et al. (2018), we developed an R script to assess the accuracy of the model results numerically. If the GEOBIA-detected polygon's overlapping area exceeded 50% of the area of the reference landslide polygon, then it was considered a correctly identified landslide (Eeckhaut et al., 2012; Knevels et al., 2019). The TP, FP and FN numbers and percentages were calculated according to MI and MII. Then, in addition to number-based AA, area-based AA (hectares [ha]) was adopted to obtain more detailed information about the absolute areas correctly detected as landslides (i.e. TP), undetected landslide areas (i.e. FN) and areas incorrectly mapped as landslides (i.e. FP). To achieve this, we overlaid the inventory map polygons (reference map) on the GEOBIA-based polygons, which included these three components, to calculate the percentage of each category and determine whether the use of the optimal moving-window size in MII improved the semi-automatic GEOBIA-based mapping results (Fig. 6). The script for this analysis was developed and implemented

in R using the GEOBIA results according to previously reported key concepts and algorithms (for further details, see Eisank et al., 2014; Cai et al., 2018).

3.3.2 Segmentation metrics

An R script developed using the *segmetric* package to calculate the segmentation accuracy of the objects of interest through various metrics (Simoes et al., 2023). As outlined in Table 6, we analysed key metrics relevant to landslide studies: area fit index (AFI), over-segmentation (OS), under-segmentation (US), F-measure, recall and precision. These metrics were based on area proportions, with values between 0 and 1 except for AFI. A value closer to zero indicated a better spatial match between the test and reference datasets (Dias et al., 2023).

4 Results

This chapter presents the main results of this study, specifically the optimisation results of window sizes for LSVs in MII, the results of GEOBIA-based landslide detection and the model performance evaluation results from different AA approaches.

4.1 Optimisation of window sizes for LSVs in MII

Figure 3 shows the variation in the optimal window size for each LSV across multiple runs, highlighting noticeable differences between landslide scarps and bodies. Some LSVs (e.g. TO, plan curvature and profile curvature) have consistent window sizes, whereas others (e.g. slope and TRI) show greater variability. Table 1 shows the final window sizes used in the analysis for both landslide components in MII, along with the default values used in MI for comparison. The optimal window sizes differ not only between LSVs but also between scarps and bodies within the same LSV. Hence, separate rule sets were developed in eCognition for each landslide component. Segmentation, classification, refinement and AA were then performed independently for the scarps and bodies.

4.2 GEOBIA-based landslide modelling results

The GEOBIA-based landslide modelling results, specifically those of landslide scarps and bodies for both models (MI and MII), were compared with the inventory map to assess their spatial correspondence (Figs. 4 and 5). Figure 4a shows the MI results (default window sizes). The brown and yellow polygons represent the model-detected landslide scarps and bodies, and the blue and pink polygons indicate the landslide scarps and bodies in the reference map for comparison. Figure 5a shows the same area but illustrates the MII results. In both figures, the polygons within the black-dashed-line regions are further discussed in Sect. 5. A visual inspection

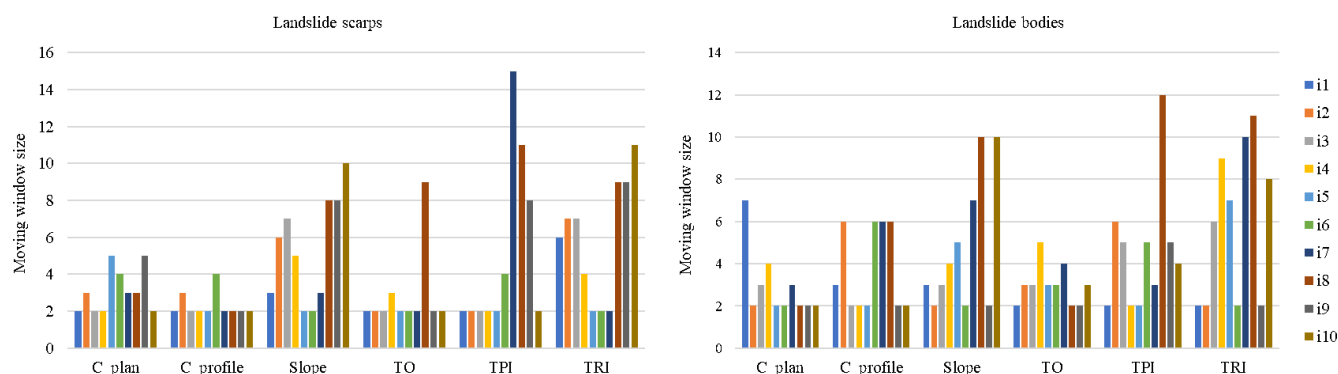


Figure 3. Optimal window sizes for each LSV in predicting landslide scarps and bodies. Note: i1, i2, ..., i10: number of iterations; C: curvature; TO: topographic openness; TRI: terrain roughness index; TPI: terrain position index.

Table 1. LSVs and corresponding window sizes per model.

Models/LSVs		Slope	C_plan	C_profile	TO	TRI	TPI
I*	Scarp and Body	3 × 3	3 × 3	–	3 × 3 and 25 × 25	3 × 3	33 × 33
	Scarp	11 × 11	7 × 7	5 × 5	5 × 5	7 × 7	11 × 11
II**	Body	11 × 11	5 × 5	7 × 7	7 × 7	9 × 9	13 × 13

* Default window size, ** optimal window size.

of these maps shows that MI covers a larger portion of the landslide body areas compared with MII, but MII performs better in detecting scarp zones. However, on-screen analysis shows that MII is more precise than MI for each landslide component, as indicated by the brown and yellow polygons (GEOBIA-based results) and the blue (scarps) and pink (bodies) polygons (reference map). This is particularly evident when considering the accuracy of landslide size and FPr. These results are assessed more thoroughly in Fig. 6 and Sect. 4.3.

The morphological characteristics of the landslides (scarps and bodies) in the Jena region highlight notable distinctions between these components, as summarized in Tables 2 and 3. The results show that scarps have slope mean values of 48 and 40.5° in MI and MII, respectively, whereas bodies maintain a consistent slope mean value of approximately 20° across both models. This suggests that scarp areas are more sensitive to the optimized approach applied in MII, while body areas remain relatively unchanged. Scarps exhibit positive values for plan curvature (C_plan), while bodies show lower values. Similarly, for profile curvature (C_profile), scarps display positive values, whereas bodies exhibit negative values, further emphasizing their distinct morphological characteristics. The TRI mean values further differentiate scarps and bodies, with scarps showing significantly higher values (3.73 and 5.09 for MI and MII, respectively) compared to bodies (0.95 and 1.93 for MI and MII, respectively). Additionally, TPI values for scarp areas are higher in MII

than in MI, while for body areas, the TPI values are notably lower in MII compared to MI.

4.3 Accuracy assessment results

4.3.1 Thematic accuracy assessment

The thematic accuracy assessment is conducted using two complementary approaches: object-based (number-based) and area-based accuracy metrics. First, the number-based AA results (Table 4) show a significant improvement in the scarp zones for MII, with a higher TPr and significant reductions in both FPs and FNs. In the landslide body areas, the FPs were also significantly reduced, indicating an overall improvement in classification accuracy under the optimised window size. Next, the area-based AA results are summarised in Table 5, with MII showing significant improvements over MI. As for scarp detection, MII increases the TP area from 6.3–9.1 ha and reduces the FNs accordingly, demonstrating better detection performance than MI. Although the FPs remain relatively high, they moderately decrease under MII. As for landslide body detection, MII significantly reduces the FPs from over 760 ha in MI to approximately 155 ha, indicating a significant improvement in mapping accuracy. However, a trade-off is observed, with the FNs increasing slightly. These trends are also noticeable in Figs. 6 and 7, which shows a significantly lower FP in MII (red polygons in Fig. 7) than in MI (Fig. 6).

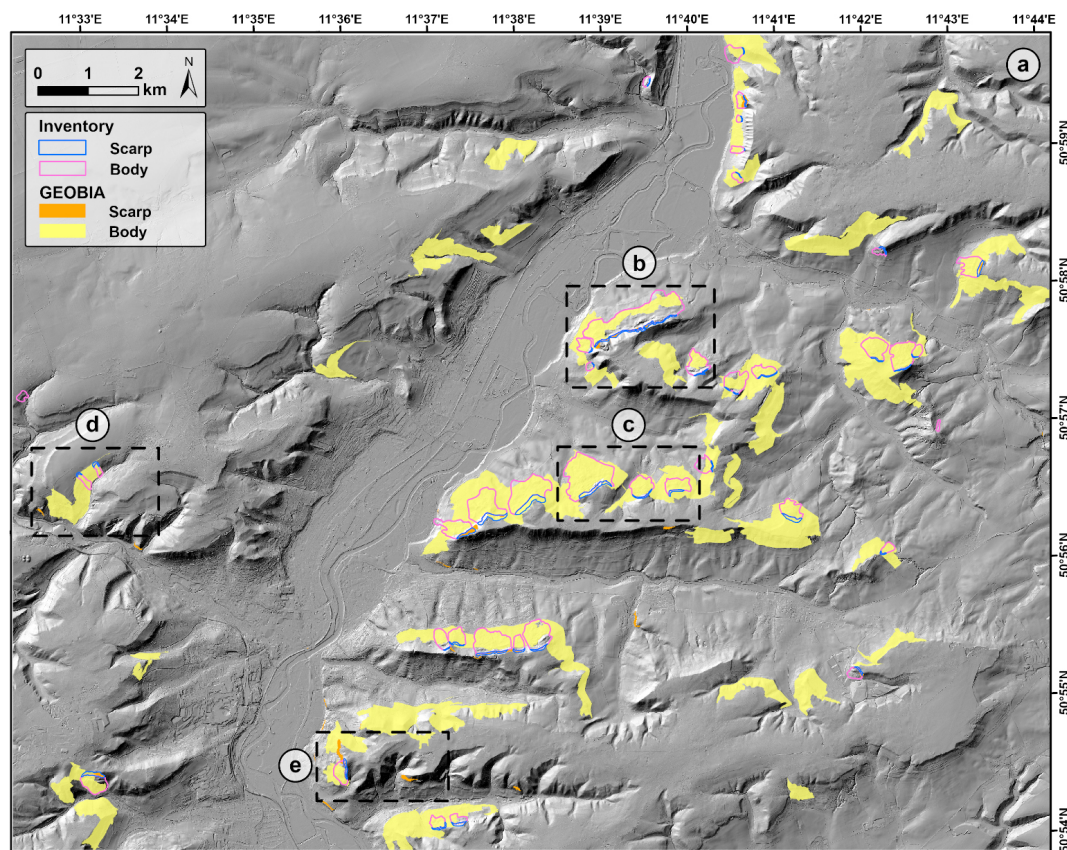


Figure 4. Final map of semi-automatic landslide detection using MI, displayed over hillshade DTM (TLUBN, 2019) throughout study area. Detected landslides are shown as coloured polygons (brown: scarps; yellow: bodies), while the inventory map is also displayed for comparison. The insets outlined by black dotted lines are magnified and analysed in Fig. 8.

Table 2. The morphological characteristics of landslides (scarps and bodies) in Jena region as detected by GEOBIA, Model I.

LSVs/value	Scarp			Body		
	min	max	mean	min	max	mean
Slope (°)	34.9	61.5	48.2	14.88	25.69	20.28
C _{plan}	−1.04	12.19	5.57	−0.032	0.128	0.048
TO3 × 3	−0.003	0.029	0.013	−0.00085	0.00051	−0.00017
TO25 × 25	−0.001	0.099	0.049	−0.00201	0.00373	0.00086
TRI	1.82	5.64	3.73	0.68	1.22	0.95
TPI	0.1	2.8	1.4	−0.07	0.05	−0.01

4.3.2 Segmentation metrics

The US values for both models are below 0.50 in landslide scarp detection. Specifically, the US value drops from 0.84 in MI to 0.60 in MII, demonstrating that the use of the optimal window size in MII significantly improves the results (Table 6). Likewise, the OS value for scarps decreases from 0.53 in MI to 0.33 in MII. Additionally, the precision value improves in MII, confirming the effectiveness of the optimised approach.

5 Discussion

This study highlights the efficacy of integrating GEOBIA with high-resolution DTM data for the inventory mapping of forest-covered old landslides in middle-mountain regions. The implementation of the optimal window size (MII) substantially enhances landslide detection accuracy while significantly reducing both the number and total area of FPs relative to the use of the default window size (MI). These results align with those of Sirbu et al. (2019), who demonstrated window size variability across different LSVs for landslide

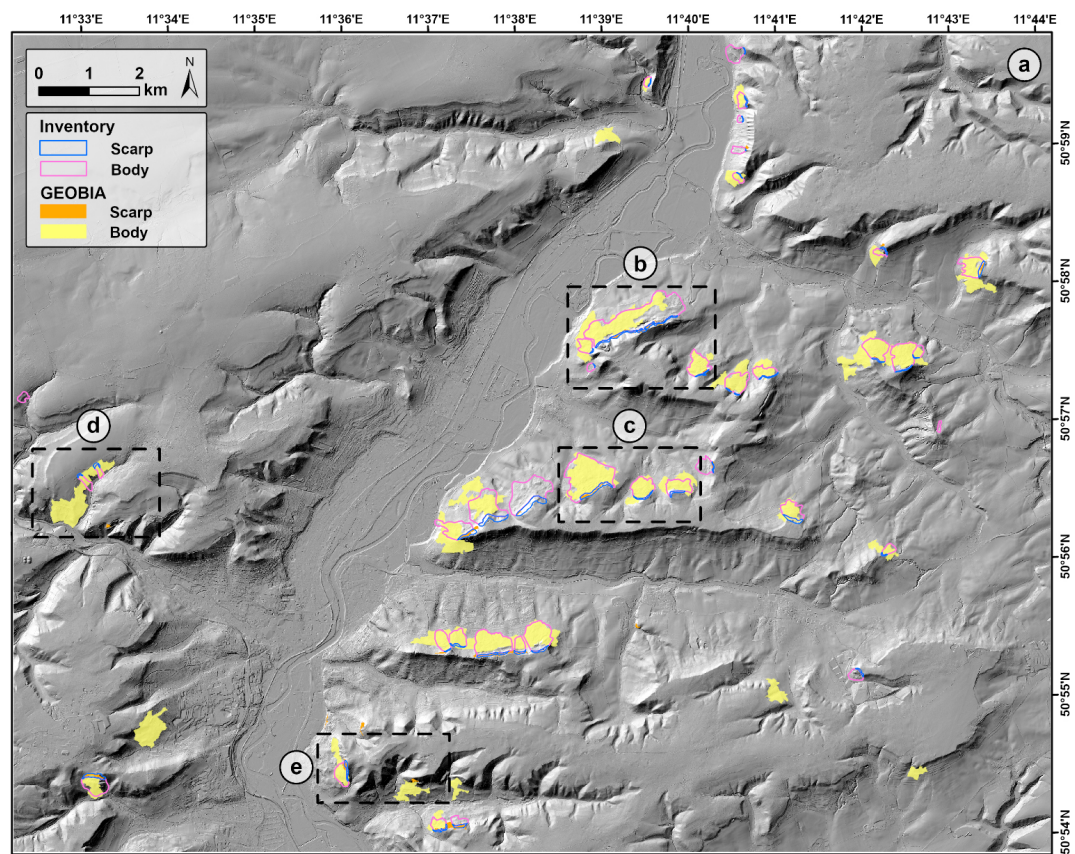


Figure 5. Final map of semi-automatic landslide detection using MII, displayed over hillshade DTM (TLUBN, 2019) throughout study area. Detected landslides are shown as coloured polygons (brown: scarps; yellow: bodies), while the inventory map is also displayed for comparison. The insets outlined by black dotted lines are magnified and analysed in Fig. 8.

Table 3. The morphological characteristics of landslides (scarps and bodies) in Jena region as detected by GEOBIA, Model II.

LSVs/value	Scarp			Body		
	min	max	mean	min	max	mean
Slope (°)	33.4	47.7	40.5	15.9	27.9	21.9
C _{plan}	0.0001	0.0205	0.0107	−0.0044	0.0014	−0.0015
C _{profile}	−0.0028	0.0040	0.0006	−0.0014	−0.0001	−0.0012
TO	−0.0014	0.0086	0.0036	−0.00186	0.00003	−0.00091
TRI	3.77	6.42	5.09	1.32	2.54	1.93
TPI	1.59	13.24	7.41	−3.83	0.11	−1.86

scarps. Our study broadens this understanding by analysing both scarp and landslide body areas, revealing that window sizes differ not only across LSVs but also between landslide scarp and body areas within the same LSVs (Fig. 3 and Table 1). Consequently, landslide scarps and bodies should be detected separately within the model for an accurate analysis of each landslide component.

In our study area, large forest-covered landslides (> 0.5 ha) are more successfully detected than smaller landslides, as they mostly show a strong geomorphological signature (Fig. 8b). This is similar to previous findings (Kn-

evels et al., 2019; Dias et al., 2023). However, MII has a lower proportion of misclassified areas within the same inset (Sect. 4.3.1 and Fig. 7), highlighting its ability to delineate landslide features accurately throughout the study area. Additionally, some automatically delineated landslide polygons extend beyond the boundaries of the inventoried actual landslide areas (Figs. 4 and 5). These deviations can be attributed to limitations in the segmentation and classification algorithms, which may produce irregular or overly coarse objects, or potential misclassifications or errors in object merg-

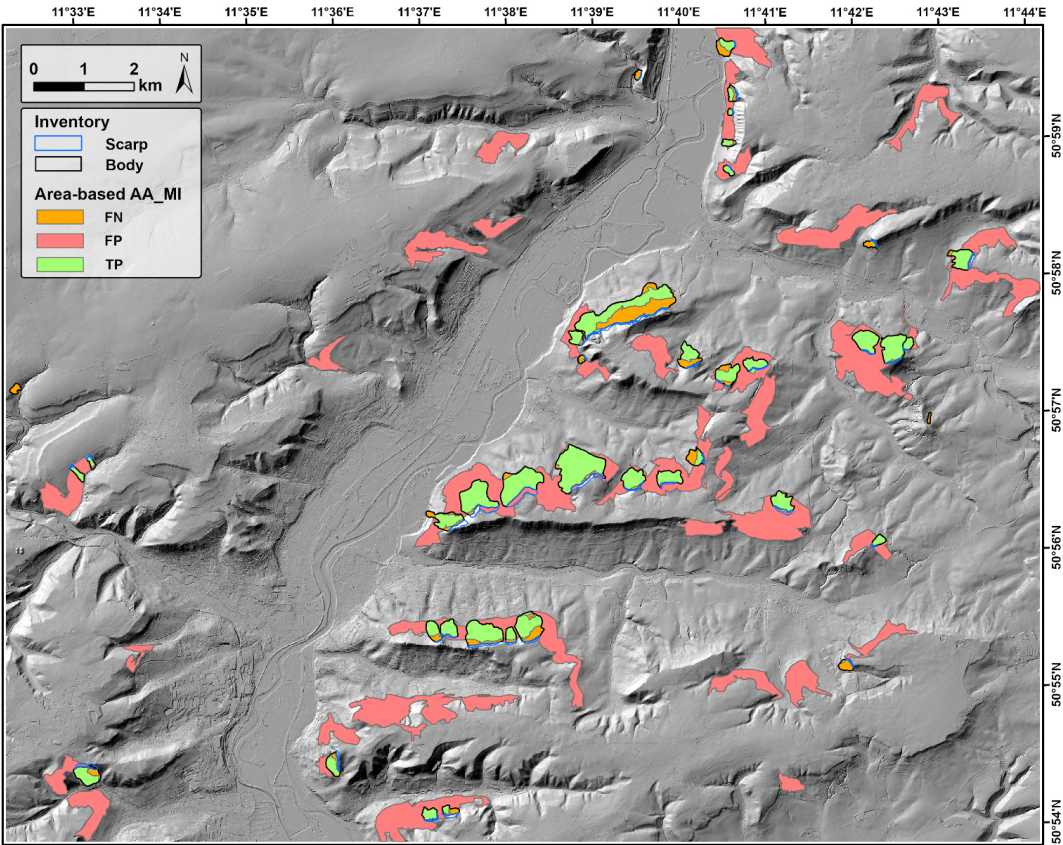


Figure 6. Area-based accuracy assessment of landslide body mapping using GEOBIA in Model I (True Positives (TP), False Positives (FP), and False Negatives (FN)), displayed over hillshade DTM (TLUBN, 2019).

Table 4. Number-based comparison of True Positives (TPs), False Positives (FPs) and False Negatives (FNs) in landslides detection per model.

Landslide	Model	TP	(%)	FP	(%)	FN	(%)
Scarps	I	21	55.2	24	53.3	17	44.8
	II	25	65.8	5	16.6	13	34.2
Bodies	I	17	42.5	21	52.5	23	57.5
	II	21	52.5	8	20.0	19	47.5
Inventory	38 (scarps) / 40 (bodies)						

ing due to the use of a low threshold for object characteristics during refinement and the final layout.

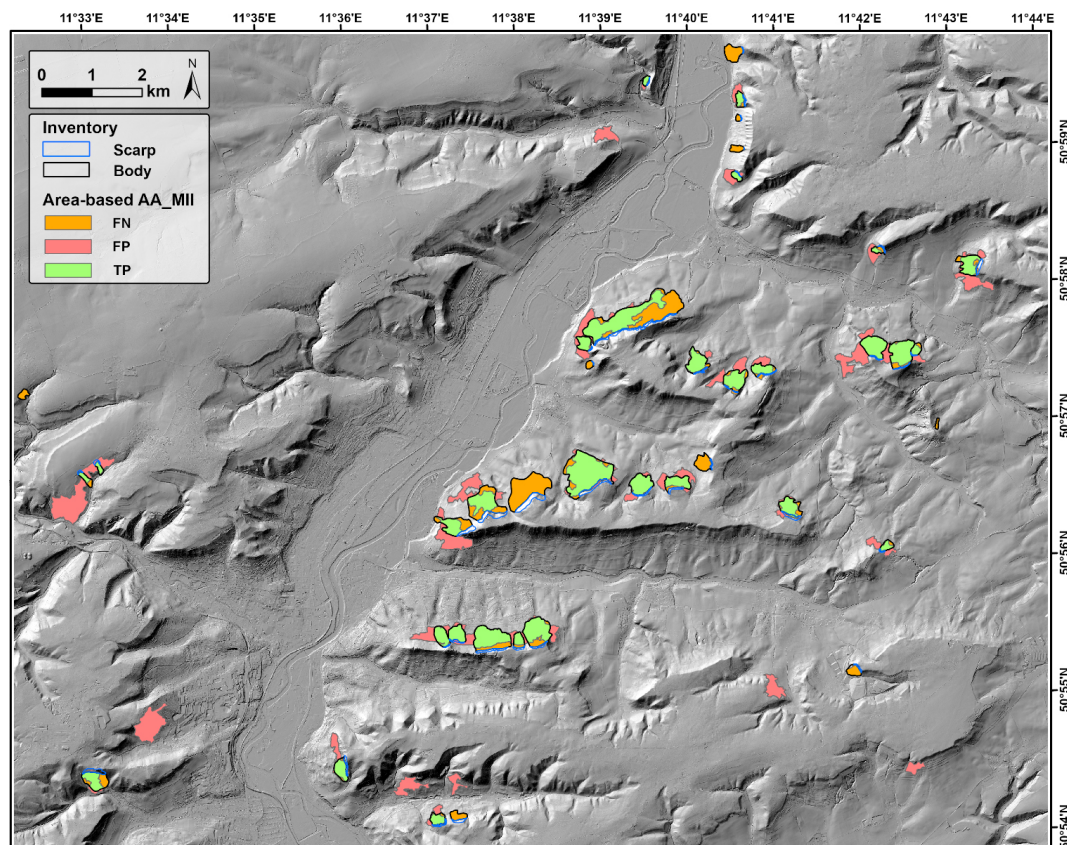
We should acknowledge that in one instance (see Fig. 8b), a large mapped landslide may in fact consist of multiple individual events. Due to uncertainty regarding the precise boundaries between these possible landslides, we decided to map the area as a single, large landslide in the inventory map. However, this issue is partially addressed through the area-based accuracy assessment presented in Sect. 4.3.1, which minimizes the impact of such limitations on model validation. Future studies could improve the accuracy further by labelling such ambiguous cases as “uncertain” or separating

them from clearly defined landslides in the inventory. This would help to better assess model performance and transferability.

Other misclassifications occur in areas where the geomorphological signature or roughness resembles the characteristics of landslide body or scarp candidates defined by the developed rule set. Both models incorrectly detect a scarp in the same inset/window in Fig. 8d but in different locations. The parameters in these areas are similar to those of actual landslide scarps, so distinguishing them solely based on DTM data is difficult. The misclassified area is actually rock outcrops, which are common in this region due to its local-scale

Table 5. Comparison of True Positives (TPs), False Positives (FPs) and False Negatives (FNs) in landslides detection per model (area in hectares).

Landslide	Model	TP	%	FP	%	FN	%
Scarps	I	6.3	30.6	9.3	59.6	14.3	69.3
	II	9.1	43.8	8.0	47.0	11.6	56.2
Bodies	I	191.2	78.7	769.2	80.0	51.8	21.3
	II	161.9	66.6	155.8	49.0	81.0	33.3
Inventory	243 (scarps) / 20.7 (bodies)						

**Figure 7.** Area-based accuracy assessment of landslide body mapping using GEOBIA in Model II (True Positives (TP), False Positives (FP), and False Negatives (FN)), displayed over hillshade DTM (TLUBN, 2019).

variations in lithology, where different layers and materials respond differently to weathering and erosion (see the geological map of the region in Zangana et al., 2023b). Most landslide scarp FPs in our study can be attributed to this issue. In addition, both models misclassify landslide scarps as landslide bodies for two landslides from the inventory map in the same location in Fig. 8d. Thus, the scarp and landslide body areas in these cases are highly similar, possibly due to landslide type/age and human activity, so the rule set cannot easily differentiate them from the rest of the

study area. However, the landslides are successfully mapped, highlighting the need for detecting different landslides separately. This shortcoming of our approach is similar to those reported in previous studies on forest-covered landslides (Li et al., 2015; Pawłuszek et al., 2019), demonstrating the challenges of performing inventory mapping without FPs using DTM data alone (Eeckhaut et al., 2012; Bell et al., 2012; Goetz et al., 2014; Knevels et al., 2019).

Furthermore, both models identify the same location in Fig. 8e as a landslide candidate (as a landslide scarp or a landslide body). The right-hand part of Fig. 8e in MII shows a landslide that is excluded from the initial inventory due to

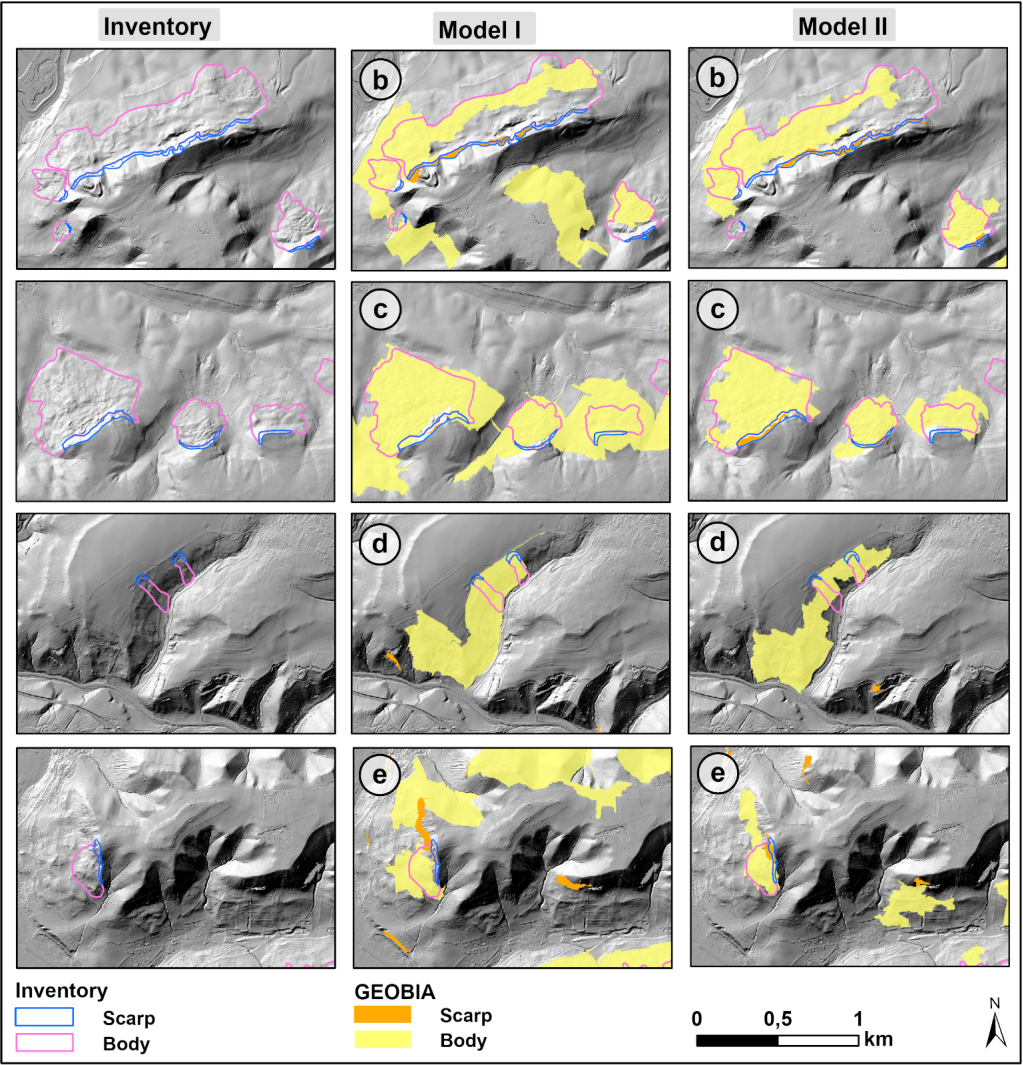


Figure 8. Detailed results of Model I (MI) and Model II (MII) for selected areas. The left column shows the landslide inventory overlaid on the hillshade DTM (TLUBN, 2019). The middle and right columns display MI and MII results, respectively, corresponding to the inset areas b–e shown in Figs. 4 and 5. These zoomed-in views highlight differences in model performance within representative subregions.

Table 6. Metrics used per landslide component per model.

Metric	Scarp		Body	
	M I	M II	M I	M II
AFI	−0.37	−1.25	−10.21	−3.89
OS	0.53	0.33	0.18	0.18
F_measure	0.42	0.50	0.28	0.57
US	0.30	0.43	0.84	0.60
recall	0.36	0.48	0.80	0.77
precision	0.50	0.52	0.17	0.45

its dissimilarity with the other landslides and its small size. In MII, the body area of this landslide is incorrectly mapped over cropland, grassland and built-up areas. On the left-hand

side of the same window (Fig. 8e, MI), the landslide body is wider than the inventory map area that may correspond to the inventory map but is excluded from the initial inventory due to the insufficiency of the available information for it to be classified as a large landslide. In the MI image in Fig. 8d, the FP area extends over a wide region, particularly into forested areas and erosional rims, demonstrating that this model has lower landslide detection precision than MII. Therefore, landslide size should be addressed in future studies. Detecting landslides of different types and sizes at various levels can enhance detection rates and further reduce the FPr.

An analysis of the AA results reveals that MII outperforms MI in detecting landslide components (bodies and scarps) in terms of correctly identified areas and FP reduction. For instance, MII reduces the FPr by approximately 30 % and 20 %

for landslide scarps and landslide bodies, respectively (Table 4). MII slightly underestimates the landslide body areas; the TPr for landslide body detection decreases, offset by an increase in the TPr for scarp areas. Although MI yields a higher TPr for landslide body areas, its FPr is approximately 30 % higher than that of MII, highlighting the importance of considering the FPr alongside the TPr and FNr for a comprehensive evaluation of model performance. MII has considerable potential, effectively reducing the FPr while maintaining a strong TPr. However, further research is needed to enhance the applicability of this approach across various environments and datasets.

Our TPr is comparable to that of Eeckhaut et al. (2012), who investigated the semi-automatic detection of landslides using lidar data and identified 71 % of landslides using object-based detection. In comparison, MII achieves TPr values of 65.8 % and 72.5 % for landslide scarps and landslide bodies, respectively. However, our approach demonstrates significantly better accuracy through minimising of FPs. Eeckhaut et al. (2012) identified 18 FP landslides in an area affected by 38 deep-seated landslides (47 %), and Martha et al. (2010) reported 73 FP landslides for 55 expert-identified landslides (132 %). As shown in Tables 2 and 3, our study identifies only 5 FP landslide scarps (20 % relative to the TPs) and 7 FP landslide bodies (24 % relative to the TPs). Therefore, MII detects landslides more efficiently than MI and the abovementioned approaches. However, some studies (Martha et al., 2010; Eeckhaut et al., 2012; Knevels et al., 2019) do not provide the number or total area of FPs or only present them numerically, hindering a comprehensive comparison of methods. Conversely, our evaluation is more detailed, enabling a systematic assessment of model precision in identifying a specific number of TPs while minimising FPs.

Misclassification also occurs in areas with degraded geomorphological signatures (Fig. 8d and e). Landslide scarps are often misidentified in regions with features resembling those of scarp candidates. These errors may be attributed to human-made structures, such as roads, pits, ridges and rock toes. Similar false detections are observed in areas with partially eroded or weathered limestone formations, particularly in areas where they overlay sandstone. This misclassification pattern aligns with commonly reported results (Eeckhaut et al., 2012; Hölbling et al., 2017; Knevels et al., 2019; Dias et al., 2023).

Selecting the appropriate window sizes for the LSVs is challenging (Fig. 3 and Table 1). The results show considerable variability across the 10 runs, with the optimal window sizes often being larger for scarp zones than for body areas. For example, the TPI and TRI significantly deviate between the optimal and default window sizes, highlighting the need to fine-tune window sizes based on the specific geomorphometric characteristics of each landslide feature. By contrast, the default window sizes used in MI often result in under- or over-segmentation, especially in scarp zones, compromising

detection accuracy. These results highlight the complexity of adjusting window sizes for accurate scarp and body detection and emphasise the advantages of the tailored approach of MII in overcoming these limitations.

Compared with MI, MII is more effective in detecting individual landslides as distinct polygons and separating them from neighbouring landslides. Additionally, MII significantly reduces the FP number and area, as shown in the model comparison in Fig. 7. This highlights the robustness of the optimal window size approach of MII, which is more effective for landslide detection than default or manually selected window sizes, which have been commonly used in many studies for decades. Overall, this approach is a valuable advancement in improving semi-automatic landslide inventory mapping, particularly in forested areas, where the limited availability of optical data often hampers complete inventory mapping (Eeckhaut et al., 2012; Li et al., 2015; Knevels et al., 2019). Although Stage III was first developed in the Jena region, the framework and rulesets can be applied to other areas where landslides are well expressed in hillshade and distinct from their surroundings. This condition is often met for forest-covered landslides of varying ages, and may also apply to younger landslides, with no or limited human impact. While some refinement parameters may need local adjustment, the method is not restricted to a specific landslide type or setting, and its broader applicability should be further evaluated in future studies.

6 Conclusion

A GEOBIA-based approach is developed and used for the semi-automatic mapping of landslide inventories in the forested areas of the middle-mountain regions of Jena, Germany. The proposed method effectively maps forest-covered landslides, with a particular focus on medium and large landslides (greater than 0.5 ha), but does not detect smaller landslides. MII, which uses the optimal window size, maps landslide scarps with higher accuracy than MI, which relies on default window sizes. MII shows a significant (15 %) improvement in scarp detection during number-based AA while reducing the FPr by 30 %. However, this FPr reduction entails a trade-off, as the FNr increases by approximately 15 %. Nonetheless, MII remains highly effective for semi-automatic landslide mapping in forest-covered areas.

High-resolution DTM derivatives serve as the base data for landslide mapping using GEOBIA, which incorporates an optimal window size to detect forest-covered old landslides in middle-mountain regions. Our analysis shows that this approach may significantly improve the accuracy of landslide mapping in areas with sparse or no vegetation and in regions where landslides are newly formed or have recently altered the terrain. This is due to the superior ability of DTM data to show recent landslide features compared with historical ones.

This study emphasises the importance of calculating window sizes separately for different landslide components, as landslide scarps and bodies require distinct window sizes for accurate detection. This factor should be considered thoroughly before any calculation or modelling process involving landforms of interest. As landform detection depends on the defined window size, our automated objective approach is highly suited for future research and semi-automatic landform modelling. However, further evaluation is required to ascertain the transferability of this method to other regions; nonetheless, this method should be globally applicable to the detection of landslides with well-defined geomorphological features using high-resolution DTM data. As the pioneering use of GEOBIA for landslide inventory mapping in the Jena area, this study serves as a foundation for future research on landslides in this region. Furthermore, it can be used as a base map for hazard and risk assessments, especially as climate change may reactivate old landslides, as has occurred in many areas across Germany and around the world.

Appendix A: Ruleset Model I

Table A1. Landslide Scarps Refinement Steps.

Refinement Step	Actions	Conditions/Criteria	Additional Notes
Refinement 1	Remove objects	IF SLOPE < 33 AND TRI < 2 Remove IF TRI < 1.7	Then → Merge objects
	Expand objects	IF non-Scarp (Rel. Border to Scarp Candidate > 0.1 AND TRI > 2.5 AND SLOPE > 45) Remove IF AREA < 1500 pixels AND Length/Width > 5	Then → Merge objects
Refinement 2	Remove objects	IF TPI < −0.01 AND (SLOPE < 33 AND TRI < 2) Remove IF (TRI < 1 AND TPI < 1) Remove IF Length/Width > 3 AND TRI < 1.8 Remove IF Rectangular fit < 0.1 AND Roundness > 2	Then → Merge objects
	Remove objects	IF (AREA > 20000 pixels AND TPI < 0.1) OR AREA < 100 pixels	AND IF TPI < 0.02 OR Length/Width > 10 OR C_plan < 0
Refinement 3	Remove objects	IF SLOPE < 34 OR C_plan < −3 Remove IF TOP > 0.03 OR TOP < −0.004 Remove IF TPI < 0.1	Then → Merge objects

Table A2. Landslide Bodies Refinement Steps.

Refinement Step	Actions	Conditions/Criteria	Additional Notes
Refinement 1	Expand objects	IF unclassified (SLOPE > 12 AND Rel. Border to Body Candidate > 0.5)	
		IF non-Body (Rel. Border to Body Candidate > 0.5 AND Rel. Border to non-Body $\leq$ 0.2)	Then → Merge objects
		IF non-Body (Rel. Border to Body Candidate > 0.6)	
		IF non-Body (SLOPE > 10, C _{plan} < 0.1 AND Rel. Border to Body Candidate $\geq$ 0.1)	
		Remove IF AREA < 5000 pixels	
	Expand objects	IF non-Body (Rel. Border to Body Candidate $\geq$ 0.1 AND C _{plan} < 0.2 AND SLOPE > 12)	
		IF non-Body (Rel. Border to Body Candidate $\geq$ 0.4, C _{plan} < 0.3 AND SLOPE > 15)	
		IF non-Body (Rel. Border to Body Candidate $\geq$ 0.7 AND C _{plan} < 0.3 AND SLOPE > 10)	
	Remove objects	IF Length/Width $\geq$ 6.1 OR (Length/Width $\geq$ 5 AND SLOPE < 15)	Then → Merge objects
		Remove IF AREA < 15 000 pixels	
Refinement 2	Remove objects	IF SLOPE < 14 AND TRI < 0.6	
	Expand objects	IF unclassified (Rel. Border to Body Candidate $\geq$ 0.5 AND SLOPE $\geq$ 12)	
		IF non-Body (SLOPE > 10, C _{plan} < 0.1 AND Rel. Border to Body Candidate $\geq$ 0.1)	
		Remove IF non-Body (Rel. Border to Body Candidate > 0.5 AND Rel. Border to non-Body $\leq$ 0.2)	Then → Merge objects
		Remove IF (TRI < 0.7 AND TPI < −0.05) OR AREA < 15 000 pixels	
	Expand objects	IF unclassified (Rel. Border to Body Candidate = 1)	Then → Merge objects
		→ Expand IF (TRI > 0.6 AND C _{plan} > 0.3)	
		Remove IF AREA < 46 000 pixels	
	Expand objects	IF unclassified (Rel. Border to Body Candidate > 0.5, C _{plan} > 0.1 AND TRI > 0.45)	OR IF Rel. Border to Body Candidate > 0.5 → Merge objects
	Remove objects	IF (AREA < 150 000 pixels AND C _{plan} < 0) OR SLOPE < 5	
Refinement 3	Remove objects	IF SLOPE < 14	
		IF TPI < −0.1	
		IF C _{plan} < −0.04 OR C _{plan} > 0.2	Then → Merge objects

Appendix B: Ruleset Model II

Table B1. Model II Landslide Scarps Refinement Steps.

Step	Action	Conditions/Criteria	Notes
Initial Pre-processing	Segmentation	MRS 20 (Shape: 0.1, Compactness: 0.5)	
	Initial classIFication	Remove plateau AND floodplain AREAs by identIFying “Initial Scarp AREA” to retain Landslide polygons AND buffers	
Potential Scarp IdentIFication	Remove segments	IF mean SLOPE ≥ 0.3 , TPI ≥ 0.65 , TRI ≥ 0.8	Define as Potential Scarp
	Expand AREA	IF mean SLOPE > 0.7 AND Rel. Border to Potential Scarp ≥ 0.45 Or mean SLOPE ≥ 25 , TPI ≥ 1.5 , mean TRI ≥ 2.5	
	ClassIFication	SVM (Scarp vs. Non-Scarp)	
Refinement 1	Expand Scarps	IF Rel. Border to Scarp > 0.85 AND mean SLOPE ≥ 0.4 Or Rel. Border to Scarp > 0.3 , mean TPI ≥ 12 , mean SLOPE > 0.6	
	Remove Scarps	IF $-29 < \text{mean } C_{\text{profile}} > 6.3$ AND $-5.2 < \text{mean } C_{\text{plan}} > 37$ IF $-0.04 < \text{TOP} > 0.14$ IF mean SLOPE > 0.45 AND mean TPI < 0.14 or mean TRI < 1.14	
	Further Expand Scarps	IF mean SLOPE > 0.65 , mean TRI > 2.2 , mean TPI > 7 , AND Rel. Border to Scarps > 0.2 For unclassIFied/non-Scarp: mean SLOPE > 0.4 AND Rel. Border to Scarps > 0.9	
	Remove Scarps	IF Rel. Border to Scarps < 0.4 AND AREA > 2000 pixels	
	Merge segments	Merge all segments	
	Remove Scarps	IF AREA < 1000 pixels AND mean SLOPE < 0.74	
	Expand Scarps	IF mean SLOPE > 0.45 , Rel. Border to Scarps > 0.25 , Rel. Border to non-Scarps < 0.01 Or mean SLOPE > 0.7 , Rel. Border to Scarps > 0.3 , mean TRI < 2.15 Or mean SLOPE > 0.65 , Rel. Border to Scarps > 0.1 , mean TRI < 2.1 , Rel. Border to non-Scarps < 0.5 , AREA < 6800 pixels	
Refinement 2	Merge non-Scarps	IF mean SLOPE > 0.48 , TRI > 1 , mean TPI > 7	
	Further Expand Scarps	IF mean SLOPE > 0.5 , Rel. Border to Scarps > 0.3 , Rel. Border to non-Scarps > 0.43 , TRI < 1.7	
	Remove Scarps	IF Rel. Border to non-Scarps > 0.85 , AREA < 3000 , mean SLOPE < 0.7 AND IF mean TPI < 2.45 , mean SLOPE < 0.65 , AREA < 1600 Or mean SLOPE < 0.75 , AREA < 8000 , mean TPI > 10 Or mean SLOPE < 0.7 , AREA $< 10\,000$, mean TOP < 0.028	
Landslide Bodies			

Table B2. Model II Landslide Bodies Refinement Steps.

Step	Action	Conditions/Criteria	Notes
Initial Pre-processing	Segmentation	MRS 30 (Shape: 0.1, Compactness: 0.5)	
	Potential Body Segments	Remove IF mean SLOPE ≥ 0.2 , TPI < 7 , TRI ≥ 0.5	
	ClassIFication	SVM (Bodies vs. Non-Bodies)	
Refinement 1	Expand Bodies	IF Rel. Border to Body ≥ 0.8 AND mean SLOPE > 0.25 , or Rel. Border ≥ 0.9	
	Merge Body segments	Merge all Body segments	
	Expand further	IF Rel. Border to Body ≥ 0.7 , Rel. Border to non-Body < 0.3 , mean SLOPE ≥ 0.25	
		Or Rel. Border to Body ≥ 0.8 , Rel. Border to non-Body < 0.3 , mean TRI ≥ 0.35	
		Or Rel. Border to Body ≥ 0.4 , Rel. Border to unclassIFied < 0.01	
		Or Rel. Border to Body ≥ 0.55 , Rel. Border to non-body < 0.2 , mean TRI > 0.6	
		Or Rel. Border to Body ≥ 0.6 AND mean TRI > 0.4	
		Or Rel. Border to Body ≥ 0.15 , mean TRI > 1 , mean SLOPE > 0.4	
Refinement 2	Merge Body segments	Merge all Body segments	
	Expand Bodies	IF Rel. Border to Body ≥ 0.3 , mean SLOPE > 0.2 , mean TRI > 0.6	
	Remove Bodies	IF $-0.0022 < \text{mean TOP} \leq 0.003$	
		Or AREA $< 10\,000$ pixels AND mean SLOPE > 0.25	
		Or AREA $< 25\,000$ pixels AND mean SLOPE < 0.25	
		Or AREA $> 400\,000$ pixels	
		Or mean C_plan < 0.0 AND/or mean C_profile < 0.0 AND AREA $> 50\,000$ or mean TPI > 1.3	
	Expand from unclassIFied/non-Body	IF Rel. Border to Body > 0.99	
Refinement 3	Remove Bodies	IF mean SLOPE < 0.4 AND AREA $< 15\,000$ pixels	
		Or mean SLOPE < 0.3 , AREA $< 50\,000$, mean TPI > 0.8	
		Or mean SLOPE < 0.42 AND mean TPI < -1.9	
		Or AREA $< 40\,000$ AND mean TPI > 1.4	
		Or mean C_profile < 0.0 AND mean TPI > 1 , or mean SLOPE < 0.25	
		Or $15\,000 < \text{AREA} < 65\,000$ AND Length/Width > 1.99	
		Or mean C_profile > -0.05	
		Or $15\,000 < \text{AREA} < 100\,000$ AND $3.2 > \text{Length/Width} > 1.99$	
		Or $25\,000 < \text{AREA} < 100\,000$, or C_plan < -0.02 , or C_plan > 0.19 AND mean TPI < 1	
		Or St. Deviation of C_profile < 1.6	
	Expand Body AREA	From unclassIFied segments IF Rel. Border to Body > 0.6 , mean SLOPE > 0.4 , mean TRI > 1	
		Or Rel. Border to Body > 0.42 AND Rel. Border to unclassIFied = 0 Or from non-body AREAs IF Rel. Border to Body > 0.7	
	Remove Bodies	IF AREA $> 183\,000$ pixels AND mean TRI > 0.81	

Code availability. The code used in this research is available from the first author upon reasonable request. The first version related to optimal moving-window sizes was previously published by Sirbu et al. (2019).

Data availability. The resulting data used in this research can be obtained from the first author upon reasonable request and are also publicly available at <https://doi.org/10.22000/798> (Zangana et al., 2023a) and <https://tlubn.thueringen.de/> (last access: 29 November 2025).

Author contributions. IZ: conceptualisation, data curation, formal analysis, visualisation, writing (original draft, review and editing). RB: conceptualisation, visualisation, writing (review and editing). LD: conceptualisation, data and software implementation, writing (review and editing). FS: developed and calibrated the original R script to obtain the optimal moving-window sizes, writing (review and editing). LS: conceptualisation, writing (review and editing), supervision. All authors have read and agreed to the published version of the paper.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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Geomorphology

Transferability of Semi-automated Landslide Mapping Based on High-Resolution DTMs, Swabian Alb, Germany --Manuscript Draft--

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Abstract:	Landslides represent a major natural hazard with significant impacts on human life, infrastructure, and land use. This highlights the need for reliable mapping for hazard assessment and risk management. While mapping in vegetated terrain is challenging due to labor-intensive, expert-dependent conventional approaches, semi-automated techniques use high-resolution Digital Terrain Models (DTMs) to improve efficiency and consistency. However, their transferability across environments is insufficiently tested. Therefore, this study aims to assess the transferability of a Geographic Object-Based Image Analysis (GEOBIA) approach that employs optimized moving-window sizes in vegetated terrains. Developed for the Jena region, the model is applied to the Swabian Alb escarpment in Germany. It examines performance across land use classes and the influence of DTM quality. The area is characterized by Jurassic limestones overlying marls and clays and is dominated by rotational slides, slump-earth flows, and translational landslides. A compiled landslide inventory was used for validation. DTM derivatives from the 2003 and 2023 datasets were generated using defined optimal window sizes. The workflow combines multi-resolution segmentation, support vector machine classification, and expert-based refinement. The results confirm the transferability of this model. Detection rates reached 75% using the 2003 DTM and increased to 86% with the 2023 dataset, demonstrating the importance of improved data quality. In forested areas, performance improved, with an increase in true positives of about 15% and a comparable reduction in false positives. The method performs best for rotational landslides and shows strong potential to detect landslides with distinct geomorphological signatures across regions.

Highlights:

- GEOBIA-based landslide mapping shows strong transferability across regions
- Higher resolution DTM data improves detection accuracy
- Forested areas yield highest true positive detection performance
- Method performs effectively for cuesta-related landslides

Transferability of Semi-automated Landslide Mapping Based on High-Resolution DTMs, Swabian Alb, Germany

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Abstract:

Landslides represent a major natural hazard with significant impacts on human life, infrastructure, and land use. This highlights the need for reliable mapping for hazard assessment and risk management. While mapping in vegetated terrain is challenging due to labor-intensive, expert-dependent conventional approaches, semi-automated techniques use high-resolution Digital Terrain Models (DTMs) to improve efficiency and consistency. However, their transferability across environments is insufficiently tested. Therefore, this study aims to assess the transferability of a Geographic Object-Based Image Analysis (GEOBIA) approach that employs optimized moving-window sizes in vegetated terrains. Developed for the Jena region, the model is applied to the Swabian Alb escarpment in Germany. It examines performance across land use classes and the influence of DTM quality. The area is characterized by Jurassic limestones overlying marls and clays and is dominated by rotational slides, slump-earth flows, and translational landslides. A compiled landslide inventory was used for validation. DTM derivatives from the 2003 and 2023 datasets were generated using defined optimal window sizes. The workflow combines multi-resolution segmentation, support vector machine classification, and expert-based refinement. The results confirm the transferability of this model. Detection rates reached 75% using the 2003 DTM and increased to 86% with the 2023 dataset, demonstrating the importance of improved data quality. In forested areas, performance improved, with an increase in true positives of about 15% and a comparable reduction in false positives. The method performs best for rotational landslides and shows strong potential to detect landslides with distinct geomorphological signatures across regions.

1 Introduction

Landslides are fundamental drivers of landform evolution, yet they pose a substantial hazard worldwide, often causing fatalities and economic losses that exceed those from earthquakes, volcanic eruptions, and floods (Froude & Petley, 2018; Petley, 2012).

30 In specific geomorphic settings, the risk associated with landslide activity is particularly high, emphasizing the need for accurate hazard assessment. Within this context, landslide hazard is defined as the probability of a landslide of a specific magnitude occurring within a given time period and a predefined geographic area (Corominas et al., 2014; Guzzetti et al., 1999). High-quality landslide inventories are essential for hazard assessment, as they systematically record the location, type, and dimensions of slope failures (Guzzetti et al., 2012; Malamud et al., 2004). Traditionally, such inventories are compiled
35 through the stereoscopic analysis of aerial photographs, corroborated by field surveys and the synthesis of historical archives (Santangelo et al., 2010; van Westen et al., 2008). However, while field mapping remains a fundamental geomorphological practice, the identification of landslides, particularly relict or dormant features, is frequently compromised by logistical and environmental constraints (Brardinoni et al., 2003). These include the sheer scale of landslide complexes, restricted field perspectives, and the obscuring effects of dense forest cover, post-failure erosion, and anthropogenic modifications (Bell,
40 Petschko, Röhrs, & Dix, 2012; Jaboyedoff et al., 2012). In contrast, remote sensing methods, including high-resolution digital terrain models (DTMs) and aerial imagery, provide more consistent and objective detection of landslides, enhancing inventory precision and reproducibility (Santangelo *et al.*, 2010; Bell *et al.*, 2012; Guzzetti *et al.*, 2012; Crawford, 2014; Petschko et al., 2016; Schmaltz *et al.*, 2016; Gazibara et al., 2019).

In recent decades, Geographical object-based image analysis (GEOBIA) has made an important contribution to semi-
45 automated landslide mapping techniques. A multi-scale GEOBIA approach was used by Lahousse et al. (2011), to map landslides; such approaches are usually area and/or landslide type dependent. A fuzzy logic approach was suggested by Aksoy and Ercanoglu (2012), proposing semi-automated inventory mapping based on thematic data and spectral information. Feizizadeh and Blaschke (2013) presented a rule-based classification method utilizing remotely-sensed data. Hölbling *et al.* (2016) used historical and recent aerial images to detect spatiotemporal landslide hotspots. Hölbling *et al.* (2017) determined
50 the performance of GEOBIA-based semi-automatic landslide mapping relative to manual mapping and noted that the accuracy decreases in vegetated areas. Furthermore, Karantanellis *et al.* (2020, 2021), reported that integrating machine learning within GEOBIA improved local-scale sub-zone landslide mapping. Dias et al. (2023), demonstrated that the application of GEOBIA-based methods to high resolution satellite imagery could effectively detect shallow landslides and debris flows with an accuracy of greater than 70%, while Dias et al. (2025) highlighted the influence of inventory type on susceptibility modelling and the
55 challenge of maintaining accurate, consistent datasets in tropical environments. Karantanellis and Hölbling (2025), further emphasized the potential of the use of high-resolution digital data combined with GEOBIA-based methods to improve landslide mapping and assessment accuracy.

Selecting appropriate window sizes for different land surface variables (LSVs) is critical for semi-automated landform detection, as scale affects mapping accuracy (Drăguț and Eisank, 2011). Seijmonsbergen et al. (2011) showed that employing

multiple window sizes for LSV calculation improves semi-automatic landform mapping, though window selection relied on manual comparison with expert-mapped features. Pawluszek et al. (2018) examined how varying window sizes influence automatic landslide detection using DTMs, finding that rescaled DTMs yielded higher modelling accuracy than original datasets. Sîrbu *et al.* (2019) later introduced an automated method for determining optimal LSV window sizes for landslide scarp detection, although landslide bodies were excluded, highlighting a gap in comprehensive inventory generation. To advance semi-automatic GEOBIA-based landslide mapping, our recent study by Zangana *et al.* (2025) developed a semi-automatic landslide mapping framework using high-resolution LiDAR-derived DTM data in the Jena region, Germany. The approach integrated multiresolution segmentation, support vector machine (SVM) classification, and rule-based refinement, with window sizes optimized separately for scarps and bodies. Validation against expert inventories demonstrated high detection rates, reduced false positives, and suitability for cuesta-related rotational landslides larger than 0.5 ha.

However, despite the recent progress made in semi-automatic landslide mapping, the transfer of models to regions with different geomorphological and environmental conditions remains a significant challenge that has yet to be resolved. Approaches that perform well in their original study areas often require substantial re-parameterisation when applied elsewhere. Therefore, it is essential to systematically evaluate the robustness and transferability of models across regions with varying terrain characteristics and land use patterns in order to develop operational and scalable mapping workflows.

Within this context, this study evaluates the transferability of a GEOBIA-based model that was originally developed for mapping forest-covered landslides in the cuesta landscape of the Jena region, by applying it to the Swabian Alb escarpment in southwestern Germany. The aim is to determine whether the framework can be effectively applied under different environmental and data conditions, thereby extending its applicability to regional landslide inventory mapping.

This study addresses the following research questions: (Q1) To what extent is the previously optimized GEOBIA-based approach transferable to a new study area, and what limitations arise under different environmental conditions? (Q2) How does integrating land use/land cover data influence the accuracy of mapping forest-covered landslides? And (Q3) How do landslide detection results differ between models based on the 2003 and 2023 DTMs as a function of data quality, and how does this influence mapping accuracy?

2 Study area

The study area selected for this research is located in the central Swabian Alb and covers approximately 356 km² (Figure 1). The Swabian Alb (in German: Schwäbische Alb) is a mid-latitude low mountain range and cuesta escarpment in southwest Germany, spanning roughly 10,000 km² within the state of Baden-Württemberg. Elevations range from approximately 800 m in the east to 1,000 m in the west (Bell et al., 2012). The escarpment rises 300–400 metres above its foreland and is characterised by its very steep slopes and forming a distinctive morphological feature that has been shaped by gravitational mass movements throughout the Quaternary period (Bell, 2007; Terhorst & Kreja, 2009). The escarpment's

northwest-facing slope exhibits a typical cuesta morphology with steep scarps transitioning to gentler dip slopes, creating favourable conditions for various types of slope instabilities (Terhorst & Kreja, 2009).

Geologically, the Swabian Alb is dominated by Mesozoic sedimentary sequences, primarily consisting of Middle and Upper Jurassic sediments dipping 1–2° to the southwest. The stratigraphic succession includes competent limestone and marlstone units of the Dogger and Malm groups, underlain by mechanically weak Callovian clay-rich layers that serve as critical failure planes for deep-seated landslides (Bell et al., 2012; Terhorst & Kreja, 2009; Wilde & Terhorst, 2025). At the highest elevations, the sequence begins with the Upper Jurassic Untere Massenkalk Formation (joMu), characterized by massive limestone and marl, which is underlain by the Zementmergel (ki5) and Lacunosamergel (ki1) formations. The Wohlgeschichtete Kalk Formation (ox2) forms a prominent plateau at approximately 660 m, comprising a series of stratified limestone beds. Beneath this plateau, the Impressamergel (ox1), an alternating sequence of marl and clay-marl, constitutes the steep, landslide-prone slopes. In this unit, material is frequently relocated downslope by rotational processes (Thiebes, 2012).

The region experiences a temperate oceanic climate. The average yearly rainfall varies between 800 mm and 1,300 mm, gradually rising from the drier south-western regions, where the Black Forest has a lee effect, to the wetter north-eastern regions (Bell, 2007). Seasonal groundwater fluctuations and increased spring discharge during wet periods are recognized as primary triggers for slope reactivation, reducing effective stress and shear strength in clay-rich horizons (Terhorst & Kreja, 2009; Thiebes et al., 2013). These hydrological dynamics, combined with the geological predisposition, result in episodic landslide activity that poses ongoing risks to settlements and infrastructure along the escarpment.

Landslides in the Swabian Alb exhibit significant morphological and temporal diversity, primarily occurring as rotational slides, slump-earthflows, and translational slides. The landscape is dominated by large Pleistocene rotational failures characterized by distinct block morphologies and pronounced headscarps, many of which have undergone multiple phases of Holocene reactivation (Bell et al., 2012). A prominent example is the Mössingen landslide, which underscores the frequent reactivation of older landslide complexes in the region.

Failures in this region are typically triggered by either short-duration, high-intensity rainfall or prolonged precipitation events, often exacerbated by snowmelt (Bell et al., 2012; Goetz et al., 2014). It is estimated that over 20,000 landslides exist across the Swabian Alb (Bell, 2007). In 2013, the region experienced widespread landslide reactivation (Wilde & Terhorst, 2025). Several of these recent movements were identified through the analysis in this study, as evidenced by the high-resolution DTM data (e.g. Figure 3 and 4, inset c).

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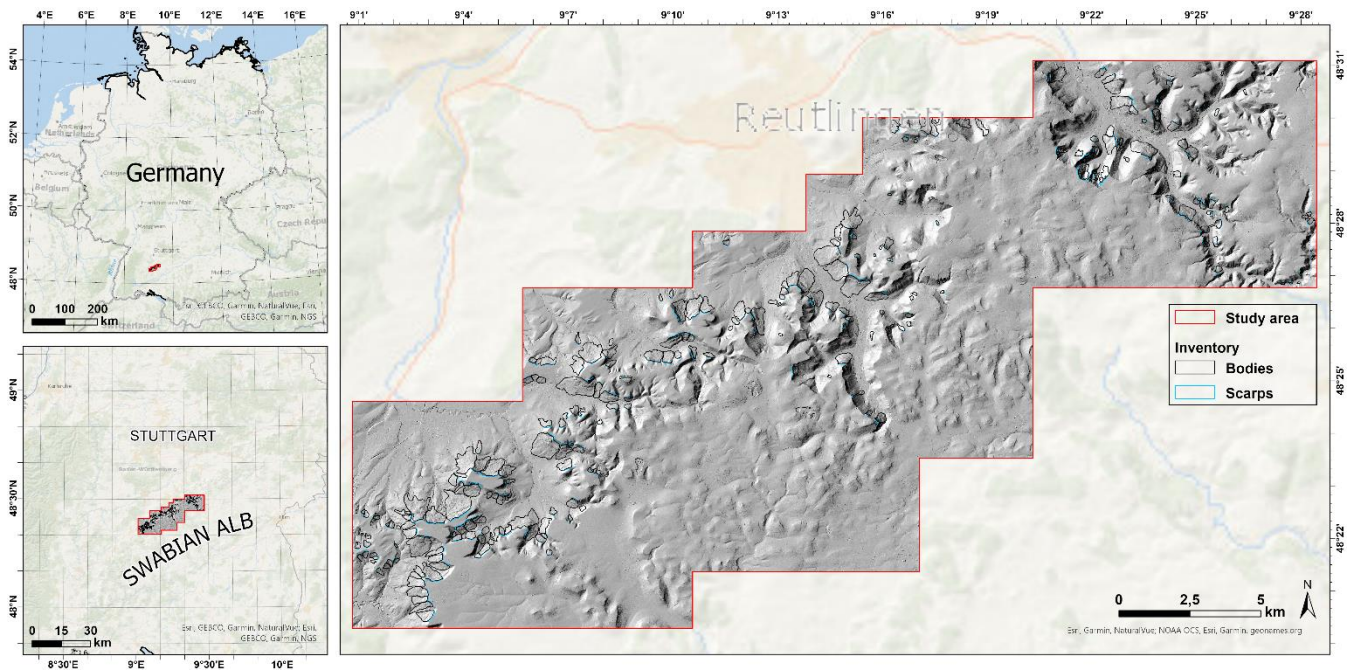


Figure 1. Location of the Study area and mapped landslide inventory. DTM: Source: © LGL, www.lgl-bw.de. And OpenStreetMap

3 Methodology

3.1 Data Sources and Preparation

125

The study utilized LiDAR-DTMs from 2003 and 2023 (1 m resolution), provided by the State Office for Geoinformation and Land Development (Landesamt für Geoinformation und Landentwicklung Baden-Württemberg (LGL-BW, <http://www.lgl-bw.de>, last access: 20.04.2026). These DTMs served as the foundational dataset for both the manual reference inventory and the semi-automatic model runs. A set of terrain-based LSVs were derived from the original DTM, including: slope, plan and profile curvature, Topographic Openness (TO), Terrain Roughness Index (TRI), and Topographic Position Index (TPI). Furthermore, the digital landuse/land-cover map (DLM25, scale 1:25,000) for 2003 was acquired from the relevant Baden-Württemberg state authority (LGL-BW, <https://www.lgl-bw.de/Produkte/Landschaftsmodelle/Basis-DLM/index.html>; Bell, 2007) and was incorporated into the analysis for model validation and accuracy evaluation. The use of the 2003 dataset ensures temporal consistency with the landslide mapping conducted in this study.

135

Manual Delineation of the Inventory Map

A foundational step in this study involved the manual creation of a high-resolution landslide inventory map (reference map) based on the 2003 LiDAR-DTM data. The inventory was delineated by the first author, who has extensive experience in geomorphological and landslide mapping. The delineation was systematically reviewed and discussed with the second co-

author, who has long-standing expertise in interpreting landslides from DTM data and has previously published multiple
140 studies on landslides in the same study area of Swabian Alb (Bell, 2007; Bell *et al.*, 2012; Goetz *et al.*, 2014). This collaborative
review ensured consistency and geomorphological plausibility in feature identification.

Mapping was conducted via on-screen digitization in QGIS 3.34. The primary visual base layers were traditional and
multi-directional hillshade images, interpreted according to the established methodology of visual identification (Schulz,
2004). Feature identification focused on classic landslide geomorphic expressions, specifically scarps and body morphology,
145 and was executed at fine scales (ranging from 1:1,000 to 1:200) to guarantee the precise boundary delineation of the features.
To address regions where topographic manifestation was subtle, additional LSVs, including curvature, TO, TPI, and TRI,
served as supplementary layers for enhanced boundary delineation and interpretation. Consistent with the approach of Zangana
et al. (2023), a composite visualization of LSV was employed to further improve feature detection. The final inventory includes
263 distinct landslide bodies and 282 landslide scarp features. The higher scarp count is attributed to mapping discontinuous
150 scarp segments as separate polygons, rather than as a single feature across the landslide body.

3.2 Semi-automatic mapping workflow

We adopted the semi-automatic landslide mapping approach (ruleset and workflow) originally developed by Zangana
et al. (2025). This model, designed for mapping old and forest-covered landslides in the Jena region of Germany, was
implemented using the software eCognition 10.3. The resultant outputs were exported as ESRI Shapefiles via QGIS for
155 subsequent analysis and validation. The overall methodological framework, which comprises three main stages, is illustrated
in Figure 2.

3.2.1 STAGE I: Data Preparation

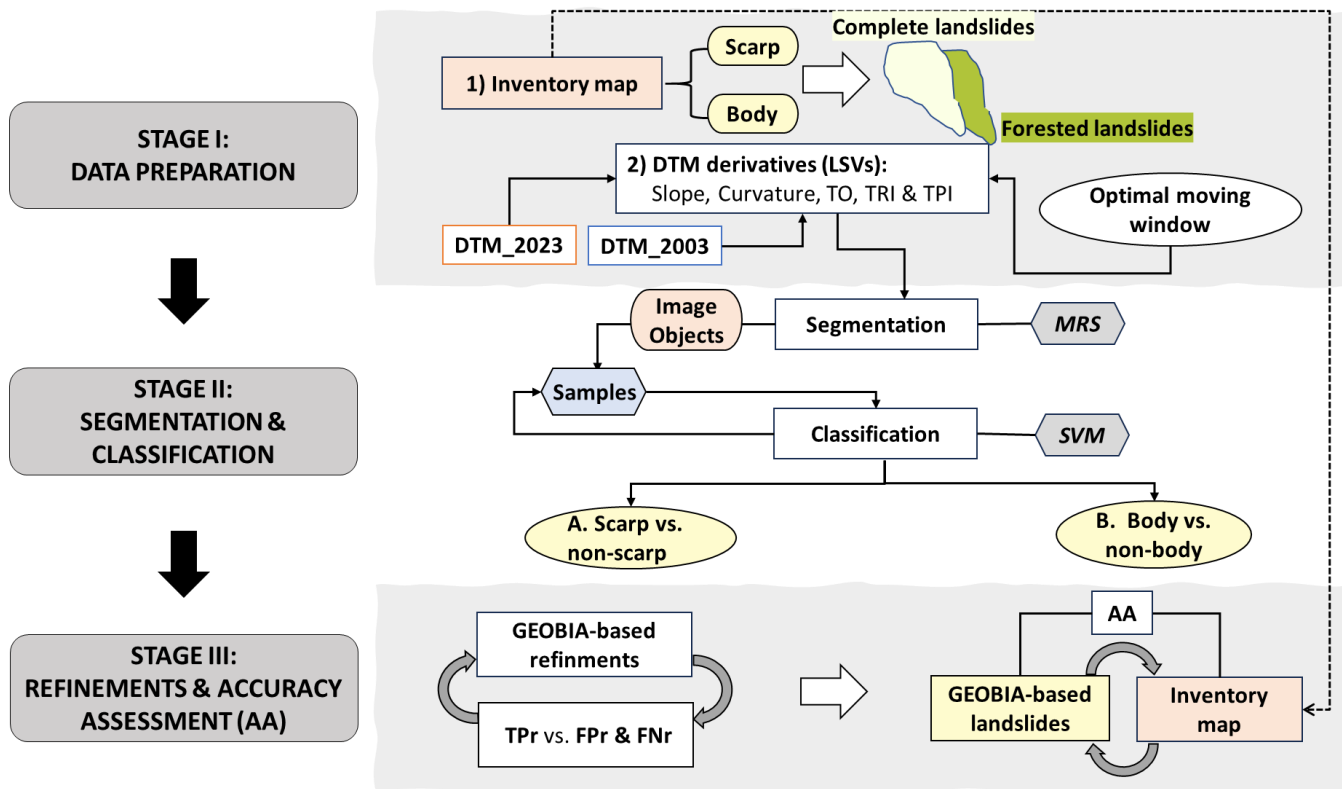
This stage consisted of two main steps:

Step 1: Reference Inventory Generation and Stratification

160 A reference landslide inventory was manually prepared using high-resolution 2003 LiDAR-DTM hillshade data, supported by
visual interpretation of LSVs; for detailed see Section 3.1).

To evaluate model performance under vegetated conditions, the reference inventory was subsequently stratified into
two datasets: (i) the complete landslide inventory, and (ii) a forest-restricted subset derived through spatial intersection of the
inventory polygons with the land use/land cover (LULC) dataset. This procedure involved a GIS-based spatial filtering of the
165 original inventory; no reinterpretation or remapping was conducted. The 2023 DTM was not involved in the creation or
stratification of the reference data.

The complete inventory and the forest-restricted subset were used separately in the accuracy assessment (AA) to evaluate
overall detection performance and performance within forested terrain.



170 **Figure 2.** The Methodology flowchart of semi-automatic landslide mapping. The workflow initiates with data preparation, including the generation of DTM derivatives using pre-determined optimal window sizes. This is followed by segmentation (MRS) and classification (SVM). The process concludes with a phase of refinement and Accuracy Assessment (AA), based on the comparison of the automated GEOBIA results with the manual reference map.

Step 2: DTM Derivatives and Optimization

175 In this step, LSVs (i.e. DTM derivatives) were generated twice from the Digital DTM 2003 and 2023 using the QGIS and R software environments. The generation of these variables required the selection of an appropriate moving window size for each LSV. Rather than performing a new optimization, we applied the pre-calculated optimal moving window sizes determined by Zangana et al. (2025). That previous study utilized an automated approach originally proposed by Sîrbu et al. (2019), which identifies the optimal size by maximizing the statistical distinction between landslide and non-landslide areas.

180 Using these pre-optimised parameters ensures that the LSVs generated in this study already have maximum discriminability based on local topographic relief. The specific optimal window sizes applied for each variable are presented in Table 1.

Table 1. LSVs and corresponding window sizes per landslide components. Adapted from Zangana et al. (2025).

Landslides/LSVs	Slope	C_plan	C_profile	TO	TRI	TPI
Scarp	11x11	7x7	5x5	5x5	7x7	11x11
Body	11x11	5x5	7x7	7x7	9x9	13x13

3.2.2 STAGE II: Segmentation and Classification (GEOBIA)

This stage, performed within the eCognition software environment, involved object segmentation and classification at two hierarchical levels.

Multi-Resolution Segmentation (MRS)

Segmentation was executed using the Multi-Resolution Segmentation (MRS) algorithm (Baatz & Schäpe, 2000). We adopted a trial-and-error approach (Drăguț et al., 2010; Li et al., 2015) to identify the optimal scale parameters for the distinct geomorphological features. Specifically, separate projects and rulesets were employed for landslide scarps and landslide bodies. Following Zangana et al. (2025), segmentation scales of 20 for scarps and 30 for bodies were applied, using a shape parameter of 0.1 and a compactness value of 0.5. Although the surface characteristics of the two study areas differ, the parameters were intentionally kept unchanged in order to assess the transferability of the previously developed model. Area-specific parameter optimization may be considered in future studies if necessary.

Supervised Classification (SVM)

Following segmentation, supervised classification was performed using a Support Vector Machine (SVM) algorithm (Tzotsos and Argialas, 2008; Hong et al., 2017). Training samples were derived from the image objects produced by the segmentation process. Objects spatially intersecting the reference landslide polygons were assigned to the corresponding landslide classes (body or scarp), while objects outside the reference polygons were selected as non-landslide samples. The algorithm was then trained and applied to classify the segmented objects. To improve agreement with the reference inventory map, the classification was conducted iteratively by refining the training samples after each run. Misclassified image objects were identified through comparison with the reference polygons, and the training dataset was adjusted by adding representative samples and removing ambiguous ones. This process was repeated until classification performance stabilized and no substantial improvement was observed.

3.2.3 STAGE III: Refinements and Accuracy Assessment (AA)

215 This stage involves two main steps: GEOBIA-based refinement and rigorous accuracy assessment (AA). Since the initial classification often resulted in a significant presence of false positives and false negatives, the refinement step is necessary to enhance accuracy. We execute the ruleset within eCognition to improve the True Positive Rate (TPr) relative to the False Positive (FPr) and False Negative Rates (FNr). This ruleset utilized a comprehensive suite of morphometric parameters, including mean LSV values, standard deviation, length-to-width ratio, object area, and relative border, to refine the classified objects (for more detail about the refinements, see Tables A1-B2 in the Appendices from the study by Zangana et al. (2025)).

220 The final classified output, termed 'GEOBIA-based landslides', was then evaluated against the expert-based reference inventory using object- and area-based procedures (see Section 3.3 for details).

3.3 Accuracy assessment

225 The final model results ('GEOBIA-based landslides') underwent a rigorous Accuracy Assessment (AA) through comparison with the manual reference inventory (i.e. the full inventory map and the forest-restricted subset). A key objective was to evaluate the model's performance under various conditions; consequently, the assessment was systematically conducted across four key dimensions:

- **Feature Type:** Results were assessed separately for landslide bodies and landslide scarps.
- **LULC Stratification:** Results were assessed against the full inventory (all landslides over the entire study area) and against the forest-covered landslide subset only.
- 230 • **DTM Performance Comparison:** The final GEOBIA-result generated from the 2003 DTM and the 2023 DTM were assessed independently and then quantitatively compared to evaluate the quality of different DTM performance and improvements.
- **Metric Application:** Both object/number-based and area-based metrics were employed (more details below), reflecting different evaluation criteria.

235

Object-based (number-based) Accuracy Assessment

For the object-based (number-based) assessment, we adopted a method based on the degree of spatial overlap between the GEOBIA-detected objects and the reference inventory polygons (Eeckhaut et al., 2012; Knevels et al., 2019). This approach provides a measure of positional accuracy for individual features.

240 The classification was evaluated using the following criteria, which are based on the percentage of overlap between the classified object and the reference polygon:

- a) **Correctly mapped:** The overlapping area exceeded 50% of the reference landslide polygon's area.
- b) **Almost mapped:** The overlapping area fell within the range of 40% to 49%.

c) **Not mapped:** The overlapping area was less than 40%.

The differentiation of the area below the 50% threshold into the 40%-49% and <40% categories was implemented to allow for a more nuanced evaluation, specifically to distinguish near-misses from completely undetected features.

Area-based Accuracy Assessment

Traditional metrics of True Positives (TP), False Positives (FP), and False Negatives (FN) were used for the area-based assessment. Accuracy was calculated based on the spatial overlap between mapped landslide polygons and the reference inventory, allowing quantification of correctly detected and misclassified areas relative to the total inventory area. (for further details, see (Cai, Shi, Miao, & Hao, 2018; Eisank, Smith, & Hillier, 2014; Zangana et al., 2025))

Assessment of Forest-Covered Areas

A specific focus was placed on evaluating the models' ability to detect features in vegetated terrain. The AA results for the forest-covered areas (i.e. forest-covered landslides) were compared with the 2003 DTM results and the 2023 DTM results to explicitly assess the improvement in detection accuracy achieved over these two periods and to assess the model performance over the forested areas solely.

4 Results

This chapter presents the key results of the study, including the outcomes of the GEOBIA-based landslide mapping, and the model performance evaluation derived from different accuracy assessment approaches.

4.1 GEOBIA-based landslide mapping results

4.1.1 Landslide Mapping Results for the Entire Study Area

The GEOBIA-based modelling results for landslide scarps and bodies were compared with the manual inventory map (i.e. the reference map) to evaluate their spatial correspondence (Figures 3 and 4). These figures illustrate the detected landslide features: dark-yellow polygons represent correctly mapped True Positives (TP), open-yellow polygons indicate False Negatives (FN), and pink polygons represent areas incorrectly classified as landslides, referred to as False Positives (FP), for both model-detected scarps and bodies. Black and blue polygons show the corresponding landslide features from the reference inventory. Areas outlined by black dashed boxes are discussed in more detail in Section 5.

Visual and on-screen analyses demonstrate that the model accurately captures individual landslide components and shows strong spatial agreement with the reference inventory. This accuracy is particularly evident in the precise delineation of landslide extents and the low False Positive rate (FPr) especially in the forested areas. A more comprehensive quantitative evaluation of the results is provided in Tables 2 and 3 in Section 4.2.

4.1.2 Landslide Mapping Results for Forest-Covered Areas

275 Figures 5 and 6 present the model results restricted to forested areas, where landslide bodies are located beneath forest
cover. Landslides occurring outside forested regions across the study area were excluded from this evaluation. The green dotted
polygons represent the forest-only landslide inventory, which was derived by intersecting the original inventory with the forest
land use layer. This filtered inventory therefore includes only landslides within forested areas and serves as the reference
dataset for this assessment. Model outputs derived from the 2003 and 2023 DTMs were compared exclusively against this
280 forest-based inventory. Detailed mathematical interpretations can be found in the subsequent section and are summarized in
Tables 4 and 5 in Section 4.2.

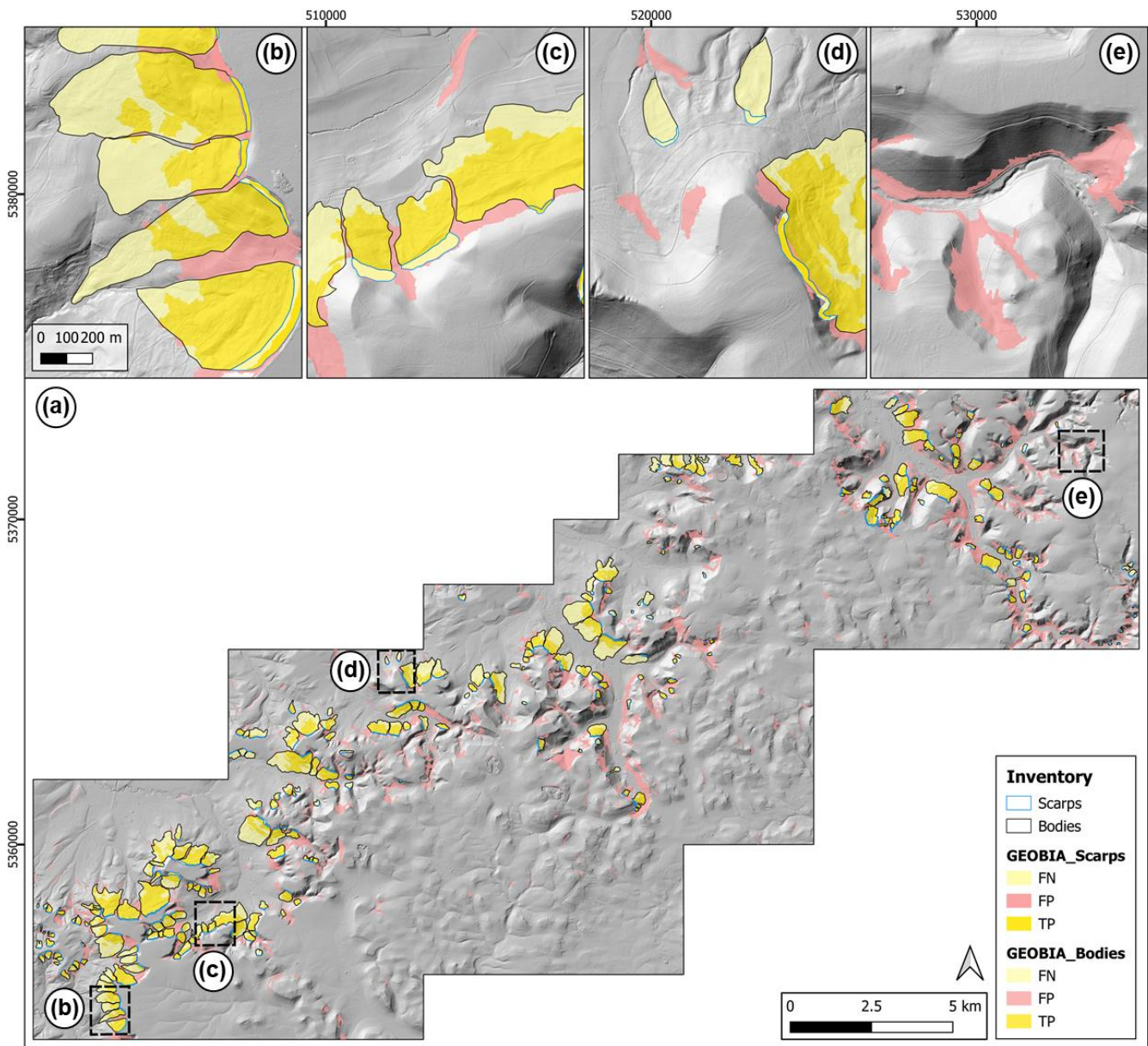


Figure 3. Final map of semi-automatic landslide detection based on the 2003 dataset, displayed over a hillshade DTM (Source: © LGL, www.lgl-bw.de) for the entire study area (a). Detected landslides are shown as coloured polygons (dark yellow: True Positives, TP; pink: False Positives, FP; yellow: False Negatives, FN), while the reference inventory map is also displayed for comparison. Insets (b-e) provide detailed views of selected sites.

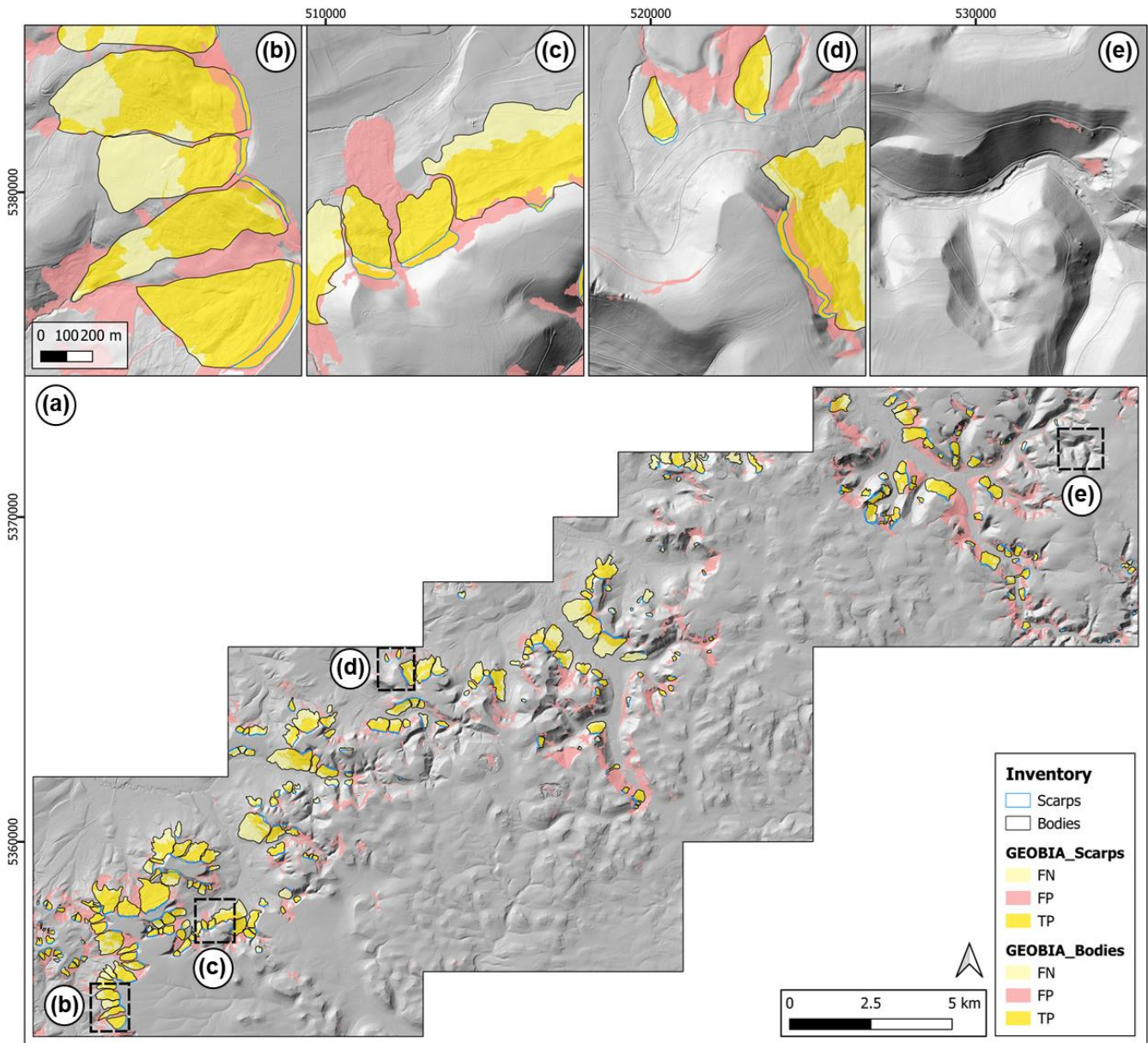


Figure 4. Final map of semi-automatic landslide detection based on the 2023 dataset, displayed over a hillshade DTM (Source: © LGL, www.lgl-bw.de.) for the entire study area (a). Detected landslides are shown as coloured polygons (dark yellow: True Positives, TP; pink: False Positives, FP; yellow: False Negatives, FN), while the reference inventory map is also displayed for comparison. Insets (b-e) provide detailed views of selected sites.

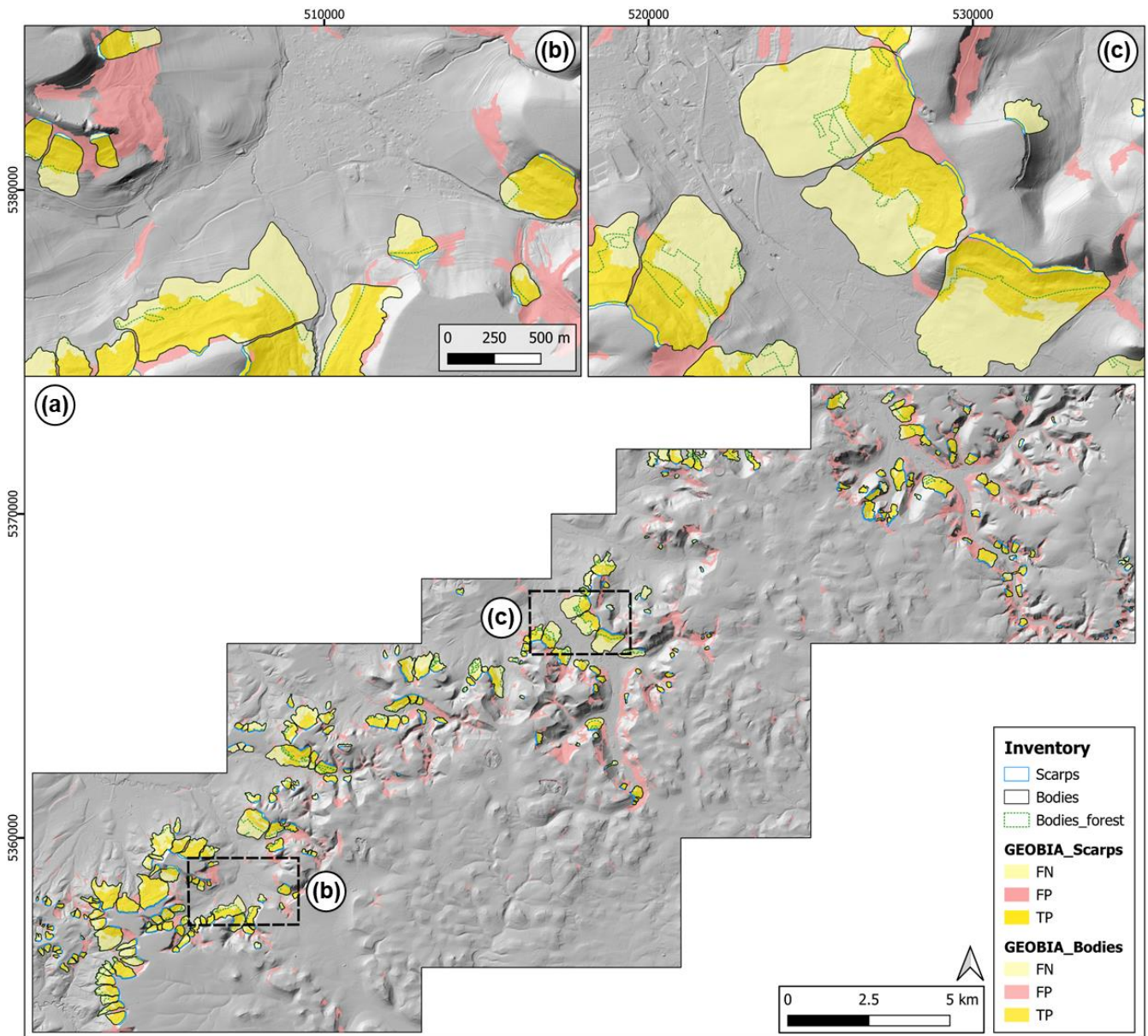


Figure 5. Final map of semi-automatic landslide detection based on the 2003 dataset within forested areas (a), displayed over a hillshade DTM (Source: © LGL, www.lgl-bw.de). Detected landslide bodies are shown as coloured polygons (dark yellow: True Positives, TP; pink: False Positives, FP; yellow: False Negatives, FN), while the reference inventory map is shown for comparison. Insets (b) and (c) provide detailed views of selected forested sites.

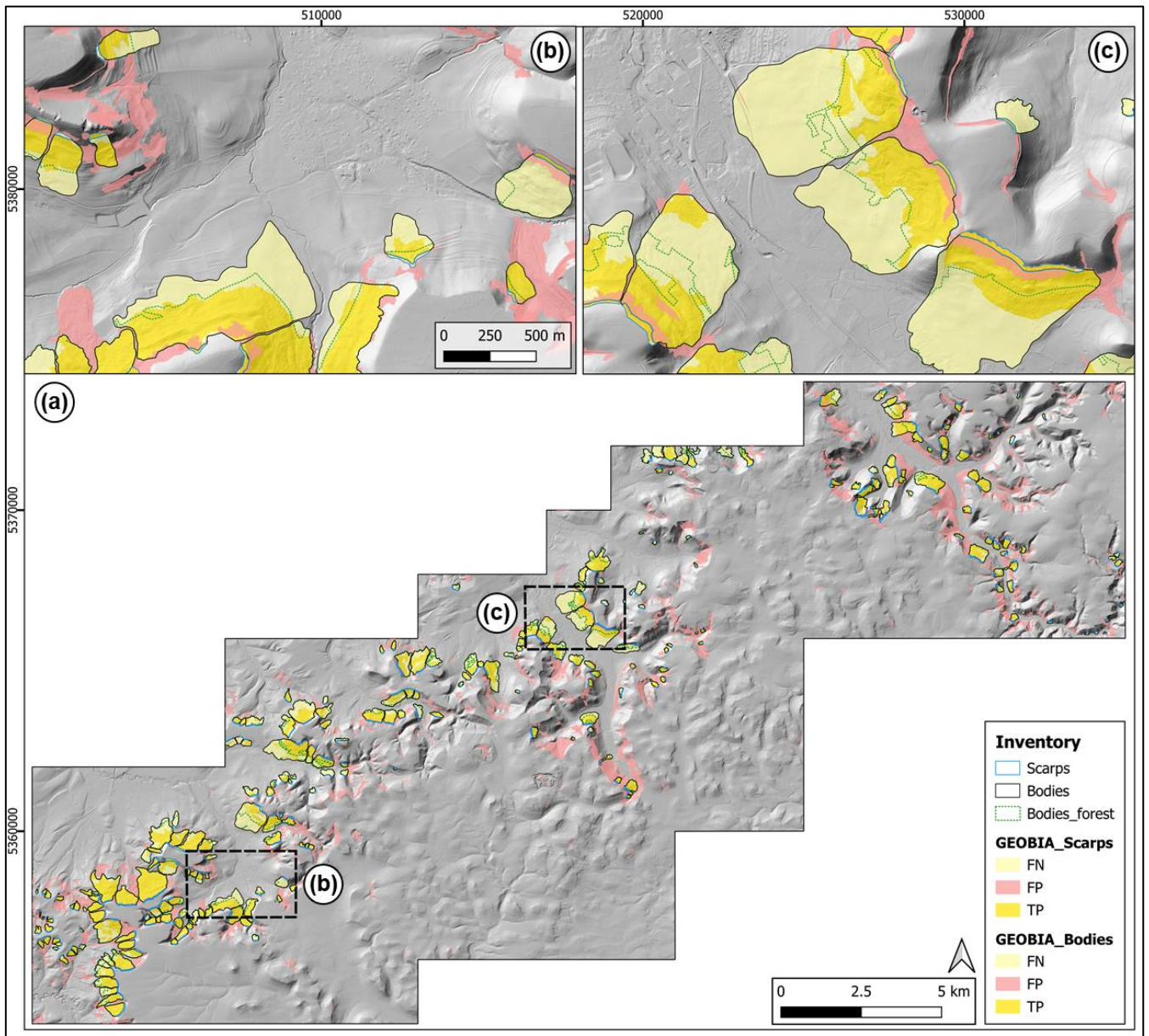


Figure 6. Final map of semi-automatic landslide detection based on the 2023 dataset within forested areas (a), displayed over a hillshade DTM (Source: © LGL, www.lgl-bw.de). Detected landslide bodies are shown as coloured polygons (dark yellow: True Positives, TP; pink: False Positives, FP; yellow: False Negatives, FN), while the reference inventory map is shown for comparison. Insets (b) and (c) provide detailed views of selected forested sites.

4.2 Accuracy assessment results

4.2.1 Thematic accuracy assessment

310 The thematic accuracy assessment was conducted using two complementary approaches: object-based (number-based) and
area-based accuracy metrics, applied to the 2003 and 2023 datasets for both the entire study area and the forested area only.

Entire study area: The object-based accuracy assessment (Table 2) shows a slight increase in correctly mapped landslide
bodies from 75.3% in 2003 to 77.2% in 2023, with unmapped bodies decreasing from 15.9% to 14.8%. For scarp zones, the
number of correctly mapped features increased from 29.8% to 36.9%, while unmapped scarps decreased from 66.0% to
315 59.8%. The area-based accuracy assessment (Table 3) indicates higher True Positive (TP) areas in 2023 for both landslide
bodies and scarps. TP areas for landslide bodies increased from 57.7% to 62.4%, accompanied by a reduction in False
Negative (FN) areas from 42.3% to 37.6%. In the scarp zones, TP areas increased from 44.6% to 54.1%, while FN areas
decreased from 55.4% to 45.9%.

Forested area: Within forested landslide bodies (we analysed only the body areas as the scarps were too small to be
320 evaluate the model performance, specifically for the area-based assessment), the number-based assessment (Table 4) shows
an increase in correctly mapped features from 82.1% in 2003 to 86.9% in 2023, with unmapped features decreasing from
10.7% to 8.3%. The area-based assessment (Table 5) shows that TP areas increased from 66.7% in 2003 to 72.5% in 2023,
while FN areas decreased from 33.3% to 27.5%.

Table 2. Object-based accuracy assessment of GEOBIA landslide detection for the entire study area (2003 and 2023)

Landslide	Model/Year	Correctly mapped*		Almost mapped**		Not mapped***	
		Count	(%)	Count	(%)	Count	(%)
Bodies (Inventory: 263)	2003	198	75.3	23	8.8	42	15.9
	2023	203	77.2	21	8.0	39	14.8
Scarps (Inventory: 282)	2003	84	29.8	12	4.26	186	66.0
	2023	104	36.9	10	3.6	168	59.8

325 **Note:** * area: ≥50%; ** area: 40–49%; *** area: <40%

Table 3. Area-based accuracy assessment of GEOBIA landslide detection for the entire study area (2003 and 2023)

Landslide	Model/Year	TP (ha)		FP (ha)		FN (h)	
		Area	(%)	Area	(%)	Area	(%)
Bodies (Inventory: 2221.8 ha)	2003	1282.3	57.7	1852.8	59.1	939.5	42.3
	2023	1386.7	62.4	1864.5	57.3	835.0	37.6
Scarps (Inventory: 95.6 ha)	2003	42.7	44.6	66.9	61.1	52.9	55.4
	2023	51.7	54.1	273.3	84.1	43.9	45.9

Table 4. Object-based accuracy assessment of GEOBIA-based landslide body detection in forested areas (2003 and 2023)

Landslide	Model/Year	Correctly mapped		Almost mapped		Not mapped	
		Count	(%)	Count	(%)	Count	(%)
Bodies in forest (Inventory: 252)	2003	207	82.1	18	7.1	27	10.7
	2023	219	86.9	12	4.8	21	8.3

330

Table 5. Area-based accuracy assessment of GEOBIA-based landslide body detection in forested areas (2003 and 2023)

Landslide	Model/Year	TP (ha)		FP (ha)		FN (h)	
		Area	(%)	Area	(%)	Area	(%)
Bodies in forest	2003	1195.5	66.7	1939.5	61.9	598.1	33.3
(Inventory: 1793.6 ha)	2023	1300.2	72.5	1951.0	60.0	493.5	27.5

5 Discussion

5.1 Transferability of semi-automatic landslide-based mapping

335 The results demonstrate that the semi-automatic GEOBIA-based landslide mapping approach can be successfully transferred to the Swabian Alb, achieving overall high detection performance across different land-cover types. Landslide bodies with strong geomorphological signatures are consistently identified, with particularly high accuracy in forested environments. Using the 2023 DTM, landslide body detection in forested areas reaches approximately 87% (Table 8), representing an improvement of about 35% compared to the Jena region results (original model) reported by Zangana *et al.*
340 (2025). Furthermore, across the entire study area (i.e.: bodies inside and outside forested area), the detection reached 77.2% using 2023 data, representing a substantial 24.7% improvement over the 52.5% reported for the Jena region (Figure 8). This higher success rate in the Swabian Alb demonstrates that the transferred GEOBIA model is highly effective at identifying the region's distinct geomorphological signatures, even when applied across diverse land-cover types. These findings demonstrate that the core model logic remains robust when transferred to a different geomorphological and geological setting, and that
345 higher-resolution DTMs substantially improve the detection of both newly activated and reactivated landslides. The role of data resolution and other influencing factors is discussed in the following subchapters.

5.2 Influence of DTM quality on GEOBIA-based landslide detection: comparison of 2003 and 2023 results

350 The comparison between the 2003 and 2023 datasets demonstrates that higher-quality DTM data improve GEOBIA-based landslide detection, particularly for scarps. Object-based accuracy metrics (Table 6) show a slight increase in correctly

mapped landslide bodies from 75.3% to 203 77.2%, with unmapped bodies decreasing from 15.9% to 14.8%, while improvements are more pronounced for scarps, where correctly mapped features increase from 29.8% to 36.9% and unmapped scarps decrease from 66.0% to 59.8%. Area-based results (Table 7) support these trends, indicating reductions in False Negative areas of approximately 100 ha for landslide bodies and 10 ha for scarps in the 2023 dataset. These improvements are also evident spatially, as shown in Figure 4(d–e), where additional landslides are detected and previously misclassified areas are correctly mapped as True Positives compared with the 2003 results (Figure 3). Compared with the Jena region, scarp detection remains higher in Jena, whereas landslide body detection improves in the 2023 dataset in the Swabian Alb, reflecting differences in geomorphological settings rather than model behaviour.

Table 6. Object-based comparison of GEOBIA-based landslide detection results (SWA: 2003 and 2023, with Jena region)

Landslide	Model/Year	Correctly mapped		Almost mapped		Not mapped	
		Count	(%)	Count	(%)	Count	(%)
Bodies	SWA 2003	198	75.3	23	8.8	42	15.9
	SWA 2023	203	77.2	21	8.0	39	14.8
	Jena	21	52.5	0	0	19	47.5
Scarps	SWA 2003	84	29.8	12	4.3	186	66.0
	SWA 2023	104	36.9	10	3.6	168	59.8
	Jena	25	65.8	0	0.0	13	34.2

Table 7. Area-based comparison of GEOBIA-based landslide detection results (SWA: 2003 and 2023, with Jena region)

Landslide	Model/Year	TP (ha)		FP (ha)		FN (ha)	
		Area	(%)	Area	(%)	Area	(%)
Bodies	SWA 2003	1282.3	57.7	1852.8	59.1	939.5	42.3
	SWA 2023	1386.7	62.4	1864.5	57.3	835.0	37.6
	Jena	161.9	66.6	155.8	49	81	33.3
Scarps	SWA 2003	42.7	44.6	66.9	61.1	52.9	55.4
	SWA 2023	51.7	54.1	273.3	84.1	43.9	45.9
	Jena	9.1	43.8	8	47	11.6	56.2

5.3 Performance of GEOBIA-based landslide mapping: Forested areas vs. Entire study area

The model performs best in forested areas, consistent with its original development for forest-covered landslides in the Jena region by Zangana *et al.* (2025). In Figure 4(c) (GEOBIA-based 2023 DTM), landslides with pronounced geomorphological signatures—including fresh or recently reactivated landslides—are effectively detected. However, a

proportion of landslide bodies in this subset are classified as FN when compared with the reference inventory. This does not indicate model failure but reflects that the inventory was derived from the 2003 DTM and therefore does not include landslides activated or expanded after 2003 (Figure 3-c). Updating the inventory with the 2023 data would improve accuracy assessment outcomes. This aligns with findings by Dias, Hölbling and Grohmann (2025), who noted that the reliability and type of input inventory directly impact the accuracy of the resulting landslide map.

Number- and area-based results (Tables 8 and 9) show improved performance in forested areas between 2003 and 2023. Correctly mapped landslide bodies increased from 82.1% to 86.9%, while unmapped features decreased from 10.7% to 8.3%. Similarly, the True Positive area increased from 66.7% to 72.5%, accompanied by a reduction in False Negative area from 33.3% to 27.5%.

Compared with the entire study area in 2003, forested areas mapped using the 2023 dataset show substantially higher detection rates, with correctly mapped landslide bodies increasing from 75.3% to 86.9% and True Positive areas increasing from 57.7% to 72.5% (Table 9 and Figure 7). These results demonstrate improved detection sensitivity when the model is applied to forested environments using higher-quality DTM data.

Table 8. Object-based comparison of GEOBIA landslide body detection performance (Swabian Alb and Jena region)

Landslide	Model/Year	Correctly mapped		Almost mapped		Not mapped	
		Count	(%)	Count	(%)	Count	(%)
	Swabian Alb						
Bodies (Inventory: 263)	2003	198	75.3	23	8.8	42	15.9
	2023	203	77.2	21	8.0	39	14.8
Bodies in forest (Inventory: 252)	2003	207	82.1	18	7.1	27	10.7
	2023	219	86.9	12	4.8	21	8.3
	Jena	21	52.5	-	-	19	47.5

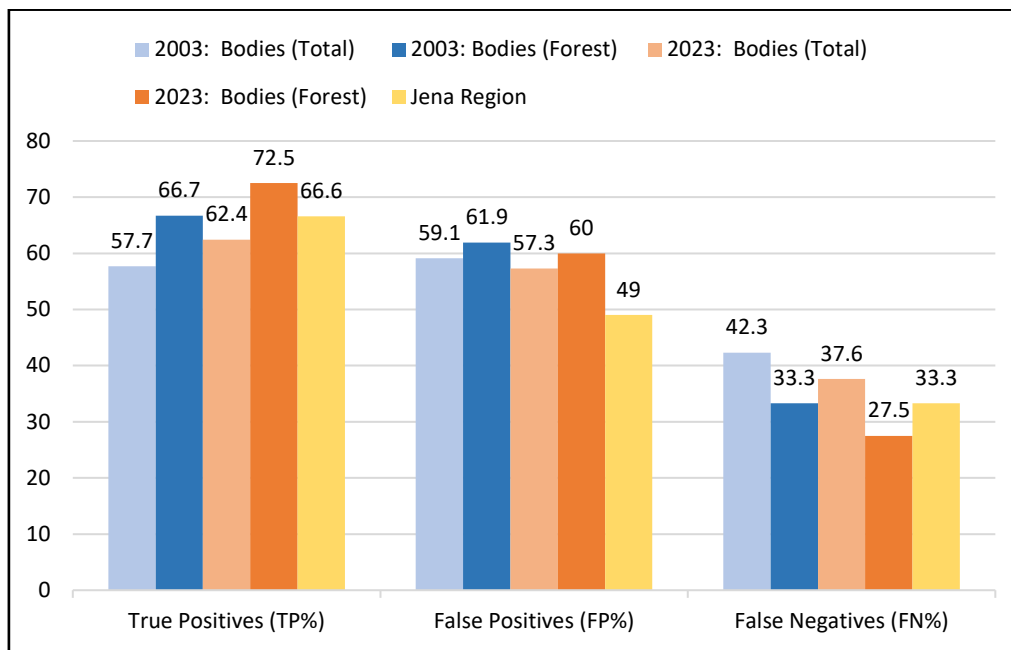
Table 9. Area-based comparison of GEOBIA landslide body detection performance (Swabian Alb and Jena region)

Landslide	Model/Year	TP (ha)		FP (ha)		FN (ha)	
		Count	(%)	Count	(%)	Count	(%)
	Swabian Alb						
Bodies (Inventory: 2221.8 ha)	2003	1282.3	57.7	1852.8	59	939.5	42.3
	2023	1386.7	62.4	1864.5	57.3	835.0	37.6
Bodies in forest (Inventory: 1793.6 ha)	2003	1195.5	66.7	1939.5	61.9	598.1	33.3
	2023	1300.2	72.5	1951.0	60	493.5	27.5
	Jena	161.9	66.6	155.8	49	81	33.3

5.4 Limitations and challenges

390 Despite the strong overall performance, some limitations typical of GEOBIA-based landslide mapping remain evident. In this study, FP rates are approximately 10% higher than those reported for the Jena region (Table 9). This is primarily related to the dense spatial clustering of landslides in the Swabian Alb, where adjacent or overlapping landslide bodies are difficult to delineate as separate objects without sacrificing TP detection (Figures 3 and 4, inset b). In addition, complex reactivation patterns—where younger movements partially overprint older landslide bodies—introduce internal boundary noise, further increasing FP rates (Figure 4, insets b–e). Similar behaviour has been widely reported in previous GEOBIA-
395 based studies and reflects the inherent challenge of mapping compound and overlapping landslides (Dias et al., 2023; Martha et al., 2010; Van Den Eeckhaut et al., 2012; Zangana et al., 2024; Zangana et al., 2025). Importantly, despite the elevated FP rates relative to the Jena region, the commission errors observed in the Swabian Alb remain comparable to—or lower than—those reported in earlier studies, such as Martha *et al.* (2010), where FP counts exceeded expert-mapped inventories.

Landslide scarp detection represents a further challenge, with lower accuracy compared to the Jena region. This is
400 primarily attributed to the strong geomorphological similarity between landslide scarps and rock outcrops in the Swabian Alb, particularly within steep limestone terrains and areas affected by anthropogenic modification. Similar misclassification patterns were also observed in the Jena region and others, indicating that scarp delineation is sensitive to lithological context and slope morphology (Van Den Eeckhaut *et al.*, 2012; Knevels *et al.*, 2019; Zangana *et al.*, 2025). Future refinements of the original ruleset, aimed at improving scarp detection and minimizing FP from landslide bodies, are therefore needed to reduce
405 commission errors and enhance model performance in complex terrains further.



410 **Figure 7.** Comparative Area-based performance analysis of landslide body detection in the Swabian Alb (total vs. forested terrain) with reference to the Jena region.

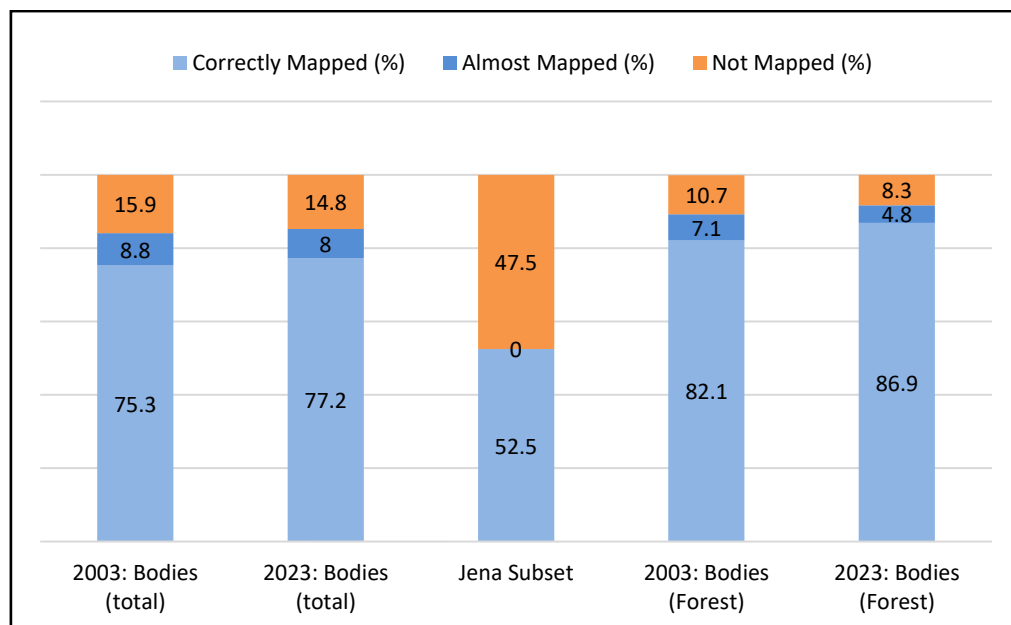


Figure 8. Comparative Object-based performance analysis of landslide body detection in the Swabian Alb (total vs. forested terrain) with reference to the Jena region.

6 Conclusion

415 This study demonstrates that the semi-automated, GEOBIA-based landslide mapping framework, originally developed for the Jena region by Zangana *et al.* (2025), can be successfully transferred to the cuesta landscapes of the Swabian Alb in Germany without any modifications to the original rule set. Using high-resolution terrain data, landslide body detection reached 77.2% across the entire study area and approximately 87% in forested terrain, exceeding detection rates previously reported for the original study region. These results confirm that the geomorphological signatures of landslides can be robustly
420 captured across different geological and land-cover settings when suitable terrain data is available.

Comparison of the 2003 and 2023 models indicates that differences in detection results partly reflect landslides that became visible in the newer dataset but are not represented in the older one, underlining the value of using recent high-resolution DTMs for landslide mapping. While landslide bodies are reliably detected, challenges remain in scarp delineation and in separating spatially clustered or overlapping landslides, particularly in steep limestone terrain, where morphological
425 similarities rock outcrops and anthropogenic features increase commission errors. Future developments should therefore focus on improved segmentation strategies and classification refinements, as well as on distinguishing between active and stable landslides, in order to better identify zones of elevated hazard.

Overall, the demonstrated transferability and performance of the GEOBIA workflow suggest that it can be applied to other regions with only slight modifications. The resulting high-resolution landslide inventories are important for future
430 susceptibility and risk assessments, as well as for regional land use planning and hazard mitigation. Furthermore, the results confirm that the method is highly effective in forested areas, particularly at detecting landslides with clear geomorphological signatures in high-resolution DTMs. More broadly, this study highlights the value of object-based terrain analysis for large-scale geomorphological mapping and for enhancing our understanding of landslide processes in complex landscapes.

CRediT authorship contribution statement

435 **I. Zangana:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **R. Bell:** Writing – review & editing, Methodology, Investigation, Data curation. **L. Drăguț:** Writing – review & editing, Investigation, Validating. **L. Schrott:** Writing – review & editing, Validation, Supervision, Investigation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

445 Data will be made available on request.

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