

Active and transfer learning methods for rapid landslide hazard assessments

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Dedication

To my mom, my father, and the rest of my family, friends, and the teachers that
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Summary

Active and transfer learning methods for rapid landslide hazard assessments

Due to the hazardous nature of landslides, timely and effective landslide susceptibility and detection results are needed for pre-disaster land management and spatial planning as well as post-disaster response, respectively. Also, interpretable models and outputs can contribute to the understanding of landslide processes and triggering factors by researchers. Nowadays, artificial intelligence (AI) has helped researchers and decision makers to bolster natural disaster management. However, major challenge in building AI-based models relates to the cost of searching and labeling the training data as well as the quality of the training data. Recently, training data minimization and historical natural hazard datasets have shown potential for the rapid construction of models. That is, the utilization of a small amount of data from a target area and historical landslide inventories from other areas (historical data) has the potential to be an emerging low-cost approach for constructing landslide models.

Active and transfer learning have recently received increasing attention in various research fields including natural hazards, ecology and remote sensing image classification. These approaches are capable of building models with good predictive performances by using historical data and a small amount of data from unseen areas, respectively. Although some studies have shown that active and transfer learning can provide accurate predictive results for image classification, domain-specific results are still lacking in landslide studies. Open research questions include: (i) whether the commonly used strategies in active learning are suitable for landslide studies; (ii) whether transfer learning is applicable to landslide studies; (iii) what the factors successfully transferring historical information in landslide studies are; (iv) what the limitations of active and transfer learning in landslide studies are. Meanwhile, it is necessary to overcome the limitations of active and transfer learning to better apply active and transfer learning to landslide studies. Therefore, the purpose of this thesis is to enhance our understanding of using active and transfer learning for rapid landslide assessment. It consists of three main contributions. That is, using case studies from our own and published landslide inventory analyzes the applicability of active and transfer learning methods in landslide studies. Also, developing a framework overcomes the limitations of active and transfer learning.

In order to understand the suitability of active learning in landslide studies, a comparative analysis of different active learning strategies is needed. In the first part of this work, the performances of commonly used active learning strategies based on pool-based sampling were analyzed in landslide detection assessment. These strategies were uncertainty sampling and query-by-committee, and random sampling (RS) was used as a benchmark. In addition, support vector machines (SVMs) were used as active learning models due to their generalization capacity and non-linearity. Overall, it was found that with only a small amount of training data (20% of the amount of data used for random sampling), the commonly used active learning strategies, especially uncertainty sampling, were able to obtain comparable predictive results to random sampling in a study area in Ecuador.

Homogeneity and non-transferability are very important for transferring information from historical data to a target area. In the second part of this work, two transfer learning approaches based on different ideas of acquiring the similarity between source and target areas to landslide susceptibility assessment were compared and analyzed. The first one was case-based reasoning (CBR). It compared the overall similarities of environmental characteristics and data resolution between source and target areas, and then used source areas with high similarities ("related" source areas) to build landslide susceptibility models to predict in a target area. The second one was the landmark-based domain adaptation (LBDA). It considered the data distribution of source and target areas. Sub-datasets from each source area with similar distribution to data from a target area were extracted, and then these subsets were used to construct landslide susceptibility models for predicting in a target area. Meanwhile, the combination of CBR and LBDA was also considered (CBR-DA). To assess the suitability of these two approaches and their combination, two benchmarks were used as comparison criteria: 1) training with data from the target area (the target benchmark); and 2) applying the model trained with data from a source area to a target area without using transfer learning. In particular, this work also explored the scenario where multiple source areas exist, and therefore a multiple-source method was proposed based on the overall similarities between "related" source and target areas.

Overall, this work applied CBR, LBDA, and CBR-DA to 10 different regions in 3 countries and considers data with different spatial resolutions (1 m, 10 m, 25 m; 17 data sets in total). It was found that only considering the data distribution of source and target areas (i.e., only using LBDA) in landslide susceptibility assessment did not improve the predictive performance of a transferred model. The approaches involving CBR can successfully transfer information from historical data to a target area by considering the overall similarity in environmental characteristics and data resolution between source and target areas. In particular, the predictive

performance obtained by CBR was always comparable to that obtained by the target benchmark.

In the third part of this work, a new framework was presented to overcome the limitations of active and transfer learning in landslide studies. First, a new active learning strategy was proposed to reduce the sampling bias caused by the imbalance in the number of landslide and non-landslide observations. Then, by combining CBR and the proposed active learning strategy, the labor cost for constructing the initial training data was reduced as well as the quality of the initial training data was improved. Next, a novel function was proposed to combine the model obtained by CBR with that trained by a small amount of training data from a target area. As a result, model predictions did not change across different training data from the same region, and the information from source and target areas can be used and interpreted independently. Meanwhile, the predictive accuracy obtained by the proposed framework was only 2% lower than that obtained by the target benchmark in a study area of 229 km² in Indonesia, reducing 80% of the efforts of building the training data compared to only using the active learning framework. Moreover, due to its availability as a reference for modeling other natural hazards, the proposed framework has the potential to become a generic framework for modeling natural hazards.

In conclusion, this thesis provides new insights for rapid landslide assessment by using active and transfer learning. Meanwhile, the proposed framework can help decision makers to prevent and respond to natural hazards by providing timely and accurate suggestions for land management, spatial planning, and post-disaster response. Future work can focus on the integration of the proposed framework into a user-interactive implementation, e.g., the combination of open-access satellite data (e.g., Sentinel-2) or cloud-based processing platforms (e.g., Google Earth Engine) with the proposed framework.

Zusammenfassung der Dissertation

Active und Transfer Learning Methoden für die schnelle Bewertung der Hangrutschungsgefahr

Aufgrund der Gefährlichkeit von Hangrutschen, werden rechtzeitige und wirksame Ergebnisse zur Gefährdung (engl. susceptibility) durch und Erkennung von Hangrutschen für das Landmanagement und die Raumplanung im Vor-Katastrophenfall und der Post-Katastrophenhilfe benötigt. Interpretierbare Modelle und Ergebnisse können zudem zu einem verbesserten Verständnis von Hangrutschungsprozessen und auslösenden Faktoren beitragen. Die Anwendung Künstlicher Intelligenz (engl. Artificial Intelligence, AI) hat Forschern und Entscheidungsträgern dabei geholfen, das Management von Naturkatastrophen zu verbessern. Die wesentlichen Herausforderungen beim Aufbau eines AI-basierten Modells sind jedoch die Kosten für die Suche und Kennzeichnung der Trainingsdaten sowie die Qualität der Trainingsdaten. In den letzten Jahren wurde gezeigt, dass auch Techniken zur Datenminimierung von Trainingsdaten und historische Naturgefahren Datensätze eine potenzielle Grundlage für eine schnelle Erstellung von Modelle sind. Das heißt, dass die Verwendung einer kleinen Datenmenge aus dem Zielgebiet und historischer Daten aus anderen Gebieten ein neuer, kostengünstiger Ansatz zur Erstellung von Gefährdungsmodellen sein kann.

Ansätze des Active Learning (Aktiven Lernens) und Transfer Learning haben in Forschungsbereichen der Naturkatastrophen, Ökologie und Klassifizierungsproblemen (z.B. von Fernerkundungsbildern) zunehmend an Bedeutung gewonnen. So können über diese Ansätze auch aus einer kleinen Menge von Daten aus unbekanntem Regionen bzw. historischen Daten, Modelle mit einer hohen Vorhersagegüte erstellt werden. Obwohl einige Studien gezeigt haben, dass das Active und Transfer Learning Vorhersageergebnisse hoher Genauigkeit für die Bildklassifikation liefern kann, sind diese Ansätze bei Hangrutschungen noch nicht vollständig erforscht. Offene Forschungsfragen sind, (i) ob die allgemein verwendeten Strategien des Active Learning für Hangrutschungsstudien geeignet sind, (ii) ob das Transfer Learning auf Hangrutschungsstudien anwendbar sind, (iii) welche Faktoren für eine erfolgreiche Transferierung von historischen Informationen in Hangrutschungsstudien ausschlaggebend sind und (iv) was die Einschränkungen von Active und Transfer Learning in Hangrutschungsstudien sind. Insbesondere ist es notwendig, sich mit den Einschränkungen des

Active und Transfer Learning auseinanderzusetzen, um diese Methodiken besser auf Hangrutschungen anwenden zu können. Ziel dieser Dissertation ist es, das Verständnis für den Einsatz von Active und Transfer Learning bei der Untersuchung von Hangrutschungen zu verbessern. Die Dissertation setzt sich aus drei Hauptbeiträgen zusammen. Das heißt, anhand von Fallstudien aus unserem eigenen und veröffentlichten Hangrutschungsinventar wird die Machbarkeit von Active und Transfer Learning in der Hangrutschungsforschung analysiert und ein neuer Rahmen entwickelt, um Active und Transfer Learning Grenzen zu überwinden.

Um die Eignung des Active Learning Ansatzes bei der Gefährdungsmodellierung zu explorieren, ist ein Vergleich verschiedener aktiver Lernstrategien erforderlich. Im ersten Teil dieser Dissertation wurden die Erkennung von häufig verwendeten Active Learning Strategien, die auf poolbasiertem Stichprobenverfahren basieren, in Hangrutschungsstudien analysiert. Bei diesen Strategien handelte es sich um Uncertainty Sampling und query-by-committee, wobei Zufallsstichproben (engl. random sampling, RS) als Vergleichskriterium herangezogen wurden. Darüber hinaus wurden support vector machines (SVMs) aufgrund ihrer Verallgemeinerungsfähigkeit und nichtlinearen Modellierung als Active Learning Modelle verwendet. Es wurde festgestellt, dass die allgemein verwendeten Active Learning Strategien in der Lage waren, mit einer geringen Menge an Trainingsdaten (20% der für die Zufallsstichprobe verwendeten Datenmenge) gute Vorhersageergebnisse in einem Untersuchungsgebiet in Ecuador erzielten, insbesondere mit uncertainty sampling.

Homogenität und Nichtübertragbarkeit sind sehr wichtig für die Übertragung der Informationen von bestehenden Datensätzen auf das Zielgebiet. Im zweiten Teil dieser Dissertation wurden zwei Transfer Learning Methoden verglichen und analysiert, die auf unterschiedlichen Ideen zur Erfassung der Ähnlichkeit zwischen source areas (Herkunftsgebieten) und Zielgebieten für Studien zur Rutschungsgefährdung basieren. Der erste Ansatz war case-based reasoning (CBR). Dabei wurden die allgemeinen Ähnlichkeiten der Umweltmerkmale und der Auflösung der Daten zwischen source areas und Zielgebieten verglichen. Anschließend wurden source areas mit hohen Ähnlichkeiten verwendet, um Gefährdungsmodelle zur Vorhersage des Zielgebiets zu erstellen. Die zweite Methode war die landmark-based domain adaptation (LBDA). Dabei wurde die Datenverteilung zwischen source und Zielgebiet berücksichtigt. Aus jeder source area wurden Teildatensätze extrahiert, die eine ähnliche Verteilung wie die Daten des Zielgebiets aufwiesen. Anschließend wurden diese Teildatensätze zur Erstellung von Gefährdungsmodellen für die Vorhersage des Zielgebiets verwendet. Darüber hinaus wurde die Kombination von CBR und LBDA berücksichtigt (CBR-DA). Um die Eignung dieser beiden Ansätze und ihrer Kombination zu überprüfen, wurden

zwei Benchmarks als Vergleichskriterien herangezogen: 1) Training mit Daten aus dem Zielgebiet (Ziel-Benchmark); und 2) Anwendung des mit Daten aus der source area trainierten Modells auf das Zielgebiet ohne Transfer Learning. Zudem wurde ein Szenario untersucht, in dem mehrere source areas existieren, und eine auf Ähnlichkeit-basierende Methode zur Kombination aller source areas mit hoher Ähnlichkeit mit dem Zielgebiet vorgeschlagen.

Insgesamt wurden in dieser Arbeit CBR, LBDA und CBR-DA auf 10 verschiedene Regionen in drei Ländern angewandt und Daten mit unterschiedlichen räumlichen Auflösungen (1 m, 10 m, 25 m; insgesamt 17 Datensätze). Es wurde festgestellt, dass die alleinige Berücksichtigung der Datenverteilung zwischen source und Zielgebiet (d. h. die ausschließliche Verwendung von LBDA) in Hangrutschungsstudien die Vorhersagegüte des übertragenen Modells nicht verbessert hat. Die Ansätze, die CBR einbeziehen, können historische Informationen erfolgreich übertragen, indem sie Umweltcharakteristika und Datenauflösung berücksichtigen. Zudem war die erzielte Vorhersagegüte der CBR immer mit der Ziel-Benchmark vergleichbar.

Im dritten Teil dieser Dissertation wurde eine neue Rahmenstruktur zur Überwindung der Einschränkungen des Active und Transfer Learning in der Hangrutschungsforschung vorgestellt. Zuerst wurde eine neue Active Learning Strategie vorgeschlagen, um Verzerrungen traditioneller Active Learning Strategien hinsichtlich der Stichprobe zu reduzieren, welche durch die unausgewogene Anzahl von Erdrutschen und Nicht-Erdrutschen verursacht wird. Durch die Kombination von CBR und der vorgeschlagenen Active Learning Strategie, konnten der Aufwand für die Erstellung der anfänglichen Trainingsdaten reduziert und die Qualität der anfänglichen Trainingsdaten verbessert werden. Anschließend wurde eine neuartige Funktion vorgeschlagen, um das durch CBR erhaltene Modell mit dem anhand der Trainingsdaten des Zielgebiets trainierten Modell zu kombinieren. Diese Kombination gewährleistete stabile Active Learning Modelle und unabhängige Informationen aus historischen Daten und dem Zielgebiet. Die Ergebnisse zeigten, dass der innovative Ansatz eine Vorhersagegenauigkeit erzielte, die lediglich 2% unter derjenigen lag, die mit der Zielbenchmark in in einem Studiengebiet von 229 km² in Indonesien erzielt wurde. Außerdem waren die Kosten für die Erstellung der Trainingsdaten um 80% niedriger als bei der ausschließlichen Verwendung von Active Learning.

Darüber hinaus hat der vorgeschlagene Rahmen aufgrund seiner Verfügbarkeit als Referenz für die Modellierung anderer Naturgefahren das Potenzial, zu einem generischen Rahmenwerk für die Modellierung von Naturgefahren zu werden.

Insgesamt liefert diese Dissertation neue Erkenntnisse für die schnelle Untersuchung von Hangrutschungen durch den Einsatz von Active und Transfer Learning Strategien. Gleichzeitig kann die präsentierte Methodik Rahmenstruktur Entscheidungsträgern helfen, Naturkatastrophen vorzubeugen und auf sie zu reagieren, indem diese zeitnahe und genaue Vorschläge für die Landbewirtschaftung, die Raumplanung und die Reaktion nach Katastrophen liefert. Zukünftige Arbeiten können sich auf die Integration der vorgeschlagenen Rahmenstruktur in eine benutzerinteraktive Implementierung konzentrieren, z. B. die Kombination von frei zugänglichen Satellitendaten (z. B. Sentinel-2) oder cloudbasierten Verarbeitungsplattformen (z. B. Google Earth Engine).

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List of Abbreviations

AI	Artificial Intelligence
AL	Active Learning
AUROC	Area Under the Receiver Operating Characteristic Curve
CBR	Case-based Reasoning
DEM	Digital Elevation Model
DEMNAS	Indonesian National Digital Elevation Model
GAM	Generalized Additive Models
GCC	Green Chromatic Coordinates
HCI	Human-computer Interaction
IQR	Interquartile Range
LBDA	Landmark-Based Domain Adaptation
LC	Least Confidence
MS	Margin Sampling
MSUE	Main Steep Slope Upper Edge
NDVI	Normalized Difference Vegetation Index
PS	PlanetScope
QBC	Query-by-Committee
RCC	Red Chromatic Coordinates
RF	Random Forest
ROC	Receiver Operating Characteristic
RS	Random Sampling
SAGA	System for Automated Geoscientific Analysis
SRS	Stratified Random Sampling
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machine
TL	Transfer Learning
TWI	Topographic Wetness Index
UAT	Unsupervised Active Transfer Learning
UNISDR	United Nations International Strategy for Disaster Reduction
US	Uncertainty Sampling

Chapter 1

Introduction

1.1 Motivation

Landslides are a type of mass wasting process that can be triggered by heavy rainfall, earthquakes, etc., resulting in the downward and outward movement of slope-forming materials consisting of natural rock, soil, artificial fill, or a combination of these materials (Dai et al., 2002; Lee and Jones, 2004; Sidle and Ochiai, 2006). Under the pressure of an increase in population and urbanization, human activities such as deforestation have developed and expanded into unstable hillside areas, which in turn has led to landslides occurring with increasing frequency (Crozier, 2010). As one of the major natural disasters, landslides cause huge losses every year, such as loss of human lives and biodiversity, property damage, and disruption in transportation services. For example, between 2004 and 2010, 2,620 fatal landslides were recorded worldwide, killing a total of 32,322 people (Petley, 2012). In conclusion, landslides can have a wide range of impacts on human life and the economy, thus it is a priority to apply effective methods for landslide risk mitigation.

Techniques for landslide susceptibility assessment are capable of identifying landslide-prone areas based on physical and environmental characteristics (Petschko et al., 2014; Kavzoglu et al., 2019). The resulting maps can inform local communities better understand the potential risks of living there and take appropriate measures to reduce those risks, such as building or installing retaining walls on steep slopes (Bell et al., 2013; Petschko et al., 2012; Stanley and Kirschbaum, 2017). Unlike landslide susceptibility assessment, landslide mapping or detection assessment is able to provide information on the distribution of landslides that have already occurred (Parise, 2001; Aslan et al., 2020; Knevels et al., 2019). For slow-moving landslides, landslide detection can contribute to saving lives. For rapid mass movements, landslide mapping is most useful as an input for landslide susceptibility models, and can also rapidly assess damages after an event affecting a large region with numerous individual landslides (Benz and Blum, 2019; Mohan et al., 2021; Ghorbanzadeh et al., 2022).

In general, the procedures for landslide susceptibility and detection assessments involve collecting and analyzing data, constructing landslide models, and analysis of results (Van Westen et al., 2008; Petschko et al., 2014; Goetz et al., 2015; Reichenbach et al., 2018). To date,

artificial intelligence (AI) plays a key role in natural hazard management. Particularly, statistical models and machine learning have shown to be useful in landslide modeling to obtain landslide susceptibility or distribution information (Goetz et al., 2015; Kavzoglu et al., 2019). However, thousands of labeled data are often required for any algorithm, especially supervised learning algorithms, to perform well (Tuia et al., 2011; Kuglitsch et al., 2022a). For landslide studies, landslide/non-landslide data collection for building landslide models is challenging (Petschko et al., 2013; Petschko et al., 2016).

Remote sensing technology can aid with data collection for landslide studies. It has become an increasingly popular tool for landslide assessment studies because it allows researchers to easily collect landslide/non-landslide data, even in large and remote regions (Hong et al., 2007; Petschko et al., 2012; Zhong et al., 2020). This technology can provide a large amount of data to support landslide modeling; however, it also further increases the burden of preparing the training data (Tuia et al., 2009; Gamba, 2014; Cheng et al., 2020). Moreover, it is crucial to assure the quality of the training data (Petschko et al., 2016; Steger et al., 2017). Therefore, the motivation of my thesis is to reduce the burden of preparing the training data as well as obtaining accurate landslide susceptibility or detection results. This is one of the important parts of landslide assessment studies, but is challenging as well (Corsini et al., 2013).

One way to reduce the costs of building training data is to use a small amount of labeled data from the target area. In machine learning, there is a hypothesis that if a learning algorithm is allowed to select the data it is curious about from the unlabeled data, then this learning algorithm will perform well in predicting the unlabeled dataset by using a small amount of labeled data from the unlabeled dataset (Settles, 2010). Active learning is based on this hypothesis and tries to break the bottleneck of constructing the training data. As a subfield of machine learning, it uses query strategies to obtain relevant responses (sampling from unlabeled data) by asking about the past (Tong, 2001). Different query strategies produce different results. For example, Tuia et al. (2011) compared the effectiveness of different active learning strategies in land use/cover classification; the results showed that different active learning strategies had their own advantages. Although this technique has been applied in several fields, such as speech recognition (Yu et al., 2010), information extraction (Wu and Pottenger, 2005), and classification and filtering (Elahi et al., 2016), the applicability of different query strategies have not been fully explored in landslide studies. Stumpf et al. (2014) used the query-by-committee strategy for landslide classification based on random forests and concluded that good results can be achieved, but no comparison was made with other query strategies. Therefore,

comparative experiments are needed in landslide assessment studies to further validate the applicability as well as the performances of query strategies of active learning.

In addition, existing landslide inventories from different regions and periods (historical landslide inventories, source areas) can provide useful information for landslide assessment (Petschko et al., 2016). Hence, it is possible to directly use information from historical landslide inventories to predict in a target area. Transfer learning is a technique to apply information from one task to a related new task, thereby not only saving time and effort but also obtaining good results (Pan and Yang, 2010). It has only recently been introduced to the field of landslide research, which means that additional research is necessary to assess and exploit the full potential of transfer learning in this context. For example, Wang et al. (2022) used transfer learning for Hong Kong, China, and indicated that the predictive accuracy can be improved; Xu et al. (2022) proposed transfer learning methods MFFENet and ADANet for earthquake-induced landslide detection and obtained accurate results; Ai et al. (2022) implemented landslide detection in Sichuan Province, China, using distant domain transfer learning and demonstrated that a good detection accuracy can be achieved. Zhu et al. (2020) proposed unsupervised feature transfer learning and improved the predictive performance of the landslide susceptibility model in Chongqing, China. Nevertheless, all these studies assumed that the environmental characteristic/data distribution is the same or at least similar between source and target areas, which is inconsistent with the reality. Furthermore, previous studies using transfer learning for landslide assessment have only considered data in source and target areas with the same spatial resolution (Lu et al., 2020; also references above). However, in landslide studies, only performing transfer learning between adjacent regions or data with the same resolution does not enhance the understanding of transfer learning due to the diversity of environmental characteristics of regions and the different impacts of different data resolutions on model predictions. In this sense, researching transfer learning with data from different regions of the world, different data sources, and different spatial resolutions is of great importance in landslide studies.

Furthermore, finding the limitations of techniques in specific applications can help researchers to deepen their understanding. Also, overcoming these limitations promotes the development of techniques to perform better in specific applications. Overall, the goal of this thesis is not only to explore the applicability of active and transfer learning in landslide studies but also to overcome their limitations in landslide studies.

1.2 Research objectives

The goal of this thesis is to reduce manual efforts in constructing the training data for landslide modeling and to enhance our understanding of the predictive performances of active and transfer learning in landslide studies. To achieve this goal, this thesis focuses on the following research questions and objectives:

How can we identify information that is useful for landslide modeling, considering both historical landslide inventories from other areas (historical data/information) and manually labeled data from the unseen target area?

Since not all landslide or non-landslide observations are equally suitable for landslide modeling, the first step is to extract “useful” information from the target area or historical landslide inventories.

The objective of this research questions is to:

- Identify “useful” information from the target area using common active learning strategies
- Identify “useful” information from historical landslide inventories based on different transfer learning ideas

How good is the predictive performance of active learning in landslide assessment studies (i.e., the performance of using a small number of “useful” labeled observations from the target area)?

Different active learning strategies select different information from the target area, achieving different predictive results. In addition, this research question explores whether common active learning strategies can be used to achieve better predictive performances and which one is better.

The objective of this research questions is to:

- Compare the performances of different active learning strategies in landslide mapping
- Assess the performances of active learning strategies by comparing them with random sampling

How good is the predictive performance of transfer learning in landslide assessment studies (i.e., the performances of using “suitable” historical landslide inventories)?

Based on different transfer learning ideas, different information can be obtained from historical landslide inventories. This research question is to explore the performances of different transfer learning techniques in landslide studies using different regions from different countries (a global scale).

The objective of this research questions is to:

- Compare the performances of landslide susceptibility models constructed by different transfer learning techniques at a global scale
- Assess the performances of transfer learning techniques by comparing them with models constructed without transfer learning and with a model constructed using data from the target area itself

What is the role of information of historical landslide inventories and the unseen area, and how do we overcome the limitations of active and transfer learning in landslide assessment studies?

Since both historical landslide inventories and target area information are of interest in landslide studies, this research question is to improve the performances of active and transfer learning in landslide studies to provide a new landslide susceptibility/detection framework.

The purpose of this research question is to:

- Find the limitations of active and transfer learning
- Develop a new landslide assessment framework to overcome limitations of active and transfer learning
- Assess the performance of the proposed framework in landslide studies by comparing it with models obtained using only active learning, transfer learning, and the target area itself

Overall, these research questions and objectives aim to validate and improve the performances of active and transfer learning in landslide studies.

1.3 Thesis outline

This publication-based doctoral thesis is organized as follows. This first chapter introduces the motivation, main research questions, and objectives of this thesis. Chapter 2 provides the scientific background and concepts of techniques for constructing landslide models, sampling training data, and reducing the manual effort used in the thesis.

Chapter 3 (paper 1) describes the need to implement rapid landslide assessment to reduce the high cost of building a large amount of training data from the target area, and compares and evaluates the performances of different active learning strategies in landslide detection assessment in a case study from Ecuador.

Chapter 4 (paper 2) identifies the utility of historical landslide inventories (source areas) and the challenges of selecting “suitable” source areas for model training, and assesses the potential of transfer learning in landslide susceptibility assessment. It extends the study of landslide model transfers to a global scale, and considers two scenarios: only one source area

available and multiple source areas available. In addition, a multiple “suitable” source areas combination method is proposed based on the overall similarities of environmental characteristics and data resolution between source and target areas.

Chapter 5 (paper submitted) overcomes the limitations of the active learning framework as well as model transfers by presenting a novel landslide assessment framework. In a case study from Indonesia, it improves the predictive performances of active learning and model transfers in landslide detection assessment.

Chapter 6 discusses the main contributions of this work, provides suggestions for future research, and draws conclusions.

Chapter 2

Background

Disaster risk management advocates the implementation of policies and measures aiming to reduce risks caused by disasters (Lavell and Maskrey, 2014; Aitsi-Selmi et al., 2015). According to the Sendai Framework for disaster risk management (Figure 1), disaster management can be grouped into four phases: prevention, response, recovery, and rehabilitation (UNISDR, 2015). The results of the first two phases can influence the decision-making during the recovery and rehabilitation phases (Petschko et al., 2014; Sreelakshmi et al., 2022).

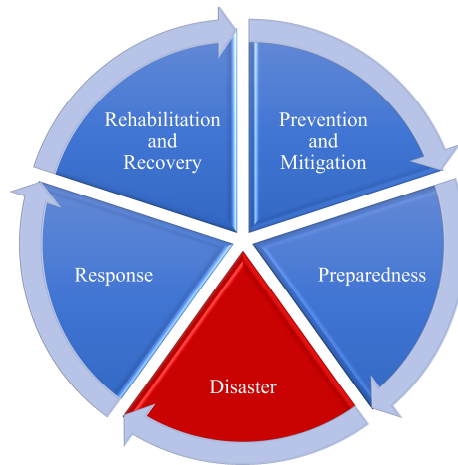


Figure 1 Overview of the disaster risk management phases.

In landslide assessment studies, landslide susceptibility and detection assessments can provide support for the prevention and response phases, respectively. Landslide susceptibility assessment can provide the likelihood of future landslides in a region to help the community with land management and spatial planning (Petschko et al., 2014). In contrast, landslide detection assessment can identify the locations of landslides in a region after landslides happen to help the community with search and rescue efforts (Ghorbanzadeh et al., 2019).

In general, data collection, landslide modeling, and analysis of results constitute the procedures of landslide assessment (Van Westen et al., 2008). How to construct a landslide model that can get accurate predictive results is an important concern in landslide assessment studies (Petschko et al., 2014; Goetz et al., 2015; Reichenbach et al., 2018).

2.1 Landslide modeling

Generally, approaches for assessing landslide susceptibility can be grouped into three basic types: knowledge-based approaches, physical approaches, and data-based approaches (Table 1) (Corominas et al., 2014). Due to the subjective nature of knowledge-based approaches and the lack of sufficient geotechnical data for physical approaches, data-based approaches show promise in identifying landslide susceptibility, especially statistical methods and machine learning (Micheletti et al., 2014; Goetz et al., 2015; Merghadi et al., 2020).

Table 1 Approaches for assessing landslide susceptibility.

Approaches	Definitions
Knowledge-based	Qualitative method; Based on expert knowledge, the weights and ranks of various landslide condition factors are evaluated and then used to predict the probability of the future landslide occurrence.
Physical	Quantitative method; The process of the landslide occurrence is modeled by taking into account geometric and geotechnical features to assess landslide susceptibility.
Data-based	Quantitative method; The statistical relationship between the location of past landslides and their inducing factors is evaluated, and then the spatial probability of the future landslide occurrence is evaluated.

In terms of approaches for landslide detection assessment, they are grouped into two main classes: conventional (i.e., geomorphologic field survey) and innovative (i.e., automated/semi-automated methods) approaches (Guzzetti et al., 2012). With the development of modern geospatial techniques (Table 2), innovative approaches have been used for recognizing changes that occurred in the terrain surface after landslides (Mohan et al., 2021). Moreover, due to the increased availability of high-resolution optical satellite sensors and improvements in computer technology, statistical methods and machine learning have become effective tools for detecting landslide distributions over large areas (Yu et al., 2020; Meena et al., 2022). The characteristics of the main optical satellite sensors used for landslide mapping are summarized here (Table 3).

Table 2 Remote sensing tools and the techniques based on them for landslide identification.

Techniques for landslide identification	Remote sensing tools
Manual interpretation	Aerial imagery
	Laser survey
	Very high-resolution / high-resolution satellite imagery
Automated / semi-automated	Aerial laser scanning
	Airborne Imagery
	Terrestrial laser scanning
	Very high-resolution / high-resolution satellite imagery
SAR interferometry	Space-borne InSAR
Stereoscopic vision (i.e., 3D acquisition)	Very high-resolution / high-resolution satellite imagery

Table 3 Overview of the main optical satellite sensors used to recognize, detect, and map landslides. P, panchromatic; B, blue; G, green; R, red; NIR, near-infrared; SWIR, short-wavelength infrared; MWIR, mid-wavelength infrared; TIR, thermal infrared (after Guzzetti et al., 2012).

Satellite	Bands	Spatial resolution (m)
Landsat 8 /OLI-TIRS	Pan	15
	Coastal/Aerosol, B, G, R, NIR, SWIR, Cirrus	30
	TIR	100
SPOT-1,2,3,4	Pan	10
	G, R, NIR, MWIR	20
SPOT-5	Pan super-mode	2.5
	Pan	5
	G, R, NIR, MWIR	10
Sentinel-2	B, G, R, NIR	10
	Vegetation red edge, SWIR	20
	Coastal, Water vapor, SWIR – Cirrus	60
PlanetScope	B, G, R, NIR	3 / 3.7

That is, remote-sensing-based image processing methods are increasingly being applied to landslide assessment studies (Huang et al., 2018; Mohan et al., 2021). These methods can be further classified into pixel-based and object-based (Van Westen et al., 2008). Object-based landslide modeling requires the grouping of pixels with similar spectral or textural characteristics into one object before modeling (Knevels et al., 2019). A number of studies have been conducted on object-based methods and confirmed their performances in landslide mapping (Barlow et al., 2003; Stumpf and Kerle, 2011; Heleno et al., 2016). However, the segmentation procedures used in object-based approaches are usually quite complex and limited in terms of transferability across regions and sensors (Knevels et al., 2019). Overall, the choice of which method to construct a model depends on the goal of the research.

Generally, a set of predictor variables (i.e., independent variables) is used as preparatory conditions for landslide modeling (Goetz et al., 2015). In recent years, most automated/semi-automated landslide modeling methods are based on the spectral or elevation characteristics of

landslides (Van Westen et al., 2008). These characteristics include vegetation cover, slope, terrain surface, surface drainage, etc. (Soeters and Van Westen, 1996; Knevels et al., 2021). In addition, considering topographic and geotechnical characteristics of a study area, other factors such as land use, distance from roads, and lithologic features have been applied in landslide modeling (Brenning et al., 2015; Knevels et al., 2021; Bajni et al., 2022). Commonly considered landslide-conditioning factors are summarized in Table 4.

Table 4 Landslide-conditioning factors and their typical predictors.

Inducing factors	Typical conditioning predictors
Topography	Elevation, slope angle, predictors related to slope (e.g., slope curvature)
Geology	Lithology, predictors factors related to faults
Hydrology	Indices used to characterize soil moisture (e.g., topographic wetness index, normalized difference moisture index), distance from drainage
Land cover	Vegetation indices (e.g., normalized difference vegetation index), land use types
Meteorology	Precipitation
Earthquake	Peak ground acceleration
Engineering	Distance from roads and settlements

However, the exact relationship between predictors and landslide occurrences is not always known a priori (Goetz et al., 2015). How to identify possible causes/preparatory factors of landslides is also one of the main objectives of landslide modeling. For example, Brenning et al. (2015) built landslide susceptibility models to analyze landslide occurrences along highways but did not intend to map landslide susceptibility. Knevels et al. (2023) constructed different landslide susceptibility models for assessing the impact of climate change on uncertainties in landslide susceptibility predictions. Bajni et al. (2022) explored rock-mass geomechanical properties in a rockfall susceptibility analysis by building a rockfall susceptibility model.

The freedom of choice in deciding which modeling approach is best suited is challenging (Elmoulat et al., 2020; Phong et al., 2021). Recently, deep learning has gained attention in natural hazards, ecology and remote-sensing image classification (Khelifi and Mignotte, 2020; Van Dao et al., 2020; Azarafza et al., 2021). However, its predictive performance relies on the tuning of hyperparameters, which is a complex process (Ghorbanzadeh et al., 2019; Ngo et al., 2021). Goetz et al. (2015) compared the performances of generalized additive models (GAMs), support vector machines (SVM), random forest (RF), etc. in landslide assessment and indicated that there was little difference in the predictive accuracies of statistical and machine learning, with GAM being the most interpretable. Moreover, numerous comparisons of landslide modeling approaches have been made, but no single best approach has been found (Yilmaz, 2010; Yalcin et al., 2011; Pradhan, 2013; Huang et al., 2020).

The ability to convey model behavior is a desirable quality of a landslide model (Brenning, 2012). However, due to the "black box" nature, the internal mechanisms that define the response representation by predictor variables are difficult to interpret in machine learning methods, especially remote-sensing-based image processing methods (Goetz et al., 2015; Knight, 2017). In contrast, statistical methods can determine how well predictors represent landslide-related processes (Frattini et al., 2010). For example, GAMs can apply automatic stepwise variable selection methods to estimate the variable importance of a model (Goetz et al., 2011; Petschko et al., 2014). In summary, the interpretability of a method should be considered before building a landslide model.

Model evaluation verifies the suitability of the chosen method for the objective of a study. Predictive performance is one of the commonly used evaluation criteria (Chung and Fabbri, 2003; Guzzetti et al., 2012; Goetz et al., 2015; Knevel et al., 2019). The area under the receiver operating characteristic (ROC) curve (AUROC) has become a common performance measurement (Brenning, 2005; Frattini et al., 2010; Petschko et al., 2014; Knevel et al., 2023). The ROC curve plots all possible true positive rates (sensitivity) and the corresponding false positive rates (1-specificity). An AUROC value closer to 1 indicates a smaller difference between the binary prediction classes. Other common evaluation criteria are success rate curves, and prediction rate curves (Sterlacchini et al., 2011). In addition, Frattini et al. (2010) pointed out that model robustness can be evaluated by the response of a model to sampling variation. In general, the prediction accuracy obtained by a model is an evaluation criterion to measure model robustness (Luoto and Hjort, 2005; Conoscenti et al., 2016; Dou et al., 2019).

2.2 The training data for landslide modeling

A growing number of studies have pointed out that although AI is becoming increasingly attractive in various fields and has led to many theoretical breakthroughs, the collection and creation of the input data remains challenging (Jo and Gebru, 2020; Sun et al., 2020; Kumar et al., 2022). Therefore, for data-driven landslide models, it is necessary to create the input data (i.e., training data) that can contribute to model performances.

2.2.1 The quality of the training data

Training data containing features that can cover landslide and non-landslide observations in a target area help a learning algorithm to obtain good predictions in a target area (Sameen et al., 2020). Previous studies have demonstrated that the quality of the training data relies on data resolution, the accuracy of a landslide inventory, the amount of information on landslides and non-landslides in the training data, and the predictor variables used in the training data (Petschko, 2014; Steger et al., 2016; Brock et al., 2020; Sameen et al., 2020).

Numerous studies have shown that reliable landslide inventories are an important component in achieving high-performance landslide models (Fell et al., 2008; Harp et al., 2011; Petschko et al., 2014). However, inventory bias is inevitable in landslide modeling (Santangelo et al., 2015). Previous studies have pointed out that the accuracy and completeness of a landslide inventory can be influenced by the type (e.g., aerial photographs) and quality (e.g., spatial resolution) of available base maps, the size and type of landslides, human factors (e.g., the accuracy of public reporting), and the processing of information sources (e.g., digitization) (Steger et al., 2017). Hence, to reduce the impact of inventory bias, it is necessary to build a landslide inventory based on high-quality data sources (Guzzetti et al., 2012; Xu et al., 2015; Santangelo et al., 2015; Petschko et al., 2016; Steger et al., 2016; Knevels et al., 2021). The use of explanatory variables is mostly based on the knowledge and understanding of landslide processes (Reichenbach et al., 2018). Some studies have conducted variable selection to analyze the importance of each variable and remove irrelevant variables, such as backward stepwise selection (Brenning et al., 2005; Iovine et al., 2014; Conoscenti et al., 2016). However, the availability of explanatory variables is based on the completeness of information in a landslide inventory. For example, Goetz et al. (2015) did not include temporally sensitive predictor variables, such as land use and rainfall, in their analysis since the landslide inventory did not have information on when landslides were triggered. Hence, in general, as mentioned in *Section 2.1*, explanatory variables derived from spectral or/and topographic characteristics of landslide/non-landslide observations are commonly used to construct landslide models.

Different training data can cause different optimal separating surfaces of a model, thereby obtaining different model performances (Yao et al., 2022). Nowadays, most sampling strategies focus on data sampling based on landslide positions (e.g., the centroid of a landslide body) (Regmi et al., 2014; Hussin et al., 2016), sample size (e.g., the ratio of the number of landslides and non-landslides) (Heckmann et al., 2014; Chen et al., 2019) or strategies for selecting the training data such as random sampling (RS) (Fernández et al., 2018; Xie et al., 2019). Nevertheless, no strategy has been found to be the most effective for constructing high-quality training data. Moreover, since constructing training data is time-consuming and laborious, the main challenge is how to reduce this burden while obtaining high-quality training data.

2.2.2 Compiling the training data

In the case of having landslide inventories, using an adequate amount of landslide and non-landslide observations allows for constructing the training data with sufficient information. In contrast, in a real situation, existing landslide inventories are scarce. That is when mass

movements occur in a region, no landslide inventory is available after this event. Quickly labeling these data is very crucial to achieve rapid landslide mapping.

A number of studies have highlighted the importance of a sampling strategy applied to statistical analysis (Erener et al., 2017; Kornejady et al., 2017; Huang and Zhao, 2018). The commonly used sampling strategies are cluster sampling, simple random sampling (RS), stratified random sampling (SRS), and systematic sampling (Table 5) (Dhakal et al., 2000; Yilmaz and Ercanoglu, 2019). Among them, RS and SRS are the most commonly used strategies in constructing training data for landslide modeling (Marjanović et al., 2011; Mezaal et al., 2017; Raja et al., 2018). In addition, a set of specific sampling strategies for landslide modeling is used in the literature, such as a two-level random sampling strategy (Ada and San, 2018), non-selective/selective nearby sampling (Erener et al., 2017), and region partitioning (Hong et al., 2018). Cormack et al. (2014) defined these strategies that randomly search and manually label training data from unlabeled data and then unidirectionally deliver these labeled data to a model as the passive learning strategy. Some studies have pointed out that using a passive learning strategy for constructing the training data usually requires relevant expert knowledge in advance (e.g., SRS) or randomly selecting a large amount of data for manual labeling (Tong 2001; Cohn, 2011).

Table 5 General sampling strategies for landslide modeling.

Sampling strategy	Definition
Cluster sampling	Normally, a given data set will be divided into several groups, and then these groups will be randomly selected or combined.
Simple random sampling	The landslide and non-landslide data are randomly selected from the entire landslide inventory, which is a type of probability sampling.
Stratified random sampling	Commonly, a certain amount of data is randomly selected from the landslide and non-landslide datasets, respectively.
Systematic sampling	Commonly, a certain amount of data is extracted at intervals in the landslide and non-landslide datasets, respectively.

Besides, the creation of the training data should try to achieve a relatively balanced amount of information on landslides and non-landslide areas (Hjort and Marmion, 2008; Heckmann et al., 2014; Petschko et al., 2014; Al-Najjar et al., 2021). Numerous studies have been conducted to explore the relationship between the number of landslide observations and the predictive performance of a landslide model (Heckmann et al., 2014; Petschko et al., 2014; Hussin et al., 2016; Li et al., 2016; Shirzadi et al., 2019). For example, Petschko et al. (2014) sampled landslide and non-landslide pixels at a 1:1 ratio over an area of 15,850 km² and concluded that the predictive accuracy increased with increasing sample size, with a slight plateauing of predictive accuracy at 25% of the landslide inventory. Heckmann et al. (2014) have pointed out

the need to maintain at least 300 to 350 non-landslide observations when the number of landslide observations is 81 in two small areas of 7 and 19 km². Overall, a relatively balanced sample size of landslide and non-landslide observations in the training data is vital for the predictive performance of a landslide model.

In summary, the collection of the input data is often the most costly and challenging part of landslide modeling (Van Westen, 2000; Chae et al., 2017). How to build the training data in favor of the predictive performance of a landslide model with less manual effort is still to be explored (Robinson et al., 2017; Bhuyan et al., 2023).

2.3 Methods for reducing manual efforts

Data minimization and transfer learning are two popular techniques for building the training data with less manual effort (Weiss et al., 2016; Aledhari et al., 2021). The ideas behind them are to reduce manual efforts and improve the predictive performance of a model by using a small amount of data from a target area or by using information from an existing dataset (source area).

2.3.1 Active learning (AL)

The key to using a small amount of data from a target area is that these data can help a learning algorithm achieve a high accuracy in predicting in a target area. Settles (2010) pointed out that if learning algorithms can select the data they are curious about from the unlabeled data, they will perform better with less training data ("useful" training data). AL attempts to use query strategies to ask the unlabeled data to automatically obtain "useful" data and give them to the annotator for labeling (Figure 2; Tong, 2001; Settles, 2010). In this way, AL aims to achieve high accuracy using as few labeled instances as possible, thus minimizing the cost of obtaining labeled data.

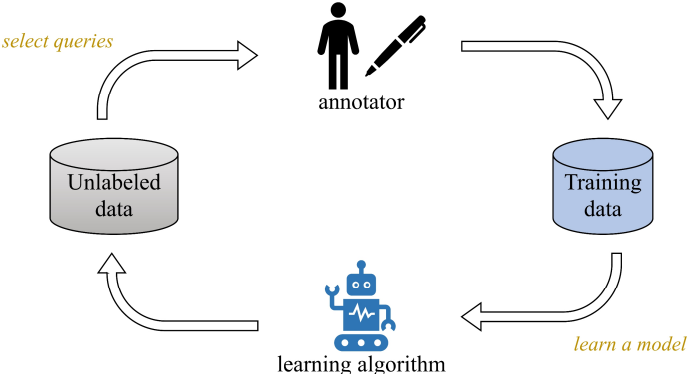


Figure 2 The process of the AL framework.

The approaches used for querying in AL can be grouped into (i) membership query synthesis (Angluin, 1988), (ii) stream-based selective sampling (Atlas et al., 1989), and (iii)

pool-based sampling (Lewis, 1995). Member query synthesis is unreliable in real-world applications due to the difficulty for annotators to interpret new instances (Liu et al., 2022). The stream-based selective sampling and pool-based sampling can address this problem. The difference between them is that the former draws one instance at a time from a target area, while the latter can query a set of instances from a target area at once. Since it can better and more efficiently handle large unlabeled datasets (Tong, 2001; Settles, 2010; Zhan et al., 2021), pool-based sampling is the main focus of this thesis.

An important part of the AL framework is how the informativeness of the data in a target area is evaluated, which is also referred to as the AL strategy. Here, an overview of the two main AL strategies is provided based on Demir et al. (2012). The unlabeled data x in a target area has k classes and y is the label of an instance. P_θ is the posterior probability as estimated by the current model θ .

1. Uncertainty sampling (US)

The objective of this approach is to query the most uncertain instances (Lewis and Catlett, 1994). It is often based on the posterior probabilities produced by the AL model. For example, the positive instances with posterior probabilities closest to 0.5 will be queried by US in binary classification. Three common uncertainty sampling AL strategies are introduced in this part.

- least confidence (LC): the instance that is most likely to be mislabeled by the current model θ will be selected, that is the posterior probability of the most likely label of the instance is closest to 0.5.

$$x_{LC}^* = \operatorname{argmax}_x (1 - P_\theta(\hat{y}|x))$$

- margin sampling (MS): the selected instance is with the smallest margin between the posterior of the first \hat{y}_1 and the second \hat{y}_2 most likely labels.

$$x_{MS}^* = \operatorname{argmin}_x (P_\theta(\hat{y}_1|x) - P_\theta(\hat{y}_2|x))$$

- entropy measure: the instance with the highest entropy value is selected.

$$x_{EM}^* = \operatorname{argmax}_x \left(- \sum_{i=1}^k P_\theta(y_i|x) \log P_\theta(y_i|x) \right)$$

2. Query-By-Committee (QBC)

A set of models $\{\theta_1, \theta_2, \dots, \theta_N\}$ trained on the current training data establishes a committee C . The instance with the largest disagreement among these models is selected. There are two main methods for measuring the level of disagreement.

- vote entropy (Dagan and Engelson, 1995): the instance with the closest number of votes between labels is selected based on the number of "votes" $V(y_i)$ obtained by all committee members' predictions.

$$x_{VE}^* = \operatorname{argmax}_x - \sum_{i=1}^k \frac{V(y_i)}{N} \log \left(\frac{V(y_i)}{N} \right)$$

- Kullback-Liebler divergence (KL-divergence) (McCallum and Nigam, 1998): the instance is selected with the largest average difference between the label distributions of any committee member and $P_N(y_i|x)$. $P_N(y_i|x)$ is the average probability that all committee members think y_i is the correct label.

$$x_{KL}^* = \operatorname{argmax}_x \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^k P_{\theta_n}(y_i|x) \log \frac{P_{\theta_n}(y_i|x)}{P_N(y_i|x)}$$

$$P_N(y_i|x) = \frac{1}{N} \sum_{n=1}^N P_{\theta_n}(y_i|x)$$

In binary classification studies, the US strategies described above are mathematically equivalent. In this thesis, MS was adopted for representing US (Chapter 3), and also a new AL strategy was proposed based on MS (Chapter 5). Meanwhile, due to excellent properties in measuring the distance between distributions (Tong, 2001), KL-divergence was used in QBC in this thesis (Chapter 3).

Formally, the AL procedure used in this study for landslide assessment can be described as shown in Figure 3.

Given: Labeled landslide/non-landslide points T from the target area, query strategy US or QBC , the unlabeled set U , the number of selected landslide/non-landslide points B from U

repeat

- # learn a landslide model/active learning model using the current T
- $\theta_T = \text{model}(T)$;
- # predict probabilities in the unlabeled set
- $P_U = \theta_T(U)$
- # query B the most informative landslide/non-landslide points and label them
- $x_B^* = QBC(P_U)$ or $US(P_U)$;
- $y_{x_B^*} = \text{label}(x_B^*)$;
- # move the labeled landslide/non-landslide points $(x_B^*, y_{x_B^*})$ from U to T
- $T = T \cup (x_B^*, y_{x_B^*})$;
- $U = U \setminus x_B^*$;

until some stopping criterion (e.g., the number of epochs)

Figure 3 The AL framework for landslide assessment studies in this study.

2.3.2 Transfer learning (TL)

A different idea from AL is to use existing datasets (source areas) as the training data to train a model to reduce manual efforts, that is, transfer learning. It is a technique that aims at utilizing the labeled data or extracting information from existing datasets to help a learning algorithm achieve a good performance in a new target area (Weiss et al., 2016).

This technique has been well-developed in many fields, such as natural language processing (Blitzer et al., 2006), sentiment classification (Blitzer et al., 2007), and image classification (Wu and Dietterich, 2004). TL can be classified into four approaches: (i) instance-based TL, (ii) feature-representation transfer, (iii) parameter transfer, and (iv) model-based interpretation (Pan and Yang, 2010; Zhuang et al., 2020).

However, most approaches focus on transferring new features or weighted instances (Xie et al., 2016; Li et al., 2017; Rostami et al., 2019; Zhu et al., 2020; Alem et al., 2021; Astola et al., 2021). These approaches are appropriate for computer vision studies, but not for process-oriented studies that require further plausible interpretation (Zhuang et al., 2020; Small, 2021). For example, researchers are always interested in knowing why landslide models predict certain areas (e.g., steep hillside areas) as being more likely affected by landslides. Hence, interpreting the predictions at the observational level (e.g., topography and geology of landslides) is needed. The inclusion of new features and the changes in instance values will influence our understanding of the factors that govern landslide activity in a target area.

Hence, TL methods that do not change any actual data or use new features have more potential for real-world tasks (e.g., soil mapping). For this reason, case-based reasoning (CBR) and landmark-based domain adaptation (LBDA) methods in model-based interpretation are adopted in this thesis for landslide assessment studies.

1. CBR

CBR is a method that aims at using the information from existing “cases” to solve a new problem (Watson, 1998). By selecting, quantifying, and comparing similarity factors, a source area (“related” source area) that has the potential to achieve a good prediction in a target area is selected (Shi et al., 2009; Hammond, 2012). Previous studies have confirmed that CBR can achieve good performances in landscape-scale environmental modeling tasks involving terrain attributes (Qin et al., 2016; Liang et al., 2020a; Liang et al., 2020b), but it has not been applied to landslide assessment studies.

Some studies have provided references for the selection of similarity factors and emphasized similarity factors should be associated with the causes and processes of the event (Kolodner et al., 1996; Qin et al., 2015; Qin et al., 2016). Yates et al. (2018) have pointed out that spatial and temporal separation may have little impact on model transfer, while environmental similarity and data resolution are key factors for successful model transfers, which can be considered as spatial and temporal limits to extrapolation of model transfers. Therefore, in this doctoral research, three factors were considered for comparing similarities between source and target areas, i.e., topographic conditions (Wang et al., 2010; Van Den

Eeckhaut et al., 2012; Wang et al., 2019), geological characteristics (Segoni et al., 2020) and spatial resolution (Figure 4) (Chapter 4). Here, $Similarity_i$ is the vector of similarity values for the i th factor.

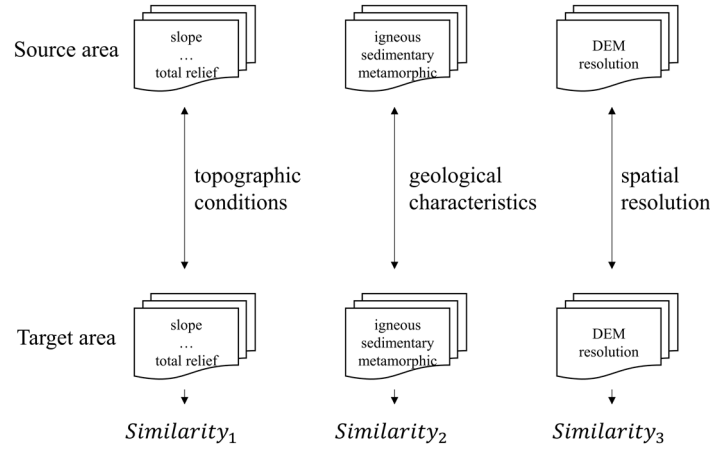


Figure 4 Schematic representation of the application of similarity measures in this doctoral research.

Zhu and Band (1994) proposed a new method to get the overall similarity between two regions, which is named the minimum operator. This method assumed that the similarity between source and target areas was controlled by the least favorable factor/the limiting factor, thus the smallest similarity value should be used to represent the overall similarity of each source area for the target area (Qin et al., 2009; Liang et al., 2020b). In this thesis, the overall similarity is therefore $S = \operatorname{argmin}(Similarity_1, Similarity_2, Similarity_3)$.

2. LBDA

Weiss et al. (2016) have stated that the data distribution of a source area should be the same or at least similar to that of a target area, resulting in better performances in predicting in the target area. To achieve this purpose, a paradigm has been extensively studied. That is, in a domain-invariant feature space, source and target areas should have the same (or similar) marginal distributions, and the posterior distributions of labels ought to be the same across areas (Ben-David et al., 2010; Pan et al., 2010; Blitzer et al., 2011; Chen et al., 2011; Gopalan et al., 2011).

Based on this paradigm, Gong et al. (2013) presented LBDA to select a subset of the labeled data in a source area that is distributed most similarly to the data in the target area, which are also referred to as landmarks. They have pointed out that LBDA can get accurate classification results in CALTECH, AMAZON, WEBCAM, and DSLR datasets. In this thesis, LBDA is introduced in landslide assessment studies.

Hence, landmarks $S_L = \{(x_{SL,m}, y_{SL,m}), m = 1, \dots, N_{SL}\}$ are the subset of labeled landslide/non-landslide observations $S = \{(x_{S,m}, y_{S,m}), m = 1, \dots, N_S\}$ from a source area that

have the most similar distribution to the unlabeled landslide/non-landslide observations $T = \{x_{T,k}, k = 1, \dots, N_T\}$ from a target area. By mapping T and S to a Reproducing Kernel Hilbert Space H based on a feature mapping function $\phi(\cdot)$, the difference $diff$ in sample means is compared. For identifying landmarks, indicator variables $\alpha = \{\alpha_m \in \{0, 1\}, m = 1, \dots, N_S\}$ are applied for minimizing $diff$. That is, if $\alpha_m = 1$, the landslide/non-landslide observation $(x_{S,m}, y_{S,m})$ is regarded as a landmark. In this way, a set of landmarks is selected.

Numerous studies have pointed out that Gaussian radial basis function (RBF) kernels are usually the most recommended choice when the underlying input space is multidimensional (Csiszár and Talata, 2006; Steinwart et al., 2006; Gong et al., 2013; 2017). One of the main reasons is that Gaussian RBF kernels are non-parametric, which means that they do not have a finite and fixed-size parametric model like other kernels (e.g., polynomial kernels). Therefore, Gaussian RBF was applied as $\phi(\cdot)$, and the process of LBDA in this doctoral research is described in Figure 5.

Given: Unlabeled landslide/non-landslide observations T from a target area, labeled landslide/non-landslide observations S from a source area, Gaussian RBF kernels $\phi(\cdot)$ to map T and S to a Reproducing Kernel Hilbert Space H , indicator variables α to identify N_{SL} landmarks S_L

Start

convert landslide and non-landslide observations from source and target areas to a Reproducing Kernel Hilbert Space
 $T_\phi = \phi(T)$;
 $S_\phi = \phi(S)$;
 # calculate the difference (H -norm) in sample means between landslide and non-landslide observations from source and target areas in a Reproducing Kernel Hilbert Space

$$diff = \left\| \frac{1}{\sum_{i=1}^{N_S} \alpha_i} \sum_{i=1}^{N_S} \alpha_i S_\phi - \frac{1}{N_T} \sum_{j=1}^n T_\phi \right\|_H^2;$$

minimize the difference to get landmarks
 $\alpha = \text{argmin}(diff)$;
 under $\alpha_m = 1, m = 1, \dots, N_{SL}$
 $S_L = \{(x_{SL,m}, y_{SL,m})\}$

end

Figure 5 The LBDA for landslide assessment studies in this study.

Chapter 3

Active-learning approaches for landslide mapping using support vector machines

First manuscript

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Article

Active-Learning Approaches for Landslide Mapping Using Support Vector Machines

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Abstract: Ex post landslide mapping for emergency response and ex ante landslide susceptibility modelling for hazard mitigation are two important application scenarios that require the development of accurate, yet cost-effective spatial landslide models. However, the manual labelling of instances for training machine learning models is time-consuming given the data requirements of flexible data-driven algorithms and the small percentage of area covered by landslides. Active learning aims to reduce labelling costs by selecting more informative instances. In this study, two common active-learning strategies, uncertainty sampling and query by committee, are combined with the support vector machine (SVM), a state-of-the-art machine-learning technique, in a landslide mapping case study in order to assess their possible benefits compared to simple random sampling of training locations. By selecting more “informative” instances, the SVMs with active learning based on uncertainty sampling outperformed both random sampling and query-by-committee strategies when considering mean AUROC (area under the receiver operating characteristic curve) as performance measure. Uncertainty sampling also produced more stable performances with a smaller AUROC standard deviation across repetitions. In conclusion, under limited data conditions, uncertainty sampling reduces the amount of expert time needed by selecting more informative instances for SVM training. We therefore recommend incorporating active learning with uncertainty sampling into interactive landslide modelling workflows, especially in emergency response settings, but also in landslide susceptibility modelling.

Keywords: active learning; landslide modelling; support vector machine; machine learning



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1. Introduction

Despite significant progress in landslide hazard assessment and mitigation, these hazards still present a major challenge for policymakers to reduce monetary losses and casualties. The occurrence probability of landslides, which broadly include a large variety of downslope movement processes on hillslopes under the effects of gravity [1], varies greatly in space and time as a result of complex patterns of predisposing factors and temporal variation in triggering factors. Considering the ongoing global trends of urbanization, deforestation, and climate change, landslide science faces the growing challenge of having to update landslide hazard assessments and provide rapid post-disaster information in the event of regional triggering events such as rainstorms and earthquakes [2–4]. For example, an earthquake in Tomakomai, Japan triggered about 10,000 landslides causing 36 deaths [3], and in 2018, landslides triggered by seasonal heavy precipitation caused approximately 105 deaths and USD 212 million in losses in China [5]. In Italy, as in many other regions worldwide, landslides are mostly triggered by intense or prolonged rainfall [6]. These hazards often cause long-term economic loss, population displacement, and negative effects on the natural environment.

Landslide mapping refers to the manual or automated detection and delineation of actual landslides that are appreciable in remote-sensing imagery or based on their topographic footprint [7–9]. Additionally, the growing availability of light detection and

ranging (LiDAR) derived high-resolution digital terrain models (HRDTM) allows us to detect landslides where passive optical sensors are limited (e.g., within the forest) [10,11]. This classification task is related to landslide susceptibility mapping, which focuses on estimating the probability of future landslide occurrences based on predisposing factors: usually topographic, geological, and land use/land cover conditions. Evidently, factors that control susceptibility can also provide valuable information for landslide mapping [12], which also requires post-event remote-sensing data (e.g., optical or LiDAR). Conversely, landslide inventories created by means of landslide mapping are a necessary input for landslide susceptibility mapping using supervised classification models. Together, landslide mapping and susceptibility modelling play a critical role in providing information that is necessary for decision making in emergency situations and for reducing risk in the development of spatial planning strategies.

Machine-learning techniques are increasingly being adopted in landslide modelling, as they have the potential to better adapt to complex nonlinear Earth surface processes and their interactions with land use than parametric statistical techniques such as logistic regression. Examples for black-box machine-learning models include the SVM, artificial neural networks, and random forests, whereas the generalized additive model (GAM) as an intermediate-complexity model is popular due to its nonlinear but more interpretable structure [13–16]. However, these data-driven supervised learning algorithms need a large number (e.g., thousands) of observations of landslide presence/absence, which are usually derived from manually digitized landslide inventories. Creating landslide inventories and more generally the manual labelling or annotation of these instances is a very time-consuming task, which increases the cost of landslide modelling studies and leads to delays in post-disaster situation awareness.

Active learning (AL) is a framework that promises to reduce this burden by selecting “informative” instances for the user to label [17,18]. In each of these queries to the user, an additional small batch of unlabelled instances (e.g., grid cells) is selected based on an informativeness measure and then presented to an “oracle” (i.e., a human annotator) for labelling. Active learning aims to achieve better accuracies using as few labelled instances as possible, thereby minimizing the cost of obtaining labelled data. Active learning has increasingly been adopted in remote-sensing classification [19–21] but has rarely been adopted in the context of landslide mapping [22].

The SVM has become increasingly popular in the context of landslide modelling along with other nonlinear techniques such as the generalized additive model [15,23,24]. Compared to the less flexible GAM, the SVM is capable of modelling nonlinear interactions among predictors while avoiding overfitting through regularization. Therefore, active learning based on the SVM for predicting landslides was adopted in this paper.

Hence, the main objective of this study is to assess the potential of different active-learning strategies for landslide mapping based on limited amounts of labelled data. We consider two popular active-learning query strategies in combination with the SVM in a case study from the Andes of southern Ecuador [25].

2. Materials and Methods

In this study, we use active-learning strategies [26] to sample “interesting” (i.e., informative) locations for training SVM models for landslide detection, and we compare this approach to a simple random sampling strategy (Figure 1). In active learning, a small training data set is initially retrieved to obtain a preliminary SVM fit. This model’s classifications then allow us to identify relevant additional instances that have the greatest potential to improve the model fit. These instances are then labelled, and the SVM is retrained with the additional training data. This step is repeated to investigate changes in model performance with increasing instance size. Hyperparameters are tuned in each individual step, and model performances are estimated in identical test sets to ensure comparability. Details of this procedure are explained in the following sections, and Settles (2010) [26] provides a detailed overview of active-learning strategies.

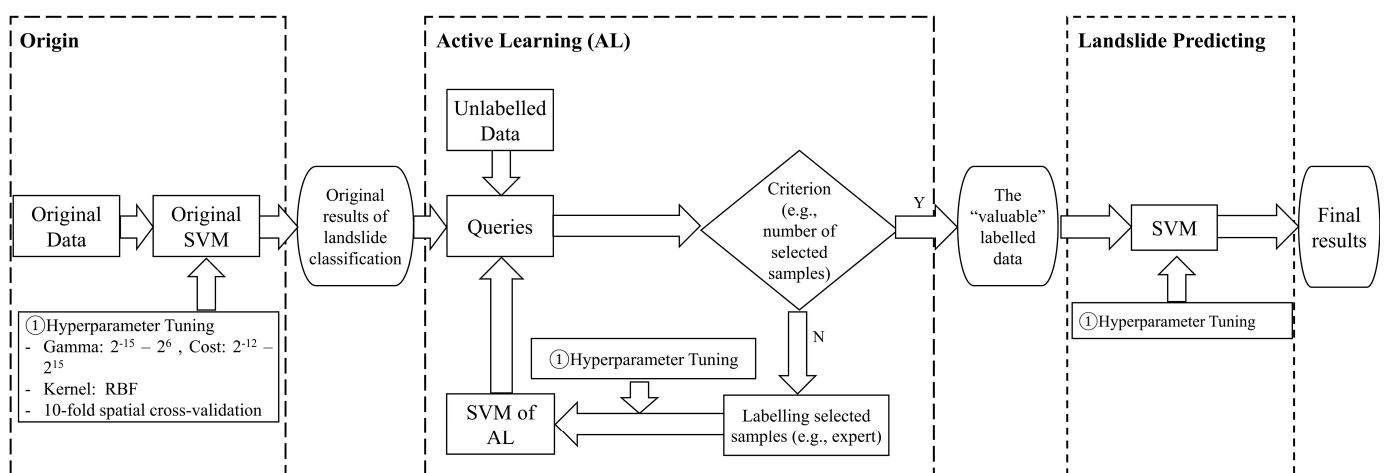


Figure 1. Overview of the workflow of active learning for landslide detection based on the SVM.

2.1. Active-Learning and Traditional Learning Strategies Used

Active learning is a subfield of machine learning that is also referred to as query learning or optimal experimental design in the statistical literature. It is a very broad field encompassing many different approaches [26–30]. In general, the purpose of active learning is to require as few labelled instances as possible while achieving a level of high accuracy. After starting with a small initial training set, small batches of additional “informative” instances are presented to an expert for labelling.

There are three different settings of active learning, namely membership query synthesis, stream-based selective sampling, and pool-based sampling [26,27]. For our study area, we have a large collection of unlabelled data. Due to uncertainty in the random generation process of instances using membership query synthesis [31] and the high cost of labelling selected instances one by one using stream-based selective sampling, pool-based sampling was adopted in this study. Pool-based sampling can be further divided into two main categories: uncertainty sampling and query by committee [19].

We denote the unlabelled data set as x and the classes of the unlabelled data set as y . P_θ is the posterior probability as estimated by the current model θ in a given active-learning step.

2.1.1. Uncertainty Sampling

Uncertainty sampling chooses the instances that are predicted with the lowest confidence, i.e., that are associated with the greatest uncertainty in the current model [32]. It may be the most common and simplest active-learning approach. We briefly present three popular uncertainty-sampling strategies, but we choose only margin sampling due to the mathematical equivalence of these approaches in two-class situations.

(1) Least Confidence

The least-confidence strategy for a sequence of models queries the instances for which the current model has the least confidence as the predicted classes are equally likely [33]. Therefore, the most “informative” instances are selected by

$$\hat{y} = \operatorname{argmax}_y P_\theta(y|x), \quad (1)$$

$$x_{LC}^* = \operatorname{argmax}_x (1 - P_\theta(\hat{y}|x)), \quad (2)$$

where \hat{y} is the most likely label, i.e., the class label with the highest posterior probability under the current model θ . x_{LC}^* represents the instance that the current model θ is most likely to mislabel.

(2) Margin Sampling (MS)

Margin sampling (MS) was proposed to additionally take advantage of information regarding the posterior probabilities of all of the labels, not only the most likely one [34]. Here, instances with the smallest margin between the posterior of the first and the second most likely labels are selected. Since these are more ambiguous, the model has difficulty in differentiating between the two most likely class labels. Hence, knowing the true label would help the classifier to discriminate them more effectively. The instances are selected using

$$x_{MS}^* = \operatorname{argmin}_x (P_{\theta}(\hat{y}_1|x) - P_{\theta}(\hat{y}_2|x)), \quad (3)$$

where \hat{y}_1 and \hat{y}_2 are the first and the second most likely labels, respectively.

(3) Entropy measure

One of the more general pool-based sampling strategies is based on the entropy measure [35]. This strategy uses entropy, which is an information-theoretic measure of uncertainty of a random variable. It aims at using information from all of the remaining classes to detect the most informative instances. Intuitively, the entropy measure strategy should perform better than the least-confidence and MS strategies, especially for very large label sets. Instances are selected using

$$E(y, x) = - \sum_{i=1}^k P_{\theta}(y_i|x) \log P_{\theta}(y_i|x), \quad (4)$$

$$x_{EP}^* = \operatorname{argmax}_x E(y, x), \quad (5)$$

where $E(y, x)$ is the entropy value of class y for instance x . Instances with the highest entropy value, which imply more uncertainty in the distribution, are selected as x_{EP}^* .

Each of these uncertainty sampling strategies have their own application scenarios. In binary classification, however, all three are equivalent in selecting instances with the posterior class probabilities closest to 0.5 [26]. We implemented uncertainty sampling using the equation given for margin sampling, and we therefore refer to it as margin sampling in the rest of the paper.

2.1.2. Query by Committee

Query by committee (QBC) is another more theoretically motivated active learning algorithm that selects informative unlabelled instances based on different models (a committee) trained on the current labelled training set [26,36]. Based on the posterior probabilities predicted by the different committee members, the unlabelled instances with the maximum disagreement are selected. Two important measures of disagreement among the models are the Kullback–Leibler (KL) divergence [37,38] and vote entropy [39]. Because KL divergence applies several independent justifications and calculates the average difference between the label distributions of any committee, it is considered the better approach to selecting informative instances [30]. Hence, KL divergence was adopted in this study. Let $C = \{\theta(1), \dots, \theta(C)\}$ denotes the set of models forming the committee. Then

$$P_C(y_i|x) = \frac{1}{|C|} \sum_{c=1}^C P_{\theta(c)}(y_i|x), \quad (6)$$

corresponds to the committee's average posterior probability of class label y_i , and

$$D(P_{\theta(c)}||P_C) = \sum_i P_{\theta(c)}(y_i|x) \log(P_{\theta(c)}(y_i|x)/P_C(y_i|x)), \quad (7)$$

denotes the KL divergence, which we try to maximize on average over all committee members:

$$x_{KL}^* = \operatorname{argmax}_x \frac{1}{C} \sum_{c=1}^C D(P_{\theta(c)}||P_C), \quad (8)$$

This strategy focuses on the instances x_{KL}^* with the larger average difference with respect to the label distributions of any one committee.

Various strategies can be applied to creating a committee, such as bootstrap resampling of the training data [40,41]. We decided to set up a committee of SVM classifiers trained using different hyperparameter values since the behaviour of the SVM strongly varies with its cost and bandwidth parameters, C and γ [42]. In each active-learning round, we randomly sampled 250 pairs of hyperparameter values ($\log_2 C$ between -12 and $+15$ and $\log_2 \gamma$ between -12 and $+6$). The best-performing 25 hyperparameter settings were then selected to form a committee for that round.

2.1.3. Random Sampling as a Baseline

In addition to the active-learning strategies described above, simple random sampling (RS) was used for comparison. It randomly selects instances from the unlabelled data with equal probability and does not try to assess the utility of the data for landslide mapping.

2.2. Landslide Classification Model

In this study we used a support vector machine (SVM) model, which is a flexible supervised machine-learning technique [43]. It has previously shown competitive performances in landslide modelling [12,15,44,45]. This technique is particularly appealing in active learning because its flexibility can be tuned extremely well, allowing it to transition from a strongly penalized simple model to a more complex one as the sample size grows larger. The SVM can be applied in both one-class and two-class cases. Yao, et.al. (2008) compared one-class and two-class SVM on landslide analysis and concluded that two-class SVM could have better prediction efficiency than one-class SVM [46]. Therefore, in this study, we applied two-class SVM as the active-learning classifier.

Because the flexibility of the SVM is controlled by its hyperparameters γ (bandwidth) and C (cost), a k -fold cross-validation was used in each active-learning iteration to optimize them [47]. In this cross-validation, the training set is split into k equally sized partitions, one of which is retained for testing the model, and the remaining $k - 1$ partitions are used as training data. This process is repeated k times, and every partition is used once as the validation data. Performance estimates are averaged over the k partitions to obtain a cross-validation estimate of the performance measure. We used $k = 10$, which is a commonly used setting. Given the spatial nature of our data, we used k -means clustering of the sample coordinates to generate spatial cross-validation partitions [48]. The choice of the SVM kernel function is less critical; therefore, the radial basis function kernel was adopted.

The area under the receiver operating characteristic (ROC) curve [49,50] (AUROC) [51] was used as a measure of predictive performance. Its range is between 0.5 (no predictive skill) and 1 (perfect separation).

2.3. Repetition and Performance Estimation

The workflow described above was repeated 150 times in order to eliminate the influence of random variability on our results. In active learning as well as random sampling, we draw an additional batch 25 points in each iteration or epoch after an initial random sample of 210 points in the first step. This initial data contains 10 landslide points and 200 non-landslide points, roughly representing the spatial landslide density within the study area. With the chosen batch size, on average, one additional landslide point will be drawn from the study area even in random sampling, given the 4% landslide density. We performed 50 iterations in order to observe the convergence of results for large instance sizes, although such large sample sizes (1460 labelled instances) are not of practical relevance.

The entire study area (87,223 non-landslide and 2569 landslide grid cells) as the target area for landslide mapping was used for analysing and comparing AUROC performances obtained by SVMs with active- (MS, QBC) and passive-learning strategies (RS). We ex-

tracted 55,887 non-landslide and 1663 landslide grid cells from the overall data set to serve as a pool of candidate grid cells from which we sampled the training data set.

In order to gain insight into the importance of predictors at different active-learning stages, we further calculated the permutation-based variable importance as a simple overall measure of predictive importance [52]. This was applied in a spatial cross-validation framework, i.e., by making predictions on spatially disjoint cross-validation test sets [53]. Accumulated local effects (ALE) [54] plots were further generated to visualize the shape of the relationships between important predictor variables and SVM landslide classifications.

All statistical analyses were conducted using the open-source statistical software R (version 3.6.3) [55] and its contributed packages “sperrorest” for spatial cross-validation [56], “e1071” for SVM modelling [57], “ROCR” for AUROC estimation [58], and “iml” for model interpretation [59]. The R package “RSAGA” [60] and the open-source GIS SAGA [61] were used for geodata processing.

2.4. Study Area and Data

The study area of our case study is located in the Andes of Southern Ecuador in the Reserva Biológica San Francisco (RBSF). The RBSF is located between the provincial capitals of Loja and Zamora (3°58′30″ S, 79°4′25″ W) [62]. The slopes are steep (1st quartile of slope angle: 28.8°, median: 36.5°) and covered with evergreen lower and upper mountain rainforest [63]. The annual precipitation in the study area ranges from 2000 mm in the lower parts to more than 6000 mm between 2900 and 3100 m a.s.l. with nearly daily rainfall [64]. This area is characterized by a high frequency of landslide occurrences, which underlines the potential utility of active-learning techniques for generating event-based landslide inventories on demand with as little labelling as possible. In this study area, landslides are important ecosystem disturbances that trigger local vegetation successions and thus contribute to habitat complexity in this unique hotspot of plant biodiversity [65,66]. Landslide processes were previously studied in more detail with a focus on geomorphic process rates and the possible effects of human land use [25,67]. In this case study, we focus on the “natural” part of the RBSF study area of Muenchow et al. (2012). The dataset includes 178 landslides with a mean landslide size of 793 m². We refer the reader to Muenchow et al. (2012) for further geomorphological detail and an analysis of landslide susceptibility [25].

We used a high-resolution orthorectified aerial photograph of the study area as a direct optical indicator of vegetation disturbance by landslides. The image was acquired in 2001 and has a 0.3 m × 0.3 m spatial resolution (data source: E. Jordan and L. Ungerechts, Düsseldorf; DFG Research Unit FOR 816). Small cloudy patches and other errors were masked out manually (Figure 2). Landslides were mapped in this imagery by J. Muenchow (Erlangen), who analyzed the landslide distribution and characteristics in this study in more detail as part of a regional-scale comparison [25].

Vegetation indices (VIs) play an important role in mapping landslides and other forest disturbances [68,69]. Although the near-infrared part of the spectrum is particularly useful for identifying photosynthetically active, healthy plants, the imagery available for this case study is limited to the visible part of the spectrum, while having the benefit of offering the resolution required to detect the narrow, elongated landslides of this study area. Considering the spectral characteristics of the available orthophoto, we used the green chromatic coordinate (GCC) vegetation index [70], which has been shown to compare favourably to other indices in the visible part of the spectrum in distinguishing the forest from the soil [71]. The GCC is generally effective in suppressing the effects of changes in scene illumination [72], which is important in our mountainous study area. GCC is defined as

$$GCC = G / (R + B + G), \quad (9)$$

where R, G, and B represent the red, green, and blue bands of the ortho-photo. The red (RCC) and blue (BCC) chromatic coordinates are calculated in the same way. Because RCC

and BCC are strongly correlated (correlation coefficient: 0.95), we used GCC as a vegetation index as well as RCC.

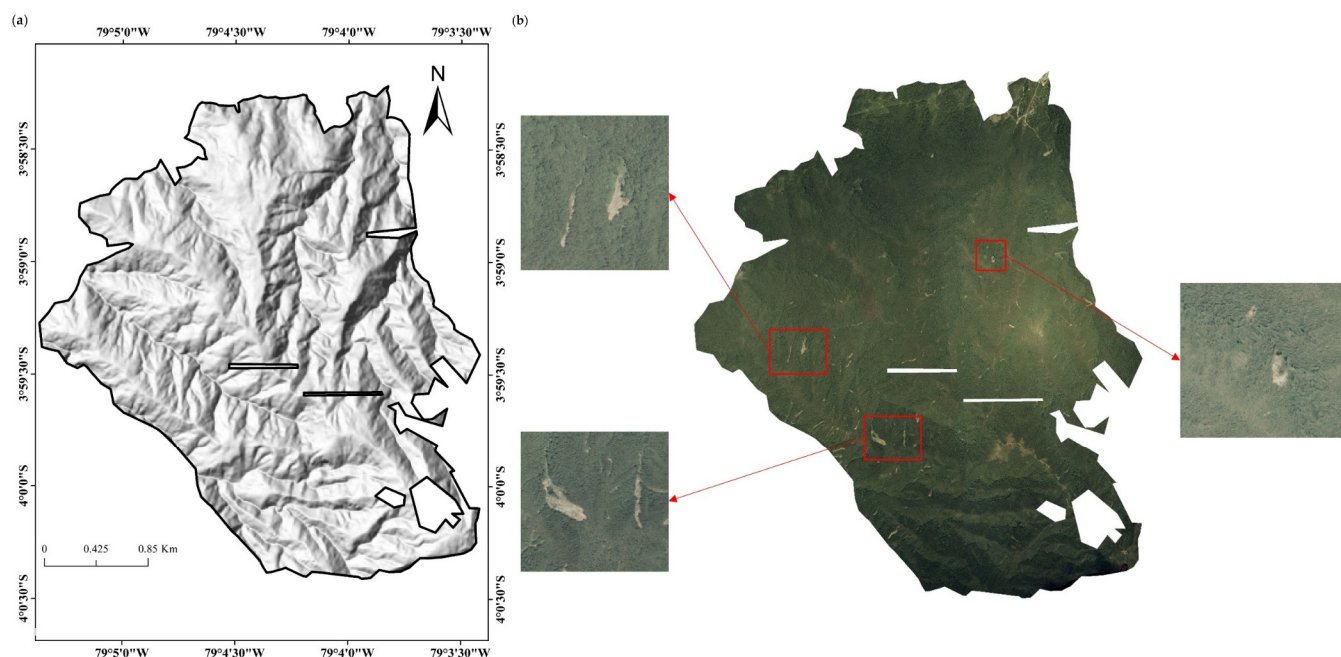


Figure 2. The study area: the Reserva Biológica San Francisco (RBSF), (a) hillshade with $10\text{ m} \times 10\text{ m}$ resolution in 1997, and (b) the orthophoto with $0.3\text{ m} \times 0.3\text{ m}$ resolution in early 2001.

A digital elevation model (DEM) of the RBSF at a $10\text{ m} \times 10\text{ m}$ resolution produced by E. Jordan and L. Ungerechts (Düsseldorf) was generated from stereo aerial photographs from the year 1997. Following Muenchow et al. (2012) [25], we derived the following terrain attributes from the DEM, as they are commonly included in landslide distribution models as preparatory factors: local slope angle (slope), plan and profile curvature (plancurv and profcurv), and the slope angle (cslope) and logarithm of the size of the upslope contributing area (log.carea) [15]. These terrain attributes are intended to act as proxies for destabilizing forces (slope, cslope), water availability (log.carea, concave curvatures), and exposure to wind (convex curvatures) as well as general variability in the characteristics of soil and vegetation [25]. Our expectation is that these terrain attributes will further improve landslide classification.

Overall, our feature set consisted of five terrain attributes and the GCC and RCC as remote-sensing variables. Predictors that presented outliers were winsorized at the 1st and 99th percentile.

3. Results

3.1. Model Performance

Overall, active learning using margin sampling outperformed query by committee and random sampling after only four epochs, i.e., starting with a learning instance size of 310 grid cells (Figure 3). The SVM with MS increased continuously from this point, going from 0.80 in epoch 3 with only 285 grid cells to 0.83 after epoch 8, i.e., with label information for >410 grid cells. Mean AUROCs obtained with RS and QBC were very similar; they both reached ~ 0.79 for only large sample sizes. The similar performances of QBC as an active-learning strategy and RS for passive learning suggest that the instances labelled in QBC-based active learning were no more informative than the ones retrieved with simple random sampling. Nevertheless, SVM performances with QBC were less variable than those completed with RS.

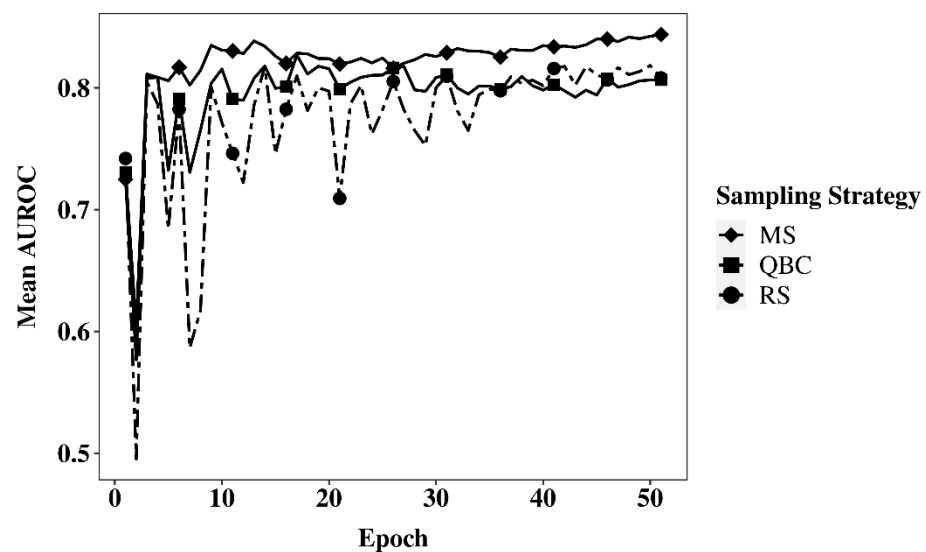


Figure 3. Performance versus epochs: mean AUROCs of SVMs across all 150 repetitions for different sampling methods in the target area.

Similarly, the random variability of AUROC performances over the 150 repetitions revealed much less variable results for MS-based active learning than for QBC and RS, which show similar results (Figure 4). Differences in variability between MS and QBC/RS were at least twofold across all epochs, which indicates that informative instance data not only improves the performance but also reduces the probability of obtaining poor results due to random variability.

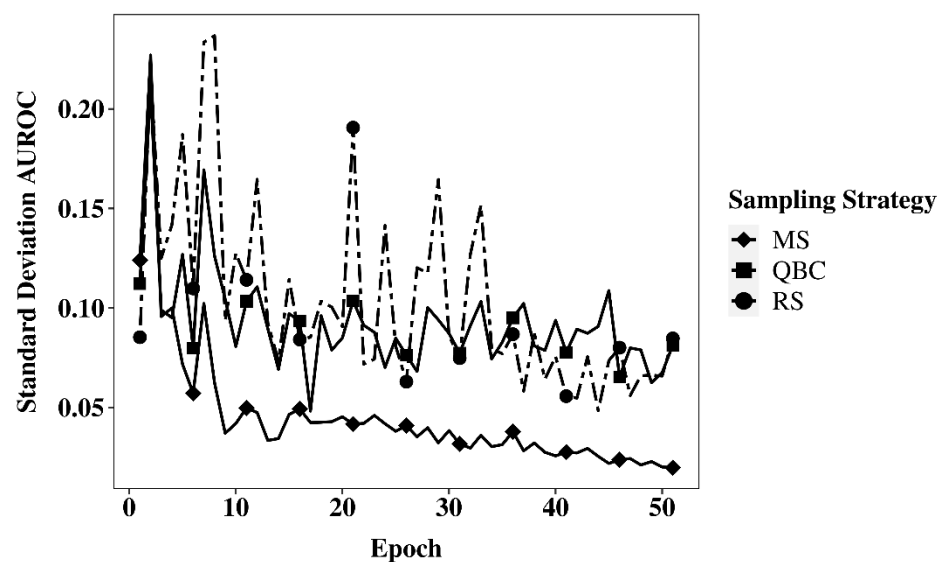


Figure 4. Standard deviation of AUROC estimates across all 150 repetitions for different sampling methods in the target area.

Considering the importance of the cost and gamma hyperparameters for the flexibility of the SVM, we examined the variability in optimal hyperparameters for different active-learning epochs in margin sampling. As the sample size increased, the optimal cost parameters across the repetitions were increasingly concentrated around the 2^0 to 2^5 region and the optimal γ to around 2^{-5} , although the optimal region extended diagonally towards higher cost values when combined with larger γ values (Figure 5).

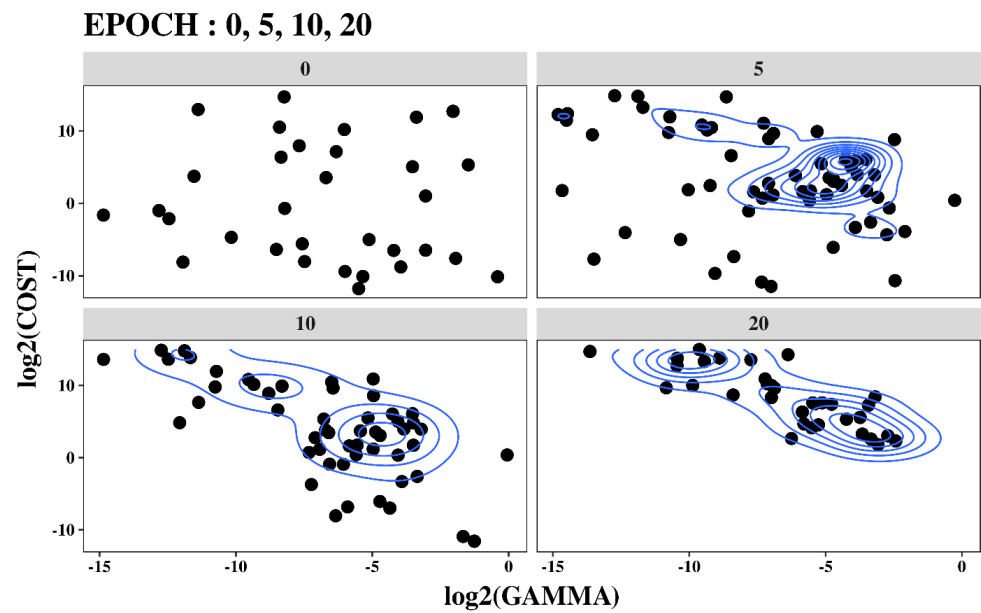


Figure 5. Optimal hyperparameters for the SVM with margin sampling in epochs 0, 5, 10, and 20 for all 150 repetitions.

3.2. Model Interpretation

A permutation-based variable importance assessment for the SVM with margin sampling revealed that the most important predictors were GCC and RCC, which was followed by a logarithm of the catchment area and catchment slope (Figure 6). Thus, predictors that are commonly used in landslide susceptibility modelling helped to improve the performance of models for landslide mapping consistently across all epochs. Note that there are moderate to strong correlations between the slope variables as well as between the upslope contributing area and the two curvature variables (Table 1).

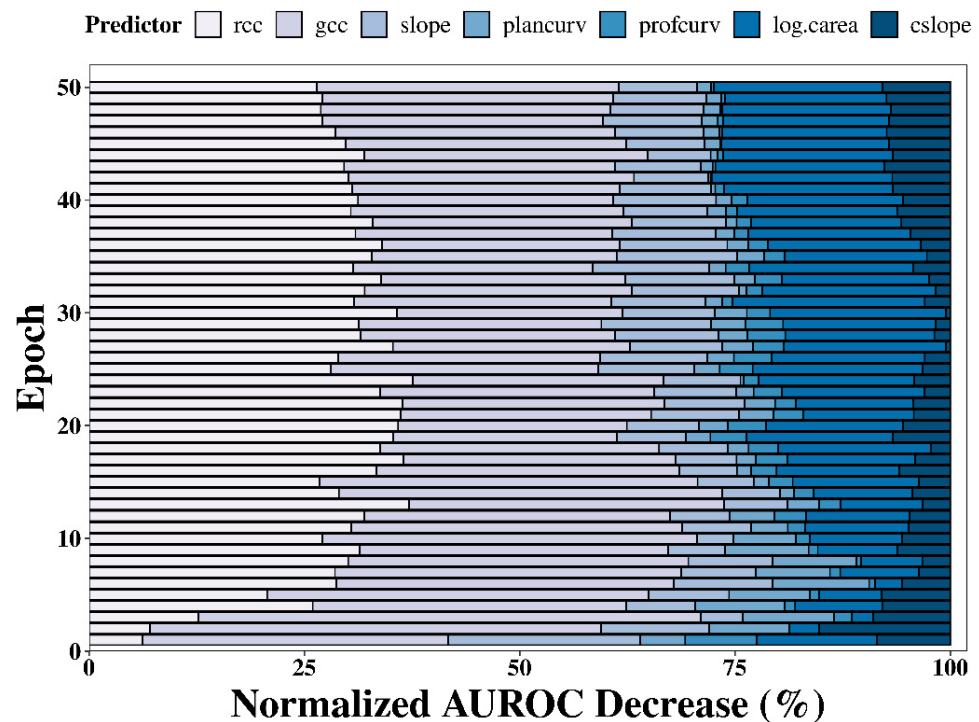


Figure 6. Variable importance plot for SVM using margin sampling in each epoch.

ALE plots for the 20th epoch of the 1st repetition display the averaged relationships between predictors and responses (Figure 7). Broadly speaking and as expected, landslides are primarily characterized by low vegetation vigour as represented by a low vegetation index, and to a smaller extent, by a steep upslope area. They are also rarely found in the valley bottoms, where the upslope contributing area is large, or directly on ridges or hilltops, where the upslope contributing area would be small. Ridges and hilltops often show reduced vegetation canopy due to factors other than landslides, such as windthrow, and the inclusion of the upslope contributing area therefore reduces confounding with these patterns, resulting in a geomorphologically more plausible classification.

Table 1. Correlations among the predictors (%).

	RCC	GCC	Slope	Plancurv	Profcurv	Log.carea	Cslope
RCC	100	−36	−11	9	8	−16	−17
GCC	−36	100	14	−18	−18	34	28
Slope	−11	14	100	3	3	−3	75
plancurv	9	−18	1	100	52	−68	−17
profcurv	8	−18	3	52	100	−58	−23
log.carea	−16	34	−3	−68	−58	100	22
cslope	−17	28	75	−17	−23	22	100

Local slope angle (slope), plan and profile curvature (plancurv and profcurv), the slope angle (cslope) and logarithm of the size of the upslope contributing area (log.carea), and green chromatic coordinate (GCC) and red chromatic coordinate (RCC).

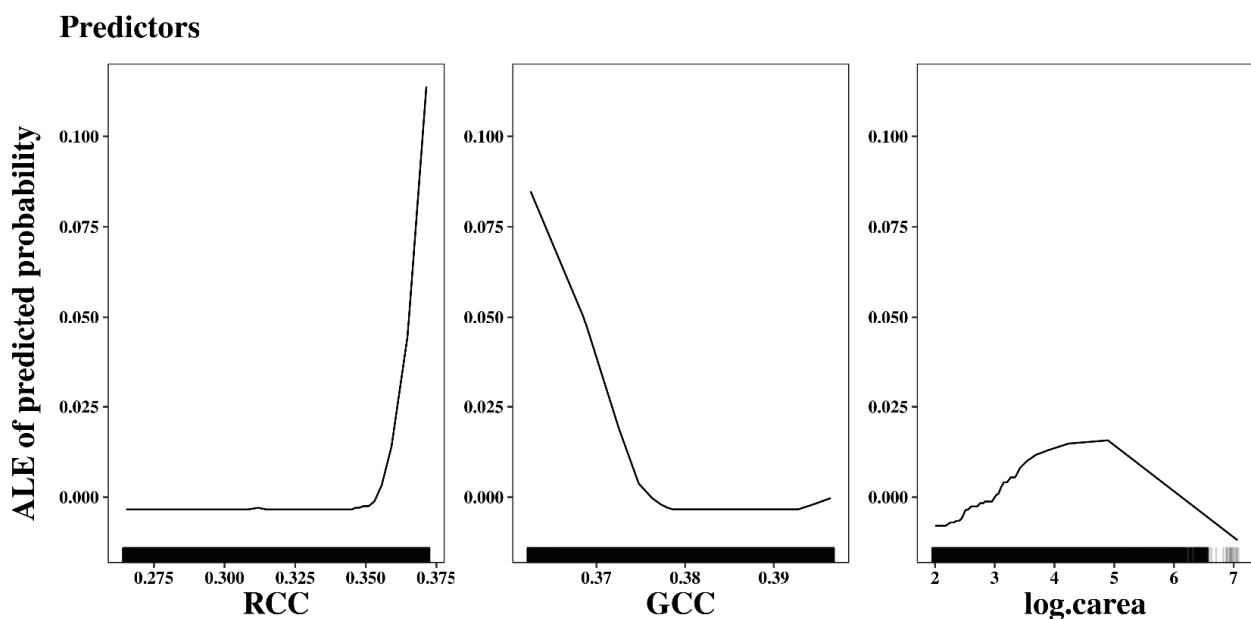


Figure 7. ALE plots of the most important predictors (green chromatic coordinate, GCC; red chromatic coordinate, RCC; logarithm of the size of the upslope contributing area, log.carea) for the SVM with margin sampling in repetition 1, epoch 20.

Landslide maps predicted by SVM with margin sampling clearly depict many of the landslide-affected areas even after only five epochs (Figure 8). There is little change in the spatial pattern of mapped landslides after more than five epochs, which is consistent with the relatively stable model performances and variable importance reported above. Despite the visual similarities between epochs 5 and 10, it should be remembered that quantitative performances in terms of the mean and standard deviation of AUROC did substantially improve from epoch 5 to epoch 10, as hyperparameter tuning started to stabilize as well around epoch 10.

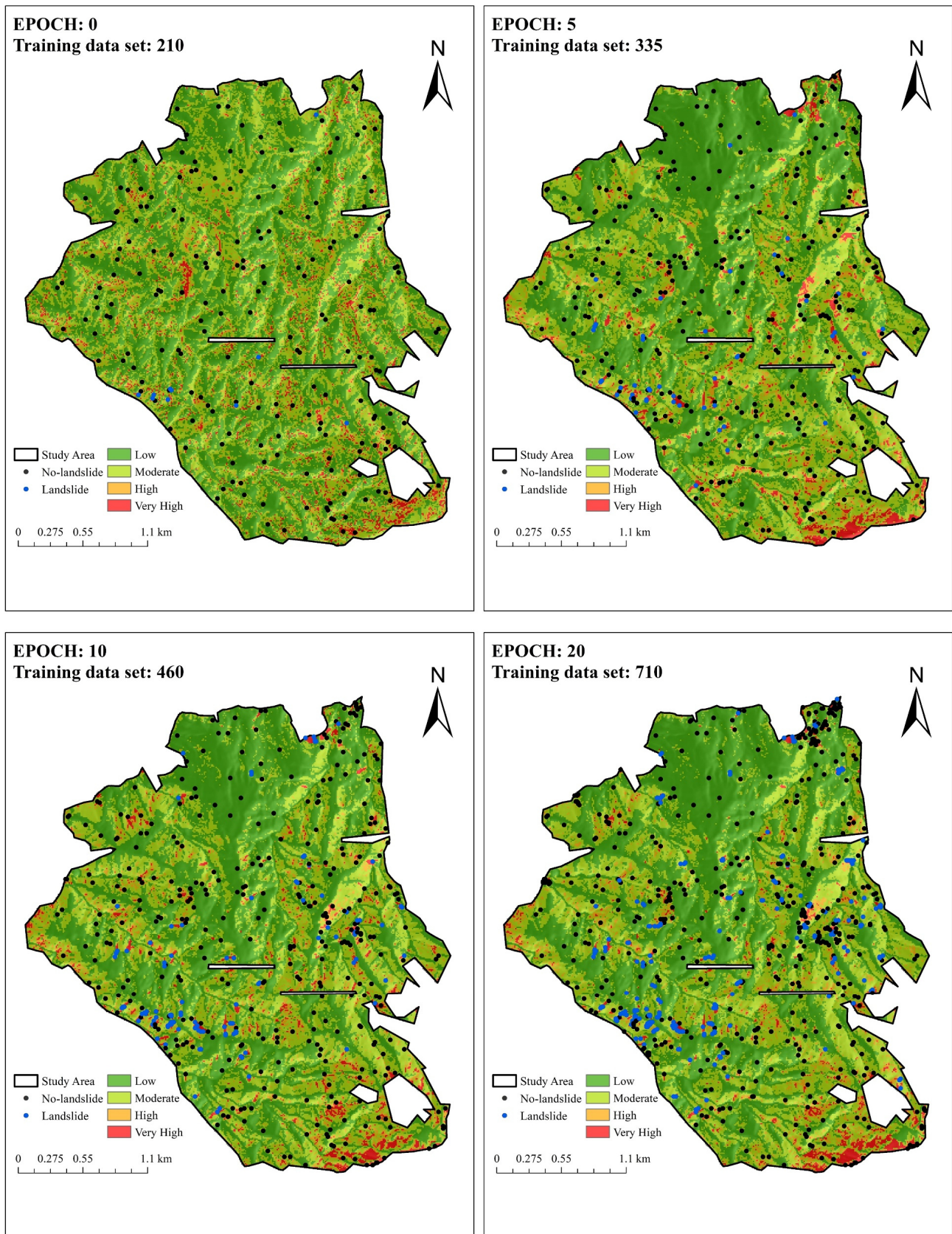


Figure 8. Landslide classification maps of SVM with margin sampling in epochs 0, 5, 10, and 20. Predicted probabilities are classified into four classes (very high, high, moderate, and low) using the top 4th, 10th, and 50th percentile as class boundaries.

4. Discussion

4.1. Potential of SVM with AL

Overall, our results confirm the potential of AL for remote-sensing applications and for landslide mapping in particular [19,22], and demonstrate the suitability of uncertainty sampling strategies. AL retrieves the data that it believes is more likely to be misclassified [26]. For the learning process of SVM, it builds a margin to classify the instances based its features. If a new candidate point's distance from the margin is too small, this instance is more likely to be misclassified by the model and labelling these instances therefore has the greatest potential to improve model performance.

Landslide data is always imbalanced, which poses a particular challenge in classification modelling that can be addressed using uncertainty sampling. In this study, landslides covered only 4% of the study area, and consequently, random sampling is very poor at collecting information on positives. In contrast, AL strategies can reduce the impact of imbalance by retrieving more "useful" instances, including more positives (Table 2 and Figure 9). This is especially true for MS.

Table 2. Number of landslide and non-landslide instances in the training set after 50 epochs using different sampling strategies.

Sampling Strategy	Non-Landslide	Landslide
Margin sampling	1013	447
Query by committee	1280	180
Random sampling	1415	45

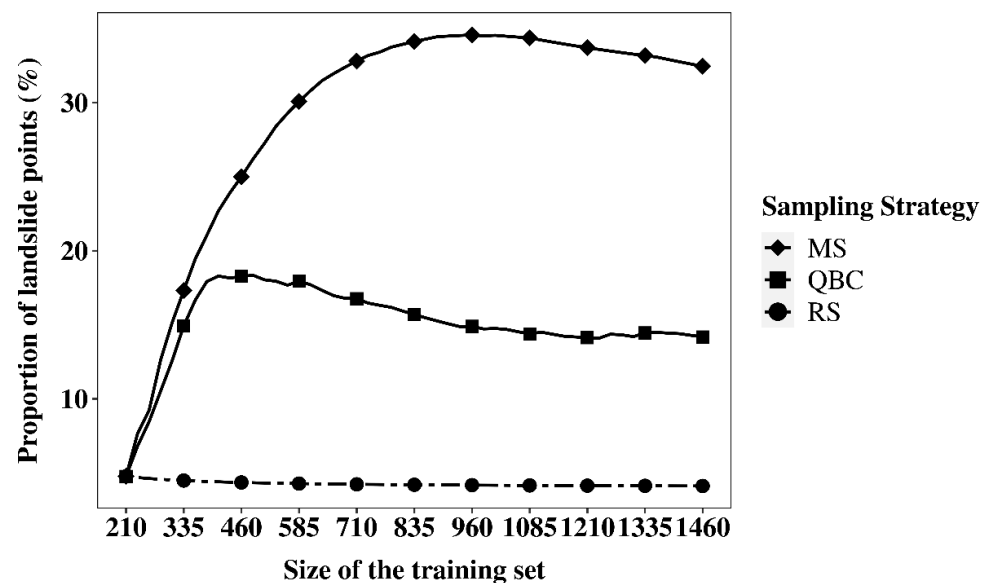


Figure 9. Number of landslide instances in the training set in each epoch using SVM with different sampling strategies.

4.2. Limitations of SVM with AL

A possible limitation of AL in the context of SVM classification is the interaction between the hyperparameters and the query strategy. Specifically, since AL queries depend on posterior probability, they are sensitive to SVM hyperparameters. If hyperparameters cannot be reliably estimated, as is the case in the initial epochs with small sample sizes, model performance can be highly variable and sometimes poor (Figures 3 and 4). When this occurs, AL query strategies may be close to random sampling, or they may even oversample irrelevant regions in the featured space [73,74]. The QBC strategy may be particularly sensitive to this problem since SVMs with 25 different hyperparameter settings were used to form a committee. In general, it can be difficult to strike the right balance between diversity

and goodness-of-fit of committee members, and the use of the top hyperparameter settings may not achieve an optimal committee. Although other strategies could be used, it was beyond the scope of this work to experiment with these additional design options. Xu et al. (2020) used three different pre-trained SVMs as committee members to conduct classifications and concluded that pre-trained SVMs made QBC more robust in iterative training [42]. Stumpf formed QBC committees using 500 fully grown trees from a random forest (RF) and concluded they can achieve good results [22], but no comparison with other, model-independent QBC approaches or with other query strategies was made. Considering these limitations and the positive results achieved with uncertainty sampling strategies, we suggest that the latter offers several advantages ranging from a simpler, model-agnostic implementation to fewer design decisions and reduced computational cost.

5. Conclusions

In this study, active-learning strategies for training landslide detection models outperformed models trained using randomly sampled data. The mean AUROCs of the SVM with margin sampling as an active-learning strategy was 0.80 with only 285 instances and 0.83 with 410 instances. In contrast, SVMs with query-by-committee and random sampling achieved AUROCs around 0.79 but only for large sample sizes. Meanwhile, the SVM with margin sampling was more robust than the other strategies. Therefore, uncertainty sampling is particularly promising as it achieved the best performance, was best able to handle imbalanced data, and is straightforward to implement regardless of the machine-learning model being used.

Labelling a large number of instances using human experts is a time-consuming process that cannot be executed in sufficient detail under time constraints, e.g., in emergency situations. Additionally, human experts cannot recognize which additional instances would be the most “useful” for predicting the response to, or in our case for identifying, landslides. Active-learning methods are therefore a promising strategy as part of an interactive landslide detection workflow, especially in an emergency response setting.

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Chapter 4

Transfer learning for landslide susceptibility modeling using domain adaptation and case-based reasoning

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Transfer learning for landslide susceptibility modeling using domain adaptation and case-based reasoning

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Abstract. Transferability of knowledge from well-investigated areas to a new study region is gaining importance in landslide hazard research. Considering the time-consuming compilation of landslide inventories as a prerequisite for landslide susceptibility mapping, model transferability can be key to making hazard-related information available to stakeholders in a timely manner. In this paper, we compare and combine two important transfer-learning strategies for landslide susceptibility modeling: case-based reasoning (CBR) and domain adaptation (DA). Case-based reasoning gathers knowledge from previous similar situations (source areas) and applies it to solve a new problem (target area). Domain adaptation, which is widely used in computer vision, selects data from a source area that has a similar distribution to the target area. We assess the performances of single- and multiple-source CBR, DA, and CBR–DA strategies to train and combine landslide susceptibility models using generalized additive models (GAMs) for 10 study areas with various resolutions (1, 10, and 25 m) located in Austria, Ecuador, and Italy. The performance evaluation shows that CBR and combined CBR–DA based on our proposed similarity criterion were able to achieve performances comparable to benchmark models trained in the target area itself. Particularly the CBR strategies yielded favorable results in both single- and multi-source strategies. Although DA tended to have overall lower performances than CBR, it had promising results in scenarios where the source–target similarity was low. We recommend that future transfer-learning research for landslide susceptibility modeling can build on the similarity criterion we used, as it successfully helped to transfer landslide susceptibility models by identifying suitable source regions for model training.

1 Introduction

Landslides are among the most common and severe natural hazards in mountain areas. Globally, the destruction caused by landslides continues to have severe impacts on human activity and life (Froude and Petley, 2018; Haque et al., 2019). Landslide susceptibility mapping, the modeling of areas prone to landslide occurrence, is an effective method to assist land managers in decision-making aimed at minimizing landslide risk. These models are typically data-driven and rely heavily on terrain characteristics to capture conditions that can lead to landslide occurrence (Goetz et al., 2015; Reichenbach et al., 2018). One of the most challenging aspects of building data-driven landslide susceptibility models is establishing the landslide inventory data for model training and testing (Lin et al., 2021). Landslide inventories from different areas and time periods can provide relevant knowledge for predictive landslide susceptibility modeling (Petschko et al., 2016). In the case where a region has insufficient landslide data to produce a susceptibility model, previous studies in ecology and on landslides have demonstrated that model transfers can aid the prediction of susceptibility in adjacent regions (i.e., regional susceptibility modeling), and allow us to improve process understanding (Wenger and Olden, 2012; Sequeira et al., 2016; Rudy et al., 2016).

Machine learning is currently the most applied method for solving the problem of landslide prediction (Goetz et al., 2015; Kavzoglu et al., 2019; Merghadi et al., 2020). Traditional machine learning operates on the condition that the training and test data are taken from the same input feature space and data distribution (Pan, 2014). In the case of spatial and temporal predictions, this means that most fitted machine-learning models are limited to the spatial and temporal bounds of the input data. Thus, when extrapolating or

transferring traditional machine-learning models to new spatial and temporal domains, model performance can be degraded due to differences in feature space and/or data distributions (Shimodaira, 2000; Pan and Yang, 2010; Yates et al., 2018).

A successful model transfer does not necessarily rely solely on the extent of geographic or temporal separation, but rather on the similarity of the environmental conditions between the source and target areas (Yates et al., 2018). The field of transfer learning offers various techniques to exploit this observation, which have yet to be fully utilized by the geospatial modeling communities – including landslide susceptibility modeling. For example, Wang et al. (2022) combined deep learning and transfer learning for landslide assessments in Hong Kong and obtained good prediction results. Xu et al. (2022) demonstrated landslide model transfers for regions with earthquake-induced landslides. Qin et al. (2021) applied distant domain transfer learning for landslide detection in the city of Shenzhen, Guangdong province, China. However, these studies required training samples from the target region, which may lead to problems, such as the timing of sample acquisition, and whether the selected sample can correctly characterize the entire region. Thus, unsupervised transfer learning is highly attractive in landslide assessments. Zhu et al. (2020) proposed unsupervised feature learning and improved landslide susceptibility model transfer performance in Chongqing, China. These studies were based on landslide data and predictors from the same or adjacent areas with the same spatial resolution as the target area: i.e., their environmental characteristics and data distributions were highly similar, which may not always be the case. It is therefore necessary to find more suitable landslide transfer-learning methods without the limitation of scale and spatial resolution. Transfer-learning techniques such as domain adaptation (DA) and case-based reasoning (CBR) are emerging techniques to tackle the challenge of model transfer. In general, they have been developed to select the most suitable data and corresponding models from source areas with similar data characteristics for predicting a distinct target area in space and time.

The general concept of transfer learning is to solve new problems by applying knowledge gained from previous experiences in which similar problems were solved. That is, transfer learning has the potential to allow us to take existing knowledge of landslide occurrence from previous modeling experiences and apply it to new locations that lack any landslide data. Thus, this approach has great potential to minimize the considerable time and effort needed for building landslide inventories for susceptibility modeling in new areas, especially in large and geographically remote areas where landslide mapping and detection is particularly challenging.

In CBR, we consider multiple landslide inventories from various source areas, each of which contains a large amount of information. The problem is that not all inventories (so-

called “cases”) are suitable for training a model that can be applied to the new target task. Furthermore, processing the large amount of information for each case is time-consuming. Therefore, it is desirable to compare the overall characteristics of each case to transfer the appropriate knowledge. Case-based reasoning is a method to solve these problems by identifying similar cases and applying them to a new target area. This CBR similarity analysis can be performed by considering various attributes, such as data structure and topographic characteristics (Shi et al., 2004; Qin et al., 2016; Liang et al., 2020a, b, 2021). In contrast, instead of finding best cases using the overall similarity of source areas to a target, which is done by CBR, DA transfer-learning techniques can be applied to select the observations within a source area that match the data distribution of the target area. Previous applications of CBR in the geosciences have focused on selecting one source area to transfer to a target area (Qin et al., 2016; Liang et al., 2021). Yet, there is also potential for using CBR and DA to combine cases from multiple source areas to generate transferable models.

The objective of this study is to assess the potential of transfer learning using CBR and DA techniques for enhancing model transferability of machine-learning landslide susceptibility models. We evaluate the performance of transferred susceptibility models using DA, CBR and a combined CBR–DA technique, as well as the sensitivity of these methods to spatial resolution. We consider two scenarios for training landslide susceptibility models: only one source area available (single-source area) and multiple source areas available for model training (multi-source area). We examine both scenarios and compare them to benchmark situations, where susceptibility models are applied to a new target area without using transfer-learning techniques.

2 Methods and data

In transfer learning, the general goal is to train a model f on data from a single or multiple source areas $S = \{S_1, S_2, \dots, S_N\}$ to make predictions in an unseen target area T with N_t observations, regardless of spatial and temporal differences. A source area S_i consists of N_{S_i} observations of a set of predictors, x_j , and the corresponding labels y_j (e.g., landslide or non-landslide), $j = 1, \dots, N_{S_i}$.

Altogether, we evaluate five different transfer-learning strategies for landslide susceptibility modeling that consider the use of data from a single or multiple source areas, which are applied to CBR, DA, and both combined (CBR–DA) (Fig. 1). To assess the relative performance of the transfer-learning strategies, we include benchmark landslide susceptibility models that are simply trained using data from a single source area (single-source transfer benchmark), multiple source areas (multi-source transfer benchmark), and the target area (target benchmark), and then applied to the target area. In the case where multiple source areas were used, the

benchmark transfer model was calculated by averaging the model predictions of multiple source areas without weighting (Table 2). The target benchmark, which is trained and tested with all target data, is meant to represent an overoptimistic yet potentially obtainable performance for a given target area.

In this section, we first introduce the general CBR and DA methods separately (Sect. 2.1 and 2.2). We then explain how CBR and DA models as well as the combined CBR–DA approach are trained and tested in this work (Sect. 2.3). The data used for demonstrating the proposed approaches is then briefly presented, referring the readers to the relevant literature for more details (Sect. 2.4).

2.1 Case-based reasoning method

In machine learning, case-based reasoning (CBR) is one of the most well-known methods for solving a new problem by referring to similar cases, which can translate the knowledge from geographical space to parameter space (Shi et al., 2004, 2009; Hammond, 2012). It finds cases in a data collection that are similar to the current case in terms of metadata and/or data distribution, and then adopts those similar cases for training models (Liang et al., 2020a). This method has been reported to reduce the users' modeling efforts while achieving good performances in use cases involving terrain attributes (Qin et al., 2016; Liang et al., 2020b).

The CBR strategies are designed to find source areas $S = \{S_1, S_2, \dots, S_k\}$ that are most similar to the target area based on statistical summary information and metadata; these selected areas are referred to as *related* areas. In generating a CBR model, the individual models trained on the selected source areas are combined as a weighted sum:

$$f(x) = \sum_{i=1}^k w_i f_i(x), \quad (1)$$

where w_i are weights that correspond to similarity scores and are normalized to sum up to 1. The individual models f_i may be trained using conventional sampling strategies as well as DA strategies, both of which are described in detail below.

Generally, CBR consists of the case problem and the corresponding case solution parts (Qin et al., 2016; Liang et al., 2020b). In our study, the challenge of formalizing the similarity of areas in landslide susceptibility modeling is to contrive a way to adequately describe the data and areas' contextual information, such as how a study area's spatial data can describe the pattern of landslide occurrence.

In applying CBR, it is first necessary to define and calculate similarity measures for relevant attributes that describe the data distributions of the source and target areas. In this study, we chose geological characteristics, spatial resolution, and topographic characteristics. Similarities in each attribute were estimated based on a similarity function (Table 1).

The geological characteristics of a region are an essential factor that influences multiple landslide conditioning factors such as the geomechanical and hydrological properties of

hillslopes (Segoni et al., 2020). Considering the difficulties in matching geological descriptors such as heterogeneous chronostratigraphic units in different areas, we chose a simplified approach as a first-order approximation. Specifically, we used an indicator method that is based on whether the main rock types (igneous, sedimentary, and volcanic rocks) coincide in source and target areas.

Topographic conditions were described by measures of total relief, standard deviation of slope angle, and mean slope angle (Wang et al., 2019). Total relief describes the overall terrain situation of a study area by subtracting the minimum elevation from the maximum elevation within the study area. The relief, which reflects the macroscopic characteristics of surface topography in a large area, has been found to describe well landslide susceptibility (Wang et al., 2010). The standard deviation of the slope is used to describe the topographic complexity of a study area. It is one of the most influential topographic variables in landslide susceptibility studies (e.g., Van Den Eeckhaut et al., 2012).

The similarity values obtained for each factor were combined into a single indicator by taking their minimum value (Zhu and Band, 1994; Qin et al., 2009, 2016). In this study, for a given target area, we referred to source areas that have an overall (i.e., minimum) similarity score ≥ 0.65 as *related* source areas.

2.2 Domain adaptation

The general machine-learning approach of domain adaptation (DA) aims to solve a learning problem in the target area by utilizing data from different source areas to construct a learning sample (Wang and Deng, 2018). At first, a latent feature space is defined in which the source and target areas have the same distribution; as a consequence, classifiers trained on labeled data from source areas are likely to perform well in the corresponding target area (Baktashmotlagh et al., 2013; Patel et al., 2015; Wilson and Cook, 2020). There are supervised DA techniques that require labeled data from the target area, and unsupervised methods that do not require such data (Ben-David et al., 2010; Courty et al., 2017). We adopt unsupervised DA in our study because its smaller data requirements seem more appealing for practical applications.

Domain adaptation used in our study is a strategy for selecting instances $D_i \subset S_i$ (i.e., sample locations or grid cells for training) from a source area S_i in such a way that their distribution is more similar to the target area's data distribution. In situations with multiple source areas, DA is applied to each of them independently to obtain instance sets $D = \{D_1, D_2, \dots, D_k\}$ on which k models are trained. The predictions from these models are either averaged (referred to as "plain" DA), or a weighted average is calculated when combined with source-area selection from CBR. The DA is conventionally used as a single-source strategy, which is also included in this study for comparison, although multi-source

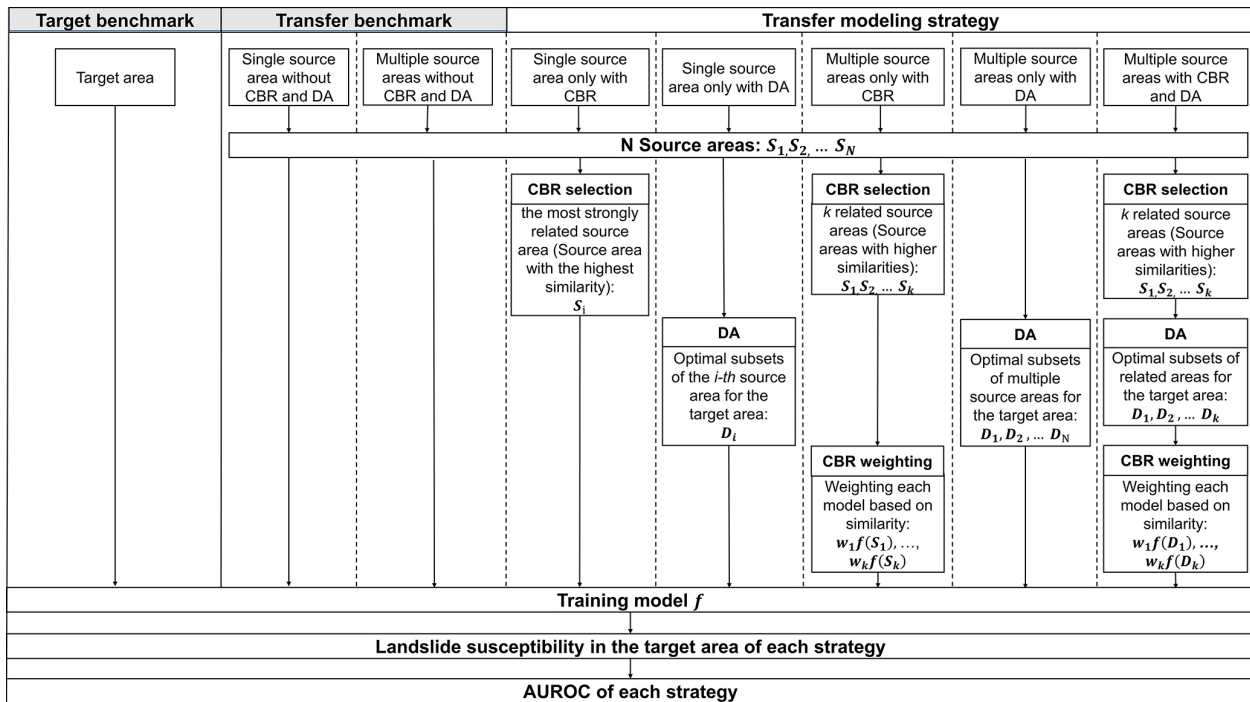


Figure 1. Flow chart of transfer-modeling strategies and benchmarks for landslide susceptibility mapping in a target area. Case-based reasoning (CBR) involves selection and weighting steps. In the single-source situation, weighting does not apply. Domain adaptation (DA) can be used by itself or combined with CBR to select source areas.

Table 1. Similarity functions for the attributes used in CBR to identify related source areas: geological characteristics, data characteristics, and topographic characteristics of the study area.

Factor group	Attribute	Similarity function	Description
Geological characteristics	Igneous	$\text{Sim} = \frac{1}{3} \sum_g I_g$	where $I_g = 1$ if unit g present or absent in the source and the target area, and 0 otherwise.
	Sedimentary		
	Metamorphic		
Data characteristics	Resolution [m]	$\text{Sim} = 2^{-(2 \log_{10} R_t - \log_{10} R_s)^{0.5}}$ or $\text{Sim} = 1$	The similarity is 1 if the resolution of the source area is smaller than in the target area, otherwise Sim; R is the DEM resolution.
Topographic characteristics	Total relief [m]	$\text{Sim} = 1 - \frac{ \text{Relief}_t - \text{Relief}_s }{\max(8848 - \text{Relief}_t, \text{Relief}_t)}$	Relief is the total relief.
	Standard deviation of slope	$\text{Sim} = 2^{-(2 \log_{10} \text{SD}_t - \log_{10} \text{SD}_s)^{0.5}}$	SD is the standard deviation of slope angle.
	Mean slope [degree]	$\text{Sim} = 1 - \frac{ \text{Slope}_t - \text{Slope}_s }{\max(40^\circ - \text{Slope}_t, \text{Slope}_t)}$	Slope is the mean slope.

Note: Sim is the similarity of each individual attribute between the target area t and a source area s , which is in $[0, 1]$. The following constants were used for normalization: 8848 m is the elevation of Mount Everest. For mean slope, 40° can properly cover the mean slope in all study areas.

strategies may seem more appealing in real-world applications.

Many DA strategies for transferring or weighting features can result in models that are difficult to interpret in terms of the physical process’s modeled influence on the response. Moreover, not all instances from different source areas may be suitable for transfer to a target area (Jiang and Zhai, 2007;

Gong et al., 2013; Long et al., 2013). Thus, the landmark-based domain adaptation (LBDA) approach (Gong et al., 2013) was applied in our study. This method selects the instances (or landmarks) from source areas with the same or similar distribution as the target area without creating new predictors. It aims at minimizing the difference in sample means in latent feature space.

In our study, considering computational constraints, a randomly selected set of 50 000 unlabeled (landslide and non-landslide) points x_n from the target area were used as reference points, and were compared to a randomly selected set of 30 000 labeled $(x_{S,m}, y_{S,m})$ (landslide and non-landslide) points from the source area S as reference points from which to select a subset with similar data distribution as the target area. In the case of some of the smaller source areas in our study, all observations were used for subset selection.

The DA selects training data by formally solving the optimization problem:

$$\min \left\| \frac{1}{\sum_{m=1}^{N_S} \alpha_{S,m}} \sum_{m=1}^{N_S} \alpha_{S,m} \phi(x_{S,m}) - \frac{1}{N_t} \sum_{n=1}^{N_t} \phi(x_{t,n}) \right\|_H^2, \quad (2)$$

subject to

$$\frac{1}{\sum_{m=1}^C \alpha_{S,m}} \sum_{m=1}^C \alpha_{S,m} y_{S,m} = \frac{1}{N_S} \sum_{m=1}^C y_{S,m}, \quad (3)$$

where indicator variables $\alpha = \{\alpha_m \in \{0, 1\}, m = 1, \dots, N_S\}$ are used to judge whether a landslide/non-landslide point in the source area is a landmark for minimizing the difference between source and target areas in the latent feature space. When α_m is 1, $(x_{S,m}, y_{S,m})$ is regarded as a landmark, i.e., a landslide/non-landslide point that can provide valuable information for the landslide susceptibility model of the target area. In order to determine an optimal α , it is necessary to apply a selection threshold (for a quantity β in Gong et al., 2013); we chose $1/N_S$ as this would allow us to select all source points as landmarks in the ideal situation where the source and target areas have identical latent feature space distributions. Furthermore, ϕ is a nonlinear feature function to map x to a reproducing kernel Hilbert space (Gretton et al., 2006). Following Gong et al. (2013, 2017), Gaussian RBF kernels are used for ϕ in our study; C is the number of landslide or non-landslide points. The collection α is chosen so that the quantity in Eq. (2) is minimized, i.e., the difference is minimized. Equation (3) is the constraint that considers the distribution of labels in the selected landmarks. This problem can be solved efficiently with convex optimization.

2.3 Susceptibility model training and testing

The transfer-learning strategies were applied using generalized additive models (GAMs) for susceptibility modeling. The logistic GAM, which performs a binomial classification of the absence or presence of landslides, has been well established as a method suitable for landslide susceptibility (Goetz et al., 2011; Petschko, 2014; Conrad et al., 2015; Bordoni et al., 2020). In fitting our model, we assumed that the feature space is the same for source and target areas. We therefore only used common predictors of landslide susceptibility

(Goetz et al., 2015) that are available in all source and target areas, which include local slope angle, plan and profile curvature, catchment slope angle, and upslope contributing area. These terrain attributes are intended to act as proxies for destabilizing forces (slope, catchment slope angle), water availability (logarithm of upslope contributing area and concave curvatures), and exposure to wind (convex curvatures), as well as general variability in characteristics of soil and vegetation (Muenchow et al., 2012).

We used the *mgcv* package (Wood, 2006) for GAM modeling. We set the dimension of the basis used to represent the smooth term k as 4. Since it can be difficult to separate landslide scarp and body from medium to low-resolution data (Dou et al., 2020), landslide presence points were randomly sampled from the entire landslide polygon and non-landslide points were randomly sampled from the area where the mapped landslides were excluded. At the same time, landslides that are smaller than one grid cell were excluded from our study.

In turn, each study area was used as a target area. The landslide label data from the target area were not involved in the training process of all strategies embedded in CBR, DA, or CBR–DA. Model performance was assessed using test data only within a target area. The training dataset was composed of an equal number of landslide and non-landslide observations. These landslide and non-landslide grid cells were obtained from the whole study area, or a subset of the study area based on DA.

Altogether, we explored five CBR and DA strategies for susceptibility modeling based on single and multiple source areas, which are summarized in Table 2. In our implementation of CBR, only source areas related to the target area were used for modeling, where we defined related areas as source areas that had a (minimum) similarity score ≥ 0.65 . In the case of DA (without CBR), multi-source models were created for all N source areas, excluding the target area. The final susceptibility models for multi-source CBR, DA, and CBR–DA strategies were based on combining model predictions from multiple source areas (described in Table 2).

The area under the receiver operating characteristic (ROC) curve (AUROC) (Hosmer et al., 2013) was used to assess the predictive performance of the transferred models based on their predictions in the target area. In choosing the AUROC, we treated model predictions as relative scores instead of actual probability estimates, which is common practice in landslide susceptibility modeling.

2.4 Case study transfer source and target areas

We demonstrated the application of CBR and DA for transfer learning using 10 case study areas for source and target areas from three distinct geographic regions (Fig. 2): the Andes of southern Ecuador (the Reserva Biológica San Francisco (RBSF) area, and a highway corridor; Muenchow et al., 2012; Brenning et al., 2015), the Emilia Romagna Region in

Table 2. Transfer strategies and benchmarks adopted in our study.

Transfer strategies	Final predictive model f	Description
Single source area with DA (single-source DA)	$f_i(D_i)$	The final prediction model is trained on the DA-derived subset of data from each source area.
Single source area with CBR (single-source CBR)	$f(S_{\text{highest}})$	The final prediction model is trained using all data from the <i>most strongly related</i> source area.
Multiple source areas only with CBR (multi-source CBR)	$\sum_{i=1}^k w_i f_i(S_i)$	The final prediction model is the weighted mean of different predictive models trained on the <i>k-related</i> source areas.
Multiple source areas only with DA (multi-source DA)	$\frac{1}{N} \sum_{i=1}^N f_i(D_i)$	The final prediction model is the average of predictions from all landslide models trained on the <i>DA-selected data</i> from different source areas.
Multiple source areas with CBR and DA (multi-source CBR–DA)	$\sum_{i=1}^k w_i f_i(D_i)$	The final prediction model is the weighted mean of predictions from landslide models trained on the <i>DA-selected data</i> from the <i>k-related</i> source areas.
Benchmarks		
Multiple source areas without CBR and DA (multi-source transfer benchmark)	$\frac{1}{N} \sum_{i=1}^N f_i(S_i)$	The final prediction model is the average of predictions from all landslide models trained on different source areas.
Single source area without CBR and DA (single-source transfer benchmark)	$f_i(S_i)$	The final prediction model is trained on a (specific) single source area.
Target benchmark	$f(T)$	The final prediction model is trained on data from the target area itself (only for comparison – not a model transfer situation).

northern Italy (Bologna, Modena, Parma, Piacenza, and Rimini areas; Rossi et al., 2010; Segoni et al., 2018; Piacentini et al., 2018; Ciccarese et al., 2021), and eastern Austria (Burgenland, Waidhofen and Palldau areas; Gasser et al., 2009; Petschko et al., 2012; Knevels et al., 2019, 2020). Rainfall is considered the main trigger of landslides in all study areas.

All study areas have similar types of igneous rocks (e.g., basalt), sedimentary rocks (e.g., sandstone), and metamorphic rocks (e.g., schist), except that the RBSF area has no igneous and sedimentary rocks. The above references provide additional detailed information on the study areas. We also summarized the geological information of all study areas in Table A1 in the Appendix.

In our study, DEMs with different resolutions were available for the Austrian, Italian, and Ecuadorian study areas. For Ecuador, the 10 m × 10 m DEMs were produced by Ekkehard Jordan and Lars Ungerechts (Düsseldorf); for Italy, an EU-DEM with a 25 m × 25 m resolution was used; and an airborne lidar-derived digital terrain model (DTM) with a 1 m × 1 m resolution was available for the Austrian areas from the governments of Styria and Burgenland. Landslide inventories in our study were provided by Jannes Muenchow (Erlangen) for Ecuador, who also did a more detailed study in Muenchow et al. (2012). Additional information can fur-

thermore be found in SGSS (2019) for the Emilia-Romagna region, Knevels et al. (2019) for Burgenland, and Knevels et al. (2020) for Waidhofen and Palldau. For the Emilia-Romagna region, we chose the subset of landslides labeled as active.

We furthermore resampled the DEMs with 1 m resolution to 10 and 25 m, and the data with 10 m resolution to 25 m in order to use up to three dataset versions to mimic various mismatches in target and source resolution. Resampling was based on B-spline interpolation in SAGA (System for Automated Geoscientific Analysis) GIS 7.4.0 (Conrad et al., 2015). Overall, we therefore had 17 datasets (Table 3). For brevity, we combined the place name with the resolution, e.g., Waidhofen 10 for Waidhofen with a 10 m resolution.

3 Results

3.1 CBR similarity analysis

For the majority of the areas, mean slope angle and spatial resolution were the most limiting and therefore the most influential similarity attributes in determining which source areas were related to the target area. For some target areas, multiple similarity attributes contributed to differentiating candi-

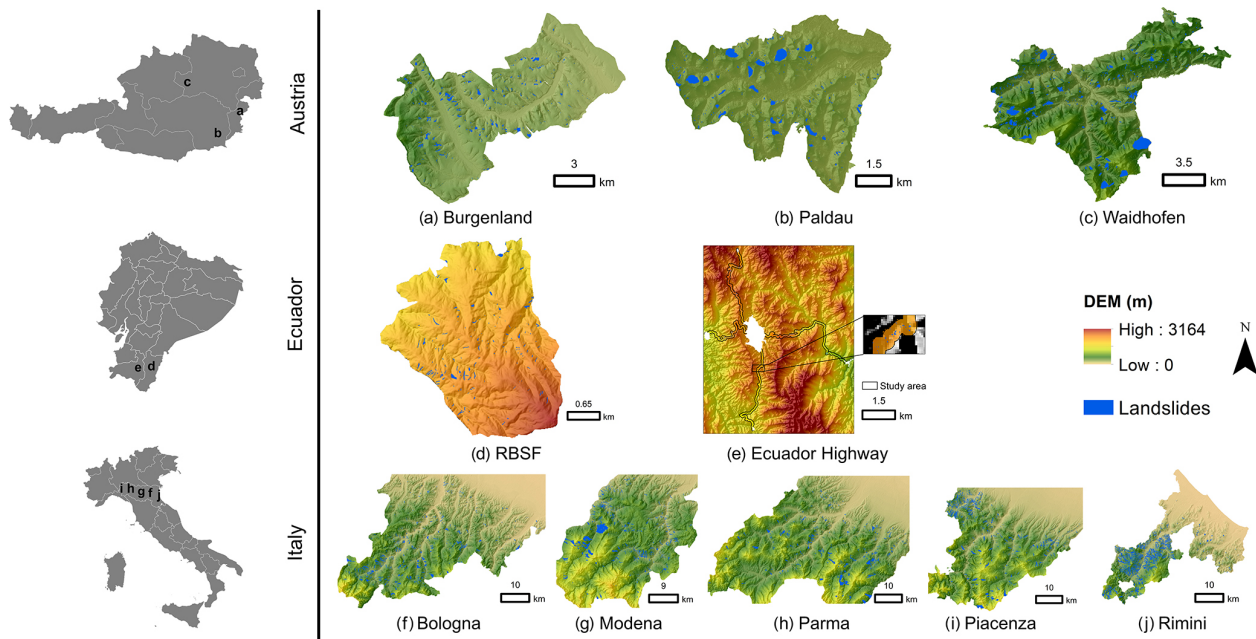


Figure 2. Overview of study areas for landslide susceptibility mapping in our study. The study areas are shown as DEM map in the same scale. Landslide inventories of study areas are shown as blue polygons. From top to bottom, study areas are from Austria, Ecuador, and Italy. Map extents correspond to study areas, with the exception of the Ecuador highway area, where the study area is limited to a 300 m buffer on both sides of the highway and outside urban areas.

date source areas, while for others, a single attribute (mean slope or resolution) dominated the exclusion of unrelated source areas (Fig. 3). For high-resolution datasets, the resolution attribute was primarily responsible for the overall similarity. The combination of spatial resolution and the standard deviation of slope or mean slope affected the overall similarity as the resolutions of the source and target areas got closer. In general, as the spatial resolution of the target and source areas became coarser, the number of related source areas tended to increase. Mean slope, standard deviation of slope, and geological units had more influence on the overall similarity assessment when resolutions were similar. Topographic characteristics and resolution were generally the main attributes that determined the overall similarity.

Most of the target areas (14 out of 17) had one or more related source areas. There were only 3 cases where the target had no related source areas (RBSF 10, 25, and Waidhofen 1), 2 cases with only one source area, and 12 with multiple related source areas (Fig. 4). Target areas with a resolution of 25 m tended to have a larger number of related source areas. Some target areas had related source areas in different geographic regions (e.g., Italian Alps and Burgenland).

Three representative target areas were selected to show the contribution of each attribute to the overall similarity because similar patterns were observed elsewhere (Fig. 3; complete results in the Supplement).

3.2 Single-source learning

In single-source transfer learning, CBR achieved the highest model performance overall. The DA resulted in stronger predictive performances only when source and target areas were substantially dissimilar (Figs. 5, 6). The AUROCs obtained by single-source CBR were always distributed between the median and maximum values of transfer benchmark models and close to the AUROCs obtained by the model trained using only target data (Fig. 5 and Table A2 in Appendix). For example, when Bologna 25 was the target data, the AUROCs of a model trained in the most related source area Piacenza 25 was 0.762 and that of the model trained with Bologna 25 data as source was also 0.762. Moreover, the majority of median AUROC performances obtained with single-source DA were greater than the median AUROC performance of single-source transfer benchmark models (Fig. 5). This distribution trend implied to some extent that single-source DA improved performances, which was consistent with the results shown in Fig. 6. Specifically, for similarities below 0.27, AUROCs achieved with DA were up to 0.14 higher than without it. When the overall similarity of the source area for the target area gradually increased up to ~ 0.60 – 0.65 , the difference values were centered at around $+0.03$. As the overall similarity was greater than 0.65, the AUROCs obtained by single-source DA were close to the ones achieved by the single-source transfer benchmark.

Table 3. Summary of the landslide datasets used in this study.

Study areas	Resolution (m)	Number of landslide	Mean landslide Size (m ²)	Main landslide types	Main triggering factor		Region
Burgenland	1 10* 25*	382	6330				Alpine fringe
Paldau	1 10* 25*	418	3879	Earth and debris materials (Knevels et al., 2019, 2020)	Rainfall	Austria	Styrian Basin
Waidhofen	1 10* 25*	621	11 235				Ybbstaler Alps
RBSF	10 25*	178	733.9	Shallow landslides (Muenchow et al., 2012)	Rainfall	Ecuador	South Ecuadorian Andes
Ecuador highway	10	1588	2725.4	Shallow and deep-seated landslides (Brenning et al., 2015)			
Bologna Modena Parma Piacenza Rimini	25	1354 1240 1261 1583 2229	33 272 38 816 41 444 37 502 34 679	Debris flows (Piacentini et al., 2018)	Rainfall and earthquake	Italy	Italian Alps

* resolution of resampled data

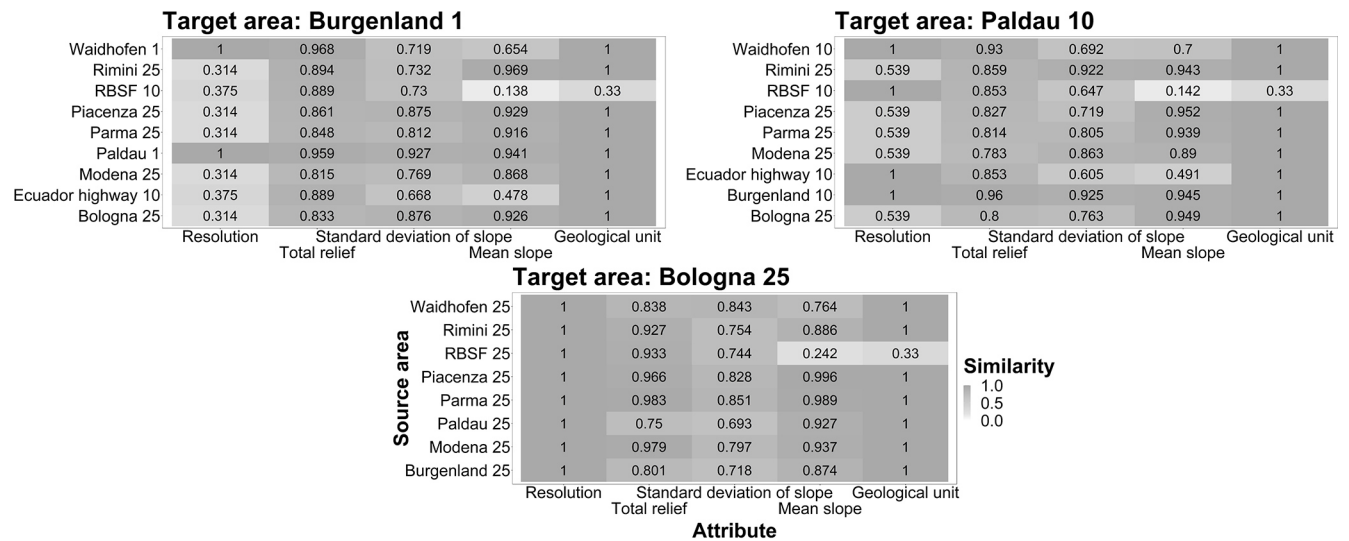


Figure 3. Similarity scores for three selected representative target areas (Burgenland 1, Paldau 10, and Bologna 25). Light colors represent smaller similarities. The overall similarity value of each source area is marked with a black box.

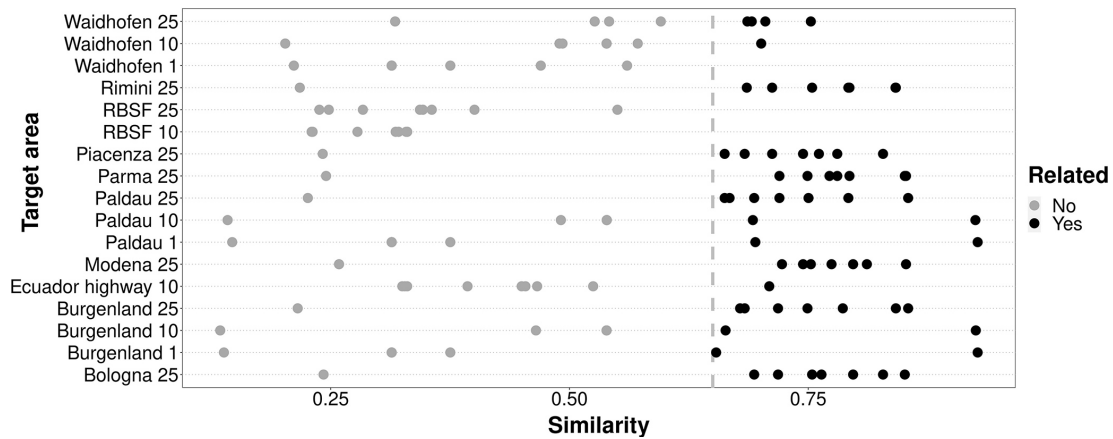


Figure 4. Distribution of related (black points) and unrelated (gray points) source areas for different target areas in the CBR transfer-learning strategies. Related source areas are defined as having a minimum similarity score ≥ 0.65 (vertical line).

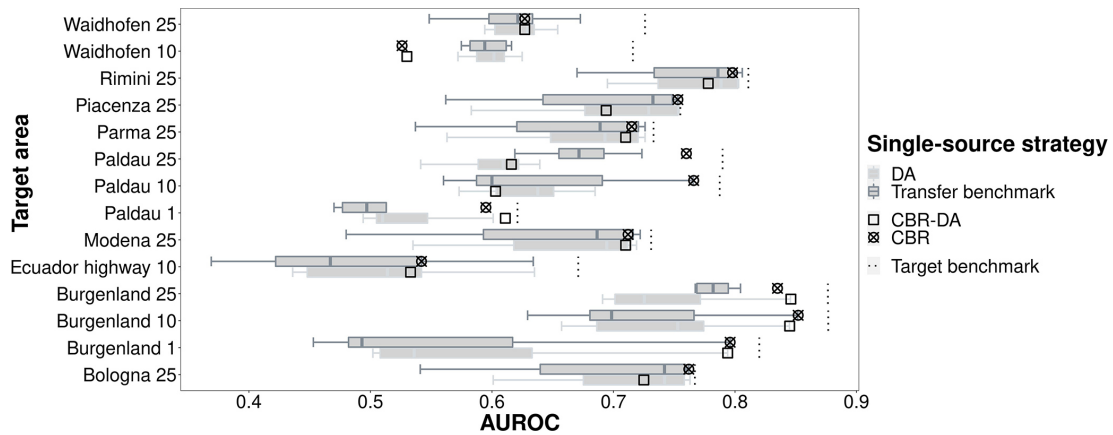


Figure 5. Comparison of single-source strategies: AUROCs obtained by models trained on individual source areas with case-based reasoning (CBR), domain adaptation (DA), combined CBR–DA, and in the single-source transfer benchmark.

CBR–DA also showed good performances. Its results were located in the upper part of transfer benchmark results (Fig. 5). This may be due to the contribution of CBR rather than DA. Throughout all the results, single-source CBR demonstrated more stable prediction performances compared to the results obtained by the strategies involving DA.

From this perspective, it can be concluded that by selecting the related areas, CBR was effective in identifying a suitable source area that resulted in favorable performances regardless of the use of DA.

3.3 Multi-source learning

The strategies that involved CBR had better prediction performances in multi-source transfer learning compared to the multi-source transfer benchmark and multi-source DA (Fig. 7). Multi-source CBR obtained good performances regardless of the number of related source areas and whether the related source areas were from the same region (Figs. 4

and 7). However, multi-source CBR–DA underperformed in general, usually having predictive performances lower than the multi-source transfer benchmark. When comparing the average of AUROCs of different strategies for all target areas in multi-source transfer learning, CBR was the best multi-source strategy followed by the transfer benchmark and CBR–DA, while DA had the worst multi-source performance. Furthermore, with respect to the stability of the results, multi-source CBR performed best since the performances it obtained were always in the top two of all performances obtained by different multi-source transfer-learning strategies. In contrast, the results obtained for strategies involving DA were highly variable and always inferior to the results of the corresponding multi-source transfer benchmark.

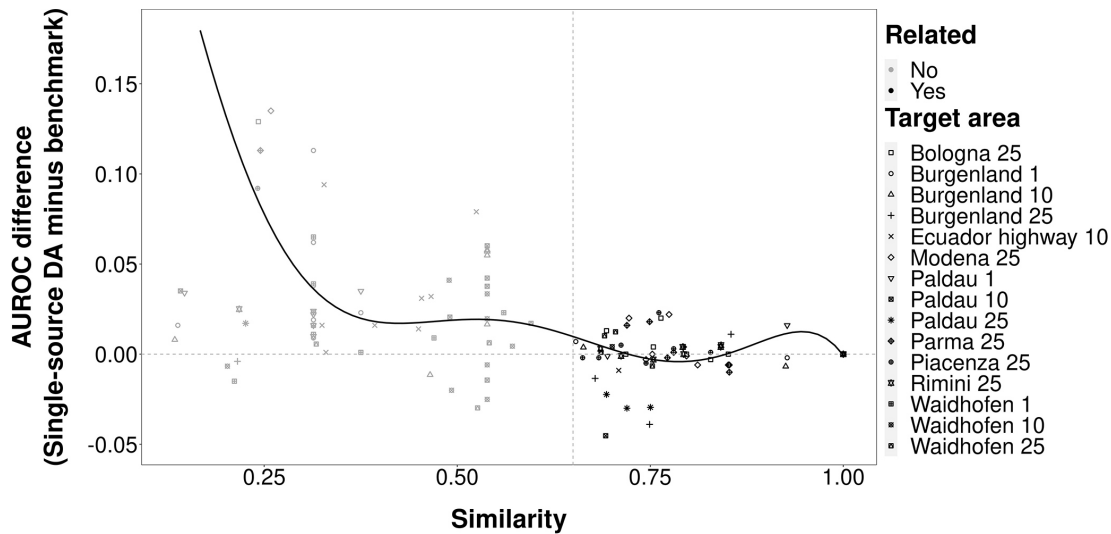


Figure 6. Similarity scores vs. AUROC differences between models trained on individual source areas with DA and models without DA (“single-source DA” minus “single-source transfer benchmark”).

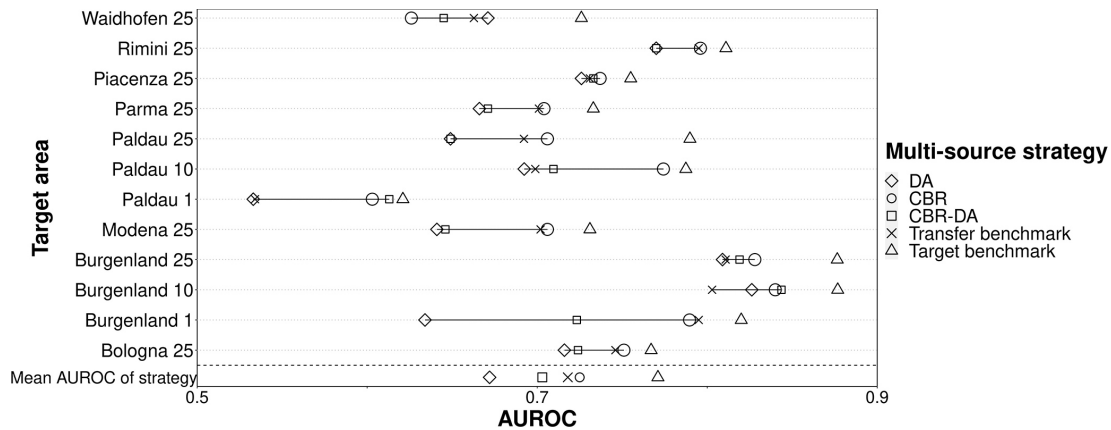


Figure 7. AUROCs of models trained on multiple source areas with case-based reasoning (CBR), domain adaptation (DA), combined CBR–DA, and the multi-source transfer benchmark (averaged across all source areas) and target benchmark.

3.4 Comparing single- and multi-source learning

For the majority of target areas, single-source CBR was the best-performing transfer-learning strategy, closely followed by multi-source CBR (Fig. 8). Both were located between the median and the maximum of single-source transfer benchmark and tended to be closer to the maximum, which meant that CBR-based source selection was highly effective at identifying the most suitable sources of training data. On average, the single-source and multi-source CBR AUROCs were below the overoptimistic target benchmark (training and testing in target area) by only ~0.05. The strong performance of CBR in both single- and multi-source strategies indicated that the most effective transfer-learning methods were to train the predictive model using the most related source area or performing a weighted combination based on the simi-

ilarity scores of the predictive models trained on the most strongly related source areas.

3.5 Comparing susceptibility map appearances

The best-performing transfer-learning strategies (single-source and multi-source CBR and CBR–DA) had spatial patterns of landslide-prone areas that most resembled the target benchmark (Fig. 9). Strategies with CBR, which considers target–source similarity, were able to better avoid falsely detecting landslide-prone areas. Using classified landslide susceptibility maps for Burgenland 10 as an example, the lower-performing, multi-source DA (Fig. 9h) and the multi-source benchmark (Fig. 9e) appeared to overpredict susceptibility in some areas (e.g., on alluvial fans) compared to the target benchmark (Fig. 9a) and the better-performing CBR-based transfer-learning strategies (Fig. 9c, f, and g). The suscep-

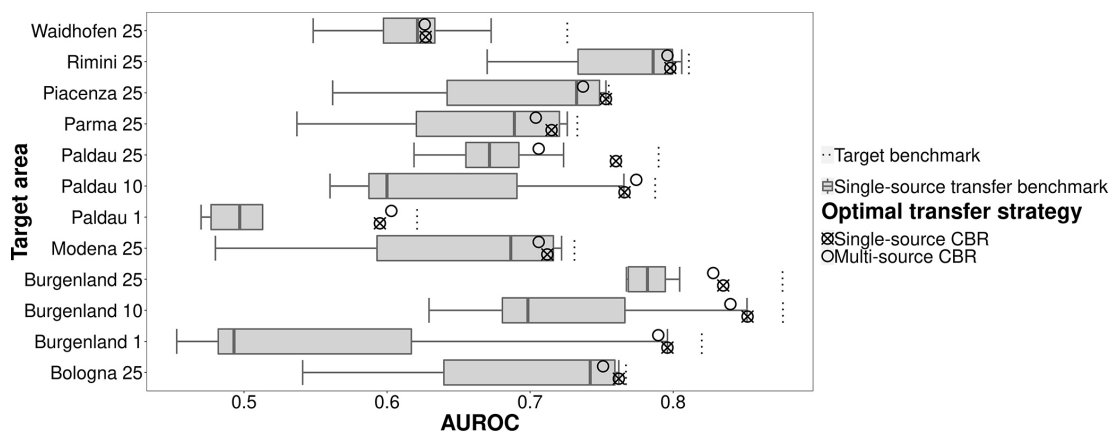


Figure 8. Comparison of single- and multi-source CBR strategies and the single-source target benchmark.

tively maps also showed that if a single source area had a high similarity (e.g., Paldau 10 and Burgenland 10) to the target area, DA strategies (Fig. 9d) can also properly detect landslide-prone areas. The difference in landslide-prone areas of single- and multi-source benchmarks compared to the target benchmark also indicates that not all source areas were suitable for predicting landslides for unseen areas.

4 Discussion

4.1 Case-based reasoning in landslide assessment studies

By calculating the similarities between source and target areas to find the most transferable source area(s), CBR is able to transfer the knowledge from source areas to the target area. In our study, we considered data from a variety of regions, and our results provided a comprehensive understanding of the potential of CBR in single- and multi-source transfer learning. Consistent with the literature for digital soil mapping and digital terrain analysis (Qin et al., 2016; Liang et al., 2020a, 2021), our results further support the adoption of CBR and provide useful methodological information for landslide assessment studies.

Case-based reasoning may give fresh insight into improving the understanding of knowledge transfer in landslide susceptibility modeling. It is an effective method to capture past experiences to improve the predictive capabilities of models (Wang et al., 2020; Bannour et al., 2021). In particular, it only needs to consider the basic characteristics of the data and the region to quickly match historical scenarios to the current study area and thus solve the task at hand. Additionally, the use of CBR to compare similarities between datasets makes it possible to reuse existing predictive models. These attractive abilities may benefit landslide mapping for emergency response as well as landslide susceptibility modeling for hazard mitigation. Moreover, we determined that by using sim-

ilarity as the basis for the weight of each related source area and the strategies involved, CBR in multiple source areas displayed good and robust performance in our study (Fig. 7).

Until now, model transfer in landslide modeling have usually relied on a homogeneous availability of data and a strong model generalization to avoid local overfitting and allow the application of a model in an adjacent target region (Goetz et al., 2011; Wenger and Olden, 2012; Petschko et al., 2014; Bordoni et al., 2020). Although this approach has been identified as a robust method for regional susceptibility modeling, its model transferability is often limited to nearby locations that have the same feature space and a nearly identical data distribution. However, when the data distribution is different, the above approach may not be effective, even though the training data are from adjacent regions. Yates et al. (2018) have pointed out that the spatial and temporal separation may have little impact on model transfers, while environmental dissimilarity and data resolution are critical factors for successful model transfer. These factors could be considered as the spatial and temporal limits to extrapolation in model transfers, as well as for landslide susceptibility model transfers; CBR may be able to handle these limits by calculating the overall similarity, indicating the suitability of landslide susceptibility model transfers between different study areas. In Figs. 3 and 7, we found that combining data from multiple related source areas with CBR yielded excellent results, even though some of the related source areas are from different regions than the target area.

After selecting related source areas, the predictors designed for training the model need to be examined. In our study, we assumed that the source and target areas used the same predictors and focused on topographic predictors. However, when the source and target areas have different predictors, one of the problems is that topographic predictors are not the only factors that play a key role in landslide prediction. Thus, a method should be implemented to select suitable predictors for model transfer since not all predictors can be used in the training process. Liang et al. (2021) se-

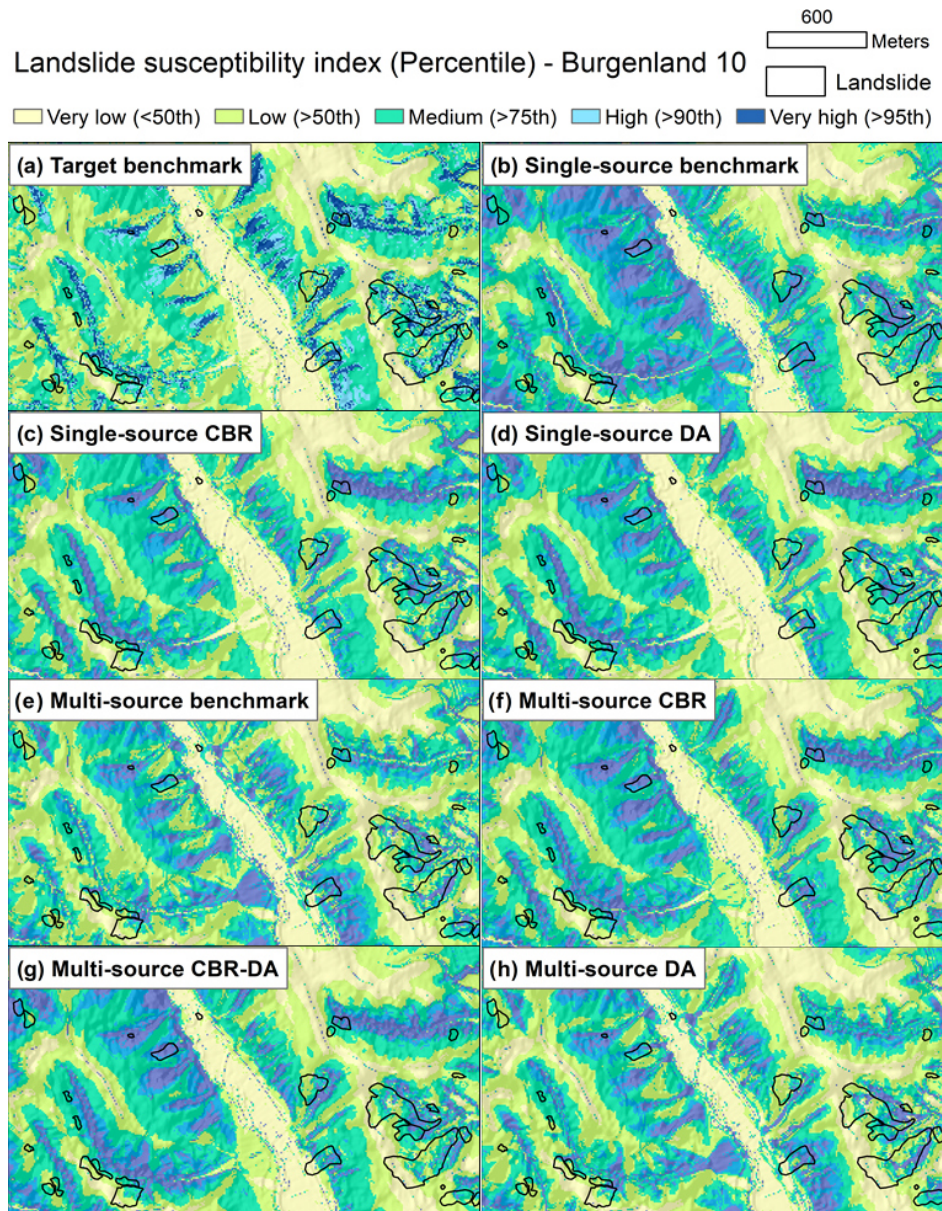


Figure 9. An example of classified landslide susceptibility maps for each benchmark and transfer-learning strategy for the Burgenland 10 target area. Predicted probabilities were classified into five susceptible levels (very high, high, moderate, low, very low) using the top 5th, 10th, 25th, and 50th percentile of each strategy's predictions. The results of single-source CBR and single-source DA are illustrated using models trained on Paltau 10 data. The single-source benchmark result is illustrated using a model trained with Waidhofen 10 data.

lected suitable predictors for a new task by using each model trained by individual predictors of the source area to predict in the target area; they concluded that this method was effective. However, since they only focused on terrain attributes, it is unclear how this approach would work on other predictors such as antecedent rainfall intensity, which, in addition to regional rainfall pattern variations, can strongly differ from one region to another. From this perspective, we would suggest that future research using CBR transfer learning could focus on the selection of features that are more likely transferable.

4.2 CBR similarity criteria

The proposed similarity scores in this study based on geologic, topographic, and data characteristics (i.e., spatial resolution) worked quite well in supporting CBR strategies for identifying the most similar and thus transferable source areas. These similarity attributes do not explicitly account for landslide type, which is an important factor to consider when modeling landslide susceptibility (Huang and Zhao, 2018). However, geologic attributes and terrain attributes such as

slope angle, may work together as a suitable surrogate to anticipate the most likely landslide types given little to no landslide data in the target area. Landslide type information is also difficult to collect and often lacking in landslide inventories (Mezaal and Pradhan, 2018). Prior information on unseen areas or integrating expert experience may be helpful in formulating landslide types for transfer learning.

In general, the use of similarity indices can be somewhat arbitrary since there are currently no clear criteria for how to select suitable similarity indices. For example, Liang et al. (2020a) analyzed the importance of each attribute for digital soil mapping based on previous studies to select the similarity index. Qin et al. (2016) indicated that the similarity indices should be structured to effectively represent the contextual information relevant to digital terrain analysis applications, hence the similarity indices used were based on knowledge and experience. Wang et al. (2020) selected similarity indices based on their importance for disaster situations.

For CBR applied to landslide susceptibility modeling, more elaborate criteria that could be indirectly used to account for differences in landslide type could focus on preparatory and triggering conditions such as land use (Steger et al., 2017; Knevels et al., 2021) and the density of paved and unpaved road networks (Brenning et al., 2015). Adding more process-related similarity indices may lead to improved CBR transfer learning, but this may not be easy to implement across different study regions in different countries with different mapping agencies and standards. Therefore, similar to selecting individual features for landslide susceptibility modeling (without model transfer), we recommend the use of expert knowledge to help guide the selection of similarity attributes.

In terms of choosing related source areas, the minimum operator method worked well in our study and avoided selecting a “falsely” related source. However, we did observe a scenario where one area was considered to be related but the reciprocal area not (Paldau and Waidhofen; Fig. 4). As pointed out by Humphreys et al. (2003), when using CBR for similarity evaluation, the evaluation criterion used may be different in different categories and situations. By analogy, we can assume that the threshold settings for similarity may also differ for different attributes in different study areas in landslide assessment studies. Additionally, there are other methods to obtain the related area, such as Manhattan distance, gray relational analysis, or k -nearest neighbors (Dou et al., 2015).

4.3 Utility of domain adaptation in geospatial learning and other limitations

Our study showed that DA did not generally improve transfer-learning performance in landslide susceptibility modeling. This holds true for single-source as well as multi-source DA with and without CBR-based source selection. Nevertheless, DA increased the AUROC performance when

the source area was rather dissimilar to the target area (Fig. 6), which is less relevant in landslide studies that have access to a large and geographically diverse case base.

It is impressive that models trained on multiple related source areas with CBR and DA showed good performances. For instance, when Paldau with a $1\text{ m} \times 1\text{ m}$, and Burgenland with a $10\text{ m} \times 10\text{ m}$ resolution were the target areas, AUROCs obtained by multi-source CBR–DA were nearly equal to those achieved by the best single-source transfer benchmark and higher than the other strategies (Fig. 7). The reason may lie in the improvement of DA through the weighting of source areas.

A further consideration is to use labeled data from the target area. Fang et al. (2021) proposed a new domain adaptation for landslide inventory mapping by considering pre-landslide and post-landslide conditions and concluded that the proposed method was successful. This new method could be considered as supervised DA in landslide susceptibility mapping. In other geospatial learning fields, such as land cover mapping, Mboga et al. (2021) compared two unsupervised DA strategies (the correlation alignment domain adaptation network and the domain adversarial neural network) and found that classification performance was improved by adding labeled data from the target area. We suggest that active-learning strategies (Wang and Brenning, 2021) could be useful in efficiently generating limited amounts of labeled data for transfer learning, which should therefore be investigated in a next step.

Although the study areas cover a wide range of climates with different land cover types and landslide process types, our set of source areas is by no means complete and the results may therefore not be fully representative for the performances that might be achieved at a global scale. Future work should therefore broaden the database of source areas.

4.4 The potential of the novel methods for landslide assessment

Deep learning is getting more and more popular in the study of landslide model transfer. For example, Ai et al. (2022) proposed a supervised method by combining deep learning and transfer learning for landslide susceptibility modeling. Liu et al. (2021) performed landslide classification using VGG-19 and transfer learning based on limited data from the unseen area. Lu et al. (2020) mapped landslides based on deep learning and transfer learning. These studies show that deep learning is a potential method in landslide model transfer studies, although they are limited to a regional scale or require training data from the target area.

Combining CBR with deep learning could be a worthy unsupervised method in landslide assessments. By calculating similarities between the target area and source areas and selecting related source areas, deep learning can directly use them to train landslide models for the target area, which might avoid the need for tuning hyperparameters.

5 Conclusions

The aim of our study was to examine the performances of geographically informed case-based reasoning (CBR) and unsupervised domain adaptation (DA) in geographically transferring knowledge for landslide susceptibility modeling in “new” target areas without landslide inventory data. We extended the study of landslide model transfers to a larger global scale and considered the effect of different spatial resolutions on landslide model transfer. In addition, different scenarios (single source area and multiple source areas) were considered, which made methods and results much closer to practical applications in the real world. Moreover, in the multi-source scenario, we proposed a method to combine multiple landslide models based on environmental similarity. Our comparative study revealed that CBR strategies with a single source area and multiple related source areas were robust and effective in developing highly transferable landslide susceptibility models without requiring prior knowledge of landslides in the target area. In particular, single-source CBR was the most effective method for performing model transfer to the target area in most situations. Its performance was also very close to that obtained by models trained with data from the target area itself. The CBR similarity criteria in our study are still preliminary, and datasets used in our study might not be enough for an application at a global scale, which should therefore be considered in future research.

Overall, the findings of this paper demonstrated that the proposed transfer-learning approaches can alleviate the burden of collecting and labeling data, resulting in a more expedited preparation of landslide susceptibility maps for large and data-scarce regions. By calculating the similarity between data and region characteristics, trained models can directly be used for the new task, especially in situations that require rapid model development, such as emergency situations. Furthermore, we suggest that novel methods such as deep learning may also benefit greatly for landslide model transfer studies.

Appendix A

Table A1. Information of all study areas.

	Original dataset									
	Burgenland	Palldau	Waidhofen	Ecuador highway	RBSF	Modena	Parma	Piacenza	Rimini	Bologna
Slope angle (degree)	Min	0	0	0	2.5	0	0	0	0	0
	Max	82.5	66.6	87.5	52.9	76.2	71.8	66.6	64.1	67.2
	Mean	9.2	10.9	19.8	25.3	35.7	11.8	11.4	8.2	11.5
	Standard deviation	8.2	8.3	10.7	12.2	10.7	7.5	8.6	6.5	7.9
Area (km ²)	117.8	39.3	131.3	88	9.6	1293	2576.8	1834.8	921.2	3707.6
Main geological units	Igneous	✓	✓	✓	✓	×		✓		
	Sedimentary	✓	✓	✓	✓	×		✓		
	Metamorphic	✓	✓	✓	✓	✓		✓		
Elevation (m)	Max	766.7	463.1	1114.9	2960.4	3164.2	1827.3	1726.3	1399.3	1923.5
	Min	243.1	282.7	324.5	948.8	1714.4	34.8	49.7	3.8	11.0
Predictor variables for landslide and non-landslide observations										
Slope angle (degree)	Landslides median (IQR)	15.9 (13.95)	11.36 (11.63)	19.05 (13.84)	30.02 (17.43)	43.37 (10.67)	11.03 (6.49)	10.81 (5.83)	10.17 (4.93)	11.2 (5.5)
	Non-landslides median (IQR)	6.7 (8.24)	9.23 (10.53)	18.00 (15.12)	23.03 (17.56)	36.27 (14.59)	11.30 (9.74)	10.31 (1.08)	7.18 (9.88)	10.9 (10.1)
	Landslides median (IQR)	-0.001 (0.33)	0.00136 (0.39)	-0.0034 (0.3648)	0.00086 (0.0152)	-0.017 (0.052)	-0.00124 (0.00785)	-0.00102 (0.0081)	-0.00182 (0.00813)	-0.00214 (0.0079)
Plan curvature (radians per 100 m)	Non-landslides median (IQR)	0.00019 (0.42)	0.00294 (0.46)	-0.0009 (0.2762)	0.00028 (0.0117)	0.0054 (0.043)	0.00037 (0.00935)	0.00027 (0.00999)	0.00052 (0.01118)	0.0004 (0.01)
	Landslides median (IQR)	-0.0001 (0.0014)	0.00025 (0.08558)	-0.0015 (0.1028)	0.00056 (0.019)	-0.0025 (0.013)	-0.00015 (0.00143)	-0.00014 (0.00135)	-0.00019 (0.00127)	-0.0002 (0.0014)
Profile curvature (radians per 100 m)	Non-landslides median (IQR)	0.00024 (0.05)	0.00046 (0.07183)	-0.0006 (0.0738)	-0.00036 (0.013)	0.00147 (0.014)	-0.00002 (0.0014)	-0.00002 (0.00132)	-0.00002 (0.00101)	-0.00003 (0.0015)
	Landslides median (IQR)	1.74 (1.08)	1.56 (0.95)	1.87 (0.997)	3.04 (0.65)	3.03 (0.61)	4.16 (0.71)	4.18 (0.73)	4.07 (0.72)	4.1 (0.71)
Upslope contributing area (log ₁₀ m ²)	Non-landslides median (IQR)	1.67 (0.97)	1.56 (0.95)	1.88 (0.734)	3.15 (0.80)	2.80 (0.60)	3.81 (0.70)	3.82 (0.74)	3.71 (0.68)	3.7 (0.67)

Table A2. AUROCs of models trained on individual source areas with domain adaptation (DA) versus without domain adaptation. The results are shown as DA/target benchmark. The bold font indicates that the source area corresponding to this AUROC was the most related for the current target area.

	Target areas									
	Bologna 25	Burgenland 1	RBSF 10	Ecuador highway 10	Modena 25	Paldau 1	Parma 25	Piacenza 25	Rimini 25	Waidhofen 1
Bologna 25	0.767	0.515/0.432	0.524/0.505	0.446/0.415	0.719/0.72	0.494/0.47	0.72/0.726	0.754/0.753	0.803/0.806	0.5/0.435
Burgenland 1	–	0.82	–	–	–	0.611/0.595	–	–	–	0.562/0.553
RBSF 10	–	0.633/0.617	0.772	0.635/0.634	–	0.547/0.513	–	–	–	0.543/0.558
Ecuador highway 10	–	0.536/0.628	0.704/0.713	0.671	–	0.505/0.47	–	–	–	0.502/0.501
Modena 25	0.756/0.756	0.502/0.493	0.468/0.406	0.448/0.369	0.731	0.512/0.502	0.705/0.715	0.743/0.748	0.802/0.798	0.496/0.48
Paldau 1	–	0.794/0.796	–	–	–	0.621	–	–	–	0.587/0.564
Parma 25	0.762/0.762	0.504/0.466	0.629/0.594	0.514/0.482	0.706/0.712	0.499/0.477	0.733	0.753/0.75	0.795/0.795	0.496/0.473
Piacenza 25	0.757/0.76	0.595/0.482	0.54/0.428	0.436/0.422	0.719/0.722	0.51/0.494	0.721/0.72	0.755	0.803/0.804	0.499/0.488
Rimini 25	0.763/0.759	0.508/0.489	0.681/0.552	0.483/0.467	0.709/0.715	0.507/0.497	0.726/0.722	0.753/0.748	0.811	0.533/0.494
Waidhofen 1	–	0.77/0.763	–	–	–	0.601/0.602	–	–	–	0.652
Burgenland 10	–	–	0.657/0.533	0.542/0.448	–	–	–	–	–	–
Paldau 10	–	–	0.73/0.73	0.63/0.614	–	–	–	–	–	–
Waidhofen 10	–	–	0.709/0.662	0.533/0.542	–	–	–	–	–	–
Burgenland 25	0.728/0.728	–	–	–	0.683/0.661	–	0.681/0.663	0.715/0.717	0.782/0.777	–
Paldau 25	0.601/0.588	–	–	–	0.535/0.515	–	0.563/0.547	0.583/0.585	0.715/0.711	–
Waidhofen 25	0.677/0.657	–	–	–	0.619/0.619	–	0.643/0.645	0.684/0.661	0.744/0.741	–
RBSF 25	0.67/0.541	–	–	–	0.615/0.48	–	0.65/0.537	0.654/0.562	0.695/0.67	–
	Burgenland 10	Paldau 10	Waidhofen 10	Burgenland 25	Paldau 25	Waidhofen 25				
Bologna 25	0.686/0.629	0.5/0.560	0.608/0.575	0.705/0.768	0.639/0.662	0.627/0.617				
RBSF 10	0.774/0.766	0.726/0.691	0.587/0.594	–	–	–				
Ecuador highway 10	0.657/0.669	0.638/0.617	0.530/0.526	–	–	–				
Modena 25	0.753/0.736	0.642/0.6	0.602/0.582	0.722/0.784	0.615/0.645	0.594/0.601				
Parma 25	0.510/0.696	0.651/0.591	0.610/0.616	0.728/0.767	0.589/0.619	0.654/0.642				
Piacenza 25	0.735/0.681	0.61/0.572	0.572/0.597	0.569/0.791	0.541/0.659	0.632/0.631				
Rimini 25	0.756/0.698	0.573/0.587	0.625/0.584	0.691/0.780	0.588/0.682	0.632/0.626				
Burgenland 10	0.877	0.603/0.766	0.596/0.616	–	–	–				
Paldau 10	0.845/0.852	0.787	0.616/0.612	–	–	–				
Waidhofen 10	0.807/0.803	0.6845/0.73	0.716	–	–	–				
Burgenland 25	–	–	–	0.876	0.616/0.760	0.643/0.673				
Paldau 25	–	–	–	0.846/0.835	0.790	0.605/0.588				
Waidhofen 25	–	–	–	0.791/0.805	0.603/0.723	0.726				
RBSF 25	–	–	–	0.765/0.769	0.699/0.681	0.554/0.548				

Code availability. The scripts of strategies used in our paper are available at <https://doi.org/10.5281/zenodo.7376782> (Wang, 2022).

Data availability. Austrian study areas: landslide inventories for Paldau and Waidhofen are available in Knevels et al. (2021) (<https://www.mdpi.com/article/10.3390/land10090954/s1>, last access: 2 December 2022) and in Knevels et al. (2019) for Burgenland (<https://www.mdpi.com/2220-9964/8/12/551/s1>, last access: 2 December 2022). Lidar-based HRDTM of Burgenland, Paldau, and Waidhofen can be requested from the GIS Department of the Styrian Government, the Government of Burgenland, and the Provincial Government of Lower Austria, respectively.

Italian study areas: landslide inventories of the Emilia-Romagna region can be downloaded at <https://ambiente.regione.emilia-romagna.it/it/geologia/cartografia/webgis-banchedati/cartografia-dissesto-idrogeologico#consulta-dati-shp> (Regione Emilia-Romagna public administration, 2022). The DEM for the Emilia-Romagna region is available at <https://www.eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-eu-dem> (European Union, 2022).

Ecuadorian study areas: landslide data for the RBSF area are available as part of the open-source “sperrorest” package in R (<https://cran.r-project.org/package=sperrorest> (Muenchow, 2022), dataset “ecuador”), and the Ecuador highway landslide data are available from Alexander Brenning upon request. The DEMs used can be requested from the DFG Research Unit FOR 816 (Jörg Bendix, University of Marburg, Germany).

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Chapter 5

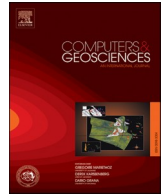
Unsupervised active–transfer learning for automated landslide mapping

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Unsupervised active–transfer learning for automated landslide mapping[☆]

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ABSTRACT

Detailed landslide inventories are required for multiple purposes including disaster damage assessments, susceptibility mapping for spatial planning, and disaster risk reduction. Active learning is an artificial intelligence strategy that can achieve good performances in landslide mapping by training a machine-learning model with a reduced number of landslide/non-landslide observations, which can save time and effort in labeling training instances. Nevertheless, active-learning models are unstable at the beginning of sample selection due to the limited initial knowledge of landslide distribution. Transfer learning can help make the learner robust by transferring a landslide model trained on an existing landslide inventory from a different, but geographically similar source area, to the unseen target area. In order to adjust a transferred machine-learning model to the possibly unique environmental characteristics of the unseen area, we proposed a new framework called Unsupervised Active-Transfer Learning (UATL). This framework used a weight function to combine the landslide model transferred from the source area, with a model trained on a small, but increasing number of landslide/non-landslide observations from the target area to efficiently build a more robust learner. We examined two methods, adaptive UATL and regular UATL, which differed in the way they assign weights to the combined learners. We evaluated our proposed new methods by comparing them with three benchmark methods (active learning only, model transfer only, and the model trained in the unseen area itself) by means of the partial area under the receiver operating characteristic (ROC) curve (AUROC) as the evaluation criterion. The results showed that the new methods, and especially adaptive UATL, can achieve good predictive performances. With only about 235 training instances from the target area, the partial AUROC obtained from adaptive UATL was only 2% lower than that obtained from the model trained in the target area itself, and consistently outperformed the other two benchmarks. Overall, we suggest that the framework proposed can be applied to the natural hazards management workflow for assisting in emergency response, especially in data-scarce regions (e.g., mountainous areas and developing countries).

1. Introduction

Landslides driven by climatic, tectonic, and/or land-use processes threaten people's lives, physical assets, and livelihoods (Bennett et al., 2016; Petley, 2012). From 2004 to 2016, an estimated 56,000 people were killed by landslide events (Froude and Petley, 2018). Landslide mapping, the identification of the occurrence and extent of landslides, is a prerequisite for modelling and mapping the susceptibility and causes of landslides in order to ultimately aid land managers in making decisions aimed at minimizing losses.

Given the development of remote-sensing technology and the increased openness of data, more and more data are available to help construct training data that allows to build machine-learning models for

identifying landslides in an unseen, new area (target area), where landslides have not previously been mapped systematically. For example, high-resolution optical satellite constellations provide imagery for pre- and post-event landslide assessments (Amatya et al., 2019; Lu et al., 2022). In terms of digital elevation models (DEMs), in addition to the free, nearly global DEM available from the Shuttle Radar Topography Mission (SRTM), some national mapping agencies have released higher-resolution DEMs more recently, which may help to identify landslide-prone slopes. Furthermore, existing landslide inventories from source areas with similar geographical characteristics can be reused to build a landslide model for the target area (Wang et al., 2022).

Nevertheless, previous research has established that the size and quality of the landslide inventory available for model training affect the

[☆] Programming language: R.

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performance and possible bias of landslide susceptibility models (Gaidzik and Ramirez-Herrera, 2021; Hong et al., 2019; Steger et al., 2017). Meanwhile, labeling and constructing the landslide inventories for training the machine-learning model is one of the most challenging aspects in landslide assessments (Lin et al., 2021). Active learning (AL) is a promising artificial-intelligence strategy to obtain good predictive performances by selecting a small number of “informative” landslide/non-landslide observations based on posterior probabilities derived from the active learner (Wang and Brenning, 2021). It can not only reduce the burden of manually labeling samples but also reduce the challenge of dealing with imbalanced datasets. However, although recent landslide-related studies have emphasized the importance of the quality of training data, the relevance of the initial training data is often ignored (i.e., random selection) in AL applications (Tuia et al., 2011; Stumpf et al., 2014; Pradhan et al., 2022). Thus, how to select the most “informative” initial training instances and reduce manual efforts is an important problem that needs to be addressed in order to optimize the contribution of the “human in the loop” to the landslide mapping task. Moreover, due to the instability of models trained on a small sample (Varoquaux, 2018; Vabalas et al., 2019), AL models that only use data from the target area may perform poorly when using small amounts of labeled data (Wang and Brenning, 2021).

Model transfer can transfer the existing knowledge from a source area to the target area, thus allowing it to become a component of the AL model, helping it to achieve good predictive performances and reduce the manual labeling effort. Yet, it is hard to decide which fitted landslide model should be transferred. Wang et al. (2022) demonstrated that by selecting a source area with similar environmental characteristics as the target area using case-based reasoning (CBR), the landslide model trained in a suitable source area can achieve a good predictive performance in the target area. The advantage of this method is that it exploits existing landslide inventories by comparing meta-information; it therefore reduces the time and effort required to process and analyze these inventories. Only using the transferred model may not be suitable enough for predicting in the target area because the available predictor sets may differ between source and target areas. When this is the case, valuable additional features available in the target area for improving predictive performance, such as land use (Brenning et al., 2015; Knevels et al., 2021) will be ignored. Therefore, combining the transferred landslide model and the landslide model trained locally on a small, but highly “informative” training sample from the target area (AL model) seems very promising; this approach will be explored in this study. In combining these models, the relative information content of the transferred model furthermore decreases as the amount of labeled data from the target area increases. As a consequence, the weight assigned to the transferred model should decrease as active learning progresses.

In this study, we therefore proposed a new framework called unsupervised active-transfer learning (UATL) to train a more robust active-learning model for landslide mapping in the target area by optimally weighting both models. We developed two weighting schemes referred to as adaptive UATL and regular UATL. We compared these methods to each other as well as to the following three benchmark situations: 1) “plain” AL based on a randomly selected initial training set (AL; compare Wang and Brenning (2021)); 2) only using the transferred model (CBR; see Wang et al. (2022)); 3) only using a training set from the target area (target benchmark). As a case study, we considered the situation of mapping co-seismic landslides in one target area in Sulawesi (central Indonesia) using a landslide inventory from earlier post-seismic landslides in Sumatra (western Indonesia) as a source area for UATL.

2. Study area and data

2.1. Study area

For our use case, we chose source and target areas that are located in Indonesia in the same ecozone, but at a substantial distance of more than

2000 km. Landslides in these areas have been investigated in detail by Tanyas et al. (2021a), who created landslide data sets that are suitable and large enough for model training and testing (see Section 2.2).

The source area (Reuleut area) is located in the western Aceh province of Sumatra, and the target area is in the southern Palu province of Sulawesi, both in Indonesia (Fig. 1). The source area belongs to the Barisan Mountains, where earthquakes and heavy rainfall are important landslide-triggering factors. Its elevations range from sea level to 1851 m a.s.l. Primary tropical rainforest, agricultural land, and settlements are the main land cover types in the source area (Margono et al., 2012).

The target area (Palu area) lies in the central part of Sulawesi, central Indonesia. Elevations in this area range from 202 m to 2331 m a.s.l. The target area mainly encompasses primary tropical rainforests, settlements, and agricultural land (Nurdin et al., 2022). Additional information can be found in Tanyas et al. (2021b). The source and target areas both present various metamorphic, sedimentary, and igneous rock types as bedrock (Irfan et al., 2021; Nugraha and Hall, 2022; Tanyas et al., 2021a; Zhang et al., 2018).

Landslides in both study areas occur frequently and may be triggered by seismic activity as well as heavy rainfall or their combined effect. On December 7, 2016, the 6.5 magnitude earthquake that occurred in Reuleut resulted in a large number of casualties, and heavy rainfall in the post-seismic period (starting on December 14, 2016) caused numerous landslides resulting in severe damages. On September 28, 2018, a magnitude 7.5 earthquake 70 km (43 miles) from Palu triggered many landslides, resulting in the destruction of many buildings, the death of hundreds of people, and many others missing.

2.2. Data

To characterize the topography, we used the Indonesian National Digital Elevation Model (DEMNAS), available from the Geospatial Information Agency at an ~8 m resolution. This DEM was created by combining Interferometric Synthetic Aperture Radar (IFSAR) data with TerraSAR-X and ALOS PALSAR (Julzarika, 2019; Rosenqvist et al., 2007; Simons and Rosen, 2007; Werninghaus and Buckreuss, 2009).

High-resolution PlanetScope (PS) optical satellite imagery was available for both areas for the days before and after the earthquake (Planet Team, 2021). Considering cloud cover and acquisition dates of available imagery, PS Visual Basemaps with a resolution of 4.77 m × 4.77 m in the source area and PS Ortho Scene Product with 3 m × 3 m in the target area were selected (Table 1). PS Visual Basemaps have been radiometrically and geometrically corrected and normalized to a MODIS-based monthly surface reflectance target to minimize inter-scene variability and reduce atmospheric effects, orthorectifying based on ground control points and Shuttle Radar Topography Mission (SRTM) DEM (30–90 m posting); PS Ortho Scene Product has been

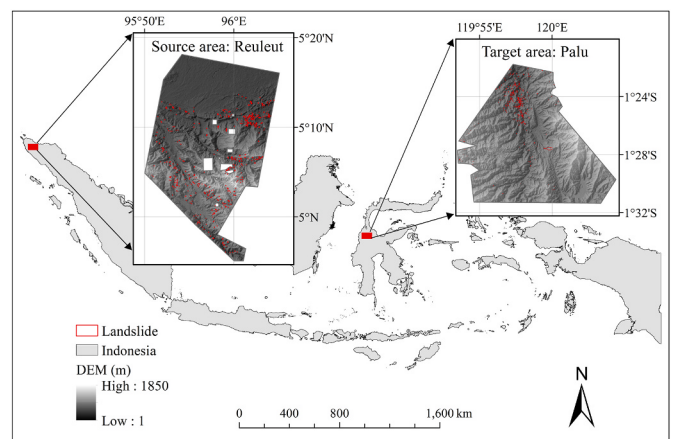


Fig. 1. Location of the study areas in Indonesia.

Table 1
Information on pre- and post-event PlanetScope imagery for the source area (Reuleut) and target area (Palu).

	Source area (Reuleut)	Target area (Palu)
Spatial resolution (m)	4.77	3
Spectral characteristics	band 1: red (590–670 nm) band 2: green (500–590 nm) band 3: blue (455–515 nm)	band 1: blue (455–515 nm) band 2: green (500–590 nm) band 3: red (590–670 nm) band 4: near infrared (780–860 nm)
Pre-image time	2016-Oct-01, -Nov-14, -Dec-15, -Dec-17	2018-Sep-22
Post-image time	2018-Feb-06, -Feb-12	2018-Oct-02

orthorectified, scaled top-of-atmosphere radiance (at the sensor) or surface reflectance image products for analytical and visual applications (Planet Labs, 2020; Planet Team, 2021). SAGA (System for Automated Geoscientific Analysis) (Conrad et al., 2015) was used to remove the cloud-covered areas in the pre- and post-event images and to obtain the overlapping areas of the two images, as well as to resample the imagery to the DEM’s coarser 8 m resolution using cubic convolution.

The landslide inventories, created by Tanyas et al. (2021a), were manually mapped from multi-temporal high-resolution satellite images available in the open-access NASA Landslide Viewer. The landslide inventory of the Reuleut source area consists of post-seismic landslides (from 14-Dec-2016 to 12-Feb-2018), triggered by heavy rainfall, while co-seismic landslides (from 26-Sep-2018 to 2-Oct-2018) related to the 2018 Palu earthquake occurred in the target area. Most details can be found in Tanyas et al. (2021a, 2021b). Based on the results of optical image processing, the full landslide inventories initially included 751 and 332 landslide polygons, including landslide scarp and body. Table 2 summarizes the information of both study areas. Considering a minimum mapping unit (MMU) of four pixels (Garcia-Alvarez et al., 2019; Plank et al., 2016), we only included landslides greater than 256 m² in our analysis. We therefore used data on 507 landslides in the source area and 320 landslides in the target area.

2.3. Predictor variables

Predictor variables for landslide mapping included terrain attributes derived from the DEM to represent predisposing factors, and pre- and post-event vegetation indices derived from the satellite imagery to detect vegetation disturbances. By combining these data sources, we aimed to identify geomorphologically plausible landslide-related vegetation disturbances.

As terrain attributes, we selected elevation, local slope angle, plan and profile curvatures, catchment slope angle, topographic wetness index (TWI), and upslope contributing area, which are common predictors in landslide modelling (Goetz et al., 2015). These predictors act as proxies for destabilizing forces (local and catchment slope), water availability (logarithm of the size of the upslope contributing area,

Table 2
The information on source and target areas.

	Source area (Reuleut)	Target area (Palu)
number of landslides	751	332
number of landslides (MMU)	502	320
landslide type	post-seismic	co-seismic
landslide process	mainly shallow landslides	
size (km ²)	715.1	228.5
mean slope angle (°)	13.2	24.6
elevation (m)	max 1850.3 min 1.3	1728.4 294.2
geological units	metamorphic, sedimentary and igneous rocks	
triggering mechanism	rainfall	earthquake

concave curvatures), and exposure to wind (convex curvatures), as well as for the spatial variation in soil and vegetation characteristics (Muenchow et al., 2012). They were derived from the DEM using SAGA (Conrad et al., 2015) through the R package RSAGA (Brenning, 2008).

Several vegetation indices that can be derived from multispectral optical satellite imagery are available as proxies for vegetation structure and photosynthetic activity and are therefore suitable for identifying disturbances caused by landslides in densely vegetated areas. The normalized difference vegetation index (NDVI) has been used previously in landslide assessments (Shahabi et al., 2021). We calculated pre- and post-event NDVIs from the near-infrared (NIR) and red (R) spectral bands using the following general definition of NDVI:

$$NDVI = (NIR - R) / (NIR + R) \tag{1}$$

We assessed vegetation change using the NDVI difference between pre- and post-event imagery, and also included pre-event NDVI in the models in order to characterize general pre-event vegetation patterns. However, in our study, the NDVI was only available for the Palu area, and as a consequence, training data from the target area is required to exploit this additional information that is unavailable in the transfer-learning source area.

Similarly, the green (GCC) and red (RCC) chromatic coordinates are meaningful for distinguishing the forest and landslides in the visible part of the spectrum (Gillespie et al., 1987; Larrinaga and Brotons, 2019; Sonntag et al., 2012; Wang and Brenning, 2021). Pre- and post-event GCCs and their difference were calculated based on this general definition of GCC,

$$GCC = G / (G + B + R) \tag{2}$$

where R, G, and B represent red, green and blue bands, respectively. GCC and RCC variables are available in source and target areas, but were only used as predictors in the source area since the NDVI was unavailable there.

Overall, 11 predictor variables were used for landslide classification modelling in the source area, and 9 in the target area (see Table 3).

Table 3
Predictor variables used for landslide mapping. NDVI variables were only available in the target area (Palu), and GCC/RCC variables were only used in the source area (Reuleut).

Predictor variable	Landslide median (IQR)		Non-landslide median (IQR)	
	source area	target area	source area	target area
slope angle (°, slope)	17 (12)	37 (17)	12 (17)	25 (15)
plan curvature (10 ⁻³ m ⁻¹ , plancurv)	0.32 (11.49)	-0.27 (17.44)	0.43 (17.21)	0.67 (23.34)
profile curvature (10 ⁻³ m ⁻¹ , profcurv)	-0.14 (2.78)	-0.14 (6.44)	-0.04 (2.69)	0.12 (6.76)
upslope contributing area (log ₁₀ m ² , log.carea)	3.0 (0.6)	2.9 (0.6)	2.9 (0.7)	2.8 (0.7)
elevation (m, dem)	454.2 (571.5)	581.2 (230.7)	328.4 (590.6)	899.4 (309.8)
TWI	8.3 (1.7)	7.2 (1.6)	9.1 (6.4)	7.5 (2.3)
catchment slope angle (°, cslope)	16.4 (9.2)	31.7 (10.3)	12.4 (15.3)	23.5 (10.7)
pre-event NDVI (preNDVI)	-	0.87 (0.03)	-	0.88 (0.04)
pre-event GCC (preGCC)	0.49 (0.05)	0.48 (0.04)	0.49 (0.07)	0.50 (0.05)
pre-event RCC (preRCC)	0.26 (0.03)	0.28 (0.04)	0.27 (0.04)	0.28 (0.04)
GCC difference (diffGCC)	-0.09 (0.07)	-0.09 (0.04)	-0.035 (0.057)	0.018 (0.04)
RCC difference (diffRCC)	0.10 (0.05)	0.11 (0.04)	0.057 (0.040)	0.008 (0.038)
NDVI difference (diffNDVI)	-	-0.31 (0.10)	-	0.01 (0.03)

3. Methods

Since the segmentation procedures used in object-based approaches are usually quite complex and limited in terms of transferability across regions and sensors (Knevels et al., 2019), a pixel-based experiment was conducted in this work. In the proposed UATL framework for landslide mapping, the general approach is to enhance the stability of the active-learning model by optimally combining it with a model transferred from another area, the source area (Fig. 2). We compared the predictive performance achieved with this approach to “plain” active learning and “plain” transfer learning strategies, which are outlined in detail in Sections 3.1 and 3.2, respectively.

In the proposed UATL strategy, a small number of “informative” initial training landslide/non-landslide points were selected and labeled based on information obtained from a combination of the trained, transferred landslide model (CBR model), and the active-learning strategy applied in the target area. During the selection of “informative” instances from the target area in each epoch of the active-learning phase, the weighting part combined the CBR model f_2 and the AL model f_1 by choosing weights to obtain the combined UATL model f for each epoch. Motivated by Brenning (2012), we used k -means clustering algorithm and stratified sampling to compare the partial AUROC values (false positive rate from 0 to 0.1) (pAUROC) of the combined UATL models to obtain the optimal weights. The AUROC, or area under the receiver operating characteristic (ROC) curve, is independent of a specific decision threshold and may range between 0.5 (undifferentiated) and 1.0 (fully differentiated). The pAUROC ingrates the ROC curve only within a restricted domain, which allows us to assess the model’s ability to predict landslide occurrence while correctly classifying most non-landslide sites as stable (Brenning, 2012; Goetz et al., 2015). We considered two optimization strategies: 1) In adaptive UATL, the weighting function’s parameter c was re-estimated in each epoch, allowing it to adapt as the AL sample size increases. 2) In what we referred to as regular UATL, the parameter was kept constant after optimizing it only once in epoch 1. Note that even in regular UATL, the weight of the AL model continues to increase gradually as the sample size increases, but this increase is parameterized only once, at the beginning.

More details for methods used in our study can be found in Section

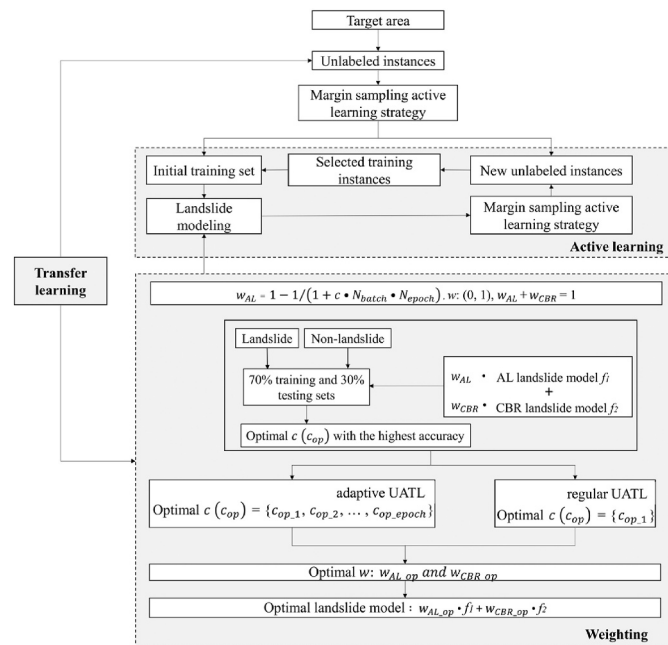


Fig. 2. Flow chart of the proposed unsupervised active-transfer learning workflows for landslide mapping.

3.1 for AL, Section 3.2 for CBR model transfer, and Section 3.3 for the weighting function.

3.1. Active learning

AL is an artificial-intelligence framework designed to use as few labeled instances as possible to obtain a good result (Settles, 2010). In our study, we focused on pool-based AL and adopt the margin sampling (MS) strategy since it has demonstrated its utility in landslide assessments (Wang and Brenning, 2021). In our study, we further addressed challenges associated with the low prevalence of the feature of interest by using a low-prevalence MS (LP-MS) adjustment that reduces the sampling bias caused by the imbalance in the number of landslide and non-landslide observations. Therefore, for labeling new landslide presence/absence points, LP-MS will select the unlabeled candidate points x whose posterior probability of landslide occurrence, $f(\hat{y}_k|x)$, is closest to a specified probability value p :

$$x = \operatorname{argmin}_x (f(\hat{y}_k|x) - p) \quad (3)$$

In a landslide classification context, Knevels et al. (2019) indicated that a predicted probability of at least 0.8 was required to classify landslide entities. Lin et al. (2017) used 0.9 as one of the breakpoints to classify landslide susceptibility based on a global dataset. We therefore chose a value of $p = 0.9$ for obtaining more “informative” instances, but additional research is needed to identify general strategies for adjusting p regionally.

In the whole framework, we selected an additional batch of 25 points in each iteration or epoch after an initial selection of 85 points in the first step. The total number of iterations was limited to 60; this setting aimed to detect possible changes in predictive performance and the expected convergence of results for large sample sizes and therefore abundant training data from the target area.

3.2. Case-based reasoning method

CBR is a well-known transfer-learning method, translating the geographical knowledge on the suitability of source areas for model training into mathematical knowledge to obtain similar regions for training a model (Hammond, 2012; Shi et al., 2009). This strategy can reduce the amount of time required to construct models in digital soil mapping (Liang et al., 2020, 2021) and landslide assessments when choosing the most “similar” source area (Wang et al., 2022). Here we used geological characteristics (presence of igneous, sedimentary, and metamorphic rocks), data characteristics (resolution), and topographic characteristics (total relief, standard deviation, and mean slope) for calculating the similarity between source and target areas (Table 4). The overall similarity is the minimum of all five similarity measures. A “related” area is required to have a similarity value of at least 0.65, which is the setting used by (Wang et al., 2022).

The overall environmental similarity of the two study areas in this study was 0.67, which can be considered sufficient. The similarity of the slope criterion was 0.67, while the remaining scores were greater than 0.9.

3.3. Weighting function

In our study, a weighting function determines the contributions of the AL and CBR models to the overall UATL-based model. Since the AL model will become better adapted to the target area as the sample size grows from epoch to epoch, it seems reasonable to let the AL model’s weight change (i.e., increase) systematically with increasing sample size. In Viering and Loog (2022), the error rate decreases exponentially as the number of training set increases. By analogy, the contribution (i.e., weight) of CBR models should decrease exponentially as the size of the training set increases. Hence, we proposed the following function to

Table 4

Similarity functions for the attributes used in CBR to identify related source areas: Geological characteristics, data characteristics, and topographic characteristics of study area.

Factor group	Attribute	Similarity function	Description
Geological characteristics	Igneous	$Sim = \frac{1}{3} \sum_g I_g$	where $I_g = 1$ if unit g present or absent in the source <i>and</i> the target area, and 0 otherwise.
	Sedimentary Metamorphic		
Data characteristics	Resolution [m]	$Sim = 2^{-(2 log_{10}R_t - log_{10}R_s)^{0.5}}$ or $Sim = 1$	where the similarity is 1 if the resolution of source area is smaller than in the target area, otherwise Sim . R is the DEM resolution.
Topographic characteristics	Total relief [m]	$Sim = 1 - \frac{ Relief_t - Relief_s }{\max(8848 - Relief_t, Relief_s)}$	where $Relief$ is the total relief.
	Standard deviation of slope	$Sim = 2^{-(2 log_{10}Sd_t - log_{10}Sd_s)^{0.5}}$	where Sd is the standard deviation of slope.
	Mean slope [°]	$Sim = 1 - \frac{ Slope_t - Slope_s }{\max(60^\circ - Slope_t, Slope_s)}$	where $Slope$ is the mean slope.

Note: Sim is the similarity of each individual attribute between the target area t and a source area S , which is in $[0,1]$. The following constants were used for normalization: 8848 m is the elevation of Mount Everest. Following Surjandari et al. (2021) and Rusdi et al. (2015), the critical slope angle is set as 60° for calculating similarity of mean slope in Indonesia.

calculate the AL model’s weight value, which is a value between 0 and 1:

$$w_{AL} = 1 - 1 / (1 + c \bullet N_{batch} \bullet N_{epoch}) \tag{4}$$

where N_{batch} is the batch size, and N_{epoch} the number of epochs. The parameter c controls the speed at which the AL model’s weight increases. When c or N_{epoch} is 0, the weight of the landslide model obtained by CBR is 1.

We optimized this weighting function by using the k -means clustering algorithm and stratification across the landslide and non-landslide classes to select the optimal c value. In regular UATL, we optimized c only once, in the first epoch, and used this value throughout the selection of “informative” instances. In adaptive UATL, in contrast, we re-estimated the optimal c in each epoch based on the training data acquired from the target area during the previous epochs.

We tuned c in the 0.005–0.015 range using steps of 0.001. In addition, a weight of 1 was also included as a candidate value as this would effectively switch to the AL model.

3.4. Landslide model training and testing

Generalized additive models (GAMs) were adopted as AL as well as CBR models. It has previously been observed that the logistic GAM can be suitable for landslide assessments in performing a binomial classification of landslide/non-landslide observations as it allows for nonlinear relationships between the features and the response while maintaining interpretability (Bordoni et al., 2020; Goetz et al., 2011; Petschko et al., 2016). The R package *mgcv* (Wood, 2017) was used for GAM implementation. We limited the degrees of freedom of the spline smoothers to six to avoid overfitting.

As a result of the wider spectral range of imagery available for the target area, we were able to include NDVI in the AL model as an additional predictor although it was not included in the CBR model. Because datasets at this resolution are difficult to split landslide scarp and body (Dou et al., 2020), landslide points were randomly sampled from the entire landslide polygon in our study, and non-landslide points from the remaining area.

In adaptive UATL, we employed k -means clustering to divide the labeled non-landslide and landslide points from the previous epoch into 10 folds and then built training (70%) and validation (30%) datasets from the clusters. Stratification was used to ensure that landslide as well as non-landslide instances were present in both sets even in early epochs, when the sample size was still small. We repeated the process 50 times to reduce random variability in the calibration process. It should be noted that since we did not have information about the target area at

the beginning, it is possible that the training set does not have landslide points from the target area in the early epochs. In this situation, we set c value to 0 to ensure that the CBR model always gets the highest weight value in our parameter settings. In this situation, the optimal c value for regular UATL was the c value obtained when the AL model was first involved in creating the combined UATL model.

For assessing the predictive performance of a soft classifier, ROC was adopted (Brenning, 2008; Goetz et al., 2011). According to Brenning (2012) and Goetz et al. (2015), the pAUROC should be applied to measure the model’s ability to detect high-risk areas for hazard mitigation. Therefore, for the overall validation, we used the “known” landslide inventory of the target area and calculated the pAUROC.

4. Results

4.1. Predictive performance of adaptive UATL and regular UATL

Compared to AL and CBR benchmarks, adaptive UATL consistently obtained the highest pAUROCs since the initial period of “informative” instance selection (Fig. 3). As the sample size increased, adaptive UATL gradually approached the performance of the target benchmark (pAUROC: 0.096), while the regular UATL approach remained between the CBR and the target benchmark even for very large sample sizes.

Both proposed frameworks clearly outperformed the AL benchmark. Although pAUROCs obtained by AL increased due to the increase in “informative” landslide/non-landslide observations, AL obtained the

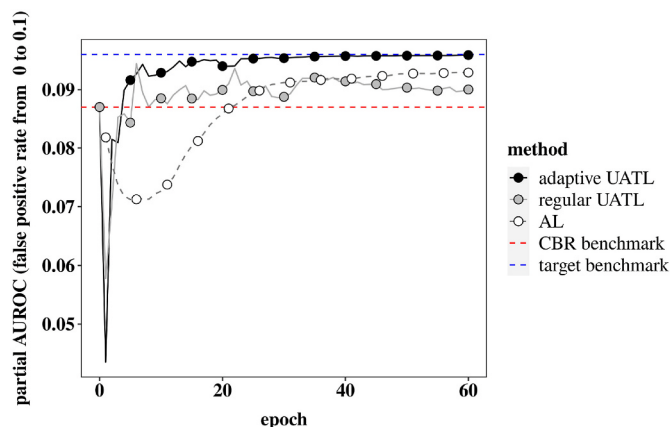


Fig. 3. Partial AUROCs for the proposed UATL strategies and the benchmark methods.

same predictive accuracy (pAUROC: 0.087) as the plain CBR benchmark only after 40 epochs, i.e., 1060 landslide/non-landslide observations from the target area. Moreover, pAUROCs obtained by adaptive UATL were always higher than the ones obtained by AL while the predictive performance of regular UATL was better than that of AL before epoch 45 (i.e., less than 1185 training landslide/non-landslide observations).

The regular UATL achieved a good predictive performance, but its increase was not obvious compared to the CBR benchmark. (Fig. 3). From epochs 0 to 5, the pAUROCs obtained by regular UATL were lower than the ones obtained by CBR. For larger sample sizes, pAUROCs were fairly constant and always slightly higher than the CBR benchmark. The performance of adaptive UATL displayed the same trend. Yet, the difference was that adaptive UATL performance was higher and more stable (Fig. 3). After epoch 4, pAUROCs of adaptive UATL increased by over 8% relative to the CBR benchmark, and the gap between pAUROCs obtained from adaptive UATL and the target benchmark gradually vanished. At the same time, adaptive UATL had a stable predictive performance throughout the AL process. In conclusion, adaptive UATL always exhibited more robust and better performances than regular UATL. With only 235 landslide/non-landslide observations from the target area in epoch 7, adaptive UATL can obtain a pAUROC of 0.094.

4.2. Weight distribution of adaptive UATL

As the optimal weight was always below 1 (with one outlier as an exception), the CBR model was always involved in the process of landslide mapping as well as sample selection for AL (Fig. 4(a)). This showed that the CBR model continued to contribute useful information even for larger AL sample sizes, as it would otherwise have been weighted down to 0. The contribution of the CBR model to the optimal UATL model changed more strongly during the first four epochs. The weights stabilized gradually after about seven epochs.

When comparing the adaptive UATL strategy to various fixed c values, we found that after epoch 4, the predictive performance of adaptive UATL always ranked in the center to the top of the predictive performances (Fig. 4(b)). Here, it is important to understand that for different c values, the entire AL sampling sequence takes a different path, i.e., the individual data points shown in Fig. 4(b) for a given epoch actually represented different samples, not just different weights for the same sample.

4.3. Variable importance of adaptive UATL

Vegetation indices – especially the difference features – were the most important predictors in adaptive UATL and the CBR benchmark based on a permutation-based variable importance assessment (Fig. 5). Slope angle, catchment slope angle, and plan curvature played an important role in the adaptive UATL model. But in the CBR benchmark, the two curvature variables had no substantial influence on model performance, and TWI was followed by catchment slope angle. Overall, predictors that are commonly used in landslide modelling helped to improve the performance of models for landslide assessment studies.

4.4. Landslide maps obtained with adaptive UATL

The landslide map generated by adaptive UATL distinguished landslide and non-landslide locations clearly, even with a relatively small number of training points (e.g., 185 training points after 5 epochs) (Fig. 6). Compared to the CBR benchmark (Fig. 6(b)), adaptive UATL successfully managed to change zones that were incorrectly classified as having high or very high probabilities of landslide occurrence to medium or low values from epoch 7. Moreover, as the number of “informative” training instances from the target area increased, the contrast between predicted landslide and non-landslide areas increased as well, and the map became more similar to the landslide map produced by the target benchmark. Highly likely landslide locations were mainly concentrated in the northern and southern regions, which was also where most of the over-prediction of landslides took place.

In addition, we showed the areas that are most likely to be landslides in the landslide map that was obtained with adaptive UATL using only 235 landslide and non-landslide points (Fig. 7). Almost all landslides were covered by areas categorized as being very likely to present a landslide, which was consistent with the numerical performance indicators obtained above (Fig. 3).

5. Discussion

5.1. Potential of the proposed UATL framework

The proposed artificial-intelligence framework for constructing a robust active-learning model was shown to produce more accurate landslide predictions than the two benchmarks — AL model only and model transfer only—, and to achieve a similar performance as the target benchmark. In particular, adaptive UATL, which finds an optimal model weight in each epoch, outperformed the other approaches. This can be interpreted as adaptive UATL finding the optimal weight value for each epoch to obtain more “informative” training points, thereby making more effective use of the labeling efforts of the “human in the loop” (Fig. 4(b)). The proposed weighting function is consistent with the general expectation that the contribution (i.e., weight) of the transferred model should decrease as the size of the training set from the target area increases. However, the CBR model was still an indispensable component of the optimally weighted model combination as it continued to contribute about 20% even after many epochs (Fig. 4(a)).

Our proposed low-prevalence MS active-learning strategy appeared to be more effective at extracting “informative” data thereby helping the new framework to obtain good predictive accuracies. The decision boundary to determine whether the data is “informative” or not is set differently depending on the distribution of the data (Locatelli et al., 2018; Settles, 2010). Therefore, the method is also applicable for other geoscientific and remote-sensing applications, especially for situations with imbalanced datasets, and can serve as a reference for those who will use AL for future research.

Our results further confirmed that CBR is a useful transfer-learning method in landslide assessments, which is consistent with Wang et al.

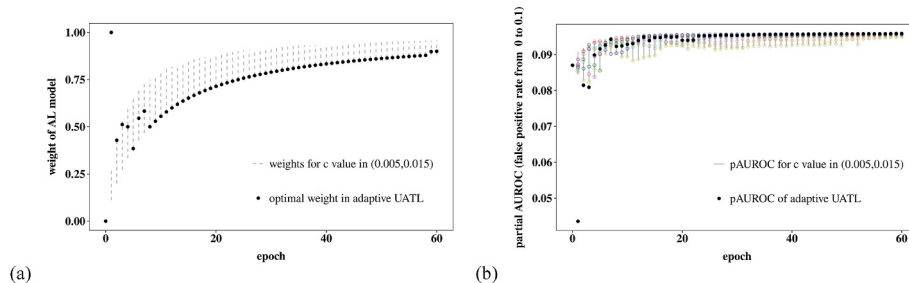


Fig. 4. (a) Optimal weights assigned to the AL model in each epoch using the adaptive UATL strategy; (b) the corresponding partial AUROCs (for false positive rates from 0 to 0.1) for adaptive UATL. The plots show, for comparison, the results obtained for the full range of c values considered, i.e., 0.005–0.015.

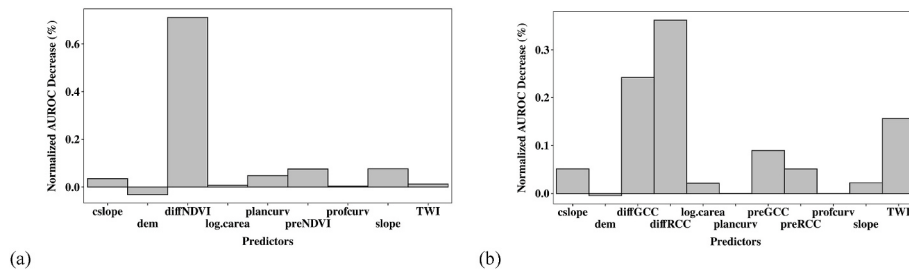


Fig. 5. Variable importance plot for (a) adaptive UATL in epoch 7 with 235 landslide/non-landslide points from the target area and (b) the CBR benchmark.

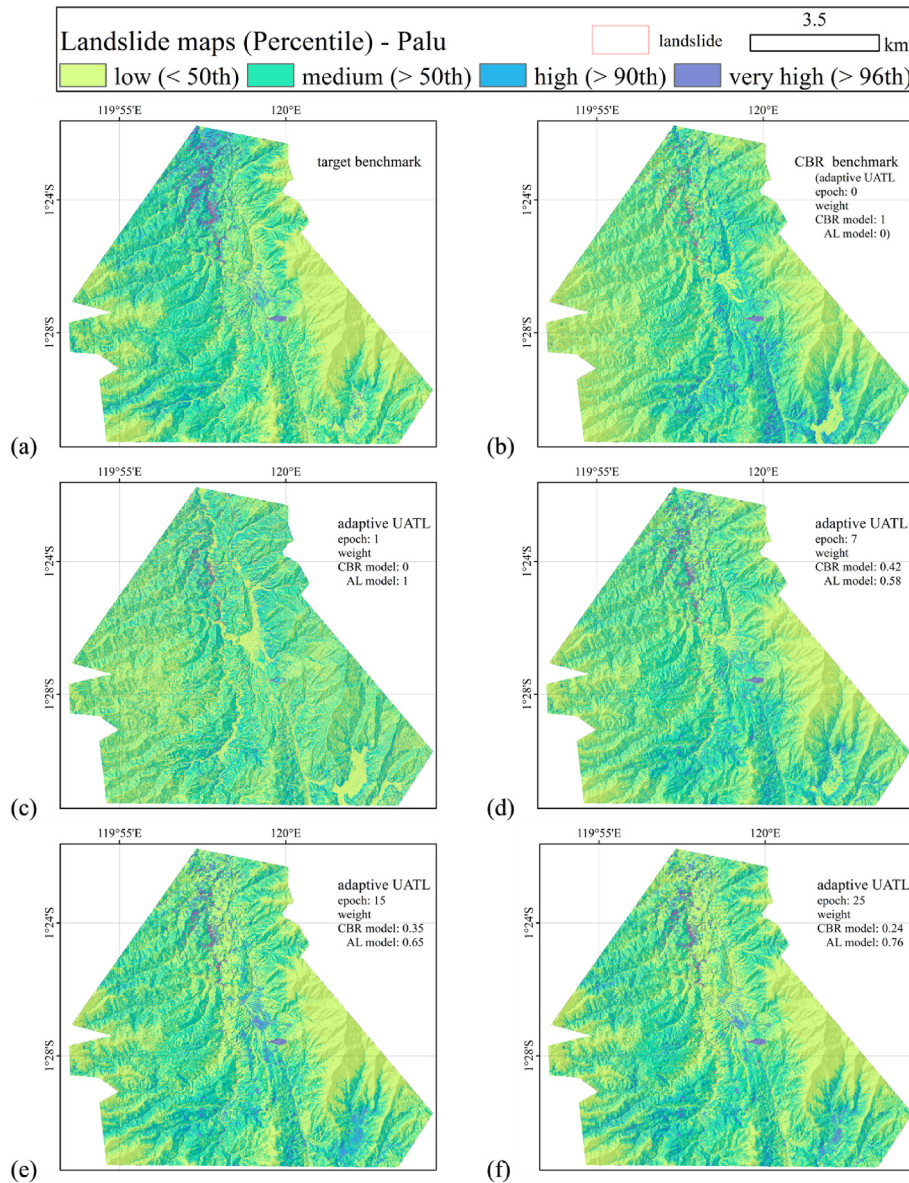


Fig. 6. Landslide maps of adaptive UATL based on different numbers of training instances (85, 235, 435, 685 training points in epoch 1, 7, 15, 25), CBR and target benchmarks. Predicted probabilities are classified into four classes (very high, high, medium, and low) using the 96th, 90th, and 50th percentile as class boundaries.

(2022). Knevels et al. (2021) pointed out that a direct model transfer between regions can cause implausible effects when some important environmental characteristics are not comparable. CBR transfer learning can avoid this situation by taking into account the degree of similarity. In addition, Yates et al. (2018) have pointed out that direct model transfer cannot respond to new conditions and have encouraged the

adaptation of transferred models for situations where new conditions arise. The framework proposed in this paper was able to solve this problem. It furthermore leveraged predictor variables (here: NDVI) that were unavailable in the CBR source area, but available and potentially beneficial in the target area.

Although there is a growing body of literature addressing data

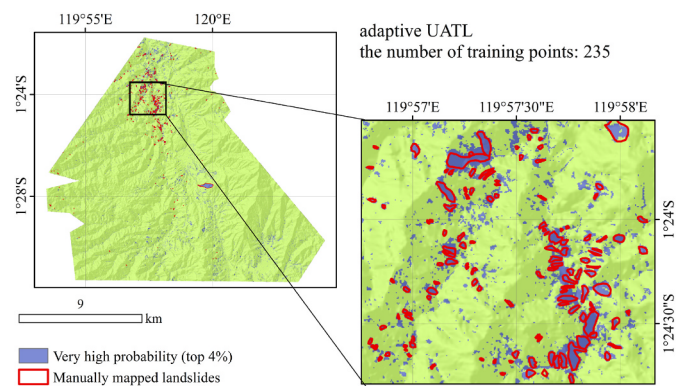


Fig. 7. Landslide map showing only predictions in the “very high” category as mapped landslides. The map is based on adaptive UATL with 235 training points.

scarcity in geoscientific and remote-sensing applications by using active and transfer learning, such as digital terrain analysis (Qin et al., 2016), remote-sensing image classification (Stumpf et al., 2014), and hydrological studies (Ma et al., 2021), the combination of active and transfer learning is still in its infancy in these fields. Meanwhile, our proposed new framework has the potential to improve machine-learning model performance in these fields by using unique information from the target area and considering the low prevalence of features of interest.

Furthermore, in future practical applications, by providing a semi-automated, “human-in-the-loop” pipeline from open geospatial raw data (e.g., Sentinel-2, SRTM DEMs) to information products, this framework demonstrates the potential for advancing research data management workflows to facilitate natural hazards research and reduce disaster-related risks. Moreover, by integrating and sharing data on natural hazards (e.g., landslides), researchers can more reliably identify precise triggering conditions of the rare event (e.g., critical rainfall thresholds of landslides).

5.2. The function of knowledge from source and target areas

The proposed framework not only enabled simple reuse of existing landslide inventories but also allowed flexible use of additional knowledge acquired in the target area. The results obtained with the proposed active-transfer learning strategy supported the expectation that prior knowledge in the form of pre-trained models can facilitate the achievement of better predictive performance, which is consistent with Pradhan et al. (2021) and Chen et al. (2022). Fig. 3(a) indicated that the methods (CBR model, adaptive and regular UATL) that took into account “related” prior knowledge can gain better predictive results than the method (AL benchmark) that does not. This may also lead to more “informative” points selected from the target area, allowing the AL model to learn well the landslide/non-landslide information of the target area and thus achieve stable and accurate predictive performances.

In addition, the knowledge of the target area cannot be ignored in landslide assessments. For example, Mboga et al. (2021) found that unsupervised landslide classification performance can be improved by using labeled instances from the target area. Fang et al. (2021) showed that considering pre- and post-landslide conditions in the target area can achieve better landslide predictive performances. In our study, we also found this phenomenon: after considering the target area knowledge, that is adding the AL model, there was a significant increase in the predictive performance obtained throughout the sample selection phase (Fig. 3). In addition, despite the similar environmental characteristics in the source and target areas, a model trained in the “suitable” source area still differs from a model trained on data from the target area, for example through the dependence on the predictors used (Fig. 5). This is

the reason why knowledge from the target area needs to be taken into account, and possibly the reason for the improved performance with the inclusion of knowledge from the target area.

The above findings can also be observed in other fields, such as flood susceptibility mapping (Zhao et al., 2021), soil moisture prediction (Li et al., 2021), and remote-sensing image classification (Li et al., 2017). We suggest that semi-supervised approaches to landslide mapping can be of great benefit to landslide science and disaster risk management alike as they allow gathering critical information more efficiently, which also provides a reference for other fields.

5.3. Limitations and outlook

In this paper, the proposed framework showed good performance in mapping landslides (i.e., binary classification), but its performance in multi-class classification still needs to be further explored, e.g., the classification of landslide type (Amato et al., 2021). Meanwhile, other fields of environmental science also require multi-class classification, such as land cover classification (Talukdar et al., 2020). Therefore, it is necessary to explore the validity of the proposed algorithm in multi-class classification to validate its wide applicability.

In addition, the GAM, which is a widely used, state-of-the-art landslide modelling technique, was adopted and supported the effectiveness of the proposed framework. However, other innovative techniques have shown their effectiveness in landslide assessment in recent years, such as deep learning (Azarafza et al., 2021; Nikoobakht et al., 2022). Hence, future research should determine the potential of the proposed approach using deep learning models that are pre-trained in different areas.

The main limitation of this combined framework is that possible applications are especially in fields where human experts are capable of labeling additional instances interactively through image interpretation, as is the case in land use/land cover mapping with its numerous facets. Nevertheless, modelling tasks in which the labeling of additional instances would require field sampling or laboratory analyses are less suitable for machine-learning approaches with an active-learning component. In this case, we therefore suggest that the CBR transfer-learning method might be a better option to address the data scarcity problem.

6. Conclusion

We proposed a combined unsupervised active-transfer learning framework (UATL) for landslide mapping, which achieved better predictive performances than active learning and case-based transfer learning alone. By fully taking advantage of the existing, older landslide inventory from a geographically distant, but similar source area, a small number of “informative” data points from the target area were sufficient for achieving excellent predictive performances with a little help from the “human in the loop”. This can be highly instrumental in rapid landslide mapping after a regional triggering event occurred, and it allows researchers to generate much-needed event-based landslide inventories with limited human labeling. Future research is needed to establish the utility of this framework in different application settings (e.g., land cover classification) and with different machine-learning models (e.g., deep learning).

Computer code availability

Name of the code/library: uatlslide.

Contact: Zhihao Wang (zhihao.wang@uni-jena.de) and Alexander Brenning (alexander.brenning@uni-jena.de).

Hardware required: No requirements.

The source codes are available for downloading at the link <https://github.com/W-Zhihao/uatlslide.git>.

Authorship contribution statement

ZW and AB contributed to conception and design of the study. ZW carried out the implementation, performed all analyses, and took the lead in writing the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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

The landslide inventory used in this paper can be found in Tanyas et al. (2021a). The DEM data can be found online at <https://tanahair.indonesia.go.id/demnas/#/>.

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Discussion

The goal of this dissertation is to enhance the understanding of active and transfer learning methods in landslide assessment studies (i.e., landslide susceptibility and detection assessments), thereby improving the efficiency of landslide susceptibility and detection modeling. To achieve this goal, this thesis focuses on assessing the potential of active and transfer learning methods in achieving rapid landslide assessment and developing more sophisticated methods based on both. In this section, the importance of this work in relation to the research questions outlined in *Section 1.2* is discussed. In addition, the relevance of the methods, results, and findings in this thesis to fields beyond landslide assessment studies is discussed.

6.1 Definition and retrieval of "useful" information

The foundation of any AI-based approach is high-quality training data (Kuglitsch et al., 2022b). A growing body of literature has emphasized that the quality of the training data can reduce the dependence on the quantity of the training data (Dhakal et al., 2000; Kalantar et al., 2018; Gaidzik and Ramirez-Herrera, 2021). This can also be found in other fields such as geomorphological modeling (Hjort and Marmion, 2008) and ecological modeling (Coro et al., 2015). Therefore, the quality of the training data ought to receive considerable attention in any field, e.g., landslide studies and image classification. Furthermore, automated/semi-automated technologies today still rely on large datasets to get automated responses (Faraj et al., 2018). The volume and complexity of new data require manual judgment to assure high-quality input data for automated algorithms (Gronsund and Aanestad, 2020). To reduce the costs of preparing the training data and to get high-quality training data, this thesis compares and evaluates different ideas for constructing the training data, depending on whether the data comes from a target area or historical landslide inventories.

6.1.1 "Useful" information from a target area

For a constant dataset size, the performance of a model grows as the information diversity of the training data grows. Previous studies have pointed out that intraclass diversity in the training data can improve the predictive performance of a model (Shi et al., 2020; Madan et al., 2022). For example, in remote-sensing image classification, churches of the same religion (e.g., Christianity) appear in different architectural styles; in landslide studies, the source and body of a landslide have different characteristics. In addition, the training data should also contain enough information about all classes (Cheng et al., 2020; Madan et al., 2022). For example, in land use/cover classification using remote sensing images, each land cover type should be

sampled in sufficient quantity (MohanRajan et al., 2020). Therefore, establishing the amount of information in the training data, i.e., finding and adding information not contained in the training data, can reduce redundant information (less cost) and ensure a good model performance (high accuracy) (Tong, 2001; Kumar and Gupta, 2020; Berger et al., 2021).

Instances that are not covered by the information in the training data have high uncertainties in model predictions (Settles, 2010; Maddox et al., 2019). Also, a model shows high uncertainty for the class with an extremely small amount of data in the entire dataset (Khan et al., 2019). In this way, by sampling and labeling data with high uncertainties in model predictions, both intraclass diversity and a relatively balanced amount of information between classes are likely to be guaranteed. That is, by sequentially sampling and labeling based on the uncertainties in model predictions, it is possible to reduce redundant information inclusion and thus obtain a small amount of training data with sufficient information on all classes.

When a sufficiently large dataset is available, the information in the training data can be guaranteed by using a common sampling strategy (e.g., RS) to select a large training sample (Manku et al., 1999; Salloum et al., 2019; Mahmud et al., 2023). However, when extreme events (e.g., avalanches, earthquakes, and landslides) occur, the availability of data is limited (Kuglitsch et al., 2022a). The passive learning strategy is not an effective and efficient way to build “useful” training data, because it requires extensive time and effort as well as corresponding expert knowledge to search through a region for obtaining adequate information on extreme events (Žliobaitė et al., 2013; also see *Section 2.2.2*). In addition, Tharwat et al., (2023) have pointed out that the training data obtained by the passive learning strategy has a low chance of covering information about the entire area, which in turn affects predictive results.

An appropriate sampling strategy amplifies the possibility of obtaining “useful” training data and thus reduces the manual effort. Unlike the passive learning strategy, the AL strategy can identify and actively select high-uncertainty instances as well as deliver them to annotators for judging and labeling. Whether or not data availability is limited, the AL framework is more likely to achieve high-accuracy predictions and save time and effort in obtaining the training data with relatively balanced classes, which is also confirmed in this thesis and other studies (Chapter 3 and 5; Tuia et al., 2009; 2011; Stumpf et al., 2013). Furthermore, as presented in this thesis and other studies, the AL framework has more potential to cover spatial information of the entire region (Chapter 3 and 5; Tharwat et al., 2023).

6.1.2 "Suitable" existing information for the target area

Common data deficiencies, accelerating global change, and limited research funding have made model construction difficult in numerous scientific disciplines, including landslide studies

(Clark et al., 2001; Sequeira et al., 2018; Wang et al., 2022). The existing datasets can help solve this problem (Li et al., 2017; Hao et al., 2020; Mizdos et al., 2021). For example, an important resource for landslide studies is historical landslide inventories, which can provide detailed information about past landslides in an area, including the locations, types, and characteristics of landslides (Petschko et al., 2013). However, transferring the information from existing datasets to a target area must consider homogeneity and non-transferability (Yates et al., 2018).

Not all prior information is suitable for a direct transfer to a target area (Gong et al., 2017). Hence, determining how the source and target areas are “related/similar” is the key to achieving information transfer (Pan & Yang, 2010; Gong et al., 2017). Numerous studies have shown that when the characteristics of source (“related” source area) and target areas are identical or at least similar, a model trained by the data in this source area performs well on a target area, that is, the performance of a model on a target area is positively correlated with similarities between source and target areas (Blitzer et al., 2007; Gopalan et al., 2011; Blitzer et al., 2011; Chen et al., 2011; Qin et al., 2016; Liang et al., 2020a; Yates et al., 2018).

The idea for selecting “related” source areas is specific with respect to the study task (e.g., image classification and species distribution mapping) (Gong et al., 2017; Yates et al., 2018; Hoffmann et al., 2021). For example, only considering the similarity of data distributions in source and target areas can achieve much higher predictive accuracy in cat and dog image classification than that obtained without transfer learning (Tammina, 2019). However, as found in this thesis, under the prerequisite of being able to do further plausible model interpretation, the predictive accuracy was not improved in landslide susceptibility assessment when only considering data distributions (Chapter 4).

Comparing the environmental characteristics and data resolution of source and target areas allows the selection of “related” source areas to improve the predictive performances of models in natural hazard and ecological studies (Watson, 1998; Soininen and Luoto, 2014; Wang et al., 2022). Yates et al. (2018) have indicated that transferring models to non-analogous environments can pose many well-documented dangers. For example, Knevels et al. (2021) have shown that the predictive accuracy was poor when directly transferring information from one study area with steep topography to another study area with more gentle topography. Meanwhile, transferring models between data with different resolutions affects the effectiveness of information transfer (Barbosa et al., 2011; Yates et al., 2018). For example, in ecology, low-resolution data can observe relationships between species and biogeography but may not capture important aspects of species ecology, thereby causing the predictive bias by

transferring the information in data with low resolution to that in data with high resolution (Scales et al., 2017); in landslide studies, landslide detection and susceptibility accuracy can be influenced by the spatial resolution of digital elevation models (DEMs) (Grohmann, 2015; Brock et al., 2020). Therefore, the predictive performance of a source area in a target area may be positively correlated with the similarities of environment characteristics and data resolution between source and target areas in landslide studies. As shown in this thesis and other studies (Chapter 4; Qin et al., 2016), “suitable” information can be extracted from the source area with the highest overall similarity to the target area in terms of environmental characteristics and data resolution. Meanwhile, the model trained with the "suitable" information obtains a comparable result to that obtained by the model trained using data from the target area itself in this thesis.

If the goal of a study is to reveal the drivers of an event or to transfer a model to a new area, a rigorous selection of similarity factors related to the event is necessary (Liang et al., 2020b; Dorodnykh et al., 2022). For example, in species distribution mapping, bioclimatic variables and elevation are the main factors influencing the spatial distribution of species (Fourcade et al., 2018). In landslide studies, climate (especially precipitation), topography, and geological structures are particularly associated with landslide processes (Glade et al., 2005; Knevels et al., 2021; Knevels et al., 2023). However, as pointed out by Liang et al. (2020a), the data availability of similarity factors, as well as the knowledge availability of quantifying similarity factors have to be considered when selecting similarity factors (also see *Section 6.4.2* for more details). In this thesis, due to the lack of detailed information on the time of landslide triggering and the geological structures in study areas, factors related to topography and geology were considered.

6.2 Challenges in using "useful" information in landslide assessment studies

Accounting for the limitations of AL (Chapter 3) and TL (Chapter 4) is essential for improving the predictive performance of a model in landslide assessment studies. In this section, their limitations in landslide assessment studies are discussed, which can also provide useful ideas for other natural hazards, ecology, and remote-sensing image classification studies.

6.2.1 The impact of data bias on AL and TL

The inherent bias in data (e.g., inventory bias and digitization bias) and noise/outliers can affect the predictive performance of a landslide model (Steger et al., 2016). Although it is beyond the scope of this thesis, an overview of the impacts of these biases on AL and TL is introduced.

For TL, all biases in a source area will be transferred, which can lead to incorrect predictive results or even affect model interpretation (e.g., variable importance). For example, a landslide model trained by a source area with inventory bias may incorrectly capture the governing factors of landslides in a target area. Data pre-processing can help reduce the impacts above (Wieland and Pittore, 2014; Phiri et al., 2018; Zou et al., 2020).

Unlike TL, there is no existing labeled data when applying AL in a target area in real-world applications. Hence, sensor errors as well as human errors that are generated during data acquisition and data pre-processing need to be considered when applying AL (Settles and Craven, 2008; Feizizadeh and Blaschke, 2016; Zhong et al., 2020). For example, systematic and random errors in DEMs may affect terrain properties as predictors and confound the expected relationship between predictors and governing factors of landslide occurrence (Wilson and Gallant, 2000); inappropriate use of data pre-processing techniques can result in distribution shifts. These biases are possible to change the characteristics of landslide observations thus making them perform with high uncertainties (“useful” instances) in model predictions. Consequently, the AL model cannot accurately learn information about landslide and non-landslide observations in a target area.

6.2.2 Challenges in the AL framework

The quality of the initial training data is fundamental to the predictive performance of AL. Although current studies (e.g., landslide susceptibility and detection assessments, remote-sensing image classification) have emphasized the importance of "useful" training data, the quality of the initial training data is often ignored (i.e., random selection) in AL applications (Tuia et al., 2011; Stumpf et al., 2013; Pradhan et al., 2022). Meanwhile, in AL, a model cannot be iteratively fine-tuned and tested due to the lack of independent test data. Thus, “useful” initial training data contribute to the quality of the subsequently selected data, which in turn affect the performance of the final model. However, only using the AL framework can be difficult to obtain “useful” initial training data. In this thesis, this challenge was addressed by combining the AL strategy with TL (Chapter 5).

A robust predictive capability allows for obtaining accurate results (*Section 2.1*; Hjort and Marmion, 2008; Parker, 2011). As demonstrated by Vabalas et al. (2019), the stability of a model can be affected by an extremely small amount of training data. As shown in this thesis, at the beginning of data selection in AL, models performed poorly in terms of the standard deviation of predictive accuracies (Chapter 3, Figure 4). In addition, the stability of a model also relies on its learning ability (Goetz et al., 2015; Brock et al., 2020; Merghadi et al., 2020). That is, predictions obtained by a model should not change much across different training data

from the same region. Based on this criterion, models that depend on hyperparameters may not be suitable for AL. In terms of predictive performance, if a model's hyperparameters cannot be tuned reliably, then its performance is highly variable (Schratz et al., 2019; Kovacs et al., 2022). In this way, "useful" data obtained by AL may effectively be less informative than data obtained by random sampling. From the efficiency point of view, the hyperparameter tuning time is based on the complexity of hyperparameters that a model has, meaning that the more complex hyperparameters of a model are, the less efficient it is. The goal of AL is to obtain better predictive results as well as improve efficiency. Consequently, learning algorithms with fewer design decisions and good learning capability should be considered first in AL.

The decision threshold in AL should be set in accordance with the expected data distribution in a target area. In general, for AL strategies based on posterior probabilities, the decision threshold is usually set to 0.5 in the binary classification, i.e., the instance with the class probability closest to 0.5 will be selected (Settles, 2010; Tuia et al., 2011). It is reasonable to identify "useful" instances in this way when the class proportions are close to each other. However, if class proportions in a dataset are skewed (e.g., landslide, earthquake), a decision threshold of 0.5 will ignore the class that makes up a small proportion of a dataset (Settles, 2010; Žliobaitė et al., 2013; Huijser et al., 2017; Locatelli et al., 2018). Therefore, considering class proportions in a dataset and allowing a more flexible decision threshold can help AL to be better applied to a wide range of fields, which has been achieved in this thesis (Chapter 5).

6.2.3 Challenges in model transfer

Accuracy is a necessary condition for methodological progress, but understanding and interpreting a method is essential (Small, 2021). Improving the understanding of model transfers in natural hazards and ecology studies can help researchers increase their confidence in enhancing the performances of transferred models as well as assist decision-makers in making better informed management decisions in the face of data scarcity (Yates et al., 2018). In computer science, a model can be considered to be successfully transferred as long as a high predictive accuracy can be obtained (Weiss et al., 2016; Li et al., 2020). Based on this criterion, many studies using state-of-the-art techniques (e.g., deep learning) have demonstrated that TL was useful in natural hazards and remote-sensing image classification studies (Liu et al., 2021; Ai et al., 2022; Wang et al., 2022). However, their main drawback is that the interpretation of models and the understanding of the factors that can successfully transfer the information are limited, or even impossible to achieve (Knight, 2017). This leads to a disconnection between studies on model building and process-oriented analysis. Hence, the key to successful model transfers in natural hazards and ecological studies is to achieve accurate predictions and provide

the opportunity to do plausible analysis. This point has been explored in this thesis by considering environmental characteristics and data resolution between source and target areas (Chapter 4).

Considering the information of a target area in model transfers can help researchers to analyze the factors that govern landslide activity in a target area more precisely. Previous studies have also indicated that in landslide studies, the collection of data from a target area allows for a systematic retrospective analysis of past events (Steger et al, 2016; Chae et al., 2017; Steger et al., 2017). As found in this thesis, the variable importance of the transferred model and the model trained by data from the target area was different (Chapter 5, Figure 10). Therefore, it is still necessary to sample the data from a target area. The challenge is to sample data from a target area at a low cost and combine them with historical data to obtain high accuracy and interpretable results. In this thesis, this challenge was addressed by combining AL and TL (Chapter 5).

The combination of multiple "related" source areas can increase the opportunity to use information that is closely related to a target area (Yao and Doretto, 2010). Although some studies have explored TL with multiple source areas, such as image processing (Lu et al., 2019) and landslide susceptibility studies (Bordoni et al., 2020), these studies directly transferred information from multiple source areas without considering the similarity between source and target areas. This way of transferring multiple source areas may reduce the performance of a model. Nowadays, available landslide inventories are gradually increasing. For example, Regione Emilia-Romagna public administration (2022) provides multiple landslide inventories of the Emilia-Romagna region. NASA Landslide Viewer contains landslide inventories of different regions of the world (Kirschbaum et al., 2010; Kirschbaum et al., 2015). However, in the scenario with multiple source areas, selecting and combining "suitable" source areas to obtain accurate predictions requires additional research. In this thesis, high-accuracy predictions are achieved by considering the overall similarities between source and target areas (Chapter 4).

6.3 Achievements of methodology

This thesis overcomes the above-mentioned challenges and provides further support for the application of AL and TL in landslide assessment studies. Here, the main achievements of this thesis are summarized.

If a method is specific with respect to a study task (e.g., land cover classification), then it should be demonstrated that it is also effective for other fields (e.g., landslide classification) (Small, 2021). In this thesis, the applicability of AL strategies in landslide detection studies is

further confirmed; in particular, this thesis compares and analyzes the applicability of different AL strategies in landslide detection (Chapter 3). Likewise, this thesis further demonstrates the applicability of model transfers in landslide studies; in particular, the range of applicability analysis of CBR and LBDA to natural hazards research is broadened (Chapter 4). Moreover, for the situation in which multiple “suitable” source areas are available, this thesis proposes a method for combining their information based on the overall similarities between "related" source and target areas, obtaining a predictive accuracy close to the target benchmark and maintaining the model interpretability.

A flexible and transferable framework (i.e., allowing using data from a target area and historical data) is necessary for researchers and policy makers in reducing the impacts of natural hazards. Researchers and policy makers can use "suitable" historical data to accurately predict natural hazards when data are severely lacking or when a region requires a high cost to obtain data; when data are available for a target area, a small amount of "useful" training data from the target area can be used to achieve the same or better predictive results than using a large amount of data from the target area. In this thesis, a new framework is proposed to achieve low manual efforts and high accuracy by combining AL and TL to flexibly use historical data and data from a target area.

To reduce the sampling bias caused by imbalanced data (*Section 6.2.2*), a novel AL strategy is presented in this thesis. It assigns the decision boundary based on expert knowledge for specific applications (e.g., landslide studies). This adapted AL strategy can be in other fields as well (e.g., digital soil mapping). Together, combining TL with this new AL strategy assures the quality of the initial training data with low costs. The results show that this combination helps to rapidly improve the predictive performance of the model when iteratively selecting and adding "useful" information compared to the AL framework (Chapter 5, Figure 8). Moreover, to address the challenge in the stability of the AL model, the GAM was selected for learning the data (AL-based data) selected by the proposed AL strategy due to its robustness to sampling variation (Hjort and Marmion, 2008; Goetz et al., 2011; Goetz et al., 2015); at the same time, a new function is proposed to combine the transferred model and the model trained by the AL-based data. The results show that model predictions are more stable than those obtained by AL (Chapter 5). Overall, compared to only using AL, the proposed framework achieves a predictive accuracy 2% lower than the target benchmark with around 80% less training data (Chapter 5, Figure 8).

It is necessary for analysts to give meaning to the numerical results obtained (Steger et al., 2017). Also, as discussed in *Section 6.2*, predictive model building should take into account the

subsequent analysis. In this thesis, this principle is followed in both the use of predictor variables and the choice of model algorithms (e.g., GAM). In this way, the results obtained by the proposed framework are meaningful and helpful for analyzing the process of landslide activity in the target area (e.g., variable importance) (Chapter 5, Figure 10).

Overall, in this thesis, the applicability of AL and TL in landslide studies is further demonstrated. Meanwhile, the proposed framework not only improves the predictive performances of AL and TL in landslide assessment studies by overcoming their limitations but also expands the possibility of adding them to the natural hazards management workflow.

6.4 Future work

6.4.1 Enhancing the understanding of AL

The AL strategies of selecting "useful" data from a target area in this thesis are the commonly used uncertainty sampling and query-by-committee (Chapter 3). However, many other AL strategies are available (Ren et al., 2022). Therefore, future work remains to benchmark AL strategies to select "useful" data for a target area. In addition, this thesis proposes a modified AL strategy, low-relevance marginal sampling, whose decision boundary can be set for the specific application. This new strategy performs very well in this thesis but still needs further research in other fields.

Many fields within the environmental sciences require multi-class classification (e.g., land cover classification (Talukdar et al., 2020), forest cover (Jayasinghe, 2022), including, in a landslide context, the classification of landslide type (Amato et al., 2021)). In this thesis, the methods used are useful and helpful in binary classification (landslides and non-landslides). Although multi-class classification can be transformed into a series of binary classification tasks where one class is the target and the remaining are the non-target, the validity of AL in the multi-class situation requires further research. For example, it is worth investigating whether AL can obtain enough information on each class.

Overall, the future of this work may focus on evaluating the performance of other AL strategies in landslide assessment studies and comparing them to the proposed active learning strategies.

6.4.2 Optimizing CBR similarity criteria

There are still many other factors to be considered for analyzing the "similarity" between source and target areas. For example, climatic conditions and land use can also influence landslide occurrence (Knevels et al., 2021; Knevels et al., 2023). However, using these factors can be challenging due to the difficulty of obtaining information on potentially landslide-triggering

rainfall and the variability of land cover classification systems used in each region (Verburg et al., 2011; Kuemmerle et al., 2013; Goetz et al., 2015). Furthermore, there is no study to generally discuss how to compare these factors between source and target areas. Therefore, how to select CBR similarity factors still needs further study, and the similarity criteria in this thesis can provide basic support for future studies.

6.4.3 The potential of AL and TL in the natural hazards management workflow

The ultimate purpose of academic research is to provide useful information for real-life applications or to propose methods that are applicable to help people solve real-life problems. AL and TL have the potential to advance research data management workflows by providing a semi-automated, human-in-the-loop pipeline from open geospatial raw data (e.g., Sentinel-2, SRTM DEM) to information products that enable landslide studies and disaster risk reduction. For example, by adding AL and TL to the global mapping workflow, existing published landslide inventories can be integrated for people around the world to analyze.

In addition, AL and TL have the potential to help researchers explain the specific events that led to particular landslides. For example, researchers are able to extract useful information from integrated data to reliably identify critical rainfall thresholds or precise triggering conditions. Meanwhile, the pooling of data in the landslide community can overcome the limitation of "one-off" case studies that do not empower a broader academic community to generate remotely-sensed landslide inventories.

Overall, it is necessary to provide a set of general tools and mechanisms for data integration and analysis provision for the landslide community as well as related fields. The main advantage of the proposed framework in this thesis is that it can be used as a reference for modeling other natural hazards. Therefore, the main future research is to integrate the proposed framework to make it applicable to real-life applications.

6.5 Conclusions

The goal of this thesis is to improve our understanding of active and transfer learning in rapid landslide susceptibility and detection assessments. To achieve this goal, this thesis compares and analyzes different active learning strategies and transfer learning techniques, as well as proposes a new, flexible, and stable framework. Although the focus of this thesis is on rapid landslide susceptibility and detection assessments, the findings in this thesis may also be useful for studies focusing on other natural hazards, ecology, and remote-sensing image classification. Here, the main conclusions of this thesis are summarized.

Due to the need to reduce the costs of obtaining landslide information in a target area, investigating rapid landslide assessment is crucial. As demonstrated in this thesis, the quality of the training data is an important part of constructing a landslide model. Active learning strategies used save about 80% of the cost of building training data compared to random sampling under the same predictive accuracy. At the same time, by comparing and analyzing different active learning strategies, it is found that the choice of a learning algorithm may affect the performance of active learning in landslide studies, and further research is needed to explore which learning algorithm is more suitable for the active learning framework. Overall, the findings can enhance the understanding of active learning, thereby improving the effectiveness of active learning in future research.

Achieving the reuse of historical data is possible and helpful through transfer learning. Identifying factors that characterize the similarity between source and target areas is important in this context. As shown and discussed in this thesis, the factors associated with landslide activity and data resolution play an important role in successfully transferring models. By comparing these factors between source and target areas, a good predictive performance (i.e., very close to the predictive accuracy obtained by the target area itself) on the target area can be achieved by applying historical data with similar environmental characteristics and data resolution ("related" source area). In addition, this thesis examines model transfers in landslide assessment studies at a global scale, which can give guidance in land management and emergency response for data-scarce regions (e.g., mountainous areas and some developing countries).

The flexible use and combination of data from a target area and historical data can improve the predictive performance of a model. This thesis proposes a framework that can further reduce labor costs for preparing labeled landslide and non-landslide observations and improve the predictive accuracy in the target area compared to the active learning framework. That is, it achieves a predictive accuracy 2% lower than the target benchmark with only 20% of the efforts of building the training data compared to only using the active learning framework. Moreover, by combining active and transfer learning, the proposed framework is more robust than the active learning framework.

Future work should focus on integrating the proposed framework in a human-computer interaction (HCI) implementation to enable researchers to create multiple event-based inventories for landslide studies as well as help people build landslide models with low costs. Overall, in this thesis, comparative findings and the proposed framework provide strong support for active and transfer learning in rapid landslide assessment as well as give new sights to

researchers for understanding the potential of active and transfer learning in the natural hazards management workflow.

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Supplement manuscript 2

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Supplement of

Transfer learning for landslide susceptibility modeling using domain adaptation and case-based reasoning

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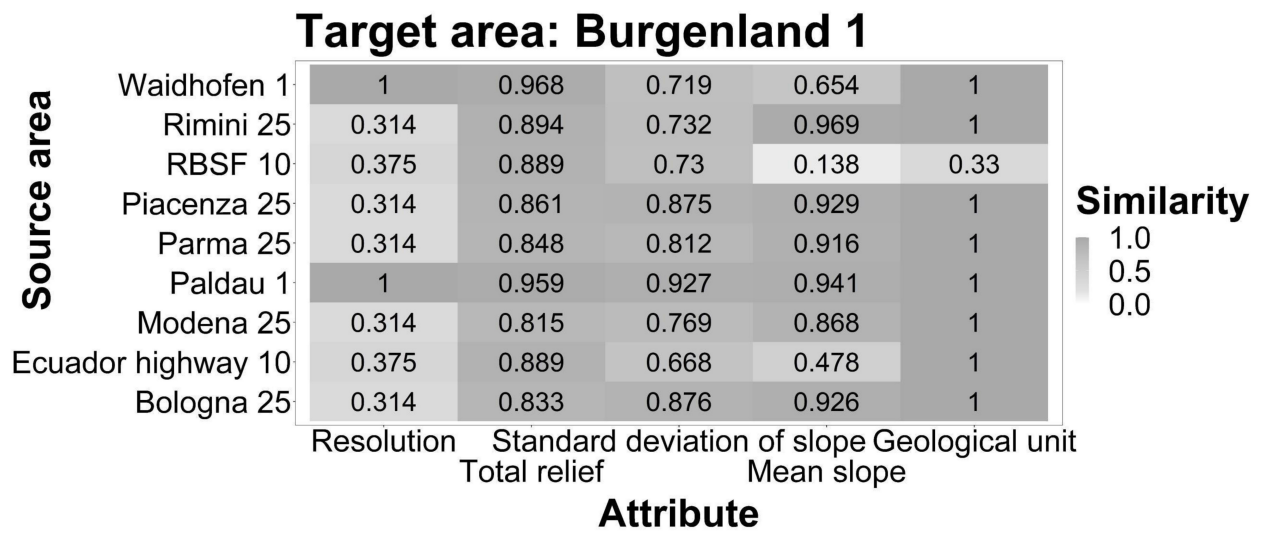


Figure S1: Similarity scores of different attributes for Burgenland with a 1 m x 1 m resolution. Light colours represent smaller similarities.

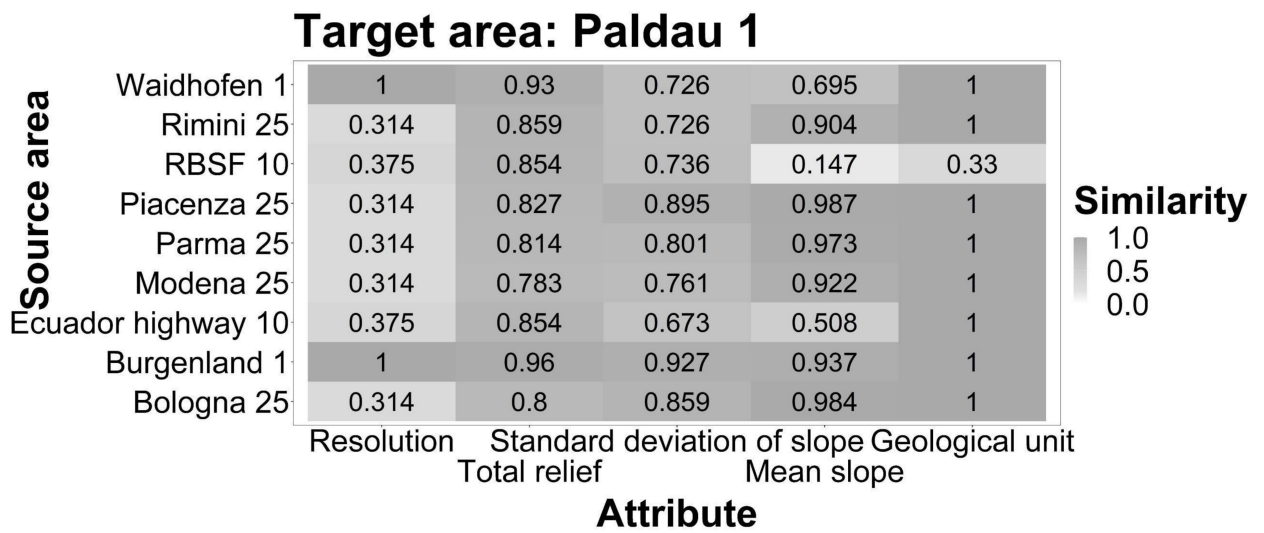


Figure S2: Similarity scores of different attributes for Paldau with a 1 m x 1 m resolution. Light colours represent smaller similarities.

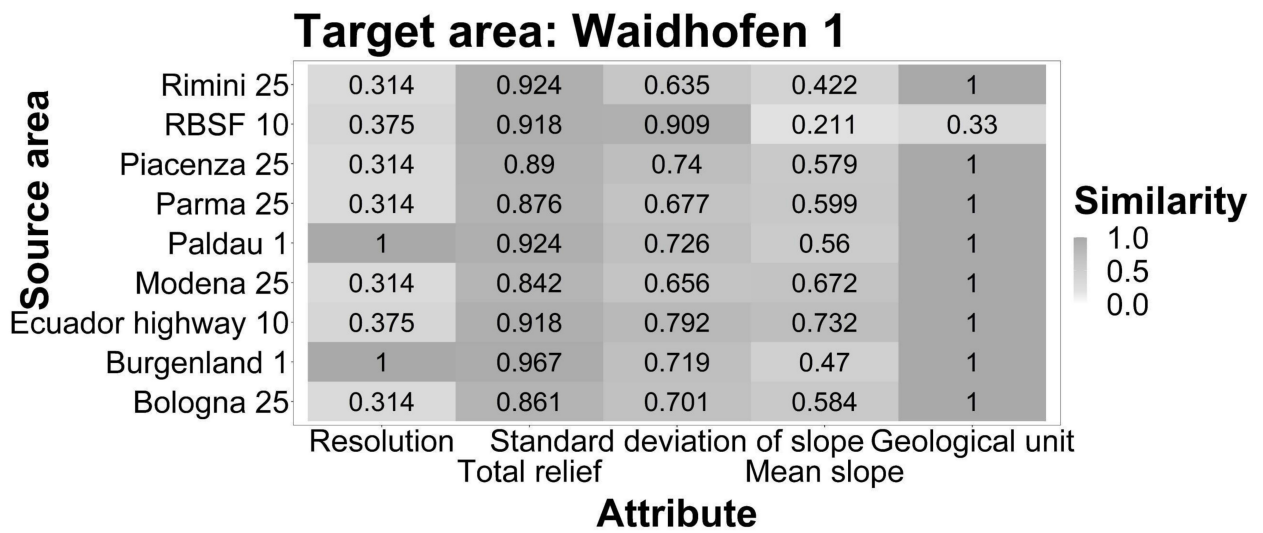


Figure S3: Similarity scores of different attributes for Waidhofen with a 1 m x 1 m resolution. Light colours represent smaller similarities.

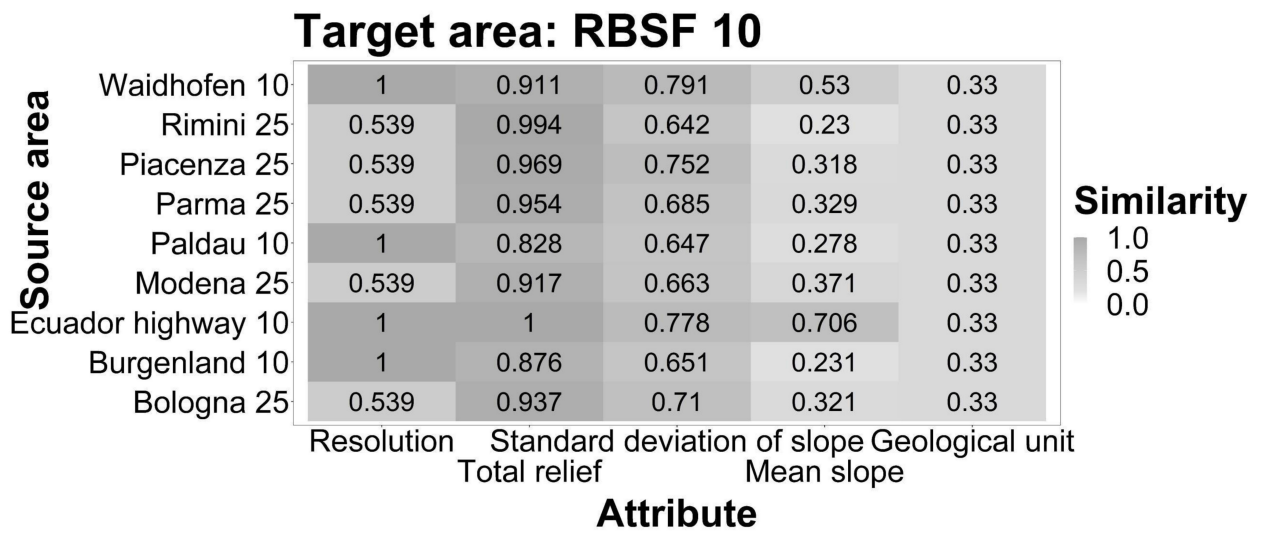


Figure S4: Similarity scores of different attributes for RBSF with a 10 m x 10 m resolution. Light colours represent smaller similarities.

Target area: Ecuador highway 10

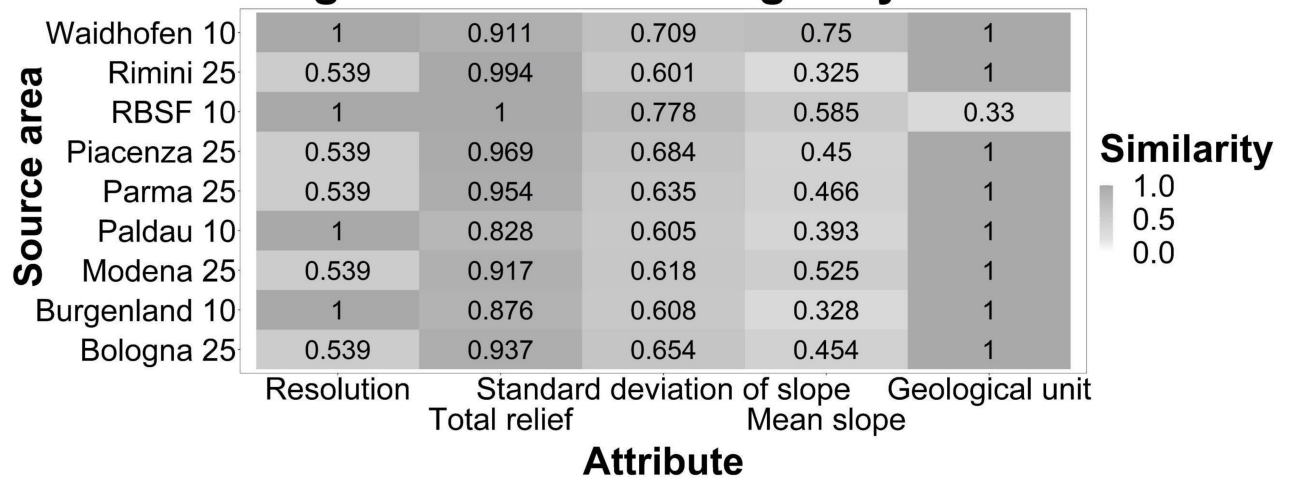


Figure S5: Similarity scores of different attributes for Ecuador highway with a 10 m x 10 m resolution. Light colours represent smaller similarities.

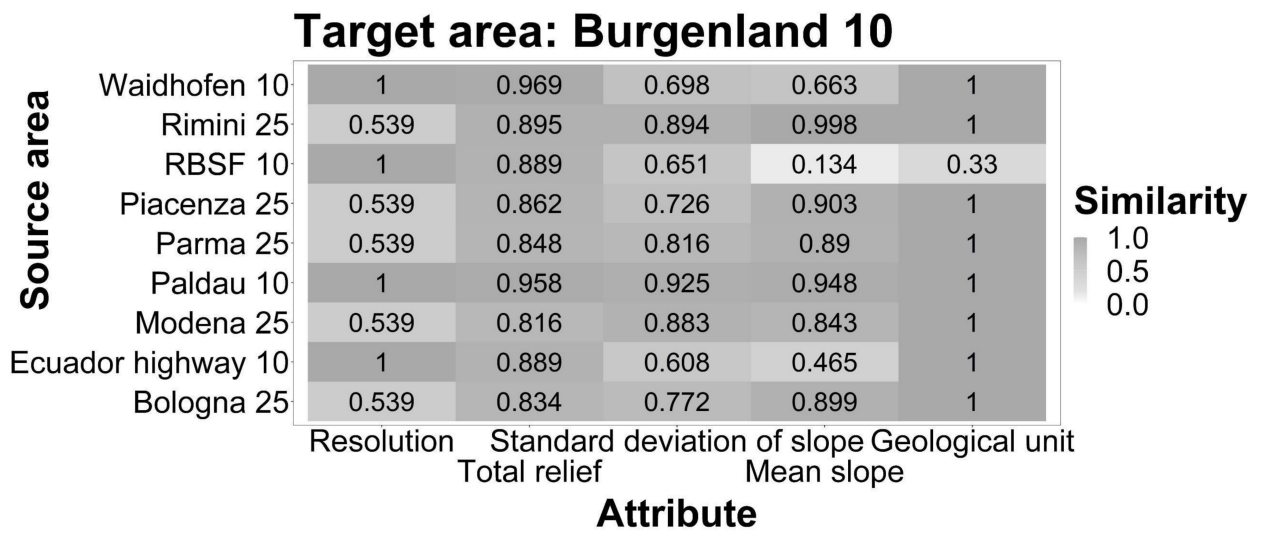


Figure S6: Similarity scores of different attributes for Burgenland with a 10 m x 10 m resolution. Light colours represent smaller similarities.

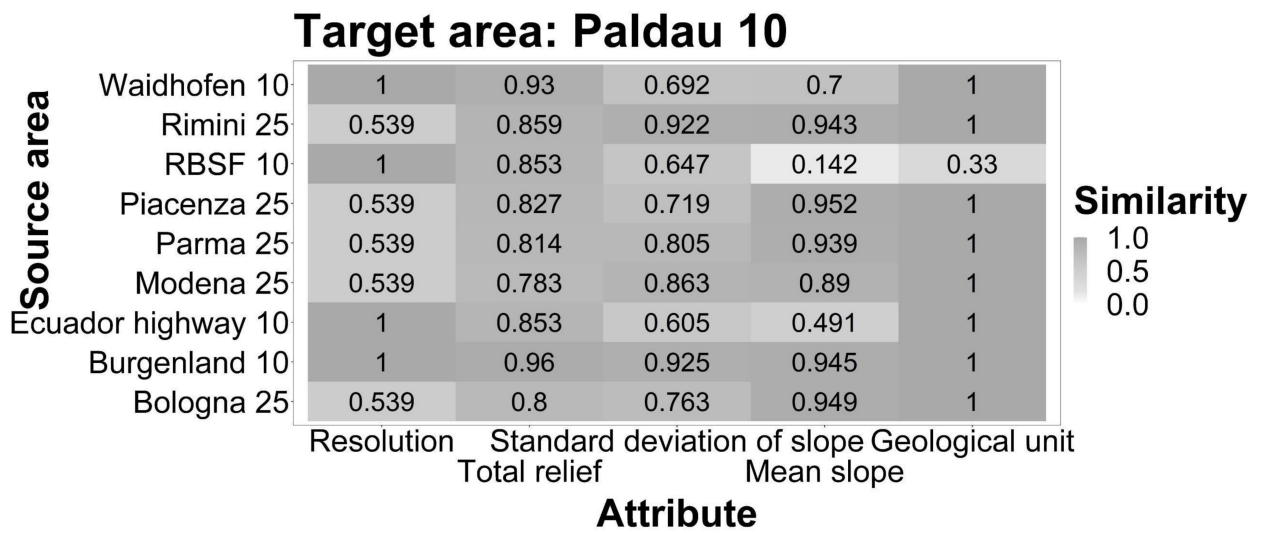


Figure S7: Similarity scores of different attributes for Paldau with a 10 m x 10 m resolution. Light colours represent smaller similarities.

Target area: Waidhofen 10

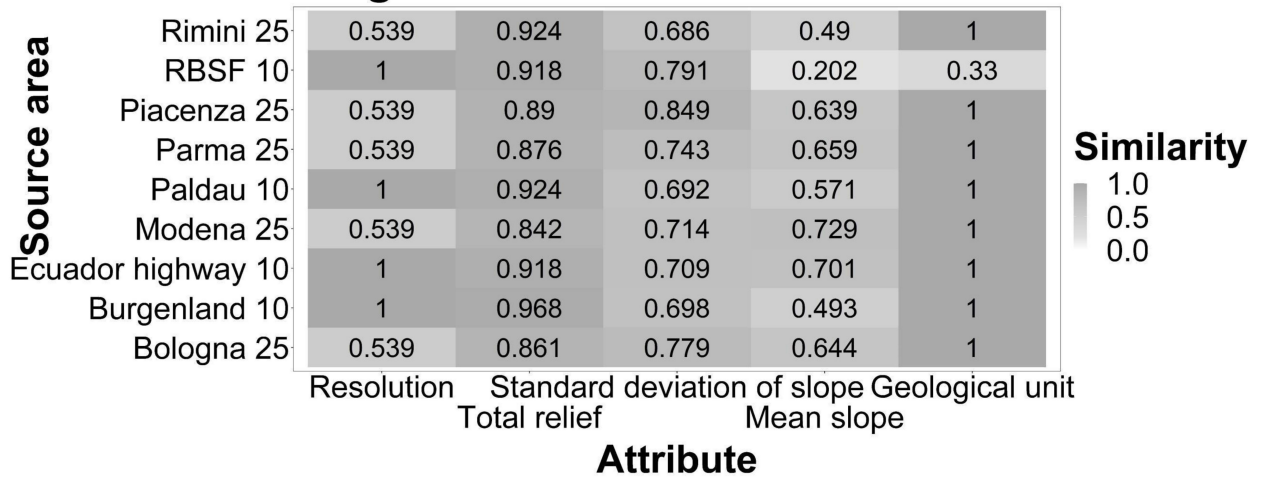


Figure S8: Similarity scores of different attributes for Waidhofen with a 10 m x 10 m resolution. Light colours represent smaller similarities.

Target area: Bologna 25

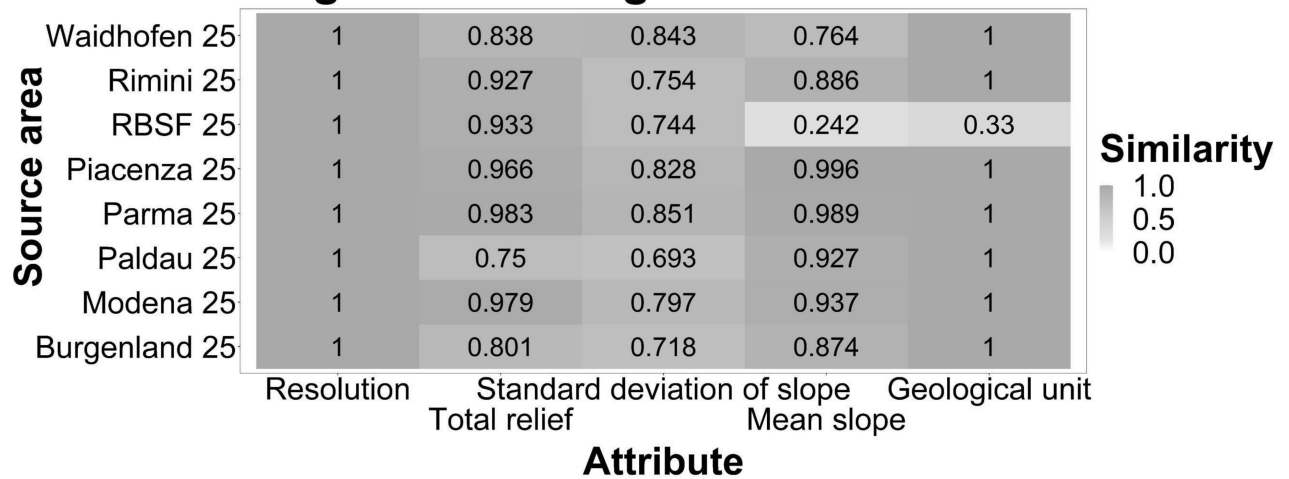


Figure S9: Similarity scores of different attributes for Bologna with a 25 m x 25 m resolution. Light colours represent smaller similarities.

Target area: Modena 25

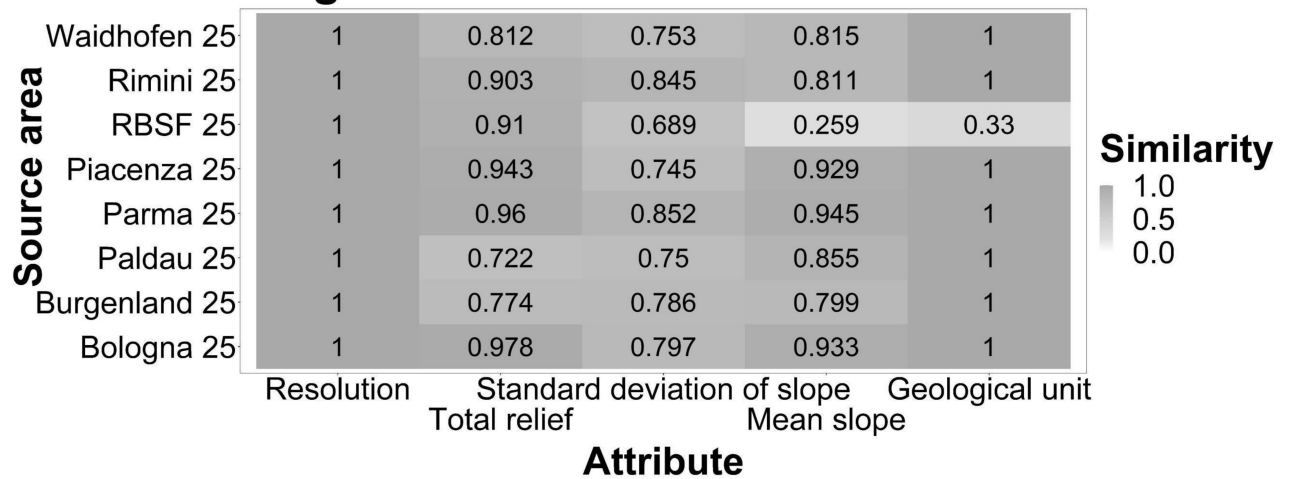


Figure S10: Similarity scores of different attributes for Modena with a 25 m x 25 m resolution. Light colours represent smaller similarities.

Target area: Parma 25

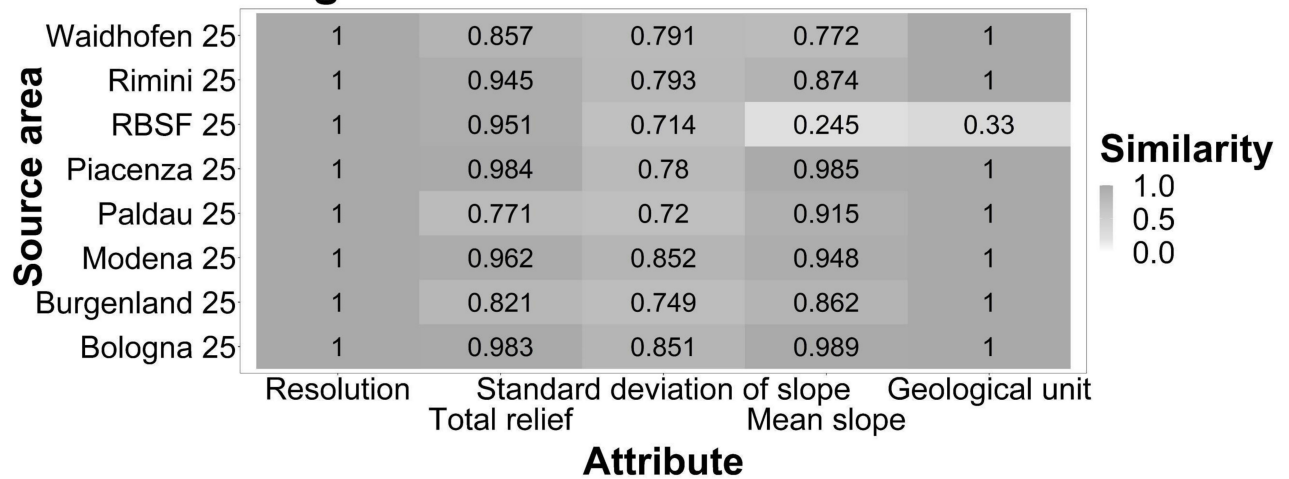


Figure S11: Similarity scores of different attributes for Parma with a 25 m x 25 m resolution. Light colours represent smaller similarities.

Target area: Piacenza 25

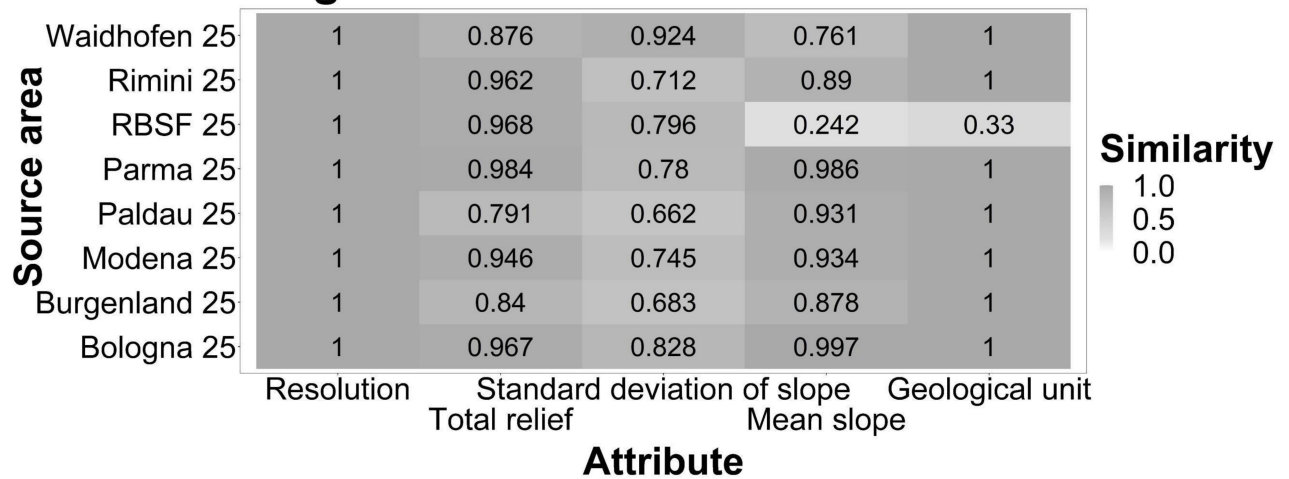


Figure S12: Similarity scores of different attributes for Piacenza with a 25 m x 25 m resolution. Light colours represent smaller similarities.

Target area: Rimini 25

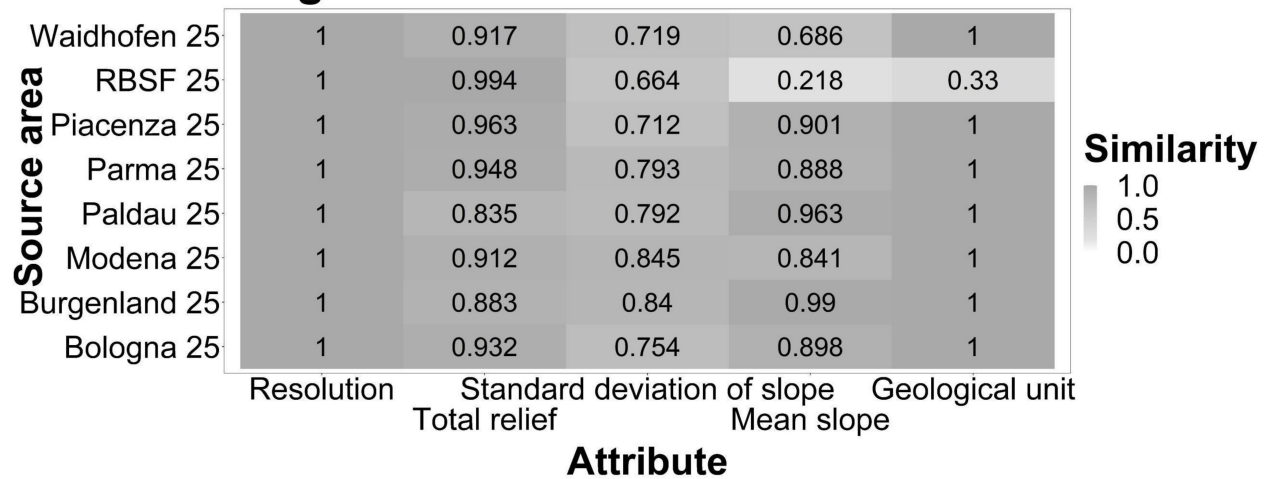


Figure S13: Similarity scores of different attributes for Rimini with a 25 m x 25 m resolution. Light colours represent smaller similarities.

Target area: Burgenland 25

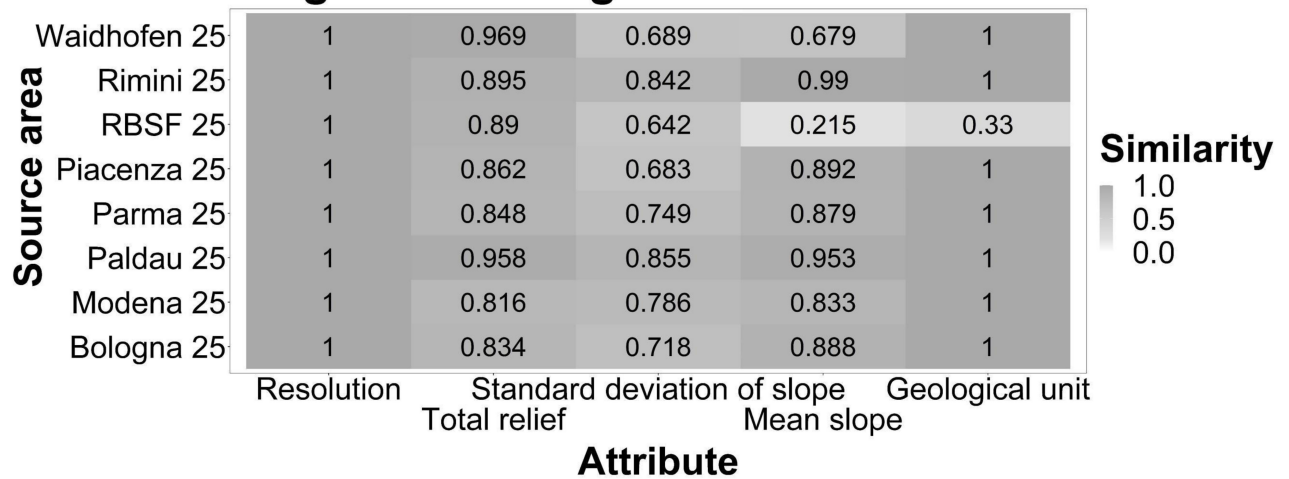


Figure S14: Similarity scores of different attributes for Burgenland with a 25 m x 25 m resolution. Light colours represent smaller similarities.

Target area: Paldau 25

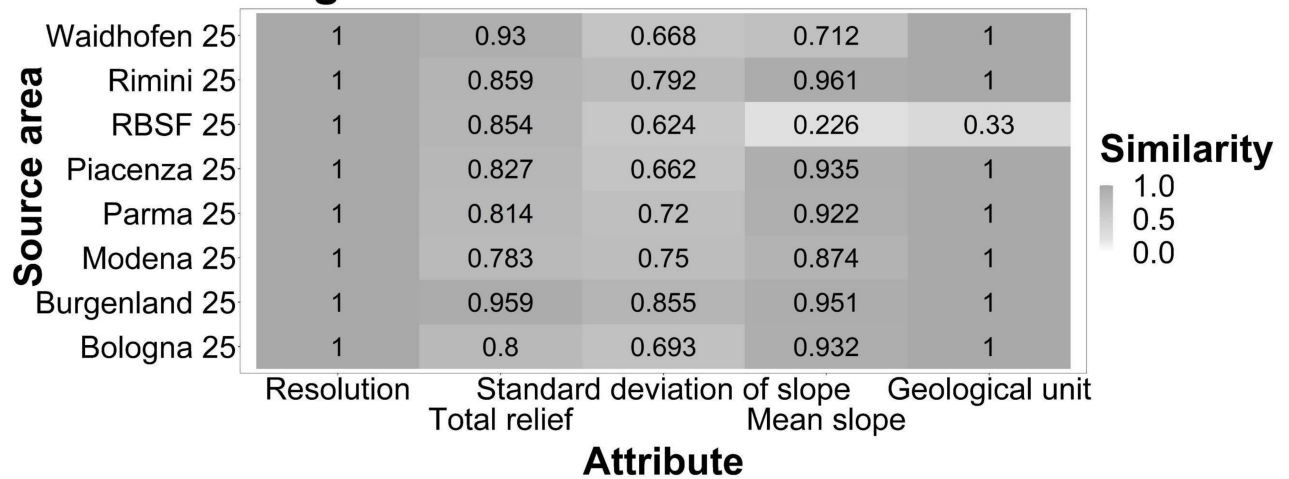


Figure S15: Similarity scores of different attributes for Paldau with a 25 m x 25 m resolution. Light colours represent smaller similarities.

Target area: Waidhofen 25

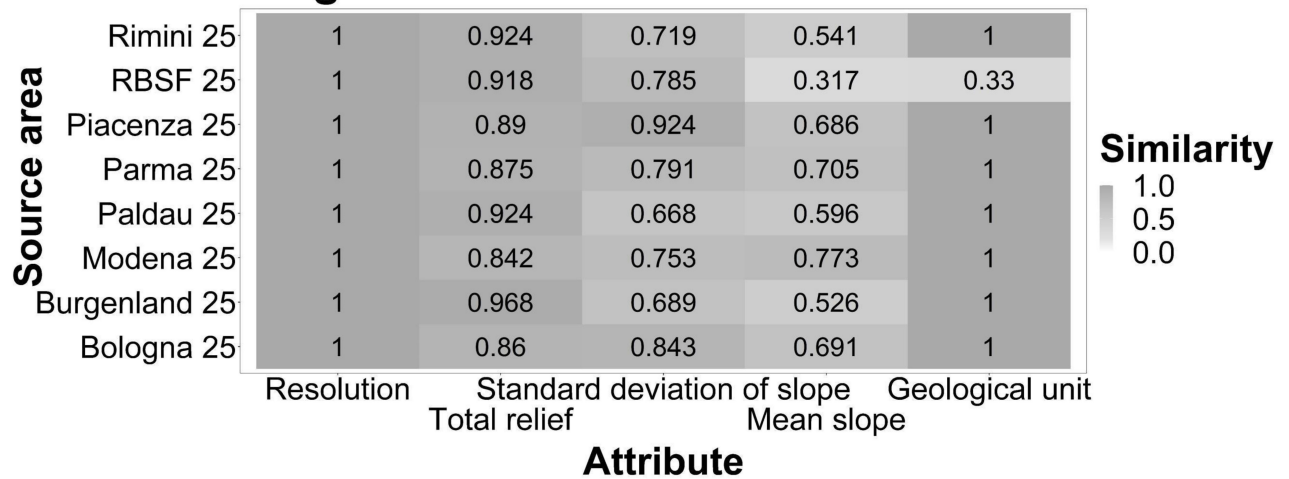


Figure S16: Similarity scores of different attributes for Waidhofen with a 25 m x 25 m resolution. Light colours represent smaller similarities.

Target area: RBSF 25

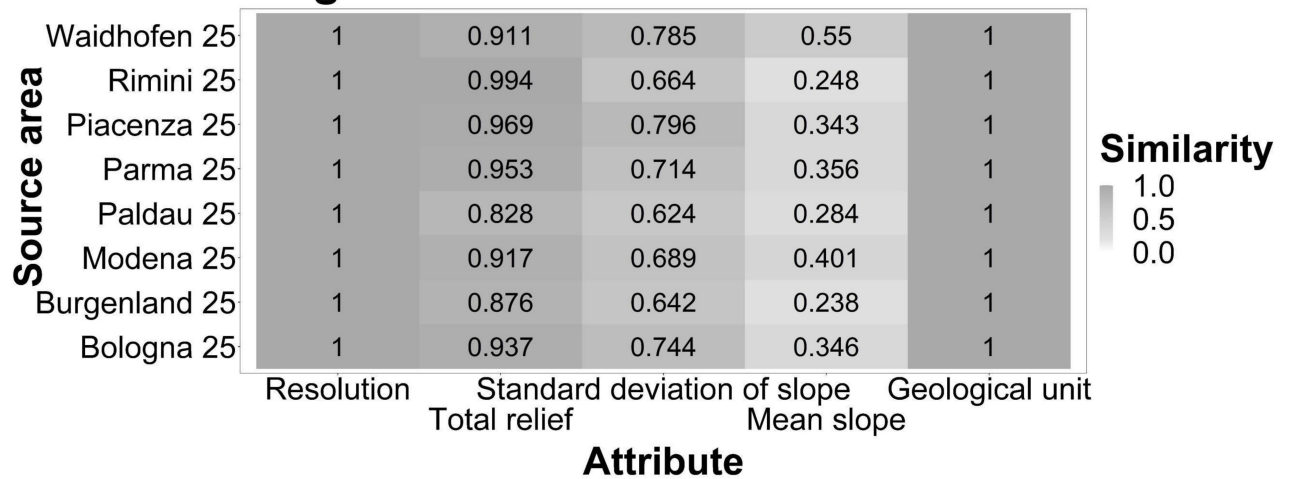


Figure S17: Similarity scores of different attributes for RBSF with a 25 m x 25 m resolution. Light colours represent smaller similarities.