Remote Sensing of Environment 186 (2016) 88–104

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Derivation of long-term spatiotemporal landslide activity—A multi-sensor time series approach

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ARTICLE INFO

Article history:
Received 2 September 2015
Received in revised form 15 June 2016
Accepted 9 July 2016
Available online 20 August 2016

Keywords:
Landslide identification
Landslide detection
Landslide frequency
Optical remote sensing
Change detection
Time series analysis
NDVI-trajectories
Multi-sensor
Spatiotemporal analysis
Landslide hazard
Kyrgyzstan
Central Asia
Tien Shan
Regional scale

ABSTRACT

This paper presents a remote sensing-based method to efficiently derive multi-temporal landslide inventories over large areas, which allows for the spatiotemporal analysis of landslide activity, which is an important prerequisite in systematic regional landslide hazard and risk assessment. The developed method uses globally archived satellite remote sensing data for a retrospective systematic assessment of past multi-temporal landslide activity. Landslides are automatically identified as spatially explicit objects based on landslide-specific vegetation cover changes using temporal NDVI-trajectories and complementary relief-oriented parameters. To enable the long-term analysis of large areas with highest possible temporal resolution, the developed method facilitates the use of a large amount of optical multi-sensor time series data. The database of this study consists of 212 datasets that comprise freely available Landsat TM & ETM + data and SPOT 1 & 5, IRS1-C LISSIII, ASTER, and RapidEye data. These data were acquired between 1986 and 2013 and cover a landslide-prone area of 2500 km^2 in southern Kyrgyzstan. We identified 1583 landslide objects ranging in size between 50 m^2 and 2.8 km^2. Spatiotemporal analysis of the landslides that were detected during these 27 years reveals continuous landslide activity of varying intensity. The highest overall landslide rates occurred in 2003 and 2004, exceeding the long-term annual average rate of 57 landslides per year by more than a factor of five. The areas of highest landslide activity are also determined, whereas most of these areas were persistent over time.

1. Introduction

"The past and present are keys to the future" (Varnes, 1984) is a long-standing principle in landslide hazard and risk assessment, which indicates that future landslides are more likely to occur under the same or similar conditions as past landslides (Corominas & Moya, 2008; Fell et al., 2008; Guzzetti et al., 2012). To enable spatiotemporal analysis of past landslide activity, systematic, and area-wide landslide inventories need to be established, which comprise the locations, extents, and dates of past landslides and other qualitative and quantitative parameters (Malamud, Turcotte, Guzzetti, & Reichenbach, 2004; van Westen, Castellanos, & Kuriakose, 2008). Landslide inventories can be differentiated into historical, event-based, seasonal, and multi-temporal inventories (Guzzetti et al., 2012). Multi-temporal inventories represent repeated documentation of landslides independently of specific triggering events during a longer period. Dates of occurrence are either precisely known or assigned to the period between repeated documentation. Such multi-temporal landslide inventories allow the determination of spatiotemporal variations in landslide frequencies representing an important requirement for probabilistic landslide hazard assessment (Guzzetti, Reichenbach, Cardinali, Galli, & Ardizzone, 2005; van Westen et al., 2008). However, these multi-temporal inventories are largely unavailable for most parts of the world because of the very high mapping effort that is required (Guzzetti et al., 2012). Existing ones have mostly been prepared for relatively small areas (several tens of square kilometers) by combining field investigations, analyses of archival data, and the visual interpretation of optical remote sensing imagery, such as aerial photographs and high-resolution satellite data (Fiorucci et al., 2011; Galli, Ardizzone, Cardinali, Guzzetti, & Reichenbach, 2008; Ghosh et al., 2012; Klimeš, 2013; Saba, van der Meijde, & van der Werff, 2010). In general, the temporal update rate of existing inventories is often limited to several years or even decades. To improve the spatial and temporal completeness of such multi-temporal inventories, the development of efficient landslide mapping strategies is of utmost importance.

To date, several studies have demonstrated the potential of optical remote sensing for the (semi-)automated mapping of landslide events. These studies mostly aimed to systematically assess the spatial

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http://dx.doi.org/10.1016/j.rse.2016.07.017
0034-4257/

variations in landslide activity that is related to an individual well-known triggering event, such as earthquakes (Lacroix, Zavala, Berthier, & Audin, 2013; Lodhi, 2011; Parker et al., 2011; Yang & Chen, 2010) and extreme hydrometeorological events (Borghuis, Chang, & Lee, 2007; Mondini et al., 2011; Tsai, Hwang, Chen, & Lin, 2010). For this purpose, either mono-temporal classification techniques have been applied to imagery from a single acquisition date after the triggering event (Barlow, Franklin, & Martin, 2006; Othman & Gloaguen, 2013), or various change detection techniques have been used to identify landslide-related surface changes that occurred between pre-event and post-event data acquisitions (Hölbling, Friedl, & Eisank, 2015; Lu, Stumpf, Kerle, & Casagli, 2011; Nichol & Wong, 2005; Stumpf & Kerle, 2011).

Although optical remote sensing data have been widely used to identify the spatial variability of event-based landslide activity, little attention has been paid to the systematic analysis of temporal variations in landslide activity over time. Allowing such systematic analyses requires efficient strategies to automatically derive multi-temporal landslide inventories. Recently, Martha, Kerle, van Westen, Jetten, and Vinod Kumar (2012) and Martha, van Westen, Kerle, Jetten, and Kumar (2013) presented a study for the semi-automatic derivation of a multi-temporal inventory. They applied an approach that had been initially designed for event-based mapping to a multi-temporal database of annual data coverage from 1998 to 2009 for an area of 81 km^2 in the Indian Himalayas.

However, the evaluation of spatiotemporal landslide activity requires the analysis of larger areas with high temporal resolution over longer time spans. For this purpose, remote sensing imagery of different sensors must be considered to provide the highest possible spatiotemporal data coverage during the analyzed time span. Such remote sensing databases contain a large amount of data with variable image characteristics, which originate from different sensor characteristics and from seasonal and inter-annual variations in data acquisition. A multi-temporal landslide mapping based on such a heterogeneous database requires a landslide identification approach that can compensate for spatially, temporally, and spectrally diverse remote sensing data. This approach must also be able to compensate for natural variability in landslide surface properties, persistence, and expression over a range of conditions in natural environments.

In this context, the objectives of this study are

- to develop an automated remote sensing-based approach for retrospective long-term multi-temporal landslide mapping based on a multi-sensor remote sensing time series, and
- to derive a 2500 km^2 multi-temporal landslide inventory for the period from 1986 to 2013, including the evaluation of spatiotemporal landslide activity patterns.

For this purpose, this study extends our approach for multi-temporal landslide mapping based on RapidEye time series data (Behling, Roessner, Kaufmann, & Kleinschmit, 2014). Our approach detects landslide objects in a dense optical time series (2009–2013) using landslide-related vegetation cover changes over time, which are supported by relief-based parameters derived from a digital elevation model. The transformation of the RapidEye-based approach into a long-term multi-sensor approach requires methodological extensions that deal with challenges from irregular temporal resolutions that are inherent in long-term time series data, the variability that is introduced by the implementation of multiple sensors, the high amount of variable datasets, and the irregular and patchy spatial availability of remote sensing data throughout a large study area. Moreover, the natural variability in landslide phenomena (i.e., different types, sizes, and shapes) and their variable appearances in a heterogeneous remote sensing database must be considered. To compensate for this variability, our landslide identification process implements uncertainty-related algorithms, resulting in object identifications that are characterized by a likelihood of being a landslide. This uncertainty-related nature of the approach facilitates the efficient derivation of large multi-temporal landslide inventories in a fully automatic way or within an expert-based semi-automatic approach, where the landslide likelihood of the automatically derived results acts as a decision support system for subsequent manual editing and interpretation.

Section 2 provides an overview of the study area, the available remote sensing database, and the variable appearances of landslides in multi-sensor time series imagery. Section 3 describes the approach for multi-temporal landslide mapping from pre-processing until the resulting landslide likelihood-differentiated objects. Section 4 validates the approach with respect to automated and semi-automated usage, presenting mapping accuracies for two individual subsets. After applying the approach to the complete remote sensing database, an expert-based editing of the automatically derived landslide objects is performed to achieve the final multi-temporal landslide mapping (Section 5). It is further analyzed in terms of its spatiotemporal activity patterns to show its potential use for subsequent hazard assessment. The methodological developments and achieved spatiotemporal landslide results are discussed in Section 6, followed by concluding remarks in Section 7.

2. Study area and database

2.1. Study area

The 2500 km^2 study area (Fig. 1A, Fig. S1) is located in southern Kyrgyzstan along the eastern rim of the Fergana Basin, where the foothills of the Tien Shan mountain range are largely affected by high landslide activity (Golovko, Roessner, Behling, Wetzel, & Kleinschmit, 2015; Havenith et al., 2015; Roessner, Wetzel, Kaufmann, & Sarnagoev, 2005). This region is an important human living space, so landslides represent a major natural hazard, causing fatalities and severe economic losses. Large mass movements mostly occur as deep-seated landslides within weakly consolidated Mesozoic and Cenozoic sediments, which have been subjected to ongoing tectonic deformation (Roessner et al., 2005). Observations of landslide activity in southern Kyrgyzstan have been conducted by local organizations since the 1950s, focusing on areas in the vicinity of settlements, whereas these efforts have largely decreased after the independence of Kyrgyzstan in 1991 (Ibatulin, 2011; Kalmetieva et al., 2009).

2.2. Remote sensing database

The multi-temporal satellite remote sensing database comprises data from seven optical sensors, i.e., SPOT 1 & 5, IRS1-C LISSIII, Landsat TM & ETM+, ASTER, and RapidEye. All the datasets were obtained in the form of orthorectified standard data products to reduce preprocessing efforts (Behling, Roessner, Segl, Kleinschmit, & Kaufmann, 2014). The spatial resolution of the datasets ranges from 30 m for the Landsat sensors to 5 m for the RapidEye sensors (Fig. 1E, F). A comprehensive overview of the data in this study, including the sensor characteristics, can be found in Behling, Roessner, Segl, et al. (2014). The database consists of 212 datasets that cover a time span from 1986 to 2013. Since the first datasets, which were acquired by SPOT 1 (Fig. 1E), cover only subsets of the study area, the analyzable time span begins in 1990 for the remaining parts (Fig. 1A). In total, the database contains data acquisitions for at least 18 different years (Fig. 1C), whereas the temporal resolution varies in different parts of the study area and during different periods of the covered time span. The number of acquisitions varies between 50 and 70 datasets (Fig. 1B), depending on the location within the study area. The time intervals between subsequent acquisitions ranges from six years (1990–1996) in the beginning of the time series (Fig. 1E) to two weeks between the high-temporal-resolution data from the RapidEye sensor, which were acquired between 2009 and 2013. In addition to multispectral remote sensing data, this study uses a digital elevation model (DEM) with 30-m spatial resolution that was