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Detecting Himalayan glacial lake outburst floods from Landsat time series

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ABSTRACT

Several thousands of moraine-dammed and supraglacial lakes spread over the Hindu Kush Himalayan (HKH) region, and some have grown rapidly in past decades due to glacier retreat. The sudden emptying of these lakes releases large volumes of water and sediment in destructive glacial lake outburst floods (GLOFs), one of the most publicised natural hazards to the rapidly growing Himalayan population. Despite the growing number and size of glacial lakes, the frequency of documented GLOFs is remarkably constant. We explore this possible reporting bias and offer a new processing chain for establishing a more complete Himalayan GLOF inventory. We make use of the full seasonal archive of Landsat images between 1988 and 2016, and track automatically where GLOFs left shrinking water bodies, and tails of sediment at high elevations. We trained a Random Forest classifier to generate fuzzy land cover maps for 2491 images, achieving overall accuracies of 91%. We developed a likelihood-based change point technique to estimate the timing of GLOFs at the pixel scale. Our method objectively detected ten out of eleven documented GLOFs, and another ten lakes that gave rise to previously unreported GLOFs. We thus nearly doubled the existing GLOF record for a study area covering ~10% of the HKH region. Remaining challenges for automatically detecting GLOFs include image insufficiently accurate co-registration, misclassifications in the land cover maps and image noise from clouds, shadows or ice. Yet our processing chain is robust and has the potential for being applied on the greater HKH and mountain ranges elsewhere, opening the door for objectively expanding the knowledge base on GLOF activity over the past three decades.

1. Introduction

Melting glaciers in the Hindu Kush Himalayan (HKH) mountain ranges feed several thousand moraine-dammed and supraglacial lakes (Ives et al., 2010; Nie et al., 2017). Embedded in loose debris and surrounded by sources of falling debris and ice, many of these water bodies are prone to glacial lake outburst floods (GLOFs) (Clague and Evans, 2000). GLOFs can release and transport millions of cubic meters of water and sediment within few hours (Bajracharya et al., 2007; Cenderelli and Wohl, 2001; Wang et al., 2012). Quaternary outburst floods in the HKH have been shaping major valley trains for thousands of years (Korup and Tweed, 2007; O'Connor et al., 2013; Scherler et al., 2014). GLOFs have also killed several hundreds of people in the past decades and caused substantial damage to infrastructure, hydropower stations, livestock and farmland (Kattelmann, 2003; Richardson and Reynolds, 2000; Yamada and Sharma, 1993). Data on loss and damage are crude, though Nepal and Bhutan may have suffered the highest socio-economic impacts by historic GLOFs worldwide (Carrivick and Tweed, 2016). In any case, GLOFs clearly rank among the most publicised glacial hazards in the Himalayas (Richardson and Reynolds, 2000).

Difficult access and high alpine conditions make detailed field-based monitoring of lakes prone to outburst impractical; several studies thus resorted on measuring lake bathymetry, dam material, and the surrounding topography (Fujita et al., 2013; Wang et al., 2012; Worni et al., 2013). Moreover, data on historic GLOFs in the HKH are scarce and vague about outburst parameters. Local GLOF inventories often contradict each other, at least judging from data that we collected on 36 GLOFs from moraine-dammed lakes in the Himalayas since the 1950s (Ives et al., 2010; Komori et al., 2012; Liu et al., 2014; Wang et al., 2012; Table 1).

Current research aims at linking global climate warming to glacier melt, and the formation and changes of meltwater lakes, including the probability of catastrophic lake outburst (Harrison et al., 2017). Negative glacier mass balances (Brun et al., 2017) and increases in glacial lake number and area (Nie et al., 2017; Song et al., 2017; Zhang et al., 2015) have characterized many parts of the HKH over the past decades, and thawing permafrost in glacier dams and surrounding rock walls may further destabilise the glacial lake system (Haeberli et al., 2017). While all these observations are in line with a hypothesized increase in

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Table 1
Documented GLOFs between 1988 and 2016. ID corresponds to labels in Fig. 1. We visually assessed whether drainage was complete (C) or partial (P).

ID	Lake	Country	E [°]	N [°]	Elevation [m a.s.l.]	Loss in lake area [m^2]	Date	Type of drainage	Source
1	Chorabari	India	79.06	30.75	3881	11,700	2013-06-17	C	Allen et al. (2016); Das et al. (2015)
2	Zanaco	TAR/China	85.37	28.66	4737	66,600	1995-06-06	C	Liu et al. (2014)
3	Zhangzangbo 2	Nepal	86.06	28.08	4501	10,800	2016-07-07	C	Cook et al. (2017); Gimbert et al. (2017)
4	Sabai Tsho	Nepal	86.84	27.74	4492	163,800	1998-09-03	P	Lamsal et al. (2015); Osti and Egashira (2009)
5	Lemthang Tsho	Bhutan	89.58	28.07	4273	53,100	2015-06-28	C	Gurung et al. (2017)
6	Chongbaxia Tsho	TAR/China	89.74	28.21	5028	227,700	Spring–Summer 2001	P	Komori et al. (2012)
7	Tshojo glacier	Bhutan	90.16	28.10	4273	81,900	2009-07-29	P	Yamanokuchi et al. (2011)
8	Luggye Tsho	Bhutan	90.28	28.09	4623	140,400	1994-10-07	P	Fujita et al. (2008); Watanbe and Rothacher (1996)
9	Gangri Tsho III	Bhutan	90.81	27.90	4826	26,100	Spring–Summer 1998	P	Komori et al. (2012)
10	Ranzeria Co	TAR/China	93.53	30.47	5051	246,600	2013-07-05	P	Sun et al. (2014)
11	Tsho Ga	TAR/China	94.00	30.83	4760	140,400	2009-04-29	P	Nie et al. (pers. comm., 2017)

GLOF frequency, this remains difficult to test given commonly observed rates of up to one event per year, and only a few dozen reliably documented events (Carrivick and Tweed, 2016; Harrison et al., 2017). This mismatch could reflect a censoring bias such that only extreme events and their impacts have been reported.

Clearly, a database of past events as complete as possible is essential for robust and reliable GLOF hazard assessment (Emmer et al., 2016). Time series from satellite imagery find widespread use for compiling multi-temporal glacial lake inventories, especially for rapidly expanding lakes that are thought to have an elevated outburst potential (Nie et al., 2017; Wang et al., 2015a, 2011). To our knowledge, no study has systematically explored the Landsat archive for retrospective GLOF detection in the HKH, although it offers a largely continuous, nearly 30-year time series with regional coverage every 16 days. For tracing past GLOFs, we build on the experience that lakes most often disappeared or shrank abruptly and exposed debris fans and sediment tails in river channels downstream. Only Komori et al. (2012) used these two indicators to visually scan satellite archives for unreported GLOFs in the Bhutan Himalayas. Since glacial lakes often re-fill or re-expand within few years after an outburst, previously used mapping intervals of five to ten years might be too coarse to detect GLOFs from lake inventories (Zhang et al., 2015). Dense cloud cover during the monsoon, lake freezing in winter, and mountain shadows are the main challenges for pursuing the glacial lake area over time. Multiple noise-free images per year may be desirable to detect reliably sudden lake changes, but remain rare in the Himalayan weather conditions. Expert-based manual mapping from multi-temporal medium to high resolution (< 30 m) imagery has so far offered high-quality lake inventories, but is resource-intensive and thus restricted to few selected glacial lakes (Shrestha et al., 2013; Wang et al., 2015a; Yao et al., 2012) or single catchments (Bolch et al., 2008; Che et al., 2014; Jain et al., 2012). Semi-automatic mapping using chains of decision rules along band and topographic indices allows for monitoring of glacial lakes over larger areas, but requires time-consuming post-processing (Gardelle et al., 2011; Li and Sheng, 2012; Song et al., 2016). Machine learning classifiers such as Random Forests (RF) have rapidly advanced the mapping of changing land cover and water bodies (Mueller et al., 2016; Rover et al., 2012; Tulbure et al., 2016), thereby accompanying a high potential for GLOF detection. Random Forests (Breiman, 2001) are ensemble classifiers that use bagging to grow and aggregate multiple independent decision trees from a bootstrap sample of predictor variables. The classifier can deal with non-monotonic and non-linear relationships between the predictors and response variables, and is robust against overfitting (Rodriguez-Galiano et al., 2012). Hence, RF are a powerful alternative to single, parametric classifiers (Waske and Braun, 2009), especially for spectrally variable target classes such as glacial lakes of differing depth and turbidity. Random Forests offer fuzzy or probabilistic class memberships, which offer richer information about the likelihood of change in land-cover time series (Foody and Boyd, 1999; Metternicht, 1999).

Change detection of water bodies with Landsat time series focused either on long-term trends of lake growth or shrinkage (Fraser et al., 2014; Nitze and Grosse, 2016) or on the estimation of flooding frequencies (Mueller et al., 2016; Tulbure et al., 2016). Automatically extracting distinct events of rapid lake decrease, as is the case for GLOFs, has rarely been of interest (Olthof et al., 2015). Change-point detection in Landsat time series is well-established for forest disturbance mapping, where pixels of vegetation indices are scanned for level shifts (Hermosilla et al., 2015; Kennedy et al., 2010) or structural breaks in fitted harmonic models (DeVries et al., 2015; Verbesselt et al., 2012). However, alternative techniques are required, as these approaches are difficult to apply to Himalayan glacial lakes where indices such as the Normalized Difference Water Index (NDWI; McFeeters, 1996) share similar spectral characteristics with clouds or shadows (Li and Sheng, 2012).

Our aim is to develop, validate and apply a technique to automatically detect past Himalayan GLOFs. We present a processing chain that traces losses in lake areas from nearly three decades of seasonal Landsat imagery building on (1) a Random-Forest based land cover classification and (2) a novel, likelihood based change-point algorithm to approximate the time stamp of GLOFs. We apply this processing chain to a spatial subset of the HKH, validate our method with documented GLOFs and present newly detected GLOFs. Our search includes sediment tails downstream of drained lakes, allowing us to trace the location, timing, and size of GLOFs, and thus contributing to a more complete GLOF inventory of the Himalayas.

2. Study area

Of all 36 documented GLOFs over the past seven decades, we could visually identify eleven GLOFs in Landsat images (Fig. 1). We obtained information on the date, location, and type of drainage for each GLOF, using the drained lake area as a key metric for comparing pre- and post-GLOF images (Table 1).

These GLOFs occurred in four different regions (Fig. 1) between the central-western Himalayas of northern India (a), the central Himalayas of Nepal and Bhutan (b and c), and the eastern Nyainqentanglha Mountains of China (d). The number of present-day moraine-dammed and supraglacial lakes in these areas is challenging to establish. Estimates for the whole HKH range from 2276 (Fujita et al., 2013) to > 8000 (Ives et al., 2010), depending on definition, mapping scale, and size of study area. In the central Himalayas, glacial lakes grew by 23% in size between 1990 and 2015. Lakes grow less rapidly in area in the western (5.0–5.4%) and eastern Himalayas (7.7–11.1%) (Nie et al., 2017), and mostly tied to glacier melt (Gardelle et al., 2013; Kääb et al., 2012; Song et al., 2017; Wang et al., 2015b).