Object-based analysis of unmanned aerial vehicle imagery to map and characterise surface features on a debris-covered glacier

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A B S T R A C T

Debris-covered glaciers in the Himalaya may have spatially-averaged rates of surface height change that are similar to those observed on bare-ice glaciers, despite the insulating effects of thick debris. Spatially heterogeneous melt patterns caused by the development and evolution of ice cliffs and supraglacial pond systems result in substantial mass losses over time. However, mechanisms controlling the formation and survival of cliffs and ponds remain largely unknown. To study the distribution and characteristics of these surface features we deploy an unmanned aerial vehicle (UAV) over a stretch of the debris-covered Langtang Glacier, Nepal. Acquired images are processed into high-resolution orthomosaics and elevation models with the Structure from Motion (SfM) photogrammetry algorithm. Ice cliffs and ponds are classified using object-based image analysis (OBIA) and their morphology and spatial distribution are analysed and evaluated using object, pixel and point cloud approaches. Results show that ice cliffs are predominantly north-facing, and larger ice cliffs are generally coupled with supraglacial ponds, which may affect their evolution considerably. The spatial distribution of ice cliffs indicates that they are more likely to form in areas where high strain rates are expected. The spatial configuration of ponds over the entire tongue reveals high pond density near confluences, possibly due to closure of conduits via transverse compression. We conclude that the combination of OBIA and UAV imagery is a valuable tool in the semi-automatic and objective analysis of surface features on debris-covered glaciers. The technique may also have potential for upscaling to the use of spaceborne imagery, and the use of UAV-derived point clouds to analyse ice cliff undercuts is promising.

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1. Introduction

Glaciers are an important component of the rivers in High Mountain Asia (HMA) that provide a large number of people with water for irrigation, electricity production, sanitation, and religious practices (Immerzeel et al., 2010). With the exception of the Karakoram, glaciers in HMA have experienced negative glacier mass balances over the past decades (Bolch et al., 2012; Gardelle et al., 2012; Kääb et al., 2012, 2015). Sustained negative mass balances have resulted in a decreased volume of ice stored in these mountain ranges. Under current climate projections, accelerated glacier mass loss and increased glacier melt water runoff are expected in the coming decades (Shea et al., 2015). Towards the end of this century, however, the reduction in glacier area and volume will result in decreased ice melt contributions to streamflow (Immerzeel et al., 2013).

To increase our ability to predict and adapt to these future changes induced by climatic change, it is key that we learn more about the melt processes of glaciers in this region. Debris-covered glaciers in particular, which account for about 10% of the glaciers in HMA (Bolch et al., 2012), are relatively understudied because of difficulties in both accessibility and the collection of in situ measurements. Very thin layers of supraglacial debris will enhance ice melt, but buried ice is insulated from melt once a critical debris thickness of a few centimetres is reached (Mattson et al., 1993; Östrem, 1959; Reznichenko et al., 2010). Spatial variability of debris thickness (Nicholson and Benn, 2013) and properties such as albedo, roughness, porosity and moisture content, further complicate the effects of debris cover on local glacier melt (Evatt et al., 2015). The lower...
elevations of debris-covered glaciers, i.e. the areas where melt rates are typically greatest for bare-ice glaciers, generally have thick debris which thins upglacier (e.g. Anderson and Anderson, 2016; Nicholson and Benn, 2013; Rounce et al., 2015). Supraglacial debris should consequently have an overall melt-reducing effect. However, several studies report that debris-covered glaciers in the Himalaya have melt rates similar in magnitude to uninsulated, bare-ice glaciers in the same region and at the same altitude (Gardelle et al., 2013; Kääb et al., 2012).

This debris-cover anomaly (Pellicciotti et al., 2015) may be linked to ice cliffs that form on debris-covered glaciers (Fig. 1) and provide a mechanism for high melt rates because of their low albedo and surface exposure (Sakai et al., 1998). Recent studies confirm that the ice cliffs accelerate melt locally (Buri et al., 2016; Immerzeel et al., 2014; Miles et al., 2016a; Reid and Brock, 2014; Steiner et al., 2015). However, their exact effects on and interplay with larger scale glacier melt dynamics are still largely unknown.

Ice cliffs on debris-covered glaciers are thought to form in three different ways: slumping of debris from steep slopes, calving into supraglacial ponds or by the collapse of englacial voids (Benn et al., 2012). Once ice becomes exposed, a positive surface energy budget will result in ice melt and backwasting of the cliff. The main components of ice cliff energy budget include both direct and diffuse solar radiation as well as longwave radiation from the atmosphere and surrounding debris (Sakai et al., 2002). South-facing ice cliffs (in the northern hemisphere) generally disappear quite quickly after their formation (Buri et al., 2016; Steiner et al., 2015). It is hypothesized that bases of such ice cliffs receive less incoming solar radiation than the tops of the cliffs and experience less ice melt. This causes slope relaxation and eventually burial by debris when the slope becomes less than about 30 (Sakai et al., 2002). In contrast, north-facing cliffs do not experience direct solar radiation because of shading by the cliff itself. The surface energy budget is thus composed mainly of diffuse shortwave radiation and longwave radiation from the surrounding debris and the atmosphere. Because the debris-view factor (Reid and Brock, 2014) is larger at the base, north-facing cliffs experience more incoming longwave radiation than those which tend to steepen and sustain the cliffs (Buri et al., 2016; Reid and Brock, 2014; Steiner et al., 2015).

Some ice cliffs have adjacent supraglacial ponds, i.e. water bodies of a similar scale as the ice cliffs that touch the base of the exposed ice (Fig. 1). Observations show that these ponds fill and drain over time (e.g. Benn et al., 2000; Gardelle et al., 2011; Immerzeel et al., 2014; Röhl, 2008; Wessels et al., 2002). Ponds may be filled by surface runoff, englacial conduits, or cliff melt, and drainage occurs via conduits (Benn et al., 2012; Gully and Benn, 2007). Total pond area on debris-covered glaciers is largest at the onset of the melt season, because of snow and ice melt. As the melt season progresses, and water is transported through the englacial hydraulic system, the drainage efficiency increases (Miles et al., 2016b). Energy stored in the water is transferred to the surrounding ice, conduits are enlarged, and englacial conduit collapse could lead to the formation of ice cliffs (Miles et al., 2016a). Changes in the hydrological regime from a slow distributed drainage to fast channelled drainage also has consequences for glacier velocity and deformation (Björnsson, 1998; Hewitt, 2011; Mair et al., 2010) and may therefore also contribute to the difference in pond outflux between the seasons.

When water is in contact with an exposed ice cliff, energy is transferred from the water to the cliff face through two processes. Firstly, the density/temperature relation of water causes pond circulation and promotes melt along the ice-water interface through this free convection. Secondly, wind fetch may force currents that drive thermal erosion of the exposed subaqueous ice surface (Miles et al., 2016a; Sakai et al., 2009). These processes result in thermal undercutting, notch development, and ice cliff calving (Röhl, 2006).

In recent years there have been many developments in the use of unmanned aerial vehicles (UAVs) for environmental monitoring. As the technology has advanced, their use has become a viable option for scientists to perform detailed remote sensing surveys. At present, UAVs are being used in an increasing number of fields of natural sciences (Colomina and Molina, 2014), and have been proven to be exceptionally useful and a promising tool in glaciology (Bhardwaj et al., 2016; Immerzeel et al., 2014; Kraaijenbrink et al., 2016; Ryan et al., 2015; Westoby et al., 2012, 2016; Whitehead et al., 2013). For debris-covered glaciers, UAVs offer a valuable addition to traditional measurements. Although capable of measuring the true glaciological mass balance, glaciological mass balance measurements on debris-covered glaciers (e.g. Vincent et al., 2016) require the installation of ablation stakes through a debris layer, which disturbs the surface. The spatial and temporal resolution of spaceborne remote sensing imagery is typically too coarse to study glaciers in detail. Satellite revisit periods can be considerable and atmospheric disturbances and clouds can render image scenes useless (Lillesand et al., 2015). UAV imagery fits a gap here as it allows the acquisition of on-demand, high spatial and temporal resolution imagery for continuous surfaces on a medium spatial scale of up to several square kilometres. Overlapping images acquired by UAVs can be used to create highly-accurate 3D-models and orthorectified image mosaics using Structure from Motion (SfM) photogrammetry (Snavely, 2008, 2011; Szeliski, 2011). UAV data are therefore valuable for debris-covered glacier studies, including surface feature morphology (Brun et al., 2016) and energy balance modelling (Buri et al., 2016).

Traditionally, remote sensing image classification and image entity extraction is done using pixel-based image analysis (PBIA). Every pixel is evaluated and grouped together on the image level by means of statistical clustering of pixel values, with or without the use of training samples in the clustering process (Lillesand et al., 2015). When pixel sizes are similar in size or coarser than the entities of interest PBIA is the preferred technique. On the other hand, when dealing with high spatial resolutions the analysis of objects that are constructed by multiple pixels is preferred (Blaschke, 2010; Blaschke et al., 2014). This object-based image analysis (OBIA) requires the segmentation of an image into near-homogeneous groups of pixels, i.e. objects (Baatz and Schäpe, 2000). This is performed by growing objects, starting from a pixel-scale, and iteratively merging them with neighbours. The merges are directed by relative object heterogeneity and internal homogeneity criteria that are based on

Fig. 1. Photograph of an ice cliff on Langtang Glacier with an adjacent, partly-drained supraglacial pond typically found on debris-covered glaciers in the Himalaya.
weighted spectral and shape characteristics (Trimble, 2015). OBIA techniques thus have important advantages compared to traditional pixel-based methods, and are much closer to how we as humans observe the world around us.

The set of objects that result from OBIA segmentation provide great advantages compared to the pixel clusters available in PBIA. Namely, polygonal objects can be analysed to provide more than just spectral information. Spatial, contextual, hierarchical and textual attributes of the objects allow for highly complex image analyses and classifications that can improve classification accuracy (Blaschke et al., 2014; Liu and Xia, 2010; Robson et al., 2015). As the objects consist of groups of pixels, statistical properties of each of the objects’ pixel population are also available for analysis. Moreover, multiple sources of pixel data can be used simultaneously in OBIA in both the segmentation and analysis stage, e.g. optical and elevation data. Actual classification of objects is performed via two main strategies or a combination of them: (1) by statistical classifiers such as nearest neighbour or a random forest, or (2) by rule-based classification (Lillesand et al., 2015). A difficulty with OBIA is the selection of object scale in the segmentation procedure (Addink et al., 2007; Gao et al., 2011). There is the possibility of over- and under-segmentation, i.e. either too small or too large objects with respect to the features of interest, which can result in reduced classification accuracy (Liu and Xia, 2010). Methods have been developed to mitigate the effects and provide more objectivity to the segmentation (Drágut et al., 2014), which is especially valuable for the classification of large scale areas with different entities of different sizes.

In glaciology, there have been relatively few studies that utilise OBIA. The technique has so far been used to map glacier extents (Ardelean et al., 2011; Bajracharya et al., 2015; Karimi et al., 2015; Nie et al., 2010; Nijhawan et al., 2016; Rastner et al., 2014; Robson et al., 2016), glacial lakes (Nie et al., 2013; Qiao et al., 2015), icebergs (Foga et al., 2014) and glacial landforms (Eisank et al., 2011) from satellite imagery using mostly rule-based classification strategies. Most studies combine different types of data, e.g. optical, thermal, radar and elevation, and show that such a strategy improves the classification. Rastner et al. (2014) noted that glacier outlines mapped using OBIA have an overall higher quality than those obtained by PBIA. In particular, they find that contextual OBIA resulted in a 12% improvement in accuracy.

For the delineation of surface features on the almost exclusively gray-shaded surfaces of debris-covered glaciers OBIA may be preferable to PBIA. Spectral contrast between different surface elements is low and thus analysis of shape is key. Considering high-resolution UAV data this is particularly true, as its pixel size of a few centimetres is considerably smaller than the features of interest that are usually in the order of tens of metres. A study by Watson et al. (2016) suggests that this idea is valid as they successfully mapped supraglacial ponds on a debris-covered glacier using OBIA of high-resolution satellite imagery.

In this study we analyse the spatial distribution of ice cliffs and supraglacial ponds on the lower part of the debris-covered Langtang Glacier in Nepal. The features are delineated by OBIA of UAV-acquired data of May 2014. We then systematically analyse the features based on their geometric characteristics and spatial configuration. Additionally, we use a satellite image to perform an analysis of pond presence on the entire debris-covered tongue of the glacier. Our study has two main objectives:

- To test whether quantitative data on ice cliffs and supraglacial ponds can be extracted from high-resolution imagery using a semi-automatic object-based classification approach.
- To examine the distribution and morphology of these features on Langtang Glacier and discuss their formation, dynamics and relation to the overall glacier dynamics.

2. Study area

Langtang Glacier is located in the Langtang valley in the Nepalese Himalaya (Fig. 2). The glacier has a debris-covered tongue approximately 15 km long and 800 m wide, and it is the largest glacier in the valley. The tongue ranges in elevation from approximately 4500 to 5200 m above sea level (asl), while its largely debris-free accumulation zone ascends steeply to Langtang Ri (7205 m asl). The glacier has four confluences from smaller tributaries located at approximately 1.5, 8.0, 12.0 and 13.5 km from the terminus. Additionally, avalanches that originate from the steep slopes on each side of the tongue feed the glacier at numerous locations. Glacier melt runoff from the terminus of Langtang Glacier marks the start of Langtang Khola, the main river in the Langtang catchment and an important tributary of the Trishuli River.

On the debris-covered surface of Langtang Glacier there is a high abundance of ice cliffs and supraglacial ponds. Surface velocities on the lower reaches of the debris-covered tongue range from 0 to 10 m a\(^{-1}\), with higher velocities (20 to 30 m a\(^{-1}\)) in the upper parts (Pellicciotti et al., 2015; Ragettli et al., 2016). These velocities are comparable to those observed in the same studies on the other debris-covered glaciers in the Upper Langtang Valley. Compared to Lirung Glacier, which is located further downvalley, surface velocities observed at Langtang Glacier are considerably higher. A recent UAV-based study found surface velocities between 1.5 and 3.5 m a\(^{-1}\) for Lirung Glacier (Kraaijenbrink et al., 2016).

Over the past decade, mean surface lowering of −0.89 ± 0.06 m a\(^{-1}\) has occurred on debris-covered portions of Langtang Glacier (Ragettli et al., 2016). This rate is slightly lower than that observed on other glaciers in the valley.

In this study, a ~3 km long section of the snout of the glacier is analysed first in high detail using UAV data. Subsequently, the entire debris-covered tongue is examined on a coarser resolution using satellite imagery (Fig. 2).

3. Data and methods

3.1. UAV survey

A 3 km long section of the snout of Langtang Glacier was surveyed by UAV on 7 May 2015 during clear conditions and relatively soft winds. To cover a glacier surface area of 2.7 km\(^2\) (Fig. 3) two 25-minute flights were performed with the eBee (SenseFly, 2015), a fixed-wing UAV produced by the Swiss company SenseFly. The UAV was launched from the western moraine and was programmed to land in a nearby field.

In flight, the UAV followed waypoints of a predefined flight plan at an altitude of approximately 200 m above the take-off elevation (4580 m) using its built-in GPS. The flight plan allowed for lateral and longitudinal overlaps of ~60% and 75%, respectively, and a ground resolution of ~6 cm per pixel (px). The camera mounted for the survey was a Canon IXUS 127 HS compact camera carrying a 16 megapixel sensor. The focal length of the camera’s zoom lens was set to its widest setting of 4.3 mm to increase image overlap and reduce the number of required photos and flight time. The camera’s uncalibrated RGB images are stored in the JPEG format. In total the UAV acquired 286 separate images of which seven were discarded after visual inspection because of poor image quality, i.e. exposure or motion blur issues.

In order to improve the geodetic accuracy of the output product during processing, 16 ground control points (GCPs) in the form of 1.0 by 1.2 m pieces of red fabric were distributed on the lateral moraines beforehand (Fig. 3A). The coordinates of the centre of the markers were measured using a differential global positioning system (dGPS), i.e. a Topcon GB1000 antenna with a PG-A1 receiver. This particular system...
has a reported base station accuracy of \( \sim 0.2 \) m in x, y and z (Immerzeel et al., 2014; Kraaijenbrink et al., 2016; Wagnon et al., 2013).

3.2. UAV data processing

Images from the UAV survey \( n = 279 \) were processed using SfM as implemented in the software package Agisoft Photoscan Professional version 1.1.6 (Agisoft LLC, 2014). In the workflow (e.g. Immerzeel et al., 2014; Kraaijenbrink et al., 2016; Lucieer et al., 2013; Westoby et al., 2012), feature recognition and matching algorithms are applied to the input set of overlapping images to generate a sparse point cloud via bundle adjustment (Szeliski, 2011). Camera positions and orientations, initialised by GPS coordinates recorded by the UAV for every image, are also solved in these calculations using the very high image overlap.

The sparse point cloud was cleaned from poorly localised points and false matches by thresholding the point reprojection error, i.e. the distance in pixels between a projected point and a measured one (Agisoft LLC, 2014). All points that were localised with an error larger than 0.6 pixel were removed from the cloud. Accurate georeferencing of the output product in an absolute coordinate system is achieved by introducing the dGPS-measured GCPs and adjusting the sparse point cloud accordingly. In contrast to traditional photogrammetry, this is done after the bundle adjustment in SfM (Fonstad et al., 2013).

Using the optimised camera positions and the image data itself, multi-view stereo techniques (Westoby et al., 2012) were applied to produce depth information per image and a dense 3D point cloud of the glacier surface. The dense point cloud was used to construct a gridded DEM (Fig. 3C) with a resolution of 0.2 m by averaging the points within a pixel. Additionally, the elevation information was used to create an orthomosaic with a resolution of 0.1 m (Fig. 3B). All processing steps in Agisoft Photoscan, i.e. feature matching, bundle adjustment and densification, were performed with the quality settings set to high to achieve an optimal balance between required processing time and output accuracy.

The geodetic accuracy of the DEM and the orthomosaic was estimated by measuring the difference between the GCP coordinates and their positions on the output orthomosaic \( (x, y) \) and DEM \( (z) \) in a geographical information system (GIS). Unfortunately, because of the inaccessible terrain it was not feasible within the weather window to place additional independent GCPs that could be used for accuracy checks, as all the control points were required for processing. However, as no geodetic comparison is made here between datasets from different acquisition times, this has no effect on the analyses and results presented in this study.

3.3. Object-based UAV imagery classification

3.3.1. Classification preprocessing

Before classification, UAV data were cropped to a manually digitised outline of the area where ice was assumed to be present under the debris. This pre-processing step aims to minimise the possible negative influences of non-glacier areas on the classification procedure. Six different UAV data derivatives were chosen as input to the classification: (1) blue band of the orthomosaic, (2) green band of the orthomosaic, (3) red band of the orthomosaic, (4) brightness, i.e. the mean signal of the three bands, (5) DEM and the (6) DEM-derived slope.

All three visible bands were included to utilise the limited spectral information that the UAV system provides. Elevation and slope were included because cliffs and ponds both have a specific elevation signature, i.e. relatively uniformly sloped and completely flat, respectively. However, because of the high resolution of the UAV data the local variation of the slope map is relatively large. Small scale variation in morphology of ice cliffs could negatively influence the classification of these much larger features of interest. A 3 by 3 pixel averaging filter was therefore applied to spatially smooth the slope map.
Ice cliffs generally consist of a relatively homogeneous, dark gray surface with a few lighter patches and occasionally banding patterns. Debris has a spectrally more uniform distribution because of the small boulders and the shadows they cast (Fig. 1). To make better use of this contrast between cliff and debris in the classification, the 0.1 m resolution brightness raster was processed into two different products: (1) a local brightness variation map made by applying a 5 by 5 pixel standard deviation filter, and (2) a smoothed brightness map produced using a 3 by 3 averaging filter. Finally, to reduce the influence of noise in the UAV-data and to increase the potential use of the classification procedure on similarly high-resolution satellite imagery in the future, all input data were resampled to 0.5 m.

### 3.3.2. Image segmentation

To create objects a multi-resolution segmentation algorithm (Baatz and Schäpe, 2000) was applied to the input layers in the OBIA software eCognition Developer 9.1.2 (Trimble, 2015). Most entities on a debris-covered glacier, except for supraglacial ponds, exhibit considerable variation in elevation and slope. As finding homogeneous regions drives the segmentation, elevation and slope data were thus excluded from the segmentation procedure. The object-to-object heterogeneity is determined using both spectral and shape characteristics (Benz et al., 2004), which can be weighted by the user. Ice cliffs and ponds have a distinct shape compared to the surrounding debris and therefore a relatively high weight of 0.4 was given to the shape parameter. The segmentation is also influenced by a compactness setting, which is defined by the ratio of the object circumference and the number of pixels forming an object (Benz et al., 2004). As ice cliffs are usually elongated and ponds are compact a moderate compactness setting of 0.5 was used.

The surfaces of most ice cliffs are not solely bare ice, and there are often patches of debris or snow (Fig. 1). A similar situation exists for supraglacial ponds that can contain debris mounds or floating ice. The scale of the output objects in the segmentation procedure was therefore not set to the scale of the cliffs or ponds, but the scale of these subfeatures. Because of the limited amount of features and feature scales in the study area, the optimal scale was not determined automatically (Drăguţ et al., 2014). Instead, the scale parameter in the multiresolution segmentation was determined by expert judgement, and set to 500. This provided the least (visually determined) over- and under-segmentation of the region of interest.

### 3.3.3. Object-based training, classification and accuracy

On the glacier surface four distinct main classes are present: ice cliffs, ponds, debris and snow (snow patches on debris or snow frozen to ice cliffs). For classification we first evaluated the use of a rule-based approach that used thresholds on slope, brightness and homogeneity of the objects as well as contextual rules. The rule-based approach was found to be difficult to implement as many rules would have been required to accurately classify the few objects present in the study area. Therefore, we chose to continue with a statistical classifier approach (Fig. 4) that utilised many object characteristics for classification. Classifier statistics were obtained by gathering a number of training samples randomly for each of the four classes: 20 for ice cliffs, 20 for water, 20 for snow and 50 for debris. The vast majority of the glacier’s surface consists of different types and appearances of debris, ranging from lighter to darker coloured patches. In order to obtain a representative sample population a larger number of samples were taken for this class.
To separate the classes, we use object characteristics given by the internal pixel statistics. The shapes of the cliffs, ponds and snow patches and their relations to neighbouring objects are not consistent from one feature to the next, hence shape and neighbour relations cannot be used to distinguish between classes. Debris and ice cliff objects are difficult to distinguish spectrally. On an object level, however, the two classes exhibit different textures. To describe these differences in object texture, four parameters based on the gray-level co-occurrence matrix (GLCM) were determined using the red band of the orthomosaic: contrast, homogeneity, dissimilarity, and entropy (Haralick et al., 1973; Trimble, 2015). The final object attributes selected as input for the classification procedure are the mean pixel value per object for all input data layers, the pixel standard deviation per object for all input data layers, and the four GLCM texture parameters.

A fuzzy nearest neighbour (NN) object classification procedure (Blaschke et al., 2008; Trimble, 2015) as implemented in eCognition Developer was applied to classify the object set obtained from image segmentation. We chose the NN procedure because it provided better classification results than other evaluated algorithms, such as random forests (Breiman, 2001; Genuer et al., 2012) or Bayesian classifiers (Lillesand et al., 2015; Trimble, 2015). The NN classifier predicts an objects’ class by determining a normalised difference between the average attribute value of the training set and the attribute of an unclassified object. The distances for all input training attributes are combined into a multidimensional vector and used to construct a membership function for all classes. The class with the highest membership value is assigned to the object (Trimble, 2015).

To finalise the classification a rule-based alteration was applied. Objects that were completely enclosed by cliff or pond objects were classified as cliff and pond respectively. Also, to classify the snow patches frozen to ice cliffs as cliff, all objects classified as snow that were within one object distance to an cliff object and on a slope larger than 30° were assigned the class cliff.

For the analysis of ice cliffs and ponds it is important to have a classification that is as accurate as possible, especially considering a study area with such a limited number of features of interest present. To maximize the accuracy the NN classification was altered through a multi-pass visual inspection. Misclassified objects were manually reclassified in this procedure based on expert and field knowledge. The resulting reference object set was used to create error matrices (Lillesand et al., 2015) to estimate classification accuracy. The NN classification was performed multiple times using different sets of object attributes. The estimated accuracy was then used to determine the set that provided the best classification.

To finalise the cliff and pond delineation, individual neighbouring objects of snow and debris classes were fused into single objects. The exposed ice faces of cliffs are often partially buried by debris and ponds are sometimes at a low water level that separates them into a few unconnected smaller ponds. These objects were assigned to a specific cliff or pond group by visual inspection. Finally, ponds that are assumed to be adjacent to ice cliffs for at least some time during the year were identified and jointly classified as dynamic cliff-pond systems.

3.3.4. Pixel-based classification

To evaluate the difference in classification accuracy of OBIA and PBA, a pixel-based supervised classification procedure (Lillesand et al., 2015) was performed on the preprocessed UAV data using a maximum likelihood classifier. The red band, green band, blue band and slope data were taken as input and the classifier was trained using representative samples for the classes water, cliff, snow and debris. As the small pixel size of the UAV data and the limited spectral contrast between the classes results in high-frequency classification patterns, the output was smoothed using a 3 by 3 pixel majority filter.

The accuracies of the OBIA and PBA were determined using error matrices constructed from random samples. Debris is much more abundant than the other three classes and that may impact the accuracy assessment. A stratified random sampling approach was therefore used to sample 250 random points for each of the four classes, according to the created reference object set. All 1000 points were subsequently checked visually on the orthomosaic for the actual class present at each point’s location.

3.4. Analysis of feature characteristics

Ice cliff slope and aspect as well as supraglacial pond presence are thought to be important factors in the existence and survival of ice cliffs (Buri et al., 2016; Miles et al., 2016a; Steiner et al., 2015). To assess these characteristics quantitatively, UAV-derived slope and aspect were extracted for each cliff using the classified objects. Mean and standard deviation of cliff slope and aspect were calculated and compared with exposed ice surface area, which was determined trigonometrically.

Ponds classified on the UAV imagery were analysed by their mean elevation, their area, and their relation to adjacent cliffs. The ponds appear to have highly variable concentrations of suspended sediments as their colour varies considerably from pond to pond (Takeuchi and Kohshima, 2000; Wessels et al., 2002). Pond colours range from dark blue (low sediment concentrations) to light brown/orange (high sediment concentrations). To test if the suspended sediment concentrations are dependent on pond size or the presence of an ice cliff nearby, a blue index (BI) of the ponds was calculated as:

\[
BI = \frac{\text{Blue}}{\text{Red} + \text{Green}}
\]

where the colours stand for the different image bands of the UAV-derived orthomosaic. A BI smaller than 0.5 indicates more orange

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**Fig. 4.** Flowchart of the steps and settings used in OBIA procedure used to classify the cliffs and ponds.
ponds with high sediment concentrations, and a BI greater than 0.5 indicates more blue ponds with low sediment concentrations.

To investigate the value of the UAV point cloud data for ice cliff morphology analysis, a 100 m long cross section of the UAV-derived 3D point cloud was extracted for a cliff with a large undercut using the open-source software CloudCompare (Girardeau-Montaut, 2015). From the cross section, cliff face slopes were determined using linear regression and undercut size was estimated geometrically.

3.5. Pond distribution over the entire tongue

To examine possible causes for supraglacial pond formation their spatial distribution was determined for the entire tongue of Langtang Glacier through OBIA of a 5 m resolution RapidEye satellite image from 4 March 2010. The imagery was subset using a manually digitised glacier outline, as both the recent GAMDAM (Nuimura et al., 2015) and Randolph v5 glacier inventories (Pfeffer et al., 2014) were too inaccurate for the glaciers in the study area. Previous attempts have been made to classify supraglacial ponds and lakes using ASTER and Landsat data (Chen et al., 2013; Gardelle et al., 2011; Miles et al., 2016b; Wessels et al., 2002). Classification proved difficult without using elevation data. Moreover, shadows of mountains as well as clouds caused problems for classification and require masking, which can yield difficulties for a proper classification of a single image. However, on the RapidEye imagery used here there are no shadows or atmospheric disturbances present.

For the classification, an image segmentation was performed on a small scale, i.e. the smallest objects representing ponds of about 3 pixels in size. Subsequently, 20 training samples were randomly selected for each of the classes: pond, dark debris, light debris and snow/ice. For classification of the objects a nearest neighbour algorithm was applied using each of RapidEye's five bands for training as well as a normalised difference water index (NDWI), defined as:

\[
\text{NDWI} = \frac{\text{Blue} - \text{NIR}}{\text{Blue} + \text{NIR}}
\]

where Blue and NIR are the blue and near-infrared bands of the RapidEye satellite image, respectively.

In order to determine whether pond presence is dependent on ice dynamics, surface velocity for Langtang Glacier was determined using a pair of ASTER images for the period October 2010 to October 2012. The two L1A ASTER scenes were orthorectified using 1-arc-second elevation data from the Shuttle Topography Radar Mission (SRTM) and co-registered in ENVI (Exelis, 2014). Surface displacement was determined between the preprocessed image pair using frequency cross-correlation as implemented in COSI-Corr (Ayoub et al., 2009; Leprince et al., 2007). Noise in the output velocity fields was removed by moderate non-local means filtering (Buades and Coll, 2005) from within the software.

Stresses within the ice and the resulting deformation are likely larger in areas with high curvature. To examine if this affects pond formation, the curvature of the glacier was determined by analysis of the glacier centreline. The classified ponds were finally analysed by binning them in 1 km longitudinal sections and comparing pond density to the SRTM elevation, ASTER-derived velocity and centreline curvature. These were all sampled at the glacier centreline averaged over 100 m intervals and subsequently low pass filtered to reduce noise and reveal overall trends.

4. Results

4.1. UAV data accuracy

The horizontal error of the UAV output products, estimated by comparison of the 16 DGPS-measured GCPs and the marker positions on the orthomosaic and DEM, was found to be 0.05 m on average with a standard deviation of 0.04 m and a root mean square error (RMSE) of 0.07 m. The vertical error at the marker positions has a mean of 0.08 m, with a standard deviation of 0.06 m and a RMSE of 0.11 m. Errors estimated using 10 independent GCPs in a recent study by Vincent et al. (2016) that uses the exact same UAV workflow are on average 0.04 and 0.10 in the horizontal and vertical, respectively. Compared to the cliff and pond scale these errors are small and negligible for the uni-temporal analysis performed in this study.

4.2. Image classification

The spatial subset of the UAV raster data used as input for the segmentation and classification comprised an area of 1.33 km² (Fig. 5). Segmentation of this subset resulted in a total of 5557

Fig. 5. Ice cliffs and supraglacial ponds on Langtang Glacier as classified on the May 2014 UAV imagery by OBIA. Annotation shows the numbered, grouped cliff objects that belong to the same cliff system. Additionally, cliff-pond systems are outlined with black. The extent of the imagery and elevation subset used as classification input is delineated by the dashed line. The black line at cliff 7 denotes the location of the profile shown in Fig. 8.
objects with a mean area of 240 m². We found that inclusion of the object means and standard deviations of all input layers except the DEM resulted in the highest classification accuracy. Inclusion of any of the GLCM texture parameters caused a decrease in accuracy, especially with regard to cliff delineation. Slope data, on the other hand, proved to be key as accuracy drops considerably when it is omitted. Comparison of all objects of the final NN classification with the reference object set (Table 1) shows a producer's accuracy (Lillesand et al., 2015) of 87.4% and 96.7% for ice cliffs and ponds, respectively, when considering object counts. Taking into account object area the accuracy rises to 93.1% and 98.0%, respectively, indicating that misclassification occurs mainly for smaller objects. User's accuracies are even higher, especially for object area. Kappa coefficients for the error matrix, which are a better indication for overall accuracy when having unequal class sizes (Lillesand et al., 2015), indicate good agreement between classification and reference set with a value of 0.93.

The final object set to be used for cliff and pond analysis comprised 73 separate cliffs and 77 ponds. Cliff objects were part of 22 separate cliff systems (Fig. 5). Most ponds were independent, but a few belonged to a group resulting in a total of 69 pond objects. From the set of cliffs and ponds 14 cliff-pond systems were identified. The final set of classified objects shows that 1.80% and 1.66% of the total area of this section of Langtang Glacier consists of ice cliff and pond, respectively.

Estimates of the difference in accuracy between PBIA and OBIA show that PBIA performs considerably worse on a debris-covered glacier than OBIA (Tables 2 & 3). Kappa coefficients for the classification methods are 0.463 and 0.897, respectively. PBIA has difficulty distinguishing debris from the other classes, which is especially true for the cliff class which has a producer's accuracy of only 33.7%. The classification of ice cliffs shows that there is an uneven distribution of these features over the UAV-surveyed area (Fig. 5). Upstream of the tributary confluence there are no cliffs present, while at the confluence there is a high density of large cliffs. Most of these are part of larger cliff-pond systems. Overall, the majority of cliffs (14 out of 22) are present on the south-eastern lateral half of the glacier. These cliffs comprise the bulk of the exposed ice surface area (79%). On the northern half of the glacier only a group of medium sized cliffs (cliffs 9–11 and 14–16) is present. Cliff shape varies from cliff to cliff. Some are straight and elongated, e.g. cliffs 7 and 11, while others are much more curved. Near the tributary few completely circular cliff systems that form the perimeter of a large supraglacial pond are present, (cliffs 13, and 17–18).

Ice cliff slopes are generally between 25° and 60° (Fig. 6). For the cliff-pond systems there is a small peak above 80°, which is absent for the independent cliffs, and likely related to undercuts at the pond-ice interface. More precisely, 95% of the exposed ice has a slope between 35.2° and 77.2°, and 50% of the ice area is between 35.2° and 41.7°. The mean slope for all ice cliffs is 44.6° and the standard deviation 15°. There are slight differences in slope distribution between cliffs that belong to a cliff-pond system and those that are independent. The mean slope of cliff-pond systems is almost equal, but their standard deviation and the tail of the distribution indicate the presence of few steeper slopes.

In terms of individual cliff slope statistics (Fig. 7), cliff-pond systems do not clearly exhibit the steepest slopes. In fact, among the 8 cliffs with the shallowest slopes, 7 are part of cliff-pond systems. Many of these are large systems with rather consistent slopes with small standard deviations. Only three cliff-pond systems have a relatively steep slope on average: cliffs 7, 12 and 11. Of those ice cliffs only cliff 7 can be considered large, with an exposed ice area of 4760 m².

The aspect of cliffs-pond systems on the surveyed part of lower Langtang Glacier shows a bimodal distribution with peaks at –20° (NNW) and +80° (ENE) (Fig. 6). Independent cliffs do not show this bimodal pattern but have a peak in aspect around 0° with a large right-hand tail, i.e. eastward in the polar coordinate system. Overall 19.4% of the ice cliff area faces south. For the independent

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### Table 1

Error matrix for the nearest neighbour classification and the reference classification. Matrices and confusion statistics are shown for both the object counts as the objects’ total size.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Reference</th>
<th>Object count</th>
<th>Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cliff</td>
<td>160</td>
<td>19</td>
<td>0</td>
</tr>
<tr>
<td>Other</td>
<td>23</td>
<td>4498</td>
<td>33</td>
</tr>
<tr>
<td>Snow</td>
<td>0</td>
<td>13</td>
<td>550</td>
</tr>
<tr>
<td>Snow on cliff</td>
<td>0</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>6</td>
<td>1</td>
</tr>
</tbody>
</table>

| Producer’s accuracy | 0.874 |
| User’s accuracy     | 0.889 |
| Overall accuracy    | 0.978 |
| Kappa coefficient   | 0.931 |

<table>
<thead>
<tr>
<th>Classification</th>
<th>Object area (m²)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cliff</td>
<td>19904</td>
<td>574</td>
</tr>
<tr>
<td>Other</td>
<td>1486</td>
<td>125267</td>
</tr>
<tr>
<td>Snow</td>
<td>0</td>
<td>2807</td>
</tr>
<tr>
<td>Snow on cliff</td>
<td>0</td>
<td>59</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>68</td>
</tr>
</tbody>
</table>

| Producer’s accuracy | 0.931 |
| User’s accuracy     | 0.971 |
| Overall accuracy    | 0.988 |
| Kappa coefficient   | 0.929 |

---

### Table 2

Error matrix for the pixel-based classification of the UAV data, constructed from stratified random sampling using a 1000 points.

<table>
<thead>
<tr>
<th>Pixel-based</th>
<th>Reference</th>
<th>Pond</th>
<th>Cliff</th>
<th>Snow</th>
<th>Debris</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pond</td>
<td>161</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cliff</td>
<td>1</td>
<td>81</td>
<td>0</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td>Snow</td>
<td>0</td>
<td>0</td>
<td>102</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Debris</td>
<td>85</td>
<td>159</td>
<td>142</td>
<td>259</td>
<td>0</td>
</tr>
</tbody>
</table>

| Producer’s accuracy | 0.651 |
| User’s accuracy     | 1.000 |
| Global accuracy     | 0.603 |
| Kappa coefficient   | 0.463 |

<table>
<thead>
<tr>
<th>Classification</th>
<th>Object area (m²)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pond</td>
<td>240</td>
<td>0</td>
</tr>
<tr>
<td>Cliff</td>
<td>2</td>
<td>223</td>
</tr>
<tr>
<td>Snow</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Debris</td>
<td>5</td>
<td>16</td>
</tr>
</tbody>
</table>

| Producer’s accuracy | 0.971 |
| User’s accuracy     | 0.984 |
| Global accuracy     | 0.923 |
| Kappa coefficient   | 0.897 |
cliffs and those that belong to cliff-pond systems this is 7.5% and 15.9%, respectively.

Considering the mean and circular variance of aspect (Davis, 2002) on a per cliff basis (Fig. 7), it is clear that most cliffs have relatively little variation in their aspect. Four of the largest cliff-lake systems (7, 17, 18 and 20) are not north-facing, but either west or east with a low variance. The small cliff-pond system located near the glacier terminus (cliff 1 in Fig. 5), is the only cliff that is south-facing on average. It also has the shallowest average slope. In general though, as indicated by the scatter of Fig. 7A, there is no distinct relation between slope and aspect. The per cliff variation of the parameters (Fig. 7B) does have a slight correlation ($R^2 = 0.46$).

### 4.3.2. Ice cliff cross-section

The cross-section constructed from the extracted point cloud of ice cliff 7 (Fig. 8) presents the morphology of a part of the cliff. The cliff face of 18 m in height consists of large undercut for about half of that. The low flight altitude of the UAV in combination with the wide-angle lens and oblique photos caused by UAV instability allow for the reconstruction of such overhanging parts. The maximum water depth of the pond is estimated to be ~9 m, i.e. the difference between the bed and the top of the undercut. The water level in the adjacent pond at the time of the survey is very low, it only comprises the flat area between 40 and 50 m along the profile (Fig. 5; Fig. 8). Compared to the horizontal plane, the slope of the cliff top face is 57° and the overhanging part is 123°. The size of the undercut at this cross-section is a considerable 68 m².

### 4.3.3. Supraglacial ponds

Near the terminus of Langtang Glacier the abundance of ponds is relatively low, with most ponds located further up the glacier (Fig. 5). Pond density is especially high in the triangle formed by cliffs 8, 14 and 18, as various pond clusters are present in that area. This area also houses the largest ponds. The most upstream part of the surveyed area of the main tongue, where there is an absence of ice cliffs, has again a relatively low abundance of ponds.

The distribution of area, elevation and blue index of each of the 69 ponds shows there are no clear patterns between any of these characteristics (Fig. 9). The majority of the ponds are smaller than 400 m² ($n = 59$). The few larger ponds that are present are for the most part related to a cliff-pond system. The suspended sediment concentration of ponds does not seem to be related to cliff presence, size or position on the glacier. Ponds that have high sediment concentration, i.e. low Bls, are uncommon. Only 5 ponds have a Bl of less than 0.45 and two third has a Bl that is higher than 0.50. Cliff-pond systems ($n = 14$) have a slightly lower mean Bl of 0.49 than the mean of 0.52 of the independent ponds ($n = 56$).

### 4.4. Pond distribution over the whole tongue

The longitudinal distribution of ponds ($n = 267$) over the debriscovred tongue of Langtang Glacier, determined using OBIA of RapidEye imagery (Fig. 10), is non-uniform. The number of ponds that are present in a 1 km bin decreases towards the terminus. The upper area (12–15 km from the terminus) has a high number of small ponds,
and peak pond count and coverage occurs at 11–12 km from the terminus. Most ponds in this section are present on the western lateral half of the glacier (Fig. 11), the same side as the tributary. A small peak in pond size is also present at 6–8 km from the terminus.

The ASTER-derived surface velocity of the glacier (Fig. 11) shows velocities of about 20 m a\(^{-1}\) at the most upstream part of the debris-covered tongue of Langtang Glacier. At approximately 12 km from the terminus velocities decrease over a distance of 1 km to about 10 m a\(^{-1}\). This reduction in velocity occurs at the location of the tributary and coincides with the peak in pond presence (Fig. 10). Between 10 and 8 km from the terminus, velocities decrease again to 5 m a\(^{-1}\) at a confluence and right before the peak in pond presence. The remainder of the tongue, i.e. about half of the total, experiences slow velocities in the range 0–5 m a\(^{-1}\). Surface velocities found in this study are comparable to those found using Landsat TM imagery in recent studies (Miles et al., 2016b; Pellicciotti et al., 2015; Ragentli et al., 2016). Changes in curvature of Langtang Glacier and the related stresses within the ice do not appear to influence pond presence, other than the decreased pond cover observed in the relatively straight part between 3 and 6 km from the terminus.

The ponds delineated on the RapidEye imagery for the first 2 km from the terminus show similarities and differences with the ponds classified on the 2014 UAV imagery. All RapidEye ponds appear to have been classified on the UAV imagery, except the large pond near the 1 km line, i.e. the pond adjacent to cliff 7. Pond locations shifted over the four year period between the two datasets, as a result of ice flow and ice cliff backwasting. The main dissimilarity is that a considerably larger number of ponds are classified on the UAV imagery than on the RapidEye imagery (Fig. 11), i.e. 69 versus 19. The mean pond area for UAV and RapidEye classifications is also very different, with 252 m\(^2\) and 1137 m\(^2\), respectively.

5. Discussion and recommendations

5.1. Object-based classification and feature extraction

For the spectrally uniform debris-covered surface of Langtang Glacier the semi-automatic OBIA procedure presented in this study is an accurate method to delineate ice cliffs and supraglacial ponds on UAV imagery. Especially when compared to PBIA, the value of the object-based approach is clear. As with most classifications 100% accuracy is impossible to achieve. The requirement of a modest manual alteration of the classifier’s output in order to achieve a
better dataset for further analysis shows that a fully automated procedure is not feasible, yet OBIA is a great advancement over the labour-intensive subjective manual approach. Additional analyses could utilise the cliff and pond database established here to improve the sample statistics and to develop improved rule-based classification schemes. A simple threshold method thus has considerable limitations compared to such a manual digitisation of cliff outlines. Manual digitisation is aided by expert knowledge about cliffs and may include a layer of debris or snow in order to achieve better delineation and analysis results. But this process is highly subjective. As a result, it is subject to inconsistency and not favourable for larger scale analyses. Different opinions and approaches to cliff digitisation also reduce comparability between datasets when performed by different analysts. A semi-automatic OBIA is completely objective and results are comparable and consistent, given the same type of input data. Additionally, an automated procedure makes the analysis of much larger extents and many datasets feasible.

The cliff analysis presented in this study uses a gridded DEM in which undercuts cannot be expressed. The edge of pixels that lie at the boundary between the top face and the undercut will maximally obtain slope values close to 90°. Calculations of the differences in slope between independent cliffs and cliff-pond systems are affected by this limitation and the method used in this study consequently limits the accuracy of the results. However, multiple studies have shown that for cliff-pond systems the undercuts may contribute significantly to the backwasting of ice cliffs (Brun et al., 2016; Buri et al., 2016; Ragettli et al., 2016). OBIA has disadvantages and advantages compared to such a manual digitisation of cliff outlines. Manual digitisation is aided by expert knowledge about cliffs and may include parts of the surface that are currently obscured from view by a thin layer of debris or snow in order to achieve better delineation and analysis results. But this process is highly subjective. As a result, it is subject to inconsistency and not favourable for larger scale analyses. Different opinions and approaches to cliff digitisation also reduce comparability between datasets when performed by different analysts. A semi-automatic OBIA is completely objective and results are comparable and consistent, given the same type of input data. Additionally, an automated procedure makes the analysis of much larger extents and many datasets feasible.

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Upscaling findings from in situ measurements and OBIA of UAV imagery using medium-resolution imagery such as from Landsat 8 OLI or Sentinel-2 MSI could be an important step forward in the systematic analysis of ice cliffs over large regions. Such an approach may use advanced sub-pixel classification methods, e.g. super resolution mapping (Atkinson, 2013), that are driven by the characteristics derived at the smaller scale. More accurate large scale data will mean better parameterisation of hydroglaciological models, which will improve estimates on future changes to glacier volume and river discharge.

Compared to the other methods that were used to delineate ice cliffs in the past, OBIA has distinct advantages. For example, Reid and Brock (2014) used a simple threshold of 40° on the slope and removed connected pixel groups of less than 10 m². We show, however, that substantial parts of the cliffs on lower Langtang Glacier have slopes shallower than 40°. Furthermore, 68% of the areas steeper than 40° and larger than 10 m² do not belong to the cliff class. A simple threshold method thus has considerable limitations and overestimates cliff area, while missing shallow cliffs. Other studies delineated ice cliffs on high-resolution remote sensing imagery and elevation models by digitisation (Brun et al., 2016; Buri et al., 2016; Ragettli et al., 2016). OBIA has disadvantages and advantages compared to such a manual digitisation of cliff outlines. Manual digitisation is aided by expert knowledge about cliffs and may include parts of the surface that are currently obscured from view by a thin layer of debris or snow in order to achieve better delineation and analysis results. But this process is highly subjective. As a result, it is subject to inconsistency and not favourable for larger scale analyses. Different opinions and approaches to cliff digitisation also reduce comparability between datasets when performed by different analysts. A semi-automatic OBIA is completely objective and results are comparable and consistent, given the same type of input data. Additionally, an automated procedure makes the analysis of much larger extents and many datasets feasible.

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and calibration data on volume losses can be obtained for the use in distributed energy balance modelling of ice cliffs and supraglacial ponds (Buri et al., 2016; Miles et al., 2016a). UAVs provide accurate data at high spatial resolution, and they can also be used to gather data at high temporal resolution (Immerzeel et al., 2014; Kraaijenbrink et al., 2016). Consequently, intra-seasonal changes in cliff morphology and the causes thereof can be evaluated.

A point cloud approach may also be used in the classification stages to overcome some issues and improve accuracy. As cliffs can have very steep slopes, they can be difficult to delineate from the orthogonal perspective that orthorectified UAV and satellite imagery provide. Very steep cliffs that consist primarily of an undercut may not even be detected, although this has not been encountered in this study. By developing classification methods applicable to the full 3D point cloud representation of a debris-covered glacier, such steep areas could be delineated better. This is probably also true for more gently sloping cliffs, thereby improving the analysis of cliff morphology. Full 3D representations are computationally intensive, however, which may pose difficulties for medium to large scale analyses.

5.2. Distribution and characteristics of ice cliffs

The distribution of ice cliffs and supraglacial ponds over the UAV surveyed area shows that abundance of these surface features is higher at the confluence, especially for larger cliff-pond systems. Strain on the glacier at that location is expected to be higher because the ice will experience both transversal and longitudinal compression (Gudmundsson, 1997). This supports previous suggestions that the cliff-forming processes of debris slumping and void or conduit collapses occur more frequently at high strain areas (Benn et al., 2012), caused by fracturing and hydrologically driven conduit formation (Benn et al., 2009; Gulley, 2009). Manual delineations of ice cliffs on Langtang Glacier presented in a figure in Ragetti et al. (2016) support this, as in the two main areas of deceleration there is a higher cliff density, i.e. upglacier of the confluences at 8 and 12 km from the terminus. Immediately at the confluences, however, only a few ice cliffs are present. As for the UAV-surveyed confluence, some large cliffs are already present just upstream of the confluence on the tributary itself. Consequently, longitudinal compression caused by deceleration of the tributary may be the more likely cause of their formation rather than the strain directly at the confluence itself. Also, no cliffs are present on the high-strain medial line of the confluence, although their absence here might be due to the addition of debris from the eastern moraine of the tributary glacier, causing a relatively thicker debris layer.

The existing hypothesis on ice cliff survival as a result of its aspect and pond presence is largely validated by our cliff analysis. Few south-facing cliffs are present, and more than 80% of the cliff surfaces face northwards. However, ice cliffs that belong to cliff-pond systems appear to deviate slightly from the expected pattern with the bimodal aspect distribution. This seems to be mainly caused by the two large southeast-facing cliff-pond systems at the tributary, cliffs 17 and 20. They have a consistent low mean slope of 40° and do not appear to have large undercuts present. These cliffs might survive as rapid melt on exposed south-facing ice is balanced by the subaqueous melt. Such cliffs could play an important role in the mass loss of debris-covered glaciers, as they will melt comparatively faster than others. In contrast to cliffs 17 and 20, cliff 11 also faces almost completely east, yet it has the steepest mean slope of all cliffs on the surveyed area caused by the presence of a large undercut. This is most likely because the debris view angle (Reid and Brock, 2014; Steiner et al., 2015) at the base of this cliff (109°) is greater than the angle at cliff 17 (49°), resulting in more incoming longwave radiation. Additional UAV datasets of Lantang Glacier would provide more detail on the relative backwasting rates of these cliffs compared to the other cliffs on the glacier by enabling multi-temporal analyses of UAV-derived elevation models. This could further validate the hypothesis.

5.3. Distribution and characteristics of supraglacial ponds

The RapidEye imagery reveals the presence of ponds over the entire tongue, but they seem especially dense near the decelerated areas of the main tongue at the two western tributaries. This agrees with suggestions by others that areas of low velocity and low gradient cause large scale pond development. Drainage in this area is likely reduced due to low hydrological gradients and the lack of reorganisation of englacial conduits (e.g. Miles et al., 2016b; Quincey et al., 2007; Salerno et al., 2012). However, we observe many small ponds in the upper part of Langtang Glacier as well, which is a faster flowing and higher gradient area. Also, contrary to our expectations, large ponds are absent in the region of low velocities and low curvature between 3 to 6 km from the terminus, although the slight change in gradient there might be of influence. Nevertheless, a distinct spatial pattern of pond presence with respect to velocity and gradient seems absent at Langtang Glacier.

We observe pond clustering on the main tongue just downstream of each confluence, primarily on the side of the glacier closest to the tributary, both on the RapidEye and on the UAV data. We therefore hypothesize that, in addition to factors of velocity and slope, transverse compression at confluences might promote supraglacial pond formation. Compression might result in the closure of conduits present on the main tongue and limit englacial drainage of ponds. Downglacier of the confluences the pond density reduces again as englacial drainage is no longer reduced by the confluence-induced compression. Unfortunately, the resolution and quality of the ASTER data in combination with the relatively low surface velocity at the confluences made it impossible to study the compressional flow accurately. In future research, we aim to derive accurate flow vectors using imagery from the new Sentinel 2 satellite and additional UAV surveys to further investigate the validity of the hypothesis. It is important to note that seasonality plays a strong role in pond presence (Miles et al., 2016b) and that further study of high-resolution imagery is also needed to determine if these effects at the confluences are observed during different times of the year.

Visual comparison of pond density on the RapidEye image with glacier elevation differences found for the periods 1974–2006 and 2006–2015 (Pellicciotti et al., 2015; Ragetti et al., 2016) reveal interesting patterns. In the area where pond density is largest, down-stream of the tributary at 12 km, mean surface elevation changes of −1 m a−1 are observed between 2006 and 2015. However, the pond density here would suggest greater overall surface elevation losses, and ice emergence due to longitudinal compression caused by deceleration of the tongue (Fig. 11) may play a role. Upstream of the confluence at 8 km, a reduced number and coverage of ponds was found and elevation losses for the recent period are minimal, as expected. Comparison with higher resolution geodetic mass balance studies of the glacier in the future might reveal new and improved correlations between pond presence and melt that may help to unravel these patterns.

The RapidEye classification performed in this study showed 267 ponds on Langtang Glacier, versus 53 found in a pre-monsoon Landsat classification (Miles et al., 2016b). The most likely cause of this difference is that the 5 m resolution of the RapidEye image reveals more small scale ponds than the 30 m pixels of Landsat. There may even be a greater number of ponds present, as the UAV data has revealed about 4 times more ponds than the RapidEye image. The effects of the presence of many small ponds on glacier melt have not been studied. It could be limited, but may also help to further unravel some of the spatial melt patterns observed.
6. Conclusions

In this study we have developed a method to delineate ice cliffs and supraglacial ponds on the debris-covered Langtang Glacier by using OBIA of high-resolution UAV imagery. Delineated surface features were analysed quantitatively on their geometrical characteristics and spatial distribution. Classification of RapidEye satellite imagery was performed to determine the pond distribution over the entire glacier.

Our study demonstrates that OBIA is a valuable tool for accurate delineation of surface features on debris-covered glaciers. With a combination of high-resolution UAV imagery and digital elevation models, the semi-automatic approach used here is able to objectively derive characteristics of ice cliffs and supraglacial ponds. OBIA of satellite imagery offers the potential to delineate and analyse surface features for large areas, and results can be applied to improve glacio-hydrological models. Systematic analyses of UAV-derived point clouds are a promising method for the analysis of ice cliff (undercut) morphology and evolution.

Ice cliffs present on the glacier have a predominantly northern aspect and a mean slope between 40° and 60°. Most of the large cliffs have adjacent supraglacial ponds. South-facing ice cliffs are rare and ice cliffs with aspects that deviate from the north generally have relatively low slopes and are connected to large supraglacial ponds that sustain them. Our results largely confirm current hypotheses on the survival of north-facing ice cliffs. Spatially, the ice cliffs appear to form primarily at areas where high strain rates are expected in the ice. Longitudinal compression and related englacial processes are the probable cause. Further analysis should confirm these patterns for the entire glacier.

A distinct spatial distribution of ponds over Langtang Glacier is absent. High pond densities are related to low glacier velocities and low gradients, but high pond densities are also found near cliffs. We hypothesize that the transverse compression at cliffs may close englacial conduits, limit drainage, and promote pond formation.

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References


