We are grateful to the reviewer for the highly constructive comments provided and the interest shown in the distinction between landslide mapping for disaster response and landslide mapping for scientific purposes. Here, we provide a response to both the major and minor comments in an effort to clarify the amendments that we intend to make, which are italicised throughout.

Major comments

Section 4.1: The reviewer highlights that the scale of the landslide affected area and the presence of considerable amounts of cloud cover are key drivers of the approach taken to map landslides. The approach may, therefore, be less suited to mapping in drier settings or over smaller areas. We intend to add this to our discussion, highlighting that the offset in timing between modelling and empirical mapping is likely to reduce in such instances. Further, the decision tree created for image selection (Fig. 1) can be amended to ignore reference to cloud cover. However, we feel that the general chronology of landslide assessment outputs, combined with the relative importance of image characteristics remains unchanged.

… This is an attempt to identify and develop common standards for rapid SEM for landslide-triggering events that can effectively inform humanitarian response. Prior to this, it is important to consider the wider application of the SEM approach described above. This approach was heavily determined by the scale of the rupture and the presence of cloud cover in the run up to the South Asian monsoon, both of which necessitated the collection of a considerable number of images and a means of prioritising them. In drier regions or following earthquakes or rainfall that affects a much smaller area, the chronological order of outputs is unlikely to change; however, the offset in timing between initial landslide models and the mapping of landslides using either radar or optical satellite imagery is likely to increase. The 2016 Kaikoura earthquake, New Zealand, ruptured an area 200 × 60 km in size, similar to the 120 × 80 km rupture during the Gorkha earthquake. Due to cloud-free conditions and the availability of short return interval Sentinel-2 imagery, a preliminary landslide map of 1 092 landslides was released three and a half days after the earthquake with a subsequent map of 5 875 landslides within two weeks (Sortiris et al., 2016). A smaller affected area and absence of cloud cover also requires amendment to the image selection decisions in Fig. 1, such that image cloud cover and look angle are considered less important. However, the availability of imagery in Google Earth remains critical, and the order of importance of the spectral resolution, spatial resolution, and swath widths are likely to remain unchanged. In arid environments, the occurrence of landslides may be less detectable by spectral changes to the land surface than by morphological changes. A judgement may, therefore, be required as to the relative importance of image spectral and spatial resolution.

Section 4.3: The reviewer highlights that the development of automated and semi-automated mapping techniques, combined with the availability new satellites, such as Sentinel-2, requires greater attention. Though Sentinel-2 imagery was not available following the Gorkha earthquake, having used this for subsequent landslide mapping, we agree that reference to the potential for short return interval, medium spatial-resolution, high spectral resolution imagery requires discussion and intend to add this. We feel that automated mapping is ideally placed to sit (chronologically) between landslide modelling and empirical landslide mapping. However, for the purpose of disaster response, its reliability varies considerably (for example based on the time of year) and requires considerable manual validation prior to dissemination (as presented in the paper).

… Automated and semi-automated methods hold potential for more time efficient landslide mapping, with the speed gain over manual methods increasing with the area to be mapped. In the context of landslide-triggering disasters, these methods can be broadly divided into those that detect landslides using post-event images, and those that rely on change between pre- and post-event images. Analysis of post-event imagery, often through supervised and unsupervised classification, draws upon the spectral signature of each pixel to distinguish failures from other land cover types. Techniques that define landslides using pre- and post-disaster imagery rely on changes to the spectral signature of each pixel, most often quantified as the Normalised Difference Vegetation Index (NDVI) or the image spectral angle. However, a reliance on the spectral response of a landscape to mass-wasting has two disadvantages for landslide mapping. First, discernible changes in the spectral response may only occur as a result of high-velocity failures induced by a single event, or as a result of failures occurring within densely vegetated areas. Second, misclassification of channel bank erosion and

fluvial sedimentation, instead of landsliding, as well as the misidentification of reactivations may also occur. Ultimately, these techniques typically generate many more landslides than manual image interpretation due to the misclassification of non-landslide land cover types and the division of large landslides into multiple fractions, owing to the pixel-based approach to image segmentation (Borghuis et al., 2007). While the increasing availability of VHR imagery directly enhances the accuracy of manual landslide mapping, the results of automated and semi-automated pixel-based methods that have used VHR imagery are susceptible to large spectral variance between pixels, creating intra-class variabilities, and are more sensitive to coregistration errors (Moine et al., 2009; Martha et al., 2010; Mondini et al., 2011). The development of object-based image analysis (OBIA) approaches overcomes many of the issues associated with pixel-based classification, by accounting for other metrics such as color, texture, shape and topography (Stumpf and Kerle, 2011). Such techniques may benefit considerably from the rich spectral information gathered by medium resolution sensors, such as Sentinel-2, and short revisit periods that enable access to pre-event datasets. However, the selection of useful object metrics varies from case to case and the time required to prepare the algorithms, refine the parameters, and manually validate the results may exceed that required for manual mapping of the entire area. While it can be argued that the benefit of automated methods over manual methods increases with the area to be mapped, larger areas increase the reliance upon imagery from a variety of sensors. The application of semi-automated and automated mapping with variable image characteristics and quality is yet to be reported. Future research into the use of Sentinel-2 imagery in (semi-)automated landslide mapping is therefore required, but may yield an important medium between manual landslide mapping and landslide models in the aftermath of a trigger event (e.g. Stumpf et al., 2017).

<u>Section 4.3:</u> It is noted that SAR is not included in the paper. The authors agree that this requires discussion and will, therefore, be examined in relation to mapping the potential of large-scale failures to result in potentially hazardous damming or aggradation of the channel network.

… In instances where cloud cover is prominent, the use of satellite-borne radar also has the potential to provide an assessment of large landslides that sits between landslide models and manual mapping from optical imagery. Large failures may be rapidly identified by large morphological changes, such as shifts in the channel network. Alternatively, a large-scale shift in the dielectric constant of the slope, as vegetation is removed, may be detected by changes to the amplitude of the backscattered waves (Jin et al., 2009; Mondini et al., 2017). In this manner, SAR amplitude/intensity images have been used to map single landslides at the slope scale (Raspini et al., 2015; Plank et al., 2016) and, more recently, at the catchment scale following triggering events (Casagli et al., 2016; Mondini et al., 2017). However, SAR imagery requires a considerable amount of complex pre-processing and the accuracy of change is affected by the image acquisition geometry, which can be sub-optimal in mountainous regions.

Minor comments

<u>P2 L26-30:</u> The reviewer identifies the statement that, in the longer-term, uncoordinated mapping efforts result in multiple different inventories of the same event as misleading. In the case of the Gorkha earthquake, we highlight that a five-fold increase in landslide numbers occurred within published inventories. While we agree that some of these inventories were created in the aftermath of the disaster, the scientific inferences made from them assume that their coverage of the affected area is complete. We agree that the flagging of the inventory aim and resolution of mapping should be advocated in the text.

… While some of these inventories were created in the immediate aftermath of the disaster, their use for scientific purposes nevertheless assumes complete coverage of the affected area. The resolution of mapping and the approach taken should therefore be stated clearly alongside the purpose of the inventory.

<u>P4 L12:</u> Our initial effort focussed on the relatively populous middle-Himalaya. As noted by the reviewer, debris flows, flooding and landslide dams that are sourced in the Higher Himalaya also have potential hazardous impacts in this region.

Given that our mapping included a number of debris flows, the length scale of their impacts were covered in the mapping. We acknowledge the importance of landslide dams in P9L5, but intend to clarify that, once identified, we monitored dams in subsequent imagery until they had breached. With regard to flooding, we intend to add this into the text. While our expertise does not lie in hydrology, and the, the landslide data was made available for others to use to assess the potential for flooding.

… Given the potential for secondary earthquake hazards with downstream impacts, the high Himalaya were not omitted from the mapping. Our mapping coverage was consistent with the length scale of debris flows runouts, and initial searches for landslide dams were paramount. Once identified, these were monitored until breached.

P6 L25-30: The reviewer seeks clarification over the phrasing '… small in comparison to the area that experienced shaking sufficient to trigger landsliding (~35 000 km^2)'. As noted by Marc et al. (2017), this definition is often variable within published coseismic landslide studies. The estimate was initially made in the aftermath of the event, referring to the mountainous area of Nepal that experienced moderate or stronger shaking according the USGS ShakeMap output, as well as from initial modelled probabilities > 0.5 (see: http://ewf.nerc.ac.uk/2015/04/25/nepal-earthquake-likely-areas-of-landsliding/). This matches with an envelope containing all mapped landslides at the end of mapping, irepective of landslide density within the envelope. As noted by Marc et al. (2017), this definition of the landslide-affected area is similar to that by Keefer (1984) and Hancox et al. (1997). We acknowledge that a more clear definition is required and have amended the following statements in light of this.

P6 L22 … Given the prevalence of cloud cover and off-nadir viewing angles, imagery was drawn upon from a wide range of sensors. Based upon the mountainous areas of Nepal that experienced moderate to severe shaking, as estimated by ShakeMap, the area of shaking sufficient to trigger landslides was approximated at 35 000 km^2. This estimate was supplemented by the spatial distribution of modelled landslide probabilities > 0.5 (see: http://ewf.nerc.ac.uk/2015/04/25/nepal-earthquake-likely-areas-of-landsliding/). With the exception of the EO-1 Advanced Land Imager (ALI) and Landsat 8, the swath width of sensors such as WorldView-2 (16.4 km at nadir) and WorldView-3 (13.1 km at nadir) were small in comparison to this area, and so large numbers of relatively small-footprint images were needed for complete coverage.

P6 L28 … While having a high spatial resolution (~3 m) and short return period, PlanetLabs imagery had a small image footprint (~50 km^2) relative to the affected area.

Our subsequent description of the polyline used to delimit the southernmost extent of landsliding on P9 L15-18 refers to the zone of most intense landsliding. The area above this line matches the final zone of intense landsliding mapped by ourselves and subsequently by Martha et al (2016), ca. 12 000 km^2. This has been amended and added to the text in the following locations.

P9 L15 … The aim of this was to delineate the southernmost limit of major landslide disruption, and hence the likely northern limit of unimpeded road access, using the predominantly north – south oriented drainage network. This was mapped as a solid line where the limit was observed and a dashed line where the limit was inferred in the absence of imagery. Subsequent mapping showed this line to be an accurate estimate, with the area of intense landsliding (ca. 12 000 km^2) matching our own final product and that of Martha et al. (2016).

P4 L19-21… A rapid appraisal of the first available imagery suggested that the most intense landsliding occurred in an E-W swath located north of the Kathmandu Valley, covering a large proportion of Western and Central Nepal (12 000 km^2).

P7 L3-4: The reviewer notes that the syntax of this line is awkward, with the following suggestion: 'For example, with WV2 and WV3, [...], the ability to distinguish [...] was reduced due to the lack of multispectral imagery.' In light of this, we have made the amendment presented below.

… In the case of WorldView-2 and WorldView-3, although panchromatic imagery provides greater spatial resolution, the ability to distinguish vegetation from freshly exposed bedrock and regolith in landslide scars was reduced due to the lack of multispectral imagery.

P8 L9: The reviewer highlights a mistake in the citation of Marc *et al*., which is corrected in the below statement.

… and local site geology (Meunier et al., 2008; Parker et al., 2015; Marc et al., 2016).

P8 L15: The reviewer asks for more information regarding the discrepancies between landslide models and the landslide mapping. We feel that these discrepancies are beyond the scope of this paper given that such an analysis would require comparisons of multiple different landslide models and that these have been discussed by others, such as Gallen et al. (2016). However, we intend to add that the overestimation of landslide probabilities south of Kathmandu in Sivalik Hills occurred.

… Comparisons between predicted landslide density and observed landslide density have since highlighted some important discrepancies (Gallen et al., 2016), including an overestimation of landsliding to the south of Kathmandu in the Sivalik Hills.

P8 L27: We agree that '… verifying the extent of landsliding predicted by the landslide models by examining small gaps in cloud cover within satellite imagery', requires clarification. As noted by the reviewer, verifying such a model would not be possible if the area viewed refers to a single, distant area with a complex distribution of landslide probabilities.

… This gap in cloud was ~120 km from the epicentre and provided an initial assessment of the nature, type and density of landsliding in the area, as well as supporting modelled estimates of the extent of the area affected by landsliding.

P10 L10: As noted by the reviewer, quantifying our underestimation of landsliding as the difference in number is uninformative. A ratio or percentage is suggested and amended accordingly below.

… Underestimated the number of landslides by a factor of five (up to ~19 000 landslides). However, the spatial pattern and relative intensity closely adheres to those described in both Martha et al. (2016) and Roback et al. (2017), suggesting that small areas of cloud cover, the spatial resolution of mapping, and the distinction of separate failures was lower in our approach.

P10 L27: The reviewer highlights a missing word at the end of the sentence, which is added below.

... particularly if this area is otherwise inaccessible.

P11 L1: The reviewer suggests adding the missing word ‘model’. This is added below

... Seeding an empirical landslide model with the initial rapid mapping

P11 L4: The reviewer highlights that training a landslide model using a small number (~10^2) of landslides requires that they are well distributed across the affected area and across diverse lithological settings. This is discussed by Robinson et al. (2017), to which reference is added below.

... Robinson et al. (2017) found that a small number of landslides could be used to train landslide models as long as their spatial distribution covered a large portion of the affected area.

P12 L17-35: As with major comment #2, the reviewer highlights that the discussion of automated mapping requires broadening, for example, with the potential of Seninel-2 imagery. While we do make reference to the potential of Sentinel-2 imagery at P13 L7, we have added this to the discussion of (semi-)automated methods in the amendment of major comment #2.

P13 L10-15: Given that both Sentinel-2a and 2b are now operating, the reviewer notes that our description of the reduction in revisit time from 10 days to five can be shortened. We have revised this sentence in light of this.

… In addition, the shorter return period (five days for Sentinel-2a and -2b, compared to 16 days for Landsat 8) will increase the probability of observing the ground through gaps in cloud cover, reducing the time needed to process outputs. Our effort demonstrated that once imagery is available, mapping can be rapid (two to three days), given suitable capacity.

Amendments to Table 2

The reviewer comments that the phrase ‘full inventory’ is ambiguous. We have revised instances where this is used below.

P23 *... Can be assessed qualitatively without the need for full coverage with each individual landslide identified*

P23 *... Potentially rapid generation of a polygon-based landslide inventory across the entire affected area*

P24 *... Not reliant on having a landslide inventory of full coverage*

P24 *... relatively quick to create an inventory of full coverage*

P24 *... Landslide mapping: Full coverage*

Amendments to Figures

Fig. 1: The reviewer suggests that indicative values should be added to the decision tree for image prioritisation. While certain characteristics were quantified during our selection process (e.g. cloud cover < 20%), we feel that the importance (and potential for use) of this figures lies in the order in which image characteristics are prioritised for this particular type of SEM. We are therefore hesitant to add indicative values, given that such values may not be applicable to earthquake-induced landsliding in other settings.

Fig. 3-6: We agree that showing our image footprints through time could be useful; however, the mapping was not linear through time in terms of downloading imagery from HDDS Explorer and mapping from it in ArcMap. This was because bundles of mosaicked imagery were also iteratively released through Google Crisis. Furthermore, while the spatial resolution and timing of imagery is likely to broadly correlate with mapping progress, we feel that the considerable variability in image distortion and cloud cover would perhaps be overlooked.

Amendments to References

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