Response to Reviews for Emberson et al. 2020 NHESS-434

Dear Editor,

We greatly appreciate that you coordinated two thoughtful and helpful reviews for our study. We are glad that the reviewers seem to see the originality and value of our study. Both reviewers raise important points that we are happy to acknowledge to improve our study. We feel that we are able to effectively respond to each of the reviewer comments in a way that answers their concerns and therefore enhances the study. Below, we discuss the comments from both of the reviewers and explain the ways in which we have addressed the issues raised. For most of the comments, we have already made changes, which are detailed for the relevant comments. There are other comments where we are still working to implement the changes (including in some cases reanalysis). In these cases we describe the approach that we are taking to address those changes. We look forward to your editorial consideration of our response.

Yours sincerely,

Robert Emberson, on behalf of all authors.

R1:

This is a really interesting paper, that I definitely think contributes something that doesn't currently exist: a homogeneous global measure of landslide exposure. The manuscript is well-written and there are not many problems with it that I can see.

We thank the reviewer for their supportive words, and we are glad they have identified the originality of our study as a strong point. We feel that the comments from this reviewer have allowed us to significantly improve our study.

One general comment I would make is that the LHASA model is focused on modelling rapid landslides, and states that it may be less useful for estimating the occurrence of slow moving landslides. This is fine in terms of your estimation of population exposure, but you also consider damage to infrastructure which may be effected by slow-moving landslides and, so I think it should be stated somewhere that you are mostly considering rapid landslides to avoid confusion.

This is an excellent point, and we appreciate the clarification. We have added the word 'rapid' in several places to clarify the type of failure we are studying, and have additionally added text to the end of the discussion section to address this:

"In addition, the LHASA model only models rapid landslide failures in natural settings. This means it does not capture landslides resulting from anthropogenic influence or slow-moving landslide events, which lead to a significant number of fatalities every year (Petley, 2012). Constraining exposure to this kind of failure is another important subject for future studies."

Specific comments

Line 55: From the wording of this sentence, it is not entirely clear whether it is the output that is at 1 km resolution or the input data (I assume it's both?)

We have rephrased this sentence to explain that the model outputs are at 30 arc-second resolution (approx. 1km at the equator).

Line 155: I agree - could this error be quantified better though, by comparing areas for which there is a relatively complete catalogue of landslides with the number of nowcasts received in that area?

This is a good point, but does raise some significant questions. There are inventories that are spatially complete mapping of landslides for given rainfall events, but multi-temporal mapping of landslides over even moderate time intervals is significantly less common. In order to effectively answer the question posed by the reviewer here, we need a multi-temporal inventory with year-to-year changes in landslide location mapped at relatively fine resolution. While such mapping has been conducted for some small portions of the earthquake-affected areas such as Nepal after the 2015 earthquake, the LHASA model is not designed to factor in post-earthquake changes in landslide susceptibility, meaning those inventories are not a fair test case. We are unaware of multi-temporal inventories mapped at the required temporal sampling (close to 1 year or lower, to maximize the comparison with short term nowcast outputs) in published literature. Italy has undertaken a tremendous effort to create multi-temporal inventories in many regions; however, these are typically done at 5 year intervals and is not fully comprehensive. The lead author (Emberson) has worked with multi-temporal inventories in the Western Southern Alps of New Zealand, but the mapping frequency is approximately decadal, rather than yearly, which we do not feel is appropriate for comparison with LHASA outputs. We stress that if the reviewer or other reader is aware of such an inventory in published literature, we would be delighted to hear about it, as it would represent an exceptional test of our model outputs, which the reviewer correctly points out would be a valuable step forward.

Line 247 - which average? mean?

Good catch! We have amended to clarify that this is the mean.

Figure 3 - Exactly what has been normalised by what is not really clear here e.g. in the text, it states that the population is normalised by country area but in the Figure it describes the Nowcasts as normalised but not the population

Again, thank you for catching this. We have amended the text to correct this; the figure shows Pop_exp vs area-normalised nowcasts. Pop_exp is not normalized by area. This should clear up the discrepancy.

Line 283 - I agree that this would be a useful application of the study you have done here, but given the scatter in Figure 6, it seems that the uncertainty in y value for a given x must be very high.

We agree that this relationship is at present only loosely defined. We do not attempt to use it in an interpretive way here. We have added the following text to emphasise the point of the reviewer:

"However, the degree of scatter evident in Figure 6 suggests that further data is required to explicitly define such a relationship, and error margins may be large"

Figures 7 & 8 - The conclusions you draw from Figure 7 could also be drawn from 8, so I am not convinced you need both

While we acknowledge that the same data is shown on the y-axis for both figures, we feel that Figure 7 allows for clearer comparison of countries in each continent, which are rather overlapping in Figure 8. Unless directed by the editor, we are inclined to keep both figures to ensure clarity.

Line 344 - As the Petley dataset includes anthropogenic-induced landslides, could this account for some scatter in Figure 5?

As discussed above in our response to the main comment, we have added text here to incorporate this point. The reviewer is absolutely correct and we appreciate them bringing it up here! New text:

"In addition, the LHASA model only models rapid landslide failures in natural settings. This means it does not capture landslides resulting from anthropogenic influence or slow-moving landslide events, which lead to a significant number of fatalities every year (Petley, 2012). Constraining exposure to this kind of failure is another important subject for future studies."

Technical comments

Figure 1 & the top Figure in Figure 2 have very small numbers for the bin sizes that are quite hard to read

Increased font size for bin sizes; thanks for pointing this out!

Line 158: estimate 'of' exposure, rather than 'for' exposure

Changed to 'estimate of'.

Line 259 - Do you mean misrepresent instead of miss?

Changed to 'misrepresent'.

Line 281 'further highlights' not 'does further highlight'

Changed to 'further highlights'.

Reviewer 2:

I enjoyed reading this paper and especially enjoyed looking at the maps and figures. It tackles an interesting and large problem of modeling relative landslide exposure worldwide. I think the topic the authors address is worthy of being published and the results will be of interest to many. However, the manuscript and results are not yet ready for publication. In particular, there is some potentially flawed logic and confusing methodological choices that need to be sorted out or clarified. I summarize the major points of confusion or issues that I feel need addressing below, and then provide line by line comments below.

We thank the reviewer for taking the time to provide an extremely thorough and thoughtful review. We certainly appreciate the support for the study concept, and acknowledge that there remains room for improvement. All of the comments are helpful and have allowed us to improve our study. We have provided individual responses to each of the comments below.

1) The authors say they are modeling landslide exposure globally, and though they do not specify, from the context they give I assume they mean as it exists now or in general. However, I do not think that is actually what they are modeling. By using past weather data, they are modeling what landslide exposure WAS averaged over the time period of the IMERG data. There were likely some extreme weather events in those 19 years that hit some countries and caused elevated Popexp values in this analysis that will not happen again in the next 19 years, there will be new extreme events that did not happen in the last 19 years, and also all bets are off with climate change.

The reviewer raises a good point here, and is absolutely correct that our model outputs are inappropriate for assessment of exposure under future climatic changes. We have adjusted the text in several places to better stress this, as well as highlight the value of longer term historical data and future climate data to better quantify exposure.

End of introduction: *"While the model outputs are an approximation of exposure to hazard based on historical rainfall trends, we note that future exposure patterns could be explored with the use of rainfall projections for future climate scenarios."*

In discussion section: "*In addition, since the nowcast-based estimates of hazard are based on historical rainfall data, they do not provide effective prediction of future exposure to hazard. This is particularly important given the potential for climate change to affect rainfall-driven hazards (Kleinen & Petschel-Held 2007). Our model estimates of exposure would also fail to capture rainfall driven exposure to landslide hazards in periods outside of the IMERG v06B record (pre 2001), including major rainfall-driven landslide events resulting from the 1998 El Nino event (Coe et al. 2004, Ngecu & Mathu 1999). We stress that the model outputs are representative of the historical period under analysis, rather than strictly speaking a long-term average."*

2) The second major issue I struggled with was conceptualizing the physical meaning of the various metrics they use as proxies for exposure. What is the physical meaning of population exposure, road exposure and infrastructure exposure, as currently computed? What am I supposed to make of "nowcast density" or the inclusion of the vague concept of nowcasts in the units? Nowcasts are a fuzzy concept in themselves and then the authors convert it to another confusing metric, a rate of unknown timescale and a density over, I assume, time(?), it doesn't mean anything to me and is really hard to wrap one's mind around. Why not at least do something more tangible like number of days per year of elevated landslide hazard? Or alternatively, the percentage of the time that a given cell has an elevated "nowcast"? Nowcasts represent relative landslide hazard for 3 hour time periods, so either of those seem easy to compute and would make a lot more sense. It would give the units with some physical meaning, albeit still somewhat vague: e.g., people-hours/year/km2 exposed to elevated landslide hazard or percentage of the time landslide hazard is elevated/person/km2. Either would be much clearer in my opinion than the bizarre units and metrics currently used and also easier for other people to use or compare against in future studies.

We are grateful to the reviewer for raising this point, as it has helped us improve our message and clarify the terminology. We have extensively revised several sections of the text to explain the physical meaning of a nowcast, and have propagated that understanding throughout the rest of the text. We have not removed all mention of nowcasts, since to do so might lead the reader to believe that we are using a different hazard proxy than what we derive from LHASA. However, we feel that in explaining the physical meaning and clarifying the usage throughout the text, we have reduced the ambiguity highlighted by the reviewer here.

Changes to text:
Section 2.1: "*For the purposes of our study, we use the daily nowcast output. The physical meaning of one nowcast is 24 hours of elevated landslide hazard for a 30 arc-second dimension pixel."*

Section 2.2: Revision of table 1 to explain units of exposure more accurately; we replace the term 'nowcast' with 'days exposed to landslide hazard'. This means that Pop_exp is (Days exposed to landslide hazard) x (persons) per year per km^2.

3) The authors seem to conflate their modeled results with observations/ground truth and also conflate their modeled proxy for population exposure with actual population exposure. The authors need to always be clear that they are presenting modeled results and proxies, NOT data or observations. I have noted some of these instances in the line by line comments.

This is a very important clarification, and one we appreciate from the reviewer. It is absolutely correct that these are model outputs, rather than ground-truth. We have revised the document to clearly state this difference, including by adding 'model outputs' where possible to drive this home. We have also addressed the individual line-by-line edits below.

4) The writing is sometimes hard to follow. There are many run-on sentences and some confusing and/or convoluted logic, especially in the abstract and introductory sections. I have pointed some of these out in the line by line comments.

We thank the reviewer for taking the time to highlight these places. Clarity is obviously key here, so all the input is appreciated! We have addressed the individual comments below.

5) Critical details are missing about the LHASA model updating that was done, the validation of the updated model (against, presumably, the inventories that were previously discussed as being biased?) as well as the uncertainty estimation.

Again, this is an important point and we are grateful to the reviewer for highlighting it. We did not make significant changes to the methodology of Stanley & Kirschbaum (2017) when updating our susceptibility map, but it is still necessary to provide more details as well as provide quantification of validation. As such, we have added text to the methodology section to explain the model in more detail. We have also calculated the ROC-AUC value for the updated susceptibility map with the Global Landslide Catalog as validation.

New text: *"This fuzzy overlay model uses heuristic weighting of the input variables, defined by Stanley & Kirschbaum (2017). We do not adjust the weights attached to the variables in the study here. We assess the accuracy of the new susceptibility map in the same fashion as in the study of Stanley & Kirschbaum (2017), by using the NASA Global Landslide Catalog locations to test the ROC-AUC values. Using the same GLC data that was used to calibrate the previously published version of the susceptibility model (GLC data snapshotted 2016/01/14, we calculate an ROC-AUC value of 0.822, essentially identical to the value obtained for the prior model (0.82). For the purposes of our analysis, we follow Stanley and Kirschbaum (2017) and divide susceptibility into multiple classes, and use the threshold between 'low' and 'moderate' susceptibility as a threshold for nowcasts to be generated if rainfall exceeds the historical 95th percentile. Less than 25% of landslides recorded in the GLC occur below this threshold. For the purposes of this study, we combine moderate and high 'nowcasts' together to provide a proxy for hazard that captures the bulk of landslide activity."*

6) One point needs clarifying: the authors state that they normalized the areas by squared decimal degrees rather than km2 for country-wide statistics. Do they mean they used the latitude and longitude grid? If so, that is going to skew the normalization pretty dramatically for countries away from the equator. That normalization needs to be done in units that preserve area for the proxy to be globally consistent and comparable from country to country.

We thank the reviewer for bringing this up as it allows us to fix a key issue with the initial manuscript. While we had initially described results as 'approximately 1km resolution', this is strictly speaking not true as all input data is either directly sourced at 30 arc-second resolution or (in the case of roads and infrastructure) calculated on a grid at that resolution. As such, normalization by dividing by area in square decimal degrees does preserve the area for the proxy. We have adjusted the text to explain everywhere that this is at 30 arc-second resolution, rather than 1km resolution.

Line by line:

Abstract: The logic of the abstract does not make sense to me. It introduces the problem of inventories being biased away from areas where human settlement or infrastructure are, but then it says in order to address this limitation, they are going to model global exposure to landslide hazard. . .but that isn't addressing the problem they raised in the previous sentence, they raised the problem of landslides in remote areas far from humans. It's also unclear what gaps in the inventory-based estimates (what estimates/estimates of what?) they are filling in. Then on line 17, they say they compare levels of landslide hazard "mitigation" between countries but they don't look at mitigation at all in the paper. Overall, the abstract is really confusing and could probably be rewritten.

The reviewer raises a good point here, since there is indeed some logical inconsistency in the abstract. We have revised it extensively to fix this:

"Landslides triggered by intense rainfall are hazards that impact people and infrastructure across the world, but comprehensively quantifying exposure to these hazards remains challenging. Unlike earthquakes or flooding which cover large areas, landslides occur only in highly susceptible parts of a landscape affected by intense rainfall, which may not intersect human settlement or infrastructure. Existing datasets of landslides around the world generally include only those reported to have caused impacts, leading to significant biases toward areas with higher reporting capacity, limiting how our understanding of exposure to landslides in developing countries. In this study, we use an alternative approach to estimate exposure to landslides in a homogenous fashion. We have combined a global landslide hazard proxy derived from satellite data with open-source datasets on population, roads and infrastructure to consistently estimate exposure to rapid landslide hazards around the globe. These exposure models compare favourably with existing datasets of rainfall-triggered landslide fatalities, while filling in major gaps in inventory-based estimates in parts of the world with lower reporting capacity. Our findings provide a global estimate of exposure to landslides from 2001-2019 that we suggest may benefit disaster mitigation professionals."

L36 – though it is stated later, since the authors mentioned "near-real-time" here and that has many different meanings, I would suggest moving the info about how often it is updated and with what delay here.

We have updated the paragraph to more explicitly define the previously published LHASA model, explaining the 50N-50S spatial extent and explaining the 4-hour latency of results.

L39 – why "near global"? what is missing?

See prior comment – added in text to explain that the previously published LHASA outputs are 50N-50S.

L44-46 should be in the abstract

We agree with the reviewer that this sentence was not appropriate for this position, so we have removed it and merged the text with the prior paragraph. The abstract has been revised to accommodate other comments from this reviewer, so we have not moved this sentence there.

L49 – I would just delete the part of this sentence after the semicolon, no one should be using a global map at 1 km resolution for evaluating landslide hazard except as a way of looking at overall trends or patterns on a global/continental scale.

Thanks for pointing this out – the text is definitely unnecessary and inappropriate. We've deleted it.

L50 – what pixel resolution? And I didn't think LHASA modeled exposure, does it? Isn't that what this paper is about?

Thank you for flagging this confusion; we have rephrased this accordingly:
"Our exposure model outputs derived from the LHASA model provide an estimate of exposure seasonality at 30 arc second resolution across the globe"

L51 – it does not provide a "clear picture", that phrasing implies that it is reality. It is a model. An estimate. The authors should be clear about that here and throughout.

We have rephrased this to "to provide a more spatially consistent picture of the impacts associated with landslides"

L54 – I find the concept of an "average rate of hazard Nowcast' to be very convoluted. See my earlier comment about a suggested alternative.

Removed this sentence as part of rephrasing the opening paragraph to the methodology section. We have revised this to emphasise that we draw the hazard estimates from the updated LHASA model, as well as clarify the resolution (30 arc-seconds):

"*To estimate exposure to landslide hazard, we must first derive the estimates of hazard itself. For this study, we have utilised the outputs of an updated version of the LHASA model as an approximation for hazard, which we can then combine with openly available datasets of infrastructure at a 30 arc-second resolution across the world."*

L57 – what is a "landslide climatology"?

Rephrased this sentence: "*These maps of exposure, both annually and estimated for each month to analyse seasonal variability"*

L69 – what are these thresholds based on? Also, is it the ARI that is modeled based on the susceptibility layer or the threshold that the ARI must exceed? Please clarify.

Added text to clarify: *"If the ARI value exceeds a threshold (historical 95th percentile for rainfall)"*

L74 – Forest loss since when?

Thanks for flagging! We have amended the text to explain that this is forest loss since the year 2000.

L75-79 – I found this description very hard to follow, can it be clarified?

We have made adjustments to this section to hopefully improve clarity.

L79-80 – More info needed on the methodology (generally, what is it based on/how does it work/how is it validated) even if the readers can still look to the original paper for the nitty gritty details.

We appreciate the need for more detail on the methodology. We have added more text to explain the susceptibility model detail, as well as to address major comment #5, above. Please note that as in comment #5, above, we are still in the process of calculating the updated ROC-AUC values, so while these will be included in the revised version of the manuscript, we have not been able to include them in the author response part of this review process. New text:

"*This fuzzy overlay model uses heuristic weighting of the input variables, defined by Stanley & Kirschbaum (2017). We do not adjust the weights attached to the variables in the study here. We assess the accuracy of the new susceptibility map in the same fashion as in the study of Stanley & Kirschbaum (2017), by using the NASA Global Landslide Catalog locations to test the ROC-AUC values. The updated model values are: [to be added]. For the purposes of our analysis, we follow Stanley and Kirschbaum (2017) and use susceptibility values of greater than 0.49 (on a 0-1 scale) as a threshold for nowcasts to be generated if rainfall exceeds the historical 95th percentile. [X] proportion of landslides in the GLC occur in areas above this threshold. For the purposes of this study, we combine moderate and high 'nowcasts' together to provide a proxy for hazard that captures the bulk of landslide activity."*

L89-90 – How is landslide activity anticipated? Need more details here about how these thresholds are chosen since that ultimately controls all the results of this paper. . .

We have revised this section, so that it is hopefully now more clear:

"The LHASA model generates a hazard 'nowcast' if rainfall exceeds the historical 95th percentile. Since the updated model uses IMERG v06B rather than TMPA, we have therefore re-calculated the historical 95th percentiles of a 7-day weighted rainfall accumulation. This provides a global 95th percentile map; if ARI values exceed this threshold, a hazard nowcast is issued."

L92 – I thought there were different levels of "nowcasts", how are those dealt with in this averaging?

We have addressed this in the updated discussion of the LHASA methodology, as detailed in the response to comment #5, above. The new text is as follows:

"For the purposes of this study, we combine moderate and high 'nowcasts' together to provide a proxy for hazard that captures the bulk of landslide activity."

L108-109 – They happen to line up as well? Didn't you have to resample one to the other?

As discussed elsewhere, this is actually one of the advantages of using this data. The GPW v4 data and the LHASA outputs are derived at identical resolutions – 30 arc-seconds. This means no resampling is necessary. Ultimately, resampling the population dataset to get at a 1km dataset ultimately requires interpolation of data and the assumption that to do so does not inhibit the data quality. As such, we feel that the current lat-long (rather than 1km scale exactly) model is more scientifically defensible. We have amended the text in various places to explain this; see response to main comment #6, above, for full details.

L117 – GRIP acronym needs to be defined above before its used.

Added acronym definition after first use (Global Roads Inventory Project)

L124-125 – Don't some of these road network datasets often include small "roads" like footpaths and farm roads? It seems like some levels might be worth excluding since they are not likely mapped consistently across the world whereas higher levels would be more likely to be consistent.

Thanks for flagging – the GRIP dataset does not include this kind of road (essentially it's tarmac roads or larger) so issue is of lower concern. We have added a sentence to clarify:

"*This dataset does not include footpaths or unpaved roads, for which mapping may be significantly more spatially inconsistent."*

L140 – I am very confused about how one multiplies infrastructure by a nowcast density. . .

We have revised this sentence to hopefully alleviate the confusion! New text:

"To combine the roads datasets and OSM-derived critical infrastructure with the hazard outputs, we have multiplied the raster map of infrastructure or road density by the Nowcast density raster (i.e. raster showing total days exposed to landslide hazard)"

L149 – Need to include some more info about how the model is trained in the first place in order to understand this part about assessing errors.

We feel that this has now been appropriately addressed by changes made to address earlier comments; see in particular the response to comment #5, above.

L175 – Applying what? What is "this"?

L176-178 – This sentence is confusing, can it be clarified?

We address both of the two comments above in one – we've changed this entire sentence to improve clarity:

"*The OSM completeness estimates are calculated at a national level, and it is therefore not clear how to apply them to the 30 arc-second pixels in our study, and as such we do not attempt to correct our global maps. However, to effectively normalise the exposure data at a country level, we provide the completeness measure derived from Barrington-Leigh and Millard-Ball (2017) in Supplementary Table 1"*

L180-182 – I'm not following the logic here, if the infrastructure is not completely mapped in a country, then the normalized metric will be just as wrong as the raw numbers, wouldn't it? The ratio would be off.

We are unsure of what the reviewer means here; the infrastructure exposure in each country in the supplemental figures is shown as 'exposed' elements divided by total elements. In other words, it's the proportion of total mapped elements exposed to landslide. So comparison between countries focuses on the exposed fraction. If mapping is incomplete, this does not necessarily mean the exposed fraction will be affected, if the completeness is the same across the country. Since we only have completeness estimates at a national level, we can't tell if this is true or not. Ultimately, exposed fraction gives a normalized sense of 'how much in each country is exposed' which is a more useful comparison that looking at total exposed elements. As such, we feel that the original statement is justified, although we would be happy to discuss.

L195 – The results of this study are not observations. They are modeled proxies. Please rephrase.

Changed to 'modeled estimates'.

L197 – Given the wonky units of popexp, population exposure annually is not what is modeled and shown in Figure 1, but a proxy for population exposure.

Changed to "Figure 1 shows the modeled estimates of population exposure"

L229 – Impact is not the right word here. The authors are not modeling impact at all, they are modeling exposure, and also, the wording here implies that their results represent impacts that actually occurred, but they do not.

Thanks for this – you're absolutely correct. Changed the text to: "the exposure of linear infrastructure to landslides is more widespread".

L240 – “modeled” population exposure

Added ‘modeled’

L256-258 – This point would be better made if Figure 4 showed the relative world map and the overall map side by side.

Good point. We will add this to the revised version.

L259-260 – Don’t we have the same problem if a given small country did not happen to be hit by an extraordinary precipitation event in the 19-year IMERG dataset but was next year?

This is an important point. The key factor is that all rainfall above the 95th percentile will lead to the same nowcast output – so the model isn’t massively biased by e.g. 100-year return period rainfall event, but at the same time it is relatively insensitive to those enormous rainfall events. We have added the following sentence to explain this:

“At the same time, the LHASA-based model outputs are relatively insensitive to extreme rainfall events (100-year return period, for example), since all rainfall values above the 95th historical percentile will lead to the same nowcast hazard output.”

Figure 2C – it is hard to see the colors against the black background in this part of the figure.

Thanks for raising this. We have revised this figure so that now the 2C (infrastructure exposure) part zooms in on Switzerland, to show the exposure.

Figure 5 – are the fatalities by country the total number ever, or per year, or ?

Changed text to explain that this is total fatalities: “*Figure 5: Showing the exposure of population (in person-Nowcasts/year) against the number of total fatalities recorded in the dataset of Froude and Petley 2018”*

Figure 7 – what are the x-axis offsets within each continent? Just random for visibility?

That’s correct, they’re to avoid overlap. We’ve added text to the caption to explain this:

“Offsets in the x-axis are for visual distinction between points to avoid overlap.”

Figure 8 – Here and in other similar plots, it might be useful to label some more key countries, especially the outliers

This is a good point. We have added labels to Qatar and Bahrain, since they are explicitly named in the text. We do not seek to draw attention to other countries, as we do not feel it is our place to ‘name and shame’ in any respect.

New Global Characterization of Landslide Exposure

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Abstract

Landslides triggered by intense rainfall are hazards that impact people and infrastructure across the world, but comprehensively quantifying exposure to these hazards remains challenging. Unlike earthquakes or flooding which cover large areas, landslides occur only in highly susceptible parts of a landscape affected by intense rainfall, which may not intersect human settlement or infrastructure. Existing datasets of landslides around the world ~~global landslide inventories~~ generally include only those reported to have caused impacts, leading to significant biases toward~~ both locations where impacts are common and areas~~ areas with higher reporting capacity, limiting how our understanding of exposure to landslides in developing countries. In this study, we use an alternative approach to estimate exposure to landslides in a homogenous fashion.~~ To address the limits of report-based inventories, w~~ We have combined a global~~ly-homogenous~~ landslide hazard proxy derived from satellite data with open-source datasets on population, roads and infrastructure to consistently estimate exposure to rapid landslide hazards around the globe. These exposure models compare favourably with existing datasets of rainfall-triggered landslide fatalities, while filling in major gaps in inventory-based estimates in parts of the world with lower reporting capacity. Our findings provide a global estimate of exposure to landslides from 2001-2019 that we suggest may benefit disaster mitigation professionals.~~also provide for the first time a proxy to distinguish relative levels of landslide hazard mitigation between different countries.~~

1. Introduction

Rainfall-induced rapid landslides are an important natural hazard in many countries around the world, both as independent events and within larger chains of cascading hazards due to their role in downstream debris flow hazards. Current estimates of landslide impacts suggest that they cause thousands of fatalities annually (Froude & Petley, 2018; Petley, 2012) and billions of dollars of economic damage (Dilley et al., 2005). Global hazard estimates are an important way to understand the relative efficacy of hazard mitigation mechanisms between different countries, and also provide policy-makers with tools to estimate the future challenges associated with landslide hazards. However, few studies exist at present that provide a globally-consistent set of estimates for landslide hazard, and even fewer that attempt to characterize risk and exposure.

Most studies of landslide impacts rely on observations of specific landslide events and the associated reporting of the impacts. A small number of studies have estimated global economic impacts (Dilley et al., 2005; Guha-Sapir & CRED, 2019), while other important work has collated the fatalities associated with landsliding around the world to give crucial insight into impacts (Froude & Petley, 2018; D. Petley, 2012). The reliance of these studies on landslide inventories leaves them subject to known biases associated with these inventories. ~~Specifically~~Specifically, there tends to be better reporting in developed countries (Kirschbaum et al. 2010; Monsieurs et al., 2018) and a lack of public data about landslide occurrence and impacts in more remote regions, resulting in major blind spots in Africa, portions of the Andes, western China, and parts of Indonesia and the Philippines.

The global coverage of satellite data offers opportunities to fill in data gaps that result from inventory-based assessment of landslide hazards. NASA's Landslide Hazard Assessment for Situational Awareness (LHASA) model provides ~~a near-real time~~an ~~near-global~~ estimate of landslide hazard between 50°N and 50°S, at 30 arc-second resolution, based on a global susceptibility map and inputs from NASA precipitation estimates (Kirschbaum & Stanley, 2018). This is updated every 3 hours, with a latency of approximately 4 hours, providing a near-real time output. Using this model, it is possible to estimate relative changes in landslide hazard around the world each year. More importantly, this approach does not rely on local inventories to characterize the hazard, and therefore provides a near-global, consistent estimate of landslide hazard, encompassing the vast majority of populated areas. To address the need for globally consistent data on landslide hazard and exposure, we utilize an updated and enhanced version of the global susceptibility model defined by Stanley and Kirschbaum (2017) combined with a newly available 19 year IMERG rainfall product (Huffman et al. 2014) to estimate global landslide hazard, and then combine this with global estimates of population and critical infrastructure.

~~By leveraging satellite data and open-source information on infrastructure and population, we can for the first time understand the global distribution of landslide exposure and how it varies around the world in space and time and across socioeconomic variables such as population, critical infrastructure and road networks~~. This information can also be considered together with other datasets such as Froude and Petley (2018) to assess relative vulnerability to landslide exposure in different countries. A globally consistent model could support hazard mitigation decision making and planning, particularly in developing countries with limited reporting capacity~~; it would additionally allow for more consistent evaluation of landslide hazard going forward~~. Our exposure model outputs derived from the~~The~~ LHASA model provide an estimate of exposure seasonality at 30 arc second resolution~~based outputs can provide a pixel-by-pixel assessment of hazard and exposure seasonally~~ across the globe. ~~-~~This demonstrates the value of using remote sensing data in concert with ground-based inventories to provide a more spatially consistent picture~~clear picture~~ of the impacts associated with landslides around the world. While the model outputs are an approximation of exposure to hazard based on historical rainfall trends, we note that future exposure patterns could be explored with the use of rainfall projections for future climate scenarios.

2. Methodology

To estimate exposure to landslide hazard, we must first derive the estimates of hazard itself. For this study, we have utilised the outputs of an updated version of the LHASA model as an approximation for hazard, which we can then combine with

~~To calculate global landslide hazard and exposure estimates, we have incorporated the average rate of hazard ‘Nowcast’ (a qualitative estimate of increased landslide hazard in a given location in near real time) issued by an updated version of the LHASA model, and combined them with~~ openly available datasets of infrastructure at a 30 arc-second~~1km~~ resolution across the world. These maps of exposure, both annually and~~ as~~ estimated for each month to analyse seasonal variability~~a monthly landslide climatology~~, are an important initial output in their own right, but we have further analysed the data to compare our outputs with existing estimates of global landslide hazard. This provides key insights into where existing inventory biases may exist, as well as highlights which countries and regions are most exposed to rainfall-triggered landslide hazard. Below, we detail the methods used to generate these outputs.

2.1. ~~Nowcast climatology~~Hazard estimates derived from LHASA model

The LHASA model is designed to provide near real time awareness of potential rapid landslide activity through landslide ‘Nowcasts’ (Kirschbaum and Stanley 2018). The algorithm uses a susceptibility map calculated from globally available estimates of slope, lithology, forest cover change, distance to fault zones, and distance to road networks to provide a relative estimate of static susceptibility (Stanley and Kirschbaum 2017). The susceptibility map is then compared with satellite-based precipitation estimates from NASA’s Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) and Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM (IMERG) rainfall product. To characterize the potential for landslide triggering, an Antecedent Rainfall Index (ARI), or weighted accumulation from the last seven days of rainfall, is calculated at each pixel. If the ARI value exceeds a threshold (historical 95th percentile for rainfall), either a moderate-hazard or a high-hazard Nowcast may be generated if there is moderate to high susceptibility within that area. Nowcasts are issued at a 30 arc-second (approximately 1km at the equator)~~1km~~ pixel resolution every 3 hours. For the purposes of our study, we use the daily nowcast output, which is generated based on daily rainfall totals rather than 3-hr totals. The physical meaning of one nowcast is 24 hours of elevated landslide hazard for a 30 arc-second dimension pixel.

We have updated the LHASA model for this study to incorporate data made available since the initial version of the model. We term this revised model ‘LHASA 1.1’. First, the global landslide susceptibility map (Stanley & Kirschbaum 2017) was updated to include the 2018 data on forest loss since the year 2000 (Hansen et al. 2018) and road density from the Global Roads Inventory Project (Meijer et al. 2018). Previously, the forest loss data was modelled~~upscaled~~ as a binary variable representing either the presence or absence of any 30m forest loss pixel within each 30 arc-second~~1km~~ grid cell. However, this update represents forest loss at 30 arc-seconds ~~1km~~ as a fraction of the 30m grid cells which have recently experienced forest loss (from 2000-present). The effect of this change will be to de-emphasize the role of forest loss in locations with little recent disturbance, but not to change the effect of forest loss on any 30 arc-second~~1km~~ grid cell which has experienced total loss of all forest cover. The susceptibility map was recomputed at 30 arc-second~~1km~~ resolution using the same fuzzy overlay methodology as the previous version. This fuzzy overlay model uses heuristic weighting of the input variables, defined by Stanley & Kirschbaum (2017). We do not adjust the weights attached to the variables in the study here. We assess the accuracy of the new susceptibility map in the same fashion as in the study of Stanley & Kirschbaum (2017), by using the NASA Global Landslide Catalog locations to test the ROC-AUC values. Using the same GLC data that was used to calibrate the previously published version of the susceptibility model (GLC data snapshotted 2016/01/14, we calculate an ROC-AUC value of 0.822, essentially identical to the value obtained for the prior model (0.82). For the purposes of our analysis, we follow Stanley and Kirschbaum (2017) and divide susceptibility into multiple classes, and use the threshold between 'low' and 'moderate' susceptibility as a threshold for nowcasts to be generated if rainfall exceeds the historical 95th percentile. Less than 25% of landslides recorded in the GLC occur below this threshold. For the purposes of this study, we combine moderate and high 'nowcasts' together to provide a proxy for hazard that captures the bulk of landslide activity.

Secondly, we have updated the rainfall input. Due to a recently released near 20-year record of IMERG (version 6B), we have modified the precipitation inputs to LHASA in the following ways. First, we extend the LHASA model from 50 degrees N-S, which was the latitudinal extent of TMPA, to the 60 degrees N-S extent of the IMERG product (Huffman et al. 2013). This latitudinal expansion now includes most of Northern Europe and Canada, and the only populated areas excluded are in Northern Russia, Iceland, some of Scandinavia and Canada. Because falling snow is an important component of precipitation at higher latitudes but not a major trigger of landslides, we changed the precipitation variable considered from total precipitation to just rainfall. The LHASA model does not consider snow avalanches. The effects of this change should be minimal in the tropical and temperate zones previously studied.

The LHASA model generates a hazard 'nowcast' if rainfall exceeds the historical 95th percentile and susceptibility exceeds the 'moderate susceptibility' threshold. Since the updated model uses IMERG v06B rather than TMPA, we have therefore re-calculated the historical 95th percentiles of a 7-day weighted rainfall accumulation. This provides a global 95th percentile map; if ARI values exceed this threshold, a hazard nowcast is issued. ~~Finally, leveraging the new IMERG rainfall product we recompute the thresholds above which landslide activity is anticipated at each pixel based on the 95th percentile of a 7-day ARI weighted rainfall accumulation.~~ The model is then reprocessed from 2000-present, and we build a 19~~nearly 20~~-year record of landslide Nowcasts around the world. Averaging the Nowcasts by month, we construct a Nowcast climatology, or average landslide Nowcast rate for each pixel. We also compute annual Nowcast rates. This provides a globally consistent proxy for landslide hazard over the course of the year in each location. We term this as 'Nowcast density', and it represents a proxy for intensity of landslide activity. We can then combine this with data on population and infrastructure to assess the relative exposure to landslides.

The result is a raster dataset at ~~approximately 1km~~ 30 arc-seconds resolution for each month of the years in the IMERG record. We compute additional metrics such as the inter-annual variability in Nowcast frequency and standard deviations of Nowcast frequency. This information is incorporated into the annual exposure estimates to provide a measure of the variability. This uncertainty analysis is discussed in more detail below.

2.2. Exposure datasets & integration with hazard

We have overlaid the hazard footprints derived from the LHASA-based Nowcast climatology on top of publicly available datasets of population and infrastructure globally to map the exposure of these elements to landslide hazard. We have additionally aggregated these data at a national scale to compare with existing studies. Below, we first describe the datasets used, and then the approach taken to combine them with the hazard outputs.

We use population data from the Gridded Population of the World version 4 dataset (Doxsey-Whitfield et al., 2015), adjusted to the UN WPP Population Density for 2015. Use of this dataset is in line with other studies of population exposure to global hazards (Carrao, Naumann, & Barbosa, 2016; Dilley et al., 2005; Kleinen & Petschel-Held, 2007). The resolution of this dataset is the same as the LHASA Nowcast output – ~~approximately 1km~~30 arc-seconds – and thus can be directly mapped onto the hazard data.

The definition of critical infrastructure can differ depending on the relevant stakeholder or location. The UN Global Assessment Report 2015 incorporates schools, hospitals and residential areas (De Bono & Chatenoux, 2014), and we use this as an initial basis for our estimates. We incorporate roads as defined in the Global Roads Inventory Project (GRIP) (Meijer et al., 2018), and amenities including hospitals, schools, fuel stations and power facilities as defined by OpenStreetMap. Both catalogs have a global extent and are updated regularly. Additionally, they offer a consistent set of data that can be compared across the world. While there are some caveats to this comparison, which are discussed below, we suggest that these two datasets are likely the best datasets with global coverage, open access, and recent updates.

The GRIP roads dataset harmonises nearly 60 datasets describing road infrastructure into a single, consistent dataset covering 222 countries (Meijer et al. 2018). GRIP incorporates roads derived from OSM as well as other data sources, and is considered to be a harmonised global road catalog. The daily updates for OSM are not incorporated into GRIP, but we consider the globally harmonised nature to be more important than a frequently updated catalog for the purposes of our study. This dataset is a shapefile of linear features, which is not initially directly compatible with the 30 arc-second~~1km~~ resolution landslide hazard outputs. To connect the linear road dataset with the pixel-based Nowcast based landslide hazard~~density~~ data, we have used the Line Density tool in ArcGIS to calculate the density of roads at 30 arc-second~~1km~~ resolution with an output of a road density map with units of km/pixel~~km~~^{2}. Although the GRIP database classifies roads in one of five classes depending on size and importance (e.g. primary highway, residential road), we have not distinguished between these classes in our analysis. This dataset does not include footpaths or unpaved roads, for which mapping may be significantly more spatially inconsistent. While economic impacts vary based on the type of road, our analysis is meant to highlight the total potential exposed length for all types of roads.

OpenStreetMap (OSM) is a continually updated global map of infrastructure, roads, settlement and land uses (OpenStreetMap contributors 2015). The updates are contributed by members of the public and the data is openly available for access in shapefile and XML format. While differing levels of input from different parts of the world mean that there can be differences in the level of completeness of the map depending on the region (Barrington-Leigh and Millard-Ball 2017), the specificity of the data makes it an excellent source for infrastructure information. There is detailed classification of different features in the map that allow us to isolate specific types of infrastructure, such as medical amenities or power stations. In addition, the open-source nature of OSM means this approach is highly replicable. We have used the OSM Planet data file (a single XML document of approximately 1TB, containing the information for every mapped feature in the OSM map) and parsed the xml data using a Python-based script to obtain the density of critical amenities at a 30 arc-second~~1km~~ resolution. We define critical amenities as those labelled 'School', 'Hospital' 'Fuel Station', 'Power Station' and other 'Power' nodes (including substations and transformers), based on the OSM feature definitions. The OSM Planet file was downloaded on June 24th 2019. The script used to parse this file is available in the supplementary material.

To combine the roads datasets and OSM-derived critical infrastructure with the hazard outputs, we have multiplied the raster map of infrastructure or road density ~~each~~ by the Nowcast density raster (i.e. raster showing total days exposed to landslide hazard) for each full year in the IMERG archive (2000-2018) and taken the mean value and standard deviation. The resulting datasets on exposure for population, roads, and critical infrastructure are all calculated at ~~approximately 1km resolution~~30 arc-second resolution. We have also generated month-by-month exposure rasters to estimate the climatology of exposure for the same exposed elements. Since these outputs are based upon the LHASA Nowcast output, it is important to clarify the units in which our estimates of exposure are expressed. Table 1 provides a summary of the units and the terms used in the study.

Parameter	Specific Unit	Descriptive term (shorthand used in this study)	Explanation
Population exposure	Days exposed to landslide hazard x person x ~~Person-Nowcasts~~. Yr^{-1}. Km^{-2}	Pop_{exp}	The exposure is estimated as number of Nowcasts (i.e. days exposed to elevated modeled hazard) per year in each square km multiplied by the population in that square km.

Road exposure	~~Nowcasts~~Days exposed to landslide hazard .km.yr^{-1}.km^{-2}	$Road_{exp}$	Sum of Nowcasts per square km multiplied by km of road within that square km.
Infrastructure exposure	~~Nowcasts~~Days exposed to landslide hazard.element.yr^{-1}.km^{-2}	$Infr_{exp}$	Includes the following critical infrastructure categories: hospitals, schools, fuel stations, power generation and transmission

Table 1: Summary of terms used to describe infrastructure and associated units.

In Table 1, the units for each of the exposure outputs is also explained. We use the shorthand Pop_{exp}, $Road_{exp}$, and $Infr_{exp}$ to denote population, road and infrastructure exposure, respectively.

2.3. Error assessment

Kirschbaum and Stanley (2018) assess errors in the LHASA 1.0 Nowcast hazard estimates by comparison with historical landslide events recorded in both the NASA Global Landslide Catalog (Kirschbaum et al., 2010) and the dataset of fatal landslides generated by Petley et al. (2007). They find relatively low False Positive Rates (~1%) and moderate to good true positive rates (24-60% for moderate hazard Nowcasts). However, both the Global Landslide Catalog and the data of Petley et al. (2007) are not complete, meaning that the true and false negative rates are not easily quantified. More succinctly, since a complete dataset of landslide occurrence does not exist, it is challenging to calculate the accuracy associated with any independent landslide hazard estimate. Quantifying the relationship between Nowcast density and landslide probability for a given area remains an important step for future research, and requires spatially complete landslide catalogs with high temporal revisit rates.~~.~~

To explore the relative variability in landslide activity, we estimate the standard deviation in annual Nowcast density at each point, based on the 19~~near 20~~ year IMERG rainfall input. We then propagate the error into the estimates of~~for~~ exposure for population, roads and critical infrastructure. The raster data for the standard deviations in error are available in the supplemental data.

Estimating errors associated with OpenStreetMap data can be challenging, since the data quality is determined by volunteers who contribute to the map database. Broadly, we suggest it is appropriate to consider two distinct sources of error; the location accuracy of the individual points and infrastructure, and the completeness of the inventory. As discussed by Mooney and coauthors (2010), a lack of ground data across the world makes it challenging to assess the positional accuracy. However, in some locations, data can be compared with existing sources. In the UK, Haklay (2010) suggests that OSM data points offer positional accuracy comparable with the Ordinance Survey Maps (the government standard). For the purposes of our study, where the maximum resolution available for the landslide hazard data is 30 arc-second~~1km~~, this positional accuracy is in excess of the requirements. However, completeness of the map is more problematic.

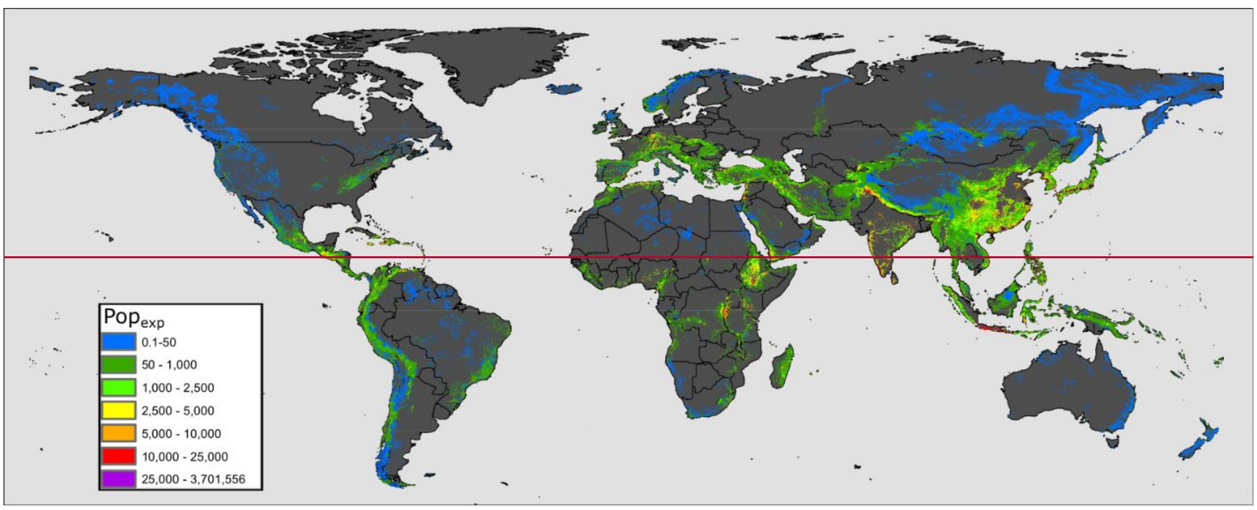
Barrington-Leigh and Millard-Ball (2017) assess the relative completeness of the OSM roads data on a country-by-country basis, finding that OSM data in many developed countries is near-complete, although this declines in some states with lower GDP. The completeness varies within individual countries, with the most complete mapping observed in the highest density cities as well as the most sparsely populated areas (reaching a low in moderately populated areas). We assume that the estimate of completeness presented by Barrington-Leigh and Millard Ball (2017) for roads is applicable to other infrastructure; we are not aware of other global estimates of OSM completeness for specific infrastructure categories, so while this assumption may not fully hold we suggest it is more informative to use this completeness estimate than none at all. The OSM completeness estimates are calculated at a national level, and it is therefore not clear how to apply them to the 30 arc-second pixels in our study, and as such we do not attempt to correct our global maps. However, ~~Applying this as an error systematically across our analyses is challenging; we can normalize national-level OSM based measurements by the completeness measure of Barrington-Leigh and Millard-Ball (2017), but at a pixel level we present the exposure 'as is', since we have no *a priori* concept of how to apply completeness estimates at this scale. T~~to effectively normalise the exposure data at a country level, we provide the completeness measure derived from Barrington-Leigh and Millard-Ball (2017) in Supplementary Table 1. In the figures in supplementary material that show $Infr_{exp}$ aggregated at a national level, we normalise the exposed elements by the total number of critical infrastructure elements in each country, which serves to provide a useful intercomparison of the relative hazard, and does not require completeness metrics.

The GRIP roads database (Meijer et al. 2018) draws a significant part of the road inventory from OpenStreetMap, and so is subject to some of the same error constraints. In Europe, the roads are derived primarily from OSM, although completeness in this part of the world is near-perfect (Barrington-Leigh and Millard-Ball 2017). GRIP also uses OSM data in China, where there is a dearth of other freely available datasets. As such, completeness estimates in China are difficult to accurately characterize, and we do not attempt to do so. Elsewhere, GRIP incorporates other road datasets to supplement OSM. These input datasets are limited to those with positional accuracy greater than 500m, which precludes significant positional errors that would affect our km-scale analysis. We are not aware of estimates of the completeness of the GRIP dataset; since it integrates datasets from all over the world, external validation datasets of completeness are unlikely to exist comprehensively. As such, while we note that there may be parts of the world where coverage is incomplete, we do not have strong constraints on this.

3. Results

The results of our analyses provide a global set of model estimates ~~observations~~ of landslide exposure, in both raster format and tabulated by country. The source data is available in the supplementary material associated with this study.

Figure 1 shows the modeled estimates of population exposure annually for each 30 arc-second~~1km~~ pixel and Figure 2 shows the exposure of population, roads, and critical infrastructure at the same scale for a portion of Northern Italy and the Alps, to highlight the nature of the different datasets. As can be observed in Figure 2, population and roads are significantly more widely distributed than critical infrastructure. Infrastructure is instead concentrated primarily in urban centers, although power distribution infrastructure follows similar transportation corridors to road networks. In other parts of the world, there are significant levels of exposure of critical infrastructure to landslide hazard. The co-location of power distribution and road network exposure highlights the potential for complex post-landslide damage and multi-sector impacts.



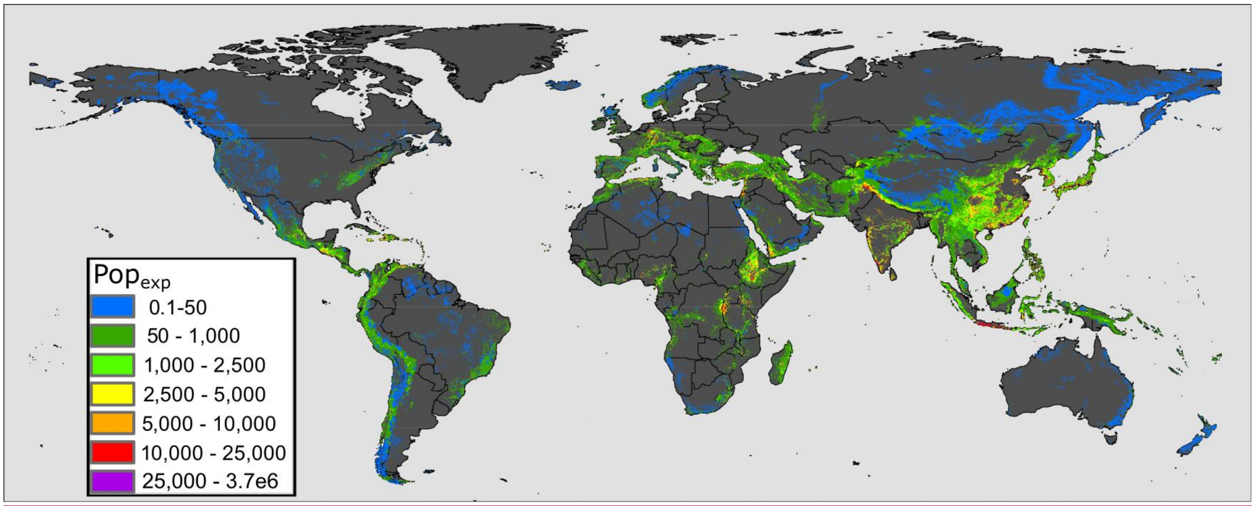
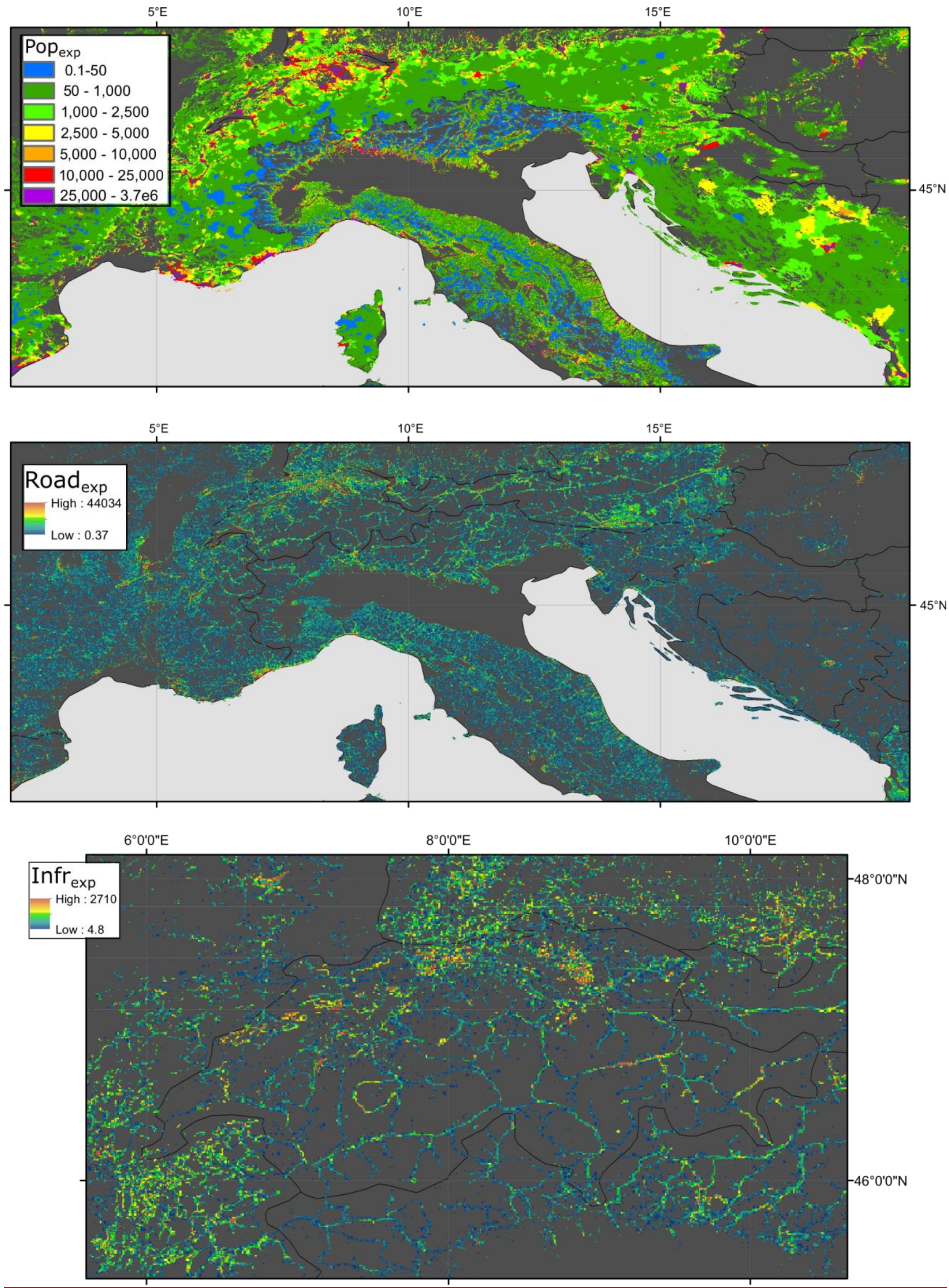


Figure 1: Global modeled population exposure to landslides (Pop$_{exp}$). Since the distribution of high-exposure areas is highly localised, we have binned the data to highlight differences at lower exposure levels more clearly.



Pop$_{exp}$
0.1-50
50 - 1,000
1,000 - 2,500
2,500 - 5,000
5,000 - 10,000
10,000 - 25,000
25,000 - 3.7e6
5°E
10°E
15°E
45°N
Road$_{exp}$
High : 44034
Low : 0.37
5°E
10°E
15°E
45°N
Infr$_{exp}$
High : 2710
Low : 4.8
6°0'0"E
8°0'0"E
10°0'0"E
48°0'0"N
46°0'0"N

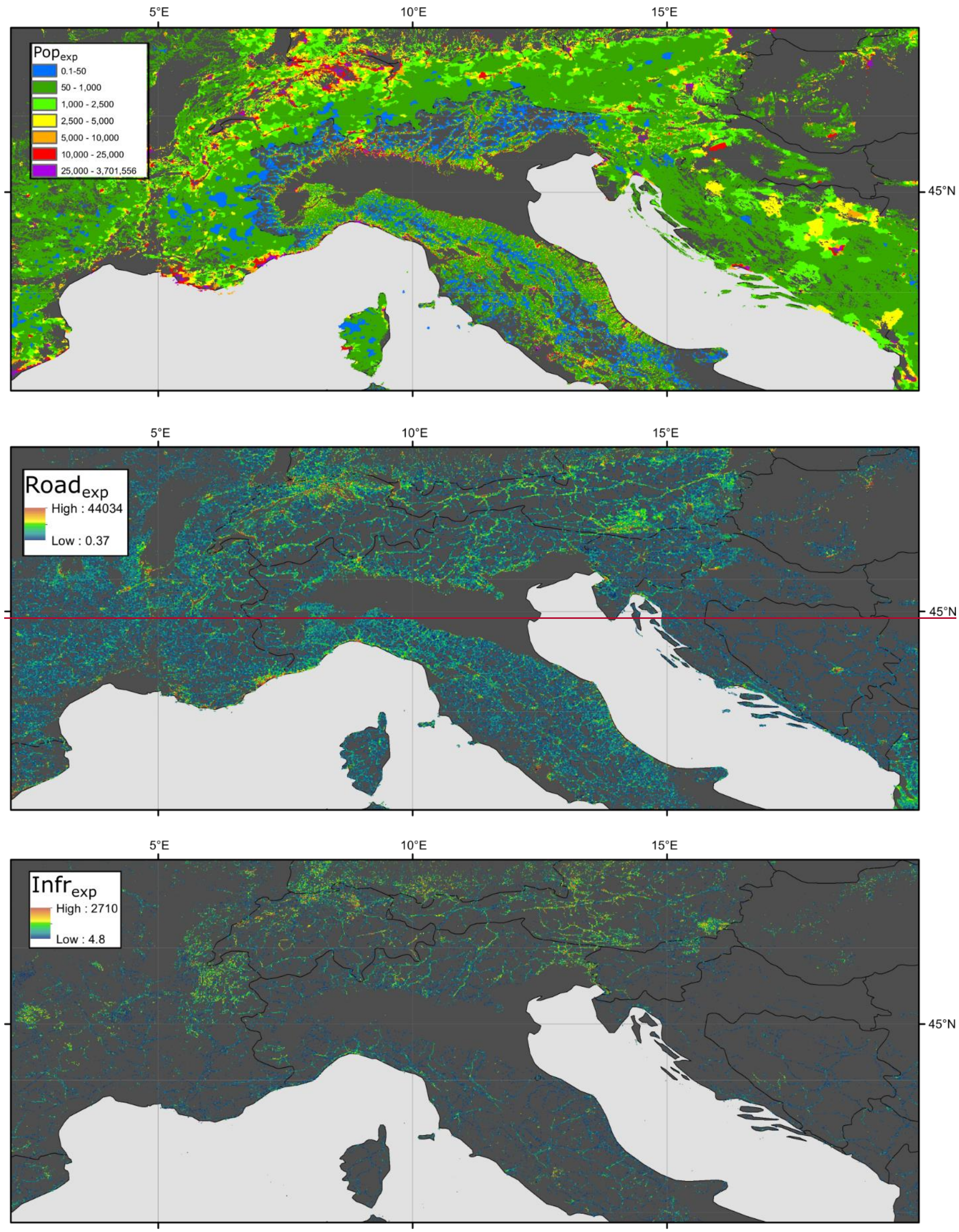


Figure 2: Showing relative exposure of population, critical infrastructure, and roads in a snapshot of the world map - in this case, the European Alps and Italy. To improve clarity, the critical infrastructure exposure is shown only for Switzerland.

For each country we have tabulated the aggregated values for Pop_{exp}, $Road_{exp}$, and $Infr_{exp}$, average annual Nowcast density. We also show the total population, total length of roads from GRIP, and total number of OSM critical infrastructure elements; this allows for calculation of the fraction of total that is exposed for each of these aspects. To normalize the number of Nowcasts for each country, we divide by area in square decimal degrees, rather than square kilometers; since the Nowcast data is output on a grid based on decimal degrees. The same aggregation approach could similarly be used at a sub-national level to assess relative impacts in different administrative areas. These data can be found in Supplementary Table 1, where all data necessary to replicate these results is available.

We also list the OSM completeness estimates from Barrington-Leigh and Millard-Ball (2017), the fatalities per country due to non-seismic landslides assessed by Froude and Petley (2018), and the landslide-linked economic impacts assessed by Dilley et al (2005). These datasets are, to our knowledge, the most current datasets that assess landslide impact in terms of economic cost and fatalities globally, and provide valuable points of comparison for our results. Comparison of calculated Pop_{exp} with recorded fatalities is shown in Figure 5, and comparison of $Road_{exp}$ with economic impacts from Dilley et al (2005) in Figure 6.

4. Discussion

The most striking initial result of our study is that significantly larger proportions of the globe are exposed to rainfall-triggered landslide hazards than are often considered. Inventory based assessments (e.g. Dilley et al. 2005) do not show significant levels of landslide hazard and exposure in sub-Saharan Africa or much of Asia and South America, while we find that many of these countries have significant proportions of the population and infrastructure exposed. It is perhaps not surprising that exposure to landslide hazard is elevated in the major mountain belts of the Andes and the Alpine-Himalayan Orogeny, but there are other key hotspots that may be less well known. These areas include much of Japan, the Rwenzori mountains in Africa, Central America and Mexico, and much of the Caribbean. We find specific hotspots for certain cities within or near mountain belts; this is particularly evident at the edges of large conurbations that abut mountainous areas, such as Taipei, Rio de Janeiro and the edges of Tokyo.

While the zones of densely packed critical infrastructure such as schools and hospitals are also in general associated with these urban areas, the exposure of ~~impact of landslides on~~ linear infrastructure to landslides is more widespread. Roads and power transmission facilities often follow similar linear corridors, and where those intersect areas of high landslide hazard the relative exposure can still be important. The localised impact of a single landslide impacting a densely populated urban zone may be very high, with several critical infrastructural elements impacted. However, the likelihood of a landslide occurring somewhere along lengthy road or power transmission segments in regional-scale rainfall events is higher, and an interruption to linear infrastructure may impact lifelines that are relevant in disaster response. Thus the localised and distributed impacts should be considered alongside one another, We suggest that highlighting the most vulnerable corridors for power transmission and road traffic is an important subject for future work.

To explore these results against independent datasets of landslide hazard and risk, we have aggregated the data at a country level (Supplementary Table 1). We can then highlight those nations with the highest landslide impact both in absolute terms (total exposed people and infrastructure) and as a proportion of the overall population or infrastructure in that country.

As might be expected, without normalising for area countries with the largest population have the highest overall modeled population exposure, although exposure in China exceeds that of India despite having a smaller population. Exposure of roads is also greatest in China and the United States, which are both highly populated with good OSM coverage. These absolute values are important, but we suggest that more insight can be gained by assessing the relative exposure of population and infrastructure in each country, as well as by comparing the different relative values between nations.

Inter-comparison of different countries can highlight those nations where the impact of landslides is greatest, and can draw attention to smaller, less developed nations where landslide statistics from report-based inventories may be lacking.

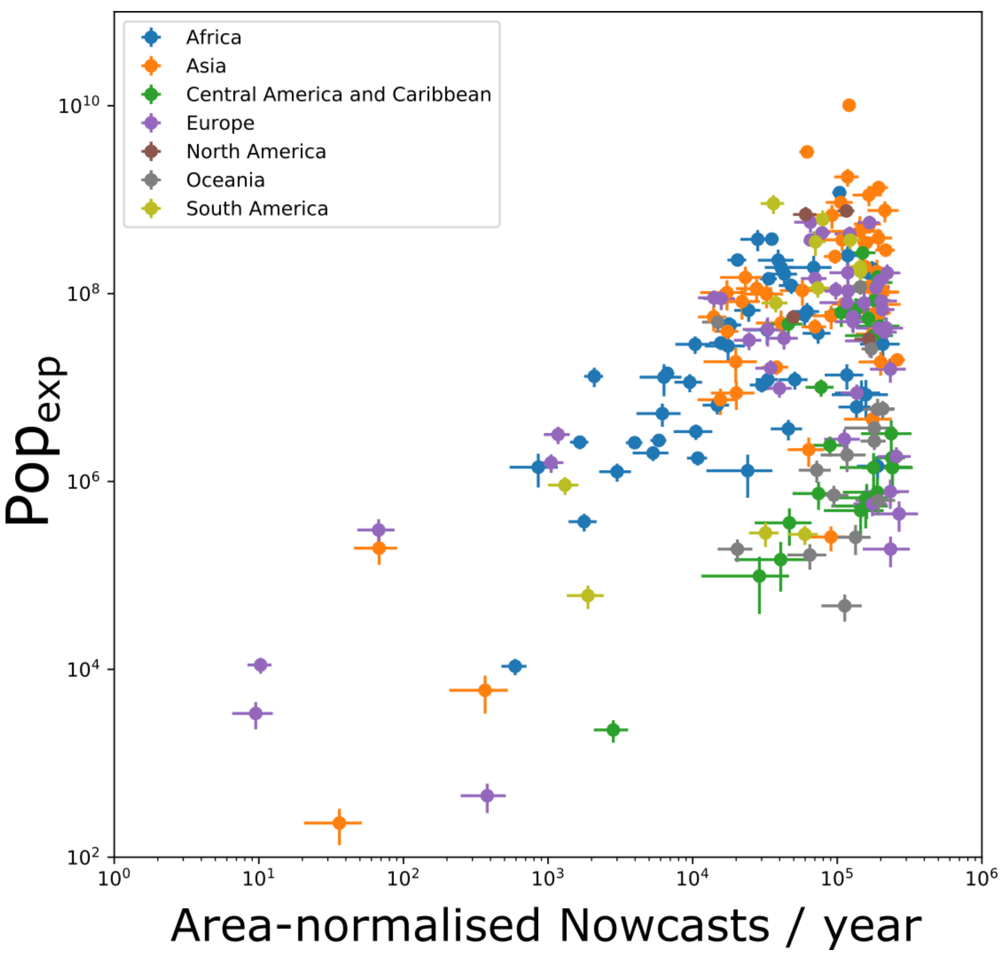
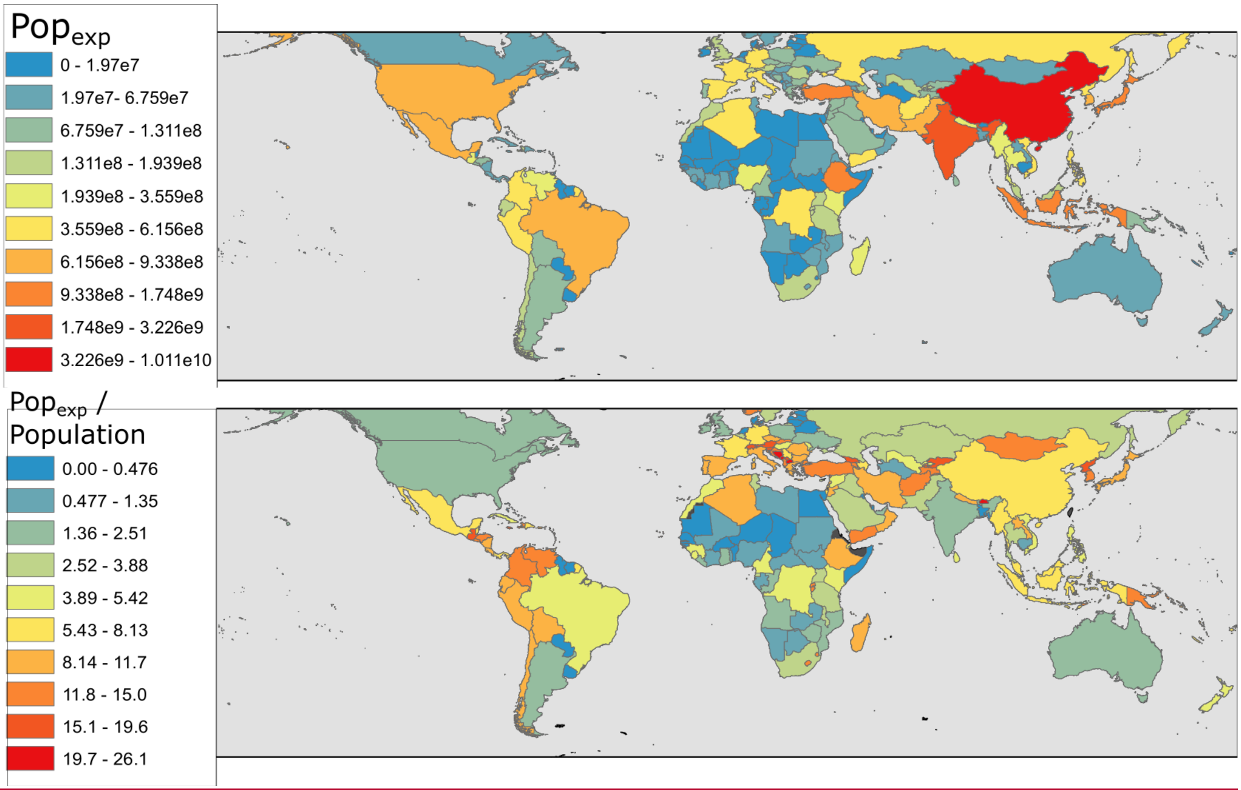


Figure 3: Nowcasts per year, normalised by country area compared with the population exposed to Nowcasts (in units of Nowcast/person-years).

Figure 3 plots Pop_{exp}, ~~normalised by area for each country~~ against the mean~~average~~ nowcast density in that country, with colors denoting the geographic region. Results indicate that hazard and exposure are generally well-correlated across different countries; similar relationships exist for both road exposure and critical infrastructure (see supplementary material for figures). At the highest end of this scale – i.e. those with high x-axis values - are smaller countries where mountainous terrain makes up much if not all of the area: Monaco, Bhutan, Andorra, and several Caribbean States: St Vincent and the Grenadines, Dominica, Grenada and St Lucia. In terms of population exposure, many countries in Asia and Africa have higher population exposure for an equivalent level of Nowcast density, when compared to European and some central American countries. This results from the generally higher population of these states.

Figure 4 plots the absolute numbers for Pop_{exp}, as well as the relative fraction of the population impacted by landslides. The relatively lower values in some of the larger countries like the United States and Brazil suggests that while the overall population impact is high in highly populated states, the relative impact can be more concentrated in smaller countries.

Given the large degree of variability in annual Nowcast frequency, inventories of reported landslides may misrepresent~~s~~ the average landslide rate in smaller countries if catastrophic landslides do not coincide with the sampling period for the inventory. At the same time, the LHASA-based model outputs are relatively insensitive to extreme rainfall events (100-year return period, for example), since all rainfall values above the 95^{th} historical percentile will lead to the same nowcast hazard output. The bulk of reported landslide events occur in larger nations where statistical variability of landsliding is likely damped over larger areas like Nepal, Taiwan, China and Japan. While we find high normalised hazard estimates in many of those states, our analysis also highlights smaller nations where the relative impact of landslides may be more significant on longer timescales. Alongside the previously mentioned nations, we also find several smaller states with higher proportions of exposed population; Montenegro, Bosnia and Herzegovina, and Macedonia are notable in the Balkan area in particular.



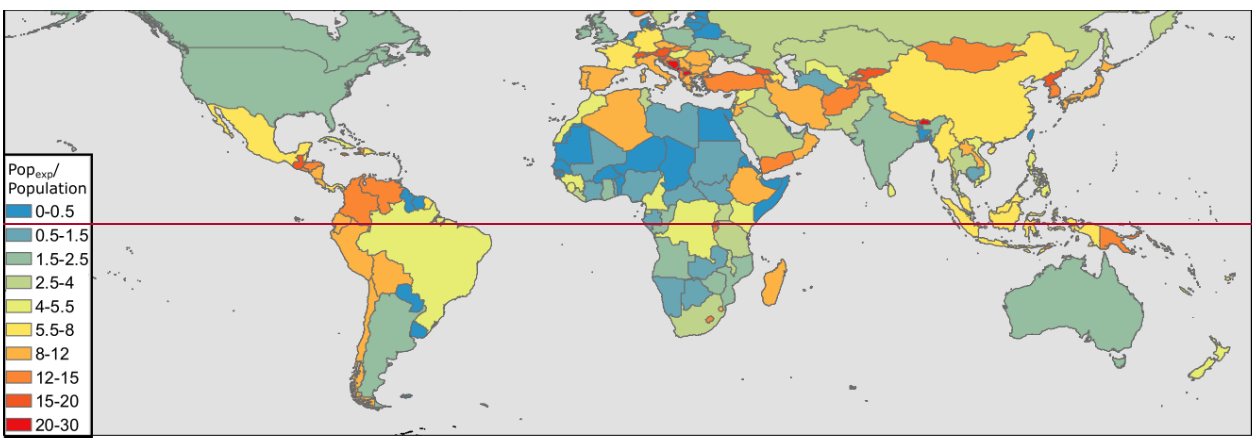


Figure 4: Above: Country wide estimates of Population exposure (Popexp); Below: Population exposure normalised by total population. This is expressed as Popexp divided by total 2018 population derived from the World Bank data archives (World Bank 2018).

To test whether the Nowcast-exposure estimates are a useful predictor of landslide risk, we can compare them to existing datasets. In Figure 5, we plot the total exposure of population in each country (in units of person-Nowcasts per year) against the landslide fatality dataset assembled by Froude and Petley (2018). This dataset, collected from 2004-2016, consists of 4862 separate landslide events that resulted in fatalities, and is the most comprehensive dataset for landslides that have caused fatalities in the world. Figure 5 highlights that there is a relatively strong correlation, with countries in Asia, Central America and Africa generally exhibiting higher numbers of fatalities for a given population exposure than observations in Europe.

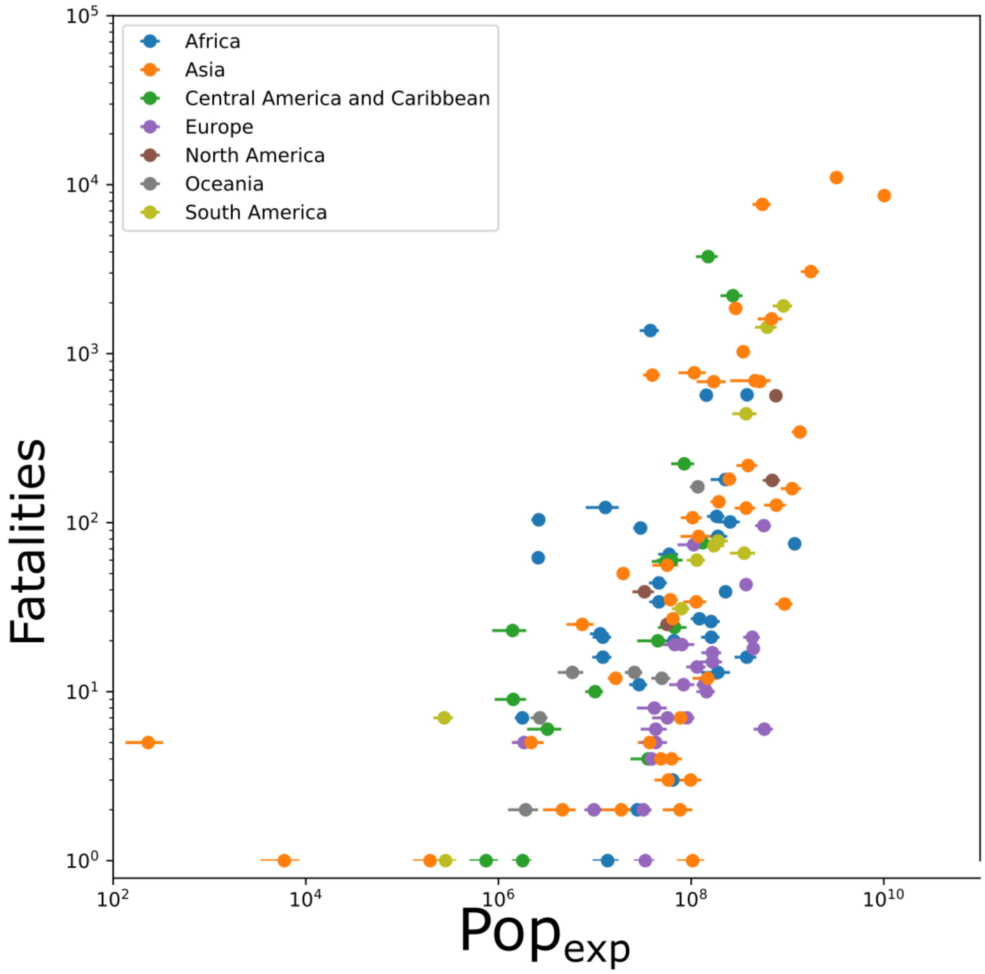


Figure 5: Showing the exposure of population (in person-Nowcasts/year) against the number of total fatalities recorded in the dataset of Froude and Petley 2018

In Figure 6, we plot the total road exposure against a derived metric of GDP impact from Dilley et al. (2005) based on the EM-DAT landslide dataset. The EM-DAT based assessment divides the globe into 2.5 degree squares and does not present absolute values of total economic loss, but instead a relative decile (1-10 with increasing risk) ranking of grid cells based upon the calculated economic loss risks. While this metric is not quantitative of the economic risk, we suggest that it is possible to compare these relative loss rates against our results. As with the comparison between Pop$_{exp}$ and fatalities, we see a relatively strong correlation. However, it is clear that the EM-DAT dataset is incomplete; the complete absence of data on costs associated with landslides in African countries limits how effectively we can compare this inventory with our model estimates. The absence of data further highlights~~does further highlight~~ the value of our globally consistent approach.

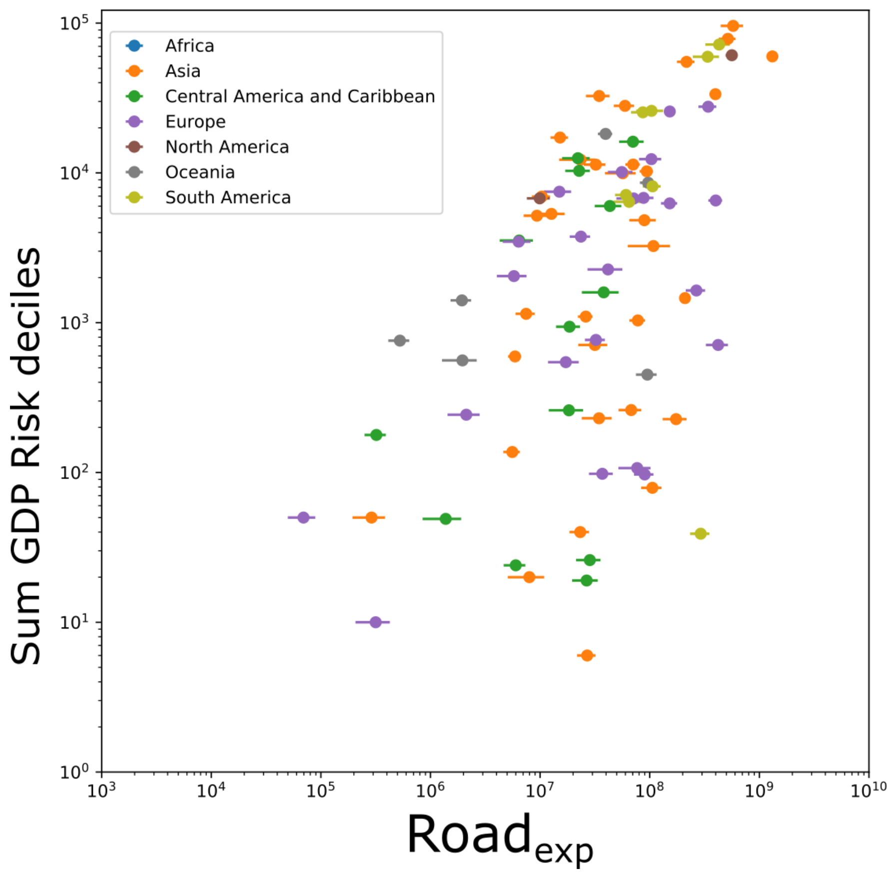


Figure 6: Plotting the exposure of roads (in road-km Nowcasts / year) against the estimated GDP cost of landslide impact estimated by Dilley et al. (2005).

Although there are countries without data in the EM-DAT derived database, it may be possible to derive these missing values based on the relationship between $Road_{exp}$ and the countries where EM-DAT data exists (points in Figure 6) – i.e., to capture the y-axis values based on a known x-axis value. However, the degree of scatter evident in Figure 6 suggests that further data is required to explicitly define such a relationship, and error margins may be large. Extrapolation and validation of this relationship is beyond the scope of this current work, but we suggest is an important topic for future research.

In order to learn which factors control the relationships between exposure and impact in different countries, we can combine the inventory data with our estimates and compare it with other variables. In Figure 7, we plot the number of fatalities recorded in the dataset of Froude and Petley (2018) divided by Pop_{exp}. This is subdivided by continent. We suggest that fatalities divided by exposure provides a proxy for the degree of hazard mitigation in a given country; lower values indicate that for a given level of population exposure, fewer fatalities are observed. We find high variability in each continent, although in general there are lower levels of fatalities per unit exposure in Europe when compared to Central America and the Caribbean, as well as

South America. Germany and Hong Kong, highly developed countries, have proportionally low fatalities despite high levels of exposure, likely a result of extensive mitigation efforts.

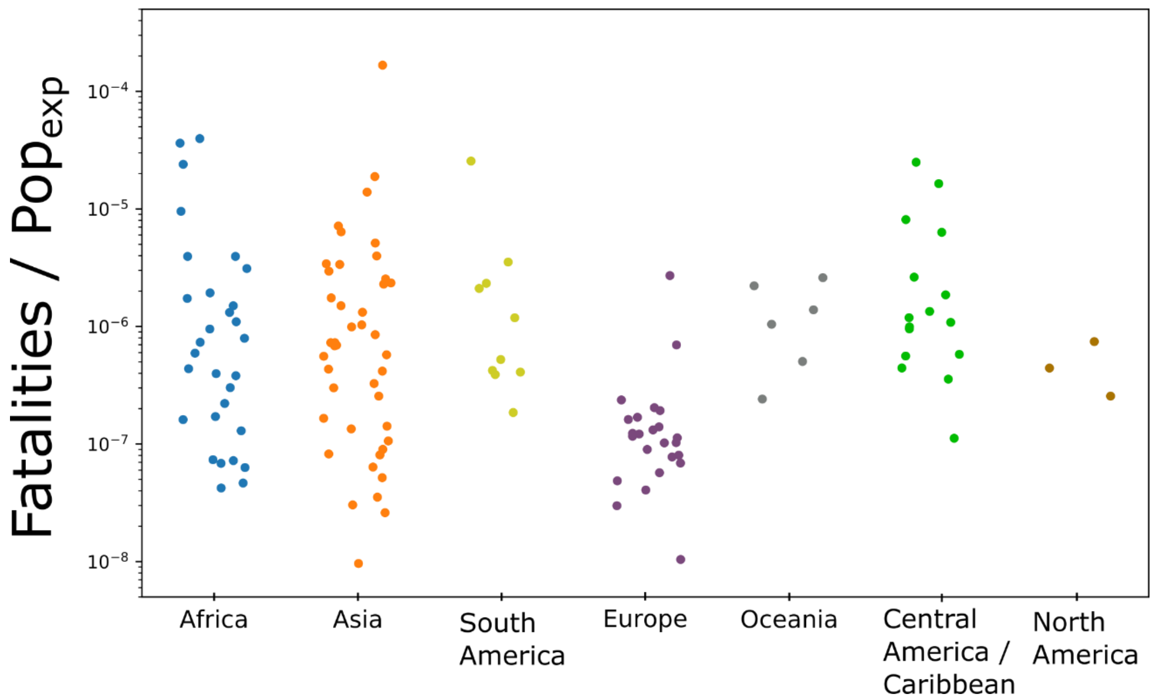
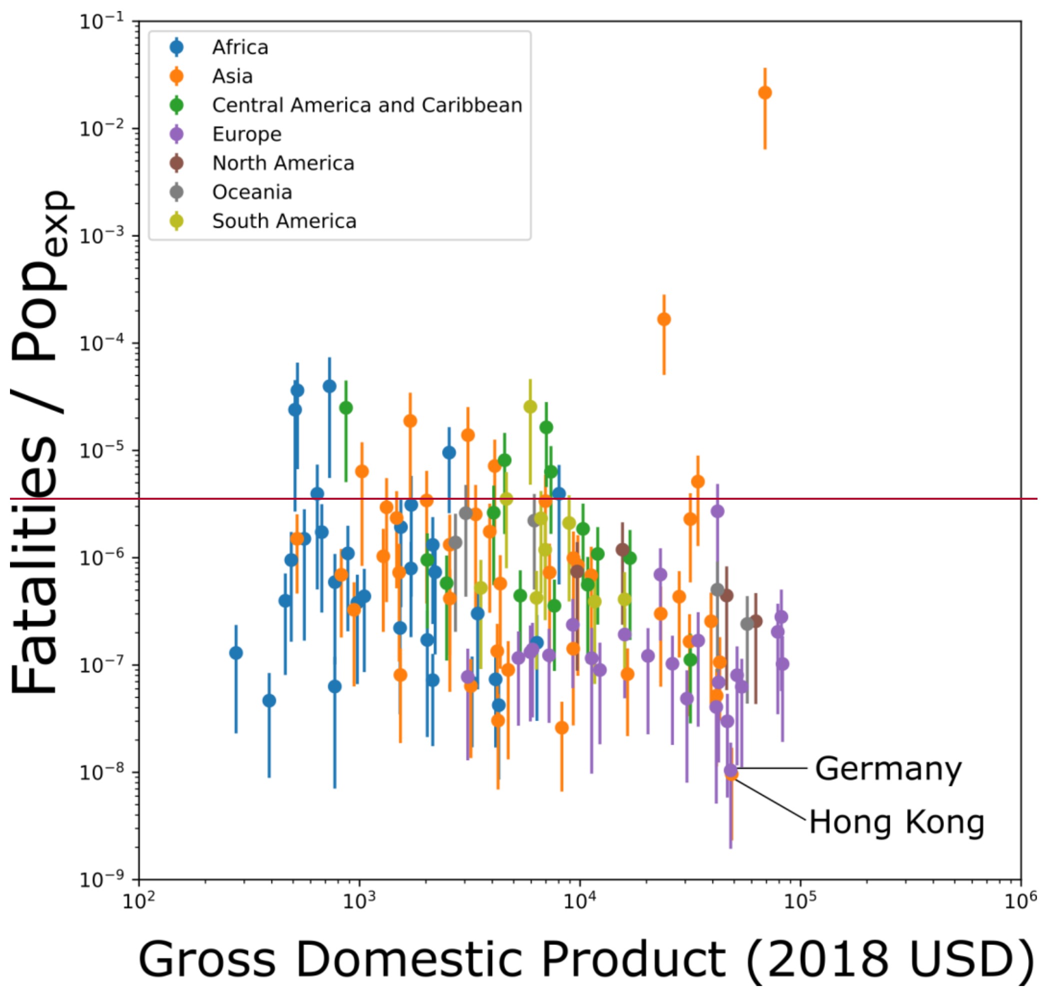


Figure 7: Number of fatalities divided by Pop_{exp}, for each continent. The wide spread of values in Africa and Asia are likely a reflection of the diversity of nation-to-nation landslide vulnerability. Offsets in the x-axis are for visual distinction between points to avoid overlap.

At the other end of the spectrum, some less developed countries exhibit higher fatalities for a given exposure; Sierra Leone, Burkina Faso, Haiti, Suriname, Bangladesh, Dominica and the Philippines have a significantly higher level of fatalities per unit of exposure. Some key outliers (Qatar and Bahrain) have high fatality per unit exposure, but these nations have very low overall exposure (see Supplementary Table 1) meaning that even a small number of fatalities increases the y-axis value in Figure 7 to a large degree. This analysis, while not at this stage comprehensive, potentially allows us to explore a proxy for national-level risk management associated with landslide hazard, or relative vulnerability to a given level of exposure

To explore whether the variability in fatalities divided by Pop_{exp} seen in Figure 7 is related to the level of development in each country, we have compared fatalities / Popexp with 2018 GDP values for each country (World Bank 2019) *A priori*, we would expect countries with greater GDP to be capable of mitigating hazard more effectively, and thus have fewer fatalities for a given level of exposure. However, while there is a small average decline in fatalities for a given exposure as GDP increases (Figure 8), with some high GDP countries showing the lowest fatality values (notably Germany and Hong Kong)- there is a significant degree of variability in this relationship, suggesting there is a more complex relationship.

We note that comparing the model-based estimates of exposure with the fatality inventory of Froude and Petley (2018) in this manner may lead to erroneous conclusions if not considered carefully. While it is likely that many, if not all of the fatal landslides in developed countries are accurately recorded, this may not be the case in states where disaster management is less advanced. As such the lack of strong relationship between fatalities per unit exposure and GDP per capita observed in Figure 8 may represent gaps in the data in countries with lower GDP per capita, and thus a systematic bias within this analysis. Phrased differently, there may still be a relationship between GDP and fatalities for a given exposure level, but this may be masked by a lower reporting capacity in less-developed nations.



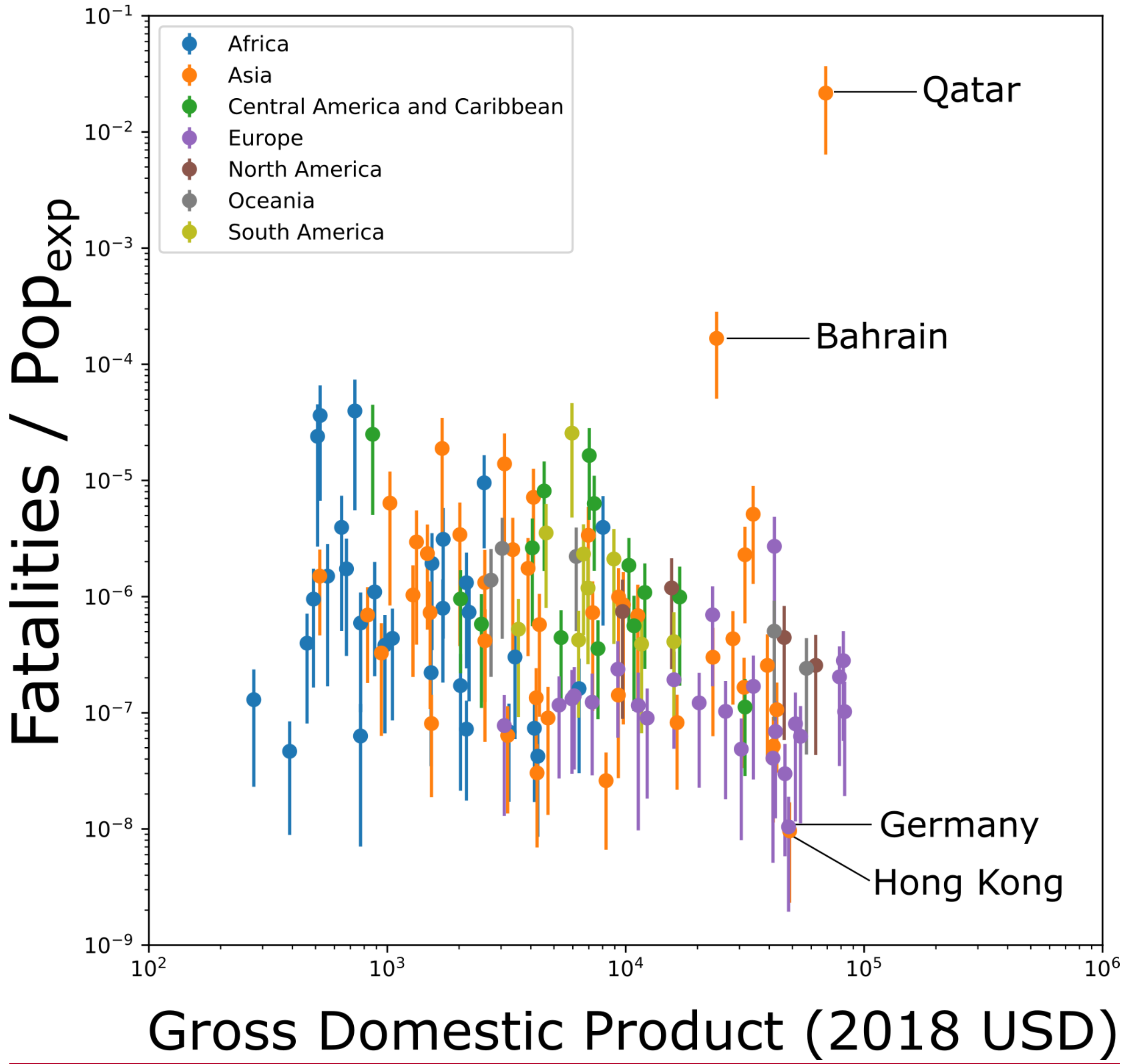


Figure 8: Gross Domestic Product per capita (World Bank, 2018) compared with the number of landslide fatalities per unit exposure.

While these results provide an independent estimate of landslide hazard and exposure across the globe that does not rely on a specific inventory, there are still assumptions and limitations that should be considered to put these results in appropriate context.

The most important caveat associated with this data is that Nowcasts do not represent a guarantee of a landslide. The LHASA model Nowcasts (Kirschbaum and Stanley 2018) are issued when there is an increased likelihood of a rainfall-triggered landslide, meaning the estimates of exposure represent the relative likelihood of exposure to landslides, rather than the reported impacts. As such, Nowcast number is a proxy for landslide hazard, rather than a quantifiable landslide hazard. However, we suggest that this disadvantage is more than offset by the global homogeneity and comparability of the Nowcast output. In addition, since the nowcast-based estimates of hazard are based on historical rainfall data, they do not provide effective prediction of future exposure to hazard. This is particularly important given the potential for climate change to affect rainfall-driven hazards (Kleinen & Petschel-Held 2007). Our model estimates of exposure would also fail to capture rainfall driven exposure to landslide hazards in periods outside of the IMERG v06B record (pre 2001), including major rainfall-driven landslide events resulting from the 1998 El Nino event (Coe et al. 2004, Ngecu & Mathu 1999). We stress that the model outputs are representative of the historical period under analysis, rather than strictly speaking a long-term average.

Additionally, since we do not have global data to quantify the vulnerability of settlements and infrastructure to landslide hazard, we cannot quantify the risk and impacts associated with landslide hazard. For example, data on fatalities associated with landsliding (Froude & Petley, 2018; Petley, 2012) quantifies the impacts, and while we can express our outputs in terms of relative proportion of population exposed to hazard, the lack of vulnerability data in our study represents an unconstrained source of variability if we compare those two datasets. Moreover, since the Nowcast output does not capture information about the size of a potential landslide in a given area, there may be differences in the severity of the landslide events that occur depending on local factors (e.g. topography).

We note that we do not identify specific hospitals or schools as exposed to landslides. The resolution of our analysis remains coarse for individual points, and identifying specific locations could lead to overconfidence in exposure estimates. We acknowledge the importance of downscaling exposure estimates to those points, and suggest it is another important future direction for landslide exposure estimation.

The resolution of the Nowcast data also presents challenges to the interpretation. While a Nowcast estimate for a 30 arc-second~~1km~~ x 30 arc-second~~1km~~ grid cell provides an estimate of the landslide hazard therein, it does not provide information about where exactly a landslide may occur. Since infrastructure and population are unlikely to be evenly distributed within a grid cell (and are likely to be located further from areas of highest landslide susceptibility if risk mitigation measures have been adopted), elements that we describe as ‘exposed to landslide hazard’ may never actually be so. Given the resolution of our input hazard data, we suggest that it is challenging to provide a more finely resolved estimate. This does highlight the need for effective downscaling methods that can be applied to coarse resolution rainfall data to assess local landslide hazard. We hope to address this in future work. In addition, the LHASA model only models rapid landslide failures in natural settings. This means it does not capture landslides resulting from anthropogenic influence or slow-moving landslide events, which lead to a significant number of fatalities every year (Petley, 2012). Constraining exposure to this kind of failure is another important subject for future studies.

The value of a homogenous global dataset is highlighted when comparing the relative exposure of population to landslide hazard based on our estimates with the GDP cost associated with landslides derived from Dilley et al. (2005). The prior study is based upon the EM-DAT inventory of damaging landslides, but the complete absence of data for countries in sub-Saharan Africa (see Supplementary Table 1) contrasts strongly with our results, which suggest that there is a significant proportion of the population in many sub-Saharan African countries exposed to landslide hazard.

5. Conclusions

Through combining rainfall, topography and other satellite-derived data, we have developed a long-term estimate of landslide hazard across the globe, which we have utilised to estimate the exposure of population and infrastructure to rainfall induced landslides. These estimates are globally consistent, and compare favourably with existing global datasets. When used in conjunction with datasets of landslide fatalities we can provide a nuanced picture of where and when landslides are most impactful. Our data highlights the importance of landslides in small, mountainous nations and islands; while the absolute numbers of fatalities may be smaller, these represent locations with extremely high hazard and exposure. Further work is necessary to both test these results in a range of settings as well as to explore how global estimates can be downscaled and compared to more local estimates.

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