Introduction

Landslides can be destructive to people, property and infrastructure in their paths. Worldwide, these natural disasters cause tens of thousands of deaths each year [@froudeGlobalFatalLandslide2018]. It is challenging to estimate the monetary costs of landslides worldwide because most countries do not systematically monitor landslides. However, landslides costs in the US alone fall between in the vicinity of 2 billion USD annually [@schusterSocioeconomicEnvironmentalImpacts2001]. In light of the far-reaching impacts of landslides, prediction and mitigation efforts are vital.

Though an accurate assessment of landslide hazard would aid mitigation efforts [@spikerNationalLandslideHazards2002], such an assessment presents a challenge in part because landslides are often triggered by a sequence of cascading natural hazards [@kloseIntroduction2015]. Landslides interact with other hazards such as heavy precipitation, wildfire, floods, earthquakes, melting permafrost and glacial outbursts [@kirschbaumAdvancesLandslideNowcasting2012; @harpLandslideInventoriesEssential2011; @budimirSystematicReviewLandslide2015; @kirschbaumChangesExtremePrecipitation2020; @cannonDebrisflowHazardsMitigation2003]. This paper will focus on a particular sequence of cascading natural hazards: the post-wildfire landslide. In these events, wildfire is followed by intense precipitation leading a debris flow or other mass movement, sometimes in combination with flooding. Post-wildfire landslide hazards depend on dynamic factors such as how long it has been since a fire, soil moisture, and weather [@kirschbaumSatelliteBasedAssessmentRainfallTriggered2018].

This study seeks to detect and characterize the influence of fire on landslide susceptibility at the regional scale, in contrast to previous work that primarily focuses on the local scale. Though there are many local studies demonstrating a relationship between wildfire and the amount of precipitation that triggers a landslide, the lack of complete landslide inventories covering a wide spatial area presents an obstacle to evaluating the role of fire on rainfall-triggered landslides in general (@kloseLandslideDatabasesState2015). This study compares landslide-triggering precipitation for 6014 burned and unburned locations from a global database using three methods. Triggering precipitation is considered to be a proxy for landslide susceptibility because areas that are less susceptible to landslides will only have landslides in the presence of a larger triggering event. We compare different regions to better understand differences in post-fire landslide hazards across areas with differing climate and topography.

Background

Evidence for increased landslide hazards due to recent wildfire

Wildfire has been linked to increased frequency and volume of debris flows in several regions of the Western U.S. [@cannonWildfirerelatedDebrisFlow2005]. A key piece of evidence for this connection comes from a series of studies based on repeated post-storm observations of burned watersheds in Southern California and the intermountain West as part of the development of the United States Geological Survey's operational post-wildfire landslide hazard predictions [@staleyUpdatedLogisticRegression2016; @cannonPredictingProbabilityVolume2010; @gartnerEmpiricalModelsPredicting2014; @gartnerMutivariateStatisticalModels2009; @rupertUsingLogisticRegression2003]. These 5 studies model the probability of landslides after a wildfire using logistic regressions to demonstrate that both burn severity [@staleyUpdatedLogisticRegression2016] and burn extent within a watershed [@cannonPredictingProbabilityVolume2010] are associated with increased debris flow likelihood. Furthermore, @gartnerEmpiricalModelsPredicting2014 found that the increase in landslide probability in a watershed due to wildfire is greatest immediately after wildfire, and lasts a total of 2-5 years. Increased likelihood of post-wildfire debris flows has also been associated with other factors such soil KF-factor (erodibility of fine sediment), soil organic matter percentage, soil clay percentage, watershed area, watershed relief ratio and underlying lithology (e.g. sedimentary or granitic rock) [@gartnerMutivariateStatisticalModels2009; @rupertUsingLogisticRegression2003]. Though none of the above studies include observations of unburned sites as a 'control', the relationship between landslides and burn severity strongly suggests that landslide susceptibility increases after a wildfire in the Western U.S..

These databases include multiple observations at each site including observations of the absence of a debris flow, a pre-requisite to a regression analysis. They do not, however, contain observations of unburned basins, and so would require extrapolation for our purposes of comparing burned and unburned basins. In addition, while these observations are high quality and extend across a remarkable range when compared to most other landslide hazard models, they still are limited to on the order of 100 sites or less concentrated in a handful of locales. (56 sites Cannon, 34 sites Staley, 119 sites Gartner 2014)

Mechanisms by which fire increases landslide hazard

Increases in landslide occurrence following wildfires are mediated by several distinct physical mechanisms. The destruction of vegetation is reported to contribute to the development of debris flows in three ways:

1. Before the fire, sediment gathers behind vegetation trunks and stems, only to be released after a fire either as dry ravel (e.g. rolls down the slope without precipitation) or during a rain storm [@cannonWildfirerelatedDebrisFlow2005].
2. Vegetation destruction clears the way for water and sediment to flow downhill more quickly [@cannonWildfirerelatedDebrisFlow2005; @shakesbyWildfireHydrologicalGeomorphological2006].
3. Immediately following a fire canopy and litter storage (e.g. water that gets trapped in leaves and other detritus on the ground) is greatly reduced, which results in increased runoff and sediment transport [@cannonWildfirerelatedDebrisFlow2005; @shakesbyWildfireHydrologicalGeomorphological2006].

Soil is also dramatically changed by fire, resulting in the following three effects on runoff generation and sedimentation

1. Burned soils have reduced organic content, which causes them to have reduced water-holding capacity [@spittlerFireDebrisFlow1995].
2. Burned soils also take on a more erosive texture [@shakesbyWildfireHydrologicalGeomorphological2006].
3. Some combinations of soil, vegetation type, and temperature can decrease wettability or produce a hydrophobic layer 1-5 cm beneath the soil, thereby dramatically increasing runoff [@spittlerFireDebrisFlow1995] . The implications of this effect vary dramatically from place to place, since fire can also destroy hydrophobic layers in the right conditions [@shakesbyWildfireHydrologicalGeomorphological2006]. In addition, these effects are not always uniform across the burned area, and the effects of changed wettability can last from days to years depending on the local conditions [@shakesbyWildfireHydrologicalGeomorphological2006].

Spatial bias in landslide studies

Post-fire landslide studies focus on only a few regions worldwide, with an emphasis on the Western United States and particularly Southern California chaparral ecosystems. The consistent patterns of post-wildfire landslides that pose a great risk to lives, property and infrastructure that characterize Southern California understandably get attention from organizations that provide hazard assessment and mitigation services. However, this spatial bias leaves open the question of whether the fire-flood patterns of Southern California are unique, or if similar hazards are just as ubiquitous but under-reported in other regions.

Strengths and weaknesses of different types of landslide data

Most publicly available landslide datasets are unsuitable for both interregional comparison and supporting robust predictive models. It is impossible to know where landslides will happen in advance, and prohibitive to continuously search for mass movements. As a result, most datasets are either an exhaustive records over a small domain, or a record of only the most disruptive landslides on a regional or global scale. [@westen_landslide_2006]

There is a large variety of predictive modeling studies based on complete landslide records, but which cover too small of a spatial domain to allow interregional comparison. For example, a municipality may choose to perform an aerial survey looking for landslides immediately following an earthquake, and the use GIS parameters such as slope and lithography to create a hazard map for future earthquakes. While such inventories can be collected through field observations, remote sensing, or some combination, they are expensive and time-consuming to compile regardless of their source. It is rare to find such a dataset that spans more than 500 square kilometers or a few weeks. Most landslide studies are based on observations made over a small area after a single triggering event. Critically for the identification of hydrologic triggers, it is nearly impossible to pinpoint when a landslide happened this way; even satellite data at the appropriate resolution is unlikely to have frequent overpasses. [@westen_landslide_2006]

To facilitate this analysis, we chose to use the NASA Global Landslide Catalog (@kirschbaumGlobalLandslideCatalog2010), which despite data gaps currently offers the largest spatial and temporal range of any catalog. The GLC shares strengths and weaknesses with the few other regional and global databases available. Though the GLC covers a broad spatial and temporal domain, has problems with precision and completeness. The source of these data are second-hand observations made by organizations like the news media or departments or transportation when landslides are causing problems for people or infrastructure. This type is relatively high location error, and substantial spatial bias towards populated areas. However, this dataset provides a large collection of events taking place in a variety of climates and triggering conditions, making it well suited for comparing the diverse circumstances in which post-fire landslides occur. This study seeks to evaluate whether or not these data contain enough information to characterize the triggering conditions of different types of landslides. [@kirschbaum_global_2010]

Methods

Precipitation in the weeks leading up to the landslide for burned and unburned sites were compared using three approaches: precipitation event percentile (see @sec:pctl), precipitation frequency (see @sec:freq), precipitation anomaly relative to bootstrapped samples (see @sec:boot).

Data

Landslides

A large sample (n=6041) of landslides was obtained from the NASA Global Landslide Catalog (GLC) [@kirschbaumGlobalLandslideCatalog2010]. Landslide locations are shown in @fig:map. The selected landslides were limited to rainfall-triggered landslides, or those with a 'landslide trigger' value of 'rain', 'downpour', 'flooding', or 'continuous rain'. Only records with a location accuracy of 15 km or less were included. In addition, only landslides between 50^oS and 50^oN latitude were included, and the events occurring before the year 2000 were omitted, so as to ensure coverage by both fire and precipitation datasets (see @tbl:datasets).

Each landslide in the GLC is labeled with a 'location accuracy' of 'exact', 1km, 5km, 10km, 15km, 25km, or 50km on the basis of how precise the source was in specifying the location [@kirschbaumGlobalLandslideCatalog2010]. The location accuracy was used to define a landslide buffer, or a zone in which the landslide might have occurred. Only landslides with a location accuracy of 15km or less were included, since it was common for the larger buffers to contain small fires every year or two that obscured whether or not the landslide was actually post-wildfire.

The landslides were paired with burned area and precipitation datasets (see @tbl:datasets). MODIS Burned Area data [@giglioCollectionMODISBurned2018] were used to classify landslides as post-wildfire (see @sec:fire). Similarly, the precipitation time series leading up to the landslide were extracted from the CHIRPS precipitation dataset [@funkClimateHazardsInfrared2015a]. Precipitation values have been normalized for location and time of year by computing a 30-day rolling percentile based on 38 years of historical precipitation from 1981-2019 at the same location (see @sec:precip). @Fig:glc shows the selected GLC landslides along with whether or not the site was burned (top panels) and the cumulative-precipitation percentiles of the 7 days leading up to the landslides.

Data source	Description	Extent	Resolution	Citation
NASA Global Landslide Catalog (GLC)	Compilation of landslides drawn from news articles and scientific reports	Global, with variable coverage in different countries	Landslide location accuracy varies from exact to 50 km range. The coarsest location accuracy used was 10 km.	[@kirschbaumGlobalLandslideCatalog2010]
Climate Hazards Infrared Precipitation with Stations (CHIRPS)	Station-corrected gridded precipitation data derived from cloud temperature observed using infrared satellite observations	50° S to 50° N	0.05°	[@funkClimateHazardsInfrared2015a]
MODIS Burned Area	Approximate dates on which a pixel was burned, derived from the Moderate Resolution Imaging Spectroradiometer sensors aboard NASA's Terra and Aqua satellites. The product uses a reprocessing algorithm that combines changes in burn-sensitive vegetation index and active fire locations.	global	500 m	[@giglioCollectionMODISBurned2018a]
Daymet Precipitation	Daily gridded precipitation estimate derived from station data by interpolation and extrapolation	North America	1 km	[@thorntonDaymetDailySurface2014]

: Datasets used in the analysis {#tbl:datasets}

Regions {#sec:regions}

To compare the differences in landslide triggers in different climates, we divided the landslides into regions. The GLC landslides are not evenly distributed around the globe, so regions were determined by the AGglomerative NESting (AGNES) hierarchical clustering algorithm [@kaufman2009finding]. The cluster tree was truncated at 40 clusters, and then all the clusters with fewer than 100 data points were eliminated. Clusters were further eliminated or joined manually to ensure that post-fire landslides made up at least 5% of the landslides. The final regions are shown in @fig:map.

Fire data {#sec:fire}

Fire affects the landscape over a large range of temporal scales in different settings, but previous studies suggest that most of the effects are observed within 3 years [@gartnerEmpiricalModelsPredicting2014]. Accordingly, burned fraction was computed as a fraction of the landslide buffer burned at some point in the 3-years prior to the event. As a result of this analysis, 511 landslides were categorized as post-wildfire events.

Though it was not used in the analysis, a burned fraction value was computed for each landslide. The burned fraction was the fraction of the landslide buffer that was burned. Due to the nature of the data used in this study 'false positive' post-wildfire landslides (meaning that the landslide was not actually at a burned locations but coincidentally both events occurred within the landslide buffer) are possible. This type of error is a function of both the burned fraction and the conditional probability of landslides occurring given that a fire has occurred. False positives are less likely in areas that are susceptible to post-wildfire landslides even if the burned fractions are low. @Fig:burned_fraction shows the distributions of burned fractions for each region.

Precipitation data {#sec:precip}

Characterizing landslide triggers requires data about precipitation at the time and location of known landslides. However, landslides can be triggered by different types of storms: Runoff-driven landslides are caused by intense, high-volume storms that mobilize sediment on the surface while infiltration-driven landslides by contrast are initiated by longer storms that saturate the shallow subsurface resulting in slope failures [@cannonWildfirerelatedDebrisFlow2005]. In order to include both of these types of storms, total antecedent precipitation from one week before the landslides was used instead of precipitation just the day of the event. This approach is less sensitive to small errors in landslide dates. While including an estimate of the soil moisture was outside the scope of this study, 7-day antecedent rainfall indices have been used by other modeling studies as a surrogate for soil moisture in a combined indicator of hydrologic landslide triggers [@kirschbaumSatelliteBasedAssessmentRainfallTriggered2018].

Landslides can be caused by precipitation events of various sizes, depending on the climate. Furthermore, it is challenging to differentiate an unusual increase in precipitation from the onset of the rainy season. To compare triggers across locations, we used a site-specific 30-day rolling percentile computed over the 38-year period of record. This statistic produces a normalized precipitation distribution that remains uniform through seasonal changes, highlighting anomalous precipitation events.

For 6% (n=372) of the landslides, no triggering precipitation event could be found. These events were likely a result of errors in the precipitation data or landslide data. A comparison with the Daymet precipitation dataset [@thorntonDaymetDailySurface2014] over the California and Nevada domain revealed that often the two precipitation datasets did not agree on these 'dry' landslide events, suggesting that the problem was mostly to do with the precipitation data. Furthermore, the dry landslides were anomalous in that there was relatively good agreement about precipitation preceding other landslides, suggesting that the 'dry' landslides were a major source of error in the precipitation data. To limit the effect of these erroneous data points on the results, all landslides with no measured precipitation in the 6 days before and 1 day after the event were removed from the study.

Precipitation percentile {#sec:pctl}

This method compares the normalized 7-day precipitation volume in the time leading up to a landslide as an indicator of how extreme the precipitation was that triggered the mass movement. The precipitation percentile distributions of all non-zero precipitation days are uniformly distributed as a result of the pre-processing described in @sec:precip, but this method of normalization cannot account for differences in the frequency of precipitation across different climates. A Mann-Whitney hypothesis test was used to ascertain whether the distributions of precipitation percentiles at burned and unburned sites were drawn from the same distribution. Deviations between the burned and unburned groups indicated by a p-value less than 0.05 on the Mann-Whitney test are indicative of statistically significant differences in the susceptibility of the two groups to landslides, since long-term climatic differences between the two groups have been accounted for by taking the percentile.

Median anomaly relative to bootstrapped samples {#sec:boot}

Some information about landslide susceptibility was contained in looking at precipitation magnitude and frequency separately. However, since there are observable differences between the burned and unburned groups using both metrics, a combined value that quantifies how unusual the precipitation was relative to the historical record was desired. For this, the precipitation was compared with random samples from the historical record.

First, samples were taken from the historical precipitation record matching the dates and locations of each landslide but from a different year. These samples are representative of normal precipitation for a particular lead time at the landslide locations and serve as a type of 'control', and were selected to match the sample sizes between burned and unburned groups. Next, the differences between the median of each control sample and the median of the observed landslide-year precipitation were taken. This produces a distribution of median anomalies that represent the degree to which the precipitation leading up to the landslides varied from the control baseline.

Precipitation frequency {#sec:freq}

Beyond the precipitation percentile, there are additional differences between the burned and unburned groups in precipitation frequency, including potential long-term persistent differences. In order to facilitate an analysis of landslide seasonality on the basis of precipitation frequency, the frequency was not normalized by location or time of year.

For each lead time (e.g. ranging from 4 years before the landslide to 4 years after), I computed the precipitation frequency for the burned and unburned groups by taking the fraction of locations in the group that had non-zero precipitation on that day. Any long-term persistent differences between burned and unburned sites were instead removed by subtracting the mean precipitation frequency of the group. Finally, I took a 90-day running average to reduce noise in the data and thereby make it easier to visually identify any long-term shifts in landslide occurrence. For the final analysis, I intend to fit a periodic function to the data in order to quantify the magnitude of any shifts.

Data inclusion

We included only events that could have been triggered by precipitation, specifically those where the Global Landslide Catalog 'landslide_trigger' field was 'rainfall', 'downpour', 'flooding', or 'continuous rain'. Even after filtering the landslides to include only rainfall-induced events, we found that approximately 20% of the landslides in the study area lacked a discernible triggering event in [any of the included precipitation products]. Many landslides occur in remote, mountainous regions with higher precipitation errors due to sparse gauging and complex topography. [cite] We validated precipitation against streamflow to diagnose errors in both precipitation and landslide data. The baseflow index for the days leading up to the event was calculated using R package `hydrostats`. We considered that a lack storm flow during the three days before and one day after a landslide suggests an error in the landslide record, while a lack of precipitation in the presence of storm flow indicates an error in precipitation data or processing. Landslides at locations and times where there was no evidence of a storm in the precipitation or streamflow data were assumed to be incorrectly detected or classified and were eliminated from the analysis. In the case of landslides with storm flow but no precipitation, we attempted to find evidence of precipitation in a different dataset.

Events with an excessively large spatial error of 25km or greater were also eliminated due to noise in precipitation and burned area data across such a large spatial domain. In particular, these areas tended to be burned in some part every year or two, making the burned fraction value meaningless.

Results

Relative magnitude of triggering precipitation events {#sec:percentile}

The distributions of precipitation event percentiles for all the included landslides and for each region separately are shown in @fig:percentile. As the landslide approaches, the percentile increases for all groups, confirming that these rainfall-triggered landslides are generally preceded not by normal rainfall but by unusually large storm events. In addition, globally post-wildfire landslides are triggered by significantly smaller (Mann-Whitney test, 95% confidence) precipitation events than landslides at unburned locations. This difference suggests that wildfire does in fact increase landslide susceptibility, since landslides in the period after a fire can be triggered by precipitation that is less extreme than would normally be required to cause mass movement.

An examination of the regions separately reveals that the difference in precipitation percentile between burned and unburned sites is driven by some regions more than others (see @fig:magnitude). The California area in particular has a strong signal, whereas tropical regions do not show any significant differences between precipitation at burned and unburned sites. A possible explanation for these differences is differences in data quality, since large landslide buffers are more likely to be flagged as 'false positive' burned areas such that the landslide actually occurred away from the burned area. This idea is supported by the larger landslide location accuracy values and lower cumulative burned fractions representative of the non-US regions (see @fig:burn_fraction). However, the high incidence of false positive burned areas itself could indicate that fires and landslides are not linked to the same degree in tropical and temperate areas. A high posterior landslide probability given that a fire has occurred would tend to greatly reduce the number of false positive burned areas by increasing the probability that a landslide occurred in the burned section of the landslide buffer.

The comparison in @sec:percentile excluded the precipitation frequency because there were long-term differences precipitation frequency between burned and unburned groups that were not normalized by taking a percentile. As a result, including zero-precipitation days risked conflation of differences in the landslide trigger with climatic or seasonal differences. We repeated the comparison by using anomalies from bootstrapped samples as a method of eliminating the differences between the burned and unburned groups. Though some of the same effects are visible in these results (seen in @fig:bootstrap), there are additional differences in the timing of precipitation in the lead-up to the landslide.

There are three main types of timing that are visible here. Firstly, in the Himalayas and Southeast Asia precipitation rises at a similar rate for each group, indicating that landslides at burned and unburned locations are triggered by similar hydrologic mechanisms. In California and the Pacific Northwest, the burned sites lag behind the unburned sites before catching up with some particularly intense storms, indicating that the post-wildfire landslides are largely runoff-driven while rainfall-triggered landslides at unburned locations are infiltration driven. Finally, in the Intermountain West the burned group seems to be characterized by a dry spell followed by a storm. This could be due to a larger group of landslides occurring immediately after a fire, or to the dry spell contributing to a more erodible soil texture.

Landslide seasonality

@Fig:season shows shifts in landslide seasonality for each region. While some regions such as the Intermountain West, Pacific Northwest, and Southeast Asia display marked differences in seasonality between burned and unburned sites, the others do no. Furthermore, among the shift in seasonality is not the same in each region that has one. In Southeast Asia and the Pacific Northwest landslides appear to happen earlier in the year at burned sites. In the Intermountain West on the other hand landslides appear to happen later in the year, specifically in the fall rather than the spring.

The results of the precipitation frequency analysis shown in @fig:frequency also reflect seasonal shifts in landslide occurrence in some regions. The precipitation frequency highlights differences in landslide seasonality between burned and unburned groups in different regions. For most regions, there is a long-term difference in precipitation frequency at burned sites as compared to unburned sites because in the absence of anthropogenic influences fires occur more often in drier climates. However, once the longterm average is removed, two general trends emerge in the annual patterns of precipitation frequency: differences in the magnitude of seasonal changes and shifts in the time of year most landslides occur. Note that because these plots are aligned based on the landslide date, a curve that is shifted to the right indicates that landslides in that group occurred more to the left, or earlier in the year.

In California and the Himalayas landslides are clearly shifted earlier in the wet season, although the shift is larger in California. This type of shift is the expected response in the case of increased landslide susceptibility due to fire, because in this case landslides could be triggered in more susceptible areas despite the less saturated soil and smaller or fewer rainstorms that occur earlier in the season. The Intermountain West also has a pronounced seasonal shift, but in this case the shift is much larger and in the opposite direction: landslides appear to occur and entire season later in the drier part of the year at burned sites in the region. One possible explanation is that the effects of fire are much greater in this region, leading to landslides occurring in the dry season but only immediately after a fire.

Other regions (Pacific Northwest, Southeast Asia) show a large difference in the magnitude of the annual cycle in precipitation frequency, but no shift in seasonality. This could be related to small sample sizes of post-wildfire landslides in these areas, or climatic differences in places that have fires within these regions. Furthermore, large landslide buffer areas could be causing noise in the precipitation data, since this precipitation frequency calculation does not distinguish between storms that cover different percentages of the buffer.

Central America also does not display a seasonal shift, although the magnitude of the variation appears to be smaller in the landslide year in unburned locations. Since there is little difference between the precipitation frequency or magnitude in this area, it is possible that wildfire does not have as much of an effect here on landslide susceptibility. It is also possible that the post-wildfire landslides in this region are false positives, which also suggests a reduced impact of wildfire on landslide susceptibility.

Discussion

There are clear differences between post-wildfire landslides and rainfall-triggered landslides at unburned locations in the magnitude of precipitation triggers, the seasonality of landslides, and the timing of triggering storms. These results suggest that wildfire increases susceptibility to landslides, especially in temperate climates. However, they also suggest that post-wildfire landslides are not a spatially uniform phenomenon. Both the mechanisms by which post-wildfire landslides are triggered and the degree to which wildfire increases susceptibility varies from location to location.

Developing a better understanding in the ways in which landslide hazards vary around the world is important for mitigation efforts as well as predicting how landslide hazards will respond to a changing climate. Data acquisition is a major barrier to this type of global analysis of landslide statistics. Both precipitation and post-wildfire status are major sources of uncertainty in this analysis due to imprecise landslide locations. High-accuracy landslide locations (e.g. 500 m) that are representatively distributed around the globe would greatly improve the quality of research comparing landslide responses across climates and regions.