Landscape memory is strongly influenced by climate in tropical mountains: implications for the spatial distribution of landslides

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Abstract

Landscape memory, the set of processes conferring resistance of disturbed areas to further disturbance, is critical for our understanding of ecosystem dynamics at large scales. Although evidence from diverse disciplines suggests that the conditions at the time of disturbance as well as the history of past disturbances are central to landscape memory, there have been few attempts to explore their relative contribution in systems in which ecological and geomorphic processes strongly interact. Among these systems, mountains disturbed by landslides stand out due to their regional and global importance. In mountainous regions, topographic and morphological attributes are known to contribute to landscape memory. However, vegetation attributes also influence geomorphic conditions in these systems, and in this way may play a role in forming patterns of landslide patterns as well. In this study I use degree of landslide overlap in combination with bioclimatic and topographic variables to explore landscape memory using a species distribution model (SDM) approach. Focusing on the Sierra de Las Minas of Guatemala, I created landslide inventories using remotely sensed data, then use these to identify overlapping and recovered landslide areas and model their relationship with bioclimatic and topographic variables. Irrespective of year, landslide occurrence was explained by three bioclimatic (positive relationship with isothermality, temperature seasonality, and precipitation during the wettest month of the year) and three terrain (negative relationship with aspect and curvature, and positive relationship with slope) variables. Overall, I observed little overlap among landslide populations. The number and type of variables explaining landslide overlapping and non-overlapping areas varied by period of observation but in general varied in significance far more than variables explaining initial occurrences. The implications of my results are three-fold. First, the retention of three bioclimatic variables in the models suggests that climate can alone, or through its effect on vegetation, influence the occurrence of landslides as well as their recovery. Second, landscape memory seems to play an important role in preventing reoccurrence as shown by the study area's great potential for recovery after disturbance. Lastly, increased precipitation and more extreme temperatures may increase landslide burden in the future.

Keywords: Landslides, landscape memory, bioclimatic variables, Sierras de Las Minas, climate change

Introduction

The organization and structure of ecosystems across the globe is mediated by patterns of disturbance (Johnstone et al., 2016; Rietkerk et al., 2004). Large-scale disturbance events are necessary occurrences to shape patterns that preserve habitat heterogeneity and species diversity within ecosystems (Schouten et al., 2009; Rietkerk et al., 2004). These large disturbance events are in turn regulated by mechanisms generated from past disturbance legacies (Johnstone et al., 2016). The frequency and intensity of disturbance has important impacts on the fate of these systems, potentially leading to catastrophic ecosystem shifts under changing conditions (Rietkerk et al., 2004). Unusual conditions resulting in excessive disturbance can pose risks not only to ecosystem health, but also to human lives and infrastructure (Westen & Terlien, 1996). In humid, tropical, and mountainous landscapes, landslides are the primary mode of disturbance, and their frequency is expected to increase as factors tied to climate change grow more erratic (Rietkerk et al., 2004; Gariano & Guzzetti, 2016). While the factors controlling landslide occurrence are fairly well understood, those affecting the probability of landslide reoccurrence, in particular the interaction of abiotic and biotic factors, require further attention in order to understand the trajectory of ecosystems.

Past research, mostly in the field of geomorphology, has drastically expanded our understanding of the role of abiotic factors on landslide frequency. Morphological and topographical elements of mountain landscapes such as slope and bedding structure impact the frequency, magnitude, and even shape of future landslide events (Guzzetti et al., 2008; Samia et al., 2017; Parker et al., 2015). Landslides also regulate the geomorphic conditions on slopes by removing topsoil and in some cases underlying bedrock, which can alter landslide frequency and shape and thus determine the types of landslides that are likely to occur. In certain conditions, landslides increase the likelihood of further disturbance at the sites in which they occur by disrupting the structure of landslide-prone slopes (Samia et al., 2017). Landslides have also been shown to serve as stabilizing factors for hillslopes, decreasing the probability of further site-specific landslide events by removing deeply destabilized areas which are prone to slippage (Parker et al., 2015). The regeneration of vegetation on recent scars can induce shallow topsoil-level slides, on or in the proximity of the past disturbance (Shimokawa, 1984). Moreover, evidence suggests that initial landslides control the shape and positioning of overlapping landslides reoccurring within a decade (Samia et al., 2017). Clearly, the process of landslide recovery is highly influential in creating future landslide regime patterns.

Disturbance events are essential aspects of vegetative succession; regular landslides maintain cycles of vegetative renewal and create biotic diversity by increasing abiotic heterogeneity (Walker et al., 1996). Vegetation development occurs rapidly post-landslide (Lin et al., 2006), and this is known to impact slope stability through root development, reinforcing soil and anchoring to bedrock (Kuriakose & van Beek, 2011; Shimokawa, 1984). Topography also influences vegetation patterns through its effect on the distribution of sunlight, water, and nutrients (Solon et al., 2007; Yang et al., 2020). Landslide occurrence and regularity are dependent on a multitude of factors which are heavily interwoven, yet the specific role of biotic factors remains largely understudied (Guzzetti et al., 2008; Restrepo et al., 2009; Solon et al., 2007). Including the influence of vegetative patterns is vital in order to understand landslide frequency holistically and create stronger models to predict landslide occurrence (Carrara et al., 2000; Restrepo et al., 2009).

The occurrence of a landslide in a given area is likely to affect the probability that a landslide might occur again in the following years. Landscape memory, the ability of ecological processes to interact with and influence one another over time, is speculated to deter further landslides in areas of recent occurrence (Peterson, 2002; Shimokawa, 1984). Memory influences the patterns of occurrence and recovery in ecosystems; when memory is strong, landslides and other disturbance events serve to maintain landscapes rather than act as a destructive force (Peterson, 2002). Landscape memory is affected by both the topographic characteristics of a given area as well as the bioclimatic conditions, but their relative effects on memory are unclear. Furthermore, landscape memory can be disrupted when landslides diverge from regular recovery schemes, for example when climate events unusual for the region occur. Therefore, understanding the effects of abiotic and biotic factors on landscape memory is important to understanding how climate change will affect the resilience of tropical mountainous ecosystems.

If vegetative factors affect the geomorphic properties which induce landslide occurrence, climate-mediated changes to vegetation communities across the globe will certainly disrupt landscape memory (Raetzo et al. 1997; Gariano & Guzzetti, 2016). Extreme changes in climatic factors, such as increasingly variable precipitation (Kirschbaum et al., 2020) and temperature (Bathiany et al., 2018) are projected to impact tropical regions. While a large number of studies have focused on the relationship between singular abiotic factors (mainly precipitation) and landslide occurrence (Chen et al., 2020; Kirschbaum et al., 2020), many bioclimatic variables remain excluded from this type of investigation. In expectation of potentially destabilizing climatic shifts, it is important to focus heavily on the relationship between bioclimatic factors and landslide occurrence.

In areas where they occur, landslides result in instantaneous changes. On one hand, they create opportunities for plant establishment and renew cycles of vegetative succession, as well as deposit patches of nutrient-rich soil in scar zones (Restrepo et al., 2009; Guariguata, 1990; Elias

& Dias, 2009). On the other hand, landslides destroy existing plant and soil communities, disrupt associated organisms, and pose risks for human infrastructure (Kirschbaum et al., 2020; Walker et al., 1996). In recent decades, hazard mapping has become a common practice for predicting the potential impacts of landslides in order to properly mediate their negative impacts on human lives and infrastructure, but deficiencies in our understanding in the biotic effects of landslide occurrence limit the effectiveness of these models (Westen & Terlien, 1996). The inclusion of bioclimatic data in hazard assessment is a necessary step in order to account for the direct (ex. precipitation) and indirect (effects on vegetation, etc.) effects of climatic conditions.

In this study, I investigated the effects of 19 bioclimatic and 4 topographic factors on landslide occurrence within 43,934 hectares of the Sierras de las Minas of eastern Guatemala. I hypothesized that a combination of bioclimatic and topographic factors would influence the likelihood of landslide occurrence. Additionally, I mapped landslides at three different time points within a 15-year period in order to examine the influence of bioclimatic and topographic factors on landscape memory, hypothesizing that the majority of landslide-impacted areas would recover in subsequent time periods. My aims were 2-fold: to determine the main predictive variables affecting the likelihood of a landslide, and the variables most affecting landscape memory (or the likelihood a landslide would not reoccur in the same location within 10 years). This study hopes to further our understanding of landslide risk factors as well as landscape resilience in a tropical mountainous environment.

Methods

Study Area

The Sierra de las Minas (SLM) of Guatemala is a 135 km by 30 km mountain range that runs east to west. The range connected to the Montañas del Mico and the Sierras de Chuacus, the latter of which is connected by a small ridge separating the Rio Negro and Rio Motagua drainages (Campbell, 1982). The mountain range drains to the Rio Polochic and Rio Chixoy watersheds to the north, and the Rio Motagua watershed to the south (Holder, 2006).

The SLM displays a great diversity of climate and vegetative conditions (Campbell, 1982). Tropical, dry forests occupy the southern slopes of the SLM between 300 – 1500 m and are replaced by dry pine and oak forests at elevations of 1500-2000 m. At elevations over 2000 m cloud forests develop due to substantially more moisture (Holder, 2006; Campbell, 1982). The height of the range causes the interception of prevailing winds, leading to greater rainfall on northern, wind-prone slopes (McAdams et al., 2015). Due to this, the northern slopes of the SLM are different in climate and structure than southern ones, and drainages to the north remove greater amounts of water and sediment from the region (McAdams et al., 2015).

The cloud forests of the SLM receive greater annual rainfall, 5000 mm in parts of the highest regions, than the Motagua valley below, which receives less than 500 mm annually (Holder, 2006). A significant amount of moisture received in cloud forests is sourced from fog precipitation, which is dependent on factors such as canopy structure, and vegetative orientation and surfaces (Holder, 2006; Brown et al., 1996). Therefore, removal of forest cover affects water availability by decreasing fog precipitation (Holder, 2006).

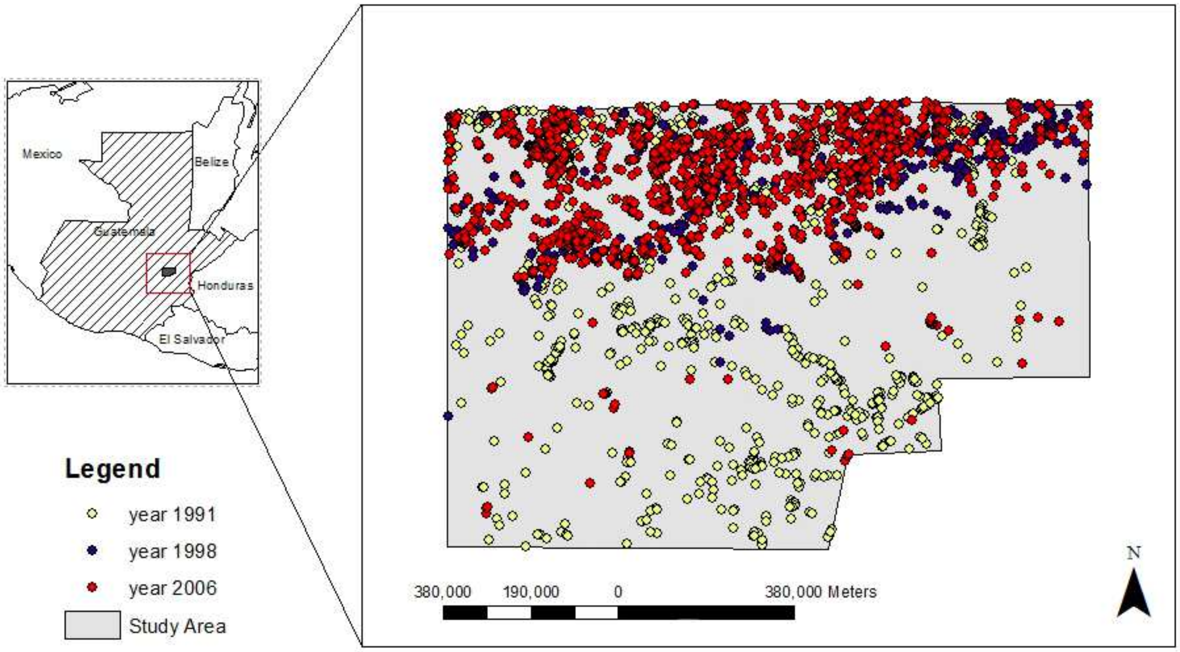

Figure 1. Location of the Study Area (left). Landslide distribution in region of study (right).

General approach

To examine the patterns of recovery creating landscape memory in the Sierras de las Minas, I combined landslide mapping and spatial analysis to determine significant influences of bioclimatic and topographic variables in landslide occurrence and overlap. This entailed a two-step process; first, a series of shapefiles representing landslide-impacted areas were composed to determine the relationship of landslide occurrence and recovery in the Sierras de las Minas. In order to examine differences between causality of singular landslide occurrence and reoccurrence, the relationship between predictors in both cases was analyzed using a species distribution model.

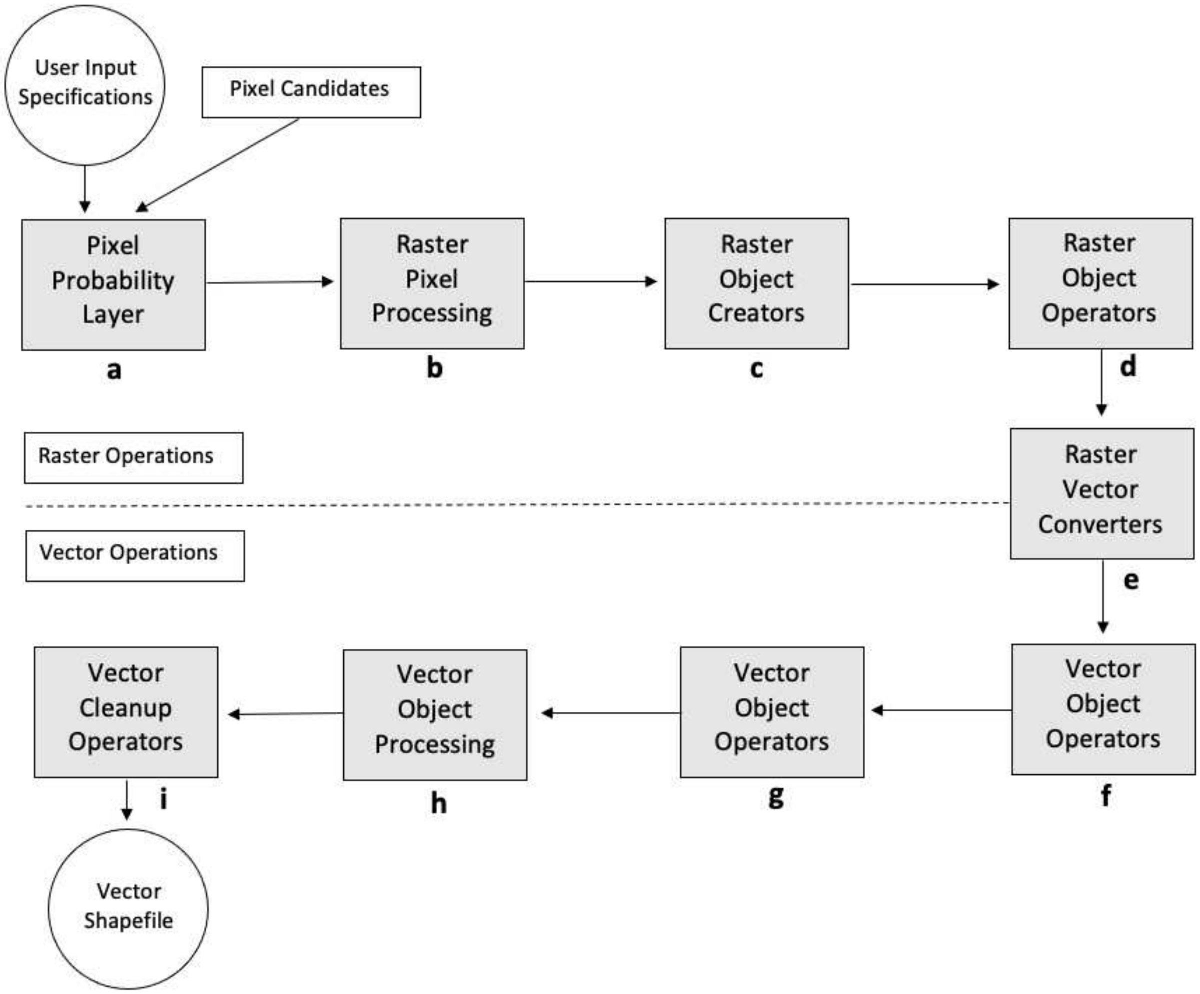

Figure 2. ERDAS Imagine Objective image processing. Stages involved in the creation of polygons from satellite imagery of the study area.

Landslide Inventories

Feature Extraction - ERDAS Imagine Objective was used to map landslides from satellite imagery of the SDM. These images were obtained from the Fundacion Defensores para la Naturaleza and orthorectified at the Large-scale Ecology Lab of the University of Puerto Rico at Rio Piedras. Objective was given an input of a raster image and identified visual cues, such as texture, color, and shape, to output a vector shapefile representing features of interest. This process involved machine learning components as well as automated steps created to filter pixels in raster layers and polygons in vector layers (Fig. 2). Before beginning the extractions, a test phase was initiated to determine the optimal sets of parameters for extracting landslides from the Sierras de las Minas images. The extractions followed an 8-step process (Fig. 2) converting groups of pixels representing landslide scars to singular vector objects.

The first step in feature extraction is to train Objective's pixel-classifying machine learning algorithm to properly identify pixels belonging to a class of interest. User input was given in the form of representative polygons, drawn within features as interest as well as polygons indicating background area. In order to maximize the consistency and replicability of the extractions, I first created a shapefile for each image in ArcGIS, referred to as "AOI" for Area of Interest, containing the designated polygons. These files were converted to .aoi files in ERDAS and were used as a file input during pixel processing.

The user-input pixel cues are used to sort all pixels of the chosen image based on their similarity to pixels in the AOI, eventually resulting in the Pixel Probability Layer (Fig. 2a). Taking the training signature as an input, Raster Pixel Processing (Fig. 2b) identifies attributes of pixels within polygons of desired features as well as polygons indicating background area. Using this information, Raster Object Creators form groups of pixels with like metrics (Fig. 2c). Typically, pixels are segmented into clumps of similarity determined by a threshold input by the user. These clumps divide all of the image's pixels into raster objects with a probability metric.

At this point, the segmented raster objects can be filtered from background objects by their attributes. ERDAS Imagine Objective offers a multitude of operators to filter potential features more accurately, such as a probability filter, clump size, and focal filters while objects are still in raster form (Fig. 2d). After this filtering, the raster object layer exported in the previous step is converted into a vector object layer (Fig. 2e), where they can be cleaned and further filtered by Vector Object Operators (Fig. 2f).

Data Cleaning – The images that I used had different quality of coloration, tone, and brightness that together with the spectral similarities exhibited by some objects (landslides, rivers, roads, agricultural fields, and buildings) resulted in incorrect identifications. I cleaned and edited the vector layers using the editing tools of ArcGIS Pro. Features were systematically inspected and modified, split apart from or merged together with other polygons, or deleted to ensure only features of interest remained. Polygons representing rivers and roads are important to the analysis as well and I allowed them to remain, labeling them to differentiate from landslides. Using a character type column in the attribute table of the dissolve layer called “class”, I labeled them as “riv” for river or “road” in order to differentiate them from landslides. Additionally, I added a classification “unkn” for unknown for polygons which needed further vetting during the review process. After the completion of this cleaning process, a reviewer gave feedback on the quality of editing. For the purposes of current analysis, a version of the shapefiles with rivers and roads removed was also created and saved.

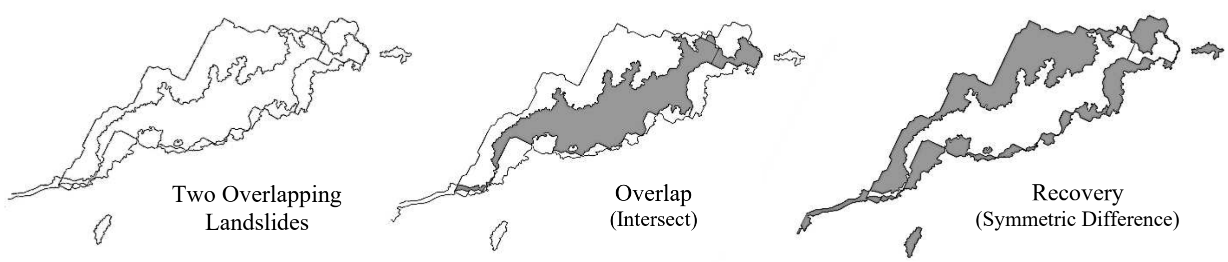

Figure 3. Example of intersect and symmetric difference functions on ArcGIS. The leftmost figure shows two overlaid landslides from different years. The central figure shows the result of the intersect function, collecting the overlapping area of the overlaid landslides. The symmetric difference function, shown in the rightmost figure, collects area unique to two different years, essentially all area where landslides do not overlap, representing recovery. Area of the vector polygons resulting from the function in use is darkened.

Spatial analysis

In order to investigate the strength of landscape memory patterns, I conducted a spatial analysis aimed at determining areas in which landslides did and did not reoccur. Towards this end I used the intersect and symmetric difference functions to identify areas of overlap and recovery respectively (Fig. 3). For each set of adjacent periods, the shapefiles of corresponding areas were overlaid in ArcGIS yielding 4 additional shapefiles, two presenting the relationship between the 1991 and 1998 periods, and 2 presenting the relationship between the 1998 and 2006 periods (Fig. 4). The symmetric difference function highlighted areas of recovery, where landslides were not detected for the second year. The intersect function highlighted areas of overlap, where landslides were detected in both years.

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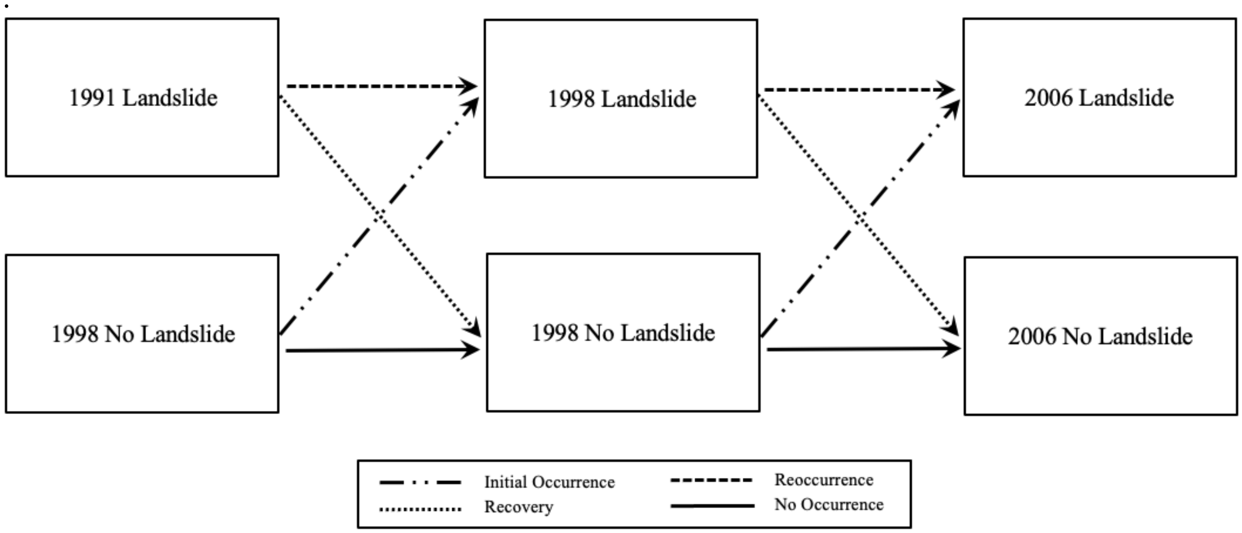


Figure 4. Landslide occurrence relationships conferring recovery and overlap. Instances of reoccurrence in neighboring periods, captured by the intersect function, confer the inability of landscapes to recover after initial disturbance, and signify the absence of memory.

Modeling landscape "memory"

I applied a Species Distribution Modeling approach to investigate the spatial distribution of landslides (Naimi & Araújo, 2016), including generating a generalized linear model with input presence/absence points (Bourne et al., n.d.). This entailed preparing the previously generated shapefiles for analysis, obtaining and formatting predictor data in raster form, creating locational occurrence points and synthesized absence points to represent area impacted and unimpacted be landslides, and applying a general linearized model to the data. I conducted analysis on the level of significance and direction of influence exerted by the chosen predictors on landslide occurrence in the study area using R's "dismo" and "usdm" packages.

Data preparation - Because the satellite images used to extract landslides differed slightly in area from year to year, it was necessary to standardize the size of the 2261-ii quadrant across all years and shapefiles. To exclude areas that might be lacking from any of the years, the overlapping area of all the 2261-ii images used for extraction was taken and turned into a vector polygon known as the "mask". All shapefiles used in analysis were cropped to be the shape of this polygon, excluding any points that fell outside the boundary.

Predictor Data - Bioclimatic and topographic data for analysis of landslide spatial distribution, referred to here as "predictors", was formatted into raster layers to be used in R (Table 1). Bioclimatic data was obtained from worldclim.org in raster form (Fick & Hijmans, 2017). Each bioclimatic layer used was cropped to the size of the study area using the mask used for data preparation. Data on the 4 topographic predictors and potential evapo-transpiration was obtained from ArcGIS using the DEM. The raster toolset within geoprocessing tools was used to create new raster files representing aspect, slope, curvature, and elevation. These factors were quantified using degree of decline in the case of slope and curvature, and in the case of aspect, a number from 0-360 represented the cardinal direction of the slope face (lowest values corresponding to northeast to east, and highest values west to northwest). All of these topographic layers were cropped using the mask like the bioclimatic predictors. I used ArcGIS to extract bioclimatic and topographic data as a raster layer.

Table 1. Raster data used as predictors during landslide distribution analysis. The 4 topographic variables, 19 bioclimatic variables, and potential evapo-transpiration chosen to be analyzed as predictors using a generalized linear model.

	Predictor	Code
Topographic Variables	Aspect	**-**
	Elevation	-
	Slope	-
	Curvature	-
Bioclimatic Variables	Potential Evapo-Transpiration	**PET**
	Annual Mean Temperature	**Bio1**
	Mean Diurnal Range	**Bio2**
	Isothermality	**Bio3**
	Temperature Seasonality	**Bio4**
	Maximum temperature of warmest month	**Bio5**
	Minimum temperature of warmest month	**Bio6**
	Temperature Annual Range	**Bio7**
	Mean temperature of wettest quarter	**Bio8**
	Mean temperature of driest quarter	**Bio9**
	Mean temperature of warmest quarter	**Bio10**
	Mean temperature of coldest quarter	**Bio11**
	Annual precipitation	**Bio12**
	Precipitation of wettest month	**Bio13**
	Precipitation of driest month	**Bio14**
	Precipitation seasonality	**Bio15**
	Precipitation of wettest quarter	**Bio16**
	Precipitation of driest quarter	**Bio17**
	Precipitation of warmest quarter	**Bio18**
	Precipitation of coldest quarter	**Bio19**

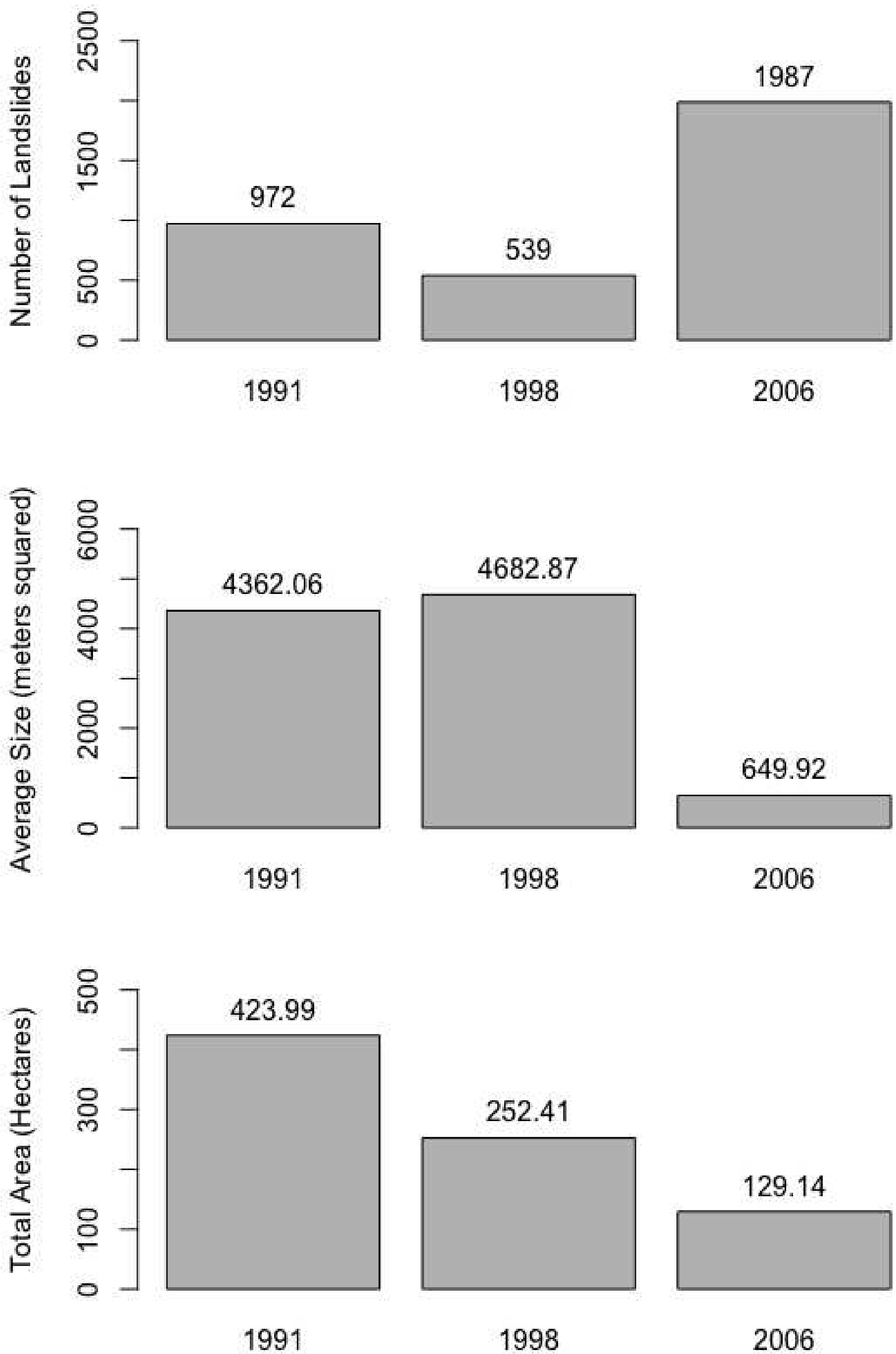
Presence/Absence data points – The landslides from the three years, as well as the intersect and symmetric difference polygon shape files were converted into point shape files using the "polygons to points" function. In addition, I randomly generated absence points, as analysis of species distribution analysis using presence-only models has been shown to exhibit greater bias than presence-absence models. A binary "occurrence" attribute was added to all points, presence points having a value of 1 and absence points having a value of 0.

Modeling the Spatial Distribution of Landslide and Memory Processes – A collinearity test was used to narrow down the number of applied variables from the set of predictors by calculating the variance inflation factors. This was conducted using the vifcor and vifstep functions in the "usdm" package from R's; model (Naimi et al., 2014). I used Generalized Linear Models with the binomial link to examine relationships between the presence/absence point distribution and bioclimatic and topographic variables using the dismo and sdm packages (Naimi & Araújo, 2016).

Results

Yearly Landslide Occurrences

The landslide inventories yielded 972, 539, and 1,987 landslides in years 1991, 1998, and 2006 respectively (Fig. 5a). The number of landslides found in the inventories was significantly higher in 2006 than the other 2 years (Fig. 5a). However, the 2006 areas were on average significantly smaller in size, while 1991 and 1998 demonstrated landslides of similar average size (Fig. 5b). Despite the high number of occurrences, 2006 demonstrated by far the least area impacted by landslides, and landslides in 1991 impacted the greatest overall area (Fig. 5c).



(a)

(b)

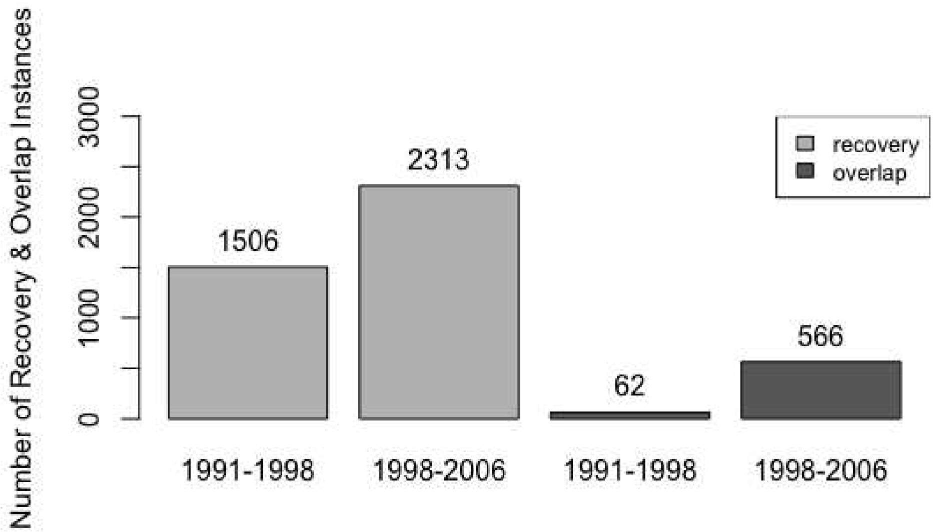
(c)

Figure 5. Landslides identified in 1991, 1998, and 2006. **(a)** The number of landslides discovered in each individual year **(b)** The average size of landslides for each year **(c)** The summed area of all landslides per individual year, representing total area impacted by landslides.

Instances of Recovery and Overlap

I analyzed two time periods of 7 and 8 years respectively to identify recovered and overlapping areas of landslide occurrence. This analysis overlaid the results from two years at the beginning and end of the period and extracted all impacted area unique to one year or the other, signifying recovery, and areas of overlap. For both 1991-1998 and 1998-2006, there were few instances of overlap (Fig. 6a). The average size of recovery areas was larger than that of overlap areas within a given time period (Fig. 6b). The average size of overlap areas was less than half of the smallest average size of either individual year, indicating that typically reoccurrences did not fully eclipse previous scars (Fig. 5b & 6b).

Using the overlap calculations, the proportion of area recovered for the first years of the two periods (1991 and 1998) was determined. For both years, the vast majority of land impacted in the first year of the time period recovered in the last year, with only small portions demonstrating landslide reoccurrence (Fig. 7a). The area of overlap instances remained under 10% for both time periods (Fig. 7b).



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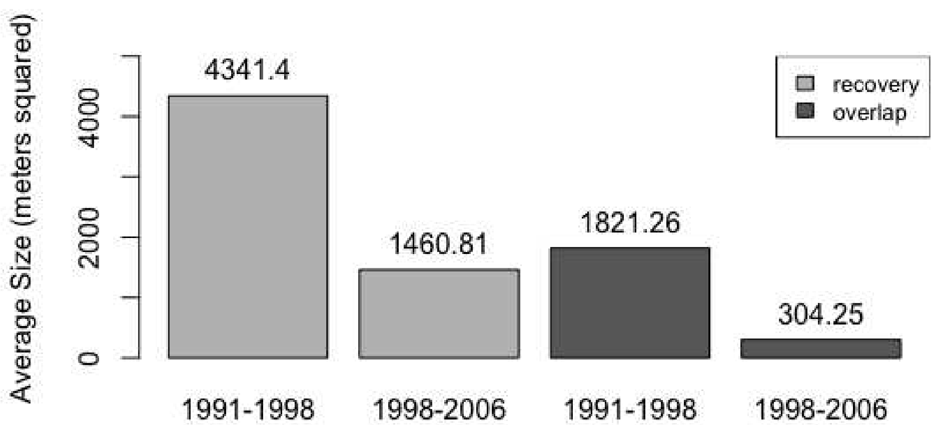
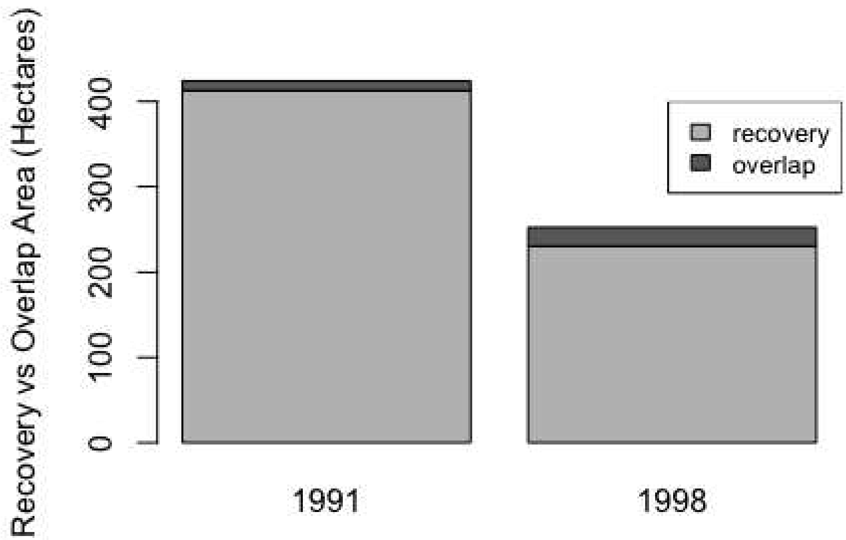


(b)

Figure 6. Areas of recovery and overlap identified between 1991-1998 and 1998-2006. **(a)** The number of instances of recovery or overlap discovered between the first and last year of the period. Instances were calculated from overlaying individual year landslides and capturing unique and shared area in ArcGIS and represent segments of landslides from the two years. **(b)** The average size of recovery or overlap areas for the given period.



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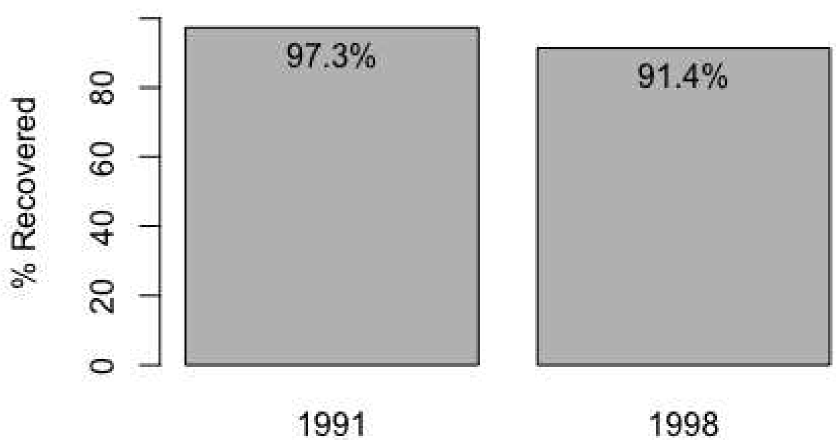

(b)

Figure 7. Area recovered from first year **(a)** The proportion of area from the first time period year (1991 for the 1991-1998 period and 1998 for the 1998-2006 period) that recovered to overlap area **(b)** The percentage of area recovered from the first year of the period.

Identifying significant predictors

Six out of the 24 predictors were retained after conducting the collinearity tests: 3 bioclimatic (isothermality, temperature seasonality, and precipitation during the wettest month of the year), and 3 topographic (aspect, curvature, and slope). The collinearity test removed predictors which correlated with other predictors, i.e. those on which landslides would appear dependent due to their correlation with another significant variable (Naimi et al., 2014). All of the retained variables significantly influenced landslide occurrence across all years investigated (Table 2a & b). Overall, landslide recovery and overlap shared the same set of significant predictors as the individual occurrences, but significance varied (Table 2a).

In the individual year models, greater curvature and aspect decrease the likelihood of landslide occurrence, while greater slope, isothermality, temperature seasonality, and precipitation during the wettest month increase the likelihood of landslide occurrence (Table 2). These results varied in magnitude of significance but were consistent in direction of influence across all years.

Table 2a. Significance level of predictors. The topographic and bioclimatic variables found to be significant to landslide occurrence as well as recovery and overlap in the study area. Non-significant relationships were left blank.

	Topographic			**Bioclimatic**		
	aspect	**curvature**	**slope**	**bio3[1]**	**bio4[2]**	**bio13[3]**
1991 year	0.005	$8.5\ e^{-9}$	0.027	$4.4\ e^{-10}$	0.066	0.044
1998 year	$7.8\ e^{-3}$	0.046	0.051	$3.0\ e^{-10}$	0.001	$< 2\ e^{-16}$
2006 year	$2.9\ e^{-8}$	$3.4\ e^{-15}$	$4.0\ e^{-7}$	$< 2\ e^{-16}$	$2.0\ e^{-4}$	$< 2\ e^{-16}$
1991-1998 recovered		$2.4\ e^{-9}$		$< 2\ e^{-16}$	$3.4\ e^{-5}$	$< 2\ e^{-16}$
1998-2006 recovered	$4.7\ e^{-7}$	$8.2\ e^{-13}$	$1.8\ e^{-6}$	$< 2\ e^{-16}$	$1.2\ e^{-6}$	$< 2\ e^{-16}$
1991-1998 overlap			0.004			0.017
1998-2006 overlap	$8.9\ e^{-9}$		0.007	$5.8\ e^{-8}$		$1.0\ e^{-7}$

[1] isothermality, [2] temperature seasonality, [3] precipitation during wettest month

Table 2b. Direction of influence of predictors on landslide occurrence, recovery, and overlap. Negativity of p-values indicates that an increase in the variable correlated with decreased landslide likelihood, while positive signs indicate that an increase in the indicated variable correlated with increased landslide likelihood. Insignificant relationships for the given distribution are blank.

	Topographic			**Bioclimatic**		
	aspect	**curvature**	**slope**	**bio3[1]**	**bio4[2]**	**bio13[3]**
1991 year	-	-	+	+	+	+
1998 year	-	-	+	+	+	+
2006 year	-	-	+	+	+	+
1991-1998 recovered		-		+	+	+
1998-2006 recovered	-	-	+	+	+	+
1991-1998 overlap			+			+
1998-2006 overlap	-		+	+		+

[1]isothermality, [2]temperature seasonality, [3] precipitation during wettest month

Recovered areas from both time periods exhibited significant dependence on curvature, isothermality, temperature seasonality, and precipitation during the wettest month. The 1991-1998 period was not significantly influenced by the topographic variables' aspect or slope but responded to decreased curvature (Table 2b). The 1998-2006 period was strongly dependent on all retained variables, similar to the individual year models (Table 2a). Comparison between the two periods suggests that high curvature will decrease the likelihood of landslide reoccurrence, while higher isothermality, temperature seasonality, and precipitation during the wettest month increase the likelihood of landslide reoccurrence.

Both overlap analyses exhibited significant reliance on slope and precipitation during the wettest month but differed on the other variables. This suggests that areas with greater slope and exposure to increased precipitation during the wettest month of the year are more likely to experience reoccurring landslides, whereas other variables are less consistent in their effects on landslide reoccurrence.

Discussion

My goals of this study were to investigate the dependence of landslide patterns (both initial occurrences and recovery) on topographic and bioclimatic variables and to examine the recovery and overlap dynamics of disturbed areas in the Sierras de Las Minas. My hypotheses were that the landscape in question would show dependence on factors from both categories, and that the majority of impacted area would recover in the subsequent time period. The results yielded two conclusive points. First, instances of overlap and recovery revealed a significantly greater proportion of landslides recovered from the first to second period in both multiyear analyses, in line with my hypothesis and demonstrating the strength of landscape memory within the study area. Second, the species distribution approach pinpointed 6 predictors of landslide occurrence in the study area, three of them bioclimatic, the same groups for both individual landslide events and patches of recovery and overlap.

Spatial analysis of recovery and overlap areas -

The vast majority of impacted area recovered from the first time period to the second, suggesting that potential for recovery is strong in the study region. The lack of overlap suggests that landslides in the first year influenced the spatial structure of landslides in the latter year, aligning with concepts of landscape memory (Peterson, 2002). Furthermore, the average size of overlap areas in both 1991-1998 and 1998-2006 was significantly smaller than that of recovered area or new landslides. This could indicate that only small sections of past landslide scars failed again in the latter period, aligning with previous studies showing landslides determine the shape and position of following events (Samia et al., 2017). Overall, this analysis of landslide reoccurrence provides another example of landslide location, size, and shape being heavily influenced by past disturbance legacies.

The conditions of predictors conferring recovery or overlap varied far more than between the individual years, indicating that reoccurrence might not be predicted by consistent variables. Overall, the individual year shapefiles demonstrated incredible consistency; all 6 predictors were significant in 1991, 1998 and 2006. For the 1991-1998 overlap areas, only slope and precipitation during the wettest month were significant, while the 1998-2006 intersect showed significance related to these variables in addition to aspect and isothermality. The recovery areas for both periods were correlated with more predictors than their respective overlap counterparts, but the 1991-1998 recovery demonstrated fewer predictors of significance than the 1998-2006 period. Overall, these results suggest that predictors influencing recovery (or lack thereof) are inconsistent and may be more reliant on time period than type of relationship to past landslides.

Of the variables influencing overlap, only slope and precipitation during the wettest month were consistent between the two periods. Notably, temperature seasonality was excluded in significance from both. This aligns with past landslide research, which has previously concluded that condensed frequency of precipitation prevents full recovery on impacted slopes (Chen et al., 2020). Theories of ecological change establish that ecosystems primed for shifts in structure and function (hence, divergence from memory and increasing landslide overlap) typically require singular catastrophic events to trigger these shifts (Rietkerk et al., 2004; Holling, 1996). While temperature seasonality may prime landscapes for landslide occurrence, it measures variation in temperature over the course of a year and is likely not able to capture the rapid and dramatic shifts which would trigger overlap events. The events that trigger landslide occurrence are likely random and sporadic, which may explain why overlap areas demonstrated the least significant relationships with the topographic and bioclimatic predictors.

My analyses of multiyear landslide relationships in the Sierras de las Minas highlights a great ability for recovery in the region, however, they assessed these dynamics on a very limited time scale. In the future, analyzing reoccurrence dynamics of larger time periods, such as the 15-year gap between 1991 and 2006, and analyzing recovery at multiple check in points, using all three-time markers 1991, 1998, and 2006, would reveal greater detail about the recovery patterns of landscapes in the decades after disturbance. Moreover, further investigation would clarify the influences of vegetative and biotic aspects as well as time period in landslide reoccurrence.

Understanding the role of predictors on landslide distribution -

Heightened understanding of all factors involved in the complex causality of landslides is important for more accurate assessments of the risk posed by their occurrence, especially in expectation of large climatic shifts (Kirschbaum et al., 2020). My results present 6 variables influencing both landslide occurrence as well as recovery and overlap to take into account in future climate-landslide research: aspect, curvature, slope, isothermality, temperature seasonality and precipitation during wettest month of the year. This analysis of the correlations of landslide occurrence to bioclimatic factors broadens our ability to assess climatic shifts directly as they pertain to landslide occurrence, taking into account both direct and indirect factors.

Topographically, decreased aspect and curvature and increasing slope values (i.e., west facing rather than east facing) correlate with increased likelihood of landslide occurrence in this area of the Sierras de las Minas. These results align with previous geomorphology research indicating that slope failure could be tied to underlying bedrock-level weaknesses or other abiotic factors (Guzzetti et al., 2008; Parker et al., 2015). However, these slope characteristics could also indirectly impact landslide occurrence in the Sierras de las Minas through their control of the area's vegetation. Aspect, slope and curvature can all be tied to vegetation structure and species diversity in ecosystems; these factors exert control over organism's access to resources such as water, sunlight, and nutrients (White et al., 2005). It is important to acknowledge that the topographic variables included in analysis likely impact landslide occurrence indirectly as well through influences on soil and vegetative properties.

Areas with increased isothermality and temperature seasonality should be expected to experience an increased landslide burden in the future. Isothermality, which quantifies how large diurnal temperature oscillations are relative to annual temperature oscillations, and temperature seasonality, which represents how much temperature varies from month to month within a year, are both depictions of temperature fluctuation (O'Donnell & Ignizio, 2012). These results have dire global implications, as there is substantial evidence to suggest that a primary manifestation of climate change in the coming decades will be unpredictable and fluctuating global temperatures (Vincze et al., 2017). Moreover, temperature variation is projected to increase disproportionately in tropical countries, which would contribute to growing inequities in recovery from these disasters (Bathiany et al., 2018). Clearly, increases in both of these metrics correlating with landslide occurrence must be taken into account in future global hazard assessment.

The third significant bioclimatic variable, precipitation during the wettest month, also correlated positively with landslide occurrence. This metric quantifies not only precipitation amount, but also frequency over a condensed time period. Previous research into landslide-precipitation relationships suggests that above-average precipitation decreases slope stability, therefore increasing landslide likelihood, and these results appeared to align with this (Kristo et al., 2017). Evidence suggests that the vegetative responses to precipitation anomalies are highly dependent on topographic factors, thus, for the purposes of this study, the influence of precipitation during the wettest month on landslide occurrence is likely due to a combination of topographic and biotic conditions (White et al., 2005). Precipitation-landslide relationships specifically have been pinpointed as an area urgently requiring increased investigation (Chen et al., 2020), and the significance of precipitation during the wettest month further emphasizes this point.

This study presents one of the first attempts to tie landslide occurrence and maintenance of landscape memory patterns to bioclimatic attributes, which takes into account the influence of climate patterns as well as resulting biotic conditions like soil and vegetation quality. The results highlight the significance of three topographic variables and three bioclimatic variables in landslide occurrence, demonstrating that in the tropical region of focus, both biotic and abiotic forces influence patterns of landslide occurrence. While these variables act separately, the known influences of geomorphology and ecology on each other suggest that they are likely compounding in their influence as well. The complexity of landslide occurrence and a landscape's development of resistance to them cannot be explained by geomorphology or ecology alone. In the future, more efforts into bridging the gaps between these fields must be undertaken to understand the shifts in landslide frequency which will be brought about by the changing global climate.

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