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INVENTORY-BASED LANDSLIDE SUSCEPTIBILITY MAPPING IN COLORADO SPRINGS, USA

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Landslides in Colorado, USA cause millions of dollars of damage, destroy homes and infrastructure, and cause loss of life. Within the state, the town of Colorado Springs and surrounding El Paso County has been identified as an area that needs ongoing attention due to the severity of landslide risk. Most of the highest risk areas are either already mapped as landslide deposits or are located on top of the Pierre Shale, a unit that is highly susceptible to landslides. Previous landslide hazard maps and predictive models tended to be coarse, with almost all the steep areas overlying the Pierre Shale classified as high hazard. Consequently, there is a need for models that are able to provide more granularity in dividing hazard levels. This study uses a landslide database of 561 events in the area to improve on previous predictive methods, and also expands the list of potential influencing factors. Using binary logistic regression methods, the most significant parameters were curvature, elevation, slope, topographic wetness index, and geology, producing models with an area under curve (AUC) ranging from 0.91-0.95. The models that generated the best maps were ones using slope and geology or using slope and elevation, parameters that are easy to generate by GIS using Digital Elevation Models and geologic maps. The first modelrelies on parameters used in previous research, but our pixel-based map provides more detail to distinguish various hazard levels. The second model uses a parameter that has not been included in previous studies and can serve as a verification. The strong correlation to slope, elevation, and geology is expected to be prevalent in other locations where weak sedimentary units are tilted upwards along linear fault-block mountain fronts, as is the case in Colorado Springs.

Keywords: Landslide, prediction, susceptibility, hazard, inventory, slope.

1. Introduction

Landslides are one of the most common natural disasters in the world. They cause up to $2.8 billion dollars of damage per year, as well as 25-50 deaths per year (Schuster and Highland, 2001). They are widespread in Colorado, USA, and are especially concerning in the town of Colorado Springs and the surrounding El Paso County.Many expensive houses have been built in the foothills and on mesas in areas that are either mapped landslide deposits or are located on top of the Pierre Shale, a geologic unit that is susceptible to landslides (Scott and Wobus, 1973; Cochran, 1997; Trimble and Machette, 1979). Colorado Springs recently began experiencing landslides within city limits that had not previously affected infrastructure (White and Wait, 2003). In 1995, 1997, 1999, and 2015 spring rainfalls exceeded averages for the area, which caused many landslides within the area, ruining homes, entire neighborhoods, and businesses (White and Wait, 2003; Henry, et al., 2017).

Landslide susceptibility maps are especially useful in landslide-prone areas to identify the most likely locations for future events and to assist in land planning and management.Existing landslide susceptibility maps for Colorado Springs tend to be coarse, with almost all the steep areas overlying the Pierre Shale classified as high hazard. Consequently, there is a need for new models that are able to provide more granularity in dividing hazard levels. This study uses a landslide database of 561 events in the area to improve on previous predictive methods, and also expands the list of potential influencing factors.

2. Previous Landslide Susceptibility Maps

White and Wait (2003) produced a landslide susceptibility map for Colorado Springs based on maps of historic landslides, geomorphic evidence of new landslides, and geology and topographyfavorable to landsliding. The resulting map captured active events well (low potential for false negatives), but high risk areas tended to closely follow the presence of the Pierre Shale, a unit that is highly susceptible to landslides. As a consequence, the map was presumed to be coarse, with many areas of false positives.

Garrett (2013) developed a landslide susceptibility map of the area using a GIS-based analysis that incorporated both infinite slope and method of slices slope stability analysis, calculated at 269 locations across the area. A potentially powerful method, the author found that the analysis calculated lower factors of safety than expected (producing false positives), with bias because of the limited strength data to define material behavior.

Similarly, Southerland (2019) produced susceptibility maps with a strong technical basis, using information from boreholes across the city, but also saw limitations because of geographically clustered data points that resulted in maps with hot and cold spots defined by data availability.

Fig. 1. Location of El Paso County and Colorado Springs, Colorado (white box on left), and image of landslide damage in 2019 (on right, photo by Jon White, Colorado Geological Survey).

3. Methodology for a New Model

Since there is a continuing need for robust landslide susceptibility mapping in Colorado Springs, the goal of this research was to develop a new model that would incorporate more geomorphic and geologic factors for predictive mapping, along with a new inventory of mapped landslides to train the model (Killen, 2023). Reducing a list of potential predictors to those with strong P-values and little cross-correlation, we used GIS- derived maps of aspect, curvature, elevation, plan curvature, slope, terrain roughness, and topographic wetness index. In addition, we included a non-numerical geology category, with geologic units at the surface classified as low, moderate, and high strength according to Lindsey (2021). The landslide inventory (Figure 2) was also developed by Lindsey (2021), and included 561 mapped events. The inventory was then used for calibration through logistic regression, with a comparable number of non-landslide points chosen to define yes-no categories. Of the landslide points, 80% of which were used as training data and 20% as testing data for each model run.

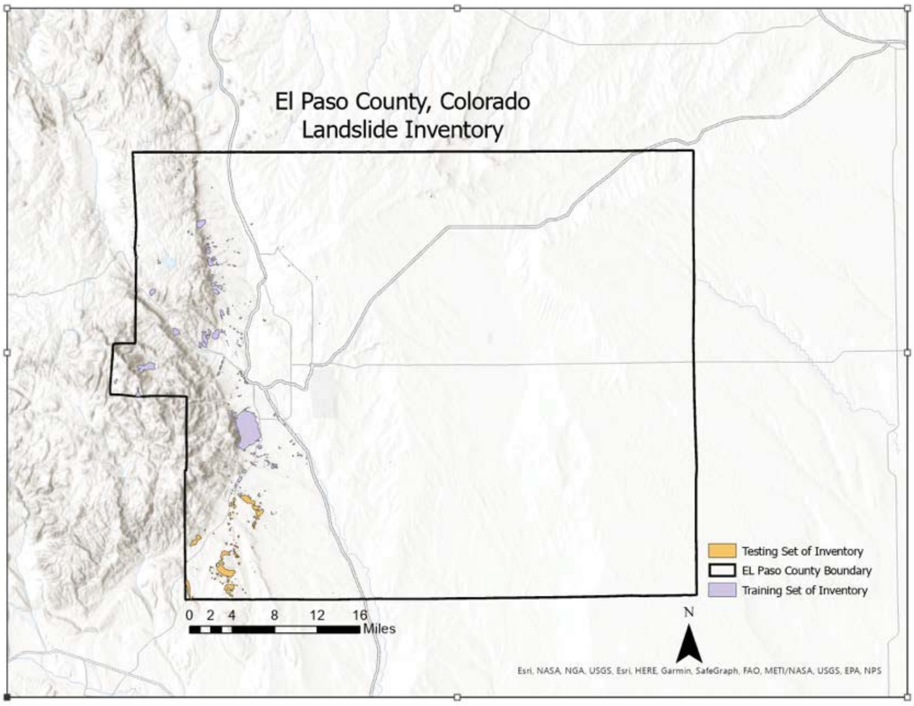

Fig. 2. The landslide inventory for El Paso County, Colorado (from Lindsey, 2021). The purple part of the inventory is 80% that was used to train the models. The gold part of the inventory is the reserved 20% used for testing the models.

4. Results and discussion

The results from the initial logistic regression showed that aspect, plan curvature, and roughness were not significant based on p values larger than 0.05, so these parameters were not used in any models. The first model used the remaining significant parameters of curvature, elevation, slope, TWI, and geology (Model 1). Because most previous studies used slope and geology as the only parameters for susceptibility maps, a model for those parameters was also generated for comparison (Model 2). Four more models were also generated: one using curvature, elevation, and slope since those are easily accessible (Model 3); one with curvature, TWI, and geology because those have the highest coefficients in the main model with the significant parameters (Model 4); one with slope and elevation to generate a model similar to Model 3 but without curvature (Model 5); and one with TWI and geology, to generate a model like Model 4 but without curvature that also includes TWI (Model 6).

Table 1 compares the results from each model. Each of these models generated a regression equation and a Receiver Operator Characteristics(ROC) plot with its corresponding value for area under the curve (AUC). On this basis alone, Models 1 and 4 are slightly stronger and Model 6 is slightly weaker. Additionally, each model was validated with the test area to show whether the model adequately predicted higher susceptibility rankings for the locations where landslides were mapped in the inventory. On this basis, Model 6 was not effective as it categorized most landslide locations as low, low-moderate, or moderate susceptibility. We conclude that the inaccuracy of this model may be due, in part, to inclusion of the TWI parameter, which producesin the calculation ofa flow accumulation layer that requires several assumptions with corresponding loss of accuracy. Model 4, which also includes TWI, also suffers from a high number of points classifying mapped landslides in the moderate category, although it showed a better overall performance.Models 2 and 3were good at categorizing landslides into moderate, moderate-high, and high categories, and Models 1 and 5 captured the most landslide locations in the high category.

Table 1. Selected predictive models that showed by strong Area Under the Curve (AUC) values, along with the number of testing data points classified in each susceptibility category (from Killen, 2023).

	Model 1 (all significant parameters)	Model 2 (only slope and geology)	Model 3 (most accessible parameters)	Model 4 (parameters with highest individual correlation)	Model 5 (model 3 with no curvature)	Model 6 (model 4 with no curvature but with TWI)
Parameters included	Curvature, elevation, slope, TWI, geology	Slope, geology	Curvature, elevation, slope	Curvature, TWI, geology	Slope, elevation	TWI, geology
AUC	0.95	0.92	0.93	0.95	0.93	0.91
Number of testing points in each susceptibility category						
Low	0	0	0	0	1	12
Low-Moderate	5	0	3	0	2	57
Moderate	14	14	10	35	12	39
Moderate-High	34	85	64	71	39	4
High	59	13	35	6	58	0

"AUC" indicates area under the curve for a Receiver Operating Characteristics (ROC) plot, which is intended to optimize the true positive to false positive ratio. "TWI" is the topographic wetness index.

The susceptibility maps for a portion of the mapped area are shown in Figure 3 to allow comparison of map quality and useability. Models 1, 3, and 4 were noisy, with a speckled pattern of interspersed high and low susceptibility pixels. We conclude that the likely cause of the low resolution and noise is the inclusion of predictive parameters curvature and TWI. The effects of TWI are noted above. Curvature, defined as the second derivative of slope, suffers from noise created as each derivative is taken, whichresults in poor resolution on the map.

Models 2 (based on slope and geology) and 5 (based on slope and elevation) had less noise than the other models. Model 5 shows slightly more detail, and it also simpler to generate, since it does not require the step of matching geological formations to their low, moderate, and high strength categories.

4. Conclusions

Colorado Springs has a unique confluence of sensitive geologic formations (most importantly, the Pierre Shale), and high slopes and elevations in the western side of the city. Based on our work here and other efforts to create landslide susceptibility maps, it has proven difficult to separate the influence of these parameters to reduce false positive areas in the maps. Our attempt to use multiple parameters (Model 1) did not produce uniform distinction from a simpler model using only slope and elevation (Model 5), although all of the produced models had low false negative rates and were therefore conservative. The models allow identification of higher risk areas so that site-specific studies can be conducted before development proceeds in these areas. The strong correlation to slope, elevation, and geology is expected to be prevalent in other locations where weak sedimentary units are tilted upwards along linear fault-block mountain fronts, as is the case in Colorado Springs.

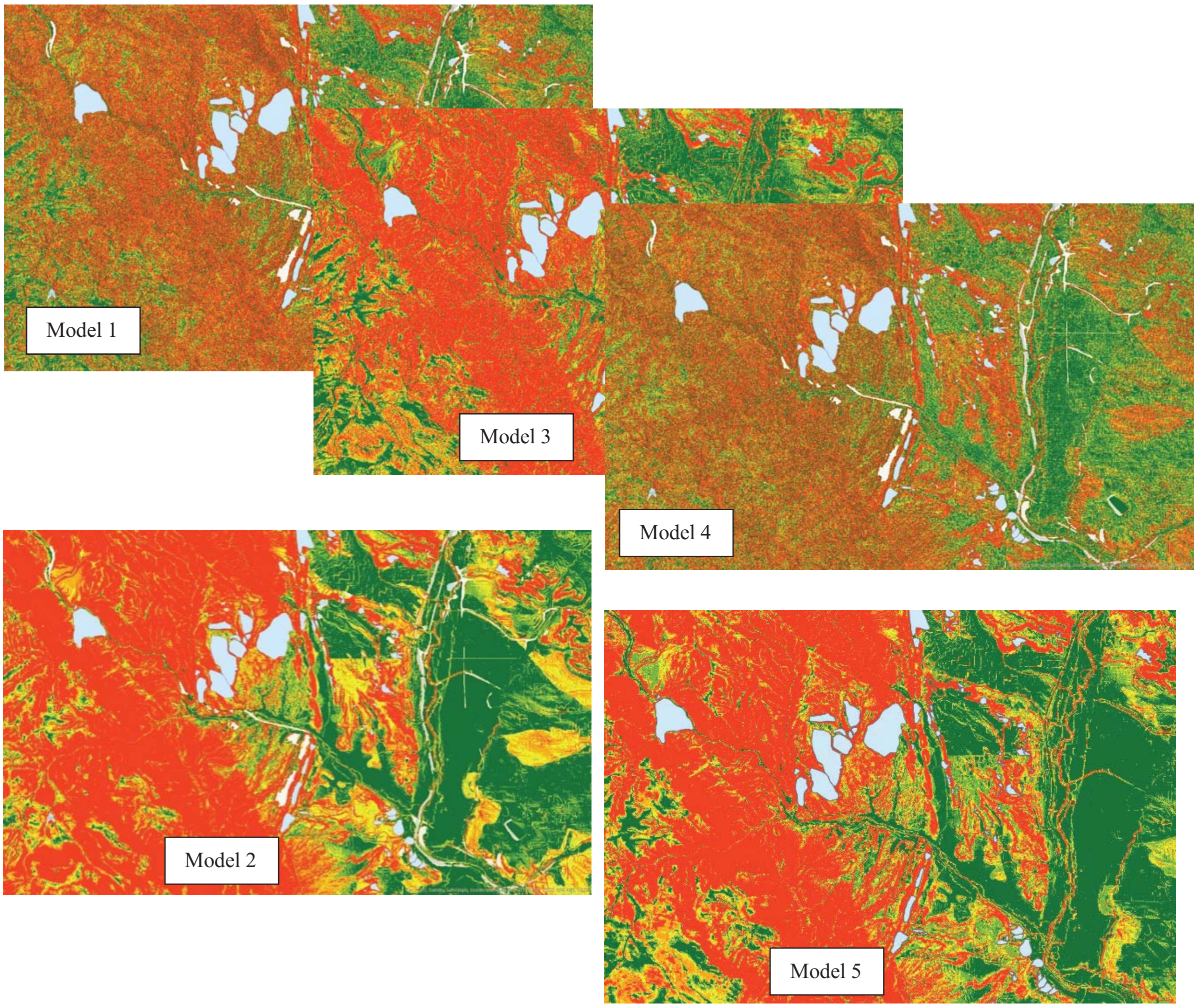

Fig. 3. Generated susceptibility maps for a portion of the Colorado Springs area (Killen, 2023). The color scale grades from red (high susceptibility) to green (low susceptibility).

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