Landslide Susceptibility in the Republic of Moldova: A Landscape and Multivariate Approach for Regional Assessment

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PAPERS OF THE

APPLIED GEOGRAPHY CONFERENCES

Volume 34

Editor

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Applied Geography Conferences, Inc.
ISSN 0747-5160

2011 BOARD OF DIRECTORS
APPLIED GEOGRAPHY CONFERENCES, INC.

EDITORIAL

It has always been an extremely rewarding experience in putting together the annual volume of the *Papers of the Applied Geography Conferences*. Working with authors of the manuscripts expanded my academic vision tremendously. I learned a great deal from interacting with reviewers taught about how to help improving manuscripts. I also enjoy making friends with so many colleagues during the process.

It is always amazing to me that authors found ways to pack in 10 pages or less their research and contributions and yet did that brilliantly. Both the authors and reviewers have been very responsive in a very tight operating schedule. I especially appreciate this as I know many of them revised their papers and communicated with me while being away from their offices or while doing their field work.

The 34th volume of the *Papers of the Applied Geography Conferences* includes papers in geography education, retail geography, applied climatology, water resources, geography of crime, transportation geography, urban studies, geospatial technology of GIS and remote sensing. These papers provide a good testimony that applied geography contributes to our society in the most direct way with innovative approaches and scientific methods.

As in most edited volumes, manuscript reviewers are the most critical to this volume's success. We are fortunate to have the reviewers who provided timely and thoughtful critiques for the manuscripts they help reviewed. In several cases, reviewers went through multiple cycles of working with authors to improve the manuscripts. The contributions by the reviewers are truly valued and appreciated by all.

I wish to acknowledge the financial supports by Kent State University, The University of Redlands, Texas Christian University, Texas State University-San Marcos, Binghamton University, George Mason University, and Florida Atlantic University. In addition, I thank the tireless effort by local organizing committee and support by ESRI, Inc. to make this year's Applied Geography Conference a successful one.
Of course, our thanks are to ESRI, Inc. for its continuous support to the conference. Without these supports, the publication of this volume would have been impossible.

With best regards, I am,

Sincerely Yours,

Jay Lee
31 July 2011

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Volume 34, 2011

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1. INTRODUCTION

Landslides are one of the most harmful natural hazards. Landslides claim lives every year and cause substantial damage to property, infrastructure, heritage, and natural capital (Chung and Fabbri, 1995; Metternicht *et al*., 2005). Inventories of landslides conducted between 1964-1999 show a steady increase in number of landslide disasters globally (Nadim and Kjekstad, 2009), and it can be presumed that this phenomenon will continue into the future. Understanding and managing landscapes with landslides is more important now than ever.

Quantitative methods for analyzing relationships between intrinsic and extrinsic variables and landslides have increased in popularity in the last decades due to development in computer and geographic information systems (GIS) technology (van Westen *et al*., 2003; Bai *et al*., 2009). Current techniques for modeling and mapping landslide risk are coupled to one or a combination of predictive, stochastic, and deterministic methods (Brenning, 2005; Huabin *et al*., 2005), and require significant computer and spatial analysis knowledge. Logistic regression and discriminant analysis via raster models have been found to be the current landslide susceptibility modeling methods of choice (Brenning, 2005). Other noteworthy landslide modeling methods are artificial neural networks analysis (Lee *et al*., 2003), weights of evidence (van Westen *et al*., 2003), fuzzy logic approach (Kanungo *et al*., 2006), multivariate analysis (Santacana *et al*., 2003), and bivariate analysis (Bai *et al*., 2009). Many methods and techniques for evaluating landsides have been proposed or implemented for analyzing landslides; however, there remains no agreement on procedures, scope for modeling neither landsliding, nor landslide hazard/risk mapping (Huabin *et al*., 2005).

While several studies have addressed the relationships between direct and indirect variables and landsliding (Brenning, 2005; Huabin *et al*., 2005), few have addressed how landscape form at the landscape scale relate to landsliding conditions, and how those results can improve regional susceptibility mapping. Additionally, there are a limited number of landslide studies that have tried to develop modeling and mapping techniques that can be useful in locations with data shortcomings.

This study aims to develop a vector based "landscape unit" spatial investigation between landscape form variables and landslide events (total affected area and count), and to further understand methods for modeling and mapping landslides and their related phenomenon. Using multivariate statistical methods two null hypotheses are tested: (1) no significant relationship exists between landscape form variables and landslide events; and (2) spatial and deterministic multivariate statistical techniques do not support and improve ordinary least square (OLS) methods. Using an inventory of landslide events, this research examines the relationship stochastically and deterministically between a digital elevation model (DEM) derived variable, land cover, forest patterns, and landsliding in the Republic of Moldova. Specifically, exploratory spatial data analysis (ESDA), OLS, simultaneous autoregressive (SAR) modeling, and classical discriminate analysis were employed in the ensuing analysis.

2. METHOD

2.1 STUDY AREA

We have focused our empirical analysis between a DEM derived variable, land cover, forest patterns, and landslide events in 74 "landscape units" in the Republic of Moldova. Several characteristics of this country make it an ideal site for this study. The annual amount of rainfall varies throughout the whole country; the average annual rainfall is roughly 555mm (1969-1990) for the country with quantities from 560mm in the north to 370mm in the south (Miţul, 2000). Moldovan geology is relatively consistent throughout the country, with the majority of exposed rock features having sedimentary consistency. The geographic zone of Moldova consists mainly of gentle steppe with maximum elevation under 430 meters. The shallow aquifer of the Republic of Moldova has sedimentary origins with a majority of it overlain by loess-like loam deposits averaging 8m thick. The water table ranges from 8m to 10m in depth for a majority of the country, with a maximum depth of 30m found in the Southern Part of the Republic of Moldova (Overcenco *et al*., 2008). With that said, the Republic of Moldova has been plagued by landsliding almost annually, and all 74 "landscape units" have representation of this geomorphological process (Figure 1).

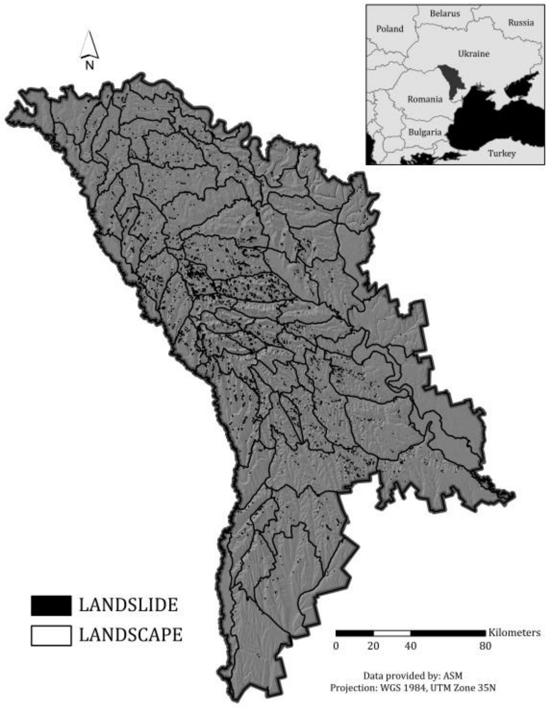

FIGURE 1
LANDSLIDES AND LANDSCAPES WITHIN THE REPUBLIC OF MOLDOVA

The country's territory is mainly comprised of Neogene sandy and clayey deposits from Pliocene-Quaternary alluvial formations. The landslides are primarily confined to sands and clays of Bessarabian sub-stage of the Sarmathian stage, which are located in the northern and central parts of the country (Tcaci and Gheorghita, 1995). To a lesser extent, landslides also form in the non-segmented substage of the Sarmathian stage, Meotian stage, and Pontian stage that are spread throughout the central and southern part of the country (Tcaci and Gheorghita, 1995).

There remains no location in the Republic of Moldova that has not been altered by anthropogenic forces. This modification of land-use and land cover has resulted in a great variety of development patterns, presenting a unique opportunity to investigate the relationships between landscape factors and landsliding dynamics. As a whole, the country's predominant land cover is overwhelmingly agricultural lands, while farming is the dominant land use activity. Minimal forestry practices currently operate throughout the country, but do still exist and should be noted. It should also be acknowledged that there is low but prevalent seismic activity here. Agricultural practices, urbanization, historical and current forestry practices, and floodplain alterations are the major contributors changing the natural configuration of the landscape in the Republic of Moldova.

2.2. MOLDOVA LANDSCAPE UNIT

The landscape scale, or specifically the "landscape unit," may be the best scale for analyzing landsliding controls and impacts. Landscape units for the Republic of Moldova are similar to other types of physiographic planning areas in the sense that they are created from the aggregation of geographically associated land resource of nearly homogenous land cover, land use, elevation, topography, climate, water resources, and soils. However, landscape units developed from the Russian school of landscape science go one step further to include elements of animal behavior and human related activities. The Russian tradition of "geographical landscape" can be linked back to Lev Semenovich Berg's senior work *Geographical Zones of the Soviet Union* (1947). It was in this work that Berg spelled out the pioneering definitions of geographical landscape and the founding principles of the Russian "landscape unit". Berg stated that the "geographical landscape is that combination or grouping of objects and phenomena in which the peculiarities of relief, climate, water, soil, vegetation, fauna, and to a certain degree human activity, is blended into a single harmonious whole" (Berg, 1947).

The development of a landscape unit comes from collecting an assortment of land data that are used to support each other during all stages of unit classification. Similar physiographic regions have been developed throughout the world. These areas denote similarities in type, quality, and quantity of environmental resources, and are designed to serve as a spatial framework for different types of research, assessment, monitoring, planning, and resource management. Source data for the Republic of Moldova landscape units comes from Proka's (1978 and 1983) works. Proka's Moldovan landscape units come from the culmination of over ten years of field surveys and the construction of a multi-hierarchical land management system. The Republic of Moldova's multi-hierarchical land management structure is systematically divided into four scales: zones (2), regions (5), landscape units (74), and elementary landscape features (120). Proka's Moldovan landscape units have been updated and digitized for current land management practices (Figure 1).

The time and costs of a landscape unit analysis are considered less than separate geographical theme surveys, and portray areas with similarity in the mosaic of biotic and abiotic components of terrestrial ecosystems. The landscape unit results are directly suitable for land evaluation and can be expressed in separate thematic maps or even a single value map (Zonneveld, 1989). For multidisciplinary projects with applied geographical and ecological aims (*e.g.*, landslide susceptibility), the landscape unit has been considered an appropriate survey and mapping approach scale (Zonneveld, 1989). Recognition and use of these multipurpose landscape areas are critical for structuring and implementing management strategies across different governmental agencies responsible for different resources within specific geographical regions. In this study, the landscape unit scale was used for data management, statistical analysis, and mapping purposes.

2.3 LANDSLIDE AND LANDSCAPE DATA

Landslide data were quantified for each of the 74 landscape units in the Republic of Moldova based on an inventory of landslide events (total affected area and count). Total affected area was calculated by hand digitizing the combined erosion scar and deposit for each individual landslide event. The inventory of landslides was created from referencing topographic maps, time periods 1986 and 1989, and LandSat Thematic Mapper (TM) imagery from 2000 and 2001. Through expert visual interpretation this inventory was conducted from 2001 to 2005 at the Institute of Geography and Ecology, Academy of Sciences of Moldova. There are a total of 2,425 landslides events in this inventory.

Topographic form is fundamental to any landslide analysis (Huabin *et al*., 2005). Due to the influence of relief on landsliding, construction of DEM derived variables (e.g., slope, aspect) are crucial to a multivariate analysis at the landscape scale. Because of limited data availability, the DEM derived variable was calculated at 90m resolution for each of the 74 “landscape units”. Using ESRI’s (2010) ArcGIS 10 Spatial Analyst extension, slope angle was created using the SRTM DEM for the Republic of Moldova. Implementing Hawth’s Analysis Tools version 3.26 (Beyer, 2006), a free extension for ESRI’s ArcGIS, mean slope angle was calculated and summarized for each of the 74 landscape units using the zonal statistics function. The DEM data used in this analysis were provided by the National Aeronautics and Space Administration (NASA) and the National Geospatial-Intelligence Agency (NGA). These data were collected in 2000-2001 via SRTM instrument at 60m resolution and after projecting can be used in raster format at 90m resolution.

Land cover (composition) and *forest patterns (configuration)* were quantified using landscape ecology metrics developed for quantifying the spatial arrangement of land cover and land use (McGarigal *et al*., 2002). Land cover data used in this analysis were hand digitized from digital orthophotographs from 2004. Through expert visual interpretation, these data were classified into two classification groups using FAO classification schemes at the Institute of Geography and Ecology, Academy of Sciences of Moldova. For this analysis, we have reclassified the FAO land cover data into eight classes based on Anderson *et al*. (1976) land use and land cover classification system. FRAGSTATS version 3.3 (McGarigal *et al*., 2002), free and publicly accessible software was used for computing composition and forest pattern metrics for each landscape. The reclassified land cover data was converted into raster format, preserving a 30m resolution. Four major land cover variables and 55 landscape forest class metrics were computed for each of the 74 landscape units used in the following statistical analysis. As there is no causal ordering in space as there is in time, and there remains no minimum set of landscape metrics for capturing the majority of landscape structure (Fortin *et al*., 2003; Wagner and Fortin, 2005), a number of forest class metrics were calculated and then statistically reduced into a highly relevant subset.

Principal Components Analysis (PCA) and Robust Pearson correlations were used to reduce the set of landscape forest class metrics. Metrics with strongest loadings that exhibited different patterns of orthogonal axes were selected. All remaining independent landscape form variables were then reduced further by Robust Pearson correlations, to remove metrics that exhibited a high degree of multicollinearity ($r > 0.75$). Fourteen explanatory landscape form variables remained to be used in the forthcoming stepwise regression analysis. To meet the assumptions of normality for all variables required during parametric tests, we used two types of transformation: negative arcsine (proportion data) and log10 (length/score data). The remaining landscape form variables were standardized using a z-transformation to set all parameters to a mean of 0 and variance of 1. Other software packages implemented in this analysis were: SYSTAT 12 and JMP version 9 (SAS Institute, 2010).

2.4 DATA ANALYSIS

The first law of geography states that things that are near are more similar (autocorrelated) than things that are farther apart (Tobler, 1970; Fortin and Dale, 2005). In spatial environmental studies it is imperative to take into account spatial autocorrelation. Spatial autocorrelation is the lack of independence between pairs of observation at given distances in time and space and is commonly found in environmental data (Legendre, 1993). In order to evaluate the spatial patterns of landslide affected area and landslide count throughout the Republic of Moldova, an exploratory spatial data analysis (ESDA) was conducted. For this study a common ESDA technique, spatial autocorrelation index global Moran's *I*-test, was applied. Spatial autocorrelation index scores vary from each other; however, positive scores indicate similar values are spatially clustered and negative scores indicate unlike values are spatially clustered (Wong and Lee, 2005). ESDA is frequently used in studies of geographical ecology and macroecology (Lichstein *et al*., 2002; Wagner and Fortin, 2005; Dormann *et al*., 2007; Rangel *et al*., 2010), and can be particularly useful when testing spatial autocorrelation in environmental systems. Spatial Analysis in Macroecology (SAM) version 4, software specifically developed to address spatial data needs found naturally in macroecological and biodiversity data (Rangel *et al*., 2010), was employed to assess the independence and level of spatial autocorrelation of landslide total affected area and count across the 74 landscapes.

Spatial autocorrelation is problematic for classical statistical test (*e.g*., ANOVA, ordinary least squares regression) because it violates the assumption of independently distributed errors (Lichstein *et al*., 2002), and the standard errors are usually undervalued when positive autocorrelation is present increasing the potential for type I error rates (falsely rejecting the null hypothesis of no effect) (Dormann *et al*., 2007). Furthermore, spatial autocorrelation can cause a shift in regression coefficients depending on whether spatially explicit or non-spatial modeling is used (Bini *et al*., 2009). Spatial autocorrelation may be particularly problematic in regional-scale studies because landscape form (*e.g*., land cover) is typically not uniformed over space and often correspond with the underlying foundation (*e.g*., geology, soils) of its landscape. In landscape scale research this phenomenon is occasionally acknowledged and rarely addressed quantitatively (King *et al*., 2005). Lennon (2000) called attention to the problems associated with autocorrelation in ecological research 'red herrings' and argued that virtually all geographic analyses had to be redone by taking into account spatial autocorrelation.

To prevent errors associated with spatial autocorrelation in the multivariate regression analysis, a simultaneous autoregressive (SAR) model was used to examine the relationships between the independent landscape variables and landslide affected area. SAR is a spatial statistical modeling technique that uses a variance-covariance matrix based on the non-independence of spatial observations (Kissling and Carl 2007). SAR and other autocovariate models address spatial autocorrelation by estimating how much the response variable at any one site reflects response values at surrounding sites; albeit, this is achieved by adding a distance-weighted function of neighboring response values to the model's explanatory variables (Dormann *et al*., 2007). Conditional autoregressive (CAR) modeling is unsuitable when directional processes (e.g., landsliding) are coded as non-Euclidean distances, resulting in an asymmetric covariance matrix (Dormann *et al*., 2007), thus SAR should be employed when directional processes are known. As in other multivariate regression techniques, the dominant autoregressive practice is to rank the standard partial regression coefficients (Sokal and Rohlf, 1995) or associated t-values of coefficients of explanatory variables (Tognelli and Kelt, 2004) under the assumption that higher coefficients represent stronger "effects" on the dependent variable (Bini *et al*., 2009). SAM version 4 was used to calculate and interpret the multivariate SAR model.

As suggested by Shaker *et al*. (2009) deterministic statistics, through the use of classical discriminant analysis, were added to this study to help validate the multivariate landscape form model and provide a means for accuracy assessment. The purpose of discriminant analysis is to find and/or test a linear equation (discriminant function) to separate two or more groups of objects with respect to several variables simultaneously (Klecka, 1980).

In this study, we categorized the number of landsides into four categories of susceptibility- low, moderate, high, and very high (Figure 2). Dividing the range of landslide count into four equal groups created the categories for landslide susceptibility: low (1-35), moderate (36-71), high (72-106), and very high (107-142). A challenge lies when investigating and comparing discriminant models with low to moderate correlations, relating to which model is the most discriminant model. Wilks' lambda is frequently used to test differences between the means of identified groups for a combination of dependent variables selected for a discriminant model (Klecka, 1980). Because Wilks' lambda is a kind of inverse measure, significance levels near zero denote high discrimination between groups. Generally, if the Wilks' lambda significance level is less than 0.05, then this represents sufficient discriminatory power.

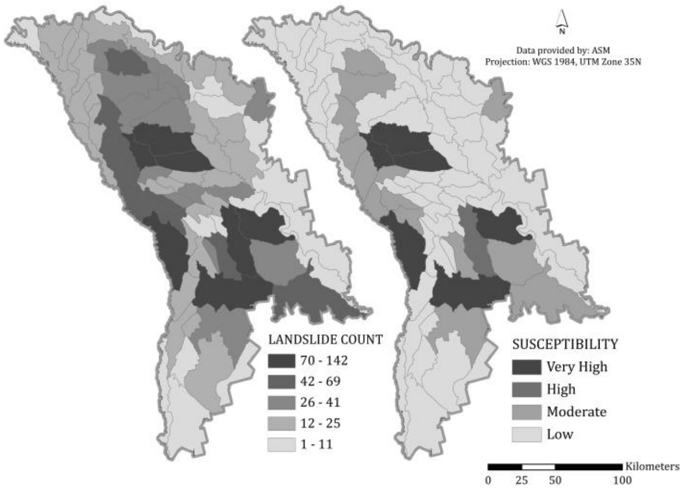

FIGURE 2
GROUPED LANDSLIDE EVENTS INTO LOW, MODERATE, HIGH, AND VERY HIGH SUSCEPTIBILITY

Independent landscape form variables were reduced to those that significantly correlated with landslide total affected area using a multivariate statistical technique. This exploratory analysis for model development used a forward stepwise regression method (*P*-value = 0.05 to remove). A multivariate landscape form model explaining landslide total affected area was created to test our hypotheses.

3. RESULTS

3.1 EXPLORATORY SPATIAL DATA ANALYSIS

Taking all 74 landscapes into account, the Global Moran's *I* analysis revealed strong spatial autocorrelation in both quantifications of landslide events. For total affected area by landslides, Global Moran's *I* index reported a score of 0.26, z-score = 4.27. For number of landslides, Global Moran's *I* index reported a score of 0.16, z-score = 2.66. Both landslide events (total affected area and count) Global Moran's *I* scores signify that there is less than 1% likelihood that these clustered patterns could be the result of random chance.

3.2 STOCHASTIC AND DETERMINISTIC ANALYSES

Results of the stepwise exploratory analysis eliminated nine of the remaining 14 independent landscape form variables. The remaining five variables combined to make a landscape form multivariate model for explaining landslide total affected area. The model consists of one topographic form metric, two land cover composition metrics, and two forest class configuration metrics (Table 1A). The one topographic form metric was *mean slope angle* (MEAN LANDSCAPE SLOPE). The two land cover compositions metrics were: *percent agricultural land* (PERCENT AGLAND) and *percent forest land* (PERCENT FOREST). The two forest class configuration metrics were: *landscape shape index* (LSI) and *Aggregation Index* (AI).

TABLE 1

SIMULTANEOUS AUTOREGRESSIVE (SAR) MULTIPLE REGRESSION FOR TOTAL LANDSLIDE AFFECTED AREA AS A FUNCTION OF MOLDOVA LANDSCAPE FORM. (A) FINAL AUTOREGRESSIVE MODEL SHOWING STANDARDIZED COEFFICIENTS; (B) OVERALL SIGNIFICANCE OF FINAL MODEL.

A. Standardized autoregressive model

Effect Variable	OLS Coeff.	SAR Coeff.	Std. Coeff.	Std. Error	t-Ratio	*P*-value
CONSTANT	< 0.001	-2.22	0.00	0.68	-3.264	0.002
MEAN DEGREE SLOPE	0.84	0.39	0.39	0.16	2.5	0.015
PERCENT AGLAND	-0.82	-0.64	-0.64	0.14	-4.59	<0.001
PERCENT FOREST	-1.42	-1.34	-1.34	0.17	-7.97	<0.001
LSI	0.41	0.62	0.62	0.10	5.95	<0.001
AI	0.51	0.78	0.78	0.14	5.81	<0.001

B. Analytical results

Dependent Variable	Landslide Affected Area
N:	74
Correlation Coefficient: R (trend)	0.78
Coefficient of Determination: R-Square (trend)	0.61
Correlation Coefficient: R (fit)	0.91
Coefficient of Determination: R-Square (fit)	0.83
Spatial Autoregressive Parameter (rho)	0.99
Alpha	1.00
F-ratio	8.84
P-value	<0.001

Trend: represents the explanation by factors only

Fit: represents the full model including space

Based on OLS methodology, the five aforementioned landscape form metrics combined to explain 61 percent of the variation in landslide total affected area ($R^2 = 0.61$, $P < 0.001$), among Republic of Moldova landscapes (Table 1B). Based on OLS methodology, the strongest positive influence of an individual landscape form metric predicting total affected area by landslides was *mean slope angle* (MEAN LANDSCAPE SLOPE, OLS coeff. = 0.84, $P < 0.015$, Table 1). Based on OLS methodology, the strongest negative influence of an individual landscape form metric predicting total affected area by landslides was *percent forest land* (PERCENT FOREST, OLS coeff. = -1.42, $P < 0.001$, Table 1).

Because a high degree of spatial autocorrelation was found in the response parameter, SAR methodology provided an improvement over OLS. The five landscape form metrics combining to explain 83 percent of the variation in landslide total affected area ($R^2 = 0.83$, $P < 0.001$), spatially through the Republic of Moldova landscapes (Table 1B, Figure 3A). Based on SAR methodology, the strongest positive influence of an individual landscape form metric predicting total affected area by landslides was *Aggregation Index* (AI, std. coeff. = 0.78, $P < 0.001$, Table 1). Based on SAR methodology, the strongest negative influence of an individual landscape form metric predicting total affected area by landslides remained *percent forest land*

(PERCENT FOREST, std. coeff. = -1.34, P < 0.001, Table 1). Investigating spatial autocorrelation of the landscape form multivariate model further, autocorrelation has been minimized from the SAR methodology based on normal distribution of model residuals (Figure 3B) and correlogram of Moran's I model residuals (Figure 3C).

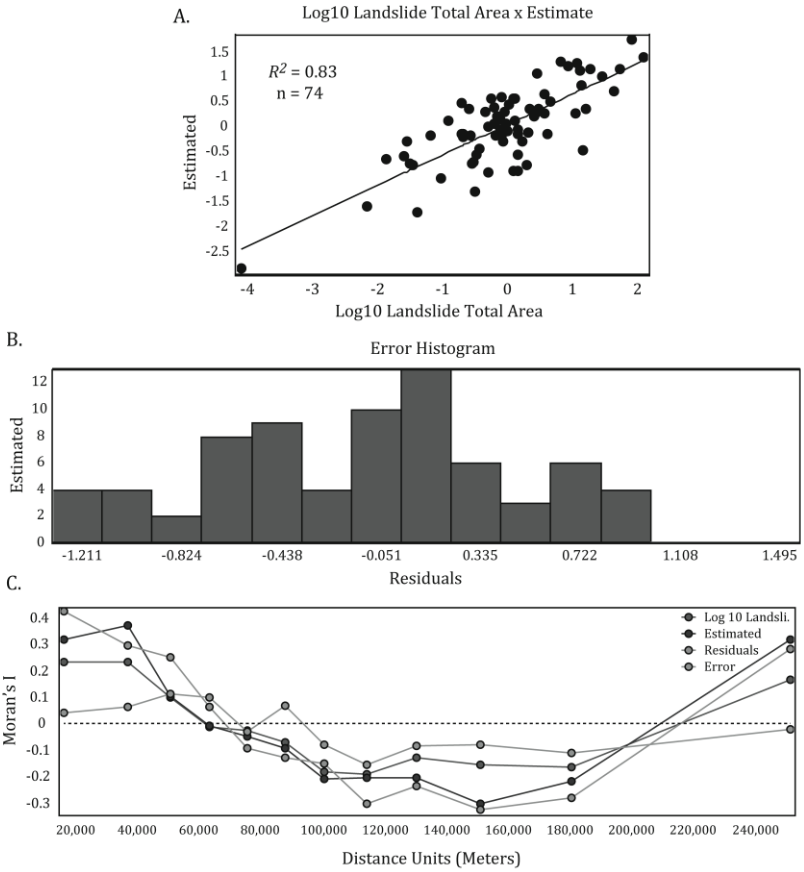

FIGURE 3
(A) ACTUAL VERSUS PREDICTED PLOT FOR LANDSLIDE AFFECTED AREA; (B) FREQUENCY DISTRIBUTION DISPLAYING DISTRIBUTION OF SAR MODEL RESIDUALS; AND (C) SPATIAL CORRELOGRAM DISPLAYING LANDSLIDE AFFECTED AREA, ESTIMATED LANDSLIDE AFFECTED AREA, SAR MODEL RESIDUALS, AND SAR MODEL ERROR.

The results from the classical discriminant analysis revealed that the five landscape form metrics combined to explain 73 percent of the variation in four groups of landside count (Rc^2 = 0.73, P = 0.000), among Republic of Moldova landscapes. Wilks' lambda significance test revealed that the landscape form model represented sufficient discriminatory power (Wilks'-λ = 0.0000). A jackknifed cross-validation technique was adopted for accuracy assessment of the discriminant landscape form model; albeit, reporting 68 percent correct across the four equal groupings of landslide susceptibility (Table 2).

TABLE 2
JACKKNIFE CLASSIFICATION MATRIX OF GROUPED LANDSLIDE COUNT FROM FINAL MODEL

	Low	Moderate	High	Very High	% Correct
Low	38	14	1	0	72
Moderate	2	9	0	3	64
High	0	0	0	1	0
Very High	0	1	2	3	50
Total	40	24	3	7	68

4. CONCLUSION

Our analysis reveals that landslide events are affected by a complexity of landscape form variables simultaneously across landscapes in the Republic of Moldova. Thus, the first null hypothesis can be rejected because statistically significant relationships were found between landscape form metrics and landscape affected area across 74 landscapes. The second null hypothesis stated spatial and deterministic multivariate statistical techniques do not support and improve OLS methods. Although covariate rank changed between OLS and SAR methods, directionality of all responses remained the same; furthermore, SAR explained 22 percent more of the variation in landslide total affected area. Deterministic statistics provided an improvement to OLS methodology with accuracy assessment. With these combined results, the second null hypothesis is also rejected. Much work remains for applied geographers to improve procedures, modeling, and mapping of landslide related phenomenon.

5. ACKNOWLEDGEMENTS

This analysis was made possible through the support of a J. William Fulbright Grant, United States Department of State. The Institute of Ecology and Geography, Academy of Sciences of Moldova provided additional resources for this research. The findings of this article are those of the authors and are not to reflect on the supporting agencies.

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