Understanding Spatial Historical and Future Landslide Variation in Africa

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Abstract

The African natural landscape reshaping in search for housing, food and infrastructure development exposes the slope to failure. However, the entire African landslide characterization is still not well known due to limited studies covering the whole continent. The authors recognize this fact and conduct this study to present the historical African landslide susceptibility (1990–2020) and the 2050 predicted occurrence under urbanization practices. Literature identifies 26,211 recent landslides and high number is localized within same areas highlighted by the 2006–2017 NASA landslide inventory. For periodical landslide susceptibility mapping, rainfall, urbanization and LULC are selected as major drivers based on literature and inventory. Each of these factors' historical maps are estimated to date (2022). These factors are combined with elevation, slope, aspects, curvature, distance to roads, distance to rivers, distance to faults, soil moisture, soil texture and lithology as of 2022 to estimate the current (2022) spatial landslide susceptibility. The Information Gain Ratio sensitivity analysis highlights urbanization (0.106), LULC (0.097), slope (0.091), elevation (0.088) and rainfall (0.083) as key landslide drivers. The Southern and Horn of Africa record above 80% of high and very high susceptibility classes. This 2022 susceptibility map is then predicted to 2050 and reclassified as that of 2050 urbanization (base map). The Southern, Eastern, Northern and Horn of Africa are landslide prone areas. This new study helps policy makers to ensure proper land planning and management practices for sustainable urbanization and lowering loss on human lives, damage on properties and environment.

1. Introduction

The understanding on the spatial pattern of landslide is still limited across different parts of the world (Bucci et al. 2021). The occurrence of landslide is driven by the characteristics of soil, debris and rock's downslope movement. Such movement can be caused by the gravity resulting from their component material such as rock, debris, soil, or mud as well as the type of movement including slide, topple or flow (Barros et al. 2021; Orhan et al. 2022). This expresses the reason why factors triggering landslide occurrence depend on the characteristics of the study area (Jacobs et al. 2017).

Over the past years, increase in human population, settlement expansion, infrastructural development such as road, market and bridge construction have raised the landslide occurrence likelihood and consequences are highly encountered by mountainous areas of poorer and developing countries (Moung-Jin et al. 2014; Zhou and Zhao 2013). The African continent is among the recently reported hosts of landslide cases with associated losses including substantially raising mortality rates (Asmare 2022). Although, the continent is still underrepresented, its rapidly growing human population stands as major driver to landslide occurrence and largely affected by the resulting losses (Broeckx et al. 2018; van Niekerk et al. 2020).

The rapidly growing African human population is recording a fast rural-urban migration increasing rate. It is reported that in 1950, 27 million inhabited Africa and increased to 567 million people in 2015 and that the continent records the global fastest urban growth. Also, its human population will double in 2050 where two third will be living in urban areas (Ogila 2021). However, landslide occurrence mainly driven by human activities including not limited to poor land management associated with intense rainfall, especially within the tropical zones of Africa, affects people's livelihoods and might increase the gravity as long as human population increase (Boudjerda et al. 2022; van Niekerk et al. 2020).This expresses how important mapping landslide susceptibility (LSM) would benefits both local communities and policy makers in Africa in planning accordingly.

LSM is an important step toward landslide hazard management and mitigation (Gong et al. 2021). LSM can be made possible by considering landslide conditioning parameters which help in spatial distribution of the risk across the study area (Gong et al. 2021; Nsengiyumva and Valentino 2020; Nahayo et al. 2019). LSM expresses the likelihood of future occurrence since it bases on the assumption that the location where previous events took place will be the likely future host as well (Pham et al. 2021). Such mapping can help policy makers, stakeholders and local community to increase landslide risk awareness on proper land use and management practices.

The tropical highlands of Africa are considered as the hotspot of landslide under their higher population densities with advanced societal vulnerabilities (Kubwimana et al. 2021). Recent studies highlighted Nigeria and South Africa among the countries highly populated and prone to landslide (Efiong et al. 2021; Romer and Ferentinou 2016). Nevertheless, as recently reported, African landslide susceptibility mapping is still limited, few studies considered the entire continent (Broeckx et al. 2018), while others were limited to regions and/or countries (Baudoin et al. 2016; Kubwimana et al. 2021; Asmare 2022; Efiong et al. 2021; Shano et al. 2021). This calls for a cross continental study which can help to indicate landslide susceptible areas from which the growing population, urbanization planning, environmental conservation and management, and other development activities should take into consideration. Therefore, this study aims to spatially distribute historical landslide susceptibility and its predicted prone areas under urbanization practices towards resilience building and risk reduction in Africa.

2. Materials And Methods

2.1 Study area

This study considered the entire African continent (Fig. 1), the second largest continent which covers around one fifth of the entire global land surface. The western Africa is bordered by the Atlantic Ocean, Mediterranean Sea at the Northern side and Red Sea on the Eastern along with the Indian Ocean at the African southern part (Broeckx et al. 2018). The continent is almost divided by the equator which makes most of its parts tropical. It is considered as the vast plateau which rises from narrow coastal strips and consists of ancient crystalline rocks. Its plateau's surface is higher in the southeast and tilts downward in northeast (Maathai 2011).

The African continent is mainly composed by a vast rigid block of ancient rock and has young geologically mountains. The continent records fewer high mountains and lowland plains and the areas above 8,000 feet are either volcanic peak or resistant massifs. The climate of Africa ranges from tropical to subarctic within its highest peaks (Henderson et al. 2017). The deserts pass in the northern while the southern and central parts contain savannah plains and dense forests. Almost 60 percent of African land is dryland and desert (Broeckx et al. 2018). Africa records an estimate of 1.37 billion people and its rapid increase is repeatedly reported to be the major cause of its natural environmental degradation which impacts on human lives, arable land availability, biodiversity, environment and properties (Güneralp et al. 2017; van Niekerk et al. 2020).

This is associated with poor settlement, unprotected highland, climate change that affects normal frequency and distribution of rainfall (Henderson et al. 2017). This as a result, leads to some disaster occurrence such flooding, landslides, mudslides affecting soil and water quality and community livelihoods as well. In order to analyze landslide susceptibility under urbanization in Africa and predict the likely future occurrence and prone areas, the authors applied the following methodological flowchart detailed in Fig. 2.

2.2 Landslide inventory

Landslide inventories are of great importance while investigating areas in which recent events took place and areas likely prone to future occurrence (Shano et al. 2021). However, landslide inventory is still difficult to make in case of large areas especially continental or global scale (Shano et al. 2021; Boudjerda et al. 2022). This was the same case for this study which considered the entire African continent and authors could not undergo a field visit to trace recent landslide events. Only satellite based-data, media, disaster databases, scientific reports and other sources were utilized to build landslide inventory of Africa (Fig. 1 and Table 1).

In the consulted literature, recent studies identified 26,211 cases within 52 out of 55 African countries (Table 1). The other inventory, employed by this study (Fig. 1) is the 2006–2017 Global Landslide Catalog of the National Aeronautics and Space Administration (NASA) (Kirschbaum et al. 2010; Kirschbaum et al. 2015) which indicates that the Eastern and Western parts of Africa recorded high number of landslide events and the areas with high number of recent event agree with the consulted literature. This inventory was assumed as of 2020, since it is the available inventory up to date.

However, it is observed that some countries record landslide events but record low number of studies on LSM. This likely increases the community exposure due to lack of awareness on appropriate risk reduction policy/measures which could be made with reference to research. This can prove that, as shown in Table 1, African continental landslide characterization is still poor since individual country case reveals limited research as the major information was referred from the data-based landslide susceptibility map of Africa (Broeckx et al. 2018). The 26,211 landslide events shown in Table 1 were collected from literature where some reports showed the number only without spatial distribution. This study only used the number to show recent cases and/or picture of the continent in terms of landslide occurrence without further use, as they all do not possess spatial distribution.

Table 1
Reviewed literature on landslide inventory per country

No.	Country	Landslide cases	Source(s)
1	Algeria	634	(Achour et al. 2017; Senouci et al. 2021; Bourenane et al. 2015; Broeckx et al. 2018)
2	Angola	1,308	(Dinis et al. 2013; Broeckx et al. 2018)
3	Benin	8	(Broeckx et al. 2018)
4	Burkina-Faso	0	-
5	Burundi	1,438	(Kubwimana et al. 2021; Désiré et al. 2018)
6	Cabo Verde	93	(Broeckx et al. 2018)
7	Cameroon	260	(Djukem et al. 2020; Che et al. 2012)
8	Central African Republic	83	(Monsieurs et al. 2017)
9	Chad	87	(Broeckx et al. 2018)
10	Comoros	33	(Broeckx et al. 2018)
11	Congo Republic	77	(Broeckx et al. 2018)
12	Cote d'Ivoire	58	(Broeckx et al. 2018; Gnagne et al. 2016)
13	Djibouti	33	(Broeckx et al. 2018)
14	D R Congo	3,657	(Kulimushi et al. 2017; Maki Mateso et al. 2021; Moeyersons et al. 2010; Broeckx et al. 2018; Nobile et al. 2018)
15	Egypt	120	(Arnous 2011; Broeckx et al. 2018)
16	Eritrea	74	(Broeckx et al. 2018)
17	Ethiopia	2,116	(Wubalem 2021; Mersha and Meten 2020; Wubalem and Meten 2020; Ayenew and Barbieri 2005)
18	Gabon	31	(Broeckx et al. 2018)
19	Ghana	16	(Broeckx et al. 2018)
20	Guinea Bissau	0	-
21	Kenya	750	(Zhou et al. 2020; Maina-Gichaba et al. 2013)
22	Lesotho	35	(Broeckx et al. 2018)
23	Liberia	6	(Broeckx et al. 2018)

No.	Country	Landslide cases	Source(s)
24	Lybia	174	(Busche 2001; Broeckx et al. 2018)
25	Madagascar	411	(Ramasiarinoro et al. 2012; Broeckx et al. 2018)
26	Malawi	177	(Msilimba 2010; Msilimba and Holmes 2010; Thiery et al. 2021)
27	Mali	35	(Broeckx et al. 2018)
28	Mauritania	129	(Busche 2001)
29	Mauritius	5	(Broeckx et al. 2018; Marsala et al. 2019)
30	Morocco	3,750	(Hailwood 1972; Broeckx et al. 2018)
31	Mozambique	334	(Broeckx et al. 2018)
32	Namibia	50	(Broeckx et al. 2018)
33	Niger	146	(Busche 2001)
34	Nigeria	461	(Efiong et al. 2021; Igwe and Una 2019)
35	Reunion	21	(Broeckx et al. 2018)
36	Rwanda	2,391	(Nsengiyumva et al. 2018; Mind'je et al. 2020; Nahayo et al. 2019; Piller 2016)
37	Sao Tome and Principe	5	(Broeckx et al. 2018)
38	Senegal	2	(Broeckx et al. 2018)
39	Sierra Leone	13	(Broeckx et al. 2018)
40	Somalia	73	(Broeckx et al. 2018)
42	South Africa	4,399	(Chiliza and Richardson 2008; Tyoda 2013; Broeckx et al. 2018)
43	South Sudan	45	(Broeckx et al. 2018)
44	Sudan	41	(Broeckx et al. 2018)
45	Swaziland	10	(Broeckx et al. 2018)
46	Tanzania	958	(Temple and Rapp 1972; Broeckx et al. 2018)
47	Togo	11	(Yang et al. 2015)
48	Tunisia	604	(Anis et al. 2019; Klai et al. 2020; Broeckx et al. 2018)
49	Uganda	976	(Jacobs et al. 2017; Claessens et al. 2007; Masaba et al. 2017; Broeckx et al. 2019; Knapen et al. 2006)

No.	Country	Landslide cases	Source(s)
50	Western Sahara	29	(Krastel et al. 2006; Broeckx et al. 2018)
51	Zambia	37	(Broeckx et al. 2018)
52	Zimbabwe	7	(Broeckx et al. 2018)
	Total	**26,211**	

2.3 Major landslide driving factors

It is reported that some factor can cause landslide occurrence in one area but not in the other and that in case of large areas, varied factors can be utilized in order to better analyze their sensitivity (Vergari et al. 2011; Wang et al. 2018). Therefore, for this study, the authors selected the employed landslide conditioning factors based on literature review, inventory, authors' knowledge and experts review as well. Based on the objective of the study which was to analyze historical and predict landslide susceptible areas, the authors subdivided landslide causal factors into major and other conditioning parameters.

The authors judged urbanization, rainfall and land use and land cover as major landslide driving parameters in Africa. This selection based on the fact was approved by recent studies (Cui et al. 2019; Zhang and Li 2020; Rahman et al. 2017) that the more urbanization takes place, the larger modification in natural landscape (changes on land use and land cover) for settling buildings and other new economic activities. Also, rainfall-induced landslide is reported at high frequency in Africa (Ojo et al. 2004). Therefore, urbanization, land use and land cover along with daily rainfall (Fig. 3–5) are considered as major factors conditioning landslide occurrence. These factors are analyzed from 1990 to 2020 and the resulting landslide susceptibility is mapped as well.

Urbanization trend

Urbanization is among the major drivers to changes on natural landscape which results into exposing the land to runoff, erosion, landslide and flooding as well (MacManus et al. 2021; Gao and Pesaresi 2021). For this study, the authors considered the urbanization (expansion of urban areas due to human activities such as construction of new buildings, commercial zones and roads recorded in Africa from 1990 to 2020. As illustrated in Fig. 3, the African urbanization trend of 1990 (a) and that of 2000 (b) reveal similar trend while the 2010 records indicate increasing trend over the continent. This 1990–2000 urbanization trend was mainly concentrated in Central and East African part. For 2020, the same Fig. 3 demonstrates urban sprawl within other parts of Africa, such as the Southern, Western and Northern. These areas with expanding urbanization are under high record of recent landslide events (Fig. 3). The utilized 1990–2020 spatial African urbanization data were provided by the Socioeconomic Data and Application Center (SEDAC) managed by NASA Earth Science Data and Information System (ESDIS) project (Gao and Pesaresi 2021).

Land use and land cover

Land use and land cover represents the material which is on the earth surface and how a portion of the earth is used such as vegetation, building and agriculture (Kühnl et al. 2022). It is reported that built-up and bare lands record high landslide susceptibility than areas covered by vegetation and that LULC has significant effect on landslide occurrence (Rwanga and Ndambuki 2017). The authors recognized the above fact and added LULC in primary landslide causal factors across Africa. For this study, the utilized LULC map of Africa was collected from the Global Land Use/Land Cover change maps of Copernicus Land Monitoring Services (Buchhorn et al. 2020) and the Sentinel-2 10 m land cover time series of the managed by Esri (Karra et al. 2021).

The 1990–2020 recorded land cover (Fig. 4) show that the largely affected land classes are cropland, grassland and forestland due to their respective decreasing trends from 1990 to 2020. With reference to recent landslide cases added in Fig. 4, it is observed that forestlands recorded fewer events that cropland, settlement and grassland which can explain the role of forest cover in reducing runoff causing landslide.

Rainfall

Rainfall is repeatedly reported among the major factors which trigger the occurrence of landslide (Chen et al. 2019). Similarly, the recently recorded landslide events in Africa, were largely rainfall-induced (Ojo et al. 2004). Hence, the authors judged it necessary to add rainfall among the selected predictive factors. As shown in Fig. 5, the 1990 daily average rainfall varied across the Central-Eastern and Western Africa than that of 2000 mainly registered in Central-Eastern and Madagascar. The 2010 daily rainfall heads towards East-southern and that of 2020 spreads over part of the Western Africa. The employed daily rainfall data were collected from the Tropical Applications of Meteorology using Satellite (TAMSAT) data and ground-based observations (Tarnavsky et al. 2014).

2.3 Other landslide causal factors

After analyzing the selected major causes of landslide in Africa (urbanization, rainfall and land cover of 1990–2020), the authors built their relevant historical landslide susceptibility maps. Thereafter, in order to estimate current (2022) landslide susceptibility map of Africa, other landslide predicting parameters (elevation, slope, aspects, curvature, distance to roads, distance to rivers, distance to faults, soil moisture, soil texture and lithology) are selected with reference to the literature on the major causes of landslide in Africa. These parameters were of 2022 and were analyzed together with the estimated 2022 rainfall, LULC, urbanization and landslide in order to estimate the 2022 landslide susceptibility across Africa (Fig. 10).

Elevation

Elevation is the height above or below a prefixed reference point of a geographical location. It is reported that the basis for spatial variation in hydrological conditions and slope stability along with environmental control are all set up by an area's elevation (Banerjee et al. 2018). This is based on while selecting elevation among landslide causal factors in Africa and Fig. 6 (a) indicated that the elevation of Africa ranges between − 376 and 5,883 m.

Slope

The slope is an important parameter in hydro-geomorphological studies mainly those of water flow management and landslide (Liu et al. 2020). For this study, the third order finite different approach is utilized to prepare the slope of Africa from the Digital Elevation Model (DEM). The slope was calculated in Eq. 1 below.

$$Slope = arctan\left[\sqrt{x^2+y^2}\right)](1)$$

Where x and y are cells' sizes within x and y directions. This results from the fact that slopes generally, decreases with the flattering of the terrain (Liu et al. 2020). The Surface Tool in Spatial Analyst Toolbox of ArcGIS 10.8 is used to prepare the slope map of the study area. As illustrated in Fig. 6 (b), the obtained slope ranges from 0 to 69.65 degrees.

Aspect

Aspect which is also a derivative of elevation was estimated as the angle between *y*-axis and the direction in which the slope is steepest in the clockwise direction (Gu et al. 2021). It is reported that the value of aspect range from 0 to 360 and that it has a direct influence on soil moisture, rainfall intensity, slope deposits' exposure to wind and sunlight (Sharma et al. 2014). The following Eq. 2 indicates how aspect algorithm is calculated. The aspect in this study (Fig. 6.c) ranges from (Flat-1) to (North (337.5–360).

$$Aspect = \arctan\left(\frac{slopeinx}{slopeiny}\right)(2)$$

Curvature

Curvature has been employed by recent studies to predict zones that are likely susceptible to future landslide (Banerjee et al. 2018). For this study, the curvature was estimated by fitting a fourth order polynomial to a 3×3 window of a DEM. The curvature was estimated by employing the Surface toolbox in ArcGIS 10.8. The obtained curvature for Africa (Fig. 6.d) ranges from − 3.44 to 2.57.

Geology

Recent landslide susceptibility mapping showed that geology owns a great control on landforms and influences the stability of slope (Ozturk and Uzel-Gunini 2022). The rock type, structure and hardness can be good indicator of an area's susceptibility to landslide due to the fact that, in most cases, landslide occurs within lithological areas with lowest strength and higher moisture content (Ding et al. 2017). This study employed geology map of Africa indicating its lithology type which was collected from the Commission for the Geological Map of the World (World et al. 2000). The obtained lithological classes in Africa are indicated in Fig. 7 (a).

Soil texture

For the soil texture, the authors employed soil texture collected from the Soil Atlas of Africa generated by the European Soil Data Center (ESDAC) (Dewitte et al. 2013). The distribution of African soil texture and its classes is provided in Fig. 7 (b).

Soil moisture

The soil moisture indicates the water content in the soil and is among the major parameters for land susceptibility analysis. Although several studies utilize the insitu measurement while estimating the surface soil moisture, it is cost and time consuming mainly when the study area is large (Ranasinghe et al. 2019; Wicki et al. 2020). This fact is recognized by authors and then the available shapefile form the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) (Ross et al. 2018) is utilized. The results in Fig. 7 (c) show that the highest soil moisture is localized within the Central, Eastern and Southern African parts.

Distance to roads

Roads are human constructions on earth surface which interfere with the earth's materials and in many cases, landslide took place close to roads which expresses that their construction is among drivers to landslide occurrence (Asmare 2022; Shano et al. 2021). This study considered distance to roads in Africa derived from the African Infrastructure Country Diagnosis (AICD) (Eberhard et al. 2008). The spatial road network in Africa distributed in Fig. 7 (d) showed that the longest distance is 20,000 m. The lowest distance (0 m) is localized mainly within northern parts featured by deserts (Fig. 7.d). This can be the reason why few activities are carried throughout the desert and hence, no need of many roads.

Distance to water

Previous studies (Nahayo et al. 2019; Maqsoom et al. 2021) have considered landslide susceptibility as a result of an area's proximity to water bodies or drainage because water bodies such as streams, lake and rivers significantly influence the slope. The utilized shapefiles of river network in Africa was collected from the African Infrastructure Country Diagnosis (AICD) (Eberhard et al. 2008). And as shown in Fig. 7 (e), longer distance (20,000–25,000 m) to water bodies is localized in the northern area which is likely the same reason to distance to roads (Fig. 7.d).

Distance to faults

It is reported that distance to faults can easily facilitate to recognize the areas highly exposed landslide due to the reason that the rock and soil structure are easily broken and weathered with certain impact on occurrence of landslide (Li et al. 2021). For this study, the employed faults were derived from the Global Geology Database (Chorlton 2007). The distance to roads, to rivers and to faults (Fig. 7. d, e and f) was estimated by using the Euclidean distance and the obtained classes are subdivided by the Jenks Natural Breaks in ArcGIS.

Table 2
Sources of selected landslide predicting factors

No.	Primary data	Format	Spatial resolution	Source
1	Urbanization	Raster	30×30m	NASA/SEDAC
2	Global Landslide inventory catalog	Catalog	Variable	NASA
3	Shuttle Radar Topography Mission (STRM) Digital Elevation Model (DEM)	Raster	30×30m	United States Geological Survey (USGS)
4	Land Use Land Cover (LULC)	Raster	10×10m	Copernicus Land Monitoring Service
5	Geology	Raster	30×30m	
6	Daily average precipitation		0.1° × 0.1°, 30-min	Tropical Applications of Meteorology using Satellite (TAMSAT)
7	Soil datasets	Raster	30×30m	Soil catalog of Africa
8	River and river network	Raster	30×30m	Africa Infrastructure Country Diagnostic (AICD)
9	Faults	Raster	30×30m	Global Generalized Geology

2.4 Data analysis

2.4.1 Landslide causal factors’ sensitivity

In the literature, existing landslide susceptibility modelling approaches were developed. These include not limited to the Statistical Index (SI), Certain Factor (CF), Frequency Ratio (FR), Logistic Regression model, Analytical Hierarchy Process (AHP), and Artificial Neural Networks (ANN), Information Gain Ratio (IGR), distribution statistics along with the Consistency (Tian et al. 2017; Nahayo et al. 2019; Nsengiyumva and Valentino 2020; Dhakal et al. 2020; Jacobs et al. 2017). However, the majority of these approaches require authors to possess landslide inventory from which the landslide points for training and validation can be subdivided. Contrarily, for this study, the exact number of landslide events recorded in Africa could not be traced. In addition, as long as the study focuses on the periodical record comparison, the authors did not prioritize the use of training and validation landslide points.

Therefore, the authors consider the above facts and then chose to employ landslide susceptibility modeling approach which does not require training and validation approaches. For this study, in order to improve the quality of landslide susceptibility map of Africa which depends on the causal factors, the authors employed the Information Gain Ratio (IGR) method recently employed (Nsengiyumva and Valentino 2020; Zhang et al. 2020; Phong et al. 2021) to evaluate the capability of the predefined predicting parameters. For the IGR method, the landslide causal parameter (s) with advanced information gain rate is the major causal factor compared to other (s) with low rate since factors with 0 do not contribute to the model prediction capacity and may be removed (Zhang et al. 2020).

The IGR value for the selected landslide causal factors in Africa was estimated through the following steps detailed in equations 3, 4, 5 and 6. The IGR method develops the ability of landslide prediction by rejecting and/or minimizing the contribution of factors with lower IGR value in causing landslide occurrence. The method assumes that the training data (T) contains n samples, and C_i (landslide and non-landslide) is the classification set of sample data, while the information entropy of factors is calculated in Eq. 3.

$$Info\left(T\right)=-\sum\nolimits_{I=1}^{2}\frac{n\left({C}_{i},T\right)}{T}{log}_{2}\frac{n\left({C}_{i},T\right)}{T}\left(3\right)$$

The estimation of information values (T1, T2, and Tm) from T by considering the driving parameter F is generated in the following Eq. 4.

$$Info\left(T,F\right)=-\sum\nolimits_{I=1}^{m}\frac{{T}_{i}}{T}{log}_{2}Info\left(T\right)\left(4\right)$$

Therefore, the IGR of landslide triggering factor (F) is calculated as explained in Eq. 5 below.

$$IGR\left(\text{Y},\text{F}\right)=\frac{Info\left(T\right)-Info(T,F)}{SplitInfo(T,F)}$$

5

Where *Split Info* is the major information obtained after dividing the training data T into m subsets. The formula for the *Split Info* is indicated in Eq. 6.

$$SplitInfo\left(T,F\right)=-\sum\nolimits_{I=1}^{m}\frac{{T}_{i}}{T}{log}_{2}\frac{{T}_{i}}{T}\left(6\right)$$

It is assumed that in case IGR is greater than one (> 1), the likelihood of landslide is higher than average and if IGR equals zero (= 0), landslide probability is equal to the average while in case the calculated IGR is lower than zero (< 0), the probability of landslide is less than average (Luo et al. 2019; Ghasemian et al. 2022).

2.4.2 Mapping landslide susceptibility

After producing the thematic map of each landslide conditioning factor, these maps were combined in order to distribute landslide susceptibility in Africa. This approach is adopted due to the reason that, as recently suggested, direct addition contributes to immediate production of the resulting map (Nsengiyumva and Valentino 2020). All appropriate factor's weights are added together to generate the susceptibility map. This map is classified into very low, low, moderate, high and very high landslide susceptibility by using the Jenks Natural Breaks classification of ArcGIS 10.8.

The authors first mapped periodical (1990, 2000, 2010 and 2020) landslide susceptibility caused by the selected major causal factors namely urbanization, LULC and rainfall. As each landslide causal factor was subdivided into four periods (1990, 2000, 2010 and 2020), the authors first combined them by using the combine option in Spatial Analysts Tools of Arc GIS. This process generated one single map of urbanization, of rainfall and that of LULC estimated as of 2022. For the periodical landslide mapping, the authors utilize each periodical map of rainfall, land cover and urbanization (Fig. 9). Thereafter, land cover, rainfall and urbanization single maps were utilized to estimate their merit value in terms of conditioning landslide occurrence in Africa by using the IGR method. This process is undertaken to other considered predicting factors (Table 3).

The sensitivity value of each predicting factor (rainfall, urbanization, LULC, elevation, slope, curvature, aspects, lithology, soil texture, soil moisture, distance to roads, distance to water, along with distance to faults) is used to estimate 2022 landslide susceptibility across Africa. This exercise is completed by using raster calculator of Map Algebra in the Spatial Analyst Tool of the ArcGIS 10.8.

2.4.3 Prediction of landslide susceptible areas

In order to predict landslide prone areas under urbanization trend in Africa, the authors employ the 2050 urbanization map with the 2022 landslide susceptibility map projected to 2050 by using the raster projection in Spatial Analyst Tools of ArcGIS. Then, both 2050 urban growth and projected landslide susceptibility are reclassified by using reclassify method in Spatial Analyst Tools of ArcGIS. After reclassification, the obtained maps of urbanization and landslide are employed to show future landslide prone areas.

This exercise is completed by using the Weighted Overlay methods where the 2050 urban growth and projected landslide susceptibility are attributed 50 percent each. Finally, the Map Algebra in the Spatial Analyst Tools of ArcGIS constructed the predicted landslide prone areas across Africa on which the recent landslide inventory was laid over as well. This also facilitated to better predict zones that might be affected by future landslide based on recent events. This exercise is done in order to indicate areas that will be prone to landslide as the results of urbanization trend.

3. Results

3.1 Importance of landslide causal factors

As indicated in equations 3–6, the significance of each individual landslide predicting factor was estimated by using the Information Gain Ration method (section 2.4.1). The findings on the significance of the selected landslide causal factors, as shown in Table 3, indicate that increasing spread of urbanization, poor land management, slope, elevation and rainfall are the primary factors exposing African continent to landslide.

Table 3
Significance of landslide causal factors by IGR method

No.	Predictive factor	Average merit	Standard deviation
1	Urbanization	0.106	± 0.051
2	LULC	0.097	± 0.042
3	Slope	0.091	± 0.036
4	Elevation	0.088	± 0.033
5	Rainfall	0.083	± 0.028
7	Distance to faults	0.052	± 0.002
8	Soil moisture	0.048	± 0.006
9	Distance to rivers	0.043	± 0.011
10	Distance to roads	0.041	± 0.013
11	Lithology	0.027	± 0.027
12	Soil texture	0.021	± 0.033
13	Aspects	0.003	± 0.051
14	Curvature	0.003	± 0.051

3.2 Mapping landslide susceptibility

As detailed in the methodology section, for this study, two types of landslide susceptibility maps are constructed. The first are the periodical landslide susceptibility maps of 1900, 2000, 2010 and 2020 built by using the periodical respective maps of rainfall, urbanization and LULC. This helped to reveal the periodical changes in terms of African continental exposure to landslide due to the judged major landslide causal factors (rainfall, urbanization and LULC). For the last landslide susceptibility mapping, as shown in section 2.4.2, the authors combine all thirteen landslide causal factors with their standard variations (Table 3). The individual factor’s merit (Eq. 7) is utilized to estimate the current spatial distribution of landslide susceptibility across the African continent.

$$
\begin{aligned}
\mathrm{LSI} = {} & (\text{Urbanization} * 0.051) + (\text{Land use land cover} * 0.042) + (\text{Slope} * 0.036) + (\text{Elevation} * 0.033) \\
& + (\text{Rainall} * 0.028) + (\text{Distance to faults} * 0.002) + (\text{Soil moisture} * 0.006) \\
& + (\text{Distance to rivers} * 0.011) + (\text{Distance to roads} * 0.013) + (\text{Lithology} * 0.027) \\
& + (\text{Soil texture} * 0.033) + (\text{Aspects} * 0.051) + (\text{Curvature} * 0.051) \qquad (7)
\end{aligned}
$$

The results on spatial periodical (1990–2020) landslide susceptibility across Africa (Fig. 8) reveal that in 1990, landslide susceptibility is high within some Eastern, Central and few Western countries of Africa. The same Fig. 8 shows that in 2000, high landslide susceptibility is localized in the East African countries like Kenya, Rwanda, Uganda and Democratic Republic of Congo. In 2010, as illustrated in Fig. 8, landslide susceptibility is largely recorded in the Eastern and Western parts of Africa. Finally, in 2020 (Fig. 8) landslide susceptibility significantly increased in Western and other parts including the Northern, Southern and Eastern regions.

The results on the estimated 2022 landslide susceptibility as shown in Fig. 9 agree with the periodical recorded increasing landslide susceptibility across Africa (Fig. 8). However, the results in Fig. 9 reveal that other regions of Africa are exposed to landslide mainly due to its urbanization, poor land management, rainfall, slope and elevation (Table 3).

4. Discussion

4.1 Landslide occurrence

The occurrence of landslide causes increasing human fatalities in both rural and urban settings and the extent results mainly from the event intensity, size and/or number of elements exposed along with their associated vulnerabilities (Małka 2021; Sharma et al. 2014). Between 1971 and 1975, it was noticed that about 14 percent of global fatalities of natural hazards results from landslide and this attracted the attention in mapping its susceptibility (Froude and Petley 2018). Landslide susceptibility mapping/zonation helps to detect the areas that are likely prone to landslide due to predicting/existing conditions. It is reported that mountainous area with higher intensity of rainfall under poor land management record high frequency of landslide occurrence and associated fatalities (Tian et al. 2017; Kim et al. 2016). Mapping of landslide susceptibility in Africa is still limited due to several reasons including not limited to inaccessibility of landslide predicting factors and its inventory which could help to trace recent and future likelihood of landside occurrence (Broeckx et al. 2018). Apart from the inventory, even studies on mapping its susceptibility are still at low level which could help to minimize the risks among people and properties (Kubwimana et al. 2021).

This study employs thirteen landslide predicting factors based on literature review and expert knowldege namely elevation, slope, aspects, curvature, land use land cover, rainfall, urbanization, lithology, soil moisture, soil texture, distance to faults, distance to road and distance to rivers (Fig. 3–7). The periodical landslide susceptibility maps (Figs. 9 and 10) indicate susceptibility variation cross Africa and confirm the fact highlighted by recent studies that in most cases, the recorded landslide events across Africa, are primarily rainfall-induced (see Fig. 5) (Kubwimana et al. 2021; Kervyn et al. 2015; Efiong et al. 2021). The results indicate that between 1990 and 2020, the changing landslide susceptibility in Africa (Figs. 8 and 9) is quite relevant to the recorded rainfall variability (Fig. 5).

In addition, some studies (Li et al. 2022; Ojara et al. 2020) report that in Africa, poor land management associated with the rapidly increasing human population and its economic activities causes landslide occurrence. This agrees with the results of this study (Figs. 8 and 9) since large susceptible areas are localized within areas with decreasing forestland and grassland (Fig. 4). This likely expresses that anthropogenic activities such as expansion of arable land and roads constructions reduced the forest cover and exposed the soil to runoff/erosion under high rainfall and its high soil moisture (Fig. 7.c)).

This is previously reported (Sibanda et al. 2021; Buba and Jaafar 2021) that African forest cover recorded decreasing trend from 17.53% in 1990 to 17.08% in 2000 and then became 15.68% in 2020. Moreover, areas with recent landslide events are at high likelihood of recording future occurrence (Govender et al. 2022). This agrees with the current study (Fig. 10) where the predicted landslide prone areas are those with high number of recent landslide events (Fig. 1). Hence, it can be noted that the larger the urbanization expands, the larger Africa becomes exposed to landslide as humans change the natural landscape in settling buildings and other economic activities.

4.2 Urbanization and landslide susceptibility

For this study, it is estimated that under urbanization practices (Fig. 10), more landslide susceptibility will be recorded within the East, West, South and Northern parts of Africa. These regions are under growing urbanization (Fig. 3), limited forestland and vegetation (grassland) (Fig. 4) which could minimize the runoff accelerated by higher rainfall, soil moisture and slope (Fig. 5–7). In addition, the predicted landslide susceptibility under urbanization growth in Africa (Fig. 10) shows that areas in the high and very high susceptibility will increase in Africa. The scenario will likely result from the rapidly growing urbanization and poor land use in Africa. For example, the LULC maps of 1990, 2000 and 2010 reveal slight decrease in forest cover. However, the LULC map of 2020 demonstrates considerable reduction of forest cover under increase of urban land in 2020 within different parts of Africa (Figs. 3 and 4).

For example, as shown in Fig. 10, Morocco, Ethiopia, Rwanda, Kenya, Burundi and part of Uganda are predicted to be largely exposed to landslide due to their urbanization increase. This can be attributed to different factors such as human population growth, raise in incomes and Gross Domestic Growth (DGP). And this consequently, leads to more economic investments and forest and grasslands clearance due to setting up new settlements and high food demand expanding cropland.

Furthermore, it is reported (Michellier et al. 2020; He et al. 2021) that African continent will record the world's largest urbanization trend form 36 percent to 50 percent in 2010 and 2030, respectively. This goes with growing number of human populations in need of land for expanding building areas, markets, schools and urban recreational zones. Consequently, if not well planned, this can contribute to lowering forest cover and grassland and slope stability. Similarly, as illustrated in Fig. 10, it is noticed that in 2050, many parts of African continent will be prone to landslide due to one or the above urban activities mentioned.

4.3 Urbanization Planning for Landslide Risk Management

Urbanization is one of the indicators of community and/or country development since it goes with growth in human incomes, infrastructure development, access to water supply and other services, and many more (Li et al. 2016). However, its expansion is associated with natural landscape modification and in many parts, due to lack of appropriate localization of urban areas, improper zones are used which lead to several losses caused by the instable landscape modified (Dos Santos et al. 2017).

In addition, as long as African continent becomes more urban, the haphazard urbanization may be recorded due to its growing and unplanned urbanization. Also, in case countries exposed to landslide continue becoming more urban, more landslide risks including human death, properties and economic loses will be high as well (Bang et al. 2019; Gero et al. 2011). This calls for appropriate policy making in controlling urbanization by ensuring that the land being urbanized is well protected against any runoff force, localizing human settlements in safe zones and that regular monitoring and mobilization are provided. This, in case well implemented, can increase the likelihood of minimizing the slope exposure to failure and loses associated with landslide occurrence.

However, apart from urbanization planning, sustainable land use and management, policy makers also need to take into consideration the fact that, the African rainfall reveals abnormal distribution (Fig. 5) and that under the changing climate, rainfall might accelerate the susceptibility. Hence, for rainfall impact minimization, urban rainwater harvesting policy should be strengthened and the decreasing forestland (Fig. 4) should be extended in order reduce the runoff, erosion and soil loss causing landslide.

Furthermore, as long as human population growth and urban inhabitants grow, several management/adaptation measures are needed. These include not limited to enforcing the building codes, expanding terraces and agroforestry zones in peri/urban areas and cropland located in urban areas to reduce landslide risks. This would specifically help the Eastern, Central, Western and Southern countries localized in the future susceptibility zones (Fig. 10) and reported as areas with the rapid urbanization trend in Africa (Adzawla et al. 2019; Güneralp et al. 2017). The adoption of such measures will help to ensure sustainable urbanization with minimum landslide risks and protection of people’s lives, properties and environment as well.

5. Conclusion

The objective if this study was to estimate areas which will be prone to landslide under urban growth in Africa. The authors employed secondary data on causal factors of landslide trend of urbanization up to 2050 and GIS is the major tool for data analysis. The periodical (1990–2020) major landslide drivers (urbanization, land management and rainfall) facilitated to reveal relevant spatial variation of landslide susceptibility in Africa. These major causes are combined and estimated as of 2022 then used in conjunction with other eleven predicting parameters (elevation, slope, curvature, aspects, lithology, distance to faults, soil moisture, soil texture, distance to roads and distance to rivers) to estimate the 2022 landslide susceptibility. This 2022 landslide susceptibility is projected to 2050 and reclassified as that of 2050 urbanization in order to predict future landslide susceptible areas under urbanization in Africa. It is noted that the proportion of high and very high landslide prone areas will increase mainly in the Eastern, Southern, Northern zones and Horn of Africa and these areas similarly record expanding urbanization. Although urban growth will lead to increasing the risk, it is good to ensure that both climate change adaptation and urbanization planning go are in action. This is due to the fact that the areas under landslide susceptibility are those with high rainfall. For Africa, promoting landslide research/education and enhancing community awareness (capacity building) on landslide causes and basic risk reduction measures at local level can be among the solutions. Also, as long as urban growth reveals a fast-growing rate in Africa, this study provides new information on the continental exposure to landslide to Policy makers and urban leaders to better understand the appropriate land management and urbanization practices to envisage with reference to the forecasted landslide prone zones across Africa. Future studies can assess the willingness of policy makers in mainstreaming landslide risk reduction in their development agendas. In addition, future studies can integrate geoscience and technological tools in assessing landslide risk exposure per each type of urban areas in order to early determine relevant management policies.

Declarations

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Ethical Declaration

Conflict of interest

The authors declare no conflict of interests.

Consent for publication

Consents for publication from all co-authors is received.

Competing Interests

This manuscript has not been published or presented elsewhere in part or in entirely and is not under consideration by another journal.

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Figures

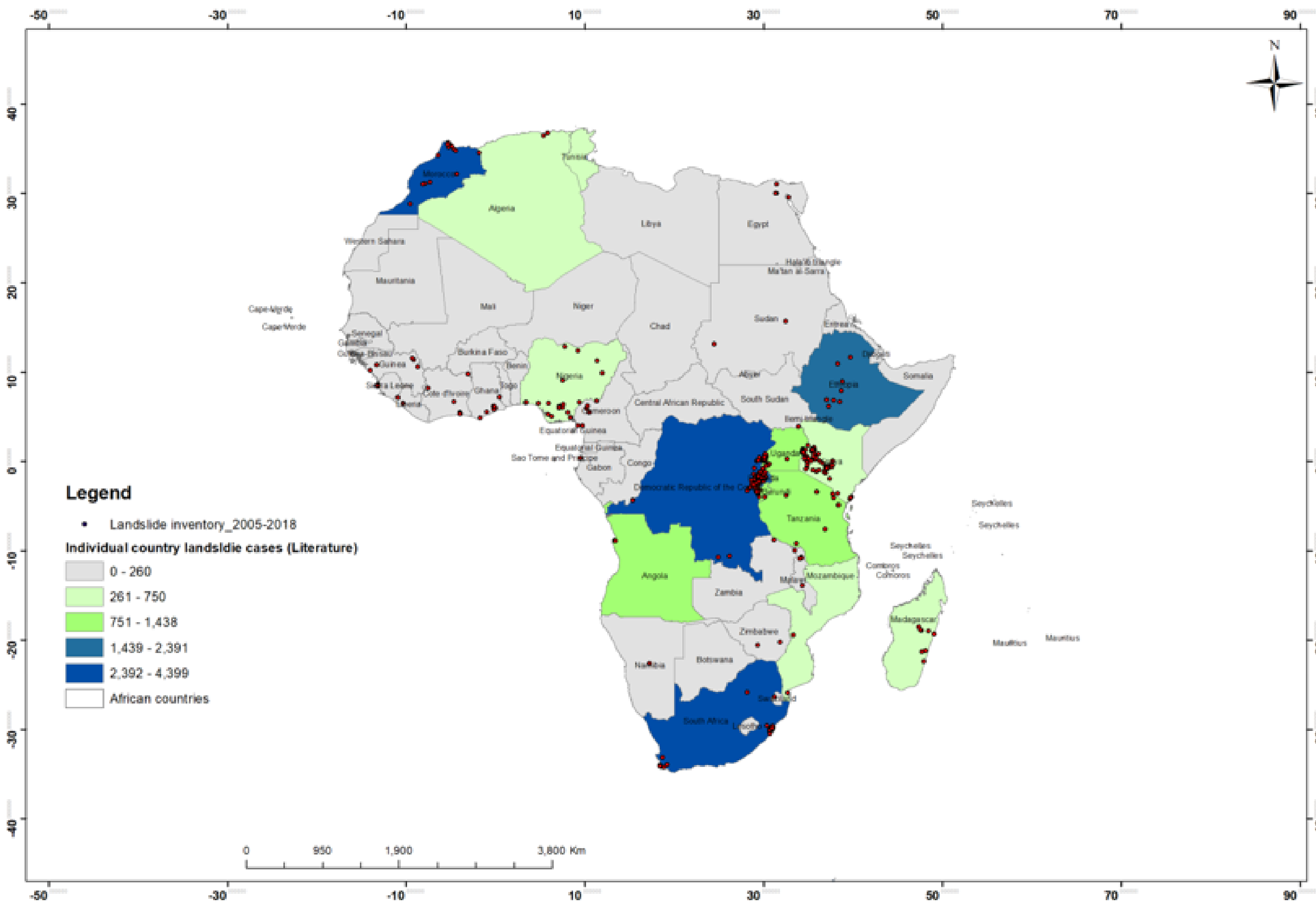

Figure 1

Map indicating the African landslide inventory extracted from the 2005-2018 Global Landslide Inventory of NASA and recent number of landslide cases per different studies consulted in the literature review

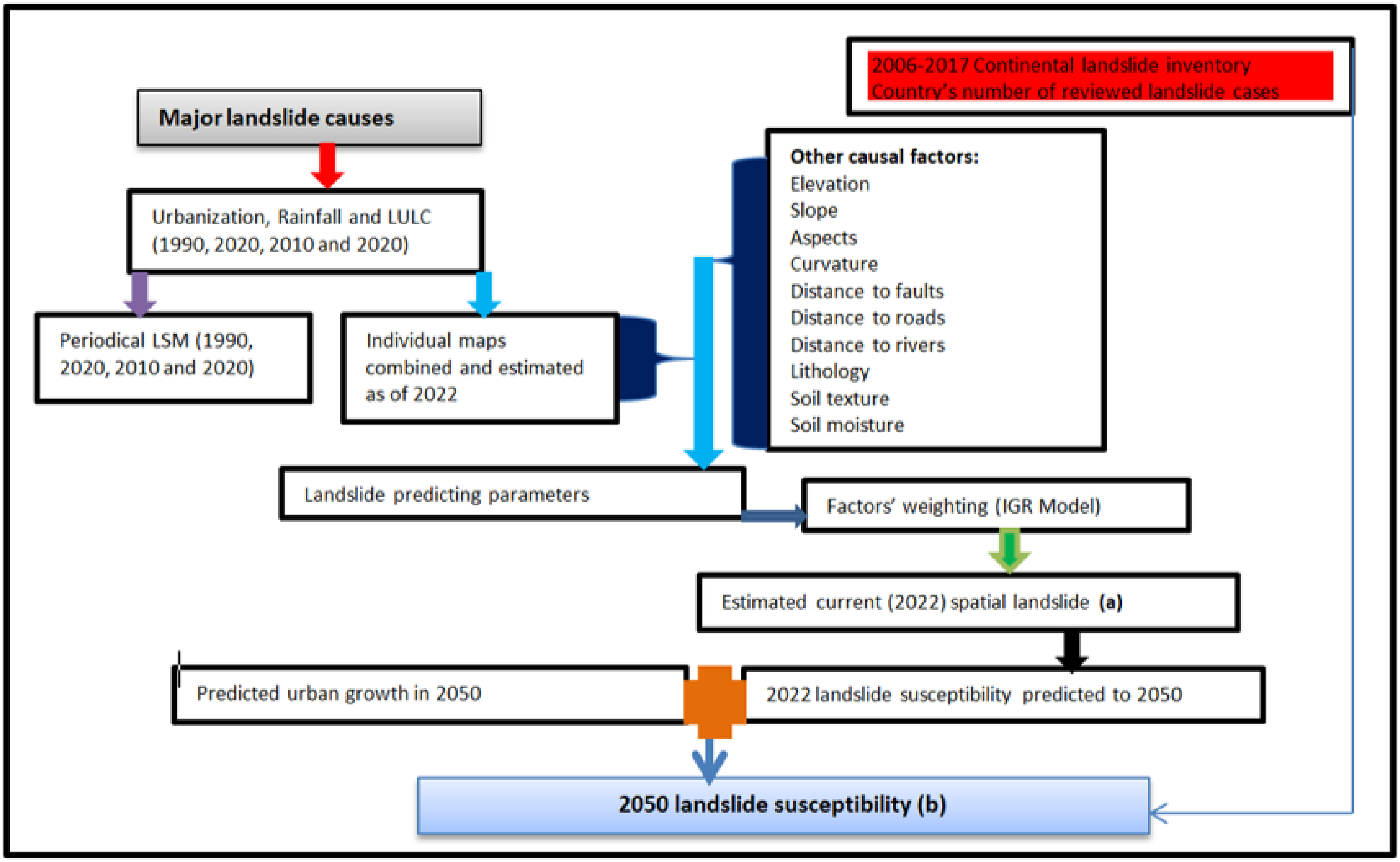

Figure 2

Methodological flowchart for predicting landslide susceptibility by (a) using periodical (1990, 2000, 2010 and 2020) causal factors to generate respective landslide susceptibility maps, combined with other 2022 predicting parameters to estimate the 2022 LSM (b) and combing the 2022 LSM predicted to 2050 with 2050 urbanization to reveal the 2050 landslide susceptible zones in Africa

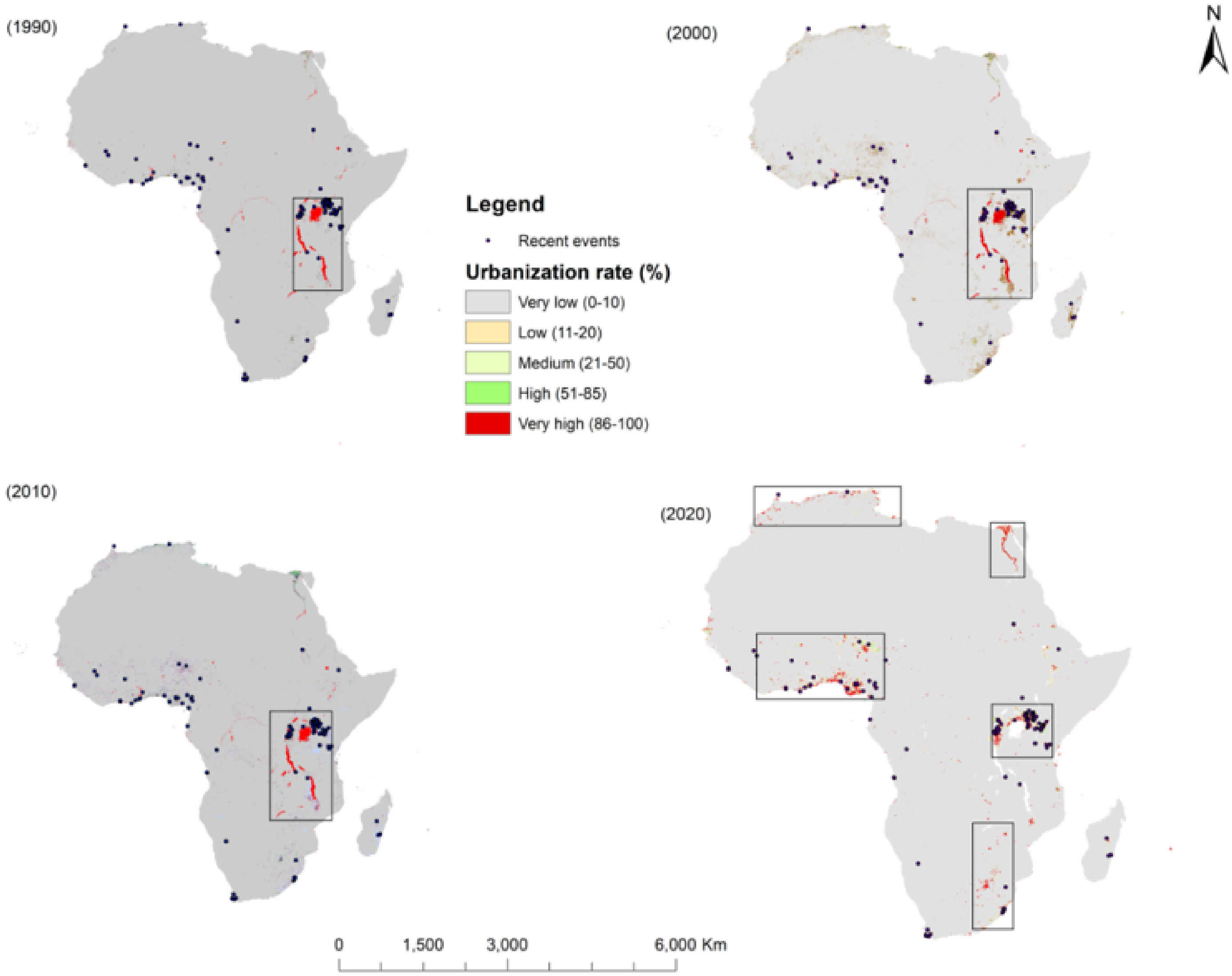

Figure 3

Spatial distribution of 1900-2020 urbanization growth in African continent

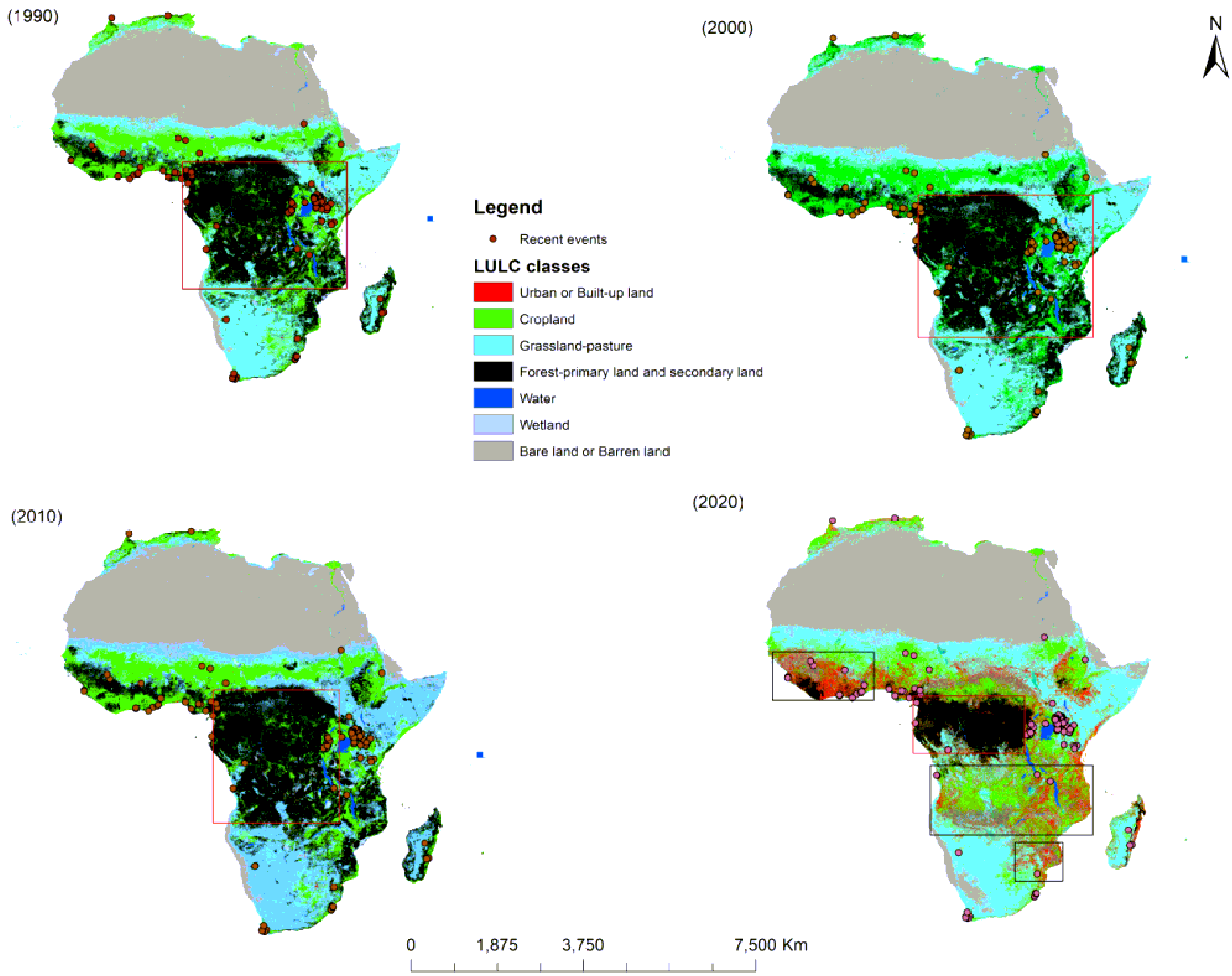

Figure 4

1990 -2020 Land use and land cover in Africa with no significant changes in terms of forest cover from 1990 to 2000 (rectangle in red) heading to slight reduction between 2000 and 2010 while significant change is recorded between 2010 and 2020 (rectangle in red) due to increasing settlements (rectangle in black).

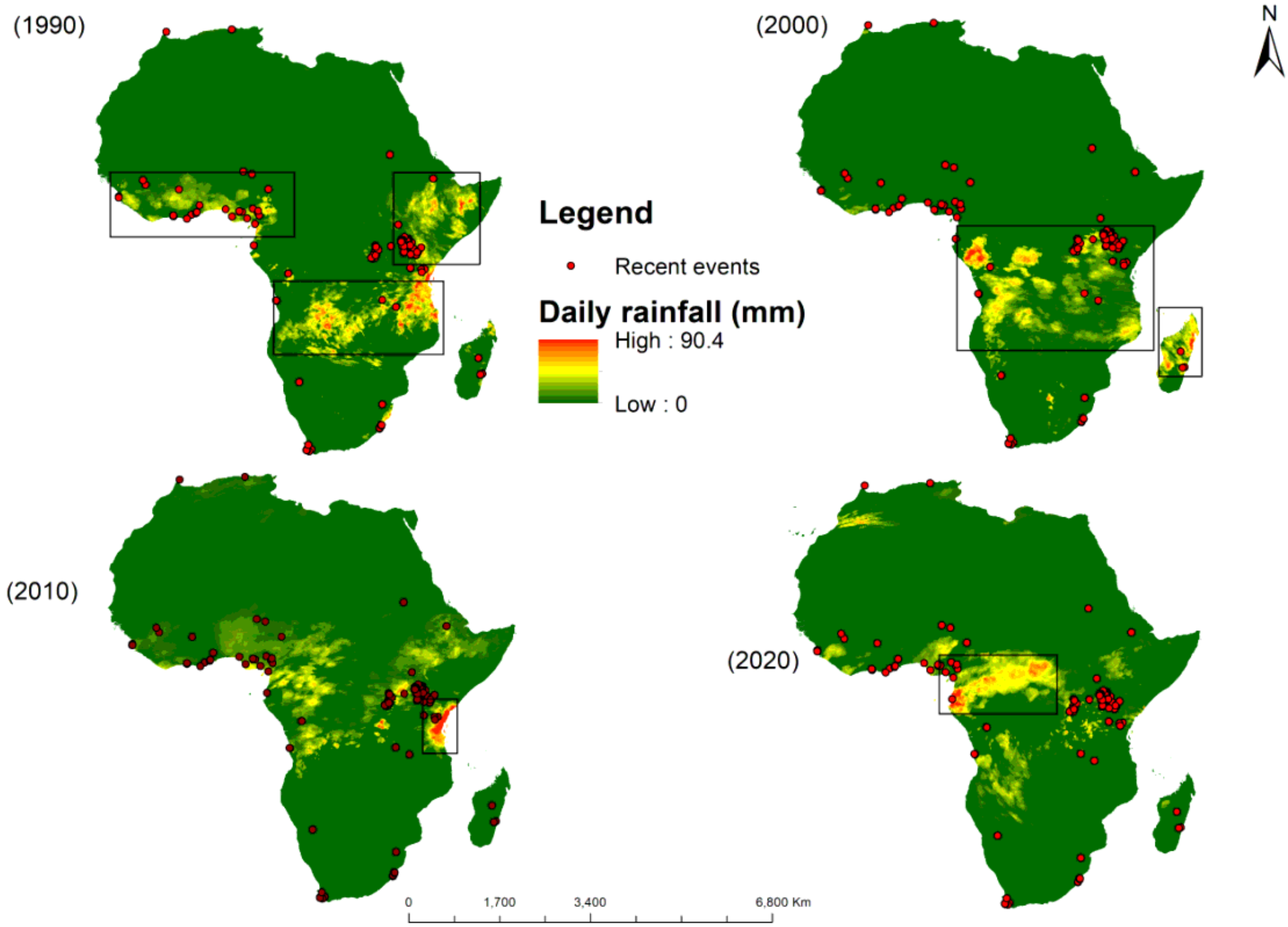

Figure 5

Distribution of daily rainfall (mm) in Africa between 1900 and 2020

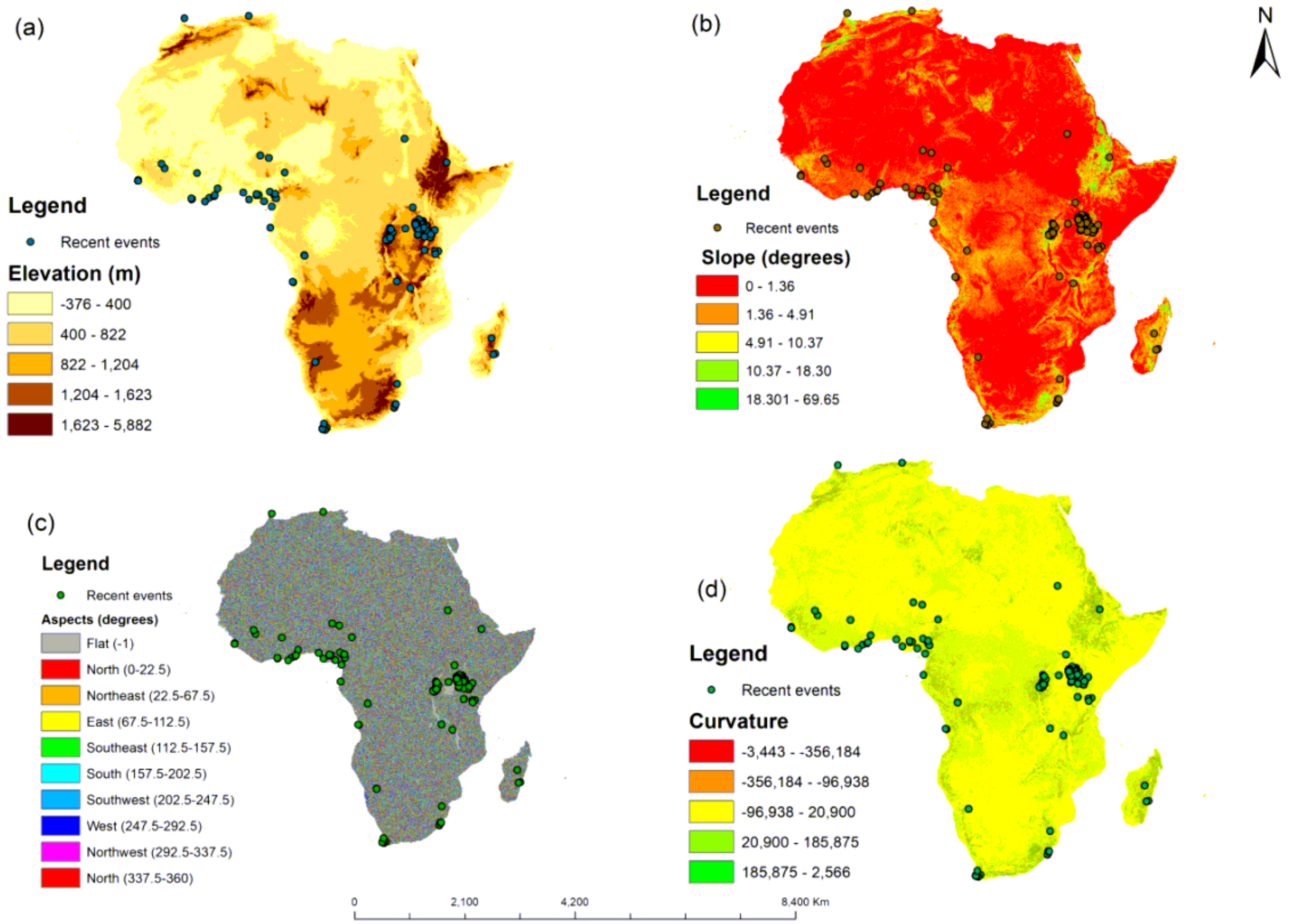

Figure 6

Landslide predictive factors: (a) elevation, (b) slope, (c) aspects and (d) curvature

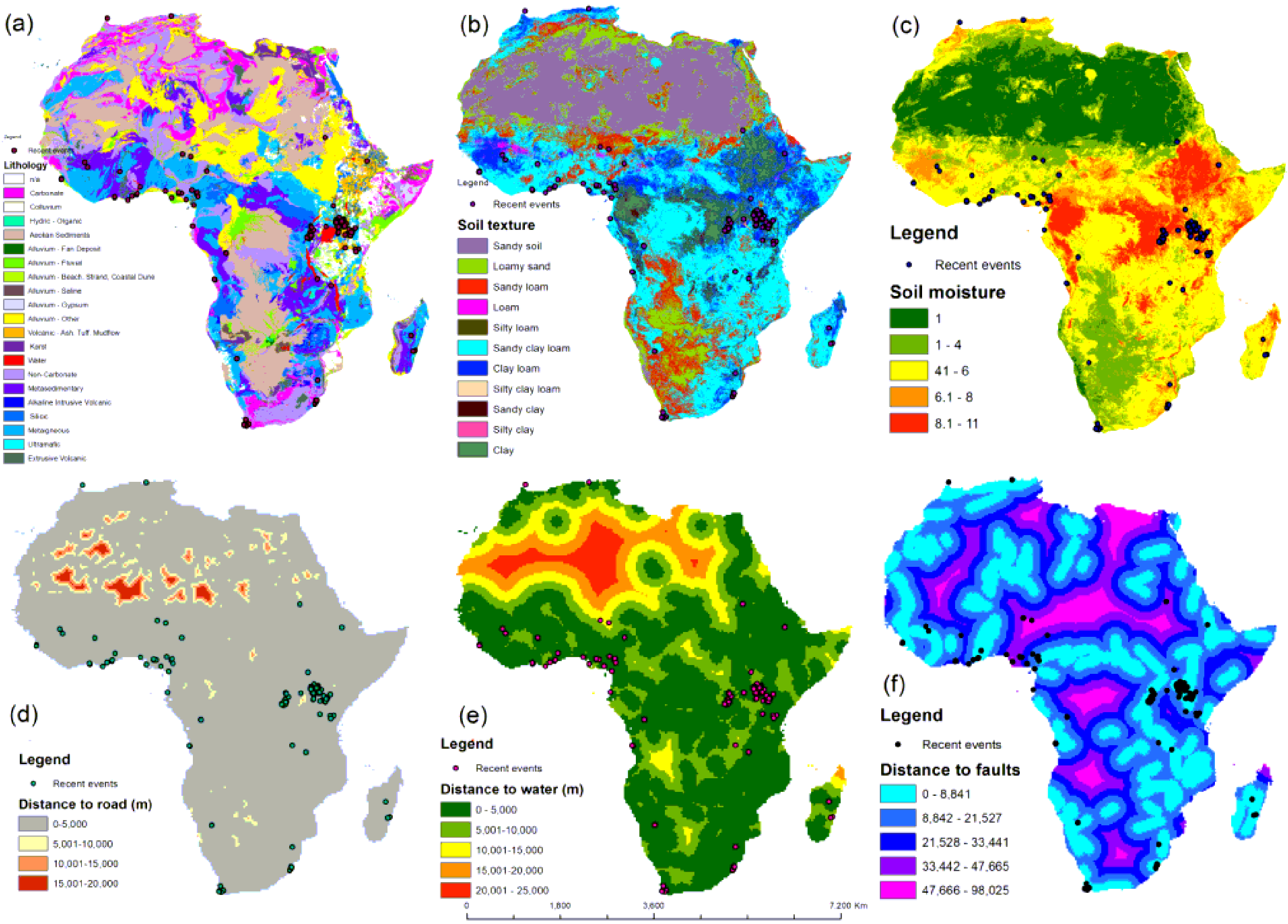

Figure 7

Landslide predictive factors: lithology (a), soil texture (b), soil moisture (c), distance to roads (d), distance to water (e) and distance to faults (f).

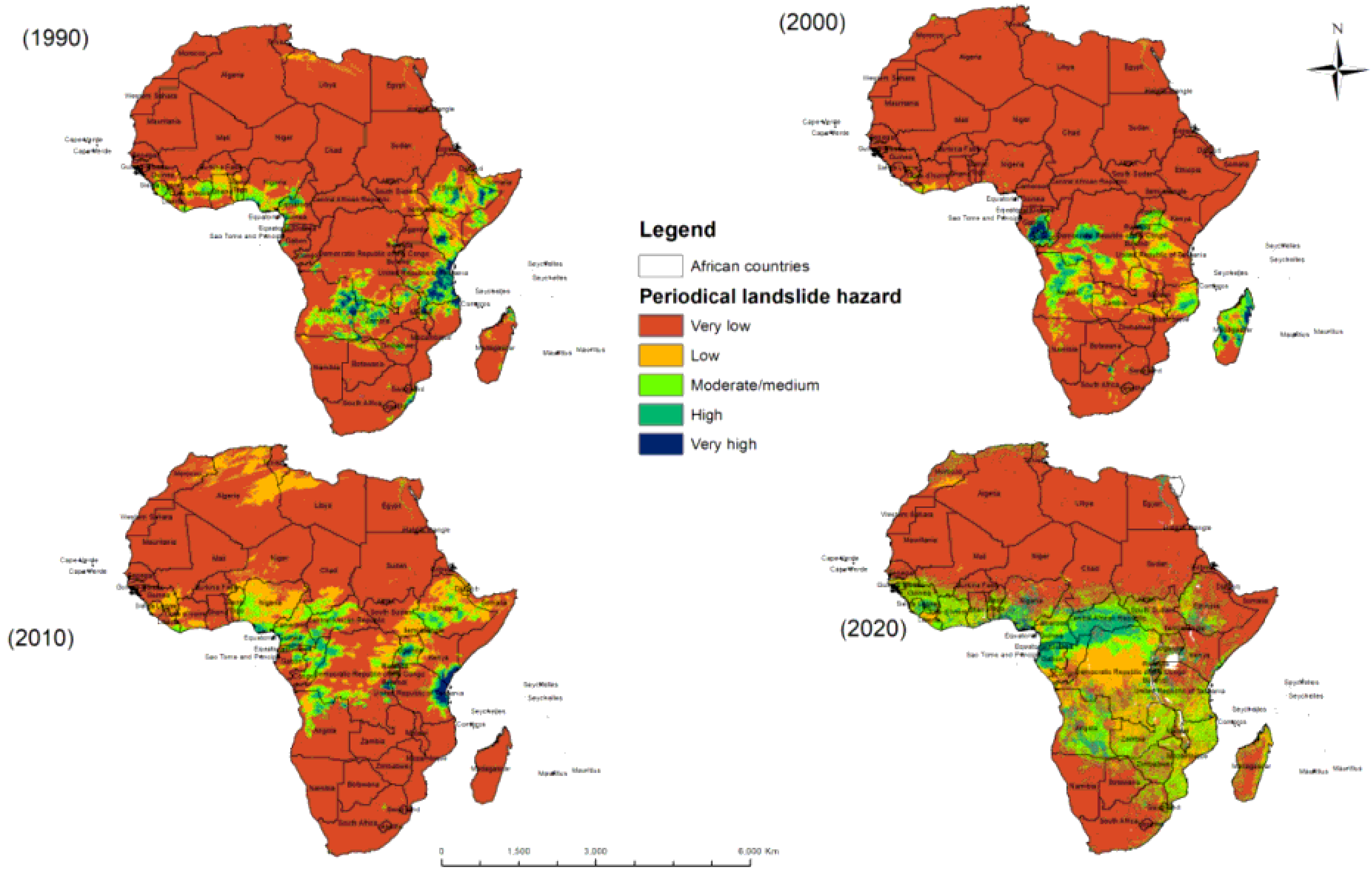

Figure 8

Periodical (1990-2020) landslide susceptibility recorded in Africa

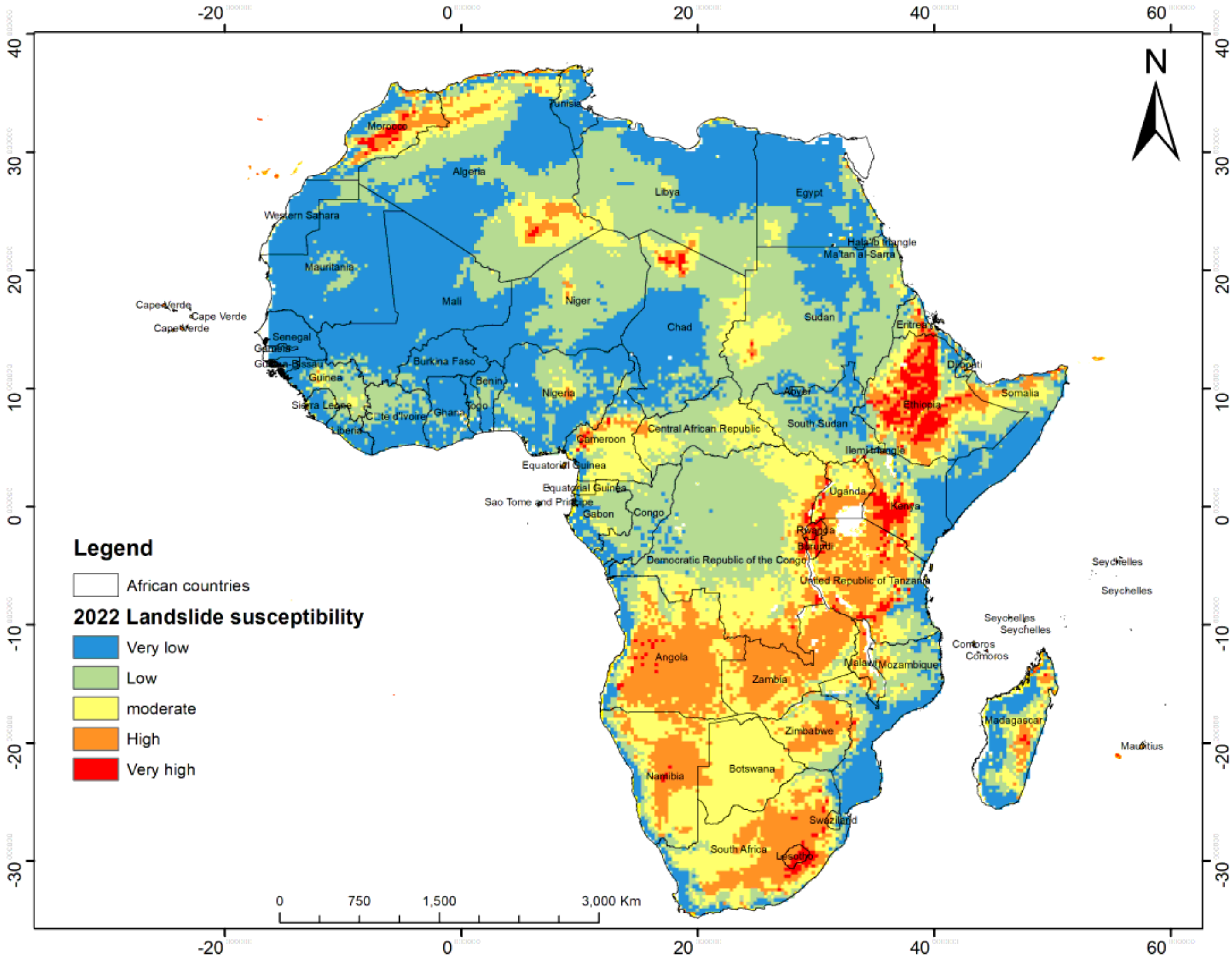

Figure 9

Estimated 2022 landslide susceptibility over Africa

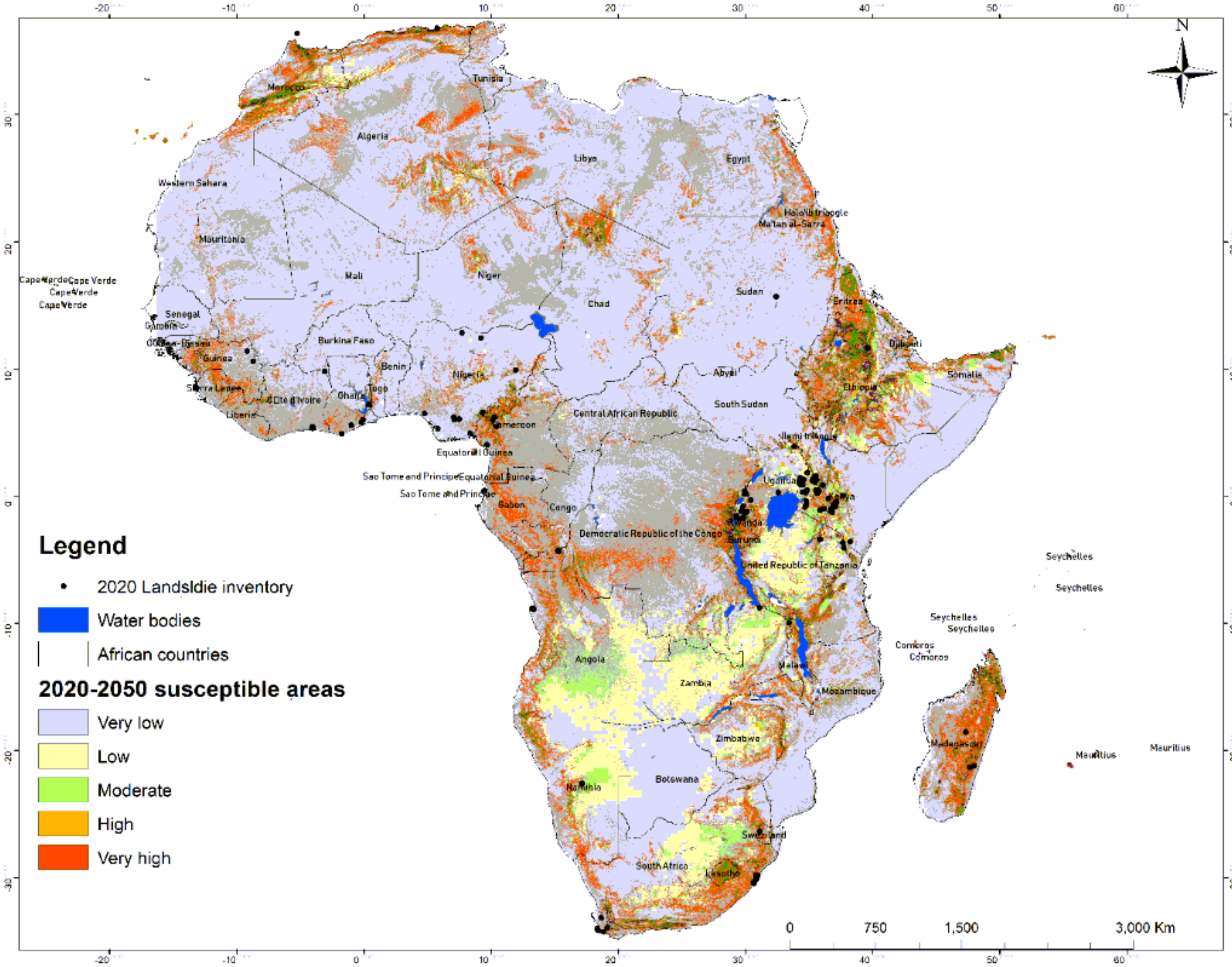

Figure 10

Map indicating the predicted landslide prone areas in Africa