Assessment of Physical Vulnerability to Flooding Using Geographic Information System (GIS)-based Multi-Criteria Decision Analysis (MDCA) in Lephalale Local Municipality in Limpopo, South Africa

Mologadi C. Mothapo[1], Godfrey Tawodzera[2] and Mbulisi Sibanda[3]

Abstract

Floods are one of the most common recurring natural disasters globally. They impact communities by damaging natural resources, disrupting economic activities, destroying property and livelihoods, displacing people and causing loss of lives. In South Africa, predictions are that flood incidences are likely to increase due to climate change, hence placing communities at risk of floods. This study sought to assess and map the physical vulnerability of areas to flooding in the Lephalale Local Municipality using a Geographical Information System (GIS)-based Multiple Criteria Decision Analysis (MCDA) approach. Using various indicators, a composite map was developed showing the different levels of vulnerability to floods in the municipal area. Physical vulnerability to floods was found to be higher in the central regions compared to the rest of the municipal area, because of the high magnitude of the rainfall in the central region, its proximity to rivers, and the presence of impermeable bare soils that increase runoff. The north, west and southern parts of the municipal region showed moderate to low levels of vulnerability due to their slightly higher elevation, longer distances from rivers, and the presence of natural vegetation land cover. The study concluded that physical vulnerability to floods in the area was largely a result of the interaction of various factors, namely: proximity to river channels, precipitation amount, altitude, and soil type. Although the study demonstrated the usefulness of the GIS-based MCDA approach in assessing physical vulnerability to floods, we recommend that future studies also consider integrating social, economic, cultural and institutional indicators to capture the multi-scale and multi-faceted dimensions of flood vulnerability.

Keywords: *Floods, vulnerability, Geographic Information System (GIS), Multiple Criteria Decision Analysis (MCDA), Limpopo, South Africa.*

[1]Lecturer in the Department of Geography and Environmental Studies, University of Limpopo, South Africa. Email: mothapoclodean@yahoo.com

[2]Senior Researcher, Institute for Social Development (ISD), University of the Western Cape, Bellville, Cape Town. Email: godfreyltawodzera@yahoo.com

[3]Lecturer in the Department of Geography, Environmental Studies and Tourism, University of the Western Cape, South Africa. Email: sibandambulisi@gmail.com

Correspondence concerning this article should be addressed to Mologadi C. Mothapo, Lecturer in the Department of Geography and Environmental Studies, University of Limpopo, South Africa, email: mothapoclodean@yahoo.com

Introduction

Floods are one of the most common recurring natural disasters in the world today (United Nations, 2019). Due to the increased frequency of floods in recent decades, Najibi and Devineni (2018, 757) argue that vulnerability to such extreme events has become the 'new normal'. It is estimated that 43% of the global total number of natural disasters between 1995 and 2015 were caused by floods, with the greatest damage and losses being experienced in Africa and Asia (CRED, 2015a). The effects of flooding include damage to social, cultural, and natural resources, disruption of economic activities and livelihoods, displacement of people, loss of property, and loss of lives (Akukwe & Ogbodo, 2015). Between 1995 and 2015, floods affected approximately 2.3 billion people throughout the world, with recorded assets losses of over US$ 662 billion (CRED, 2015b). It is predicted that flood incidences are likely to get worse in terms of magnitude and frequency due to climate change (CRED, 2015b). The Centre for Research on the Epidemiology of Disasters (CRED, 2015b) indicates that roughly 800 million people worldwide live in flood-prone areas and about 70 million of these people are exposed to floods each year. The risk and vulnerability associated with floods is therefore real and cannot be ignored if communities are to be protected from future flood incidents.

While most countries in Southern Africa are generally vulnerable to floods, the probability of risk to flooding varies, with countries such as South Africa and Mozambique being more susceptible to flooding events than other countries in the region. In South Africa, for example, 77 flooding events were recorded in the country between 1980 and 2010 (PRW, 2011). Previous flooding events in the country have resulted in the disruption of economic activities, damage to roads and other infrastructure, loss of livelihoods, displacement of people, and loss of lives (Els, 2011). Within South Africa, the probability of risk to flooding varies considerably, with some areas being more prone to flooding than others, and with areas such as the Limpopo Province experiencing frequent floods. The province is therefore more at risk of flood hazards compared to other provinces. The numerous flooding events that occurred in Limpopo caused extensive damages to both public and private infrastructure, amounting to billions of Rand annually (Donohue et al., 2000; Dyson & Van Heerden, 2001; McCusker, 2004; Nethengwe, 2007; Mekiso, 2011; Malherbe et al., 2012; Maponya & Mpandeli, 2012). In March 2014, for example, various municipalities in the province, including Lephalale, Mogalakwena, Modimolle, Bela-Bela, Thabazimbi, and Mookgopong of the Waterberg District were severely affected by floods (EPoA, 2014).

One of the most affected municipalities in the Limpopo Province was Lephalale Local Municipality, because the Mokolo, Phalala and Limpopo rivers periodically bursts their banks and floods adjacent low-lying areas. In 2014, flooding in the area caused severe damage to infrastructure and livelihoods (EPoA, 2014). Given that a huge number of people in the province still live along rivers and streams, the impact of any flooding event in the future is likely to be devastating. Given projections that heavy rainfall events may increase in the country in the near future (Ziervogel et al., 2006), the people in

Limpopo Province are even more vulnerable than before. This is because any increases in heavy rainfall events are likely to pose a significant risk to people, particularly those living in flood plains and closer to the river. Physical and environmental characteristics of an area as well as the interaction of these factors have been proven to be the root cause of water flow accumulation and flood hazards. There is, therefore, an urgent need to assess the physical vulnerability to flooding in the Lephalale Local Municipality to understand how and to what extent these areas are susceptible to any future flooding. The physical vulnerability in this study is defined as the exposure of areas to flood hazards due to pre-existing biophysical aspects of the environment where these areas are located (Smithers & Smit, 1997; Wilbanks, 2003; Fuchs & Thaler, 2018). A robust assessment of the physical vulnerability of areas to flooding requires accurate spatial and temporal biophysical information, which is often scanty and unavailable at local scales. Other than the lack of fine resolution, accurate spatial and temporal information, suitable approaches for combining such information have generally been a major challenge.

In general, flood vulnerability has been assessed by developing vulnerability maps through the use of indicators or causative factors (Ologunorisa, 2004; Connor & Hiroki, 2005; Rygel et al., 2006; Balica et al., 2009; Fekete, 2009; Müller et al., 2011; Son et al., 2011; Balica et al., 2012; Park et al., 2012; Antwi et al., 2015; Oulahen et al., 2015). Meanwhile, the indicator approach integrates Geographic Information Systems (GIS) and the Multiple Criteria Decision Analysis (MCDA) in flood vulnerability assessment. This has been widely used and proven to be a powerful tool that systematically integrates physical environmental factors of varying importance and transforming them into different levels of vulnerability for a studied area (Akukwe & Ogbodo, 2015; Chivasa et al., 2019). Although this method has been used widely in other parts of the world (Paquette & Lowry, 2012; Gigović et al., 2017; Tang et al., 2018; Abdelkarim et al., 2020; Ajjur & Mogheir, 2020; Feloni et al., 2020), not much has been done in the Southern African region, especially in flood vulnerability assessment at local scales. While GIS has the ability to capture, store, manage, analyse and visualise geographically referenced data (Coppock & Rhind, 1991; Maguire, 1991; Chrisman, 1999; Tomlinson, 2007; Kavita & Patil, 2011; Singh & Fiorentino, 2013), combining it with the MCDA offers an efficient and accurate way to systematically develop flood vulnerability maps. This is because a GIS-based MCDA approach helps in choosing, transforming, ranking, combining and weighing geographically referenced and unreferenced indicators in a manner that is accurate and less complex (Malczewski, 2006; Greene et al., 2011). This integrated approach, if used correctly, can accurately determine the level of vulnerability while being spatially explicit in indicating the vulnerable areas at various geographic scales. The ability to pinpoint vulnerability at different scales is particularly important in South Africa, given the absence of such information at the municipal level where it is required. Without information on vulnerability and risk to flooding, municipalities are unable to respond timeously and assist vulnerable communities to avert destruction. An integrated approach, therefore, offers a robust methodology for quantifying complex and dynamic vulnerability indices and has the ability to provide spatially explicit information on flood risk and vulnerability.

Given this background, this study sought to assess and map physical vulnerability to flooding in the Lephalale Local Municipality using a GIS-based MCDA approach. While, admittedly, flood vulnerability is a function of both physical and socio-economic variables, this paper concentrates only on physical vulnerability to give the necessary attention to most of the aspects that are critical in determining the physical vulnerability to floods.

Methods and materials

Description of the Study Sites

Lephalale Local Municipality is situated between 23°30’ and 24°00’ latitude and 27°30’ and 28°00’ longitude in the Limpopo Province of South Africa (Figure 1). It is located within the northwestern region of the Waterberg District, with its borders forming part of the international border between South Africa and Botswana.

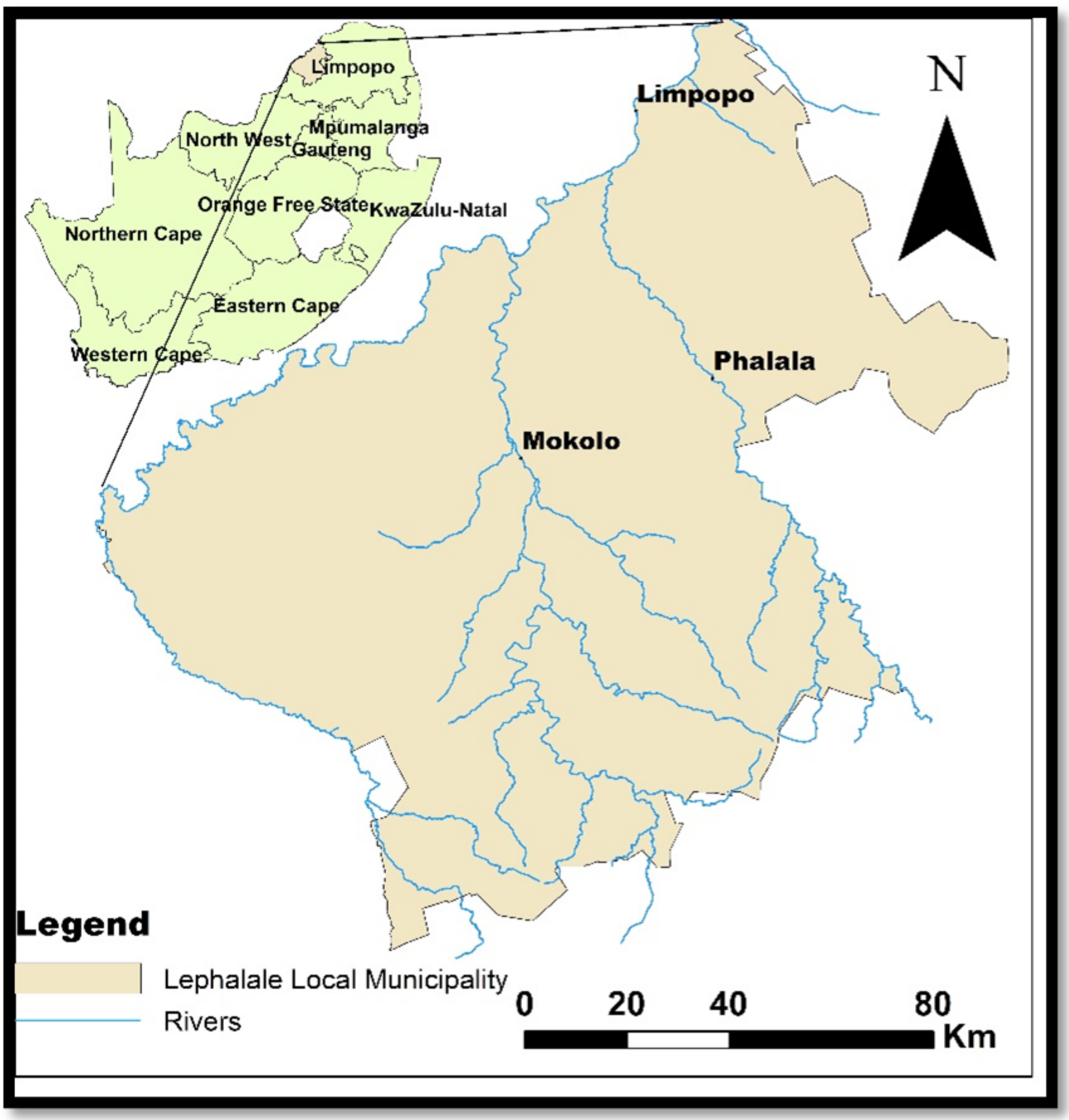

Figure 1. *Lephalale Local Municipality*

Lephalale Local Municipality receives rainfall in summer. The average annual rainfall in the municipal region is between 400-600 mm, while average daily temperatures vary between 17°C and 32°C in summer and between 4°C and 20°C in winter. The climate of the area varies spatially, becoming warmer and drier from the south to the north of the municipality (IDP, 2009). The amount of rainfall received varies spatially as well, with little rainfall being received in the central and northern regions, while most of it is experienced in the southern portion (Appendix A). This municipality is steeper on the southeast and generally flattening out towards the north, with altitude above sea level of between 700 m and 1 900 m (Appendix B). The slope is relatively gentle, ranging between 0 and 75 degrees (Appendix C). Vegetation also varies from dense, short bushveld in some areas to open tree savannah vegetation consisting mainly of dry woodlands, thorny bush and grassland in others. Thicket bushveld, bush clumps and high fynbos cover about 55% of land area in the municipality (IDP, 2009). Four main rivers (Phalala, Mokolo, Matlaba and the Mogalakwena) drain northwards into the Limpopo River (Appendix D). These rivers together with numerous lesser rivers and streams constitute a major water catchment area for the lower Limpopo basin (IDP, 2009). The soils in the study area are characterised by high clay content in the northeastern region as well as along the Limpopo River (Appendix E). The geographical size of the municipal area of jurisdiction is estimated at 14,000 km2 with large tracks of cultivated commercial rainfed land and cultivated commercial irrigated land located along the Mokolo, Phalala and Limpopo River. The villages are mainly characterised by cultivated land. The larger portion of the municipal area is characterised by degraded forests, woodland, bush clumps and thicket. The mining area and quarries also form part of land use in the municipality (Appendix F). The municipality is home to about 11,576 people and is further demarcated into 12 wards (IDP, 2009) (Appendix G). The municipality was selected as a study area because of the frequent occurrences of flooding events in the municipality over the past two decades (EPoA, 2014).

Spatial Data Collection and Pre-Processing

In developing countries, spatially referenced information is still scarce, hence this study sought to assess the utility of selected readily available datasets in characterising the extent of physical vulnerability to flooding hazards. The spatial data used in this study were collected from various sources. These sources included the South African National Space Agency (SANSA), which provided spatially referenced data on rivers, DEM (Digital Elevation Model), land cover, local municipalities and wards boundaries.

Soil clay content data were downloaded from the SOTER website (ISRIC Data Hub, n.d.), whilst river layers were extracted from the Republic of South Africa's Department of Water and Sanitation Database (2017). Historical rainfall data for eight rainfall weather stations in and around Lephalale Local Municipality were obtained from the South African Weather Services (SAWS). The data were received in the form of an Excel spreadsheet. The data were then converted into a point map and interpolated into a raster format using the Inverse Distance Weighted (IDW) method. The resultant raster maps were resampled into 30 x 30 m resolution to match it with the spatial resolution of other datasets (i.e. DEM) using GIS resampling techniques. Vector layers such as soil clay content and rivers were converted into a raster format and the Euclidean distance was computed to determine proximity to rivers. The slope (in percentage) map was derived from the Digital Elevation Model (DEM) using slope generation tools in ArcGIS 10.5 software. The rivers layer was downloaded from the online database of the South African Department of Water Affairs. Finally, all datasets were resampled to 30 m spatial resolution, clipped and projected to the WGS 1984 coordinate system. A GIS database was then subsequently developed in the ArcGIS environment for further analysis. Table 1 summarises all the data used and their effects on flooding.

Table 1. *Dataset, its source and effect on flooding*

Dataset	Source	Effect on flooding
Average annual rainfall	South African Weather Services (SAWS)	Floods are primarily caused by climatic factors, most notably precipitation. Studies have indicated that flood properties are influenced by a combination of precipitation characteristics such as intensity, duration and spatial distribution (Bracken et al., 2008). For example, high intensity torrential rainfall over a short period can lead to flash floods.
Elevation and slope	South African National Space Agency (SANSA)	Elevation and slope factors determine the severity, flow size and direction of floods (Kia et al., 2012; Saini & Kaushik, 2012). Lower elevated areas are generally at a higher risk of floods than areas at a higher elevation. Furthermore, water tends to remain in the lower area for a longer period than in higher areas (Fernández & Lutz, 2010; Kia et al., 2012; Saini & Kaushik, 2012). Meanwhile, a high mean slope facilitates the flow of water whilst a low slope enables the accumulation of water.
Proximity to rivers	Department of Water Affairs	'Distance from rivers' as well as drainage density plays a significant role in determining the flooding of an area. According to Fernández and Lutz (2010), the most affected areas during floods are those near rivers because of channel overflow.
Soil permeability	SOTER Website	Generally, soils with high permeability rates allow more water to pass through, while those with low permeability are likely to lead to high run-off, hence increasing the likelihood of flooding. Furthermore, clay soil tends to restrict rapid water flow, which causes "puddling" of water (Mao et al., 2016).
Land use and cover	South African National Space Agency (SANSA)	Land cover also has a direct and indirect influence on several parameters in the hydrologic cycle. Most areas that incurred damages from floods were those found along the rivers, located in areas characterised by bare soils and containing a low amount of green spaces (Roslee et al., 2017). Closer proximity to rivers, lack of vegetation cover and clearance of land for farming generally result in an increase in the rate of runoff and a decrease in infiltration, consequently causing flooding (Roslee et al., 2017). This includes interception, ground infiltration and surface runoff (Ntajal et al., 2017). Removal of vegetation increases surface runoff, which is more likely to lead to flooding, especially in flat and low-lying areas and on impermeable soils and surfaces. Bare soils and built-up areas tend to increase surface runoff, especially on steep slopes, where the rate of infiltration is simultaneously reduced (Ntajal et al., 2017). High run-off, therefore, increases susceptibility to flooding risk.

Developing the Flood Vulnerability Map

Indicators that are representative of physical flood vulnerability were identified from the literature and abbreviated accordingly (Table 2), proven to facilitate flooding events (Paquette & Lowry, 2012; Gigović et al., 2017; Shafizadeh-Moghadam et al., 2018; Tang et al., 2018; Abdelkarim et al., 2020; Ajjur & Mogheir, 2020; Feloni et al., 2020; Nachappa et al., 2020). The GIS-based MCDA was then used to characterise spatial variations in terms of vulnerability to flooding in the study area. The study adopted a methodological process used by Fernandez et al. (2016), which involved: (i) selecting and transforming data into indicators using ArcGIS 10.5; (ii) normalising indicators using standardisation methods, (iii) weighting indicators using the analytical hierarchy process (AHP), (iv) aggregation of weighted indicators using overlay analysis, (v) characterising the spatial variation of vulnerability in a GIS environment, and (vi) assessing the accuracy of the derived maps.

Table 2. *Selected indicators to assess floods vulnerability*

Indicators	Measuring unit	Abbreviation
Annual rainfall	mm	AAR
Elevation	m	E
Land cover	sq km	LULC
Proximity to rivers	m	PR
Slope	°	S
Soil clay content	%	SCC

Normalisation and Evaluation of the Indicator Weights

Since each indicator was measured on different units and dimensions, there was a need for standardisation. This was done based on Thomas Saaty's (1980) method (Table 3). Furthermore, flood vulnerability assessment involves indicators of varying importance; therefore, information about the relative importance of each indicator is necessary. Such information is typically obtained by assigning a weight to each indicator. The analytical hierarchy process (AHP) was used to assign weights. This was considered the best method for the study because of its flexibility and ability to check inconsistencies (Saaty, 1980; Ramanathan, 2001). A questionnaire on comparison ratings based on Saaty's 1-9 point continuous scale (Table 3) was prepared to judge and assign an appropriate weight to each indicator. This method allows the comparison of two indicators at a time whilst converting subjective assessments of relative importance into a linear set of weights. Every possible pairing was compared, and the ratings were captured in a pairwise comparison matrix. The pairwise comparison matrix takes the pairwise comparisons as input and produces the relative weights as output while AHP provides a mathematical method of translating this matrix into a vector of relative weights for the indicators. The final weightings for the indicators are the normalised values of the eigenvectors that are associated with the maximum eigenvalues of the ratio (reciprocal) matrix (Razandi et al., 2015).

Table 3. *Saaty's (1980) scale for weight assignment*

Extremely	Very Strong	Strongly	Moderately		Extremely	Very Strong	Strongly	Moderately
	Less important			Equally important			More important	
1/9	1/7	1/5	1/3	1	3	5	7	9

In the AHP process, the consistency of judgments was adequately checked by calculating the consistency ratio (CR). The CR defines the probability that the matrix weights are randomly generated, or that the level of the judgements given by the experts/ user in pairwise comparisons is consistent. The formula below (Equation 1) was used to calculate CR:

$$CR = \frac{CI}{RI} \qquad \textbf{(Equation 1),}$$

where RI is random index and CI is consistency index. The random index (RI) is the consistency of a randomly generated pairwise comparison matrix (Table 4). It depends on the number of indicators being compared and takes the following values:

Table 4. *Random Index*

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

(Source: Saaty, 1980)
Note: RI is random index and n is the number of indicators being compared.

CI is the consistency index, which provides a measure of departure from consistency and was calculated using the formula below (Equation 2):

$$\mathrm{CI} = \frac{\lambda\text{max-n}}{\text{n-1}} \qquad \textbf{(Equation 2),}$$

where λmax is the average value of the consistency vector and n is the number of indicators. The consistency index (CI) and random index (RI) table were used to compute the consistency ratio (CR). The pairwise comparisons in a judgement matrix are considered adequately consistent if the corresponding consistency ratio is at most 10% or the CR is at most 0.10 (Saaty, 1980). Saaty (1980) further suggests that matrices with

CR ratings greater than 0.10 should be re-evaluated.

Aggregation of Indicators and Mapping of Flood Vulnerability

The composite flood vulnerability map was obtained through an overlay analysis of total annual rainfall, altitude, slope, proximity to rivers, soil clay content, and land cover layers using the raster calculator in an ArcGIS 10.5 environment. In a raster calculator, all normalised indicators are multiplied by their normalised weightings (Table 6), and subsequently added together and divided by the total number of indicators used (Equation 3).

$$\text{Flood Vulnerability} = ((0.34\times AAR)+(0.20\times E)+(0.08\times LULC)+(0.12\times PR)+(0.21\times S)+(0.05\times SCC))/6$$

Equation 3, where AAR = Average annual rainfall, E = Elevation, LULC = Land use/land cover, PR = Proximity to rivers, S = Slope, SCC = Soil clay content.

The map was further categorised into five vulnerability classes: “very low”, “low”, “moderate”, “high” and “very high”, using natural breaks as guided by the vulnerability index literature (see Stefanidis & Stathis, 2013; Papaioannou et al., 2015; Dash & Sar, 2020). The area occupied by each of these vulnerability classes was quantified in ArcGIS for each ward for comparison purposes. The map was then categorised into two classes, “not-flooded” and “flooded” areas, to facilitate accuracy assessment of how well the flooded areas were correctly identified in the derived vulnerability map. A field survey was conducted to identify homesteads and villages that were previously exposed to flooding. The locations of these homesteads where floods had previously occurred as well as the homesteads where floods did not occur were located based on GPS coordinates as well as using the names of the villages during the field survey. All this information was cross-referenced with existing spatial records of flooding in these villages supplied by the South African Weather Services. The locations were converted to shapefile, which was overlaid with the flood vulnerability map during the accuracy assessment procedure. A confusion matrix was derived and used to compute the accuracy assessments as detailed in Pontius Jr and Millones (2011).

In conducting an accuracy assessment based on Pontius Jr and Millones (2011), disagreement between areas characterised using the integrated method (map) and the homesteads that encountered flooding (the reference information), was calculated. According to Pontius Jr and Millones (2011), disagreement is characterised by allocation and quantity disagreements. The amount of change between the reference information and a map (due to the less-than-perfect match in the proportions of the classes) is termed quality disagreement (Gao et al., 2011). The agreement is computed by deducting the disagreement from 100%. The accuracy assessment method devised by Pontius Jr and Millones (2011) was used in this study because it is more robust than other accuracy assessment procedures, such as Kappa. Literature underscores the fact that Kappa introduces bias with regard to the frequency of reference data such that a higher frequency of reference points would result in higher prevalence rates, which ultimately affects the accuracy of the classified map (Allouche et al., 2006; Ndlovu et al., 2018; Kumbula et al., 2019). In the next section, we discuss the study results.

Results

Normalised Indicators

Figure 2 (a) – (f) shows the normalised values of indicators ranging between 0 (least vulnerable) and 1 (most vulnerable). In assessing the spatial distribution of normalised average annual rainfall, high values were observed along the southeastern part of the municipal region, while slope and altitude exhibited high standardised values in almost the entire study area. When evaluating the spatial distribution of standardised values exhibited by river networks, high values were also observed throughout the study area. Meanwhile, land cover and soil clay content exhibited high standardised values in the interior region of the study area.

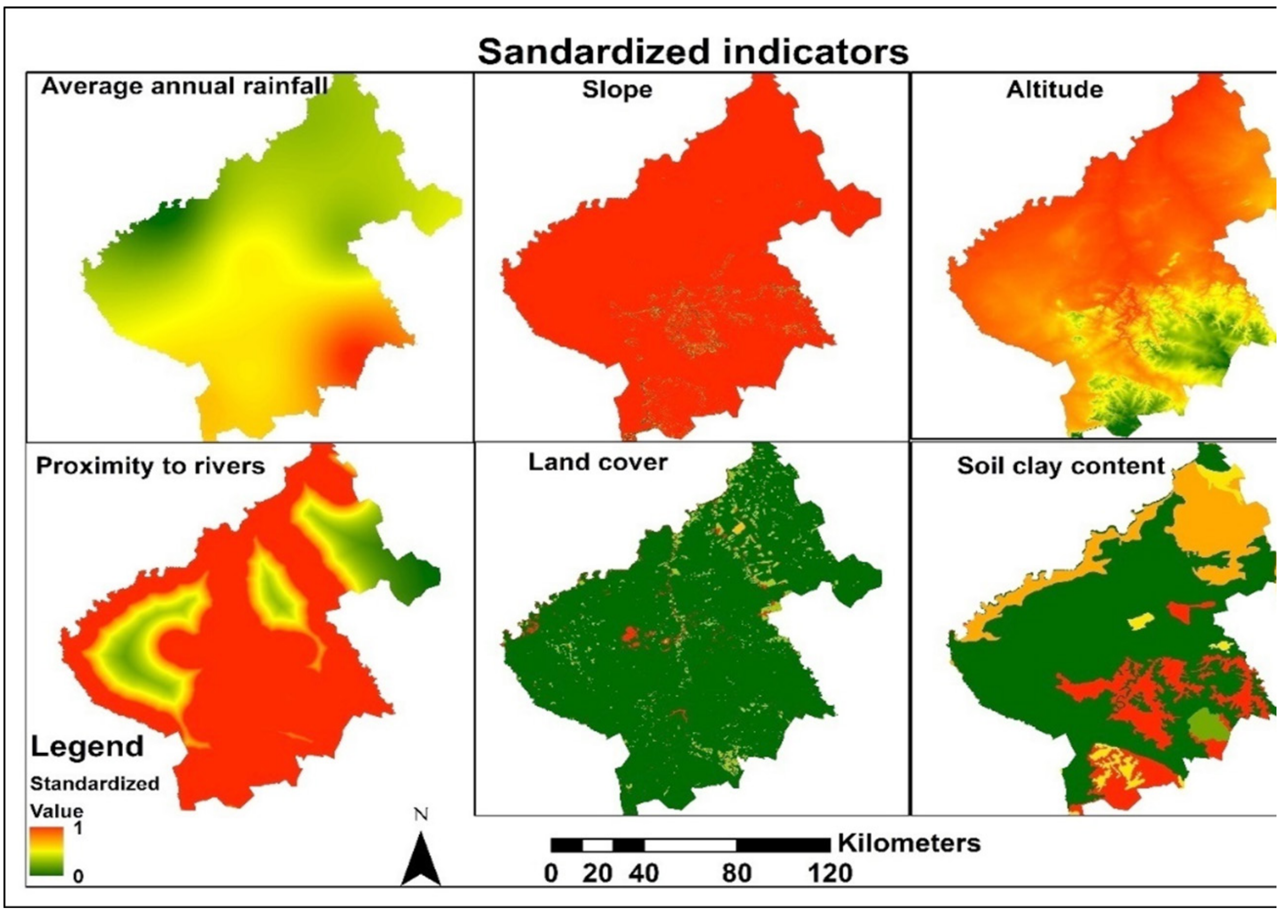

Figure 2. *(a) to (f) standardised indicators. The red shade indicates a high level of vulnerability for each of the indicators, orange indicates a moderate level, while the green indicates a low level of vulnerability to flooding*

Weighted Indicators

Table 5 shows the normalised matrix and Table 6 indicates the calculated weight score of the vulnerability indicators derived using the pairwise comparison method. The consistency ratio computed based on the pairwise comparisons was 0. Considering that the CR value was less than 0.10, the weightings were acceptable.

It can be observed that average annual rainfall (AAR) had a relatively high value of 0.34, followed by the slope (S) with a priority vector of 0.21, elevation (E) with a priority vector of 0.20, proximity to rivers (PR) with a priority vector of 0.12, land use/land cover (LULC) with a priority vector of 0.08, and soil clay content (SCC) with a priority vector of 0.05 (Table 6).

Table 5. *Square pairwise comparison matrix for vulnerability indicators*

	AAR	E	LULC	PR	S	SCC
AAR	1	2	4	3	2	5
E	1/2	1	3	2	1	4
LULC	1/4	1/3	1	1/2	1/3	2
PR	1/3	½	2	1	½	3
S	1/2	1	3	2	1	5
SCC	1/5	¼	½	1/3	1/5	1

Table 6. *Normalised matrix and the calculated weight score of the vulnerability indicators*

	AAR	E	LULC	PR	S	SCC	Priority vector	Weight (%)
AAR	0,3593	0,3934	0,2963	0,3396	0,3974	0,2500	0,3393	33,9
E	0,1796	0,1967	0,2222	0,2264	0,1987	0,2000	0,2039	20,4
LULC	0,0898	0,0656	0,0741	0,0566	0,0662	0,1000	0,0754	7,5
PR	0,1198	0,0984	0,1481	0,1132	0,0993	0,1500	0,1215	12,1
S	0,1796	0,1967	0,2222	0,2264	0,1987	0,2500	0,2123	21,2
SCC	0,0719	0,0492	0,0370	0,0377	0,0397	0,0500	0,0476	4,8
Total	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	100
				CR=0				

Spatial variations in flood vulnerability

The composite map shows that levels of flood vulnerability vary spatially and most areas vulnerable to flooding are in the central region of the study area as well as a portion in the southwestern and northeastern sections (Figure 3).

Ward 8 experiences very low vulnerability, Ward 10 experiences low vulnerability, Wards 3, 2, and 11 experience moderate vulnerability, whilst Wards 1, 4, 5, 6, 7, 9, and 12 experience high vulnerability, respectively.

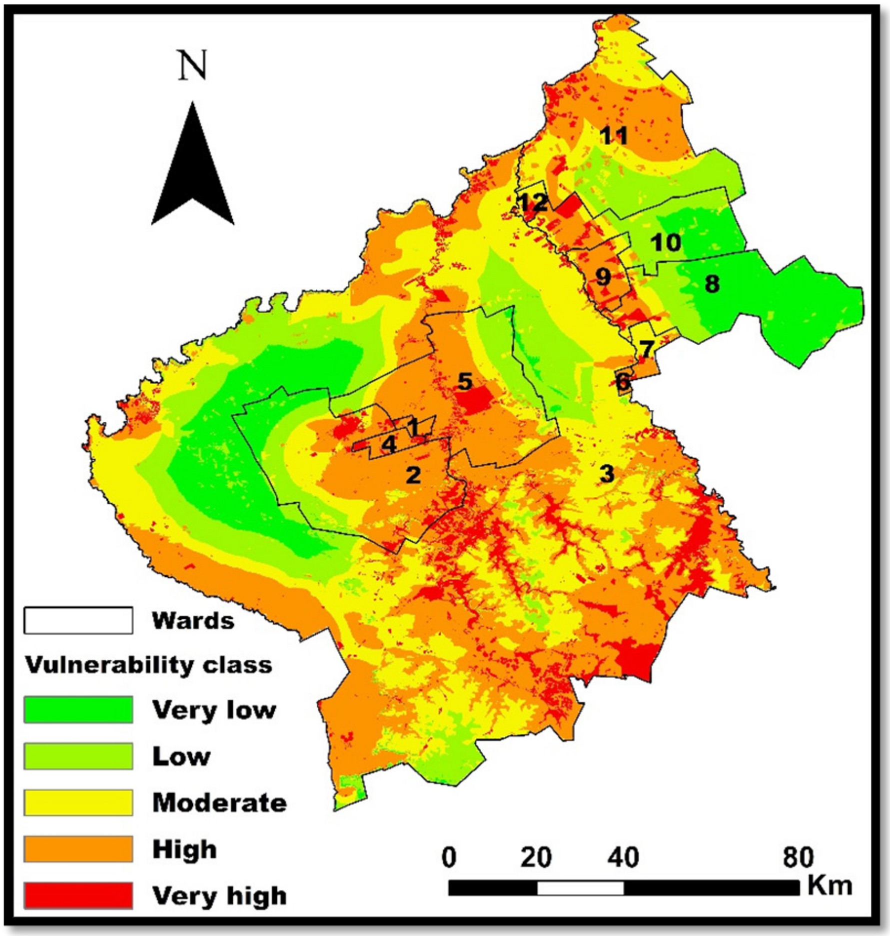

Figure 3. *Level of vulnerability in Lephalale Local Municipality*

Computed percentage areas of flood vulnerable areas indicated that about 1,648 km2 (12%), 2,335 km2 (17%), 3,854 km2 (28%), 4,740 km2 (35%), and 1,127 km2 (8%) of the total land in the study area is characterised by very low, low, moderate, high and very high level of flood vulnerability, respectively (Table 7).

Table 7. *Computed percentage areas of flood vulnerable areas*

Vulnerability class	Vulnerability level	Area (km^2)	Area (%)
1	Very low	1647,93	12,02
2	Low	2335,21	17,04
3	Moderate	3854,89	28,13
4	High	4740,08	34,59
5	Very high	1126,96	8,22

Figure 4 illustrates the accuracies derived in assessing the map, characterising the vulnerability to flooding. There was high agreement (94%) between reference data and the mapped flooding levels, whereas disagreement accounted for less than 10%. As in Gao et al. (2011), the omission and commission intensities derived in this study were less than 10%, hence they were considered not to be substantial (Figure 4b). The user and producer accuracies derived in characterising the areas highly susceptible to flooding in relation to the least susceptible, were above 90% (Figure 4c). The commission error attained in this study was 0.2 and 0.3 for the unflooded and flooded areas, respectively.

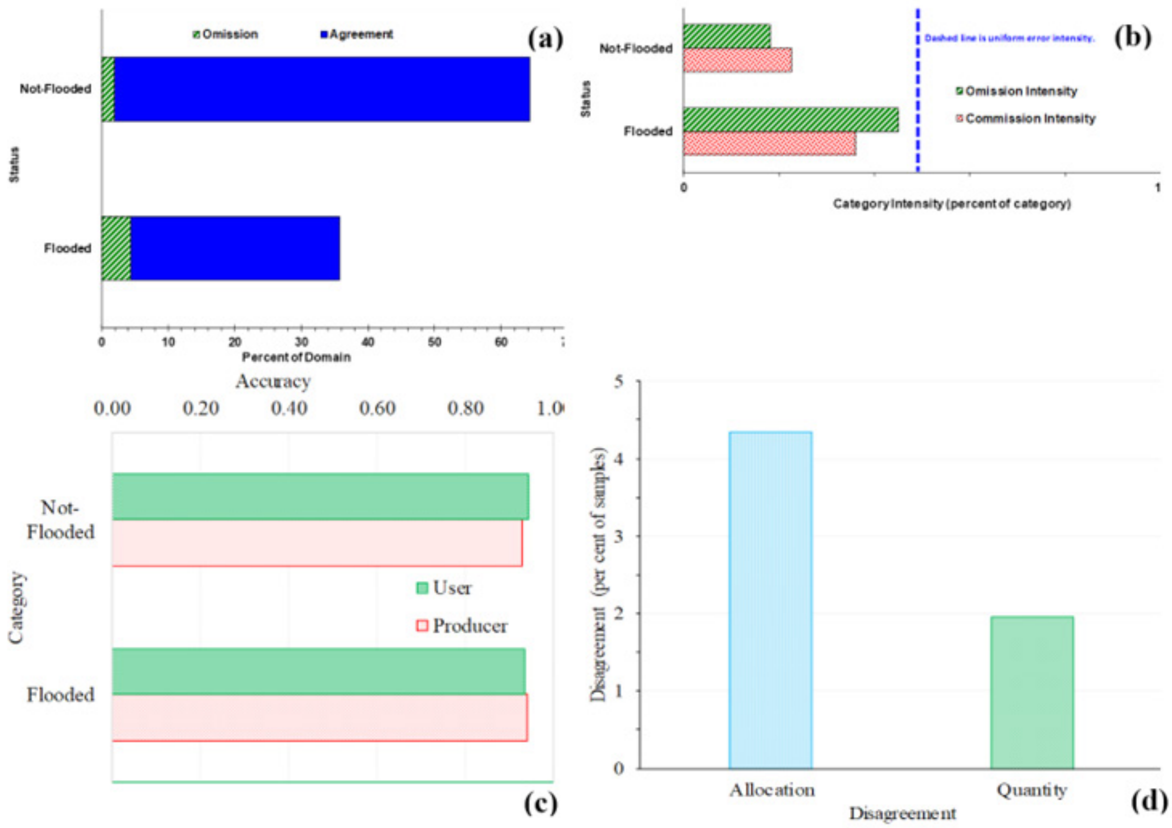

Figure 4. *Accuracy of the flooding map derived using the GIS MCDA*

Discussion

The lack of accurate fine spatial and temporal referenced information as well as the limited approaches for combing these various datasets has been a long-standing challenge in understanding flood vulnerability at local scales. In this regard, this study assessed and mapped the physical vulnerability of settlements to flooding in the Lephalale Local Municipality using a GIS-based MCDA approach.

The findings showed that vulnerability to flooding in the central regions was higher than in the rest of the municipality. Wards 1, 4, 5, 6, 7, 9, and 12 showed the highest levels of vulnerability to floods, which could be explained by the high magnitude of the average rainfall rate in relation to other areas and their proximity to the Mokolo, Phalala and Limpopo rivers. In general, areas characterised by high average rainfall rates tend to experience more floods in relation to areas where the annual average precipitation is low. High moisture content results in oversaturation of the soil by water accelerating surface water flows, which degenerate into floods due to reduced infiltration and percolation. In a similar study, Gu et al. (2012) observed that high levels of vulnerability were associated with the amount of rainfall an area experienced. Conversely, areas most likely to be affected by floods are near rivers as a consequence of channel overflow (Fernández & Lutz, 2010). This is because water can exceedingly fill up rivers and eventually overflow the river banks, leading to flooding events that affect livelihoods and threaten the lives of people living in nearby communities.

Furthermore, the high vulnerability to floods noted in the central wards could be explained by the prevalence of low altitude and slope as well as the impermeable clay soils (Figure 3) that reduce infiltration and percolation while increasing runoff. The presence of clay generally facilitates the overland flow due to the impermeable clayey soil, which has a reduced infiltration capacity and generates sheet water flows that could potentially build-up into floods. Low lying areas in the central section of the study area tend to increase the vulnerability to flooding due to water flows from a high elevation and a steep slope to lower and gentle areas. Our results concur with those of Danumah et al. (2016) in Abidjan district, who also noted that zones of higher vulnerability to floods were dominated by a gentle slope, high amounts of rainfall, and saturated and low drainage soils. However, there are still compounding challenges with regard to the accurate estimation of magnitude, occurrence and spatial distribution of precipitation despite the relevant advancements in hydrological sciences (Hornberger et al., 2012; Schumacher, 2017). There is still a need for more research in predicting the flooding response to heavy precipitation, the causes of variations in rainfall prediction accuracies, and determining how heavy rainfall and floods have changed and may continue to change in a changing climate despite all the ongoing inquests (Schumacher, 2017). These will provide accurate and reliable information for building capacity to withstanding incidences and effects of flood events.

The wards in the north, west and south of Lephalale Local Municipality, i.e., Wards 3, 2, and 11, showed moderate levels of flood vulnerability because Ward 3 was characterised by a slightly high elevation in the southern portion whilst Ward 2 and a huge portion of Ward 11 were characterised at a fair distance away from rivers in Lephalale, hence they ranked as the least vulnerable to flooding. In high areas, less water infiltrates and percolates into the soil, hence high runoff is usually generated, which leads to flooding events in low lying areas.

Furthermore, the results of the study showed that Wards 8 and 10 experienced very low and low flood vulnerability levels, respectively. This could be attributed to the fact that the major land cover in these wards was characterised as natural vegetation. Vegetation generally promotes high water infiltration and less runoff, which subsequently reduces the possibility of, and vulnerability to flooding (Rimba et al., 2017). In addition, Wards

8 and 10 stretch further from rivers, hence, they were categorised as least vulnerable. Similar results obtained by Rimba et al. (2017) indicated that over 50% of Okazaki City was categorised as having very low to low levels of flood hazard because most of the area was located far from the water source.

Very few studies have been conducted to assess the physical vulnerability of settlements to floods in Southern Africa due to spatial data scarcity. Our study illustrates the viability of the indicator approach in evaluating the flood vulnerability of settlements at a finer spatial scale such as a ward. This method could be very useful to the land planning authorities of municipalities in the Southern African countries to derive fine spatially referenced information that can support decision making, particularly when settling and resettling people to avoid flood-related disasters and loss of lives. However, it has to be noted that this approach yielded a model based on datasets that were available at the time of the study. Today there are finer sources of environmental data (i.e. drone-derived DEMs) that can be used to improve the model derived in this study.

Conclusion

The objective of this study was to assess and map the physical vulnerability of areas to floods in the Lephalale Local Municipality using a GIS-based MCDA approach. Based on the study findings, it is concluded that high vulnerability to flooding in the area occurred a result of the impact of factors which include proximity to river channels, the magnitude of precipitation, altitude and soil type. Areas regarded as having low vulnerability to flooding were characterised by high altitude and the presence of natural vegetation cover. The development of policy and procedures for intervention strategies must therefore take cognisance of these factors. For the Lephalale Local Municipality, the results of this study may serve as the basis for targeting prioritisation efforts, emergency response measures, channelling funds, and raising environmental concerns and policy interventions to mitigate flood vulnerability in the municipality. Although this study has demonstrated that a strategic GIS-based MCDA approach is useful in assessing vulnerability to floods with optimal accuracy, we nevertheless need to indicate that no single methodology is capable of completely capturing the multi-scale and multi-faceted dimensions of flood vulnerability. Future studies thus need to consider integrating social, economic, ecological, cultural and institutional indicators at various scales, while being mindful of the complexity od such an approach.

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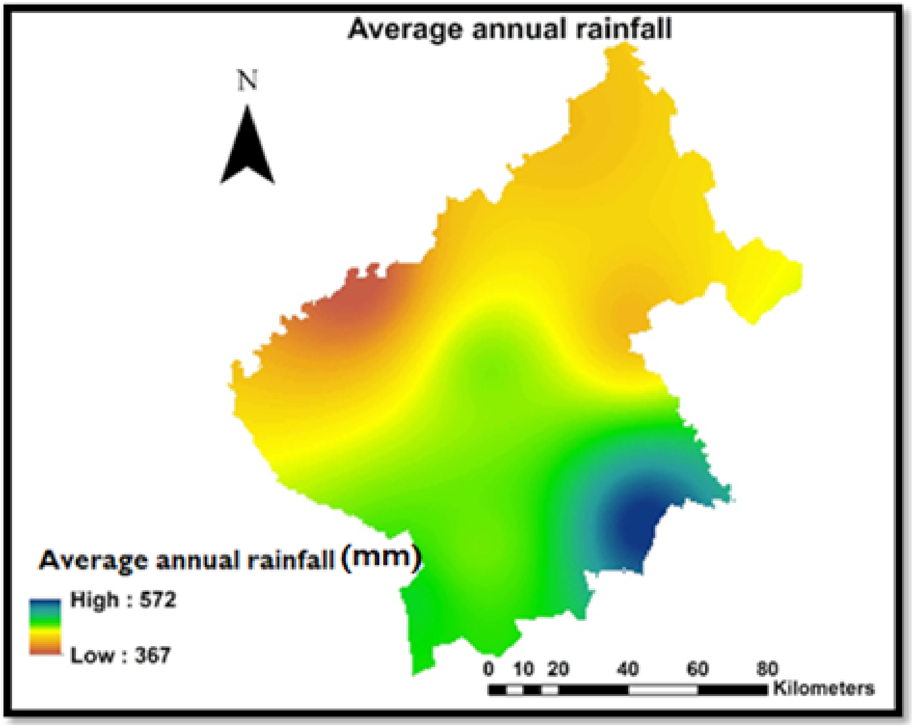
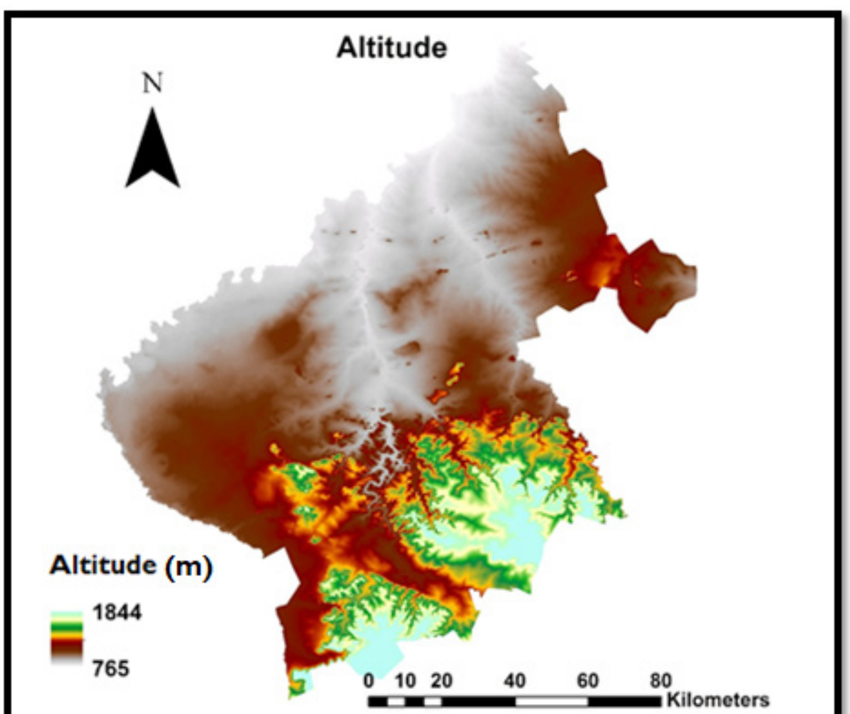
Appendices

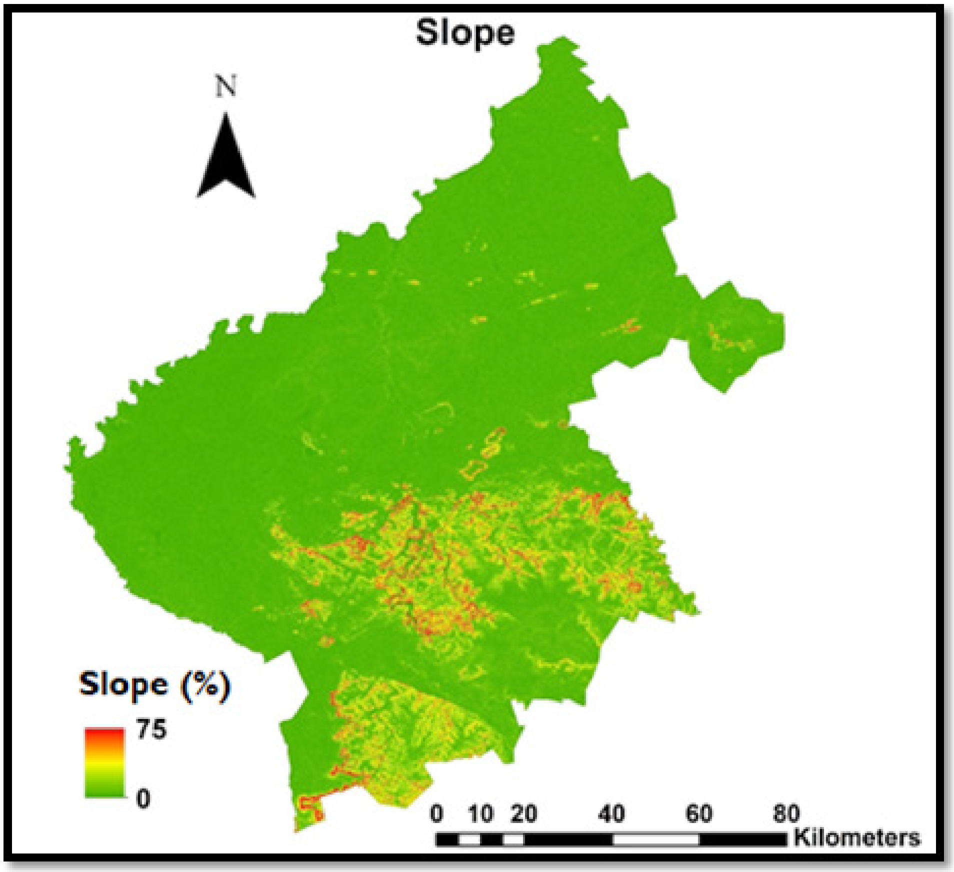
Appendix A: Average annual rainfall



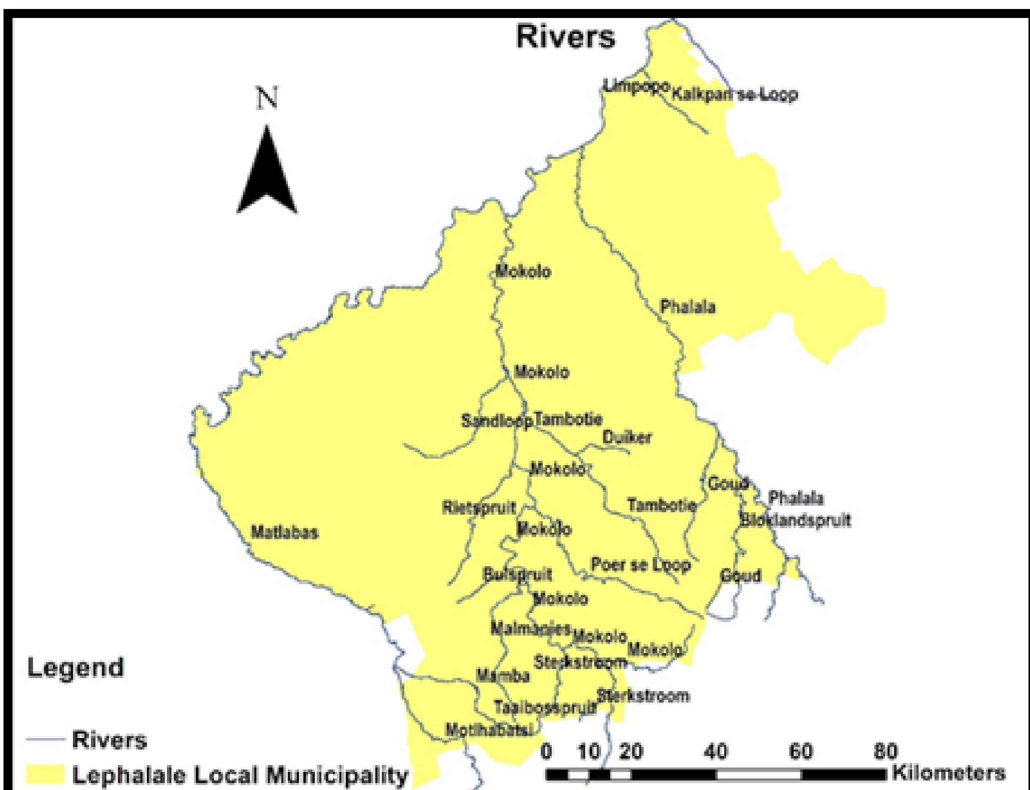
Appendix B: Altitude



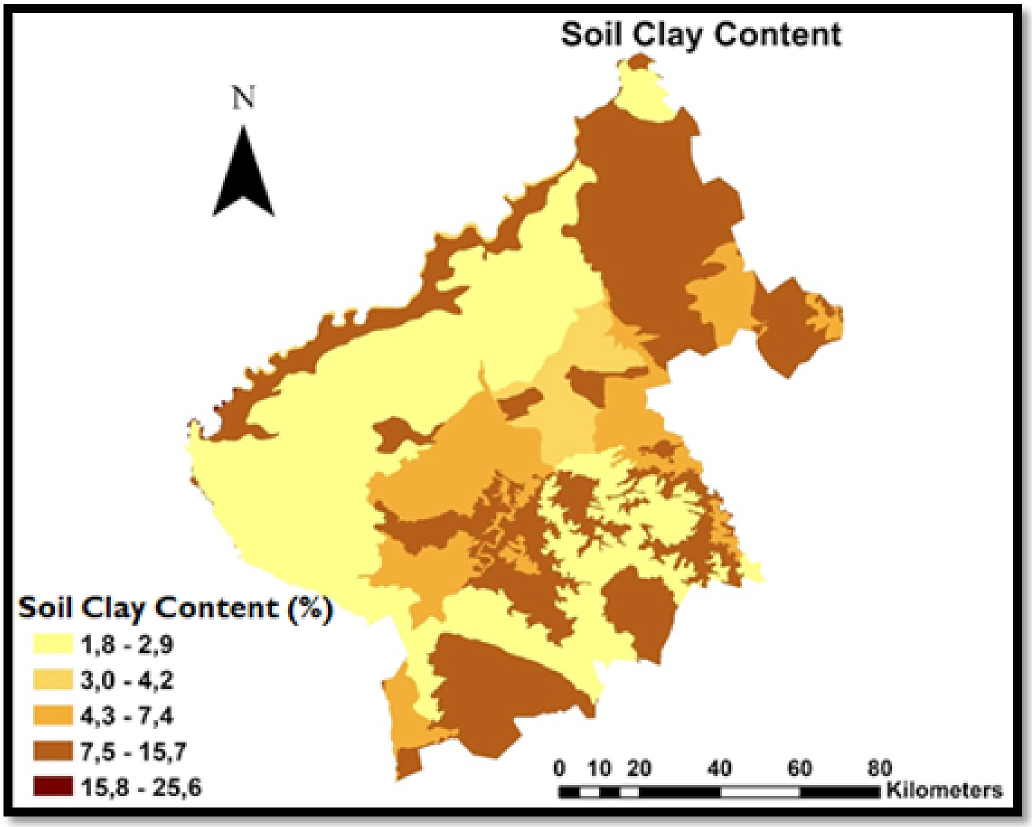
Appendix C: Slope



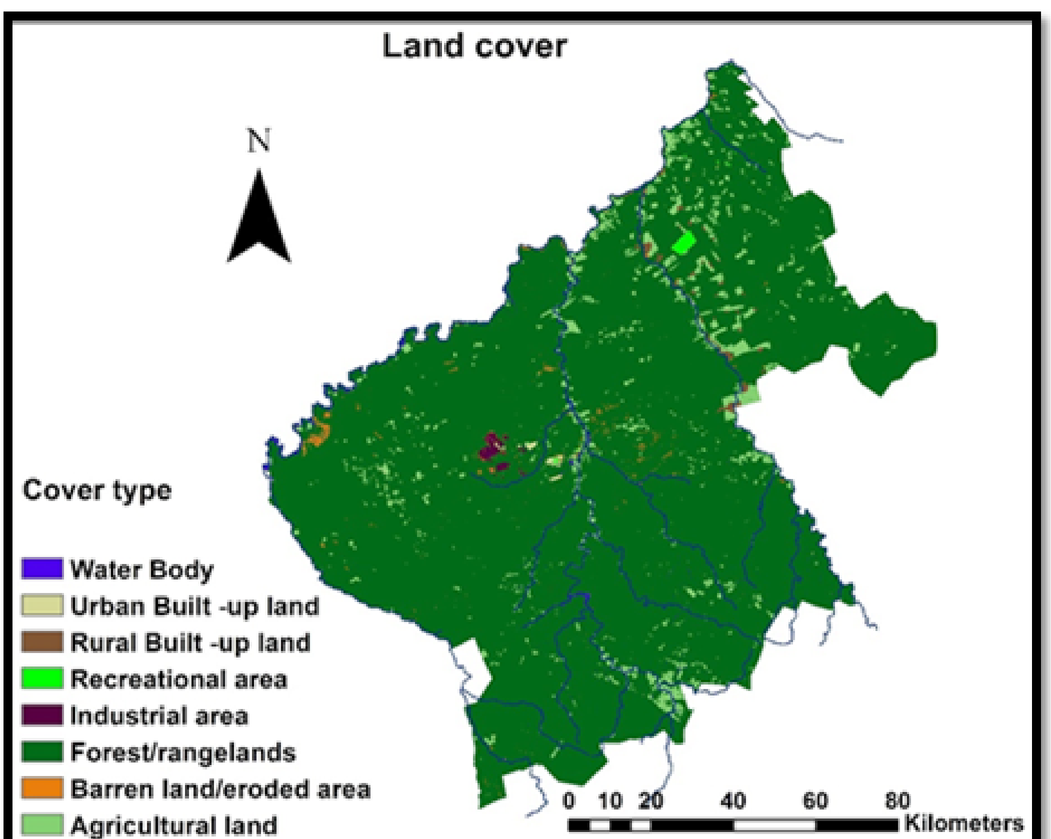
Appendix D: Rivers



Appendix E: Soil clay content



Appendix F: Land cover



Appendix G: Lephalale Local Municipal wards