AJLP & GS
African Journal on Land Policy and Geospatial Sciences

e-ISSN: 2657-2664, Vol.7 Issue.4, September 2024

https://revues.imist.ma/index.php/AJLP-GS/index

https://doi.org/10.48346/IMIST.PRSM/ajlp-gs.v7i4.48466 Category of the manuscript : Articles

Received in: 11 June 2024 **Revised in: 25 July 20204** **Accepted in**: 26 September 2024

ANALYSIS OF THE IMPERVIOUS SURFACE EXPANSION ON URBAN RUNOFF

(A CASE OF ARUSHA MUNICIPALITY)

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ABSTRACT

Context and background

Analysis of impervious surface expansion in urban areas has been a great deal all over the world. The impact of this expansion has been challenging the environment, people in particular. This study has considered the expansion in urban imperviousness as one of the root causes of urban water accumulation and the subsequent disturbances that people incur in urban areas especially during rainstorms.

Goal and Objectives:

Analyzing the relationship between urban imperviousness and the resulting urban runoff

Methodology:

The determination of the impervious surface was through the Normalized Built-up Index (NDBI) from Landsat 5 (1995 and 2009) and Landsat 8 (2017) imagery whereas the determination of runoff of the area of interest was through the SCS-CN method

Results:

The two datasets were found to be positively correlating, i.e. an increase in the impervious surface resulted into an increase in urban runoff and vice versa. It was found that, although 2017 had the lowest runoff interval of 3.907-72.08 due to a least amount of rainfall, it had a maximum coverage (imperviousness) of 93.16 Sq.km for runoff compared to 1995 and 2009

Keywords

Geographical Information Systems (GIS), Remote Sensing, Impervious Surface, Urban Runoff and SCS-CN Method

1. INTRODUCTION

Beginning with the early use of aerial photography and traditional map making, Remote Sensing and Geographic Information System (GIS) have been recognized as valuable tools for viewing, analyzing, characterizing, and making decisions about the environment (Chang, 2018). The remote sensing technology has facilitated the nowadays massive collection of the earth's observation data which together with the GIS technology enable modelling of different processes of the earth (Chang, 2018). Apart from different application areas experts have ever had with remote sensing and GIS technologies, the technology may also be used in studying the relationship between surface imperviousness (artificial surfaces that allow no water to infiltrate into the soil, for instance: roads, parking lots, pavements etc.) expansion and its impacts on urban runoff as the portion of the rainfall that runs off the surface during and after a rainstorm (Weng, 2008).

Different scholars have been able to undertake researches related to surface imperviousness, land surface temperature, runoff and urban population. Among others are: the use of Landsat Vegetation Indices to Estimate Impervious Surface Fractions for European Cities and recommended for further studies (Torben & Fensholt, 2018), impervious surface mapping using satellite remote sensing (Marvin, Impervious surface mapping using satellite remote sensing., 2002), assessment of the impervious surface connectivity and its applications for watershed management (J, Hong, & Yu, 2009). He and Zhao (2014) studied on improving the normalized difference build-up index to map urban build-up areas by using a semiautomatic segmentation approach which for this case will be used as a way to determining the built-up area. Kishna (2018) studied on normalized difference built-up index (NDBI) in automatically mapping urban areas from Landsat TM imagery, and Satheeshkumar & Verkateswaran (2017) worked on Rainfall runoff estimation using SCS-CN and GIS approach in the Pappiredipatti watershed of the Vaniyar sub basin, South India and ended up with accurate results concluding on the use of the antecedent soil moisture condition as an important factor towards determining the characteristics of different types of soils in terms of infiltration.

Arusha being one of the cities in Tanzania has impervious surface in it and in areas surrounding the municipality (sub-urban). It has also been reported to have been experiencing water accumulation around settlements especially during rain seasons. This increase in water accumulation is suspected to be caused by an increase in impervious surface. However, it remains uncertain to date. Motivated by this, the study was therefore undertaken in Arusha Municipality to analyze the relationship between the impervious surface expansion and the associated runoff as it has been happening for three different years.

1.1 Description of the Study Area

Arusha Municipality is located in the northern part of Tanzania and geographically lies between latitude 3.33°, 3.39° and longitude 36.68°, 36.71°. It covers an area of 265 sq.km with a total population of 416,442. It is a gateway to Tanzania's prominent reserves and parks and the soul of Tanzanite minerals. To west lies Serengeti National Park. It is characterized by an undulating landscape and moderate mountain ranges covered by human settlements and agricultural land. The highest elevation being 1400m above the mean sea level. It racks up an average of 873 mm of rainfall a year and 72.8 mm a month. The wettest weather being in April when the average is 223 mm of rainfall. A location map portraying the above characteristics is shown in figure 1.1 below;

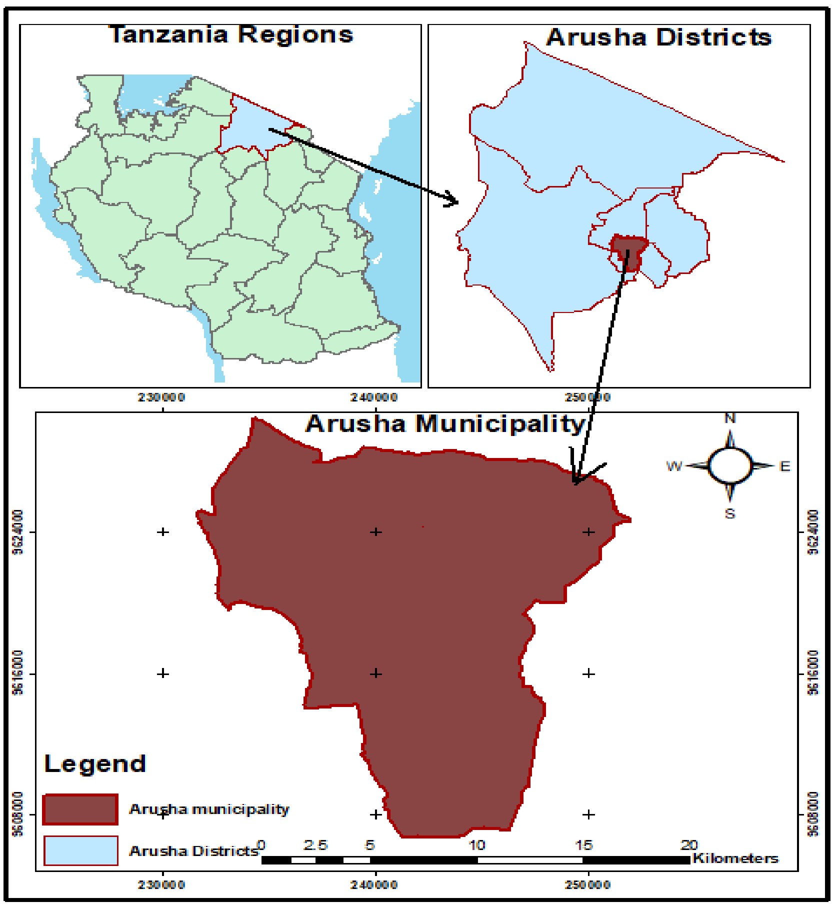

Figure 1: A location map of Arusha municipality.

2. METHODOLOGY

2.1 Overview

This chapter gives an outline of research methods that were applied in this study. It has clearly addressed all the methods used from data collection, processing, analysis and generally all the procedures that were followed in carrying out this study including the ethical issues. All these are simplified in a prepared flowchart diagram in figure 3.2 below;

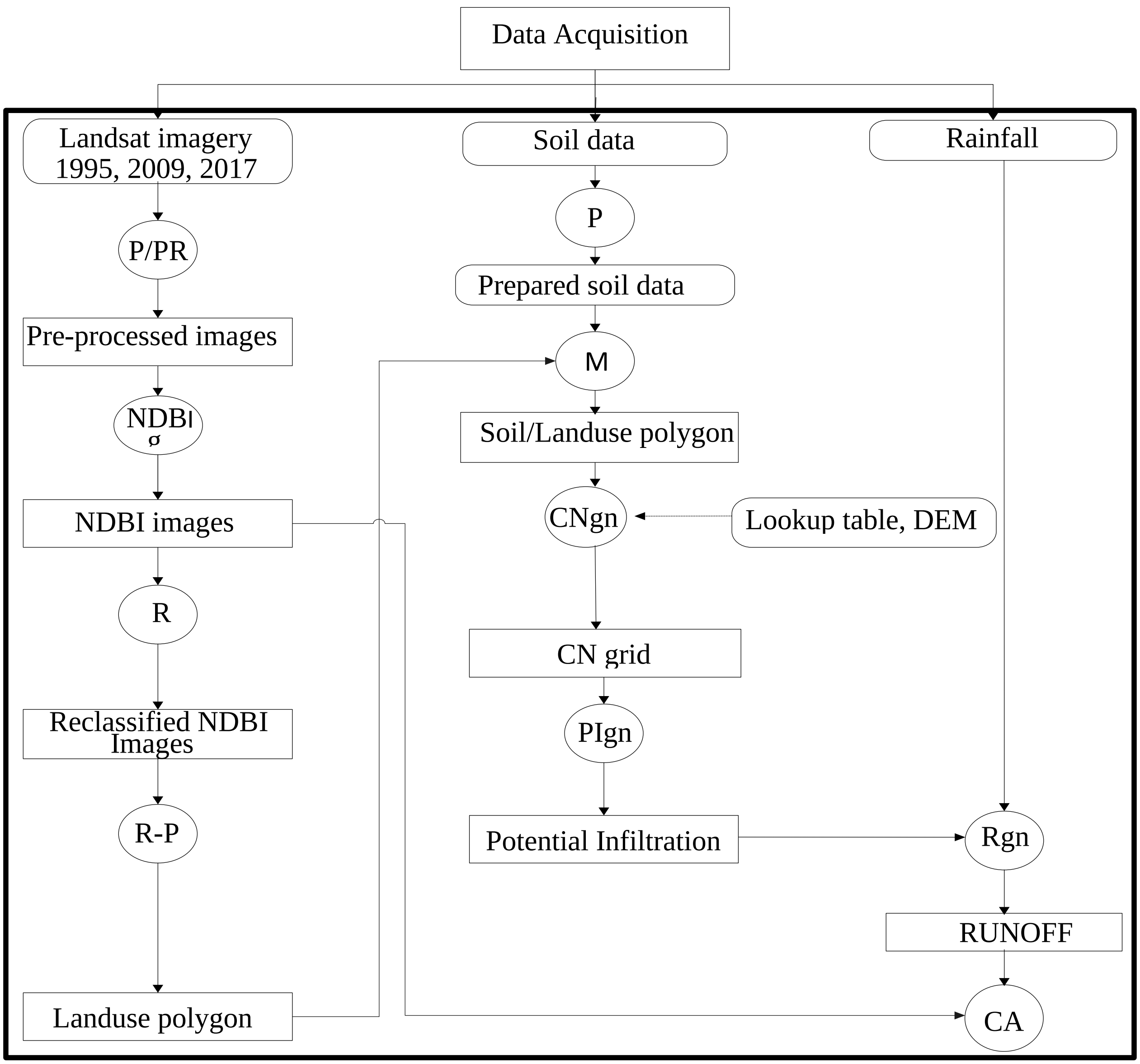

Figure 2: Representation of the workflow for the methodology.

Legend (for figure 2)

PR- Pre-processing, NDBI- Normalized Difference Built-up Index, CNgn- Curve Number generation, M-Merging, CA- Correlation Analysis, Rgn - Runoff generation, PIgn – Potential Infiltration generation, R-P-Raster to Polygon.

2.2 Data Acquisition

Three different datasets were acquired and used for the research. These were as follows;

i. Satellite imagery

Landsat images were acquired through downloading them from USGS Earth Explorer (www.usgs.gov). These were Landsat 5 for the year 1995 and 2009 and Landsat 8 for year 2017. They were acquired during the summer season. The images were assessed to be cloud-free and therefore found to be useful for the study. Table 3.1 provides a summary of the properties of the Landsat data acquired.

Table 1: Landsat imagery and their associated characteristics.

Data type	**Landsat 5,1995**	**Landsat 5,2009**	**Landsat 8,2017**	**Soil data**	**Rainfall data**
Data source	USGS	USGS	USGS	ISRIC	CHRIS data portal
Date of acquisition	30-01-1995	04-11-2009	28-12-2017	27-02-2014	1995, 2009 and 2017.
Coordinate system	WGS84	WGS84	WGS84		

ii. Soil data

Soil data that contained the soil type and terrain database for Southern Africa (SOTERSAF) was downloaded from ISRIC. The soil data was in ESRI shapefile format and the attributes' database was available in Microsoft MsAccess and SQLite format. It contained databases for Southern African countries only.

iii. Rainfall data

In situ data for annual rainfall were downloaded from CHRIS data portal for the years 1995, 2009 and 2017. Below is a table for rainfall data acquired.

Table 1: Rainfall data acquired for the year 1995, 2009 and 2017.

Year	**1995**	**2009**	**2017**
Rainfall(mm)	305.44	141.63	72.08

2.3 Data Processing

2.3.1 Impervious Surface Estimation using NDBI

NDBI stands for Normalized Difference Built up index. It is an index whose reflectance is higher towards the SWIR band and lower towards the NIR band. The index was used for estimation of impervious surface. The formula used for this was;

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

Where $SWIR$- Shortwave infrared band and NIR-Near infrared band

The SWIR and NIR bands for Landsat 8 were band 6 and 5 respectively and 5 and 3 for Landsat 5. Their maximum reflectance are shown in the table 3.3 below;

Image	Landsat 5,1995	Landsat 5,2009	Landsat 8,2017
SWIR band (max reflectance)	0.439225	0.445186	1.210700
NIR band (max reflectance)	0.652174	0.661025	1.210700

Table 2: Landsat imagery reflectance values.

2.3.2 Surface Runoff Estimation

The method used for this was the SCS-CN Method developed by the USDA Natural Resources Conservation Service. The estimation for runoff was preceded by a series of steps along with processing. The essence of this was to make an analysis between the obtained NDBI values and the soil type. These were as down below;

i. Reclassification of NDBI Images

The inputs here were the obtained NDBI images. The reason behind reclassifying was to obtain landuse maps classified into four major classes. The reclassification was according to the US Department of agriculture handbook that specifies four classes whenever SCS-CN method is used. The classes were; water, residential area, agricultural area and forestry. These classes were assigned to pixels following the characteristics of the obtained NDBI values. Below is a table of reclassification indicating the way the old pixel values for every image were replaced by the new values and new classes respectively.

Table 3: Reclassified NDBI values.

Old values	New values	Landuse
Landsat 8,2017		
-0.31 - -0.14	2	Residential
-0.14 - -0.056	4	Agricultural
-0.06 - -0.019	1	Water
0.014 - 0.26	3	Forests
Landsat 5,2009		
-0.55 - -0.115	2	Residential
-0.115 - -0.028	4	Agricultural
-0.028 - -0.055	1	Water
0.056 - 0.42	3	Forests
Landsat 5,1995		
-0.48 - -0.116	2	Residential
-0.116 - -0.057	4	Agricultural
-0.043 - -0.006	1	Water
0.058 - 0.441	3	Forests

ii. Landuse Polygon Generation

The reclassified landuse images were converted to polygons using the conversion tools in ArcMap. The pixels found with the same characteristics as per the reassigned new values resulted into a polygon. The reason behind this generation was to ensure the same dataset format between the soil data and the landuse data; that is a shapefile. This was to facilitate the merging of these datasets as a subsequent procedure towards the formation of CN grid. The cell values of the input raster became the column with the heading Gridcode in the attribute table of the feature class.

iii. Merging of Soil and Landuse Polygons

The tool used for this was union tool in Geoprocessing. The inputs were the soil data and the landuse polygons. The two datasets were merged to assign every polygon in landuse a percentage in soil type. The soil type was Sodi-Luvic Chernozems that was classified as 100% soil type B and 0% type A, C and

D dependent of the hydrological soil group characteristics. The reason for 100% soil type B is that, Sodi-Luvic Chernozems have moderate infiltration rates when thoroughly wetted and consists chiefly of moderately deep to deep, well-drained to moderately well-drained soils with moderately fine to moderately coarse textures. These soils have also a moderate rate of water transmission.

iv. Preparation of CN Lookup Table

The table consisted of certain curve numbers that were used to associate with a given landuse and soil type in the soil/landuse polygon. The polygons with for instance landuse value of 4 were assigned a curve number 77 as per hydrological soil type B. This table was used as an input into generating the CN grid.

Object ID	Landuse Value	Description	A	B	C	D
1	1	Water	100	100	100	100
2	2	Residential	57	72	81	86
3	3	Forests	30	58	71	78
4	4	Agricultural	67	77	83	87

v. CN Grid Generation

There were three kinds of inputs. The DEM, Soil/Landuse polygon and the CN Lookup table created. This was succeeded by installing a Geospatial Hydrologic Modelling Extension (HMC-GeoHSC). Within it the CN grid tool was used to generate the CN grid. Therefore, the CN grid is a function of landuse and soil data i.e. $\boldsymbol{CN = f(LU, SD)}$.

vi. Determination of Potential Infiltration

The amount of rainfall that is potentially effective to infiltrate down the soil was determined using the obtained curve number. The formula used for this was as follows;

$$S = \frac{25400}{CN} - 254$$

Where S was the potential infiltration in mm.

vii. Surface Runoff Estimation

The inputs into this were the potential infiltration and the total amount of rainfall. These parameters were substituted in the following equation;

$$Q = \frac{(P - 0.2S)^2}{(P + 0.8S)}$$

Where $\boldsymbol{P}$ was the total amount of rainfall, and $\boldsymbol{Q}$ was the total runoff.

2.3.3 Correlation Analysis

The correlation studied here was between the runoff values and their estimated impervious surfaces for the three years. Microsoft Excel was used to code for this correlation. The inputs into this were the NDBI values and the obtained surface runoff values. The formula used to determine the correlation coefficients was Karl Pearson's. It is as follows;

$$\boldsymbol{r} = \frac{\sum(\boldsymbol{X} - \overline{\boldsymbol{X}})(\boldsymbol{Y} - \overline{\boldsymbol{Y}})}{\sqrt{\sum(\boldsymbol{X} - \overline{\boldsymbol{X}})^2\,(\boldsymbol{Y} - \overline{\boldsymbol{Y}})^2}}$$

Where X and Y are the two variables from two different types and $\bar{X}$ and $\bar{Y}$ are their mean values respectively.

3. RESULTS, ANALYSIS AND DISCUSSION

3.1 Estimated Impervious Surface from NDBI

Figure 3 represents the results of NDBI estimation. The estimated impervious surface was found to be higher in the midst of Arusha municipality and continuously diminishing towards the sub-urban areas. The reason behind this was the development that has been taking place from 1995 to 2017. Away from the upper part of the municipality are found medium residential areas and some agricultural land in the lower parts of the municipality.

Most of the area in pale greenish color (negative NDBI values) represented the built-up environment, whereas the dark greenish color (positive NDBI values) represented the non-built-up environment. Therefore, the built-up area was found towards the NDBI negative values and the non-built up towards the positive values. The yellowish and pale green color in NDBI images below signified the built-up areas. For instance, the range -0.14 to +0.18 in 1995 was built-up. The pink color had an intermediate interpretation with built-up, bare soil and some thick vegetation in some areas. This was due to NDBI weakness in mixing up the bare soil and the built-up one. It is again a reason behind seeing the pink color diminishing form 1995 towards 2017. This problem was solved by validating the NDBI outputs with their respective Google Earth images to see the exact built-up environment and as a result helped in deciding for appropriate pixels to be used for correlation analysis.

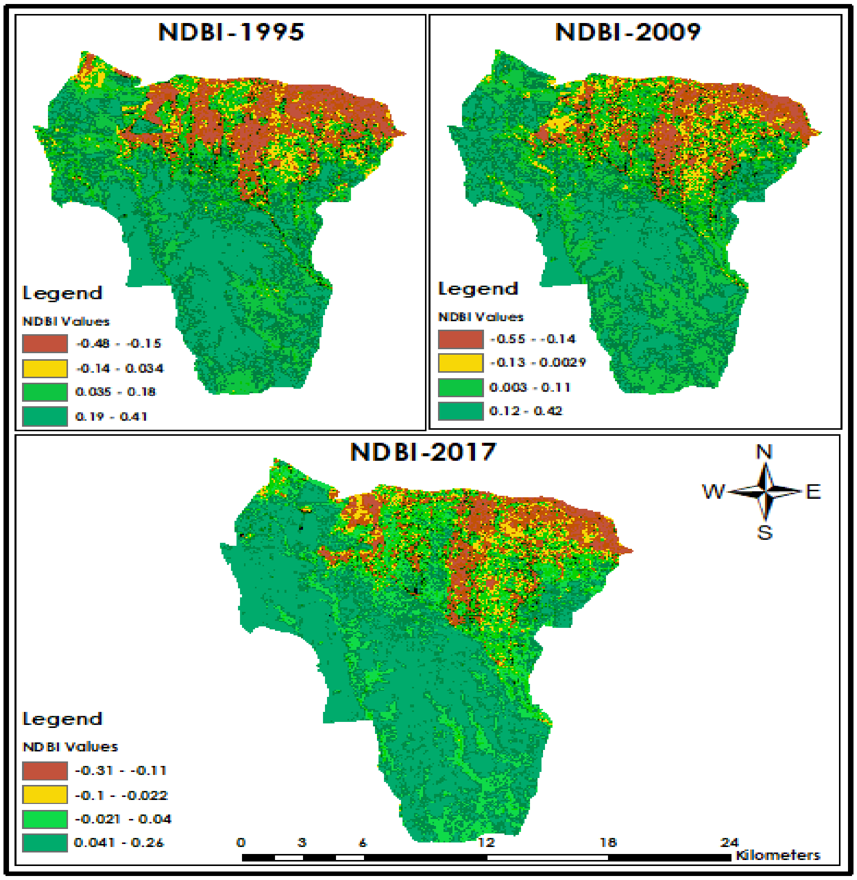

Figure 3: Obtained NDBI maps for the year 1995, 2009 and 2017.

Table 4: The obtained NDBI values for Arusha municipality in the year 1995, 2009 and 2017.

Year	**1995**	**2009**	**2017**
NDBI interval	-0.479 - 0.411	-0.554 – 0.419	-0.308 – 0.258

This signified changes in built up areas from 1995 to 2017 where the values towards -1 are many in 2017 and many towards +1 in 1995.

3.2 Estimated Runoff by SCS-CN Method

3.2.1 Estimated Potential Infiltration

Figure 3.4 represents the obtained potential infiltration. It was a succeeding step after the generation of CN grid. The higher the CN's, the lower the potential infiltration. The minimum and maximum potential infiltration obtained in mm were 0 and 183.931 respectively. Areas found to have high potential infiltration had lower runoff and those with low potential infiltration had maximum runoff. This is because where infiltration can take place, runoff tends to minimally take place. And as per the lookup table, where the curve number is lower, potential infiltration is also higher with a lower runoff in return.

The greenish color represented areas that were vegetated and bare. These areas had a maximum potential infiltration due to their ability of allowing water to percolate through the soil. The bluish color represented areas that had an intermediate potential infiltration and some hard surfaces. These areas were composed of settlements, transport facilities such as tarmac roads and parking lots, for instance Arusha airport and other surfaces. The pinkish red color represented the hardest surfaces and other surfaces that could not be reflected very well due to an obscuring atmosphere with canopies, and other roofs.

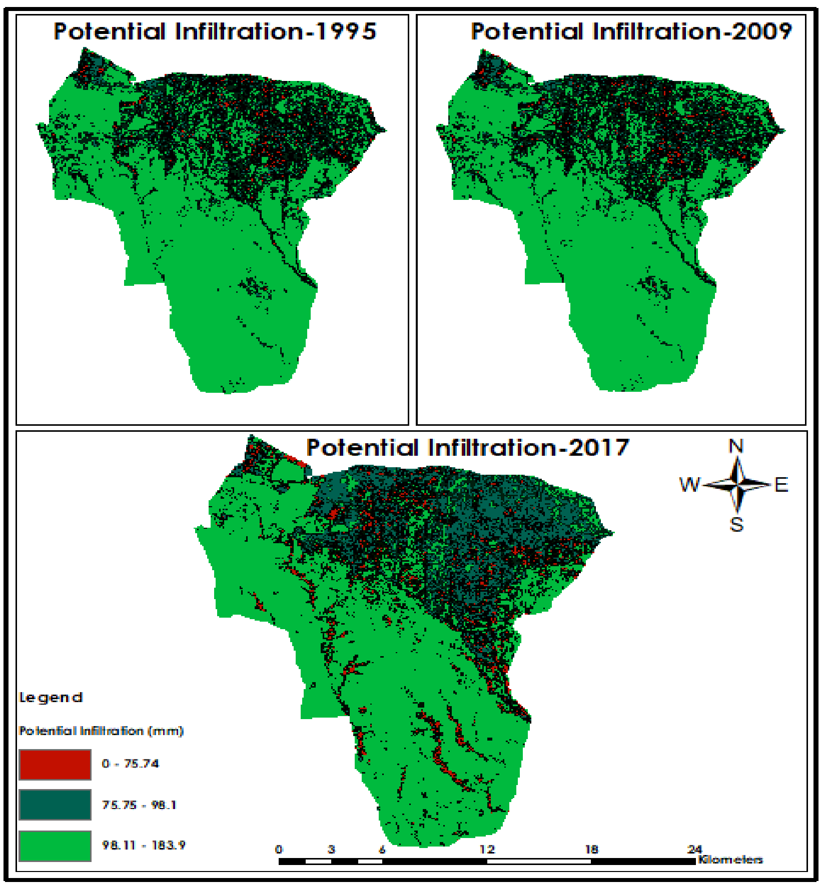

Figure 3: Obtained potential infiltration maps for the year 1995, 2009 and 2017.

3.2.2 Estimated Runoff

The results for runoff estimation are presented in figure 3.5. The intervals for the amount of water that runs off the municipality were found to vary in times and amount depending on the amount of rainfall that was recorded in a particular area and the built-up ground coverage. Pixels which were recorded as built-up had a maximum runoff and minimum for the rest of the classes; forestry, agricultural and water.

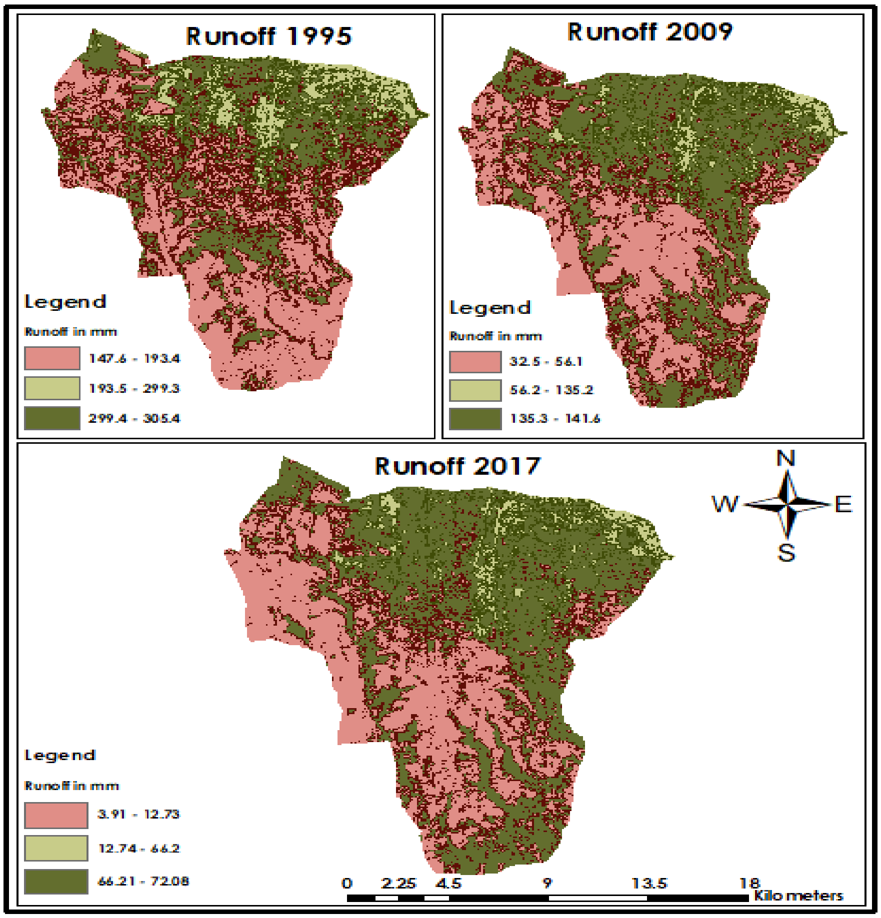

Figure 4: Obtained surface runoff maps for the year 1995, 2009 and 2017.

Table 5: Obtained runoff for Arusha municipality in the year 1995, 2009 and 2017.

Year	*1995*	*2009*	*2017*
Runoff (mm)	*147.6-305.44*	*32.52-141.6*	*3.907-72.08*

The most urbanized areas had the highest runoff and lowest potential infiltration. The amount in runoff varied simultaneously with the amount of rainfall that was used. It was found that, although 2017 had the lowest runoff interval of 3.907-72.08 due to a least amount of rainfall, it had a maximum coverage (imperviousness) of 93.16 sq.km for runoff compared to 1995 and 2009.

3.3 Correlation Analysis between Surface Imperviousness and Runoff

Figures 3.6 shows the trend in correlation to 2017.The correlation was tested using Microsoft Excel. The two datasets were found to be *positively correlating.* The expansion in urban area had an impact on runoff i.e. increase in surface imperviousness had an impact in urban runoff and vice versa. Most of the rainfall waters tend to run off the surface as a result of failing to infiltrate into the soil due to an obscuring urban surface. As a result, areas in the lower parts of the municipality tend to be a subject of the water that leaves the urbanized upper part of the municipality and brings about an impact if not to the urban dwellers themselves, to people leaving in the sub-urban and far away from the urban area. The Pearson's correlation coefficients (R) obtained were 0.9152, 0.9173 and 0.9666 for the years 1995, 2009 and 2017 respectively.

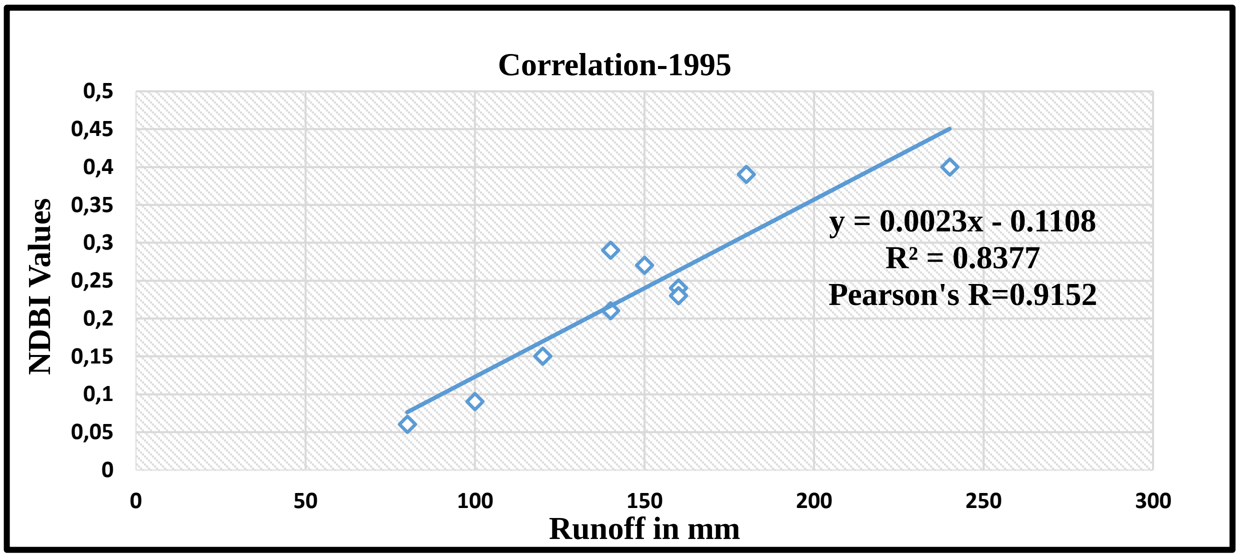

Figure 5: Correlation between imperviousness and runoff for the year 1995.

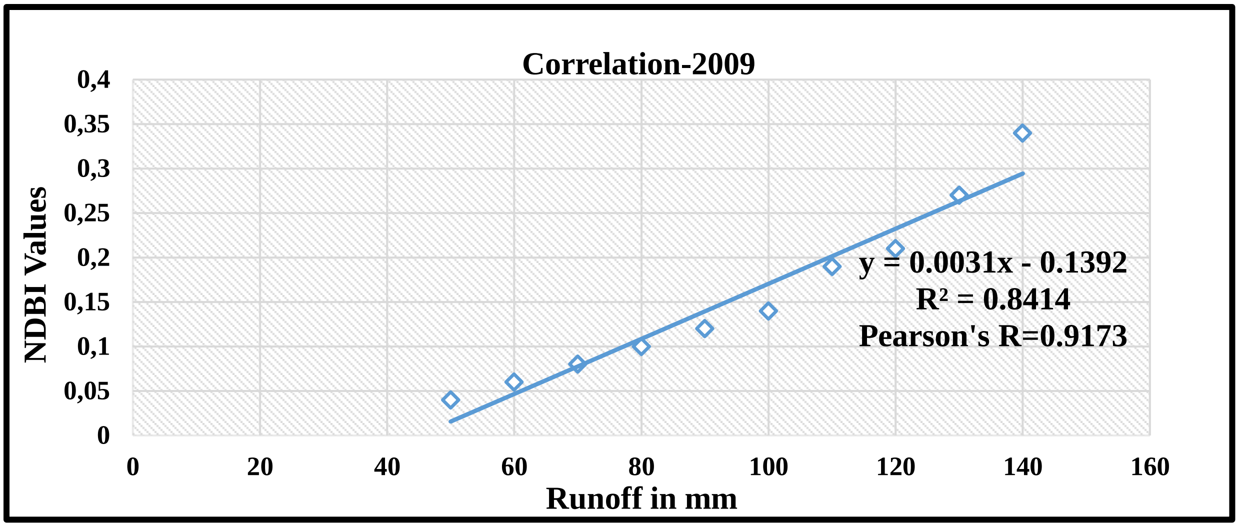

Figure 6: Correlation between imperviousness and runoff for the year 2009.

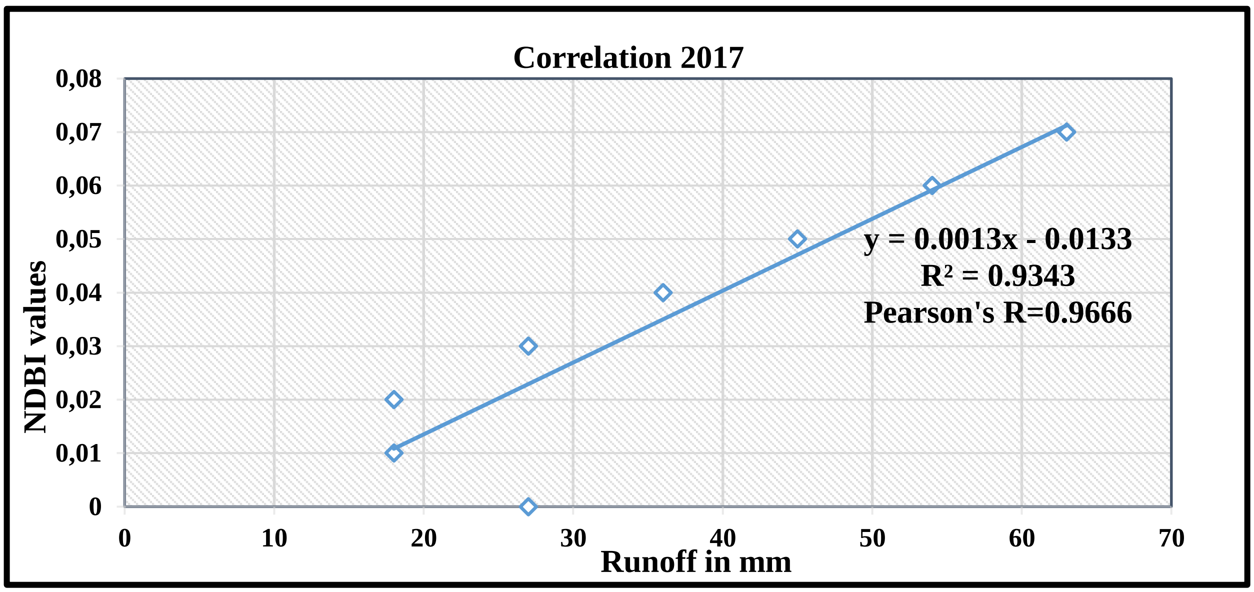

Figure 7: Correlation between imperviousness and runoff for the year 2017.

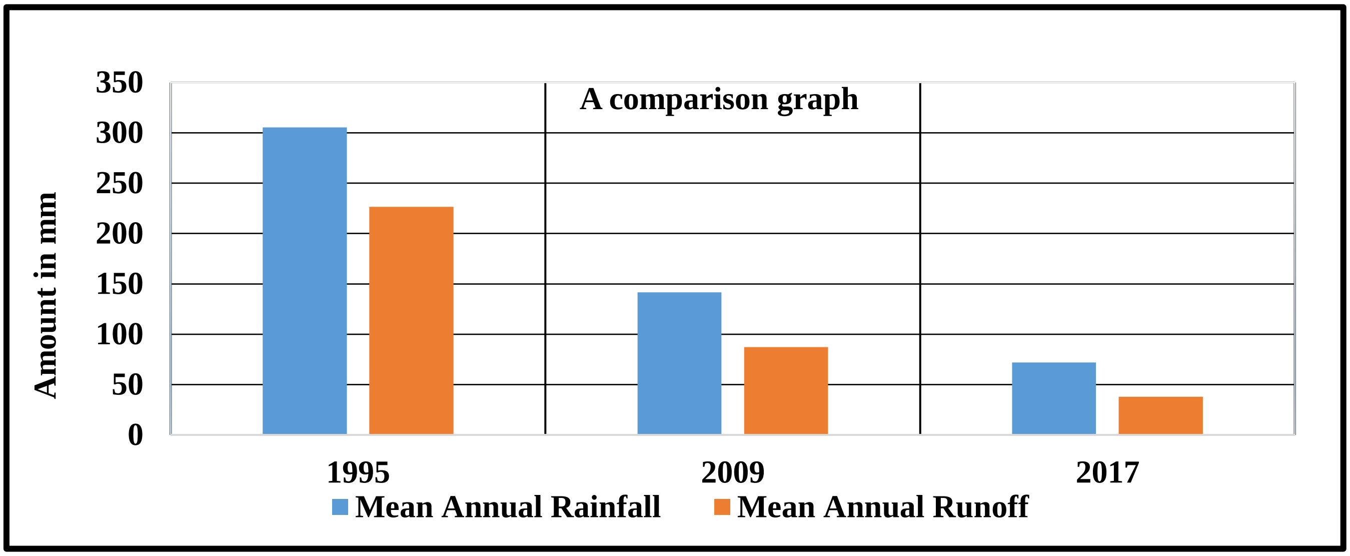

Figure 8: Comparison between actual annual rainfall and mean annual runoff for the year 1995, 2009 and 2017.

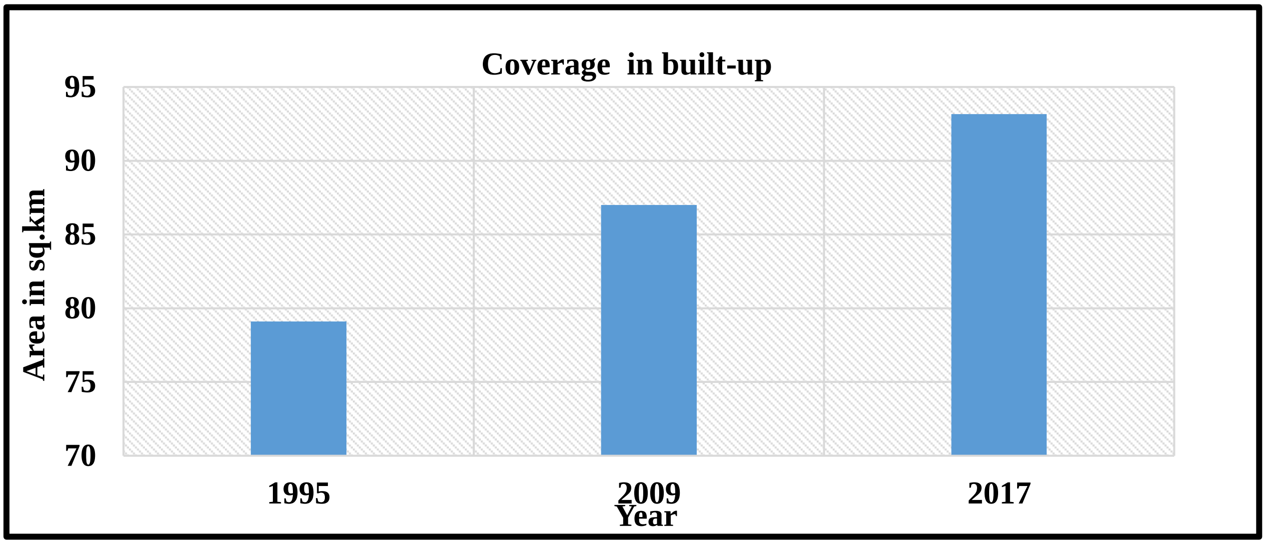

Figure 9: Built-up ground coverage for the year 1995, 2009 and 2017.

Figure 3.9 above is a comparison graph. It compares the mean annual rainfall and the mean annual runoff for the years studied. The amount of rainfall was minimum (72.08 mm) in 2017 and maximum (305.44 mm) in 1995. It is the same for mean annual runoff and inverse with the built-up area coverage in figure 3.10 which was found to be maximum (93.14 sq.km) in 2017 and minimum (79.11 sq.km) in 1995. These two conditions may therefore be contributing to the mean annual runoff. When the rainfall is maximum, runoff may be also maximum independent of the area that is built-up. It is also possible to have maximum ground coverage in built-up with a resulting minimum runoff depending on the total amount of rainfall and the nature of the infrastructure found in this place. This is a reason behind having maximum ground coverage in 2017 with minimum annual rainfall and mean annual runoff compared to 1995 and 2009.

4. CONCLUSIONS

The study intended at analyzing the impacts of the expansion of impervious surface on urban runoff. The growth in built up area was assessed through Normalized Built-up Index (NDBI). It was found to exist changes between 1995 and 2009 in built-up areas. A huge difference was observed between 2009 and 2017 where built-up areas were many compared to the past. The NDBI values made it possible to estimate the surface runoff for all the three years. The soil, rainfall and Landsat data used brought about convincing results. The amount in runoff varied simultaneously with the amount of rainfall that was used. It was found that, although 2017 had the lowest runoff interval of 3.907-72.08 due to a least amount of rainfall, it had a maximum coverage (imperviousness) of 93.16 sq.km for runoff compared to 1995 and 2009.

The correlation coefficients (r) obtained were 0.9152, 0.9173 and 0.9666 for the years 1995, 2009 and 2017 respectively. According to the correlation analysis made and the obtained correlation coefficients, it was convincing that an increase in built up area has resulted to an increase in urban runoff continually from 1995 to 2017 with a studied positive correlation between the two datasets.

5. ACKNOWLEDGMENT

I am overwhelmed in all the humbleness to convey my sincere gratitude to God for being by my side regardless of the complexities and problems that arose along the way to delivering this research satisfactorily.

I also show my great and sincere appreciation to Ms. Latifa L.R who stood as a supervisor for my research. Her guidance, supervision, patience and a motherliness way of helping over the time of my research endure.

I would also like to give thanks for the works of Mr. Victor Dancey and Mr.Yasin Simbalyoto (Ardhi University alumni) and all whom their works are cited in this report. Their works paved a way to developing this topic and researched for it.

6. FUNDING

NO FUNDING

7. AUTHOR CONTRIBUTIONS:

1. Melchior Vitalis Shukuru – Developing research title based on the statement of the problem, data

collection and analysis.

2. Edna William Machumu – Participated in data collection and analysis.

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9. KEY TERMS AND DEFINITIONS

Runoff - A portion of precipitation, such as rain or snowmelt, that does not infiltrate the ground but instead flows over the land surface and eventually reaches bodies of water like rivers, lakes, and oceans.

Geographical Information System (GIS) - A computer-based system of analyzing and presenting the desired outputs from the collected data.

Remote Sensing (RS) - A science of observing the earth's surface to obtain information about it without coming into direct contact with it. Landsat imagery is one of the outputs resulted from this observation.