EVALUATION OF SPATIAL AND TEMPORAL HYDROLOGICAL DROUGHT USING SURFACE WATER SUPPLY INDEX IN MALEWA RIVER CATCHMENT, NAIVASHA

E W. Nyokabi[1*], R M. Wambua[1], R O. Okwany[1]

[1] Department of Agricultural Engineering, Egerton University-Njoro

DOI: https://doi.org/10.37017/jeae-volume7-no2.2021-1

Publication Date: 19 October 2021

ABSTRACT:

There has been a critical problem of the devastating natural hazard (hydrological drought) which greatly affects a significant proportion of the large population particularly those living in arid and semi-arid areas. The flow regime of the Malewa River is reducing due to the river fluctuation, increasing scarcity of water during dry periods. The purpose of this research was to assess spatial and temporal hydrological drought using Surface Water Supply Index (SWSI) at Malewa River catchment. The data were based on hydro-meteorological data which included rainfall, level of water at Lake Naivasha, and streamflow of Malewa River for the years 1980-2018. They were obtained from Water Resources Authority (WRA) in Naivasha and Kenya Meteorological Department (KMD) in Nairobi, Kenya. The field data were first normalized to have all input attributes temporary variables with their distribution having zero means and a standard deviation of 1. Later the normalized data were calculated using basin-calibrated algorithm of SWSI to determine the hydrological condition. In SWSI, the highest percentage of classification for the stations were near the average of -0.9 to 1.0, with 34% for the Malewa area and 30% for the Turasha area. In spatial distribution analyses, hydrological drought severity was highest along the southern part of the catchment and lowest along with Eastern and North-Eastern areas. Therefore, hydrological drought severity was experienced in the catchment in terms of temporal and spatial analyses and increased along the flow path of the river. Hydrological drought assessment shows a technical manner for a comprehensive understanding of drought offering proper mitigation strategies and plan to control this natural disaster.

Keywords: *Hydrological drought analysis, River Catchments, SWSI*

1.0 INTRODUCTION

Drought is a global phenomenon characterized by scarcity of water when water level falls below a defined threshold level over an extended period causing significant damage to both lives of the human and the natural environment. It can occur as a result of insufficient or lack of precipitation for an extended period causing substantial hydrological imbalance (Zhang *et* al., 2015) or anomaly of temperature and evapotranspiration (Mulualem & Liou, 2020). This hazard is sometimes difficult to detect since it develops slowly failing to draw attention to the community and its impacts persist even after the end of the event. Detecting and monitoring drought in early times are thus very important to as to minimize the damages to the environment, economy, and human life (Du *et al*., 2018).

Acute drought conditions had greatly affected Africa and East Africa region where 2011-2012, 11 million people encountered famine and mass displacement. Also, in the year 2015-2016, Northern Ethiopia and 2016-2017 Greater Horn of Africa, were seriously hit by drought (Kilavi *et al*., 2018). The Government of Kenya declared a national drought in 2017 which had affected 2.7 million people (Koehler, 2018). This was double the number affected in 2016 which was 1.3 million people (Cilliers *et al*., 2018). The main reason was lack of rainfall in October, November, and December (short rains) in the year 2016 and also unusual high temperature.

Hydrological drought occurs when the volume of rainfall at a given area decreases for an extended period leading to decline in the available amount of water in both surface and sub-surface water. It is linked with the deficit in surface runoff, streamflow, reservoir, or groundwater level (Hao *et al*., 2018). Therefore, hydrological drought appears in the land phase of the hydrological cycle when there is a decrease in the available water (Nalbantis & Tsakiris, 2009). It can be caused by lack of precipitation, human activities, climate change, or overexploitation of surface water resources (Ali *et al*., 2019). Hydrological drought can be classified into surface and ground water drought (Wambua, 2014).

Lake Naivasha water level also continues to be hit by anthropogenic stressors such as loss of wetlands and eutrophication. Malewa River catchment is an area where tributaries such as Karati and Turasha streams usually dry up during dry periods as indicated by Water Resource Authority (WRA). Malewa River has a huge annual flow fluctuation which could either be caused by extreme climate conditions or land cover changes (Cheruiyot *et al.,* 2018). This will lead to hydrological drought affecting the direct or indirect decline in water resources adversely affecting quantity and quality of water resources system. Negative impacts such as water scarcity, hunger, degradation of water resources, insecurity crises, and socio-economic projects will be seen. Thus, there is a need to formulate appropriate hydrological drought mitigation measure for Malewa River catchment. During hydrological drought season, population suffers due to lack of onset of this drought and plans on how to overcome this condition. The appropriate tools for detecting and describing the hydrological drought on-set conditions in terms of spatial and temporal characteristics such as severity, duration, and frequency, in the catchment are limited.

2.0. MATERIALS AND METHODS

2.1 DESCRIPTION OF STUDY AREA

The Malewa River Catchment is located in Naivasha Basin, Nakuru County, Kenya as shown in Figure 1. It lies within the central Rift Valley of Kenya between latitudes 0º 10’ S to 1º 00’ S and longitudes 36º 10’ E to 36º 40’ E, with a UTM zone of 37 souths. Its area is approximately 1760 km^2 (Cheruiyot *et al*., 2018). Its highest altitude is about 3990 m above sea level (a.m.s.l) in the eastern side of Aberdare Ranges and its lowest altitude is about 1900 m (a.m.s.l) near Lake Naivasha in Eastern Rift Valley.

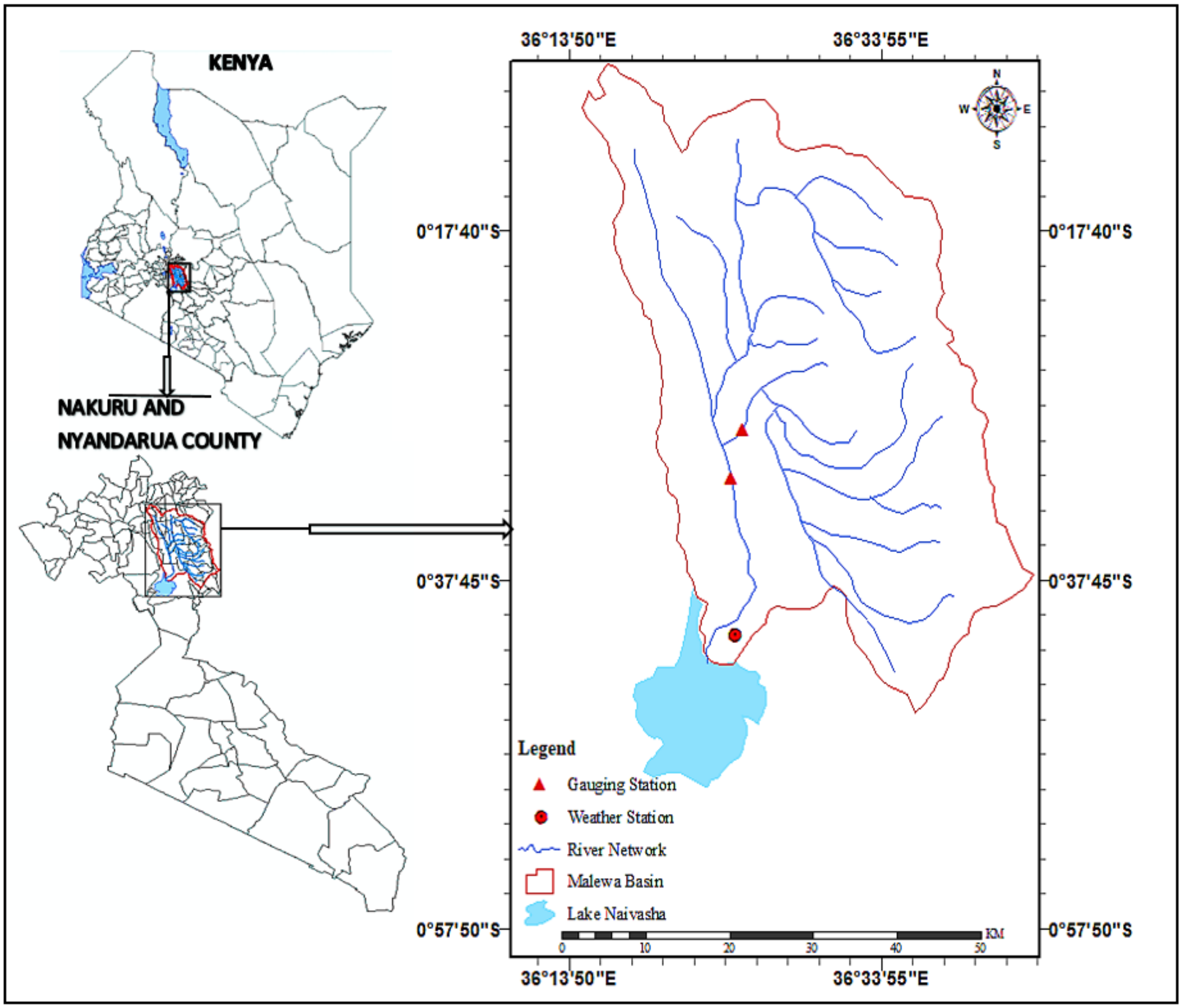

Figure 1: Map of Malewa River Catchment

The local reliefs in the catchment are Aberdare Mountain in the East and Mau Escarpment to the West makes the area have two rainy seasons (Odongo, 2016). The long rain occurs between March to May while the short rain occurs between October and November with its average annual rainfall ranging between 1525 to 610 mm (Kyambia & Mutua, 2014). The catchment experiences a daily average temperature of between 8 to 30°C and annual potential evaporation of approximately 1700 mm.

The tributaries of Malewa River are mainly Wanjohi, Turasha, Simba, Nyairoko, and Ol Kalou. This river rises in the western slopes of the Aberdare range and flows south and west to Lake Naivasha. The total discharge to Lake Naivasha contributed by Malewa River is approximately 90% (Lukman, 2003;

Kyambia & Mutua, 2014). Lake Naivasha basin is situated in the Rift Valley at a latitude of 0° 09’ to 0°55’ S and a longitude of 36° 09’ to 36° 24’ E (Odongo, 2016). The land cover types of this catchment are agriculture, grass, bush/scrub, and forest (Ogweno, 2009).

2.2 Climatic Data Acquisition

The key hydro-meteorological data sets for determining hydrological drought using stated indices from 1980-2018 were; streamflow of Malewa River, rainfall of Malewa River Catchment, and reservoir level of Lake Naivasha. These data sets were selected to determine hydrological drought conditions in the catchment for a longer period and enhance drought forecasting. The monthly rainfall data were obtained from Kenya Meteorological Department (KMD) and Water Resources and Management Authority (WRA) in Naivasha. Daily streamflow and Lake Levels were obtained from WRMA in Naivasha; however, the streamflow and Lake water level data were converted to monthly data. Four gauging stations data and rainfall data were obtained from the WRA and KMD. Only two gauging stations and one rainfall data were used because the obtained data were less than 30%.

2.3 Filling in Missing Data

The missing rainfall data were filled using the Normal ratio method as shown in equation (1)

$$P_x = \frac{1}{n}\sum_{i=1}^{i=n} \frac{N_x}{N_i}\, P_i \qquad \ldots.\ (1)$$

Where:

P_x is missing rainfall (mm)

P_i is available rainfall (mm)

N_x is the average annual rainfall of the missing data (mm)

N_i is the average annual rainfall of available data (mm)

n is the number surrounding stations

Different methods were used in filling the missing streamflow data. For a short duration, a linear interpolation was used while for a longer duration, interpolation with regression was used, provided there were suitable sections on the same river. A scatter graph was plotted to determine the relationship using equation and correlation of coefficient. A simpler linear relationship was first tried to get the missing data followed by polynomial up to order number three (3). Regression analysis produced a functioning relationship, where R was greater than 0.90. If R was less than 0.90, then it was a poor relationship and was not used to fill in the missing data.

2.4 Data Normalization

Before using the field data, they were first normalized/standardized at each station. This is to have all input attributes transformed to temporary variables with a distribution having zero means and a standard deviation of 1. Equation (2) was used to normalize the data set;

$$X_S = F_{min} + \frac{(x_0 - x_{min})}{(x_{max} - x_{\min})} x(F_{max} - F_{min}) \ldots (2)$$

Where:

X_s = normalized value

F_{min} = minimum value for standardization

F_{max} = maximum value for standardization

x_o = original value

x_{min} = minimum value present in the original data series

x_{max} = maximum value present in the original data series

All input and output values are standardized to range between F_{min} and F_{max} (F_{min} = 0.1 and F_{max} <1), however reducing the range to a very small value will have a negative influence on training which in contrast, the amount of allowed extrapolation should not exceed a certain limit. Hence, for the current study, the value of F_{min} =0.1 and F_{max}= 0.9 which perform best for drought indices (Morid et al., 2007).

2.5 Surface Water Supply Index (SWSI)

The data set of SWSI were monthly rainfall, streamflow of Malewa River, and reservoir level of Lake Naivasha. The data sets were first summed up and normalized, before determining the weighting factors. Then the monthly data were then fitted to individual probability distributions for each month and for each input variable. Equation (3) shows the calculation of SWSI.

$$SWSI = \frac{[(a*PN_{rn}) + (b*PN_{sf}) + (c*PN_{rs}) - c_1]}{c_2} \quad \ldots (3)$$

Where:

SWSI = Surface Water Supply Index (dimensionless)

PN = probability of non-exceedance (%)

rn = rainfall (mm)

sf = streamflow (m^3/s)

rs = storage reservoir level component (m)

a,*b* and *c*= weighing factors

C_1 and C_2 for SWSI are 50 and 12 respectively

The parameters a, b and c were summed and should be equal to 1 as given by the following expression:

a+b+c=1

The values of a, b and c were determined at different proportions contributing to the total water availability in the basin. For any monthly data series at each hydrometric station, the maximum entry record was identified. Then the parameter defined as the ratio of the monthly data to the maximum entry in the period of record was computed. For an instant, the monthly time series of streamflow data were computed as shown by Equation (4).

$$P_b = \frac{x_i}{x_{max}} \quad \ldots (4)$$

Where P_b is the provisional parameter associated with b, x_i is the data entry for a month i, and x_{max} *is* the maximum data entry of the period in record. Similarly, p_a and p_c are computed as the provisional parameters for a and c respectively. A total value p_T is then determined by summing up the p_a, p_b, and p_c. Then the parameters a, b, and c are computed from the relations as shown in Equation (5):

$$a = \frac{p_a}{p_T}, b = \frac{p_b}{p_T}, c = \frac{p_c}{p_T} \quad \ldots (5)$$

The probabilities of non-exceedance of monthly precipitation, streamflow, and reservoir level are computed using the relation shown in Equation (6):

$$PN = 1 - \frac{r}{n+1} \quad \ldots (6)$$

Where *PN* is the probability of non-exceedance (percent), *r* is the rank of data arranged in ascending order and *n* is the number of years considered in the analysis.

The computed SWSI values are then categorized into severity classes based on Table 1

Table 1: Hydrological Drought Classification based on SWSI (Shafer and Dezman, 1982)

SWSI Classification	Values
Extremely dry	**-4.2 to -3.0**
Moderate dry	**-2.9 to -2.0**
Slightly dry	**-1.9 to -1.0**
Near average	**-0.9 to 1.0**

Slightly wet	**1.1 to 2.0**
Moderate wet	**2.1 to 3.0**
Extremely wet	**3.1 to 4.2**

2.5: Spatial analysis of Hydrological Drought

Spatial distribution used IDW interpolation within the ArcGIS 10.4 based on the condition calculated in the SWSI algorithm. First, the catchment was clipped from Kenya DEM using raster data at data management tool. Then using SWSI results, land cover classes, rainfall and gauging stations of the Malewa River, IDW was used to capture the extent of local surface variation needed for spatial analysis through linear-weighted. Interpolation of the point data sets was used for estimating values at a station where sample points were lacking. This method of interpolation estimated cell values by averaging the values of sample data points in the surrounding processed cell. The closer a point was to the center of the cell estimated, the more influence, or weight, it was in the averaging process.

3.0 Results and Discussion

3.1 Hydro-Meteorological Data

Figure 2 shows the annual average of rainfall and streamflow from 1980-2018. Correlation was measured with the simultaneous rising or falling the rainfall bars and streamflow line in the graph below. There was a correlation of rainfall to streamflow for the years 1980 to 1998, however, the correlation started changing from the year 1999 onward as seen in the years 1999, 2013, and 2016. On annual average, the highest discharge of streamflow was 2GB05 gauging station having up to 1.09m^3/s.

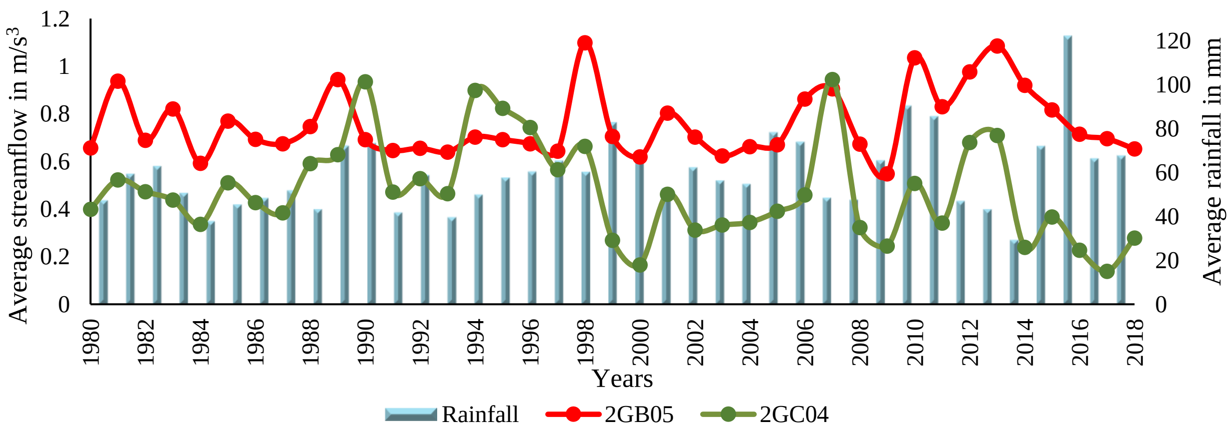

Figure 2: Annual average of rainfall and streamflow

The Malewa River catchment rainfall distribution is bi-modal. The long rains occurring between March to May and the short rains occur between October to December. This is shown in Figure 3 where average monthly rainfall distribution has a similarity with research for (Mwai, 2011) and (Becht *et al.*, 2005) studying rainfall at Lake Naivasha area.

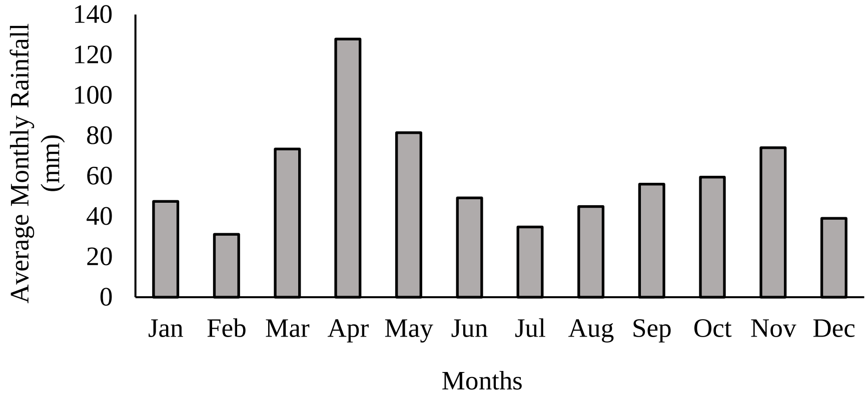

Figure 3: Average Monthly Rainfall

The lake Naivasha water level was fluctuating over the years with the lowest water level experienced in years 2006 with a level of 0.51 meters and 2009 with a level of 0.56 meters. Figure 4 shows the annual average water level of Lake Naivasha from 1980 to 2018. The Eastern Rift Valley lakes in Kenya have been having extraordinary lake level changes from the year 2011 to the current years. Similar results were indicated by Moturi (2015), due to climate change, there is seasonal variation in rainfall, and mysterious groundwater inlet being discovered.

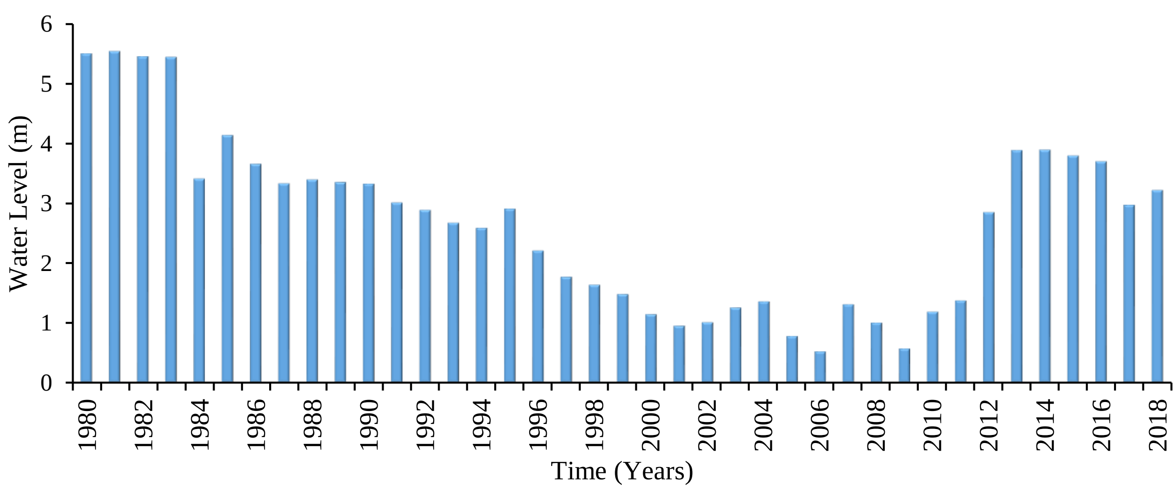

Figure 4: Annual Average Water in Lake Naivasha

3.2 Temporal and Spatial Hydrological Drought

3.2.1 Temporal analysis using Surface Water Supply Index (SWSI)

Surface Water Supply Index was calculated using its basin-calibrated algorithm to determine the condition of hydrological drought at the Malewa River catchment. In accessing hydrological drought using SWSI from the year 1980-2018, it shows that the two stations were near average having SWSI value ranging from -0.9 to 1.0. These were because they had high percentage of 34% at Malewa and 30% at Turasha area. The lowest percentage was the extreme wet condition having SWSI values of 3.1 to 4.1 where Malewa area had 3% and Turasha area had 2%. Figure 5 shows hydrological drought classification from 1980 to 2018.

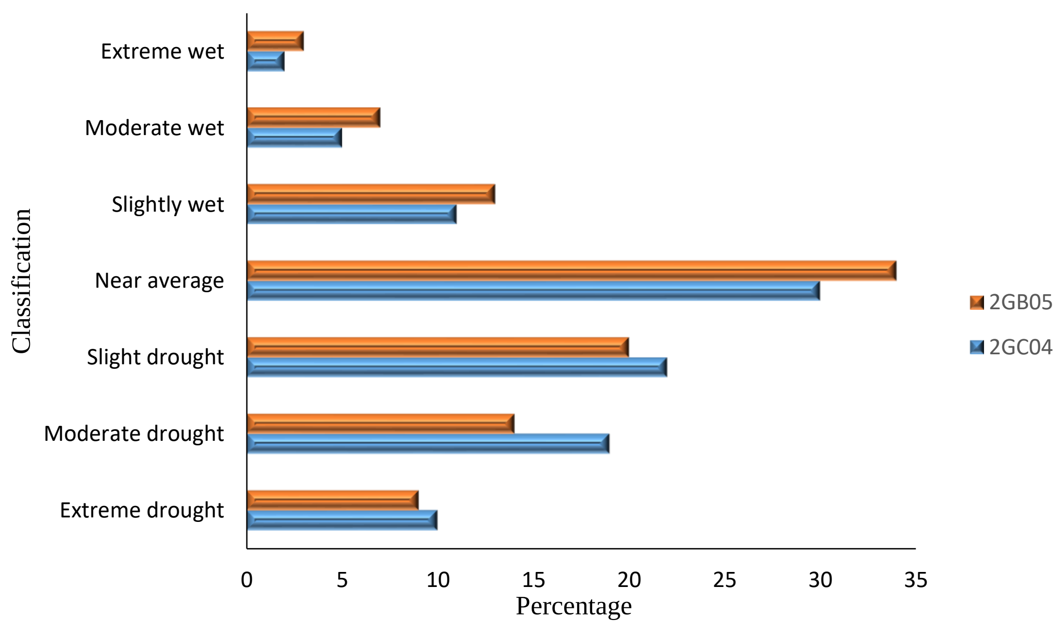

Figure 5: Hydrological drought classification in Malewa River catchment

In calculating SWSI, it shows that the Malewa River catchment was experiencing hydrological drought from 1980-2018. The slight drought was the second-highest percentage with greater than 20% followed by moderate drought in the two gauging stations. In determining hydrological drought in terms of months for the 39 years, near average of SWSI values -0.9 to 1.0 was most experienced in all months of the years in this study. The highest months at the Malewa area were February and November and had 19% while in the Turasha area the highest months were January and March having 14%. Comparing SWSI classifications in terms of years and months for the two areas, there was mutual relationships indicating that near average was most experienced in the two stations. Figures 6 and 7 show SWSI classification in terms of months

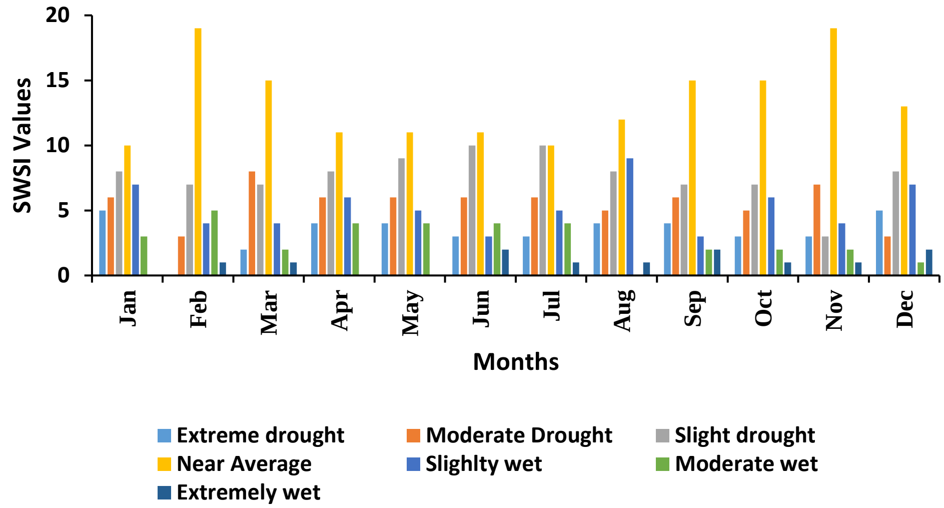

Figure 6: Hydrological drought classification in Months at Malewa

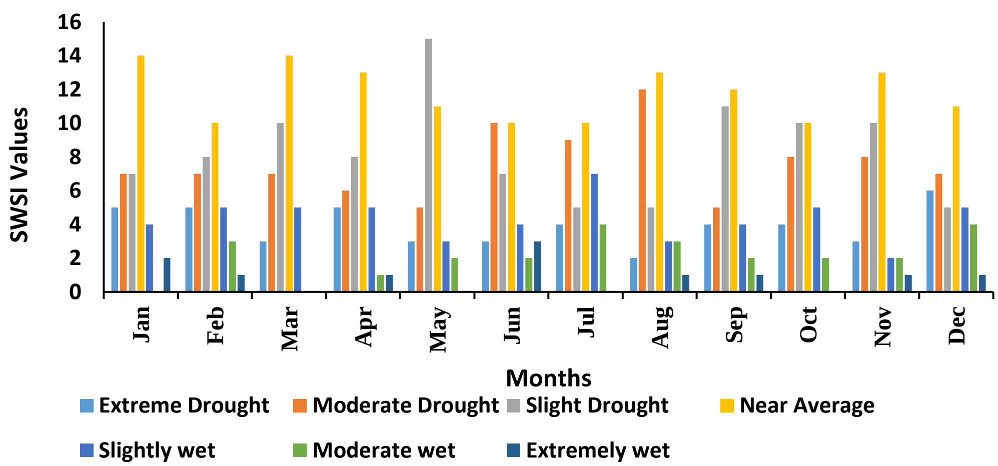

Figure 7: Hydrological drought classification in Months at Turasha

Hydrological drought was calculated in decades from 1980-2018 as shown in Figures 8 and 9. This was to determine which decade had the highest hydrological drought in the two stations in this research. The decade which had the highest severity was from 1980 to 1990 at Turasha area which had 27% for extreme drought, 35% for moderate drought, and 25% for slight drought. Similar results in decade were observed at the Malewa area where 22% was for extreme drought, 21% for moderate drought, and 27% for slight drought. The second decade which had severe hydrological drought was 2011 to 2018. The decade which had the lowest severity was 2000 to 2009. Therefore, hydrological drought classification in decades from highest severity were arranged as; 1980-1990, 2011-2018, 1991-2000 and, 2001-2010.

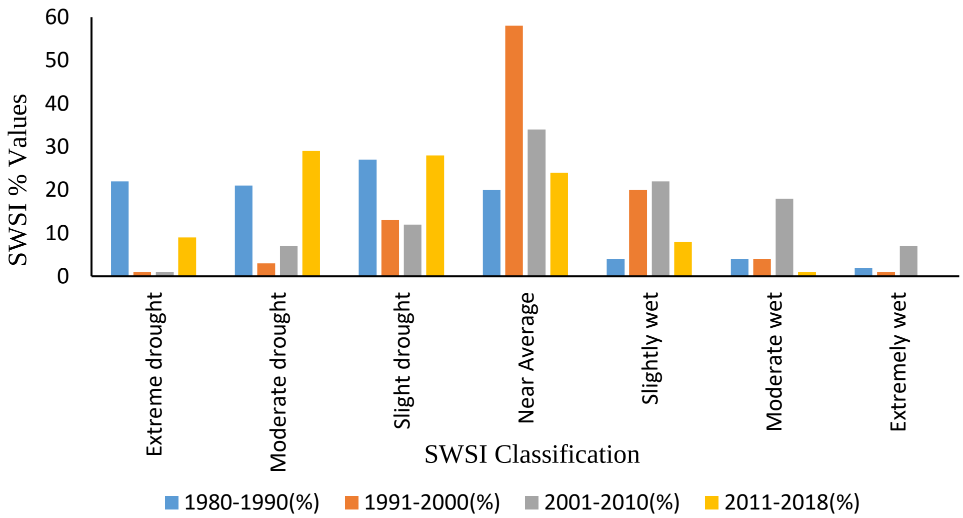

Figure 8: SWSI in Malewa Gauging Station

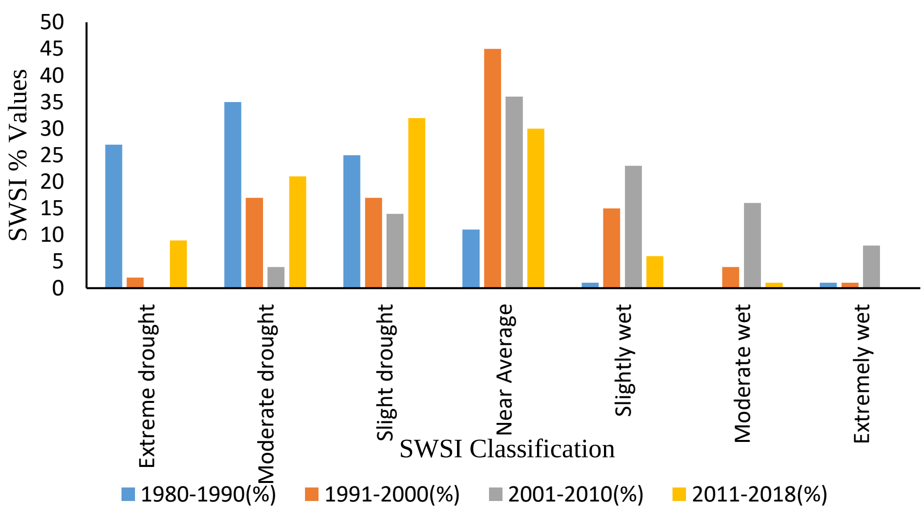

Figure 9: SWSI in decade at Turasha

Figures 10 and 11 show how SWSI classifications were varying for 468 months (1980-2018). Hydrological drought was severe from 1980 to 1989 then progressed to near average. From around 2000 to 2009 few months had a wet condition, however, from 2010 onwards, the most hit by hydrological drought severity were August 1981 at Malewa and January 2006 at Turasha area. These results contradict Wambua *et al*. (2017) drought analyses at the Upper Tana basin using SWSI where drought severities were high between 1990 to 1997 and 1973 to 1978 with SWSI values were at or below -3.0. These differences could be attributed to non-homogeneity inland cover systems or variability of hydro-meteorological factors within the basin.

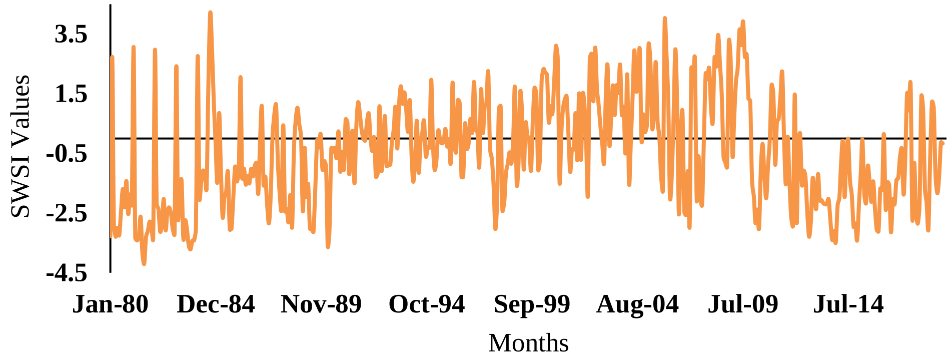

Figure 10: Hydrological Drought Classification in Malewa

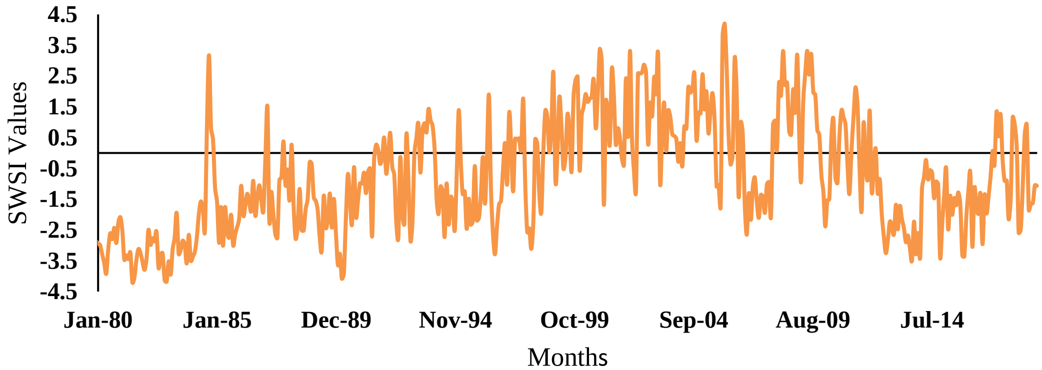

Figure 11: Hydrological Drought Classification in Turasha

3.2.2 Spatial distribution of Hydrological drought severity using SWSI

The spatial drought extent of the Malewa river catchment was done in decades from 1980-2018. Drought severity was high in the year 1980 with a range of -3.5471 to -2.0969. The hydrological drought severity of within the catchment for the years 1980, 1990, 2000, and 2010 indicated that the Southern area (around lake Naivasha) had the extreme drought. The South-west area is within the low elevation of the catchment with land-cover mainly grass/scrubland and bush hence it is arid and semi-arid areas (ASALs) having less rainfall compared to the other part of the catchment. The Eastern area of the catchment was normal for the years 1980, 1990, and 2010 with moderate wet in the year 2000. Both the Northern and Western areas for the catchment had moderate and slight drought respectively for the years 1980, 1990 and 2010 which the year 2000 having normal and slightly wet respectively. Eastern and North-eastern areas are within the Aberdare ranges with more amount of rainfall and the source of the Malewa river. It has a high altitude with their land covers mainly forests and agriculture. Spatial distribution of hydrological drought in the catchment indicates that drought severity is low at the source of the river and more prone towards the end. These results were similar to findings given by Wambua *et al*. (2017) at Upper Tana river in Kenya and Zhu *et al*. (2018) at the Inland river basin in Northwest China and both studies indicate that variation of SWSI severity was low at the source of the respective rivers and increasing along the flow path.

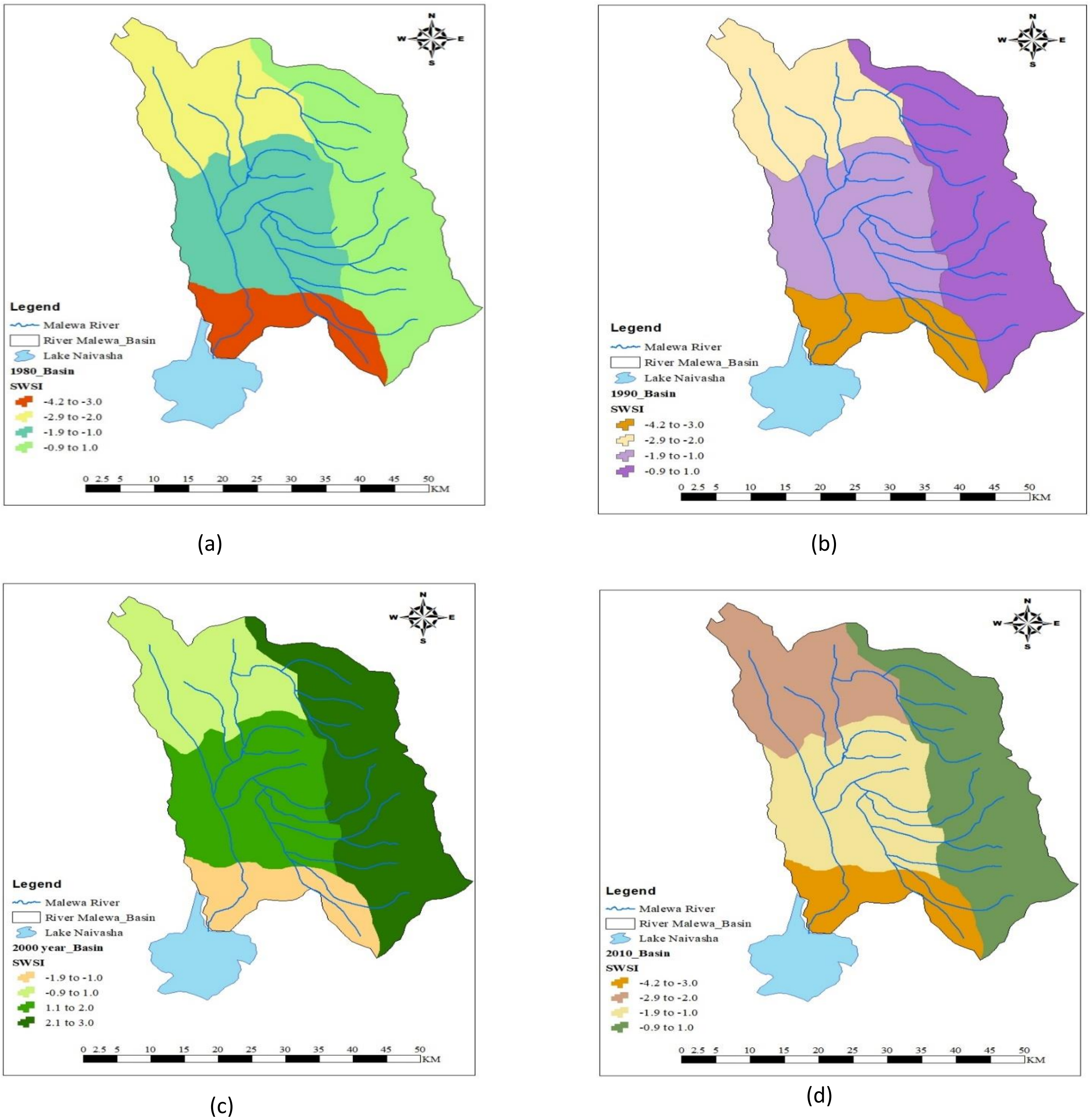

Figure 12: Spatial distribution of drought severity in the Malewa River Catchment

4.0 CONCLUSIONS AND RECOMMENDATIONS

From the results, hydrological drought classification was near average using SWSI from the year 1980-2018. In decades, the year 1980 to 1989 had the highest hydrological drought severity with 2001-2010 having the lowest drought severity. The months most hit by hydrological drought were August in the year 1981 at the Malewa area and January in the year 2006 at the Turasha area. In spatial distribution analysis, hydrological drought severity was highest along the southern area of the catchment (around Lake Naivasha region). These are located within ASALs having low elevation. Eastern and north-eastern areas had the lowest severity for they are located within Aberdare ranges. This shows that the Malewa River catchment experienced hydrological drought from 1980-2018 with severity increasing along the flow path of the river. The results of the study are significant in assessment of drought reducing adverse impacts on water resources, people livelihood, and the ecosystem. Further research should be considered to assess and evaluate hydrological drought in the catchment by using remote senses method and other indices which using variables not included in this research such as temperature.

ACKNOWLEDGEMENTS

The authors would like to thanks the Centre of Excellence in Sustainable Agriculture and Agribusiness Management (CESAAM) for funding the research. Egerton University is also gratefully acknowledged for hosting the project.

.

REFERENCES

Ali, Z., Hussain, I., & Faisal, M. (2019). Annual Characterization of Regional Hydrological Drought using Auxiliary Information under Global Warming Scenario. Natural Hazards and Earth System Sciences Discussions, February, 1–20. https://doi.org/10.5194/nhess-2018-373

Becht, R., Odada, E., & Higgins, S. (2005). Lake Naivasha: Experience and Lessons learned. ILEC, 277–298.

Cilliers, J. (Jakkie), Donnenfeld, Z., Kwasi, S., Shah, S., & Welborn, L. (2018). Kenya to 2030 and beyond. SSRN Electronic Journal, August. https://doi.org/10.2139/ssrn.3256360/2019.05.029

Cheruiyot, M., Gathuru, G., & Koske, J. (2018). Quantity and Trends in Streamflows of the Malewa River Basin, Kenya. Journal of Environmental Science and Engineering, B (7), 18–27.https://doi.org/10.17265/2162-5263/2018.01.003

Du, T. L. T., Du Bui, D., Nguyen, M. D., & Lee, H. (2018). Satellite-based, multi-indices for evaluation of agricultural droughts in a highly dynamic tropical catchment, Central Vietnam. Water (Switzerland), 10(5). https://doi.org/10.3390/w10050659

Hao, Z., Singh, V. P., & Xia, Y. (2018). Seasonal drought prediction: Adavances, challenges, and future prospects. Reviews of Geophysics, 56, 108–141. https://doi.org/10.1002/2016RG000549

Kilavi, M., MacLeod, D., Ambani, M., Robbins, J., Dankers, R., Graham, R., Helen, T., Salih, A. A. M., & Todd, M. C. (2018). Extreme rainfall and flooding over Central Kenya Including Nairobi City during the long-rains season 2018: Causes, predictability, and potential for early warning and actions. Atmosphere, 9(12). https://doi.org/10.3390/atmos9120472

Koehler, J. (2018). Exploring policy perceptions and responsibility of devolved decision-making for water service delivery in Kenya's 47 county governments. Geoforum, 92(May 2017), 68–80. https://doi.org/10.1016/j.geoforum.2018.02.018

Kyambia, M. M., & Mutua, B. M. (2014). Analysis of Drought effect on Annual stream flows of River Malewa in the Lake Naivasha Basin, Kenya. Int J Cur Res Rev, 6(18), 1–6.

Moturi, N. F. (2015). A Hydrological Study of the Rising Water Level at Lake Nakuru. University of Nairobi.

Mulualem, G. M., & Liou, Y. A. (2020). Application of artificial neural networks in forecasting a standardized precipitation evapotranspiration index for the upper Blue Nile basin. Water (Switzerland),12(3).https://doi.org/10.3390/w12030643

Mwai, M. D. (2011). Effects of Climate Change and Human Activity on Lake Levels in the Kenyan Rift (Case Study Naivasha). University of Nairobi.

Nalbantis, I., & Tsakiris, G. (2009). Assessment of hydrological drought revisited. Water Resources Management, 23(5), 881–897. https://doi.org/10.1007/s11269-008-9305-1

Odongo, V. O. (2016). How climate and land use determine the hydrology of Lake Naivasha Basin [University of Twente]. https://doi.org/10.3990/1.9789036542333

Ogweno, P. L. (2009). Hydrologic Analysis of Malewa Watershed as a Basis for Implementing Payment for Environmental Services (PES). Jomo Kenyatta University of Agriculture and Technology.

Wambua, R. M. (2014). Drought Forecasting Using Indices and Artificial Neural Networks for Upper Tana River Basin, Kenya-A Review Concept. Journal of Civil & Environmental Engineering, 04(04).https://doi.org/10.4172/2165784x.1000152

Wambua, R. M., Mutua, B. M., & Raude, J. M. (2017). Characterization of temporal and spatial drought risk events using surface water supply index ((SWSI) in a tropical river basin. 2(2), 43–50. https://doi.org/10.15406/mojce.2017.02.00026

Zhang, Y., Cai, W., Chen, Q., Yao, Y., & Liu, K. (2015). Analysis of changes in precipitation and drought in Aksu River Basin, Northwest China. Advances in Meteorology, 2015(215840), 15. https://doi.org/10.1155/2015/215840

Zhu, N., Xu, J., Li, W., Li, K., & Zhou, C. (2018). A comprehensive approach to assess the hydrological drought of inland river basin in Northwest China. Atmosphere, 9(10), 1–17. https://doi.org/10.3390/atmos9100370