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Drought Forecasting Using Indices and Artificial Neural Networks for Upper Tana River Basin, Kenya-A Review Concept

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Abstract

Due to increased impact of drought on water availability at different scales there is need to understand droughts especially in upper Tana River basin which is a critical and largest water system in Kenya. There is need to correlate trends of drought as influenced by the climate variability of the present times. Drought frequency, duration and intensity in the basin have been increasing. The influencing hydro-meteorological parameters and their interaction are necessary in developing measures for mitigating impacts of droughts. It is important to have a timely review of drought definitions and fundamental concepts of droughts, classification of droughts, types of drought indices, historical droughts and artificial neural networks with special focus of Kenyan a basin. Out of the review, this paper draws conclusions where gaps for more focused research especially for a typical river basin in Kenya exist. By developing effective drought forecasting tool for on-set detection and drought classification and drought forecasting, information on decision making on matters of drought preparedness and mitigation programmes will be available for proper water resources management.

Keywords: Upper Tana River basin; Drought frequency; Artificial neural networks; Drought indices; Drought forecasting; Drought preparedness

Introduction

Drought is one of the critical natural disasters that adversely affect people, river basins, water resource systems and ecosystems [1]. It has been may be defined as a hydro-meteorological event on land characterized by temporary and recurring water scarcity. The magnitude of the drought is indicated by extend with which it falls below a threshold level over an extended period of time [2]. Drought has been identified as the most complex natural hazard since it is difficult to detect, develops slowly and impact on numerous aspects within a region [2]. Success of drought preparedness and mitigation depends upon timely information on its onset, and propagation in terms of temporal and spatial extent. Such information is usually obtained via effective and continuous drought monitoring using drought indices. The study of spatial and temporal drought conditions is fundamental in offering a wide range of solutions for control and management water resource systems. For instance, assessment of drought conditions is critical for planning water supplies, irrigation systems, crop and food security programmes, hydropower generation, water quality management and waste disposal systems [3].

Globally, drought has become more frequent and severe due to climate variability with different regions experiencing droughts at varying scales and times. Consequently, global impacts of drought on environmental, agricultural and socio-economic aspects need to be studied. As such, four distinct types of droughts namely; meteorological, agricultural, hydrological and socio-economic are recognised. These droughts have either direct or indirect impacts on river basins. The former include degradation of water resources in terms of quantity and quality, reduced crop productivity, increased livestock and wildlife mortality rates, increased soil erosion and land degradation, and increased plant diseases and insect attacks [4,5]. Severe drought impacts have been experienced in other regions of the world leading to food insecurity and general increase in world food prices. For instance, very notable recent droughts of 2009 and 2011 in Kenya adversely affected the agricultural sector where crop yields were drastically reduced. Due to the problems mentioned above, river basin managers often have a challenge of addressing water risks, conflicts and balancing economic development while at the same time maintaining reliable water resources [6].

African countries are among the most vulnerable to impacts of climate variability and drought. The impacts adversely affect the well-being of the population. These impacts are compounded by numerous factors such as poverty, high population density, and human diseases. This is expected to multiply the demand for water, food and forage for livestock within the area in the next thirty years [6]. In East Africa, it has been projected that water availability will decline due to drought. In addition, there is a likelihood of increased desertification due to decline in precipitation especially during the dry months [7].

Droughts in Kenya have impacted adversely on rain fed agriculture, water resources, hydropower generation and ecosystems. The agricultural sector alone which contributes to more than 51% of the gross domestic product (GDP) in Kenya [8] has been critically affected by frequent droughts. Over the past 50 years, Kenya has experienced at least one main drought per decade [9]. In addition, there has been a notable increase of drought in terms of frequency, duration and intensity. Any damage caused by drought on agriculture and water resources leads to famine, humanitarian crisis, rationing of water supply and decline in hydropower generation. Effective drought forecast allow water resource decision makers to develop drought preparedness plans. Such plans are critical for advance formulation of programmes to mitigate drought-related environmental, social and economic impacts. Therefore, accurate drought assessment and forecasting with an adequate lead time is paramount for formulation of mitigation measures in river basins [10].

Drought forecasting has received a new approach especially with

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the development of the Artificial Neural Networks (ANNs). An ANN is a computing system made up of a number of simple and highly interconnected information processing elements. Such a system has performance characteristics that resemble biological neural networks of human brain. ANN has numerous merits when used for data processing. The system processes information based on their dynamic state response to external input [2]. ANNs have the capacity to model relationships that are quite dynamic and can capture many kinds of relationships including non-linear functions which are difficult or impossible to determine using other approaches [11]. The ANNs have recently been used in water resources engineering (WRE). WRE comprises the study of hydraulics, hydrology, environment and geological related variables. Such variables are dynamic and exhibit non-linear and stochastic characteristics. These properties make WRE variables complex and difficult to determine due to spatial and temporal variations. Thus due to their advantages, ANNs provides effective analytical techniques in modelling and forecasting non-linear and dynamic time series variables in WRE such as drought [11].

At present, most basins in Kenya have limited or lack of adequate quantifiable information of drought occurrence, frequency and severity. In addition, there is lack of sufficient and appropriate drought assessment and forecasting methods. Drought models can be used to estimate and forecast drought conditions on a spatial and temporal domain. To prepare for effective mitigation of drought risks in Kenya, evaluation and forecasting of drought conditions is vital. Thus, this research reviews drought assessment and forecasting methods for upper Tana River basin. Both the application of Drought Indices in conjunction with Artificial Neural Networks (ANNs) has been explored. In order to make informed decision making on matters relating to water resources, agricultural production, and hydropower

generation, data on spatial and temporal characteristics of drought at a basin scale is required.

Types and Propagation of Droughts

There are four main types of droughts as described by [12]. The four types of drought are: the Hydrological, Meteorological, Agricultural and Socio-economic droughts. The propagation of hydrological and agricultural drought originates from meteorological droughts which develop from changing phenomena within the hydrological cycle (Figure 1). The main droughts maybe categorized further into other types of drought. The hydrological drought is associated with effects of deficit precipitation on surface and sub-surface water resources. Its characteristics which are defined by magnitude, severity, duration and frequency can be studied at a basin scale. Hydrological drought may be categorized into surface and ground water droughts. The Surface Water Drought (SWD) is caused by direct reduction in precipitation that subsequently leads to low surface runoff. The SWD is also caused indirectly by reduced groundwater discharge to surface water resources. This may be attributed to reduced flow of groundwater into surface flow in influent rivers and springs. In some instances, increase in groundwater on specific areas within a basin for an effluent river contributes to the SWD. The common indicators of SWD are reduced river flows, low water levels in reservoirs and lakes. It is not necessarily a naturally induced event. It may result from a combined interaction of meteorological drought, water resources development infrastructure and operational management.

On other hand, the Groundwater Drought (GD) is a hydrological type of drought caused by significantly reduced recharge. The recharge normally takes place through permeation and inflow from sub-basins [13]. The GD may be assessed by measuring the volumetric ground
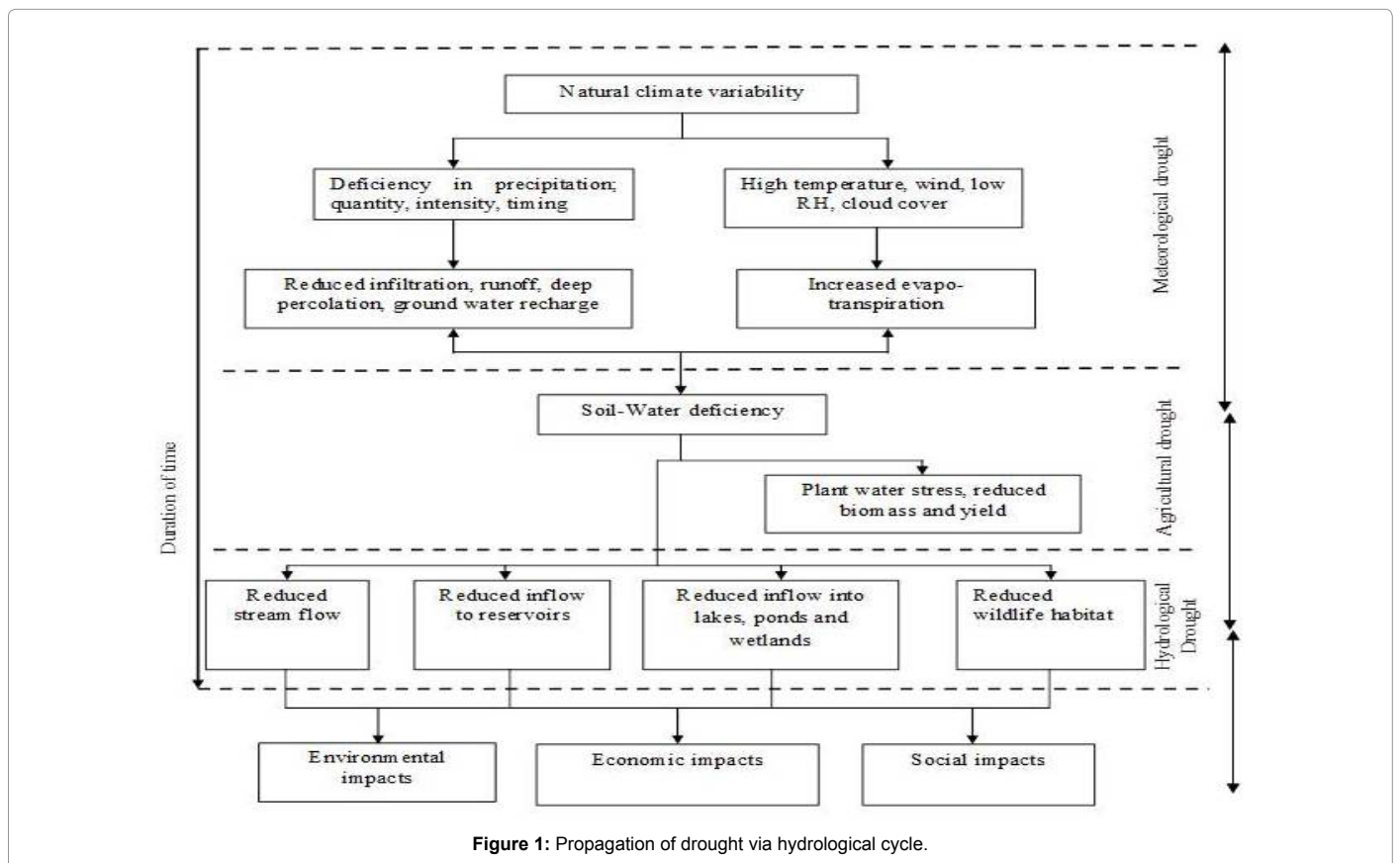

Figure 1: Propagation of drought via hydrological cycle.

water storage. However, these data are not readily available in most river basins. Thus, aquifer level is considered to be a better indicator than the volumetric ground water storage. The GD can also be determined from the evaluation of its secondary effects such as base flow into rivers.

Ground water is a vital source of water supply especially in river basins where surface water exhibits a high temporal variability. In some cases, groundwater availability is used as an indicator of relative drought risk. The meteorological drought which is the most commonly known drought is associated with long time intervals of low or no precipitation and increased temperature. The deficiency in rainfall leads to low infiltration, decreased runoff and ground water recharge. On the other hand, high temperatures lead to changes in wind characteristics, low Relative Humidity (RH), cloud cover and increased evapo-transpiration.

Agricultural drought links meteorological or hydrological drought to agricultural impact. Agricultural droughts impact negatively on farming systems whenever they occur. Their impacts are normally two-fold; environmental and economic impacts. The agricultural drought is a type associated with low agricultural production, decline in output from agro-processing industries and unemployment incidents in the agricultural sector.

Effect of Global Warming on Droughts

Global warming is caused by two main aspects; first is the climate variability which slows down the global circulation of ocean currents due to moderated differences in temperature between tropical and temperate sea water bodies. Secondly, the ice melting in the Polar Regions implying cold water entering the oceans and drifting into the tropics affect global warming. The ice melting flowing and flowing leads into cooling of tropical oceans whose effect is picking significantly of low moisture by the prevailing winds [14]. The wind takes with it the little moisture picked along its course. Global warming influences the rate and timing of evapo-transpiration. Due to global warming, some regions in the world are likely to get wetter while those that are already under dry conditions likely getting drier. Thus, global warming is likely to increase drought occurrence and expansion of the dry areas [15]. For instance, the regions in southern Africa, the Sahel region of Africa, southern Asia, south west of United States of America have generally been getting drier over the years [16]. In addition, water resources are expected to decline by up to 30% in the affected areas. These notable changes will occur partly because of an expanding atmospheric circulation pattern. This pattern is called Hadley cell in which warm air in the tropics rise, losses moisture to the thunderstorms, and descends in the sub-tropics as dry air. During this process, jet streams shift to the higher latitudes, and storm patterns shift along with them leading to expansion of arid and semi-arid lands [15].

Causes of Drought in Kenya

Climate variability and global warming that affect atmospheric circulation play a fundamental role in influencing drought occurrences in Kenya. When the Indian Ocean surface water temperature is abnormally low, it leads to the cooling of South-East and North-East trade winds. These two air masses converge near the equator within a region called Inter-Tropical Convergence Zone (ITCZ). When the winds are cool, they do not pick up enough moisture from the ocean water surface and thus lead to erratic rainfall patterns in eastern parts of Kenya [17]. On the western parts of Kenya, the Atlantic and Congo prevailing winds bring the same drought conditions in case they are abnormally too cool to pick sufficient moisture. Other factors leading to increase in drought frequency and severity include poor land use

practices and deforestation, destruction of catchment areas. Some of land use patterns combined with certain cultivation methods contributes to the global warming through atmospheric carbon changes. Most farmers in Kenya are not properly controlling on-site soil detachment and therefore most farmland is exposed to soil erosion. The fertile top-soil is continuously being eroded due to agents of erosion mainly water and wind. Due to the erosion, most of the rain water does not infiltrate into the soil and instead flows as excess runoff. This leads to depletion of soil moisture and plant nutrients.

Destruction of catchment areas and deforestation is another critical contributor of drought in Kenya. Generally the forest cover has decreased by 72% between the years 2000 and 2007 [17] to 6.1% of the total land mass in 2011 [18]. Among the five main water towers in Kenya, the Mau Complex lost the highest with 70% of the forest cover destroyed within the period. The chief causes of deforestation are the need to expand agricultural land, uncontrolled exploitation of forest resources, overgrazing and establishment of new settlements on forest land as accelerated by increasing population pressure.

Historical Droughts in Kenya

Kenya has experienced approximately 30 major droughts in the last 100 years according to [7]. Over 70% of the natural disasters in Kenya are associated with droughts and extreme weather conditions. The severity and frequency of droughts in the country have been increasing over the years. Some of the recognizable droughts include the 1952-1955, 1973-1974, 1983-1984, 1992-1993, 1999-2000 and 2009-2011 droughts [7]. The occurrence of drought in Kenya has led to major negative impacts on people's livelihoods. In addition, huge resources which would have otherwise been used for other socio-economic projects are normally diverted to cater for food insecurity crises and water scarcity (Table 1).

Description of upper Tana River basin

The upper Tana River basin has an area of 17,420 km^2 and is part of the larger Tana River basin, which is the largest river system in Kenya with an area of 100, 000 km^2 [19,20]. Its forest land resources located along the eastern slopes of Mount Kenya and Aberdares range have a critical role in regulating the hydrology and hydro-power generation within the entire basin [21]. The upper Tana River basin lies between latitudes 00^0 05' and 01^0 30' south and longitudes 36^0 20' and 37^0 60' east (Figure 2). The basin is fundamental in influencing the ecosystem downstream.

Impacts of droughts in upper Tana River basin

Drought has impacted in numerous aspects within the past period. It has led to degradation of water resources in terms of quality and quantity. Due to increased evepo-transpiration and reduced runoff as a result of decreased precipitation, the quantity of surface and sub-surface water has declined. The upper Tana River basin has been negatively affected by notable droughts such as the La Niña of 1999 to 2000, and 2008 to 2009 [22]. These led to severe water scarcity. Concentrations of sediment and chemicals have increased as there is low quantity water that can dilute these substances originating within the basin. Agricultural production and forest resources have reduced since most farming is rain-fed [20]. Due to low stream flow, hydropower generation has declined and power rationing especially during specific seasons when drought severity affects water levels in Seven-Folk dams within the basin. The indirect impacts of drought are immense and adversely affect socio-Economic Development within the basin.

Drought Assessment Indices

Drought indices or models are used for assessment of occurrence

Period (years)	Areas significantly affected	Remarks on the drought effects
1883	Coast	Caused wrosk famine in 30 years
1889-1890	Coast	One year of drought and femine
1894-1895	Coast	Information on distinct effects not available
1896-1900	Countrywide	Three consecutive rain seasons failed causing human deaths
1907-1911	Lake victoria, Machakos, Kitui and Coastal	Minor food shortages
1913-1919	Eastern and coastal areas	Impacts increased by war
1921	Coastal	Dry year recorded at coast
1925	Rift valley, central and coastal	Food shrtage, crop and livestock losses
1938-1939	Norhern, rift valley and central regions	Loss of livestock, deaths occured, Lorian swamp dried up
1947-1950	Central and coastal lands	Very severe droughtespecially in coast region
1952-1955	Eastern, central, coast, nyanza, western and rift valley regions	Food and water shortages
1960-1961	Eastern, rift valley	Caused Cattle deaths
1972	Widespread countrywide drought	Water shortage livestock deaths
1973-1974	Most areas in Kenya	Human and livestock deaths
1974-1976	Eastern, nothern, and central regions	Heavy livestock losses, food and water shortages
1980	Central, eastern, western and coast	Low crop production, water shortages
1981	Eastern	Famine and water shortage
1983	Country wide	Water shortages, human and livestock migration
1984	Central, rift valley, eastern, north eastern	Huge food shortages
1987	Eastern and central	Severe food shortages
1992-1994	Norhern, central and eastern	Moderate food shortages,
1999-2000	Countrywide	Deficit food supply, interuption of electricity supply, water scarcity
2010-2011	Eastern, central, coastal,north eastern	Food and water deficit

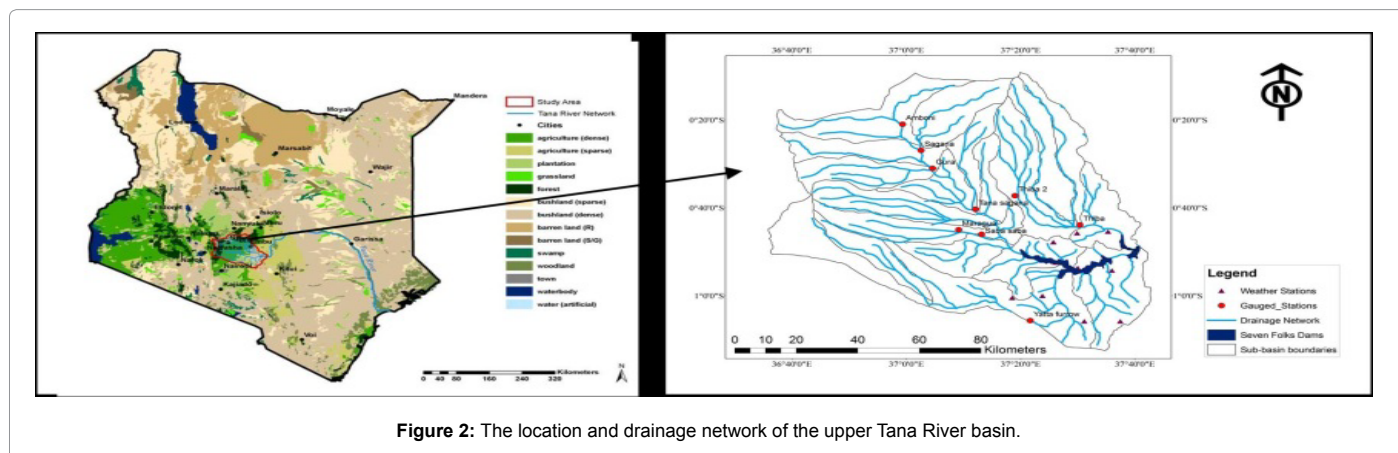**Table 1:** History of drought occurrence in Kenya. Source [6,17]

Figure 2: The location and drainage network of the upper Tana River basin.

and severity of droughts. The Drought Indices (DIs) were developed for specific regions using specific structures and forms of data input. There are two broad categories of drought indices; satellite based and the data driven drought indices [23].

Satellite based drought indices

The satellite Remote Sensing (RS) may be defined as the science and art of obtaining information of points, objects, areas or phenomena through analysis of data acquired by a sensor, which is not in direct physical contact with the target of investigation [24]. The RS provides an aerial view of land, water resources and vegetation cover. This technique gives a spatial and temporal context of measuring drought and has the ability to monitor vegetation dynamics over large surface areas. Currently, there is a considerable interest in collecting remote sensing data at multiple time scales. Such data is used to conduct a near real time information management [25]. Examples of satellite drought indices are the Vegetation Condition Index (VCI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Water Supply Vegetative Index (WSVI) and Normalized Difference Drought Index (NDDI).

Vegetative condition index: The Vegetative Condition Index (VCI) is computed from an advanced accurate and high resolution radiometer radiance data. This data is usually adjusted to match land conditions, climate, and ecology and weather conditions. The index is used for drought detection and trend tracking. It can be used to determine the time of on-set of drought, intensity, duration and associated impacts on vegetation [26]. The main challenge with the use of VCI is that it is used during dry seasons and the areas under consideration should have significant vegetation cover.

Normalized difference vegetative index: The Normalized Difference Vegetative Index (NDVI) is a satellite data driven index that is used to monitor ground vegetation which could be linked to drought conditions. The index can filter out green vegetation using Landsat Multispectral Scanner (MSS) digital data [27]. It is normally expressedas a function of the near-infrared and red bands given as:

$$NDVI = \frac{NIR - R}{NIR + R} \qquad (1)$$

Where $DDVI$ is the Normalized Difference Vegetative Index, NIR is the near-infra red band and R is the red band. The $NDVI$ is the most commonly used satellite based index. One advantage of the $NDVI$ is that it has distinct values ranging from -1 to 1 with zero taken as an approximate value denoting absence of vegetation. The negative $NDVI$ values indicate a non-vegetative surface while values closer to 1 represent dense vegetation [27].

Normalized difference water index: The Normalized Difference Water Index (NDWI) is determined based on leaf water content and vegetative type. Its value ranges from -1 to +1. The higher NDWI value the higher the vegetative water content and the higher the proportion of vegetative cover. The values of NDWI are computed by processing the satellite data in which green and near infra-red bands are used as per the relation:

$$NDWI = \frac{G - NIR}{G + NIR} \qquad (2)$$

Where $NDWI$ is the normalized difference water index, G is green band and NIR is near infra-red band. The $NDWI$ is very sensitive to soil moisture content, vegetation cover and leaf moisture content [28]. Although NDWI is used for drought detection, it is sometimes affected by land cover and pests and diseases on vegetation. However, it has an advantage of detecting drought more effectively as compared to the $NDVI$ [29].

Water supply vegetative index: The Water Supply Vegetative Index (WSVI) is a drought indicator which is based on relationship between the NDVI and the land surface temperature [30]. The higher the values of WSVI, the higher the moisture levels, canopy temperature and the lower the NDVI. On the other hand, lower values of WSVI give an indication of extreme drought. The WSVI values range from -4 for extreme drought to +4 for highly moist conditions [30]. The values of WSVI are obtained by analyzing the effect of vegetation on the reflection of red, near infra-red and thermal bands. This index is more effective in drought detection under the conditions when the NDVI is greater than 0.3. Combining the WSVI and the NDVI in drought detection provides a more sensitive approach and better results [31].

Normalized difference drought index: The Normalized Difference Drought Index (NDDI) is used for detection of drought by combining the outputs of NDWI and NDVI derived from satellite data [29]. The values of the two indices decrease with decrease in slope gradient of the cumulative precipitation. However, NDDI values decrease more abruptly during dry period than the NDVI. Thus, NDDI is more sensitive to water content and a better index for drought detection than NDVI. The NDDI has been noted to detect drought conditions on grassland than NDVI [29]. The NDDI values can be computed from the following relation:

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \qquad (3)$$

Where NDDI is the Normalized difference drought index, NDVI is Normalized Difference Vegetative Index and NDWI is Normalized Difference Water Index.

Data driven drought indices

The Data Driven Drought Indices (DDDI) uses a single or a combination of hydro-meteorological variables as input parameters to assess drought intensity, duration, severity and magnitude. Some of the data driven indices as reported by [23] include; the Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Surface Water Supply Index (SWSI), Aggregated Drought Index (ADI), Effective Drought Index (EDI), Reclamation Drought Index (RDI), Crop Moisture Index (CMI) and Murger Index (MI). The indices use various input data such as rainfall, temperature, catchment soil moisture content, snow water content, stream flow, storage reservoir volume, and potential evapo-transpiration in different combinations [12]. However, the suitability of the indices and their testing for Kenyan conditions has not been adequate, and therefore Kenya does not have generic indices for drought forecasting.

Standard precipitation index: The Standard Precipitation Index (SPI) was developed by [31] to quantify the rainfall deficit and monitor drought conditions within Colorado, USA. For calculation of SPI, long-term historical precipitation record of at least 30 years is integrated into a probability distribution function which is then transformed into normal distribution. The index requires less input data than most other drought indices and this make it flexible for wide applications [32-34]. The SPI has several advantages which make it more applicable in many river basins. First, it requires precipitation only as the input data and thus makes it ideal for river basins that do not have extensive hydrological data records. Secondly, its evaluation is relatively easy since it uses precipitation data set only. Thirdly, it is a standardized index and this makes it independent of geographical location as it is based on average precipitation values derived from the area of interest. In addition, the SPI exhibits statistical consistency, and has the ability to present both short-term and long-term droughts over time scales of precipitation variation [23]. However, the SPI has some disadvantages in its use as a drought assessment tool. First, it is not always easy to find a probability distribution function to fit and model the raw precipitation data. Secondly, most river basins do not have reliable time-series data to generate the best estimate of the distribution parameters. The SPI can be used to present significant drought conditions within a river basin. However, to identify key dry periods, it is important to analyze data for time scales greater than 6 months. This is because the high frequency of SPI values at shorter time scales conceal the critical dry periods. For time scales shorter than 6 months, there is insignificant autocorrelation while for time scales greater than 6 months, the autocorrelation increase significantly [23]. SPI drought severity classes as suggested by [31] are s shown in (Table 2).

Palmer drought severity index: The Palmer Drought Severity Index (PDSI) was developed based on a criterion for determining the beginning and end of drought or wet period spell [35]. It is a simple monthly water balance model which requires rainfall, temperature and catchment soil moisture content as input parameters, and can give various categories of drought severity (Table 3). This tool applies a concept of supply and demand over a two-layer model. In this concept, the difference between the quantity of precipitation needed to maintain a natural water balance level and the actual precipitation is determined. The index does not consider stream flow, reservoir water

Threshold Value (s)	Drought Classification
2.00 or more	Extremely wet
1.50 to 1.99	Very wet
1.00 to -1.49	Moderate wet
0.99 to -0.99	Near normal
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
-2.00 or less	Extreme drought

Table 2: Drought conditions based on SPI.

Value of Index (s)	Drought Classification
4.00 or more	Extremely wet
3.00 to 3.99	Very wet
2.00 to 2.99	Moderate wet
1.00 to 1.99	Slightly normal
-0.50 to -0.99	Incipient wet
0.49 to -0.49	Near normal
-0.50 to -0.99	Incipient drought
-1.00 to -1.99	Mild drought
-2.00 to -2.99	Moderate drought
-3.00 to -2.99	Severe drought
-4.00 or less	Extreme drought

Table 3: Classification of drought based on PDSI.

Threshold Value (s)	Drought Classification
4.00 or more	Abundant Water
3.99 to 1.99	Wet
2.00 to -0.99	Near normal
-1.00 to -1.99	Incipient drought
-2.00 to -2.99	Moderate drought
-3.00 to -3.99	Severe drought
-4.00 or less	Extreme drought

Table 4: Classification of drought based on SWSI.

balance, and other hydro-meteorological variables that influence the drought [36,37]. Several coefficients which are calculated to define local hydrological characteristics influenced by precipitation and temperature are calculated for use in PDSI. These coefficients depend on soil water capacity of the principal layers. The original PDSI has been modified to yield Palmer Hydrological drought Index (PHDI). The original PDSI does not take into account the human-induced impacts on water balances such as irrigation. However, the new version is a model mainly for evaluation and monitoring of water supply. The model has been applied on a number of catchments for detecting and planning of drought relief programmes. The PDSI has some limitations or disadvantages as a drought index. In some regions, the PDSI assumes that all the precipitation is rain. This may sometimes give misleading values in regions which experience winter season and also on high elevation areas. In addition, it under-estimates runoff since it assumes that overland flow occurs after all soil layers have been saturated. The other disadvantage is that the PSDI responds slowly to developing or ending of a drought event [26]. Lastly, the original model is more suitable for agricultural drought than hydrological drought based on the applied time series. The original PDSI and crop moisture index (CMI) have some advantages and shortcomings. The major advantages of the original PDSI and CMI include the two indices provide decision makers with measurement of abnormality of recent weather condition for a basin or region, it provides an opportunity to place current drought condition on a historical perspective and it has the capacity to express historical drought conditions on spatial and temporal domain. The shortcomings of the PDSI is that the index use a two-layers in water balance computation and this is perceived as over-simplification and may not offer accurate values, potential evapo-transpiration in PDSI is computed based on Thornthwaite method which is a poor method of estimating the variable and the original tools considered coarse resolution of land use and land cover parameters of 700-100,000 km² yet the land use changes within such a large area may be great.

Surface water supply index: Surface Water Supply Index (SWSI) was developed in for Colorado USA, as an indicator of surface water or moisture levels [38]. The index requires input variables which include; snow water content, stream flow, rainfall and storage reservoir volume.

Once the index is calculated using these input variables, the drought severity is then established at various levels (Table 4). Normally the snow water content, rainfall and storage reservoir volume are used for computing the SWSI values for winter season. However, during the summer season, stream flow substitutes snow water content. At a basin scale, the SWSI values are determined from monthly catchment average values of rainfall, reservoirs, snow water content and stream flows measured at stations within a river basin. One of the advantages of the SWSI is that it gives a representative measurement of surface water supplies across the river basin. The surface water drought index is unique for specific basins or regions. It requires long term record data for its calibration and thus may be limited in basins that lack sufficient data. Another limitation of the SWSI is that any additional change in the water management within a basin calls for modification of its algorithm. The change may be due to an addition of new water reservoirs and flow diversions that based on their weights, require to be accommodated in the algorithm [39]. Thus, it is difficult to have a homogeneous time series of the index for numerous basins.

Effective drought index: This index is based on effective precipitation. In order to derive the effective precipitation, different methods may be adopted. These methods may include direct method, drum culture technique, empirical methods and the curve number technique. To get approximate results, the resulting values from each method will be averaged to yield Effective Precipitation (PE_m). The effective drought severity index (EDI) can then be computed using monthly time step data for the weather stations within the study area [40]. The EDI development involves four main steps. The first step is calculation of effective precipitation using the relation:

$$EP_p = \sum_{m=1}^{N} \left(\frac{\sum_{i=1}^{m} PE_m}{m} \right) \tag{4}$$

Where EP_p is effective precipitation parameter (mm), N is duration of the preceding period (months), m is total period before the current month (months) and PE_m is the effective precipitation in m-1 months before the current month (mm). From the EP_p, both the mean and the standard deviations of the monthly values are determined. The resulting time-series EP is used as inputs to calculate its deviation from the mean. Then the return to normal precipitation (RNP) values is computed from the relation:

$$RNP = \frac{DEP}{\sum \left(\frac{1}{N} \right)} \tag{5}$$

Where RNP is return to normal precipitation (mm), DEP is EP_p deviations from the mean (mm) and N is previous period (months). From the calculated RNP, the EDI is derived from the relation:

$$EDI = \frac{RNP}{Std(RNP)} \tag{6}$$

Where $Std(RNP)$ is Standard deviation of a particular month's RNP values. Using the computed EDI values, the severity of the drought can be categorized based on the thresholds and classification (Table 5) adopted from [2].

Aggregated drought index: The Aggregated Drought Index (ADI) or Non-linear Aggregated Drought Index (NADI) is used for determination of three categories of drought; hydrological drought, agricultural and meteorological droughts. The specific drought is determined by selectively inserting input variables required into the model. This index can use the following input variables; rainfall, stream

Threshold Value (s)	Drought Classification
2.5 or more	Extreme drought
-1.50 to 2.49	Severe drought
-0.7 to -1.49	Moderate drought
-0.69 to 0.69	Near normal

Table 5: Drought severity based on EDI.

Value of Index (s)	Drought Classification
>-0.84 to ≤0.88	Near normal
>-1.64 to ≤-0.84	Moderate drought
>-2.27 to ≤-1.64	Severe drought
≤-2.27	Extreme drought

Table 6: Drought classification based on NADI.

flow, potential evapo-transpiration, soil moisture content, snow water content and reservoir storage volume [41]. The Principle Component Analysis (PCA) is used as a numerical method for construction of ADI using input data sets. The PCA is used to transform spatially correlated series data from a basin into two sets of orthogonal and uncorrelated functions. The principle components are used to express the original p-variable data set in terms of uncorrelated component Z_j, where $1<j>p$. The p-mode is used where the analysis explains temporal fluctuations of the input variables of a basin. The calculation of principle components involves construction of a pxp symmetric correlation matrix C_x. The matrix gives the correlation between the original data where p is the number of variables. This matrix is expressed using the relation:

$$C_x = E\left\{(x-u_x)(x-u_x)^T\right\} \qquad (7)$$

Where C_x is correlation matrix, x is vector observation data, u_x is mean value of x and T is the transpose matrix.

The correlation matrices developed undergo PCA via application of eigenvectors. The eigenvectors are unit vectors that establish the relationship between the principle components and standardized data. A unit vector may be derived from the relation:

$$Z = X \times E \qquad (8)$$

Where Z is nxp matrix of principle components, X is nxp matrix standardized observation data and E is pxp matrix of eigenvectors. The first PC to represent ADI is determined and normalized by use of its standard deviation function defined by:

$$ADI_{i,k} = \frac{Z_{i,l,k}}{\sigma_k} \qquad (9)$$

Where $ADI_{i,k}$ is ADI value for month k in year , $Z_{i,l,k}$ is the first PC for month k in year i and σ_k is the sample standard deviation overall years for month k. To determine ADI thresholds, the empirical cumulative distribution of the above ADI values are constructed. The ADI thresholds are then calculated using empirical cumulative distribution function and used to classify drought conditions based on the thresholds stated in Table 6.

The deciles index: The deciles index was developed by [42] and it has found a wide application in some regions such as Australia [2]. The deciles use long term monthly rainfall record by ranking from the highest to the lowest and then constructing a cumulative frequency distribution. This distribution is then partitioned into ten sections called deciles. One major limitation with the deciles approach is that long rainfall record of 30-50 years is required for accurate calculations [43]. The first decile is the precipitation value not exceeded by the lowest 10% of all precipitation values within the period under study. This is followed by the second decile that falls between the lowest 10

and 20% in that order. By comparing the amount of precipitation in a certain period with a long term cumulative distribution of precipitation amount in the mentioned period, the severity of the drought can be assessed.

Soil moisture deficit index (SMDI): The available water content (AWC) of the soil may be simulated using the ANNs and compared with values from other modelling or field data. For instance, Soil and Water Assessment Tool (SWAT may be used with Historical weather data as input variables into Spatial Analysis Neural Networks (SANNs) to simulate soil moisture [44]. The moisture content in soil can then be correlated with NDVI for different land use and cover types such as agriculture, grassland and forest. The Soil Moisture Deficit Index (SMDI) can be modelled using the ANNs model using precipitation, temperature and soil type as input data by applying the following function [44]:

$$SMDI_j = 0.5 \times SMDI_{j-1} + \frac{SD_j}{50} \qquad (10)$$

Where $SMDI_j$ is soil moisture deficit index for j^{th} week, j is the jth week (range 1 -52 weeks), $SMDI_{j-1}$ is the soil moisture deficit for $(j-1)^{th}$ week and SD_j is soil moisture deficit (%) for time j^{th} week of a particular year. The SMDI values for any week is calculated and optimized to range between -4 and +4. This marks the drought range of extreme drought to wet conditions. The SMDI values may be computed for four different levels using soil water available at specified depths such as; 0.3 , 0.6, 1.2 and 1.8 m. These soil depth values may be represented as SMDI-1, SMDI-2, SMDI-3 and SMDI-4 respectively to represent potential of a crop to extract water from root zone depending upon stages of most agricultural crops growth and crop type [16].

Standardized runoff index (SRI): This is an index which was developed based on concept of standardized precipitation index [45]. It was derived from hydrologic a process that determines seasonal reduction in stream flow due to effect of climate. It is mostly used to supplement SPI for study of hydrological droughts.

Drought Forecasting Models

Development in forecasting and early warning of the drought phenomena is increasingly being applied in many regions in the world. This is being done to help mitigate consequences of drought on vulnerable river basins. Different drought modeling and forecasting techniques are in use today. Some of the common drought forecasting models include; Seasonal autoregressive integrated moving average model (SARIMA), Adaptive Neuro-fuzzy inference system, Markov chain model, Log-linear model and Artificial Neural Network (ANN) model.

Artificial neural network models for drought forecasting

An artificial neural network (ANN) model is an information processing system developed with a structure and operation similar to that of a human brain [46]. The model has been improved over time by various calibration techniques. With sufficient amount of data and complexity, the ANN model can be adapted to establish any correlation between series of independent and dependent variables [47]. One of the advantages of the ANN modelling technique is that the definition of physical processes need not be done [2,48]. This property makes it appropriate in processing large and complex data sets, including that of drought forecasting.
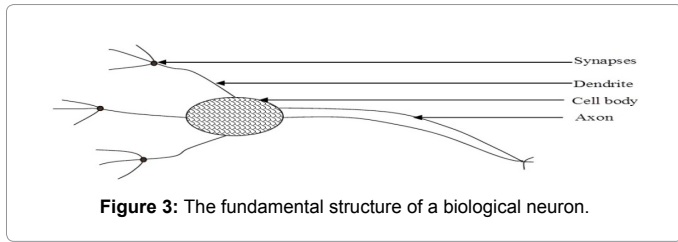
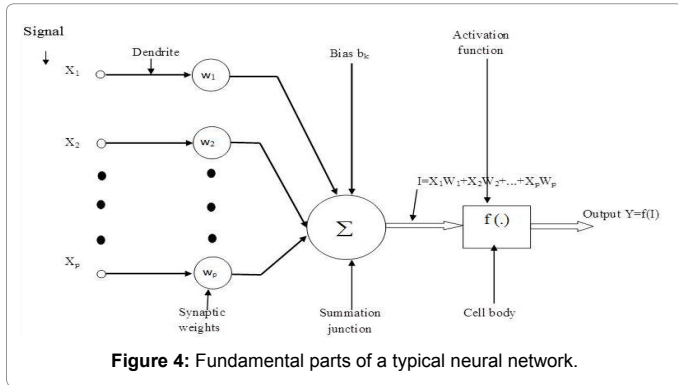**Figure 3:** The fundamental structure of a biological neuron.

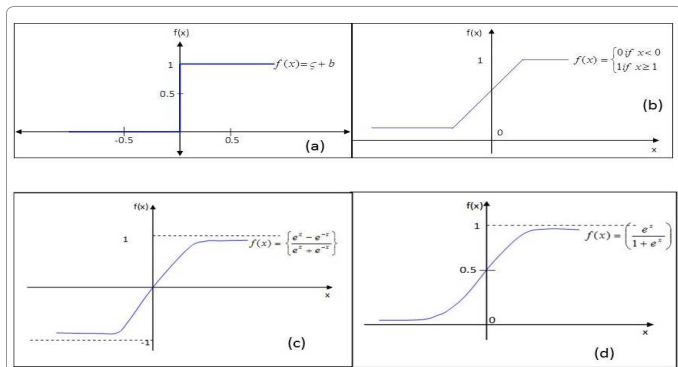**Figure 4:** Fundamental parts of a typical neural network.

Figure 5: Types of ANN activation functions.
a) ANN step function b) ANN non-linear Sigmoidal c) Hyperbolic tangent function d) Linear activation function.

Concept of ANN model

The ANN model processes information through an elaborate network of neurons that are linked together. It simulates outputs based on certain inputs by a working principle resembling that of human brain where in the human brain; the neuron receives a set of input signals and generates outputs. The nervous system of human beings is represented by a number of architectural structures that range from simple to complex structures. Whether the structures are simple or complex, the systems consist of neurons or neural cells as the chief building blocks as given in Figure 3.

The neuron has four main parts; the cell body, synapse, dendrites and the axon. A neuron receives an input signal and transmits it to the cell body where it is processed and then an output is produced. In a biological neuron, both the inputs and the outputs are electrical signals. The input signals are normally passed to the neuron through the dendrites while the output signal is released through a single channel called axon. On every dendrite contact point, there is a part called synapse which works like a valve to open or close for signal flow. This synapse allows the input signals to pass through or stops some signals based on the conditions of operation of the system [49].

The ANN model is similar to a biological neuron in that it has multiple input channels, data processing unit, and output channels called dendrites, cell body and the axon respectively as represented in Figure 4. The input signals $(X_1, X_2, \ldots, X_p)$ are passed to the neuron through the dendrites that represent different input channels. Each channel has its own weight referred to as connection weight denoted as $W_1, W_2 \ldots, W_p$. The weights are very critical since they allow for collection and processing of signals based on their magnitude and effects on input functions. If a weight function gives a non-zero value at the synapse, it is allowed to pass through the cell body. Otherwise, if it has a value of zero, it is not allowed to pass the cell body. All the conveyed signals are normally integrated by summing up all the input [39]. The integration of signals is achieved by application of a mathematical model referred to as activation function, within the cell body to generate an output signal. According to [39], the relationship between the input and output signal within an ANN model is represented using the function given as:

$$Y = f(I) = f\left(\sum_i^p W_i X_i + b_k\right) \quad (11)$$

Where X_i is the input signal i, W_i is weight attached to the input signal i, P is the number of input signals, b_k is bias at the cell of the body, Y is the output, f is activation function. Numerous activation equations or functions can be used within the neurons. The most common functions used in the ANN models include; the step-function, non-linear sigmoidal, hyperbolic tangent and linear activation functions [50,51]. These functions are represented in Figures 5a-5d.

Classification of ANN model architectures: Numerous ANN model architectures have been developed and applied in drought research. These ANN architectures are grouped into three broad categories; feed forward, recurrent and hybrid networks. The information flow in feed forward network propagates only in one direction. It moves from input layer to the output layer. The feed forward ANN architecture is further subdivided into Multilayer Perceptron (MLP), Single Layer Feed Forward (SLFF), Support Vector Machine (SVM), Generalized Regression Neural Network (GRNN), Radial Basis Function (RBF) and Neuro-fuzzy (NF) networks (Figure 6).

The single-layer network has only one input layer that links directly to the output layer (Figure 7a). In the multilayer ANNs, one or more hidden layers are found between input and output layers (Figure 7b).
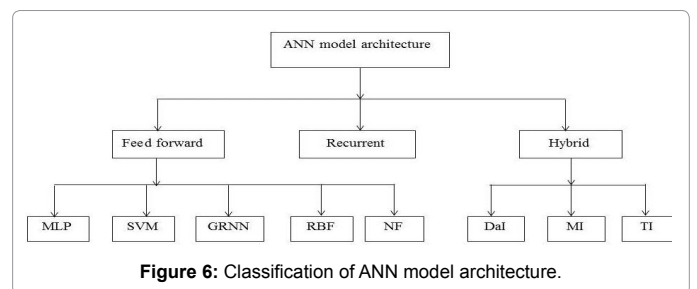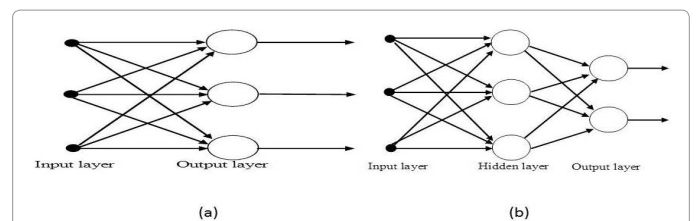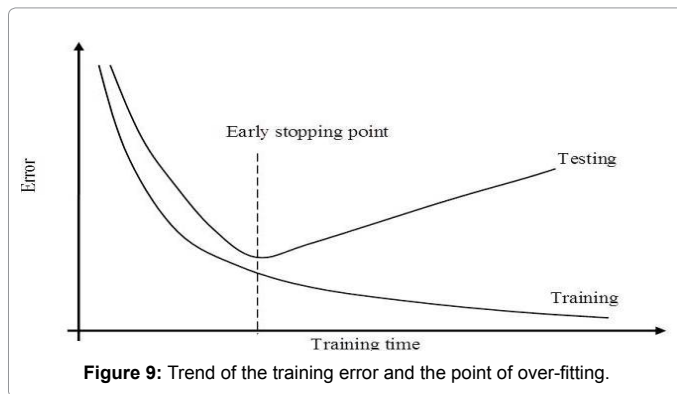

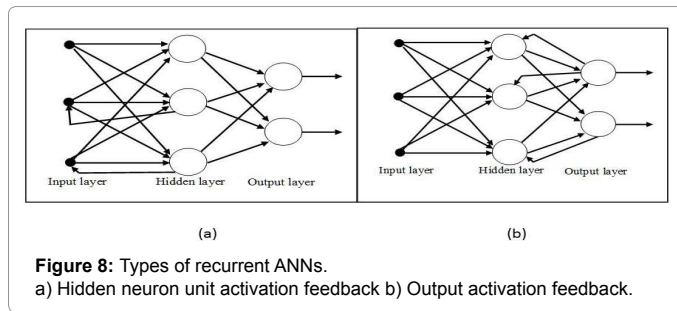
Figure 6: Classification of ANN model architecture.

Figure 7: Feed forward artificial neural networks.
a) Single-layer feed forward ANNs b) Two-layer feed forward ANNs.

Figure 8: Types of recurrent ANNs.
a) Hidden neuron unit activation feedback b) Output activation feedback.

Figure 9: Trend of the training error and the point of over-fitting.

By addition of one or more hidden layers, the network can model more complex non-linear and linear functions [52].

For the recurrent networks, information may propagate in forward and backward directions through feedback loops. In this network, the output layer neurons may transmit back the output to input and or hidden layer neurons. At least one feedback loop must exist in the network. The hidden neurons unit activation or the output values are fed back into the network as inputs (Figure 8). These models exhibit a dynamic characteristic when modeling data that depends upon different temporal and spatial resolutions [53]. The feedback links layers whose state vary with time, and has adjustable weights. This makes the neuron to depend on both the current input signal and also the previous state of the neuron [54]. The third hybrid architecture network is subdivided into Data Intensive (DaI), model intensive (MI), and Techniques Intensive (TI) networks normally applied to solve complex modeling of hydrological and environmental systems.

Drought forecasting using ANN model: The ANN modelling has been greatly used for drought forecasting in the world [55,56]. For instance, it has successfully been used in India to forecast drought in Kansabati River Basin [51]. For the Kansabati basin, two ANN models were applied and included the Recursive Multi-Step Neural Network (RMSNN) and the Direct Multi-Step Neural Network (DMSNN).These were used to forecast SPI values across the river basin. The results showed that the RMSNN performed best in one month lead time forecasting while the DMSNN was the best in four month lead time forecasting [51]. The RMSNN and the DMSNN were also applied in forecasting of Palmer Hydrological Drought Index (PHDI) in Italy. For this case study, the findings showed no significant differences between the outputs of RMSNN and DMSNN when used for forecasting of PHSI [56].

ANN data pre-processing: Prior to the use of the data within the ANN environment, it should be pre-processed. This is initial data transformation processes that convert data into a form compatible with the ANNs [57,58]. This process involves data normalization or standardization and is applied to speed up training process of the ANN. By normalizing the data, effect of outlier entries are reduced. Normalization transforms the input features of data into the same range of values thus minimizing bias within the ANN. In addition, the training period is reduced since each feature has the same range of data values and is treated the same. There are numerous ways of normalizing the data. The most common one is the statistical standard deviation for each feature across input data. The usual way is to obtain a standard deviation and mean from a training data. The output of ANNs is always in the normalized data format. These values are then de-normalized to give meaningful output by reversing the normalization process [52].

ANN learning processes

ANNs function through a learning process. A learning process refers to the property of an ANN to possess processing units capable of changing its input and or output characteristics as a result of changing environment, values or levels based on historic data [11]. These learning processes are categorized into three classes; supervised learning unsupervised learning and reinforcement learning.

Supervised learning: In supervised learning, there are is a set of training data. Such data contain some input values or variables connected with the right output values. The output values are commonly referred to as target values. Thus in supervised learning, both inputs and outputs are provided. The network processes the inputs and compares its resulting outputs with the target. Errors are then propagated back through the system, causing the network to adjust the weights which controls the network. This ensures that the error is refined every time the weight is adjusted. The training data is used by learning algorithms such as back propagation, perceptron, multi-layer perceptron and generic algorithms. The purpose of a learning algorithm is to create neural network output perfect values for the training data. However, the mission of the algorithm is to give good values for input data that is from the real world and not from the training set. There are several effective approaches to avoid over fitting or under fitting of data in supervised learning. These include early stopping, model selection, Jiltering, Weight delay and Bayesian estimation (Figure 9).

Unsupervised learning: This is a form of learning where networks are able to study on their own. They exhibit a kind of self-training. In this learning, the network is provided with inputs but not desired targets. The system decides what features it will use to group the input data in what is called adaptive training. In unsupervised learning, network is able to learn and recognize patterns in data set whenever the data is introduced to the network. It achieved through a competitive learning rule. In this rule, a neural network with two layers; input layer and a competitive layer are created. The input layer receives the data introduced to it while the competitive layer has neurons that compete with others on the response to features in the input data. The competition is done in a way that an input vector is compared with a weight vectors that a connected to the competitive layer. Any neuron with weight vectors that closely match the input vector is considered as the winning neuron. In other words, the network operates in accordance with what is called 'winner-take-all strategy' [59].

Reinforcement learning: Reinforcement learning in ANNs is technique acting by trial and error. In this approach, an agent can perceive a given state and perform certain actions. After every action, a numerical output is provided. The purpose of an agent is to maximize the total output it receives over time. Numerous algorithms are used in selecting of actions in order to explore the environment and gradually build an approach that give a maximum output. Such algorithms include model-based algorithm and mode-free algorithm [60].

Value of x	X^2	X^3	Actual y_a	Predicted y_p
1	1	1	1	0.95
2	4	8	10	9.8
3	9	27	33	32.71
4	16	64	76	75.30
5	25	125	145	145.44
6	36	216	246	245.72
7	49	343	385	385.25
8	64	512	568	568.08
9	81	729	801	800.05
10	100	1000	1090	1090.36

Table 7: Data from function and predicted y values using neural network.

Figure 10: Actual and predicted values of y based on x.
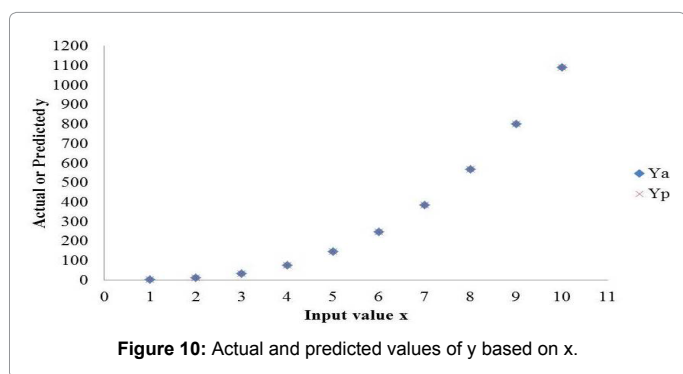
Purpose for ANNs learning process

ANNs are normally subjected to a learning process for two main reasons; classification and function approximation. To achieve the two, the networks are trained. Training a neural network in most cases is an exercise of optimizing a non-linear function. Numerous methods of non-linear optimization have been developed such as numerical analysis, operations research and statistical computing. However, there is no single best approach for such optimization. The methods are chosen based on characteristics of the problem being solved.

Learning for classification: Learning in ANNs is very useful in classification of information or outputs. In classification, the input is considered as a description of numerous objects recognized by the network. The outputs are normally studied by the network and then their class to which they belong is identified. Thus in the classification process, the target output cannot be organized along a useful continuum because each output of the network is a separate entity which is discrete from all the other outputs [52].

Learning for function approximation: ANNs have greatly been used for development and modelling of non-linear functions. The ability of an ANN fitting a non-linear function when provided with input data may be demonstrated via an example. To demonstrate the fitting ability of ANNs, a set training data is generated (Table 7) from the function:

$$y = x^3 + x^2 - x \qquad (12)$$

Where y is the output (dependent variable), x is input (independent variable). For such a case, a feed forward back propagation neural network with two layers is created. The transfer function between the input and the hidden layer is sigmoid function while the function between hidden layer and output layer is linear. There are ten neurons in the hidden layer. The input of the neuron are x, x^2 and x^3 values while the target output is the y value. These input and output combinations are fed to the network to 'learn' to fit a function to the three inputs

and one output. This learning process involves setting of weights and bias values within the neural network architecture. The numerical and predicted values of y using neural network exhibit deviation (Table 7). Data created from the function y=x³+x²-x and predicted y values from a neural network.

From the information of predicted values (Y_p), it can be observed that the resulting values of y are very close to the actual values (Y_a) (Figure 10).

Short, Medium and Long-term Drought Forecasting

The terms short, medium and long-term forecasting has been used in drought studies as indicators of lead time in months of future drought. In most of the drought forecasting research, 1 to 3 months lead time is considered as short-term forecast. The medium to long-term drought forecast is lumped into one category of 4 to 12 months lead time [6,23,61]. Forecasting of short-term drought conditions is useful for monitoring the effect of drought on agricultural systems. Under the short-term drought forecasting soil moisture and crop water stress may be defined especially during growing seasons. On the other hand, forecasting medium and long-term droughts help to comprehend the overall effect of drought on water resources at basin and regional scales. The medium to long-term forecasting is critical in water resources management. It may be used for drought risk management as emerging early warning systems in Kenya. The three categories of drought forecasting can be used to formulate long-term plans for sustainable management of water resources and agricultural systems.

Water Resources Management in Upper Tana River Basin

Water is essential for supporting life, socio-economic development and for regulating ecosystems. Water resources systems are the drivers of socio-economic development and should be well managed. For upper Tana River basin integrated water resources management is paramount. Such management should include planning, developing, distributing, financial management and controlling water use while involving all stakeholders in these aspects. At present there is great fluctuation in water levels in upper Tana River basin which is attributed to the increased frequency, duration and intensity of droughts. During such periods, water quality and quality declines within the basin causing a great challenge in allocating water domestic, hydropower generations and irrigation. There is need to have information on drought occurrence and early warning system to guide in preparedness and management of water resources.

Conclusions and Recommendations

The present study aimed at identifying the effects of drought, available methods of drought forecasting and gaps in drought studies in upper Tana River basin. This will help further studies involving drought assessment and forecasting with a view to guiding decision making in water resources management. Such information will help in forecasting the quantity of water available for different allocations such as hydropower generation, domestic water supply, irrigation and operation of hydraulic structures. During the review, no comprehensive drought studies have been reported for upper Tana River basin and yet it is a key water resource system in Kenya. From the study it is recommended that:

- Assessment of spatial and temporal drought conditions within the basin using available data driven drought indices be explored for planning purpose

- • An integrated drought forecasting tool with adequate lead time, be formulated based on available hydro-meteorological data to guide in planning mitigation programmes within the basin.

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