

# Chapter 51

## Drought Estimation–and– Projection Using Standardized Supply–Demand–Water Index and Artificial Neural Networks for Upper Tana River Basin in Kenya

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### ABSTRACT

*Drought occurrence, frequency and severity in the Upper Tana River basin (UTaRB) have critically affected water resource systems. To minimize the undesirable effects of drought, there is a need to quantify and project the drought trend. In this research, the drought was estimated and projected using Standardized Supply-Demand-Water Index (SSDI) and an Artificial Neural Network (ANN). Field meteorological data was used in which interpolated was conducted using kriging interpolation technique within ArcGIS environment. The results indicate those moderate, severe and extreme droughts at varying magnitudes as detected by the SSDI during 1972-2010 at different meteorological stations, with SSDI values equal or less than -2.0. In a spatial domain, the areas in south-eastern parts of the UTaRB exhibit the highest drought severity. Time-series forecasts and projection show that the best networks for SSDI exhibit respective ANNs architecture. The projected extreme droughts (values less than -2.00) and abundant water availability (SSDI values  $\geq 2.00$ ) were estimated using Recursive Multi-Step Neural Networks (RMSNN). The findings can be integrated into planning the drought-mitigation-adaptation and early-warning systems in the UTaRB.*

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## INTRODUCTION

The Upper Tana River Basin (UTaRB) has an area of 17,420 km<sup>2</sup>. According to TNC (2015), approximately 5.3 million persons live in the UTaRB. Generally, the area receives two rainy seasons annually with annual average amount of 2000 mm at the high altitudes adjacent to Mount Kenya, which is at highest elevation above sea level. The lowest areas receive lower amounts of rainfall. The hydrology of the UTaRB is critical to Kenyan economy (Hiho and Mugalavai, 2010). Hydrological processes in the basin when affected by drought greatly influence agricultural activities, hydro-power generation, water supply to the City of Nairobi and the national parks and reserves located within the basin. The occurrence of drought in a river basin or any area adversely affects socio-economic development. Different drought indices can be used for drought estimation. In this study, Standardized supply-demand water index (SSDI) that combines effective precipitation and crop evapo-transpiration is used to detect drought within the UTaRB.

Drought is a condition on land characterised by scarcity of water that falls below a defined threshold level. It is a disaster linked to climate that may affect a wide range of land (Ali et al., 2018). Drought may be categorized into four types; climatological, agricultural hydrological and the socio-economic. Any type of drought can last for short period of time such as weeks and months, or long periods as in seasons, years and decades. Each drought type lasting for specific period of time may exhibit specific spatio-temporal characteristics (Peters et al., 2006; Tallaksen et al., 2009; Wang et al., 2016). Droughts may be expressed in terms of indices that depend on precipitation deficit, soil-water deficit, low stream flow, low reservoir levels and low groundwater (Hao et al., 2018; Sanmartín et al., 2018). Hydrological drought adversely affects various aspects of human interest such as food security, water supply and hydropower generation (Karamouz et al., 2009; Belayneh and Adamowski, 2013). Globally, drought has become more frequent and severe due to climate variability with some regions experiencing droughts at varying scales and times. Therefore, global impacts of drought on environmental, agricultural and socio-economic aspects are great. Droughts have either direct or indirect impacts on river basins and human lives (IPCC 2014; Hao et al., 2018). Direct impacts 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 (UN, 2008; Scheffran et al., 2012). On the other hand, the indirect impacts of drought comprise reduced income, unemployment, and migration of people and animals. Worldwide, more than eleven million persons have died since 1900 as a result of drought related impacts. In addition, two billion persons have been critically affected by the impacts (FAO, 2013). The main challenges associated with drought are that it causes ill health through water scarcity, malnutrition and famine (UN, 2008; Mcevoy, 2018). The extent of the effect of drought depends on its characteristics which may be described using an index.

A drought index (DI) is a function used for assessing, quantifying, detecting occurrence and severity of droughts. The Drought Indices (DIs) were developed for specific regions using specific structures and forms of data input. There is limited information in the application of drought indices that combines both temporal and spatial drought evaluation at river basin scales. Drought has been assessed in terms of temporal and spatial domain using evapotranspiration mapping as illustrated by Eden (2012). There are two broad categories of drought indices; satellite based and the data driven drought indices (Belayneh and Adamowski, 2013). In addition, drought may be forecasted using the index in conjunction with some modelling techniques such as application of Artificial Neural Networks (ANNs) (Ali et al., 2018).

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