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Analysis of Drought and Wet-Events Using SWSI-Based Severity-Duration-Frequency (SDF) Curves for the Upper Tana River Basin, Kenya

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Abstract: Drought and wet-event patterns in the Upper Tana River basin have significantly been changing due to variation of climatic and human-induced factors. This paper presents the analysis of drought and wet-events using Severity-Duration-Frequency (SDF) curves for the Upper Tana River basin, Kenya based on Surface Water Supply Index (SWSI). The extreme value EV1 (Gumbel) frequency distribution function was used to formulate SDF curves. The developed SDF curves were used to develop isoseverity maps for the basin. From the results, the event-probability show that likelihood of drought events increased linearly with increase in magnitude of SWSI while the return period of drought events increased exponentially with decrease in magnitude of SWSI. The findings show that the probability and magnitude, the return period and magnitude of drought have linear and exponential regression coefficients of 0.984 and 0.980 respectively. On the other hand the probability of wet-period events decreased linearly with increase in magnitude of SWSI while the return period of the events increased exponentially with increase in magnitude of SWSI with regression coefficients of the linear and exponential functions of 0.804 and 0.881 respectively. This indicates that both the drought and wet-events probability and magnitude, and the return period and magnitude have a strong correlation. Spatially, it was found that generally the river basin exhibit an increasing pattern in cumulative SWSI in south-eastern areas than the north-eastern and generally a more increase in extreme wet-events than droughts in the basin. The developed (SDF) curves are critical for design of hydrologic, hydraulic and water resources supply systems while the spatial event-patterns can be incorporated in prioritized mitigation of extreme events.

Keywords: SDF Curves, Drought, Wet-Event, SWSI, Isoseverity, Return Period, Event-Probability, Upper Tana River Basin

1. Introduction

Drought-event is defined as a condition on land described by deficiency of water that falls below threshold level or normal average values for a certain period of time [18], [23], [24]. The deficiency of water has significant impact on surface and ground water resources [19]. On the other hand, wet-event is the period of time when the water availability falls above the threshold level for a certain period of time. A drought index is a single expression used to quantify drought. When expressed using drought index, drought occurs during the time when the drought index is negative while the wet-event occurs when the index is positive. However, in many studies drought indices do not explicitly define both the droughts and wet periods. Instead, the index is used to give different categories of drought some of which can be captured as wet periods [13].

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 level. Drought may be defined differently depending on the sector involved. For example, a hydrological-drought occurs whenever river or groundwater levels are relatively low and is propagated by meteorological drought [1]. In addition, water-resources drought occurs when basins experience low stream flow, reduced water reservoir volume and groundwater levels. The water resources drought is influenced by climatic and hydrological parameters within a river basin and drought management practices. The hydrological drought, mainly deals with low stream flows. This drought adversely affects various aspects of human interest such as food security, water supply and hydropower generation [12], [3].

A sequence of drought occurrence in a river basin may lead to desertification of vulnerable areas such as arid, semi-arid and sub-humid areas. Within these fragile ecosystems, water resources, soil structure and soil fertility are critically degraded by drought occurrence [7]. The occurrence of any drought in terms of magnitude, frequency, duration and severity has not been clearly understood for numerous river basins in the world, and this calls for intensified research in drought and such related fields. The study of the drought and wet-event characteristics may be investigated using integration of drought indices and development of characteristic curves.

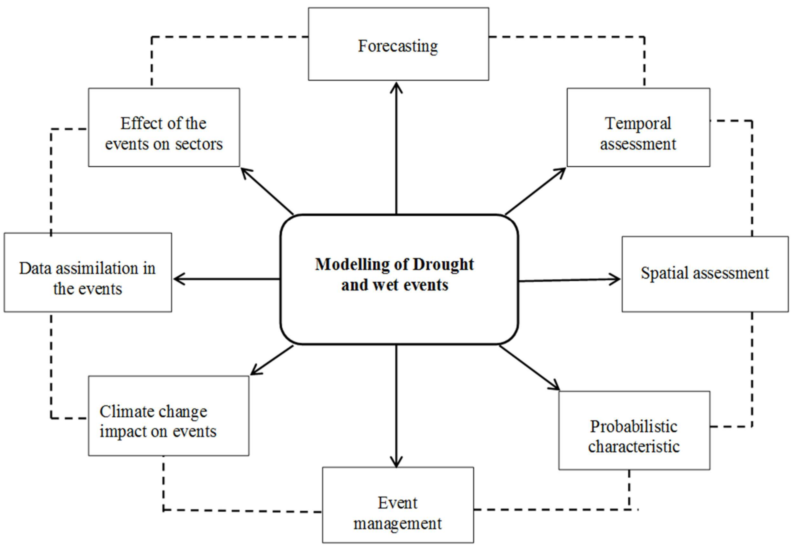
2. Surface Water Supply Index (SWSI)

The Surface Water Supply Index (SWSI) was developed in Colorado USA, as an indicator of surface water or moisture levels [17]. The index may be used for modeling of drought and requires input variables which include; snow water content, stream flow, rainfall and storage reservoir volume [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, reservoir volumes, snow water content and stream flows measured at stations within the catchment. One of the advantages of the SWSI is that it gives a representative measurement of surface water supplies across the river basin.

The SWSI is unique in 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 [2]. Thus, it is difficult to have a homogeneous time series of the index for several basins.

3. Modelling of Drought and Wet-Events

Drought modelling is a technique of using simple and or complex mathematical, scientific and conceptual representations of drought characteristics. The modelling which includes drought forecasting may use models and statistical approaches. The purpose of drought modelling is mainly to provide a concise understanding of its occurrence, characteristics and forecast. The fundamental role of modelling the drought is to offer solutions to the challenges of increasing water scarcity due to population growth, expansion in agriculture, industrial and energy sectors. The scarcity of water in the world is compounded by the droughts that affect both surface and ground water resources. Drought modelling may be categorized into eight aspects such as drought forecasting, temporal assessment, spatial assessment, probability characteristics, management, study of impacts of climate change on drought, assimilation of land data systems into drought and assessment of impacts of drought on different sectors. All the aspects of drought and wet-events may be interconnected in modelling and are inter-linked as given in Figure 1 as modified from [15].



(Modified from Mishra and Singh 2011)

Figure 1. *Network of phases of drought and wet-event modeling.*

4. Drought Monitoring in Kenya

To minimize the impacts of drought in Kenya, an effective and timely monitoring system is necessary. Such monitoring activities are meant to provide critical information in the development of early warning systems. Since drought has become a recurrent phenomenon in Kenya, different organizations are involved in coming up with methods to address drought-induced challenges.

The main organizations involved in data collection for early drought warning systems in Kenya include; the Kenya Meteorological Department (KMD), Ministry of Agriculture, livestock and fisheries, Department of Resource Survey and Remote Sensing (DRSRS), Kenya National Bureau of Statistics (KNBS), Inter-governmental Authority for Development (IGAD) Climate Prediction and Application Centre (ICPAC), World Food Programme (WFP) Kenya Office, Regional Centre for Mapping of Resources for Development (RCMRD), Livestock Network and Knowledge System (LINK), Famine Early Warning system-Network (FEWS-NET) and the Arid Lands Resource Management Project (ALRMP) [20], [18]. To prepare adequately for mitigation of the drought impacts, a thorough assessment, evaluation and forecasting of drought conditions is very critical. However, the main challenges or gaps with drought preparedness and mitigation in Kenya include the fact that:

(i). Drought assessment has been based on past and present drought indices (DIs) developed for specific regions in other countries and their suitability in Kenya has not been sufficiently tested.

(ii). Efficiency of the performance of DIs in drought forecasting for different lead times is not well explored in most basins in Kenya.

(iii). Spatial and temporal drought assessment and forecasting of drought using hydro-meteorological variables is limited for most basins in Kenya.

Due to these challenges, there is need for planning of drought and wet seasons that require development of tools that can be used for study drought characteristics. This research provide an improvement in the understanding and analysis of droughts and wet periods in terms of their severity, duration and frequency required for planning and management of water resources systems. The main objective of this research was to develop Severity-Duration-Frequency (SDF) curves based on Surface Water Supply Index (SWSI) and use them for quantitative description of droughts and wet-events across the Upper Tana River Basin in Kenya.

5. Materials and Methods

The study area, data acquisition for the computations needed in this study, calculation of the Surface Water Supply Index (SWSI) and the details for the formulation of the severity-duration-frequency cures for the present context are described in the subsequent sections.

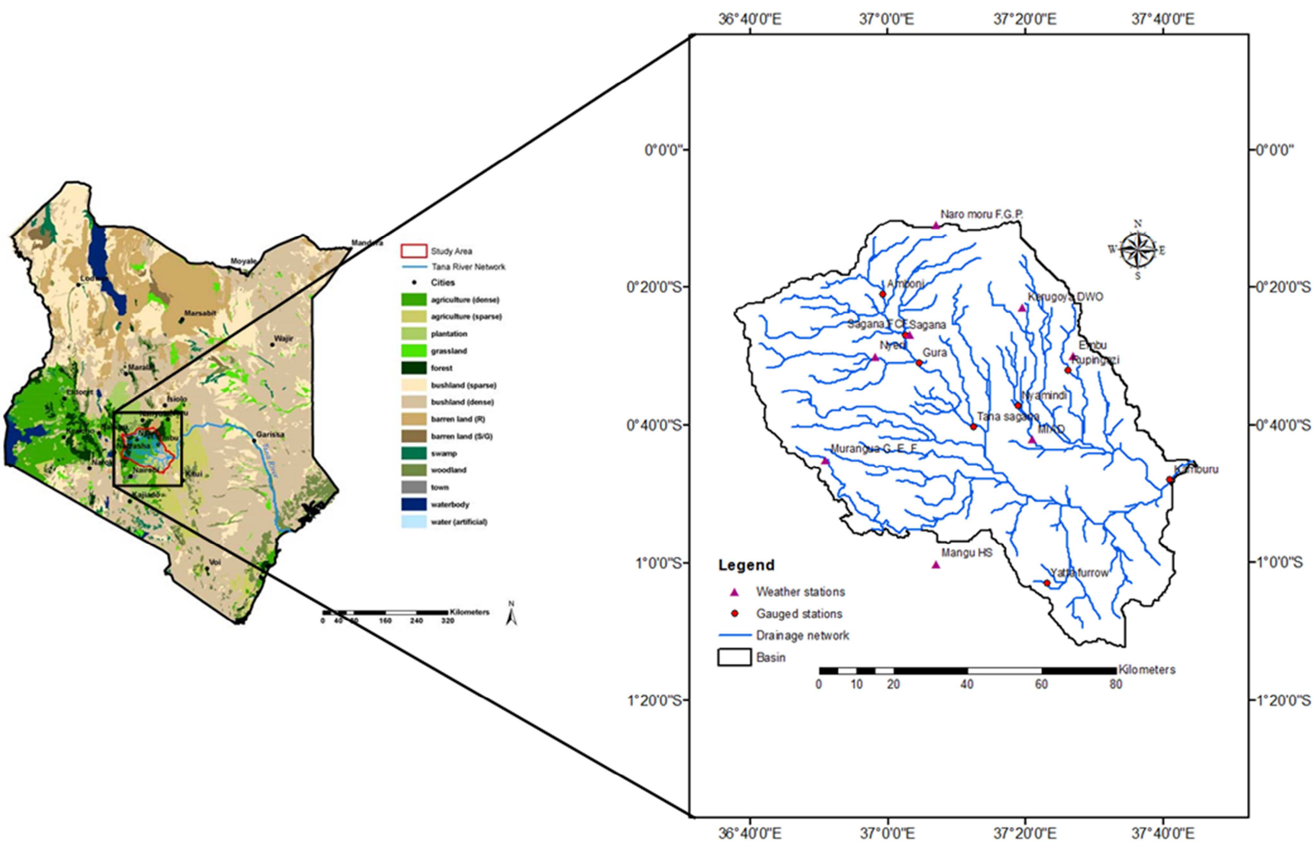


Figure 2. Map of the upper Tana River basin.

6. Study Area

The focus of this study was the upper Tana River basin with an area of 17,420 km^2 presented in Figure 2. The study area is part of the larger Tana River basin, the largest river basin in Kenya with an area of 126,000 km^2 [11], [22]. The upper Tana River basin has forest land resources located along the eastern slopes of Mount Kenya and Aberdares range which have a critical role in regulating the hydrology of the entire basin [10]. The basin was selected because it is located within a fragile ecosystem that represents all agro-ecological zones of Kenya where water resource systems, hydro- power generation and food security are negatively impacted by frequent drought occurrences. In addition, it is the area that regulates the hydrology of the larger Tana River basin.

The upper Tana River basin lies between latitudes 00° 05' and 01° 30' south and longitudes 36° 20' and 37° 60' east. The basin is fundamental in influencing the ecosystem downstream (NEMA, 2004). It drains nine counties namely; Muranga, Nyandarua, Kiambu, Kirinyaga, Laikipia, Machakos, Nyeri, Embu and Kitui [21]. The basin comprises major tributaries of Tana River whose total length from the source to the Indian Ocean is approximately 1,000 km [10]. The Tana River tributaries originate from the slopes of Mount Kenya and Aberdares range. The basin forms a principal resource in Kenya. For instance, the upper Tana River basin is critical in water supply, hydro-power generation and agricultural production.

6.1. Hydro-meteorological Data Acquisition

Different data sets were used for this study to compute the DIs and the drought forecasting models. These data include; stream flow, storage dam levels, precipitation, potential evapo-transpiration, soil moisture content and temperature. The hydro-meteorological data from 1970-2010 (41 years) used in this study for defined hydrometric stations (Figure 2). This data was selected because it was consistent for the study period. Part of this data was available while the missing data was estimated for the hydrometric stations. The available data was on daily time step but had to be re-organized into monthly average time scales for all the variables to match with the data requirements for this study. The monthly stream flow and monthly flow data was obtained from the Ministry of Environment and Natural Resources, and Water Resources and Management Authority (WRMA). Data on dam levels was obtained from Kenya Electricity Generating Company (KenGen).

Stream flow data: Fourteen hydrometric stations in the upper Tana River basin with complete and incomplete data records. However, only eight stations were selected for this study since they have long and reliable data for the period 1970-2010. The stations were in addition considered to be representative of the basin as they are located within the low, lower middle, middle and higher elevations for different agro-ecological zones. The station names and gauge identification (ID) numbers, their spatial locations are shown in the study area. In this study, only the Masinga dam levels were used because of the availability of long-term data records.

Precipitation data: In the upper Tana River basin, data from twenty four meteorological stations were obtained from the Ministry of Water and Irrigation. The meteorological data included precipitation, temperature and evaporation data while some were supplemented by the global datasets. The data were then subjected to exploratory data processing. It was found out that only eight stations had reliable and sufficient data. Where the available data contained less than 20% data gaps, then these data were selected for computation the surface water supply index (SWSI). The eight stations used in the study are located within the low (LE), lower middle (LME), middle (ME) and high (HE) elevations. The stations are located at different agro-ecological zones and sub-basins in the Upper Tana River basin.

6.2. Computation of Surface Water Supply Index (SWSI)

The Surface Water Supply Index (SWSI) was computed using monthly precipitation, stream flow, and reservoir level and dam inflow as input data. The data was first summed up and normalized using the probability of non-exceedance. The probability of non-exceedance refers to the possibility that a random drought magnitude is less than or equal to a defined real value. The values of the SWSI were computed using the relation:

$$SWSI = \frac{\left[(a \times PN_{rn}) + (b \times PN_{sf}) + (c \times PN_{rs}) + (d \times PN_{df}) - C_1\right]}{C_2} \quad (1)$$

Where; $SWSI$ = modified surface water supply index (dimensionless)

PN = probability of non-exceedence in percent

rn = the rainfall (mm)

sf = stream flow (m^3/s)

rs = storage reservoir level (m)

df = dam inflow (MCM)

C_1 = 50 and C_2 = 12 (Shafer and Dezman, 1982)

The parameters *a, b, c, d* and *e* are the weights for each component and their sum must be equal to 1 as given in the expression:

$$a + b + c + d + e = 1 \quad (2)$$

The weighting parameters *a, b, c* and *d* corresponding to the rainfall, stream flow, reservoir levels and dam inflows were estimated through a proportioning objective procedure. Such a procedure is better for SWSI determination since it computes the weighting parameters more accurately compared to the method developed by [17], where the values by these authors are based on assumptions. The procedure adopted for any monthly data series at each hydrometric station, the maximum entry of record was identified. A parameter defined as the ratio of the monthly data to the maximum entry in the period of record was computed. For instance, taking the monthly time series of precipitation data the following ratio was calculated.

$$P_a = \frac{x_i}{x_{\max}} \tag{3}$$

Where; P_a is provisional parameter associated with a, x_i is the data entry for month i and $x_{\max}$ is the maximum data entry of the period in record. Similarly P_b, P_c and P_d were computed as the provisional parameters for b, c, and d respectively. A total value P_T was then determined by summing up the P_a, P_b, P_c and P_d. Then the parameters a, b, c and d were proportionally computed from the relations

$$a = \frac{P_a}{P_T},\ b = \frac{P_b}{P_T},\ c = \frac{P_c}{P_T}, d = \frac{P_d}{P_T} \tag{4}$$

The probability of non-exceedance for monthly precipitation, stream flow, storage reservoir, dam inflow and the ground water level were determined using the function:

$$PN = 1 - \frac{r}{n+1} \tag{5}$$

Where; PN = probability of non-exceedence in percent
r = the rank of data arranged in ascending order
n = the number of years considered in the analysis

The combination of the rainfall (*rn*), stream flow (*sf*), storage reservoir volume (*rs)* and dam inflow into SWSI was conducted as per Equation 1. The product of the respective time series weighted parameters and the probability of non-exceededance were computed to get the composite factor $SWSI_f$ which after normalization was used to get the surface water supply index *SWSI*. A regression plot between $SWSI_f$ and *SWSI,* was then conducted to develop a modified $SWSI_m$ equation for the upper Tana River basin. In the normalization, the *SWSI* values were set at between -4.2 and +4.2 as minimum and maximum values respectively. The calculated SWSI values were then characterized into severity classes based value ranges adopted from [17]. These SWSI values are (>4.00), (3.99 to 1.99), (2.00 to -0.99), -1.00 to -1.99), (-2.00 to -2.99), (-3.00 to -3.99) and (<4.00) that represent abundant water, wet, near normal, incipient, moderate severe and extreme drought conditions respectively. The computed SWSI was then used for development of SDF curves.

7. Development of SDF Curves for Droughts and Wet-Events

Droughts exhibit characteristics that can be described statistically [6]. A detailed review was conducted for selection of a theoretical distribution function was conducted in which the Gumbel Extreme Value (EV1) distribution function was chosen. The EV1 was selected because of two major advantages; EV1 Gumbel is easy to apply since it is a two-parameter distribution frequency distribution function and visual inspection of EV1 in comparison with other frequency distribution functions such as Generalized Extreme Value GEV, three-parameter lognormal (LN3) and the log-Pearson (LP3) distribution indicated that EV1 gives more accurate, appropriate and acceptable estimation for dry and wet periods [5].

The next step involved fitting and testing of the distribution function against the cumulative severities values of the SWSI. In this study, Data for development of SDF for droughts and wet-events consisted of calculated monthly SWSI value time series for eight stations and for each event within the basin for the period 1970 to 2010. There were two analysis conducted; one for drought (successive negative values) and wet-events (successive positive values) (Tables 1 and 2).

Table 1. *The number of drought events for different durations in the basin.*

Drought duration (months)	The number of drought events for hydrometric stations							
	Amboni	**Sagana**	**Gura**	**Tana-sagana**	**Yatta furrow**	**Nyamindi**	**Rupingazi**	**Kamburu**
3	51	57	56	56	65	56	55	63
4	43	45	46	44	48	47	40	48
6	36	36	44	37	42	43	36	41
8	29	31	39	32	37	38	30	38
10	15	17	16	18	19	17	17	16

Table 2. *The number of wet-events for different durations in the basin.*

Drought duration (months)	The number of wet-events for hydrometric stations							
	Amboni	**Sagana**	**Gura**	**Tana-sagana**	**Yatta furrow**	**Nyamindi**	**Rupingazi**	**Kamburu**
3	64	61	63	58	48	57	58	49
4	56	57	53	53	42	53	53	42
6	45	41	40	47	35	48	49	36
8	37	32	35	37	24	36	37	24
10	25	21	24	20	13	21	22	14

7.1. Fitting the Data into Gumbel Function

For every drought and wet period, the detected magnitudes of were plotted matching their return periods. The statistical distribution was then fitted to the plotted data points. For this study, the data for Amboni hydrometric station is provided for the purpose of illustrating the drought data plots Table 3.

Table 3. *Probability table of SWSI-based drought (negative values) of four months duration for Amboni hydrometric station.*

S. No	SWSI	Return Period	Probability	S. No	SWSI	Return Period	Probability
1	-4	14.874	0^$(709	40	-2.05	2.622	0.3804
2	-3.95	14.227	0.0723	41	-2	2.508	0.3876
3	-3.9	13.450	0.0784	42	-1.95	2.534	0.3823
4	-3.85	13.015	0.0915	43	-1.9	2.295	0.4423
5	-3.8	12.987	0.1003	44	-1.85	2.102	0.3952
6	-3.75	11.340	0.1108	45	-1.8	2.432	0.3820
7	-3.7	12.450	0.1111	46	-1.75	1.923	0.4298
8	-3.65	11.349	0.1227	47	-1.7	1.975	0.4382
9	-3.6	9.788	0.1329	48	-1.65	1.890	0.4467
10	-3.55	10.856	0.1652	49	-1.6	1.954	0.4323
11	-3.5	10.394	0.1641	50	-1.55	1.730	0.4637
12	-3.45	9.952	0.1400	51	-1.5	1.418	0.4880
13	-3.4	9.129	0.1492	52	-1.45	1.357	0.4967
14	-3.35	8.741	0.1892	53	-1.4	1.298	0.5055
15	-3.3	7.235	0.1910	54	-1.35	1.654	0.5142
16	-3.25	7.123	0.2172	55	-1.3	1.164	0.5230
17	-3.2	7.676	0.2253	56	-1.25	1.077	0.5318
18	-3.15	7.352	0.2438	57	-1.2	1.031	0.5488
19	-3.1	6.821	0.2038	58	-1.15	1.654	0.5640
20	-3.05	6.386	0.2291	59	-1.1	1.102	0.6021
21	-3	6.108	0.2185	60	-1.05	1.432	0.5311
22	-2.95	5.798	0.2306	61	-1	1.010	0.5756
23	-2.9	5.544	0.2478	62	-0.95	1.432	0.5299
24	-2.85	5.300	0.2469	63	-0.9	1.126	0.5904
25	-2.8	5.068	0.2602	64	-0.85	1.077	0.5163
26	-2.75	4.027	0.2828	65	-0.8	1.453	0.6185
27	-2.7	3.540	0.2780	66	-0.75	1.018	0.5640
28	-2.65	4.234	0.2890	67	-0.7	0.974	0.6198
29	-2.6	4.210	0.2975	68	-0.65	0.931	0.6944
30	-2.55	3.350	0.2961	69	-0.6	1.230	0.6820
31	-2.5	3.959	0.3044	70	-0.55	0.879	0.6643
32	-2.45	3.964	0.2824	71	-0.5	0.757	0.7116
33	-2.4	3.792	0.3392	72	-0.45	0.823	0.6985
34	-2.35	3.627	0.3124	73	-0.4	0.754	0.7241
35	-2.3	3.352	0.3184	74	-0.35	0.665	0.7087
36	-2.25	3.206	0.3213	75	-0.3	0.677	0.7113
37	-2.2	3.196	0.3542	76	-0.25	0.610	0.7384
38	-2.15	3.057	0.3625	77	-0.2	0.585	0.7209
39	-2.1	2.924	0.3709	78	-0.15	0.560	0.7073

The first column gives the rank of the drought magnitude, the magnitude (-ve values) arranged in descending order are in column 2, while column three show the corresponding return period of the drought magnitude based on Weibull plotting position law expressed as:

$$T = \frac{(n+1)}{m} \tag{6}$$

Where, m=current ranking number

n=total number of data points

The last probability of occurrence (P) was then computed as a reciprocal of the return period mathematically defined as

$$P = \frac{1}{T} \tag{7}$$

Based on this principle (Table 3) data plots for the cumulative drought severity and cumulative wet periods are respectively plotted. The extreme value law on drought and wet severity was applied by fitting the EV1 which is of the form:

$$F(x) = \exp\left\{-\exp\left(-\alpha\left(x-u\right)\right)\right\} \tag{8}$$

Where; α=fitted parameter

U=fitted parameter computed for every duration form the data set.

These parameters were determined from the relation:

$$\alpha = \frac{1.283}{\sigma} \tag{9}$$

$$u = \bar{x} + K\sigma \quad (10)$$

$$K = -0.78\left[0.577 + \ln\left(\ln\frac{T}{T-1}\right)\right] \quad (11)$$

Where; T=return period (years) of the drought or wet-event of a defined duration.

This means that an extreme drought or wet-event event with a return period of T is K standard deviations above the average maximum drought or wet-event. The procedure for fitting all the EV1 is conducted for all the detected drought durations at each hydrometric station. To illustrate the findings**,** Figures 5 and 6 gives the fitted plots of the drought and wet-events for Amboni hydrometric station**.**

7.2. Development of Severity-Duration-Frequency (SDF) Curves

Based on the Equation 10 the drought and wet period severities that correspond to the selected return periods of 2, 5, 10, 20, 30, 50 and 100 years were computed for every event. This was followed by fitting the Severity-Duration-Frequency (SDF) curves using cumulative SWSI values with return periods 2, 5, 10, 20, 30, 50 and 100 years. For each hydrometric station different values were derived. For the purpose of illustration, the developed SDF curves for Amboni hydrometric station. Each curve in Figures 5 and 6 represents one of the selected return periods.

8. Results and Discussions

Characteristics of time series drought and wet conditions

Drought characteristics within the upper Tana River basin were established using characteristic curves that relate drought probability, return period and magnitude. It is possible to determine the probability and frequency of drought with defined severity for different gauging stations. For instance, Figure 3 presents the results of drought characteristics for Amboni gauging station (ID 4AB05) where the probability of occurrence of severe (-3.00 to -3.99) and moderate (-1.00 to -1.99) droughts is 0.18 and 0.51 while the return periods for the two drought conditions are 8 and 1 years respectively. From Figure 3, it can also be seen that the probability of drought events increased linearly with increase in magnitude of SWSI while the return period of drought events increased exponentially with decrease in magnitude of SWSI. The associated regression coefficients of the resulting linear and exponential functions of 0.984 and 0.980 respectively indicate that the drought probability and magnitude, and the return period and magnitude have a strong correlation. Thus the functions in Figure 3 can effectively be used in determining the probability and return period for any drought severity in the basin.

Similarly, wet characteristics within the upper Tana River basin were established using characteristic curves that relate wet period probability, return period and magnitude. It was possible to determine the probability and frequency of wet period with defined magnitude for different gauging stations. For instance, Figure 4 gives the results of wet period characteristics for Amboni gauging station (ID 4AB05) where the probability of occurrence of abundant water availability (+4 or more), wet (1.99 to 3.99) and near normal (2.00 or less) wet periods is 0.20, 0.45 and 0.85 while the return periods for the three wet periods are 15, 14 and 10 years respectively. The probability of wet period events decreased linearly with increase in magnitude of SWSI while the return period of drought events increased exponentially with increase in magnitude of SWSI. The associated regression coefficients of the resulting linear and exponential functions of 0.804 and 0.881 respectively indicate that the drought probability and magnitude, and the return period and magnitude have a strong correlation. Thus the functions in Figure 4 can efficiently be used in defining the probability and return period for magnitude of any wet period in the basin.

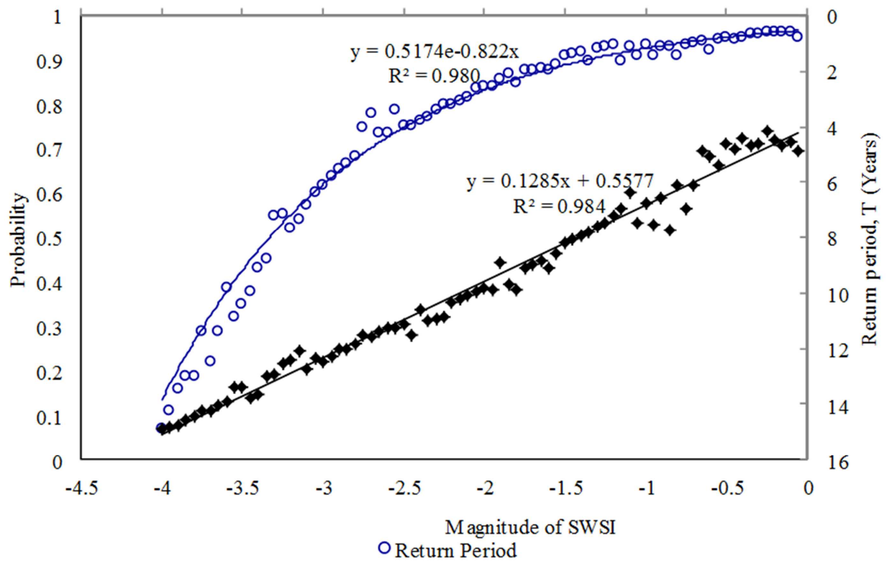


Figure 3. *Drought characteristic curves of SWSI for Amboni hydrometric station.*

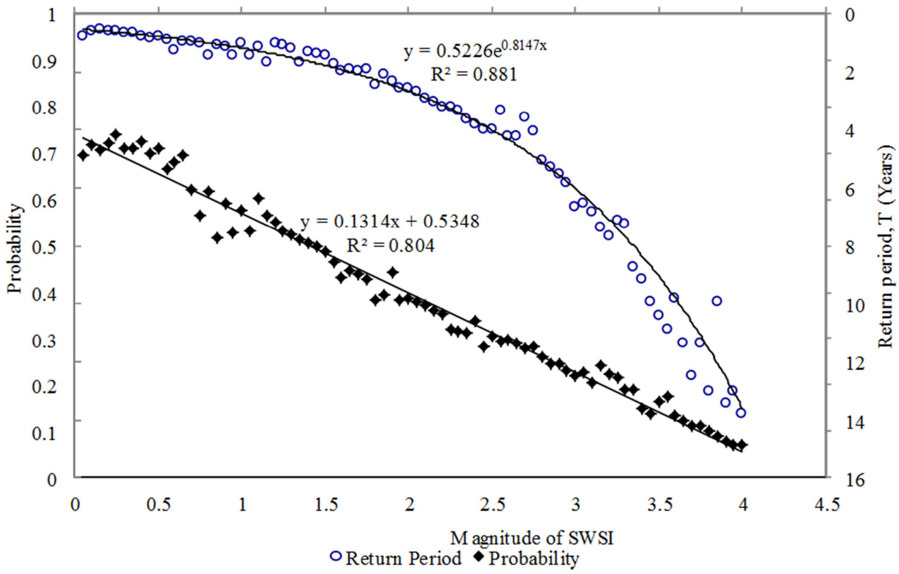


Figure 4. *Wet-period characteristic curves of SWSI for Amboni hydrometric station.*

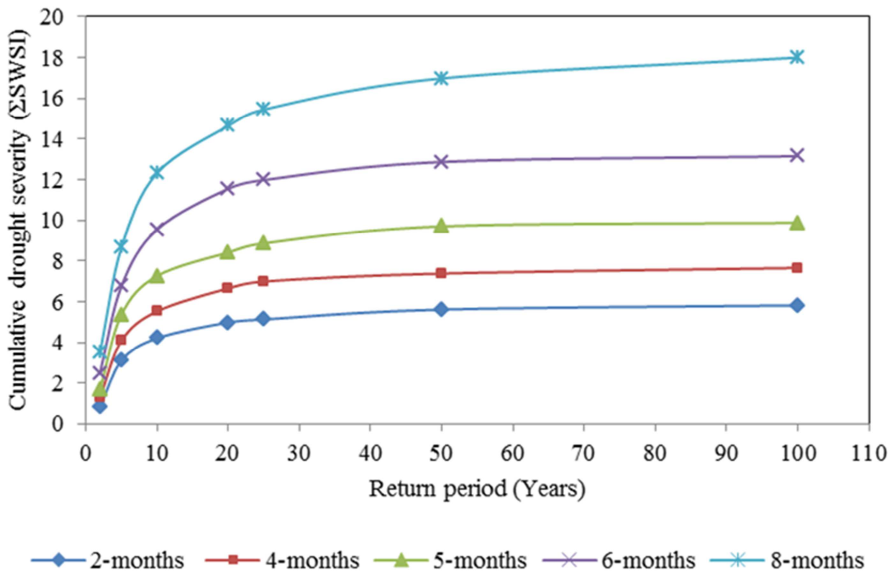


Figure 5. *Drought Severity-Duration-Frequency (SDF) curves at Amboni based on SWSI.*

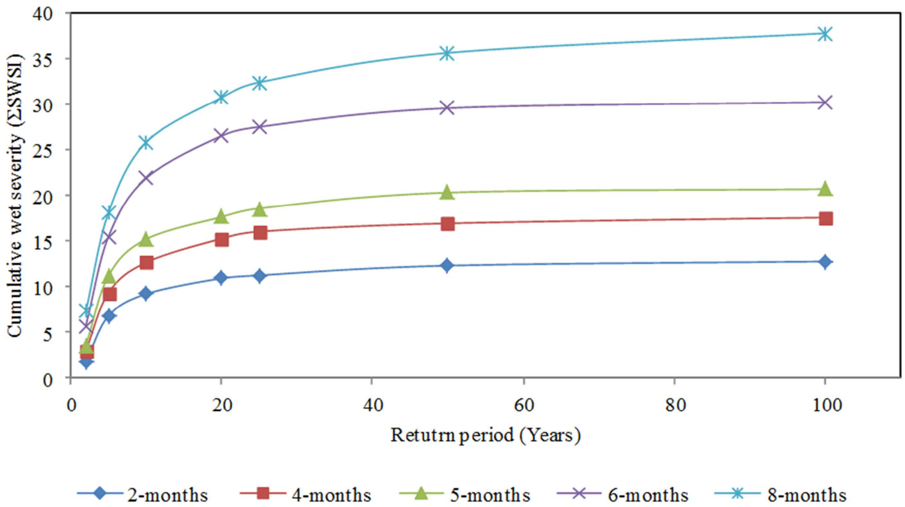
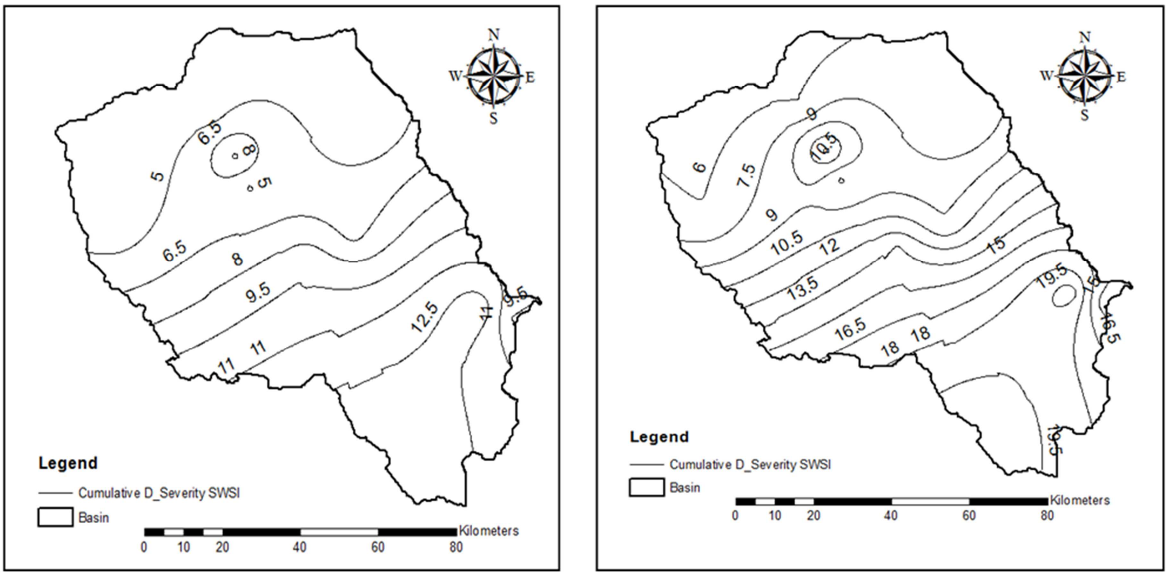


Figure 6. *Wet-event Severity-Duration-Frequency (SDF) curves at Amboni based on SWSI.*

In addition, the Severity-Duration-Frequency (SDF) curves for the upper Tana River basin were fitted for both the drought and wet-events. The results of the SDF curves at Amboni gauge station (ID 4AB05) as presented in Figures 5 and 6 show that for a 50-year return period, cumulative drought severity of 5.5, 7.2, 9.8, 13 and 17 correspond to 2, 4, 5, 6 and 8-months duration (Figure 5). The drought events of different return periods exhibit a similar trend. In addition, for a 50-year return period, cumulative wet-event severity of 10, 15, 18, 27 and 35 correspond to 2, 4, 5, 6 and 8-months duration (Figure 6). It is thus inferred that the higher the cumulative event severity for each return period, the higher the duration. The trend of the results presented in Figure 5 and 6 is similar to the SDF curves developed by [5] using cumulative drought severity of PDSI for Volos hydrometric stations in Greece.

For the purpose of illustrating the spatial extend of SWSI, Figure 7 shows isoseverity map of drought across the Upper Tana River basin. In this illustration, the maximum cumulative drought magnitude based on SWSI for the duration of 2 months which is expected to be equaled or exceeded once every 10 and 50 years are considered. The patterns and magnitude of the SWSI for the two return periods significantly differ. Severity values for 10 year return period are slightly lower than those for 50-year return period. The findings show that there is generally an increasing pattern in cumulative SWSI in south-eastern areas than the north-eastern areas of the river basin.



(a) (b)

Figure 7. *Isoseverity (ΣSWSI) mapping of droughts in upper Tana River basin for (a) 10 and (b) 50-year return period.*

9. Conclusion

The Severity-Duration-Frequency (SDF) curves were developed based on Surface Water Supply Index (SWSI). The curves were then used to quantitatively describe droughts and wet-events across the Upper Tana River Basin. Important drought parameters such as the severity, duration and frequency for the extreme events were correlated in the SDF for different hydrometric stations. Isoseverity mapping across the basin was also conducted for prioritized extreme events planning, formulation of mitigation measures, design of water supply systems, hydrologic and hydraulic structures

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