The relation between drought impacts, drought indicators, water scarcity and aridity: the case of Kenya

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Abstract. Drought is a complex natural phenomena affecting environment, economy and society at multiple levels. To better prepare and mitigate the impacts of drought, various drought indicators are developed to monitor and forecast drought events. Though widely used, their relation with actual drought impacts is complex. In particular in water-limited regions where water scarcity is prevalent, the attribution of drought impacts is difficult. This study assesses their relation by linking drought impacts to various drought indicators (SPI, SPEI, SDI and SSMI with different accumulation periods) and water scarcity across counties with different arid characteristics in Kenya. The monthly written bulletins of the National Drought Management Authority (NDMA) of the Kenyan government have been used to gather drought impact data. A Random Forest (RF) model discovers which drought indicators are best linked with drought impacts on the following categories: Pasture, Livestock deaths, Milk production, Crop losses, Food insecurity, Trekking distance for water and Malnutrition. The findings of this study suggest a relation between drought severity and the frequency of drought impacts whereby the latter also showed a relation with aridity, whilst water scarcity did not. The results of the RF model reveal that the linkage between drought impacts and drought indicators are region specific, indicated by the range of drought indicators and accumulation periods found to match best with drought impacts. While the findings strongly depend on the availability of drought impact data and the socio-economic circumstances within the research area, the study clearly demonstrates the feasibility of linking drought indicators with text-based impact reports and it reveals the link between drought impacts, drought indicators, water scarcity and aridity.

1 Introduction

Drought can be characterized as a slow-onset event with impacts building up over time whereby the extent of its impacts depend on a range of contextual factors (Heinrich et al., 2020). Differences in societal characteristics across regions determine the range of impacts when concerning a drought event with similar intensity and duration. Due to the projected increase in drought frequencies (IPCC, 2014), each successive drought event can result in increased destabilization, triggering insecurity and resource-based conflicts (Thomas et al., 2020). Monitoring and early warning (M&EW) is one important measure to enhance drought resilience. The goal of M&EW is to provide reliable and forehanded information on drought conditions (using a wide range of drought indicators) to enable local society to better prepare and act accordingly (Wilhite & Svoboda, 2007). However, there is a gap between forecasting a hydrometeorological event and the understanding of potential impacts, as recognized by the World Meteorological Organization (WMO, 2015). Linking drought impacts to drought indicators can contribute to the ongoing development and improvements of the M&EW, aiming to reduce human and financial losses arising from a drought event.

Drought is in general classified as meteorological, hydrological, and/or soil moisture drought, which are related to and influenced by both natural processes and human activities (Van Loon, 2015; Van Loon et al., 2016). Meteorological drought is often driven by precipitation deficit. The precipitation anomaly can then propagate through the hydrological cycle, resulting in soil moisture, stream flow and groundwater deficit and hence, soil moisture and hydrological drought, respectively. Hydrological drought refers to anomalies in the surface and/or subsurface water. In order to detect drought, standardized drought indices with diverse accumulation periods are used. The most simple ones use only meteorological data while others include soil moisture or streamflow data (Yihdego et al., 2019). Models using drought indicators to forecast drought can detect climate signals into soils and hydrology. Yet, the link between drought indicators and environmental/socio-economic impacts have rarely been analyzed, although it is crucial for developing future measures to reduce vulnerability to drought risks.

The assessment and monitoring of drought impacts is complex given: (1) the great variety of drought impact categories; (2) their possible propagation throughout the hydrological and social system and (3) the difficulty in drought impact attribution. Specifically for Europe and the USA, drought impact databases have been developed, namely the European Drought Impact report Inventory (EDII) and the Drought Impact Reporter (DIR) respectively. Stahl et al. (2016) studied the diversity of drought impacts across Europe exploring the database of EDII. It was found that impacts on agriculture and public water supply dominated the collection of drought impact reports since 1970. In general, impacts can be classified into direct and indirect impacts whereby reduced crop yield and increased livestock mortality rates are examples of direct impacts while reduced income for farmers can be regarded as an indirect impact (Wilhite & Svoboda, 2007). Linking drought impacts with drought indicators is regarded difficult as there is often no strong intuitive cut-off within impact categories (such as agricultural yield) between non drought and drought conditions (Hall & Leng, 2019). Some studies assessed the link between drought impacts and drought indicators, mainly with a focus on Europe. For instance, the qualitative dataset of EDII has been used to assess the link between drought impacts and indicators at continental (Blauhut et al., 2015), national (Stagge et al., 2015) and regional scale (Bachmair et al., 2015, 2016, 2018). The results of multiple studies suggest that linking drought indicators with impacts is time, region and sector specific (Bachmair et al., 2015, 2016, 2017; Blauhut et al., 2015; Ma et al, 2020; Stagge et al., 2015; Wang et al., 2020) which shows the need to study their relation in other settings.

Water scarcity is an important process within (semi-)arid regions, which is different to drought. It occurs when water demand (both societal as ecological water demand) surpasses water supply (Kimwatu et al., 2021) and often leads to long-term unsustainable use of water resources (Van Loon & Van Lanen, 2013). Whereas aridity, based on the ratio of annual precipitation and potential evapotranspiration rates (UNESCO, 1979), is regarded a constant value, water scarcity is dynamic in time and related to both decreases in water availability (drought) and increases in water demand. Water scarcity can be regarded as an impact of drought including societal, economic and political factors that drive demand for and access to water. Therefore, the simultaneous presence of both water scarcity (partly driven by anthropogenic causes) and meteorological drought can lead to a difficult attribution of the impacts experienced.

However, separation of these impacts is needed to generate reliable information to stimulate early action in the affected sectors when concerning a drought event. Nearly 40% of the Eastern and Southern Africa habitats are Arid and Semi-Arid Lands (ASALs) and are therefore prone to inadequate and extreme fluctuations in water availability (CGIAR-CSI, 2019). In addition, the main economic activity in East Africa is subsistence rain-fed agriculture and livestock farming which makes the society extremely vulnerable to drought events (Ayugi et al., 2020; Lekapana, 2013).

This study has chosen Kenya as research area because of its different arid characteristics and the presence of water scarce regions (Mulwa et al., 2021). In addition, the country has experienced frequent drought events: for instance, 2008-2011 was classified as a prolonged severe drought (Mutsotso et al., 2018) and the drought in 2016-2017 was considered a national disaster (Kew et al, 2021; Ondiko & Karanja, 2021). The country has also known a diverse range of drought impacts such as cattle mortality, wildlife death, famine, human losses and severe food shortages (Ondiko & Karanja, 2021). The drought of 2016-2017 in Kenya caused food insecurity for more than 3 million people (Thomas et al., 2020). The presence of drought, drought impacts, water scarcity and aridity makes this country a suitable study area to study their internal relations. In this context, the following main research question is formulated: What is the relation of drought impacts with drought indicators and with water scarcity under different arid circumstances?

It is expected that drought indicators will not have a spatial correlation with the different climatic zones in Kenya because of the standardized nature of drought indices and that drought severity will determine the frequency of drought impact occurrences. Drought impacts (and therefore the relationship between drought indicators and impacts) will differ across regions with different arid characteristics in Kenya because of the distinct socio-economic settings, often making arid areas more vulnerable. It is also expected that water scarcity will show a relation with aridity due to the presence of unreliable water conditions.

2 Data and methods

2.1 Study area

Kenya is a country situated in East-Africa, bound by a longitude of 34° E–42° E and latitude 5° S–5° N. The highest altitudes can be found in the central highlands (over 5000 m above sea level) while there are low-lying regions in the East, Northwest, and Northeaster sides. The country is dominated by an arid and semi-arid climate which comprises about 80% of the territory and gives home to about one quarter of the population (FEWSNET, 2010) of approximately 53 million people (The World Bank, 2020). Mean annual rainfall is less than 250 mm in the semi-arid and arid areas and more than 2.000 mm in the higher areas. Long rains are occurring from March to May (MAM) while the short rains occur during October to December (OND) (Ayugi et al., 2020). The medium to high potential agricultural areas are in the center and west of the country where the population density is six times the country's average. Farming is the primary livelihood (both subsistence as commercial) for more than 75% of the population. Less than 4% are pastoralists who mainly live in the semi-arid and arid regions which is characterized by poorly distributed and unreliable rainfall (FEWSNET, 2010). Figure 1 presents the counties considered in this study (a), the arid characteristics (b) and the livelihood zones (c). The selection is based on aridity, livelihood zones and available information. Aridity is regarded as a constant climatic feature whereby the selection of counties have diverse aridity characteristics. Marsabit is an arid county (arid index 0.03-0.20) in the Northern pastoral zone while Baringo, Kitui and Kwale are considered semi-arid (arid index 0.20-0.50). Nyeri is situated in the central highlands and encompasses a high potential agricultural zone. Both Nyeri and Narok are regarded as sub-humid zone regions (arid index 0.50-0.75).

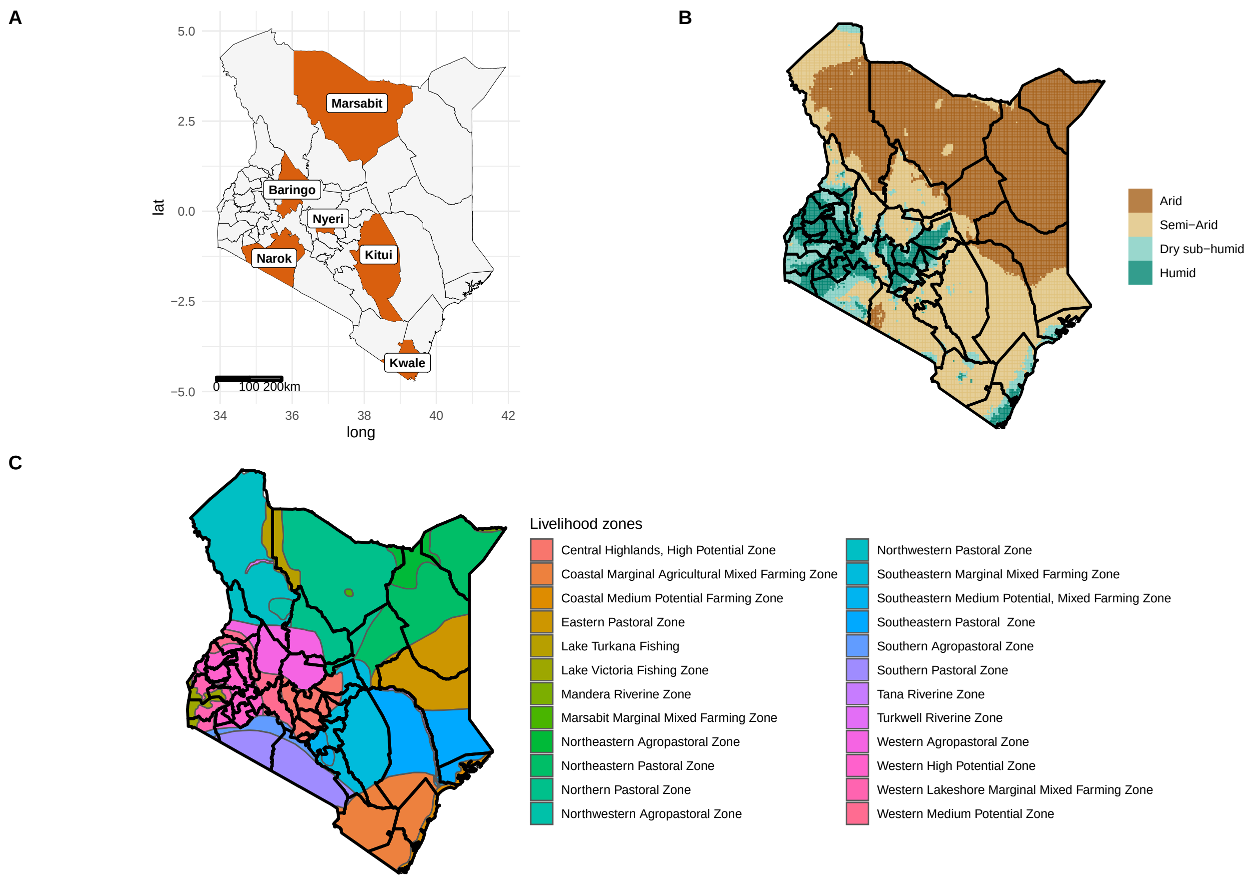


Figure 1. Maps of Kenya: the counties considered in this study (a), the aridity (b) and the livelihood zones (c).

2.2 Data

2.2.1 Drought impact data

To study the linkage between drought impacts, drought indicators, water scarcity and aridity, several datasets were used. This research used data from the National Drought Management Authority (NDMA) to gather drought impact data for the above specified counties in Kenya, concerning a time span of 2014 to 2020. The NDMA was established by the Kenyan government in 2016 with the aim to set up and operate early warning drought systems and to develop drought preparedness strategies and contingency plans (Barrett et al., 2020). Their website provides monthly bulletins assessing food security in 23 regions using socio-economic and biophysical factors. These text-based impact reports provide the input for the impact categories considered in this study. The impact categories are based on the available information from the NDMA and can therefore be regarded as categories with socio-economic relevance for Kenya. The written impact data was turned into quantitative binary values by using a specified coding sheet. The following impact categories are considered:

– Drought impacts on Pasture (i.e. livestock migration pattern, quality and quantity pasture, livestock body condition);

– Drought impacts on Livestock deaths;

– Drought impacts on Milk production;

– Drought impacts on Food insecurity;

– Drought impacts on Crop losses;

– Drought impacts on the Trekking distance to gather water for households;

– Drought impacts on the occurrence of Malnutrition.

2.2.2 Drought indicators

Several widely-used standardized drought indicators are considered to characterize meteorological, hydrological and soil moisture drought. The Standard Precipitation Index (SPI), devised by McKee et al. (1993) is based on the probability of precipitation for a known accumulation period. The Standardized Precipitation Evapotranspiration Index (SPEI) is similar to SPI but also considers the factor temperature and the influence of surface evaporation anomalies. The Streamflow Drought Index (SDI) is also a standardized index and considers monthly streamflow values (Nalbantis, 2008). Last but not least, the Standardized Soil Moisture Index (SSMI) is based on soil moisture content. SDI and SSMI are often used to present the drought propagating through the hydrological cycle, therefore showing a kind of 'memory' in comparison to SPI and SPEI. The drought indices are calculated on a monthly timescale with an accumulation period of 1, 3, 6, 12 and 24 months.

The precipitation data is retrieved from the Multi-Source Weighted-Ensemble Precipitation (MSWEP), a global product that merges with a 3-hourly temporal and 0.1 degree resolution. Potential Evapotranspiration (PET) is taken from the Global Land Evaporation Amsterdam Model (GLEAM) whereby the datasets are available at a 0.25 degrees spatial resolution and a daily temporal resolution. The SDI index is based on data from the Global Flood Awareness System (GloFAS) whereby a spatially distributed rainfall-runoff routing model LISFLOOD is used. LISFLOOD calculates a water balance at a 6 hourly or daily temporal resolution with 0.05 degree spatial resolution. Besides the PET, the SSMI index is also based on data from GLEAM. The drought indices were calculated using percentiles which were ranked and fitted through a standard normal distribution to standardize the values between -3 and 3. It was calculated on a monthly basis and then aggregated to county level for every drought indicator and corresponding accumulation period. The drought indices are calculated for the period 1980-2020, while this study takes data about the timespan 2010-2020. However, the focus of this study is on the corresponding years and months of the drought impact data.

2.2.3 Water scarcity

This study uses the water scarcity (WS) data from McNally et al. (2019), which encompasses a monthly updated water scarcity dataset for Africa between March 2018 and present. The water scarcity dataset is based on outputs from the FEWS NET Land Data Assimilation System (FLDAS) to represent streamflow and uses different population datasets as a proxy for water demand. The FLDAS's Noah 3.6 land surface model, used for calculation of the streamflow data, has a monthly temporal resolution and a spatial resolution of 0.1 degree. In order to represent the relatively local nature of water supplies, Pfafstetter level 6 are used to calculate the water scarcity index. The different classes of water scarcity are defined by the Falkenmark index. This index categorises the amount of renewable freshwater available for each person per year, shown in Table 1. The water scarcity dataset provides monthly data despite the yearly values of the Falkenmark index. However, McNally et al. (2019) used a 12-month running total of the streamflow data which explains the yearly values of the Falkenmark index being used in a monthly updated water scarcity dataset. More information about the water scarcity dataset can be found in Appendix A. The water scarcity dataset is aggregated for Kenya whereafter monthly average values per county have been calculated (using weighted average) and classified by the Falkenmark index accordingly. Different hydrological datasets were used for the water scarcity dataset and the calculation of the SDI. However, despite some inconsistencies between the datasets, both are following quite the same pattern which justifies drawing conclusions based on the water scarcity dataset. The comparison between streamflow data of the water scarcity dataset and SDI-01 is included in Appendix B.

Table 1. Falkenmark index.

Category	m^3/year /capita
No stress	>1700
Stress	1000-1700
Scarcity	500-1000
Absolute scarcity	<500

2.3 Analysis

A machine learning algorithm, namely Random Forest (RF), is used to assess the internal relation between the drought impact categories and drought indicators (Rpackage randomForest, version 4.6-14). It is a fairly new technique for linking drought indicators with impacts but showed high potential in the studies of Bachmair et al. (2016, 2017). The RF algorithm, proposed by Breiman in 2001, combines several randomized decision trees and aggregates their predictions by averaging. It is designed to minimize the overall classification error which is irrespective of the class distribution (Elreedy & Atiya, 2019). Therefore, each dataset was balanced by using a synthetic minority oversampling technique (SMOTE) and randomized under-sampling (RUS). The min-max method is used as a normalization technique to scale the datasets. The drought impact datasets were aggregated by arid characteristics: Marsabit (arid), Baringo, Kwale and Kitui (semi-arid) and Narok/Nyeri (sub-humid). For each region with the same degree of aridity, the drought impact categories were assessed separately by using the RF model. Model performance was evaluated using a subset (25%) of the original dataset as test data. The area under the ROC (Receiver Operating Characteristic) curve (AUC) describes the model's ability to predict the occurrence and non-occurrence of events correctly. A more detailed explanation about the RF model and the tuning of parameters can be found in Appendix C.

3 Results

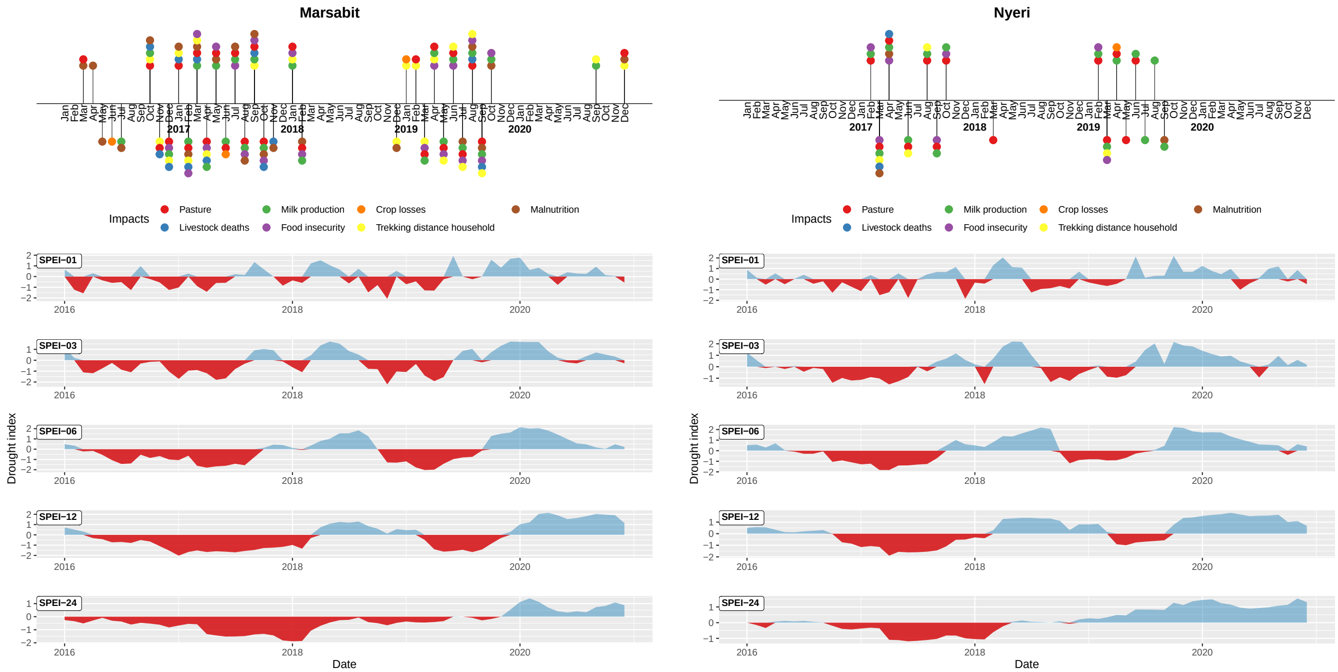
3.1 Drought indicators and drought impacts

To visualize drought impacts and drought indicators, a timeframe from 2016 to 2020 has been chosen to entail the drought of 2016/2017. Most drought impacts were reported in Marsabit and Kitui while Baringo and Nyeri has the lowest amount of impacts. Table 2 presents the share of each impact category (in %) in respect to the total number of impacts per county. Pasture and Milk production are the most reported drought impacts across the counties, with values between 17.78 and 31.82%. Noticeable is that Nyeri has the highest share in pasture related activities: Pasture impacts are 29.55% and Milk production impacts are 31.82% of the total impacts for Nyeri. The least reported drought impacts are on Crop losses, Livestock deaths and Food insecurity with average values of 3.07%, 7.75% and 10.06% respectively. Impacts related to Malnutrition are the highest in Baringo (17.78%) and Marsabit (16.94%) while Nyeri has by far the lowest amount of Malnutrition impacts (6.82%). Baringo has the highest share of impacts concerning Trekking distance for water (20.00%) while Nyeri has the lowest percentage (9.09%).

A timeline of the drought indicator SPEI for different accumulation periods (1, 3, 6, 12 and 24 months) and a timeline with drought impacts are presented for Marsabit and Nyeri in Figures 2.a and 2.b for the time period 2016-2020. Noticeable is that Marsabit experienced more extreme drought (in frequency and intensity) than Nyeri: SPEI-03 with a value of -2.22 in November 2018 was the most extreme drought for Marsabit while SPEI-12 with a value of -1.90 in April 2017 was the most extreme drought for Nyeri. SPEI-24 indicates that Marsabit experienced a multi-year drought from January 2016 to May 2019. The drought of 2016-2017 is well visible for both counties. In addition, there was a drought at the end of 2018 and 2019 which is more pronounced for Marsabit than for Nyeri. Regarding the drought impacts, Marsabit reported drought impacts (N = 124) from March 2016 until December 2020 with interruptions between March and December 2018 and between November 2019 and August 2020. Nyeri reported drought impacts (N = 44) from February 2017 until September 2019 with only one impact reported between November 2017 and January 2019.

Table 2. Total amount of reported drought impacts between 2016 and 2020 and the share of drought impact categories (%) for each county.

County	Baringo	Kitui	Kwale	Marsabit	Narok	Nyeri
Count	45	93	50	124	51	44
Pasture (%)	17.78	30.11	28.00	20.16	25.49	29.55
Livestock deaths (%)	11.11	5.38	6.00	9.68	9.80	4.55
Milk production (%)	22.22	22.58	26.00	18.55	27.45	31.82
Food insecurity (%)	4.44	10.75	10.00	15.32	3.92	15.91
Crop losses (%)	6.67	1.08	4.00	2.42	1.96	2.27
Trekking distance water (%)	20.00	15.05	12.00	16.94	17.65	9.09
Malnutrition (%)	17.78	15.05	14.00	16.94	13.73	6.82



(a) Marsabit

(b) Nyeri

Figure 2. A timeline of the drought indicator SPEI for different accumulation periods (1, 3, 6, 12 and 24 months) and a timeline with drought impacts for Marsabit and Nyeri.

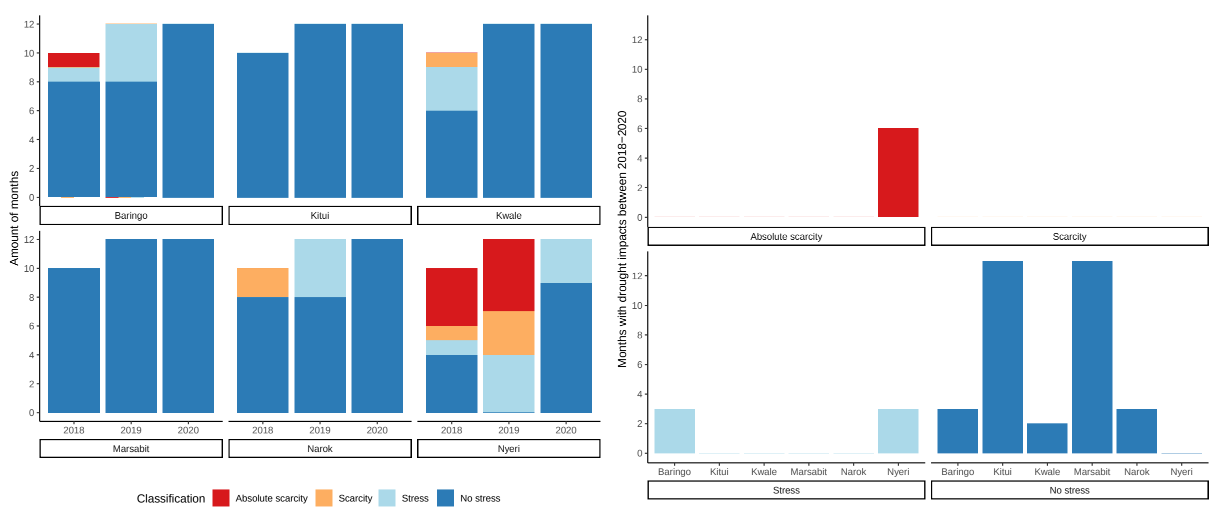
Taking the 2016/2017 drought as an example, the drought impacts reported in Marsabit are between March 2016 and February 2018 which corresponds most with SPEI-12 which is prevalent between April 2016 and March 2018. Reported drought impacts for Nyeri are between February 2017 and March 2017 which also corresponds most with SPEI-12 occurring from October 2016 until April 2018. However, specifically visible for Nyeri, drought impacts are starting later than the drought outset. A direct relation with the other accumulation periods are not prevalent, except for SPEI-24. Drought impacts in relation to SPEI-03 and SPEI-06 show a kind of lag: most impacts are occurring after the onset of the drought whereafter drought impacts are lagging while the drought has ended. Drought related to SPEI-01 is most irregular and indicates less relation with drought impact occurrence. The relation between reported drought impacts are visualized in Table 3 by using the Jaccard similarity for binary values. Pasture and Milk production are a bit related (0.63) while Crop losses are not much related to any other impact category (<0.20). Trekking distance to water points indicates a bit of relation with Pasture (0.50) and Milk production (0.47). Other relations between impact categories are not very prevalent (<0.400).

Table 3. Correlation between the impact categories (Jaccard similarity).

Impact category	Pasture	Livestock deaths	Food insecurity	Milk production	Trekking distance water	Malnutrition
Livestock deaths	0.23					
Food insecurity	0.39	0.27				
Milk production	0.63	0.23	0.42			
Trekking distance water	0.50	0.26	0.29	0,47		
Malnutrition	0.41	0.20	0.27	0.34	0.34	
Crop losses	0.15	0.04	0.00	0.11	0.11	0.11

3.2 Drought impacts and water scarcity

Figure 3.a visualizes the degree of water scarcity per year (in amount of months) across the counties. Kitui and Marsabit experienced no water stress since March 2018 while Nyeri experienced stress, scarcity and absolute scarcity during most of 2018 and 2019. Baringo, Kwale and Narok did also experience some stress and scarcity situations but with a lower frequency than in Nyeri. While Nyeri experienced all the degrees of water scarcity during 2019, most counties experienced no stress. Figure 3.b shows the amount of months with drought impacts during 2018 and 2020 in relation to the degree of water scarcity. Nyeri experienced 9 months with drought impacts whereof 6 months



(a) Water scarcity over March 2018 and 2020

(b) Water scarcity and drought impacts.

Figure 3. The degree of water scarcity per year (2018-2020) across the counties (a) and months with drought impacts in relation to water scarcity (b).

with absolute water scarcity and 3 months in a stress situation. Kitui and Marsabit had 14 months with drought impacts but did not experience any degree of water scarcity. Baringo had 6 months with drought impacts whereby half of the months were having stress situations.

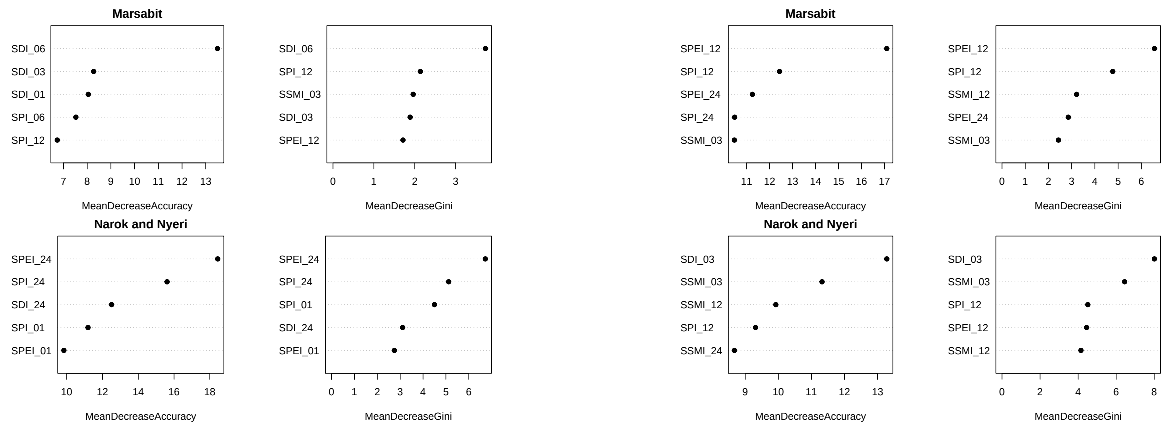
3.3 The Random Forest model

The performance of the Random forest (RF) model are visualized in Table 4. The AUC ranges from 0.50 to 1.00: the models which performed significantly good (>0.80) are visualized in green while the model performing relatively bad (<0.60) are presented in red. The performance of the model considering Pasture and Livestock deaths have the best fit, with AUC values ranging from 0.87 to 1.00. Malnutrition has the worst fit with all the AUC values below 0.600. The models concerning the arid region of Marsabit (MA) and the sub-humid regions of Narok and Nyeri (NA, NY) had the best overall fit with diverse ranges of performance among the impact categories. For instance, the model on Marsabit concerning Food insecurity has very high performance (1.00) while the one in Narok/Nyeri has not (0.53). For Marsabit and Narok/Nyeri applies that the models related to activities of pasture (Pasture, Livestock deaths and Milk production) have very high performance rates. The occurrence of drought impacts in the field of Trekking distance for water can be best predicted for the counties Narok and Nyeri. The models concerning the semi-arid counties of Baringo, Kitui and Kwale (BA, KI, KW) performed relatively bad with the exception of Crop losses (0.84).

Figures 4 and 5 show the drought indicators which are best linked with the drought impact categories: this study takes only the relations into account of the best performing models. The MeanDecreaseAccuracy (MDA: in %) represents the importance of the predictor for the model: it expresses how much accuracy the model looses when each variable would be excluded. The mean decrease in Gini coefficient is a measure of how each variable contributes to the homogeneity of the nodes and leaves in the Random Forest. In this regard, homogeneity means that most of the samples at each node are from one class. A higher MeanDecreaseGini (in %) indicates higher importance.

Table 4. Performance of the RF model per impact category and arid characteristics: good performing models are presented in green (>0.800) while bad performing models are presented in red (<0.600).

	Arid	Semi-arid	Sub-humid zone
	MA	BA, KI, KW	NA, NY
Pasture	0.87	0.62	0.96
Livestock deaths	1.00	0.71	0.97
Milk production	0.80	0.56	0.89
Food insecurity	1.00	0.67	0.53
Crop losses	0.55	0.84	0.64
Trekking distance household	0.55	0.57	0.88
Malnutrition	0.56	0.59	0.50



(a) Pasture (b) Livestock deaths

Figure 4. Drought indicators best linked with Pasture and Livestock deaths for Marsabit and Narok/Nyeri.

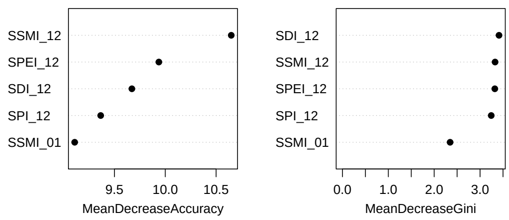
As shown in Figure 4.a, Pasture impacts for Marsabit tend to be triggered by shorter drought anomalies (6 months) than Narok and Nyeri (24 months). Furthermore, SDI is the best predictor for Pasture impacts in Marasbit while the meteorological drought indicators SPI and SPEI are the best predictors for Narok and Nyeri. SPEI-24 is by far the best performing drought indicator for Pasture concerning Narok/Nyeri with a MDA higher than 18%. When concerning Livestock Deaths (Figure 4.b), the situation is reversed: meteorological indices such as SPEI and SPI with longer accumulation periods (12-24 months) are the best link for Marsabit while the predictors SDI and SSMI with shorter accumulation periods (3-12 months) are the best link for Narok and Nyeri. SPEI-12 is by far the best performing drought indicator for Marsabit concerning Livestock deaths.

The results show that Food insecurity for the arid region of Marsabit can be well predicted with a range of drought indicators (Figure 5.a) with SSMI as the main drought predictor. However, the accumulation period is more or less stable on 12 months. For Baringo, Kwale and Kitui, high accumulation periods (6-24 months) are associated with Crop losses whereby SSMI, SDI and SPEI are the most prominent indicators (Figure 5.b). Noticeable is that SSMI-24 is by far the most prominent drought indicator for Crop Losses with a MeanDecreaseAccuracy of 24% and a MeanDecreaseGini of 10%. Trekking distance to water points for Narok/Nyeri can mainly be predicted by SDI, SPEI and SPI with an accumulation period between 6-24 months (Figure 5.c).

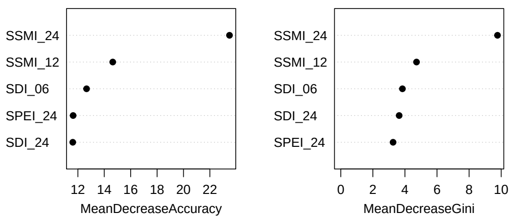
4 Discussion

4.1 Data sources and methods

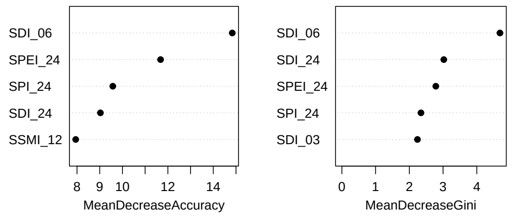
This study utilizes the water scarcity dataset of McNally et al. (2019) which uses regional streamflow data and two different population datasets, classified by a general accepted Falkenmark index. This dataset has never been validated in the Horn of Africa which could be a limitation of this research. Besides the water scarcity dataset, drought impact data have been generated by looking at the monthly and county specific reports of the NDMA. These reports had some monthly gaps and were sometimes written in different formats which made it hard to objectively appraise the



(a) Food insecurity (MA)



(b) Crop losses (BA, KW, KI)



(c) Trekking distance water points (NA/NY)

Figure 5. Drought indicators best linked with Trekking distance water points (NA/NY), Crop losses (BA, KW, KI) and Food insecurity (MA).

drought impacts. However, a predefined coding sheet partly tackled this inconvenience. Still, this study stresses the need for a general database for Africa such as the already existing databases EDII and DIR for Europa and the USA respectively. Besides this, it is recommended to consult other data sources such as the Emergency Events Database EM-DAT (www.emdat.be) to include a wider range of impact categories and to validate the results of this study.

This study used a Random Forest technique to link drought impacts with drought indictors. However, other literature used other techniques such as the Pearson correlation (Wang et al., 2020), Spearman correlation (Ma et al., 2020) and logistic regression (Bachmair et al., 2017; Blauhut et al., 2015; Stagge et al., 2015). Using RF as a tool to link drought indicators with drought impacts is a fairly new technique and has been done before by Bachmair et al. (2016, 2017) with a focus on Germany and the UK. These studies indicated a huge potential of using RF for drought M&EW. This study confirms this as well as the performance indicators (AUC) were good for several drought impact categories. However, using RF to link drought impacts with drought indicators also urges the need to expand the drought impact data collection because of its sensitivity to data availability (Bachmair et al., 2016).

4.2 Relations with aridity

The majority of the drought impact data is livestock and pasture related. It is expected that the reported drought impacts are linked with the main livelihood activity of the county. However, this study does not confirm this link. The main livelihood activity of Marsabit is pasture whereby around 50% of the drought impacts are related to this activity. However, Nyeri is a high potential farming county whereby more than 60% is related to pastoral activities. A possible explanation for the deviation between drought impacts and livelihood activities could be the skewed impact categories towards pastoral activities, limited by the NDMA database. Marsabit and Kitui had the highest reported drought impacts while Baringo and Nyeri the least amount of reported drought impacts. This suggests that drought impacts are linked with aridity because Marsabit and Kitui habitats are larger areas classified as (semi-)arid than Baringo and Nyeri. In addition, the results suggest that there is interference with the socio-economic circumstances within the counties. For instance, acute and chronic food insecurity, poverty, lack of economic development, limited access to basic social services and low education levels is highest among households in the ASALs (FEWSNET, 2010) which could explain the high amount of drought impacts found for Marsabit. These results confirm the hypothesis as formulated in the introduction that drought impact occurrences are linked to aridity.

The drought analysed for the period 2016-2020 indicated higher drought frequencies and intensities for Marsabit (arid) than Nyeri (sub-humid). Drought impacts followed accordingly suggesting a link between drought severity and drought impacts which was also expected. Maliva & Missimer (2012) stated that arid areas will have more extreme drought due to global warming which will increase the potential evapotranspiration. This could indeed influence the SPEI values which captures the factor evapotranspiration in contrary of SPI which only includes precipitation anomalies deviating from the long-term mean. Drought based on SPI still indicates higher frequencies and intensities of drought for Marsabit between 2016 and 2020. However, this study can not link drought occurrence to aridity because of the short timeframe (10 years) analyzed. The analyzation of longer timeseries could indicate if there is an interannual trend and variability of drought indices, therefore determining whether there is a drying climate or a drought event (Xu, 2021). This is interesting follow-up research whereby the term aridity will be scrutinized in relation to drought occurrences.

Most drought impacts occurred at moments without water stress, except for Nyeri. Therefore, the results suggest that WS data could not be used to predict drought impacts but also that WS should not be automatically linked with aridity as still assumed by many studies (Mulwa et al., 2021; Phillip, 2013) and what was also expected for this study. The ASALs covers about 80% of Kenyan territory but gives only home to 25 percent of the population (FEWSNET, 2010). This can explain the spatial occurrence of water scarcity since population is used as a proxy for water demand in the water scarcity dataset. Whereas aridity is regarded a constant climatic feature, water scarcity can fluctuate over time as well as space: it is a function of supply and demand at both sides of the equation which is shaped by political choices, public policies and social set up. Therefore, water scarcity can be reversed through wise usage and improved water management whereas aridity cannot (Phillip, 2013). Not all possible water scarcity related features are included in the WS dataset used in this study. It is a generalized number based on streamflow data and population data as a proxy for water demand, making it a useful tool to classify water scarcity at a national and regional scale but not on smaller scales (Rijsberman, 2006).

4.3 Drought indicators and the Random Forest model

The results show that linking drought indicators with drought impacts is very region specific, as confirmed by many other studies (Bachmair et al., 2015, 2016, 2018;

Blauhut et al., 2015; Ma et al., 2020; Parsons et al., 2019; Stagge et al., 2015; Wang et al., 2020). For instance, shorter accumulation periods were found for Pasture at Marsabit (SDI-06) while longer accumulation periods were found for Narok/Nyeri (SPEI-24). This suggests the presence of water buffers, damming the sub-annual fluctuations in water availability and therefore generating less influence on the impact category Pasture. On the contrary, Livestock deaths are linked with high accumulation periods in Marsabit (SPEI-12) and short accumulation periods in Nyeri (SDI-03). The differences between the best match between drought impacts and drought indicators suggest interference with human activities. In addition, the differences between Marsabit (arid) and Narok/Nyeri (sub-humid) suggest a link with aridity. Human activities can interfere with natural circulation processes and therefore influence the drought propagation time between meteorological and hydrological drought (Xu et al., 2019). This calls for more research towards water management practices in relation to drought indicators and drought impacts.

Regarding the drought indicators, varies drought indicators are marked as the most optimal indicator: SDI is mentioned in relation to Livestock deaths (Marsabit), Pasture (Narok/Nyeri) and Trekking distance to water points (Narok/Nyeri) while SSMI is mentioned in relation to Crop losses (Baringo, Kwale, Kitui) and Food insecurity (Marsabit). Noticeable is that SDI gives a possible link with water dependent activities while SSMI gives a possible link with agricultural practices. It is expected that SDI and SSMI would show a memory in relation to SPI and SPEI because of the propagation through the hydrological cycle, introducing a lag between meteorological, soil moisture and hydrological drought (Wang et al., 2016). Therefore, the time length and duration of SPI and SPEI can be used to express soil moisture and hydrological drought. In general a 1-month timescale is considered meteorological drought, 3-6 months as soil moisture drought and 12 months can be considered as hydrological drought (Dai et al., 2020). This link is partly visible by looking at the drought indicators in relation to the accumulation periods. For instance, SDI-06 is the best match for Trekking distance household which indicates hydrological drought. The best link after SDI-06 is SPEI and SPI with a 24 months timescale, also indicating the presence of a hydrological drought.

Studies which linked drought impact with drought indicators are mainly focused on Europe (Bachmair et al., 2015, 2016, 2018; Blauhut et al., 2015; Parsons et al., 2019; Stagge et al., 2015) and recent papers had their focus on China (Ma et al., 2020; Wang et al., 2020). Therefore, it should be noted that comparisons are quite difficult due to the different socio-economic and climatic circumstances. As studied by Bachmair et al. (2018), SPI and SPEI with an accumulation period of three and four months showed the highest correlation for the impacts on crops in Germany. This is not consistent with the results found in this study in relation to Crop losses for Baringo, Kitui and Kwale: those accumulation periods are quite high (6-24 months). As stated in the study of Bachmair et al. (2018), an accumulation period of one month was found to have a notably lower correlation with drought impacts and was often non-significant which is also confirmed by the results of this study. A reasonable explanation for this is that the occurrence of impacts have a lag behind the occurrence of drought. Another study of Bachmair et al. (2016), showed that SPI and SPEI with longer accumulation periods (12-24 months) are best linked to impact occurrence in the UK when using the RF model. In general, this does match with the results of this study: SPI-12, SPEI-12, SPI-24 and SPEI-24 are the most occurring accumulation periods, linking the occurrence of drought impacts with the presence of hydrological drought. The results indicate that impacts associated with different types of drought have different response times, as confirmed by the distinct differences in drought indicators and impact linkage pattern.

It should be noted that adaptation measures can influence the optimal drought indicator found by using the RF model. The use of adaptation measures is linked with increasing livelihood resilience whereby smallholders are better prepared for future challenges (Nyberg et al., 2020). The past years Kenya has experienced an increase in drought frequencies. This can influence the extent of adaptation measures taken and therefore the resilience against droughts which affects the final impacts. It is therefore recommended to link adaptation measures to drought impacts and indicators in order to analyze spatial differences and to map fluctuations over time.

This study contributes to the ongoing debate about the operational needs for drought monitoring by linking multiple drought indices to reported drought impacts. Results show the best drought index for a given impact which can be combined with other socio-economic and environmental data to provide enough inputs for the construction of a drought impact-based forecast, useful for stakeholders and decision makers (Heinrich et al., 2020 ; Stagge et al., 2015). In addition, this research unveils the link with water scarcity and aridity, which is valuable information for the existing literature database on drought and impacts and supports the entrance of a whole new field of research. However, it is recommended to validate the results in other research areas and on finer spatial scales whereby the influence of human activities on drought propagation and water scarcity can be analyzed. Besides this, research would benefit from a refinement of the water scarcity dataset in order to better represent human influences on the presence of water scarcity.

5 Conclusions

Drought is expected to happen more frequently in the future, generating a range of impacts in diverse sectors. This urges the need to develop early warning systems to mitigate the adverse consequences of drought and thereby reducing the human and financial costs. However, there is still no full understanding of the relation between drought impacts and drought indicators in Africa. In addition, this continent struggles with water scarcity and the presence of arid regions whereby this link has never been unveiled in relation with drought. This paper aims to fill this knowledge gap by exploring the link between drought impacts, drought indicators, water scarcity and aridity with a focus on Kenya.

The arid region of Marsabit had the most severe drought and the highest amount of drought impacts over a timeframe from 2016 to 2020. Nyeri, classified as a sub-humid region, had lower frequencies and intensities of drought and reported the least amount of drought impacts. This indicates that drought impacts are linked with drought severity and that the occurrence of drought impacts are sensitive to aridity. The skewed spatial distribution of drought impacts could be related to the fragile socio-economic conditions in the ASALs of Kenya which makes this region more vulnerable to drought than the sub-humid region of central-northern Kenya. A relation between water scarcity and aridity was not found, while this is often assumed in literature. On the contrary, Marsabit (arid) did not experience any water scarcity during March 2018 and 2020 whilst Nyeri (subhumid) did. The spatial distribution of population, used as a determinant for water demand in the water scarcity dataset, could be a reasonable explanation for this result.

With a Random Forest model, a link between drought impacts and drought indicators was made. The results indicated that every region, aggregated on aridity, had their own set of predictors for every impact category which suggests a relation with aridity. Region dependency was found by other studies as well. The models related to the livelihood activity pasture had the highest performance for the arid (arid index 0.03-0.20) and sub-humid (arid index 0.50-0.75) regions. Drought impacts related to Pasture tend to be triggered by drought anomalies of varying durations for different arid characteristics. Anomalies were shorter (6 months) for the arid region of Marsabit than for the sub-humid regions of Narok/Nyeri (24 months). For the impacts on Livestock deaths reversed results were found: lower accumulation periods were found for Narok/Nyeri (3-12 months) while longer accumulation periods were present in Marsabit (12-24 months). Drought indicators with longer timescales (>12 months), indicating a hydrological drought, were often found to best match with drought impact occurrence. The differences in linkages could be related to water management practices, hydrological regimes and climatic circumstances. However, more ground based research is needed to substantiate the diversity in results.

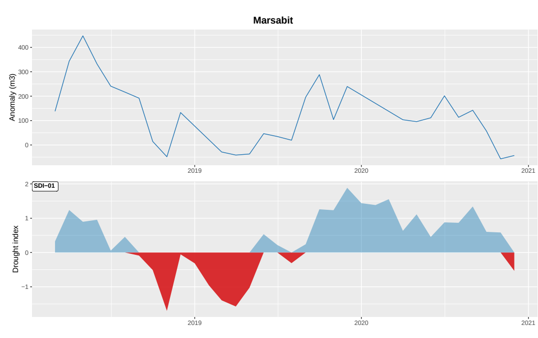
Improving the predictive ability of indicators requires the development of systematic recording of drought impacts. In addition, a finer spatial aggregation is needed to capture the regional differences in human influences on water scarcity and drought impacts. Studying other research areas and validating the results of this study on smaller scales will expand the knowledge database on drought and impacts and will substantiate the conclusions of this study. The integration of regional predictions on drought impacts will contribute to the development of early warning systems on drought and will reduce vulnerability and increase resilience of the targeted society. The unveiled link between drought indicators, drought impacts, water scarcity and aridity will open the discussion about the meaning of drought indicators in relation to drought (impacts) and opens a new arena of research.

Appendix A: Detailed explanation of the water scarcity dataset

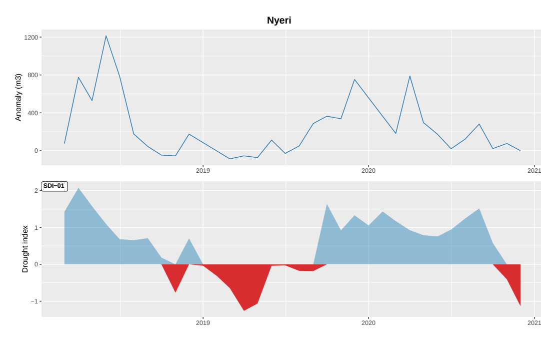
The water scarcity indicator from McNally et al. (2019) is based on outputs from the FEWS NET Land Data Assimilation System (FLDAS), which is a custom instance of the National Aeronautics and Space Administration (NASA) Land Information System (LIS). The FLDAS's Noah 3.6 land surface model is driven by the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) rainfall and NASA's Modern-Era Retrospective analysis for Research and Applications (MERRA-2) meteorological forcing. This model partitions rainfall inputs into surface and subsurface runoff (i.e., baseflow), soil moisture storage and evapotranspiration. Surface runoff is the precipitation in excess of infiltration and saturation capacity of the soil while subsurface runoff is the drainage from the bottom soil moisture layer caused by gravity. The total runoff is routed though the river network with the Hydrological Modelling and Analysis Platform version 2 (HyMAP-2) river routing scheme. The definition of catchments are based on boundaries defined by the U.S. Geological Survey (USGS) Hydrological Derivatives for Modelling Applications (HDMA) database. A Pfafstetter code, based on an hierarchical numbering system, are attributed to the catchments. For the water scarcity index, Pfafstetter level 6 basins are used in order to represent the relatively local nature of water supplies. Two population datasets are used as a proxy for water demand, namely the WorldPop 2015 dataset and the European Commission's Joint Research Center's (JRC) Global Human Settlement (GHS) data. To classify the amount of water scarcity, the Falkenmark index is used. The Falkenmark Index thresholds are specified annually while monthly data is required for the routinely updated maps about water scarcity. Therefore, a 12-month running total of the streamflow from the current and 11 previous months are used whereby the Falkenmark index (based on yearly values) can still be used on a monthly resolution. The population estimates are aggregated to Pfafstetter basin level 6 whereafter the 12-month total spatially aggregated streamflow (m^3) is divided by the population to produce an estimate of m^3/person (McNally et al., 2019).

Appendix B: The hydrological datasets: the streamflow datasources

Different hydrological datasets were used for the water scarcity dataset and the calculation of the SDI. The SDI index is based on data from GloFAS while streamflow data



(a) Marsabit



(b) Nyeri

Figure A1. Streamflow anomalies (WS) and SDI-01 between March 2018 and 2020.

for the water scarcity dataset is based on outputs from the FLDAS. If there are any discrepancies between the datasets, wrong conclusions could be made. To compare the two different datasets, SDI-01 is plot together with the streamflow anomalies of the water scarcity dataset for Marsabit and Nyeri (Figure A1). The streamflow anomalies are based on the 1982-2016 FLDAS historical record while SDI is based on the period between 1980 and 2010. Despite some irregularities between the datasets, both are following quite the same pattern. This suggest that it is reasonable to compare the results from the two different hydrological datasets.

Appendix C: A detailed explanation about the Random Forest model

Random forest (RF) is a machine learning algorithm whereby a large number of regression or classification trees on bootstrapped sub-samples of the data are constructed. Bootstrapping is a way to resample the dataset which includes replacement from the original dataset. In other words, RF's combines several randomized decision trees and aggregates their predictions by averaging. The goal of a decision tree is to create a model that predicts the value of a target by learning simple decision rules induced from the data features. A decision tree consists of nodes, edges/branches and leaf nodes. The nodes are the test for the value of a certain attribute (predictor), the edges/branches are the outcome of a test and connect to the next node or leaf and the leaf nodes are the terminal nodes predicting the outcome. In order to validate the model, a training data set and a test dataset is constructed with a proportion of 75% and 25% of the original dataset. Each tree is built on a subset of the training data set: approximately two-third of the training dataset is used for building a tree while one third is not used, called the out-of-bag error data. This generates an additional estimate of performance, namely the out-of-bag error which is a method to measure the prediction error of the random forest. For the model, two parameters needed to be tuned, namely the amount of randomized trees (ntree) and the amount of variables available for splitting at each tree node (mtry). The value of ntree has been proven to have not much effect on the overall accuracy of the model and is set to the default value of ntree = 500. For the best value of mtry, the function tuneRF function of the RandomForest package has been used which aims to lower the OOB error. The tuned parameters for mtry are visible in Table A1.

The performance of the various models for the impact categories were tested by applying the model on the test set

Table A1. Tuning of parameters for the RF model: mtry values.

	Arid	Semi-arid	Sub-humid zone
	MA	BA, KI, KW	NA, NY
Pasture	3	4	4
Livestock deaths	6	4	4
Milk production	4	6	4
Food insecurity	6	2	6
Crop losses	3	4	2
Trekking distance household	6	3	4
Malnutrition	2	6	4

data (25% of the original data set). The AUC (Area Under the Curve) ROC (Receiver Operating Characteristics) curve was used to check and visualize the performance. It describes how much the model is capable of distinguishing between the classes: how higher the AUC, the better the model is at predicting 0 classes as 0 and 1 classes as 1. The ROC curve is plotted with the Sensitivity on the y-axis and Specificity on the x-axis. These variables represent the true positives and true negatives respectively.

Acknowledgements. Writing this paper was not possible without the help of some great persons. First of all, I want to thank Ryan Teuling, Alessia Matano and Anne van Loon for their support, feedback and great supervision. You were always there to think along with my ideas and assisted where needed, many thanks for that. Especially thanks to Alessia Matano who connected me with the Red Cross 510, an organization focussed on disaster preparedness, early warning/action and disaster response. This organization welcomed me in their Teams environment where I always felt support by having the possibility to ask for help (especially with Rstudio and Python related questions) and guidance which I greatly appreciated. Especially thanks to Aklilu Teklesadik, my supervisor at 510, who supported me when needed. Thanks to Corina Markodimitraki, who gave me a very warm welcome in the 510 team and who I could always contact to connect me to any volunteer of the organization. Furthermore, thanks to all the people working at 510 who helped me and gave me a wonderful experience about working at such an organization. From the Institute for Environmental Studies (IVM) team at the VU Amsterdam, I want to thank Rhoda Odongo who provided me with data about the drought indicators and took the time to review my paper.

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