Desa’a national forest reserve susceptibility to fire under climate change

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ABSTRACT
Climate change influences spreading and occurrence of forest fire. Forest fire modeling is one of the most important tasks to fight forest fires. Climate data of current (1980–2010) was projected to near (2010–2039), mid (2040–2069) and end-term (2070–2099) using Representative Concentration Pathway (RCP4.5 and 8.5) of an ensemble of twenty General Circulation Models using R-software. Current and projected climate data were used to determine the impact of climate change on current and future forest fire using Keetch-Byram Drought Index. Current and future forest fire-vulnerable areas were mapped and weighed using Inverse Distance Weighting. The result indicates that, while no forest fire occurrence in the current, there might be a high forest fire risk in near-term. It might be become very high in mid and end-term. The size of forest fire-vulnerable areas might be increased to 12.85, 18.8, 17.1 and 46.26% in Mid-RCP4.5, Mid-RCP8.5, End-RCP4.5 and End-term-RCP8.5 respectively. Fire may occurred in winter and spring seasons. The risk might be move to higher elevation of the forest. This directs increase of forest fire occurrence and spread due to climate change. The study recommends that forest fire management should be applied before fire happened to sustain the forest and its products.

1. Introduction
Forest fire is a disaster that destroys forest and wildlife (Jaiswal et al. 2002; Böhm et al. 2011). Climate, weather conditions and topography influence the fire regime by determining the fuel distribution and the occurrence of fire (Rollins et al. 2002; Liu et al. 2012). Climatic factors such as wind, temperature and drought influences incidence and spread of forest fires (Kutiel et al. 2001; Türker 2003) and there is strong linkage between drought and forest fire (Camia and Amatulli 2009). Reduced crop and forest productivity, increased fire hazard, reduced water levels, and damage to wildlife are a few examples of drought’s direct impacts (Wilhite et al. 2007). Drought increases the probability of forest fire occurrence through drying of the plants and decreasing of soil moisture (Beverly and Martell 2005; Duffy et al. 2005). Prolonged drought and strong wind speed (Ganteaume et al. 2013) with high temperature and low rainfall (Petritsch and Hasenauer, 2014) creates natural forest fire. It is commonly occurred due to prolonged drought occurrence (Ganteaume et al. 2013; San-Miguel-Ayanz et al. 2013).

Forest fires are happening by weather conditions (Liu et al. 2010). Meteorological conditions and fire occurrence have strong relationship (Piñol et al. 1998). It has largest contribution and effect on fire ignition and spread when compared with factors like elevation. As a result, a variety of meteorological forest fire risk indices and, more specifically, drought indices have been developed to monitor forest fire (San-Miguel-Ayanz et al. 2013). Forest fire modeling is one of the most important tasks to fight forest fire destruction. Accurate forest fire modeling to expect fire spreading is one of the most important tasks to fight forest fires.

Direct measurements of forest biomass moisture and fuel are slow and time consuming. To reduce those problems forest fire modeling is better to simulate with fuel and soil moisture content in relation to meteorological factors (Keech and Byram 1968; Gillett et al. 2004). With the aim of determining the risk areas of natural forest fires, remote sensing and Geographic Information Systems (Pradhan et al. 2007; Pourghasemi et al. 2016; Pourtaghi et al. 2015) and meteorological data can be used simply (Gillett et al. 2004). Modeling forest fire vulnerability based on meteorological data is more significant (Pyne et al. 1996; Gillett et al. 2004). During the last decades, various techniques have been employed to assess the forest fire risk. The Keetch-Byram Drought Index (KBDI) (Keetch and Byram 1968) is fire potential index which is widely used in the United States where it is a part of the National Fire Danger Rating System (Liu et al., 2013). Keetch-Byram Drought Index (Keetch and Byram 1968) is a software used to estimate forest fire based on meteorological data and is one of the most commonly used method for this purpose (Janis et al. 2002; Pötzelsberger and Hasenauer 2015).

Keetch-Byram Drought Index (KBDI) is a widely used drought index intended for wildfire monitoring (Heim Jr 2002; Ganatsas et al. 2011). It has become the most worldwide used index in wildfire monitoring.
and prediction, mainly due to its easy implementation compared to other indices which normally need more meteorological data and complicated calculations (Heim Jr 2002; Ganatsas et al. 2011). KBDI is still considered a robust indicator of wildfire risk (Arpaci et al. 2013). KBDI is designed for wildfire monitoring and prediction (Janis et al. 2002). KBDI estimates forest fire risk through estimating the dryness of soil and duff layers (Keetch and Byram 1968). KBDI has primarily been used for forest fire management and planning operations (Dolling et al. 2005). KBDI is also used to monitor agricultural drought (Salehnia et al. 2018). The main purpose of this paper is to investigate the impact of climate change on the forest fire occurrence using Keetch-Byram Drought Index (KBDI) and Arc GIS in Desa’a forest in order to recommend different forest management practices to sustain the forest.

2. Methodology

2.1. Study area

Desa’a protected forest lies between 13°20’ and 14°10’ North and 39°32’ and 39°55’ East. It incorporates lowland, midland and highland altitudes (Figure 1). It is part of the northeastern highlands of Ethiopia, positioned at a strategic site in northeastern Tigray and northwestern Afar, well placed for joint regional planning and its tributaries flow towards the Afar plains (Figure 1). According to Gebreegziabher (1999) considerable part of the forest area falls within Tigray Region.

Friis (1992) and AYnekulu et al (2011) broadly classified the natural vegetation of Desa’a as “dry evergreen Afromontane forest” with Juniperus procera and Olea europaea subsp. cuspidata as the dominant species (Friis 1992; Aynekulu et al. 2011). The area is characterized by minimum and maximum mean temperatures that vary in the range of 9.3 to 14°C and 22.4 to 27.6°C, respectively. Figure 1 modestly explains that the forest area possess the characteristic of different elevations.

2.2. Methods

2.2.1. Climate input datasets

Two daily climatic variables namely; maximum temperature and rainfall were used for this study. Maximum temperature was obtained from ENACTS (Enhancing climate information services TAMSAT) satellite while gauge blended data and rainfall were obtained from CHIRPS daily rainfall data. CHIRPS data are with spatial resolution of 0.05 degree (5 Km) and temporal resolution of 5 days accumulation. Enhancing National Climate Services (ENACTS), aims to support decision makers in climate-sensitive sectors by filling spatial and temporal gaps in existing climate observations and providing an array of derived products. ENACTS and CHIRPS climate data sources are important because they are produced by interpolation of meteorological and satellite data. The data were obtained/computed from 1981 to 2016 records. Those climate data were used to fill missing values of national meteorological station using regression and normal ratio methods. The obtained current data were projected to near (2010–2039), mid (2040–2069) and end term (2070–2099) using R-programing language under ensemble twenty General Circulation Models (GCMs) in two emission scenarios called Representative Concentration Pathways (RCP) 4.5 and 8.5, RCP 4.5 and 8.5, which describes both medium and high emission scenarios. R.matlab and R.utils packages were load into the R-programing language to project the climate data. The time slices were defined the interval of thirty years. While whereas ensemble GCM method was used to reduce model uncertainty due to the structural dissimilarities among GCMs (Semenov and Stratonovitch 2010). Recently, there is a growing agreement in considering the climate impact
study by an ensemble of GCMs (Aung et al. 2016). The simulation of climate from a single GCM is insufficient to provide the appropriate information (Jacob et al. 2007). Ideally, by using the average of an ensemble of GCMs, the individual model errors are cancelled out and the ensemble uncertainty decreases as increasingly more models are used (Weiland et al. 2012). Accordingly, this study used all twenty GCMs loaded in the programing language in order to reduce the uncertainty of GCMs.

2.2.2. Keetch-Byram drought index (KBDI)

The KBDI was developed by the United States Department of Agriculture’s Forest Service for forested and wild land areas of the south-eastern United States. Over the years/decades it has also been applied to many other regions of the world in land-cover types (Dharssi et al. 2017). In the Australian states of Victoria KBDI was deployed for forest fire prediction (Finkele et al. 2006). Moreover, it was employed to study wildfire occurrence in the upper mid-west of United States (Lorimer and Gough 1988), Mediterranean regions (Ganatsas et al. 2011; Garcia-Prats et al. 2015), Hawaii (Dolling et al. 2009), Malaysia (Ainuddin and Ampun 2008), Lebanon (Bayissa et al. 2018) and to assess the impact of climate change on global wildfire potentials (Liu et al. 2010).

The use of KBDI in a wide range of geographical areas implies that the index is considered as an acceptable application. Basically it also concentrates on changes occurring in the soil moisture as a result of evapotranspiration in the ecosystem (Janis et al. 2002). It was available at: https://agrimetsoft.com/kbdis.aspx.

Keetch-Byram Drought Index (KBDI) was used to determine forest fire risk area and forest fire risk period based on daily climate conditions. Forest fire risk area and forest fire risk period were calculated using baseline and projected maximum temperature and precipitation data. The model takes maximum temperature and precipitation. The climate data used to estimate forest fire were taken from the lowland (Berahle district) and highland (Astibi district) part of the forest. KBDI of the two elevation classes were calculated. Then, forest fire risk area of the two points was interpolated to the whole forest area using the Inverse Distance Weighting (IDW), a method that uses for interpolation (Janis et al. 2002; Cao et al. 2010). The interpolation method was applied due to the presence of low meteorological station around the forest.

The Inverse Distance Weighting method was applied to the index results by using the Arc GIS software. It estimates the value of a variable for new location using interpolation of values obtained from known locations. It combines calculated KBDI values with gridded Digital Elevation Model of the study area in order to interpolate KBDI values. Therefore, in this study the IDW method was used to map fire vulnerable area while the Keetch-Byram Drought Index (Keetch and Byram 1968) was used to determine forest fire risk.

From current and projected daily maximum temperatures and rainfalls, Keetch-Byram Drought Index (KBDI) software produces and uses daily maximum temperature, daily rainfall, cumulative antecedent moisture deficiency, annual average precipitation, and evapotranspiration and soil moisture. The depth of soil in which major part of root penetrates and absorbs water and nutrient, was assumed 20 cm (Salehnia et al. 2018). Accordingly, the theory and framework of KBDI is based on different assumptions. The first assumption is that, the rate of soil moisture loss depends on density of the vegetation cover, antecedent moisture conditions, annual rainfall and evapotranspiration. The second assumption is that the field capacity of soil is 8 inches of available water. This number suites reasonably well for use in forest fire control (Keetch and Byram 1968). The amount of water lost in a forested area was calculated using the following mathematical expression:

$$dQ = \frac{(800 - Q)(0.968 e^{0.0486 T} - 8.30)}{1 + 10.88 e^{-0.0441 R}} \times 10^{-3} \quad (1)$$

The equation can be transformed easily and can be written as follows:

$$dQ = \frac{(203.2 - Q)(0.968 e^{0.0875 T + 1.5552} - 8.30)}{1 + 10.88 e^{-0.001736 R}} \times 10^{-3} \quad (2)$$

Where $dQ$ is a drought factor or soil water depletion (in mm) during a period of time dt, $Q$ is the accumulated soil water depletion (in mm); $T$ is daily maximum temperature (in °C); $R$ is mean annual rainfall (in mm); 203.2 is the field capacity of soil expressed in mm (203.2 mm = 800 hundredths inches) (Keetch and Byram 1968). 220 In equation (2), potential evapotranspiration (ETP) is estimated on a daily basis as the ratio of an exponential function of the daily maximum temperature ($T$), divided by an exponential function of the mean annual rainfall ($R$):

$$ETP = \frac{0.968 e^{0.0875 T + 1.5552} - 8.30}{1 + 10.88 e^{-0.001736 R}} \times 10^{-3} \quad (3)$$

Finally, potential evapotranspiration is converted to actual evapotranspiration as a linear function of soil water depletion, i.e., ETP is reduced as soil dries as described by equation (4):

$$dQ = (203.2 - Q) ETP \quad (4)$$

The obtained KBDI values were categorized to determine different levels of fire risk in order to interpret easily and clarify discussion on drought. In view of that, it is categorized as a Table 1. Table 1 shows the severity of forest fire.

3. Result

3.1. Forest fire risk period

The intensity of current and future forest fire using KBDI in Desa’a forest is 145, 383, 367, 425, 437, 433 and 476 in current, near term RCP 4.5, near term RCP
8.5, midterm RCP 4.5, mid term RCP 8.5, end term RCP 4.5 and end term RCP 8.5, respectively. This means, in current (at present) there is low forest fire occurrence. In near term there may be high probability of forest fire occurrence in the lowland part. However, in the medium and high emission scenario of mid and end term, there may be very high forest fire occurrence. In addition, the risk is higher in winter than spring, fall and summer in all scenarios and time slices. Besides, there may be an occurrence of moderate to high forest fire in spring (Figures 2 and 3). It is observed that the KBDI values are lowest during summer and fall, while reach the maximum level in winter and spring. The probability of fire risk increases when both time slices and emission scenario (which emission scenario) increases. This indicated that the forest soil moisture will be affected due to climate change and the plants will become a good source of fuel for fire occurrence. Nevertheless, there might not be extremely high fire occurrence in all time slices and emission scenarios. Figures 2 and 3 shows the occurrence of fire in summer (June, July and August), winter (December, January and February), and spring (March, April, and May) and fall (September, October, and November) temporally.

### 3.2. Forest fire risk area

Currently, there is no wildfire risky area in the forest. However, there might be high wildfire vulnerable area in near term of both representative concentration pathways. In current and near term there is simply low to high forest fire risky area. However, there might be very high forest fire vulnerable area in mid and end term of the century. High and very high forest fire vulnerable area may increase from zero to 12.85, 18.8, 17.1 and 46.26% in Mid RCP 4.5, Mid RCP 8.5, End RCP 4.5 and End term-RCP 8.5 of the century, respectively (Figures 4 and 5). Figures 4 and 5 shows the occurrence of fire in summer, winter, and spring and fall spatially and temporally.

There might be only low to medium forest fire occurrence in highland part of the forest due to low temperature and high rainfall. However, in lowland part of the Desa’a forest there might be source of ignition to wildfire because there is/might be high temperature and low rainfall. Additionally, there might be no very high severity of fire in current and near term. However, it might occur in mid and end term, and shifts to high elevation areas due to climate change. High fire occurrence has similar trend with very high

### Table 1. KBDI fire risk levels.

| KBDI (inches) | Risk levels | Description |
|---------------|-------------|-------------|
| < 99          | Very Low    | Upper soil and surface litter are wet and fire potential is very low |
| 100–199       | Low         | Upper soil and surface litter are moist and do not contribute to fire |
| 200–299       | Moderate    | Upper soil and surface litter are moderately dry and may contribute to fire |
| 300–399       | High        | Upper soil and surface litter are dry and contribute to fire intensity |
| 400–599       | Very High   | Upper soil and surface litter are very dry and fire suppression is a significant |
| 600+          | Extreme     | Upper soil and surface litter are extremely dry and increase wildlife occurrence |

**Figure 2.** Forest fire risk seasons in medium emission scenario A) current B) near term C) midterm D) end term.
Therefore, climate change might cause altitudinal shift of forest fire occurrence. Unlike Ethiopia, the risk of forest fire is particularly high in Mediterranean ecosystems during dry summer (Gülsen and Sönmez 2016). In addition, an increase in risk of summer droughts is likely to take place in Southern Europe (Giannakopoulos et al. 2009). However, to the contrary winter and spring seasons are dry seasons in Ethiopia where forest fire is high. Apart from the risk that comes from the dry seasons manmade forest fire is existential threat to the forest. According various studies about five forest fires had occurred in the years between 1958 and 1998. Of all the incidences, the 1970 and 1998 fire had destroyed about 1000 and 350 ha respectively. Human induced factors were mentioned as the main causes the fire to occur in the forest (Gebreegziabher 1999). Nonetheless, there were forest fires in other parts of Ethiopia triggered by drought (Dechassa and Perault 2001). On the other hand the entire forest land in Kutch Woreda, South Ethiopia burns every year during dry seasons (Mengistu 1994). Hence, in the future climate change will influence to increase, forest fire occurrence.

The result showed that forest might be exposed to wildfire. Similar studies conducted by Flannigan et al. (2009) and Anderson et al. (2000) indicate that the world forests will be vulnerable to wildfire due to climate change. Flannigan et al. (2009) study further validates that in circumboreal forest wildfire is projected to increase by 18% and 50% in near and end

![Figure 3](image1.png)  
**Figure 3.** Forest fire risk seasons in high emission scenario A) current B) near term C) midterm D) end term.

![Figure 4](image2.png)  
**Figure 4.** Forest fire risk area in medium emission scenario A) current B) Near C) Mid D) End term (green, yellow, gold and red color shows low, moderate, high and very high forest fire risk respectively).
term of the century respectively). A separate study by Liu et al., (2010) reveals that future wildfire potential may increase significantly in the United States, South America, central Asia, southern Europe, southern Africa, and Australia. The study further noted that in the globe fire potential category might increase by one level, from low to moderate potential or from moderate to high potential.

4. Conclusion

This study finds out that there is a potential wildfire occurrence due to climate change impact. The study further demonstrates that forest fire risk might be lowest during summer and fall but it can reach the maximum level during winter and spring seasons. It also signals that the probability of fire risk increases when both time slices and emission scenario increases. Notably the lowland part of the forest is more vulnerable to wildfire ignition than other part located in the high land due it vicinity to zone of great East African Rift Valley which minor eruptions and volcanic shocks are common. Apart other factors that aggravate forest fire to occur in the lowland part of the forest, forest density is treated as one and it increases from low to high elevation. Nevertheless, there might be no extremely forest fire in all time slices and emission scenarios.

Hence, the study recommends that sustainable forest fire management practices such as firebreak construction should be applied to control the fire. In addition to meteorological fire occurrence, the forest is close to volcanic eruption heat; therefore, the forest should be managed in a sustainable way. And further study should be conducted including other factors such as topography, elevations, slope, wind, vegetation, soil moisture and forest density, plant species type in order to develop more robust findings to protect the forest and wildlife.

Disclosure statement

No potential conflict of interest was reported by the authors.

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