Assessing potential locations for flood-based farming using satellite imagery: a case study of Afar region, Ethiopia

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Abstract
The dry lowlands of Ethiopia are seasonally affected by long periods of low rainfall and, coinciding with rainfall in the Amhara highlands, flood waters which flow onto the lowlands resulting in damage to landscapes and settlements. In an attempt to convert water from storm generated floods into productive use, this study proposes a methodology using remote sensing data and geographical information system tools to identify potential sites where flood spreading weirs may be installed and farming systems developed which produce food and fodder for poor rural communities. First, land use land cover maps for the study area were developed using Landsat-8 and MODIS temporal data. Sentinel-1 data at 10 and 20 m resolution on a 12-day basis were then used to determine flood prone areas. Slope and drainage maps were derived from Shuttle RADAR Topography Mission Digital Elevation Model at 90 m spatial resolution. Accuracy assessment using ground survey data showed that overall accuracies (correctness) of the land use/land cover classes were 86% with kappa 0.82. Coinciding with rainfall in the uplands, March and April are the months with flood events in the short growing season (belg) and June, July and August have flood events during the major (meher) season. In the Afar region, there is potentially >0.55 m ha land available for development using seasonal flood waters from belg or meher seasons. During the 4 years of monitoring (2015–2018), a minimum of 142,000 and 172,000 ha of land were flooded in the belg and meher seasons, respectively. The dominant flooded areas were found in slope classes of <2% with spatial coverage varying across the districts. We concluded that Afar has a huge potential for flood-based technology implementation and recommend further investigation into the investments needed to support new socio-economic opportunities and implications for the local agro-pastoral communities.

Introduction
A rising global population has increased the pressures on natural resources for agriculture, livestock and livelihood needs. Concomitantly, there is a decline in productive areas in sub-Saharan Africa partly caused by flash floods, droughts, land degradation and associated declines in soil fertility (Amede et al., 2004). The low lying regions of Ethiopia, largely located in the Great Rift Valley, are prone to extreme events of recurrent drought and flood (Gummadi et al., 2017). Land degradation is also a common problem in the region (Mihiretu and Yimer, 2018), with more than 1.5 billion tonnes of topsoil from higher elevated areas washed away by heavy rains (Tamene and Vlek, 2008; Mihiretu and Yimer, 2018).

In Ethiopia, the highlands, which occupy 44% of total geographical areas, have been under cultivation for centuries and are severely affected by soil erosion (Huriri, 1988) and deforestation (McCann, 1997). The highlands are the source of flash floods and sediment loads to the neighboring downstream lowlands. In the decades past, flood waters were reported to have spread across the low-lying grazing lands (Hailu et al., 2018), benefitting the rangelands which supported the livelihoods of (agro) pastoralists. With large numbers of livestocks and year-round grazings, the (agro) pastoral landscapes of Afar have degraded and the flood channels have become deep gullies (Van Steenbergen et al., 2011) with less chance for the waters to spread and irrigate natural pastures.

Pilot studies in the degraded Rift Valley areas of Ethiopia demonstrated that the effects of strong runoff and sporadic flash floods could be reversed by a holistic approach using water spreading weirs (WSW) (Elisabeth et al., 2015). WSW are low retention walls commonly built in the foot slopes of mountainous landscapes, designed to regulate seasonal floodwaters,
reduce runoff and minimize erosion (Haile and Fetene, 2012). The weirs could modify waterways, catchments and farms at scale. Improved management of land and water resources for the sustainable development through improved management of spate irrigation has been reported earlier (Gumma et al., 2011). Several studies have proven that successful management and use of spate irrigation and broader natural resources management would require integrated approaches considering social and biophysical processes (Moore et al., 1991; Vittala et al., 2008; Iqbal and Sajjad, 2014; Panwar and Singh, 2014) and appropriate use of tools and methods.

Remote sensing is one of the low cost but effective tools for monitoring natural resources and flooded areas on timely basis. A wide range of satellites is capturing information at various spatial, spectral, temporal and radiometric resolutions. Near real time satellite imagery helps in identifying droughts and floods for quick decisions (Gumma et al., 2017). Numerous studies have been conducted on monitoring croplands and natural resources using remote sensing and geographical information systems supported by secondary information (Rao et al., 2004; Gumma et al., 2009, 2015, 2016b; Qiu et al., 2013). Several studies mapped water bodies, flooded areas and soil moisture regimes using multiple data sets including MODIS, Landsat and sentinel (Feyisa et al., 2014; Gumma et al., 2015; Qiu et al., 2015). Temporal satellite imagery and spectral analysis were successfully used in monitoring croplands and flooded areas in various studies (Gumma et al., 2014; Dong et al., 2015; Gumma et al., 2019), including at watershed and higher scales (Khan et al., 2001; Gumma et al., 2016). For instance, Sentinel-1 is most widely used to map soil moisture and floods during rainy season (Paloscia et al., 2013; Pierdicca et al., 2014; Schlaffer et al., 2015) including for assessment of flood damage.

Flood events occur where the overflow of water submerges land due to heavy rainfall events, an overflow of water from a water body, or in the case of the Afar region, from seasonal land due to high rainfall events, an overflow of water from a pool. MOD13Q1 16-day composite, four-band data for all 23 grids of Landsat-8 imagery were used, which are connected to the highlands of Oromia, Amhara and Tigray regional states from which the lowland of Afar receives floods occurring during the belg and meher seasons.

**Data and methods**

**Satellite imagery and data preparation**

**MODIS NDVI 250 m**

MODIS Terra Vegetation Indices 16-Day L3 Global 250 m SIN Grid V005 (MOD13Q1 product) imagery were used, which are freely available from the Land Processes Distributed Active Archive Center (https://lpdaac.usgs.gov/lpdaac/get_data/data_pool), MOD13Q1 16-day composite, four-band data for all 23 composite dates during January–December, 2017 were used in this analysis. Bands and vegetation indices contained in the MOD13Q1 product include blue, red and near infrared (NIR) and mid-infrared bands and normalized differentiation vegetation (NDVI) index (NDVI generated using NIR and red bands). The product is already atmospheric corrected and cloud contamination generated using 16-days maximum composite NDVI. Table 1 provides the data used in the study and description.

**Landsat-8 imagery**

Landsat-8 images extracted from USGS Earth explorer (https://earthexplorer.usgs.gov/). In this study, we have used 11 Landsat 8 tiles (February 2017 and November 2017) which were captured in belg and meher seasons (Table 1). Image preprocessing start with image normalization, which means converting sensor captured digital number (DN) values to the reflectance.

Image normalization: The following equation is used to convert DN values to top of atmosphere (TOA) reflectance for OLI data

\[
\lambda' = M_p Q_{cal} + A_p
\]

where \(\lambda'\) is the TOA planetary reflectance (without correction of solar angle), \(M_p\) is the Band specific multiplicative rescaling factor from the metadata, \(A_p\) is the band specific additive rescaling factor from the metadata and \(Q_{cal}\) is the quantized and calibrated standard product pixel values (DN).

TOA reflectance with correction for the sun angle is then:

\[
\lambda = \frac{\lambda'}{\sin(\theta_{SL})}
\]
where $\lambda$ is the TOA planetary reflectance, $\lambda'$ is the TOA planetary reflectance (without correction of solar angle) and $\theta_{SE}$ is the local sun elevation angle provided in the metadata (SUN_ELEVATION).

Sentinel-1 data
The Sentinel-1 mission provides data from a dual-polarization C-band Synthetic Aperture Radar (SAR) instrument. This collection includes the S1 ground range detected (GRD) scenes, processed using the Sentinel-1 Toolbox to generate a calibrated, ortho-corrected product. The collection is updated weekly. The GRD scenes either of the three resolutions (10, 25 or 40 m). It consists of combinations of four bands i.e., single band VV or HH, and dual band VV + VH and HH + HV: 1. VV: single co-polarization, vertical transmit/vertical receive 2. HH: single co-polarization, horizontal transmit/horizontal receive 3. VV + VH: dual-band cross-polarization, vertical transmit/horizontal receive 4. HH + HV: dual-band cross-polarization, horizontal transmit/vertical receive (Sentinel-1 User Handbook, 2013, ESA, 2014). The data is freely available from Copernicus Open Access Hub the open hub site or it can be accessed from cloud computing platform Google Earth Engine.

In the study in order to assess the flooded areas, the freely available Sentinel-1 GRD, single band VV polarized data during peak flood periods of the Ethiopia region i.e., February–September 2017 downloaded from open access hub site (https://scihub.copernicus.eu/dhus/).

SRTM DEM data
The Shuttle Radar Topography Mission (SRTM) – a mission of NASA provides information regarding surface topography for better understanding of geospatial features of Earth which is obtained from elevation data at 90 m spatial resolution on a near-global scale to generate the most complete high resolution digital topographic database of the Earth (SRTM technical guide). SRTM data can be downloaded from USGS Earth Explorer at 30 m (1-Arc Second) and 90 m resolutions. In this study we used DEM for extraction of a slope.

Ground survey data
A ground survey was conducted in 2 different years, the first visit was done in August 2017 and the second one was during August 2018 for the meher season. The survey was conducted as training and validation, for both classifying land use/land cover (LULC) and assessing the accuracy map. Altogether 316 locations (65 locations in 2018 and 251 locations in 2017) covering major land use/land cover areas in entire river catchment were recorded. Each location, data were collected from 90 × 90 m plots and consisted of GPS locations, land use categories, land cover percentages, cropping pattern during different seasons (through farmer interviews), crop types and watering method (irrigated, rainfed) along with other LULC areas. Samples were obtained within large contiguous areas of a particular LULC. Locations were chosen based on the knowledge of field staff and agriculture officers to ensure that the crops were grown during the belg season during the survey. Overall, 316 spatially well-distributed data points (Fig. 2) were collected; of these, 68 data points were used for identification and labeling class names while an additional 248 data points were used for accuracy assessment.
Table 1. Data used for the present study and characteristics of satellite sensor data used in the study

| Imagery          | Bands # | Band width nm²/range | Potential application                                      |
|------------------|---------|----------------------|------------------------------------------------------------|
| Landsat-8 data sets |        |                      |                                                            |
| Band 2 – Blue    |         | 0.450–0.515          | Water bodies and also capable of differentiating soil and rock surfaces from vegetation |
| Band 3 – Green   |         | 0.525–0.600          | Emphasizes peak vegetation, which is useful for assessing plant vigor |
| Band 4 – Red     |         | 0.630–0.680          | Sensitive to strong chlorophyll absorption region and strong reflectance region for most soils. |
| Band 5 – NIR     |         | 0.845–0.885          | Operates in the best spectral region to distinguish vegetation varieties and conditions |
| Band 6 – SWIR1   |         | 1.560–1.660          | Discriminates moisture content of soil and vegetation; penetrates thin clouds |
| Band 7 – SWIR2   |         | 2.100–2.300          | Improved moisture content of soil and vegetation and thin cloud penetration |
| Band 10 – TIR1   |         | 10.6–11.2            | Thermal mapping and estimated soil moisture |
| Band 11 – TIR2   |         | 11.5–12.5            | Improved thermal mapping and estimated soil moisture |
| SRTM 90 m meters |         |                      | Extraction of slope |
| Sentinel-1 SAR    |         |                      | Flood mapping |
| MOD13Q1 – 250 m 16 days NDVI | NDVI | –1 to +1            | Vegetation conditions |

Fig. 2. Ground survey data locations in Afar regions during meher season.
The methodology for the identification and mapping of flood prone areas and areas targeting of new technologies is shown in Figure 3 and is described in the following sections. We have started the process with multi sensor image preprocessing.

**Land use/land cover classification**

A time series of MODIS 16-day composite vegetation index images at 250 m resolution were obtained for the period of 01 January 2017 to 31 December 2017 (MOD13Q1 data product). The 16-day composite images in the MOD13Q1 dataset are available in the public domain and are pre-calibrated (http://modis-sm.1tdri.org/html). The large scene size and daily overpass rate of MODIS makes it attractive for mapping large crop areas, and NDVI derived from MODIS has high fidelity with biophysical parameters (Gumma et al., 2018a). The 16-day NDVI images were stacked into a 23-band file for each crop year (two images per month). The monthly maximum value composites were created using 16-day NDVI MODIS data to minimize cloud effects.

Unsupervised classification as described by Cihlar et al. (1998) was used to generate initial classes. The unsupervised ISOLABEL cluster algorithm (ISODATA in ERDAS Imagine 2014™) run on the NDVI-MVC generated an initial 40 classes, with a maximum of 100 iterations and convergence threshold of 0.99. Though ground survey data was available at the time of image classification, unsupervised classification was used in order to capture the full range of NDVI over a large area. The use of unsupervised techniques is recommended for large areas that cover a wide and unknown range of vegetation types, (Biggs et al., 2006). Based on the above methodology, we classified LULC for the entire study area.
Fig. 4. Spatial distribution of LULC (derived from 2017 MODIS composite) (Note: SC, single crop; SW, surface water; DC, double crop).
SAR processing

Google Earth Engine’s collection of Sentinel-1 data contains all the GRD images from 03rd October 2014. These are the Level-1 scenes processed to backscatter coefficients ($\sigma_0$) in decibels (dB) (Sentinel-1 User Handbook, 2013, ESA, 2014). The steps involved in pre-processing of the Sentinel-1 images in order to obtain the Level-1 backscatter images are: (1) application of orbit file; (2) removal of GRD border noise and invalid data on the scene edges; (3) thermal noise removal to remove additive noise in sub-swaths; (4) radiometric calibration to compute the backscatter intensity and (5) terrain correction to compute $\sigma_0$ on the basis of Digital Elevation Model (DEM). VV polarized images were considered as advantageous for flood mapping when using Sentinel-1 data (Gumma et al., 2015; Twele et al., 2016).

Monthly composite images were computed from the pre-processed images to carry the monthly pattern of flooding during 2017 (eight images in a year). Masking of the non-water bodies from the sentinel 1 images was done using the above prepared LULC (2016–2017) as the reference map.

A well-known fact is that water bodies have low backscattering radar signals due to flat and smooth surface. A simple thresholding technique applied on the radar backscatter image, with the threshold values based on a visual inspection and expert knowledge, would effectively map the submerged areas, when these areas are open and considerably larger in size than the spatial resolution of the Sentinel-1 images. Finally, flooded areas/water bodies were mapped and non-flooded areas were masked. These steps were repeated for 3 years, 2015 to 2018, with eight independent images per year.

Submergence of flooded area

We have integrated the slope and flood files to generate the submergence of area in each of the slope category. Finally, the LULC map was integrated with the submergence (flooded) area while the extent of LULC was extracted for each class areas affected with flood. Figure 3 illustrates the overall methodology of assessing the submergence (flooded) area extent in each LULC class. A land-water threshold was manually applied to classify the images into two classes: land and water.

Assessing flood prone areas

After monthly mapping of flood for the belg and meher seasons, we quantified flood frequency during 4 years (2015–2018)
Table 4. Flooded area extent in each LULC classes along with slope

| LULC                          | 01. Flood & <2% slope | 02. Flood & 2–3% slope | 03. Flood & >3% slope | 04. Other |
|-------------------------------|-----------------------|------------------------|-----------------------|----------|
| 01. Barren land/wasteland     | 2,526,480             | 54,087                 | 120,681               | 8,799,530|
| 02. Grass lands               | 136,510               | 2431                   | 3325                  | 502,224  |
| 03. Rainfed-SC-croplands      | 31,670                | 5025                   | 38,272                | 1,418,490|
| 04. Irrigated-SC-croplands    | 9628                  | 7870                   | 26,154                | 1,219,800|
| 05. Irrigated-DC-croplands-croplands | 9005         | 236                    | 2483                  | 163,899  |
| 06. Forest/Shrub lands/grasslands | 232,097              | 17,144                 | 103,998               | 4,177,350|
| 07. Built up lands            | 717                   | 228                    | 231                   | 78,255   |
| 08. Water bodies              | 73,483                | 394                    | 83                    | 8517     |

Fig. 5a. Spatiotemporal distribution of floods in the Afar administrative region during 2015.
considering only flood class. The ERDAS modeler was used to quantify the frequency of flood from 2015 to 2018, considering pixel wise flood. Equation (3) was used to assess flood frequency from 2015 to 2018.

\[ n(FF_m) = \sum_y (FP_{my}) \]

where \( n(FF_m) \) is the flood frequency for month, \( m = (FP_my)_y \) is flood pixel for the month for corresponding year \( (y = \text{year i.e. 2015, 2016,..,2018}) \) \( (m = \text{month i.e February,..,September}) \)

Results and discussion

In this section, LULC, accuracy assessment and spatial extent of flooded areas have been generated for each district. In addition, we identified the flood frequency in each month of the belg and meher seasons. This study identified 29 administrative units affected by floodwaters.

Spatial distribution of land use/land cover

Figure 4 illustrates the spatial distribution of LULC during 2017 period for Awash basins that feed into the Afar region. The generated LULC map consisted of eight classes i.e., barren land/wasteland, grassland, rainfed-single crop (SC)-croplands,
irrigated-SC-croplands, irrigated-double crop (DC)-croplands, forest/shrub lands/grasslands, built up lands and water bodies. About 85% of total area currently accounts for non-agricultural land. The majority of LULC comprises barren land/wasteland, forest/shrub lands/grasslands etc. Built-uplands and waterbodies covered the least area i.e. 79,462 and 83,013 ha, respectively (Table 2). Rainfed agriculture covers 1,275,443 ha whereas irrigated single and double croplands cover 1,451,694 ha.

Accuracy assessment

A quantitative accuracy assessment was done through an error matrix (Jensen, 1996) to examine LULC units. The ground survey data was based on an extensive field campaign conducted throughout the Afar region during the meher seasons for the crop years of 2016–2017. Accuracy was performed on classified LULC 2016–2017 map. The remaining 363 ground data points were used as validation to assess LULC classification accuracy. Accuracy assessment was performed with independent datasets. Table 3 shows the error matrix of each product. In LULC, considering non-agricultural classes (1, 2, 6, 7 and 8) out of 170 points 149 points are correct with nearby user’s accuracy of 88%. For an agricultural class like rainfed-SC-croplands (cl_04) out of 22 points 16 were correct, while for irrigated-SC-croplands (cl_05) out of 10 points 10 were correct, while for irrigated-DC-croplands-croplands (cl_06) out of 35 points 27 were correct. Considering the overall agricultural classes, 53 out of 67 points were correct with user’s accuracy of 80%. For all the 11 classes, 213 points out of 248 matched with the same class of reference data. The accuracy for the final eight classes of 2017 was 85.89% with a k value of 0.8277 (Table 3). The loss of accuracy was mainly due to the coarse resolution of MODIS data.

Spatial distribution of flooded areas

Table 4 provides the proportion of flooded area under various LULC, disaggregated by slope category. Barren land/wasteland and forest/shrub lands/grasslands LULC classes are found to be the most flood prone areas under each slope category. Areas with a slope less than 2% comprised the dominant flooded area in Afar. About 50,303, 13,130 and 66,909 ha of the cultivated (rainfed and irrigated) land under slope category of <2, 2–3 and >3%, respectively, were found to be flood prone areas. The spatial distribution and extent of flooded area varied from month to month and from year to year (Figs. 5a and 5b).
Temporal variation of flood in Afar

In all years but 2015, the flooded areas during the *meher* season were larger than the area flooded during the *belg* season. Ground observations also showed that the year 2015 received uniquely high *belg* floods and lower *meher* flood events compared with a ‘normal’ year. In 2015, the July flood covered the smallest area of about 443,000 ha compared to the 815,000 ha in 2016; 720,000 ha in 2017 and 887,000 ha in 2018 (Fig. 5b). July is a critical month for flood-based production system due to the fact that planting depends mainly on the flood received during this month. August is a month with a large area of flood across years as it is the peak rainy month in the upstream highlands. Regular flooding in July may allow more successful implementation of feed and food production because flood would continue to occur in the succeeding month of August, with higher confidence. Generally, a minimum of 720,000 and 550,000 ha of land could be considered for planning flood-based development in Afar using the *meher* and *belg* seasons, respectively. The actual amount of land that could be developed each season could, however, be less than the identified area due to poor soils and very high temperature in the eastern part of the basin. The socio-economic conditions, particularly the pastoral settings of the community, may not also allow farming in some grids even if flood is available. Table 5 and Figure 6 show temporal variations of flooded areas across the study region. Figure 6 clearly shows that flooding was less in 2015 compared with the other years.

**Table 6. Area of land in ha and percentage of the total area in Afar that received flood corresponding to various frequencies (the number of years of occurrence within 4 years) between 2015 and 2018**

| Flood frequency | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep |
|-----------------|-----|-----|-----|-----|-----|-----|-----|-----|
| 1 year          | 573 (6.1) | 571 (6.1) | 672 (7.1) | 548 (5.8) | 586 (6.2) | 632 (6.7) | 713 (7.6) | 1038 (11) |
| 2 years         | 347 (3.7) | 342 (3.6) | 401 (4.3) | 327 (3.5) | 240 (2.5) | 369 (3.9) | 459 (4.9) | 454 (4.8) |
| 3 years         | 237 (2.5) | 242 (2.6) | 301 (3.2) | 204 (2.2) | 217 (2.3) | 269 (2.9) | 463 (4.9) | 249 (2.6) |
| 4 years         | 102 (1.1) | 148 (1.6) | 200 (2.1) | 103 (1.1) | 172 (1.8) | 172 (1.8) | 658 (7) | 121 (1.3) |

**Fig. 7. Identification of flood prone areas and number of years in which flood occurred between 2015 to 2018.**
Flood frequency and distribution during the belg and meher seasons

Flood frequency was determined as the number of months and years a certain grid receives out of the 4 years of the study period (Fig. 7). Consequently, March and April covered a larger area with the highest frequency of flood during the belg season whereas July and August covered a larger area with the highest frequency of flood events for the meher seasons. Areas with the highest flood frequency have the lowest risk of water scarcity for productive use across years.

A minimum of 148,000 and 172,000 ha of land received flood in four out of the 4 years, between 2015 and 2018 for belg and meher seasons, respectively (Table 6). With a 75% chance of occurrence (three out of 4 years), the flooded area for belg and meher seasons could increase up to 242,000 and 463,000 ha, respectively. The highest the chance of getting flood every year, the lowest the area that can be flooded and vice versa. Therefore, the selection of areas for flood-based farming could be prioritized using the flood frequency across years with the premises that ‘the highest the frequency, the higher the priority’.

Flood maps

In order to ensure sustainable production, the reduce effect of floods and minimize drought risks in these drought-prone systems, the most prospective strategy appears to partially harvest the available runoff for irrigating crops and rangelands (Sharma et al., 2006). The horrendous flood emerging from the highlands could be partly converted to productive use (Amede et al., 2009). Our research showed that these dry lowlands, which are commonly neighboring with upstream highlands receiving high rainfall amounts (>1000 mm per year) could be reliable sources of floodwaters. Furthermore, the adjacent highlands are characterized by the high frequency of intense rainfall with good flood potential compared with the lowland that receives only a few events with high intensity rainfall. Our analysis on rainfall data (1980–2010) for Chifra area and adjacent highlands depict that the lowland experienced on average 11 days of rainfall events with greater than 10 mm per day whereas the adjacent highland crossed this threshold in 32 days per year (https://public.wmo.int/en/members/ethiopia). For the higher intensity of at least 20 mm per day, the lowland receives only 2 days per year on average whereas the highland receives in 12 days per year. These demonstrate that the flood that could be available in the lowlands is a function of climate characteristics in the adjacent highlands. Therefore, the minimum area that is determined to be available for flood-based development could be affected by climate variability upstream.

Given the fact that the region is commonly inhabited by pastoral communities, the identification of potential areas should be developed in consultation with the local residents, who are
commonly implementing pastoral based and mobile livelihood strategies and considering socio-economic, agro-ecological and technical aspects (Seid et al., 2016). Therefore, once flood is received downstream, there is a huge opportunity to use it for food and feed production while at the same time rehabilitating degraded range lands (ICRISAT, 2017). Similar works have also demonstrated the use of flood for crop production (Tesfai and Stroosnijder, 2001; Tesfai and Sterk, 2002; Ham, 2008; Steenbergen et al., 2011). However, the utilization should not be limited to forage and crop production. Construction of reservoirs or alternative water storage tanks may allow (agro)pastoralists have access to livestock drinking water during extended dry periods. However, the feasibility of such alternatives needs to be understood in advance.

The month of April in the belg season and the month of August in the meher season are the periods that have larger area coverage of higher frequency flood (Fig. 8). In the Afar region, both seasons show an increase of intensity of flood from belg season to meher season. The majority of flood is under the slope of less than 2%. However, monthly flood distribution may not be the same from year to year following the climate variability in upstream highlands that are the major source of flood. The use

| Unique ID | District | belg season | meher season |
|-----------|----------|-------------|--------------|
|           | 01. Flood & <2% slope | 02. Flood & 2-3% slope | 03. Flood & >3% slope | 04. Other | 01. Flood & <2% slope | 02. Flood & 2-3% slope | 03. Flood & >3% slope | 04. Other |
| 1         | ELIDAR   | 54,507      | 1223         | 1253        | 1,326,650 | 103,028      | 2647          | 3061          | 1,274,908 |
| 2         | DALLOL   | 22,565      | 19           | 21          | 312,962   | 35,867       | 57           | 828           | 298,816   |
| 3         | BERAHLE  | 31,147      | 10           | 7           | 703,157   | 52,936       | 11           | 99           | 478,393   |
| 4         | EREBTI   | 5453        | 54           | 50          | 240,118   | 11,908       | 145          | 249           | 233,374   |
| 5         | KONEBA   | 1           | 0            | 2           | 67,537    | 7            | 45           | 67,458       |
| 6         | AFDERA   | 118,546     | 1691         | 393         | 1,216,412 | 199,242      | 3650         | 1467          | 1,132,683 |
| 7         | ABALA    | 606         | 16           | 57          | 127,358   | 1916         | 58           | 255           | 125,809   |
| 8         | MEGALE   | 3744        | 138          | 34          | 192,863   | 7342         | 282          | 202           | 188,953   |
| 9         | TERU     | 27,667      | 270          | 44          | 337,758   | 44,045       | 529          | 198           | 320,967   |
| 10        | YALO     | 4223        | 35           | 92          | 177,635   | 8355         | 153          | 572           | 172,904   |
| 11        | DUBTI    | 109,308     | 1005         | 380         | 758,533   | 166,118      | 2590         | 1238          | 699,281   |
| 12        | HABRU    | 29,213      | 191          | 94          | 271,968   | 65,802       | 693          | 374           | 234,596   |
| 13        | GULINA   | 7098        | 82           | 15          | 125,357   | 18,866       | 358          | 117           | 113,211   |
| 14        | ARTUMA   | 726         | 7            | 0           | 36,681    | 1080         | 9            | 3             | 36,322    |
| 15        | EWA      | 18,023      | 104          | 1           | 102,366   | 36,049       | 155          | 4             | 84,285    |
| 16        | AFAMBO   | 8833        | 133          | 60          | 215,409   | 25,336       | 196          | 73            | 198,830   |
| 17        | DEWE     | 2811        | 2            | 0           | 103,153   | 6137         | 11           | 7             | 99,812    |
| 18        | CHIFRA   | 11,449      | 53           | 19          | 317,587   | 32,184       | 167          | 27            | 296,729   |
| 19        | AYSAITA  | 3429        | 10           | 38          | 136,592   | 8119         | 39           | 126           | 131,765   |
| 20        | MILLE    | 23,196      | 100          | 78          | 457,435   | 52,697       | 246          | 86            | 427,779   |
| 21        | TELALAK  | 2665        | 9            | 1           | 136,425   | 6384         | 41           | 5             | 132,670   |
| 22        | GEWANE   | 39,985      | 120          | 95          | 824,990   | 76,624       | 514          | 168           | 787,884   |
| 23        | BURE_MUDAY | 5793        | 46           | 0           | 111,939   | 14,220       | 88           | 0             | 103,470   |
| 24        | FURSI    | 6973        | 48           | 1           | 121,333   | 13,170       | 76           | 8             | 115,100   |
| 25        | SIMUROBI_G | 976         | 35           | 5           | 123,722   | 1043         | 37           | 26            | 123,632   |
| 26        | AMIBARA  | 25,525      | 130          | 50          | 367,300   | 63,081       | 417          | 195           | 329,312   |
| 27        | ARGBOA_SPE | 163         | 22           | 13          | 46,898    | 254          | 42           | 56            | 46,743    |
| 28        | DULECHA  | 6330        | 226          | 13          | 120,101   | 7824         | 394          | 35            | 118,417   |
| 29        | AWASH_FENT | 748         | 7            | 2           | 101,291   | 5176         | 97           | 30            | 96,746    |
| Total area | 571,705 | 5784 | 2888 | 9,181,528 | 1,064,834 | 13,798 | 9877 | 8,673,407 |

| Table 7. Areas prone to flooded, per district, for three categories of drought frequency belg and meher season (during 2015–2018) | Area (ha) |

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of water storage facilities could buffer the impact of climate variability on downstream flood availability. It could help to utilize the excess flood that may come from highlands during wet years for use in succeeding dry periods, which on the other hand may reduce the negative impacts of floods downstream.

The total areas of flood under three slope categories, which are <2, 2–3 and >3%, these areas increase from 571,705, 5, 784 and 2, 888 ha to 1,064,834, 13,798 and 9877 ha respectively from belg season to meher season. Almost all the districts in the Afar region are affected by floods. Aldera and Dupty districts have the largest coverage of flooded area in both seasons compared with other districts in Afar (Table 7), whereas Konoba district has less flooded area. The flooded area in Aldera increased from 118,546 to 199,242 ha from belg to meher season respectively whereas in Dubti it increased from 109,308 to 166,118 ha.

Practical implementation development programs using flood made available downstream in Afar requires consideration of additional factors. Some of the locations where flood is available may not be suitable for farming due to some limiting factors such as extreme salinity, very shallow rooting depth and scattered patches of flood areas that are too small to put long term investment. Moreover, feed and crop production should consider access to main roads and market hubs, willingness of the local government to invest on flood-based technology transfer and strong commitment of the local community. We further focus on how remote sensing technology will help in renewable food systems and also focus on climate change analysis for the future sustainable food security.

Conclusions

In this study, we categorized flood prone areas in the Afar region to target the dissemination of innovation technology for improving livelihoods, livestock and food production. First, we mapped land use land cover maps for study area into eight classes using Landsat-8 and MODIS temporal data for the year 2017. Accuracy assessment was performed based on ground survey data gave 86% of overall accuracy. Secondly, we extracted the slope map from SRTM DEM. Then, the slope maps were integrated with LULC and categorized slope wise LULC areas for the study region. Third, we mapped monthly flooded areas for belg and meher seasons. Further flood maps were integrated with temporal maps for each month and classified it into four classes. The maximum possible flooded areas were integrated with slope classes and generated maps along with statistics for the districts in the Afar region.

We have mapped the flood extent and database for 4 years (starting from 2015 to 2018) in the Afar region. The methodology was used to determine intensity of flood. Mapping flood prone areas are very important to understand Afar region and identifying locations for effective utilization. Up-to-date flood maps are an important input for decision making to improve natural resource management technologies. Therefore, we conclude that the method is suitable for identifying flood potential of regions or basins to guide strategic planning of flood-based development in Afar and similar areas.

Future research can be focused on identify suitable techniques to construct water harvesting structures by using hydrological models and topographical analysis through the construction of water harvesting structures appropriate river channels. Results conclude that the methods are recommended for the identification of large scale flood mapping. Identifying various flood prone areas based on flood frequency could help implement sustainable agriculture and fodder development. The developed database, maps and statistics are very much useful for site specific decision on production and cost analysis.

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