Partitioning the Impacts of Land Use/Land Cover change and Climate Variability on Water Supply over the Source Region of Blue Nile Basin

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Abstract

Water plays a vital role in sustaining the natural functioning of the entire ecosystem that supports life on earth. It plays keys role in the wellbeing of society in numerous ways. However, climate variability and land use land cover (LULC) change have caused spatiotemporal water supply variation. Disentangling the effects of climate variability from LULC change on water supply is crucial for sustainable water resource management. The main purpose of this study is, therefore, to disentangle the relative contribution of LULC change and climate variability to the overall average annual water supply variation. Residual Trends analysis combined with Integrated Valuation of Environmental Services and Tradeoffs (InVEST) annual water yield model were adopted to perform simulations and disentangle the relative impacts of climate variability and LULC change. Ground and satellite data were used in this study. The study area has experienced a significant increasing wetness trend and significant LULC dynamics between 2003 and 2017. As a result, an increasing water supply was observed due to the joint effects of climate variability and LULC change in the watershed (203 mm). The contribution of climate variability was 94% whereas LULC contributes only 6% from 2003 to 2017. Climate variability negatively led to water supply variation while LULC change contributed positively from 2010 to 2017. Although the ongoing soil and water conservation (SWC) practices improved vegetation cover and water retention of the watershed, climate variability is the main driver of water supply variation. Therefore, SWC practices should incorporate ecosystem-based climate change adaptation strategies and scale up to community-based integrated watershed management to sustain water supply.

Keywords: water yield – LULC change -climate variability –impact –InVEST

1. INTRODUCTION

Water provisioning is a major area of interest within the field ecosystems because it is one of the essential ecosystem services, playing keys role in the wellbeing of society in numerous ways, including human consumption, agriculture, fisheries, industry, recreation, and energy production (Pessacg *et al.*, 2015; Sahle *et al.*, 2019). However, the growing level of human pressure on ecosystems resulted in human-induced threats to water ecosystem services. Land Use Land Cover (LULC) and climate changes are the main direct drivers of water supply variation (MEA, 2005;

Soytong *et al.*, 2016) as well as many other human-induced threats. As a result, freshwater supply has become a progressively scarce natural resource.

Several attempts have been made to investigate the impact of climate variability and LULC change on water supply variation during the last two decades (Krysanova & White, 2015). However, conflicting results were reported about the cause of water yield variation (Pan *et al.*, 2015). Some studies have reported that climate change in general and rainfall variability, in particular, is the primary cause of water yield variation (Ayele *et al.*, 2016; Dile *et al.*, 2013; Zhang *et al.*, 2016). Whereas, other studies have reported that LULC change is the primary driving factor of water yield dynamics (Arunyawat & Shrestha, 2016; Chakilu & Moges, 2017; Feng *et al.*, 2012; Teklaya *et al.*, 2019). Soytong *et al.* (2016) strongly argued that both climate variability and LULC change are responsible for water yield dynamics.

Despite substantial progress has been made to investigate the impacts of LULC and climate changes on water supply variation, research to date has tended to focus on either climate change or LULC change alone. For instance, Ayele *et al.* (2016) showed that water supply increased substantially due to climate change. Whereas, Chakilu & Moges (2017) found that LULC change to be the major factor of water supply change by using the Soil and Water Assessment Tool (SWAT) model. However, an in-depth understanding of the isolated and integrated impacts of climate variability and LULC change on water supply is crucial for optimum water supply management (Chawla & Mujumdar, 2015). In the absence of such information, the positive impacts of climate change or variability can mask the negative impacts of LULC change and vice versa. Therefore, partitioning the relative contribution of LULC and climate changes to the overall spatiotemporal water supply variation is vital for sustaining water provision service of the ecosystem through effective land management and climate change adaptation (Pan *et al.*, 2015). However, little has been done to isolate the impact of climate variability and LULC change due to lack of effective methods to investigate the combined and isolated impacts of climate and land-use changes (Pan et al., 2015).

Although four methods (statistical techniques such as Mann–Kendall test, experimental paired catchment approach, distributed process-based hydrological models and empirical or conceptual models) used to study the impact of climate variability and LULC change, process-based hydrological models are the most effective method to disentangling the effects of climate variability from LULC change on water supply (Praskievicz & Chang, 2009; Sharp *et al.*, 2018). To date, there are several process-based hydrological models in the public domain developed in America and Europe. However, most process-based hydrological models are data intensive. Therefore, the application of such models in data-scarce areas has resulted in poor model outputs. For example, Van Griensven *et al.* (2012) found several drawbacks of the SWAT model when applied to the source region of the Nile River including different results from several studies of the same study catchments. These drawbacks are attributed to a lack of ground data for model calibration and result validation in Upper Nile sub-basins. However, the introduction of simple, easy to use, and low input data requirements for models like the Integrated Valuation of Environmental Services and Tradeoffs (InVEST) annual water yield model, makes accurate hydrological modeling possible in data-scarce regions (Belete *et al.*, 2018; Hamel & Guswa, 2015). Hence, water supply change can be quantified using the InVEST annual water yield model in data-scare regions (Sharp *et al.*, 2018; Vogl *et al.*, 2015).

The streamflow data collected from Ribb and Gummara hydrological stations indicate that the average annual water supply of the Ribb-Gummara watershed exhibits an increasing trend in recent years. Government reports show that this phenomenon is mainly because of the ongoing soil and water conservation (SWC) practices that started in 2010. Although there is no literature, expert in the area believe that rainfall is the primary factor for the increasing trend of water supply. What is not yet clear is the relative and combined impact of climate variability and land-use change on water yield dynamics. The relative impacts of climate variability and land-use change on water dynamics are vital for water and land resource management (Kremen, 2005; Lü *et al.*, 2012). This study, therefore, sets out to investigate the combined and isolated impacts of LULC change and climate variability on water supply by combining InVEST and Residual Trends analysis. The objectives of this study are to: (i) investigate LULC change and climate variability trends, (ii) quantify and map spatial and temporal changes of water supply and (iii) segregate the impact of LULC change and climate variability on the average annual water supply.

2. MATERIAL AND METHODS

2.1. Study Site Description

The Ribb-Gummara watershed, drained by Ribb (130 km long) and Gummara (72 km long) Rivers, is a watershed in the Blue Nile Sub Basin of the Nile River source area (Ayenew, 2008; Mulatu *et* *al.*, 2018). It stretches from Mount Guna to Lake Tana in the Amhara Regional State of Ethiopia within 37.5395°-38.2474° longitude and 11.5652°-12.2389° latitude. The watershed covers a total area of 3273 km^2 with an average elevation of 2,271 m a.s.l (meter above sea level). The elevation of the watershed ranges from 4109 m a.s.l at Mount Guna to 1783 m a.s.l at the mouths of Ribb and Gummara Rivers (Figure 1). Higher elevation variation in the watershed results in diverse climate, soil and vegetation cover.

The Ribb-Gummara watershed contains a wide range of climatic and landform attributes. Among the five agro-ecological zones of the world, three of them are found in this study site. These are sub-tropical, temperate and alpine agro-ecological zones. The upstream part of the watershed has a temperate climate except for the top of Guna Mountain whereas the downstream portion is sub-tropical with a distinct summer season. The mean annual temperature and rainfall were 18.78°c and 1334.55 mm respectively between 2001 and 2017. This study site is dominated by the Fogera plain and Guna Mountain.

According to Worqlul *et al.* (2015), the major soils of the Ribb-Gummara watershed are Haplic and Chromic Luvisols as well as Eutric Fluvisols and Eutric Leptosols. Ribb sub-watershed is covered by Eutric Fluvisols (23.9%), Eutric Leptosols (36.2%) and, Chromic Luvisols (39.7%) having stony and gravelly characteristics. The Gummara sub-watershed, on the other hand, is dominated mainly by Haplic Luvisols (63.4%) characterized by high clay content and Chromic Luvisols (24.4%).

Agricultural land, forest, shrubs, grazing land, built-up area, water bodies, and wasteland are the well-known land use and land cover types in Ribb-Gummara watershed. In 2017, nearly three fourth of the study area was covered with food crops (73.61%). The remaining one fourth of the area were covered with shrubland (13.53%), grassland (8.84), forestland (2.72%), and built-up area (0.63%). Bare land (0.08%) and water bodies (0.59%) are insignificant components of the study watershed land cover.

The Ribb-Gummara watershed has Local, National and Regional implications. This watershed together with Gilgel Abay and Megech watersheds in Tana Basin, contribute 93% of the total inflow of the Lake Tana which is the primary source of Blue Nile (Setegn *et al.*, 2009). The Blue Nile is the dominant water source of the downstream Nile riparian countries before it ends up at the Mediterranean Sea (80 – 85 %) (Easton *et al.*, 2010). The survival of the Grand Renaissance

Dam being constructed in Ethiopia at the Ethio-Sudan border is mostly dependent on the healthy functioning of Ribb-Gummara ecosystem. The livelihoods of hundreds of thousands of people in the watershed are entirely reliant on rain-fed agriculture. However, land degradation has severely affected the land resources in the area due to intensive agriculture, free grazing, and population pressure (Moges & Bhat, 2017).

2.2. Partitioning LULC Change and Climate Variability Impacts on Water Supply Variation

We used the biophysical component of InVEST annual time scale water yield simulation to calculate the annual water supply of the study watershed. The model was developed by Standford University under the Natural Capital Project with the intention of it running on any standard computer using relatively simple, readily available, and limited input data (Sharp *et al.*, 2018). According to Hamel and Guswa (2015), the InVEST model has several advantages : limited input data requirement, ease of use, and spatially explicit output data. A more detailed description of the model is found in the InVEST user's guide (Sharp *et al.*, 2018).

The annual water supply capacity of each pixel in a watershed (x) is calculated as follows:

$$y(x) = \left(1 - \frac{AET(x)}{p(x)}\right) \times p(x) \tag{1}$$

Where (x) and $AET(x)$ are the annual precipitation and the annual actual evapotranspiration on pixel x respectively.

However, AET is not easily measurable. To overcome this problem, $AET(x)$ can be calculated following Fu (1981) and Zhang *et al.* (2004) based on the Budyko curve:

$$\frac{AET(x)}{P(x)} = 1 + \frac{PET(x)}{P(x)} - \left[1 + \left(\frac{PET(x)}{P(x)}\right)^{\omega}\right]^{1/\omega} \tag{2}$$

Where, $\omega(x)$ describes climatic-soil properties as a non-physical parameter where as $PET(x)$ is the potential evapotranspiration, both are described in detail below.

$PE(x)$ can be calculated as follows:

$$PET(x) = Kc(lx) \times ETo(x) \tag{3}$$

Where ETo is reference evapotranspiration, and kc is a crop coefficient of each pixel.

The empirical parameter $\omega(x)$ is also calculated following Donohue *et al.* (2012) as follows:

$$\omega(x) = Z\frac{AWC(x)}{P(x)} + 1.25 \quad (4)$$

Where Z is Zhang constant and AWC is plant available water content.

In order to differentiate the relative impacts of LULC change and climate variability on annual water production in the Ribb-Gummara watershed, we used Residual Trends analysis (Evans & Geerken, 2004; Pan *et al.*, 2015; Wessels *et al.*, 2007). Prior to commencing the water supply estimation, two scenarios were developed: (a) water supply under land-use change with constant climate and (b) water supply under climate variability with constant land use. Using the calibrated and validated annual water yield model of InVEST, we were able to calculate the annual water supply of the study area at three different periods during the past fifteen years (2003, 2010 and 2017). After obtaining the actual water supply, we calculated the water supply variation for three periods of the study (2003-2010, 2010-2017 and 2003-2017). Following this, the water yield simulation was undertaken for the two scenarios by fixing the land use and climate input parameters alternatively using InVEST water yield model. The Residual Trends were then calculated by subtracting the scenarios trends from the actual trends. In the end, the relative impacts of LULC change and climate variability to water yield variations were calculated. The procedures applied are detailed below:

$$\Delta Y = Y_F - Y_B \quad (5)$$

Where, ΔY is the total water yield variation; Y_F is the water production at the end of each period; and Y_B is the water production at the beginning of each period.

$$\Delta Y_L = Y_F - Y_{FC} \quad (6)$$

Where, ΔY_L is the land use change impact on water production; and Y_{FC} is the water yield under only climate variability.

$$\Delta Y_C = Y_F - Y_{FL} \quad (7)$$

Where, ΔY_C is the climate variability impact on water production; and Y_{FL} is the water yield under only land use change.

$$\eta_L = \frac{\Delta Y_L}{\Delta Y} \times 100 \quad (8)$$

Where, η_L is the relative impact of land use change on water supply.

$$\eta_C = \frac{\Delta Y_C}{\Delta Y} \times 100 \tag{9}$$

Where, η_C is the relative impact of climate variability on water supply.

Nine tabular and spatially explicit input data are required to run InVEST annual water yield simulation. These are detailed in section 2.3, and summarized in Table 1.

2.3. Data Sources and Processing

2.3.1 Field data

Field observation and interviews were used to collect field data in the study area. Field observation and key informant interviews were carried out from June to September 2017 to obtain general insight about the land use and to collect ground truth data for training and validation. Interviews were conducted with twelve local elderly people, three agricultural experts, and one government official. Ancillary field observation was also undertaken between May and September 2018. Based on the knowledge acquired during the field survey in 2017 and 2018 in our study, we have identified seven possible land cover classes for land cover classification in Ribb-Gummara watershed. These include cropland, shrubland, grassland, forestland, built-up area, water bodies, and bare land (Table 2). Garmin portable Global Positioning System (GPS) apparatus was used to collect 829 points using proportionate stratified random sampling technique (Jensen, 2016) at the center of each class. The mean score of horizontal accuracy was 4.7 meters. Of the total 829 points, 491 were used for training and 338 points were used for accuracy assessment of the 2017 Landsat image. For the 2003 and 2010 Landsat image, 280 training polygons from different land use types were digitized directly from geo-referenced and high-resolution Google Earth images for each image. Additionally, 264 polygons from different land-use classes were also digitized for use in the accuracy assessment of each classified maps. The polygons were initially encoded as KML file that was later converted to vector file and region of interest (ROI) through the integrated use of ArcGIS and ENVI software. When the selected samples seem inaccurate, modification of their boundaries or complete removal was performed.

2.3.2 LULC data and processing

Landsat images

The United States Geological Survey (USGS) has been offering Landsat images for monitoring changes on the surface of the Earth since 1972 for free of charge (Turner *et al.*, 2015). Three cloud-free Landsat images for the years 2003, 2010 and 2017 were obtained from the USGS Earth Explorer web portal. For the year 2003, we acquired Landsat 7 Enhanced Thematic Mapper (ETM+). Landsat 5 Thematic Mapper (TM5) and Landsat 8 Operational Land Imager (OLI) were also obtained for the years 2010 and 2017 respectively (Table 3). The year 2010 was purposefully selected to divide the study time into two equal periods. This was the year when the government has started SWC practices along with reclaiming illegally occupied land.

In Ethiopia, the dry season is from October to January. Therefore, we collected all cloud-free Landsat images in December and January at anniversary dates to reduce the impact of seasonalities on land cover change detection (Munyati, 2000).

Image Preprocessing

All the time series Landsat images used for this research were collection 1 level 1 that means the images were corrected for geometric and terrain distortions. Although the images were geometrically corrected, all optical satellite data are prone to atmospheric effects. Therefore, we applied the fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) module using the Environment for Visualizing Images (ENVI) 5.3 software to remove atmospheric effects from the images (I T T Visual Information Solutions, 2009). After the atmospheric correction of the images, it was necessary to carry out a topographic correction to remove the effect of topography using Topo-correction extension available in the ENVI 5.3 software. Following atmospheric and topographic corrections, the images were subset to one km buffer from the spatial extent of the study area. This helps the image not to lose data at the border during water yield simulation. After obtaining spatially subset images, a spectral subset was carried out and then a 5-band image consisting of all the visible (red, green, blue), near-infrared (NIR) and short-wave infrared 1 (SWIR1) bands were produced.

Optical indices can improve feature separability for land cover classification. The modified normalized difference water index (MNDWI) and the normalized difference vegetation index (NDVI) were generated. NDVI can easily discriminate vegetation from the other land cover types

(Dorigo *et al.*, 2012). Likewise, MNDWI can effectively distinguish water bodies from built-up areas in addition to restricting information from soil and vegetation and enriching the information of water (Xu, 2006). NDVI was calculated by subtracting red band from the near infrared band and dividing with the sum of the near-infrared band and red band. Similarly, MNDWI was calculated by subtracting shortwave infrared band from green band and divided with the sum of green band and short-wave infrared band. Finally, a 7-band layer stacked image was generated for LULC classification.

Image Classification

Among other things, classification accuracy is dependent on the application of an appropriate classification method. The introduction of machine learning approach and artificial intelligence paved the way to the birth of many classifiers including decision tree, artificial neural network (ANN), and support vector machine (SVM) which are highly advanced and non-parametric (HUANG *et al.*, 2002). Non-parametric classifiers do not include normality assumptions and have been found to be more relevant for diverse topographic data (Rodriguez-Galiano *et al.*, 2012). Although object-based image analysis is best performed for Landsat OLI image, SVM is suitable for all Landsat images (Phiri & Morgenroth, 2017). SVM is capable of producing high accuracy classified maps than many classifiers like maximum likelihood (Mountrakis *et al.*, 2011; Shao & Lunetta, 2012). As a result, SVM classifier was applied in this study using the algorithm embedded in ENVI 5.3 with the Radial Basis Function (RBF) kernel. Prior to the final image classification with the SVM, an unsupervised classification was undertaken with the Iterative Self Organizing Data Analysis (ISODATA) clustering algorithm intending to increase our understanding of spectral similarities and ambiguity arising from the complex nature of the topography (Alphan *et al.*, 2009).

Accuracy Assessment

Image classification is usually not free from errors. The agreement between the reference data and the classified map is expressed by an accuracy assessment (Yousefi *et al.*, 2015). The accuracies of classified land cover maps were checked visually and statistically. Whether the thematic map looked right or wrong was visually judged and continuous edits were made in line with the local experience. Then, a highly objective assessment that relied on comparing the proportion of areas of classified land cover categories with their corresponding areas in other reference datasets was measured using confusion matrix generated between classified pixels and their corresponding validation data. Detailed explanations and equations for accuracy measures were found in (Congalton, 1991). Accuracy assessment was carried out for 2003, 2010, and 2017 classified maps using ground truth data acquired from Google Earth and field survey. A post-classification accuracy assessment was carried out to generate a classification confusion matrix or error matrix. Measures of producer accuracy, user accuracy, and overall accuracy were calculated from the confusion matrix. Although Kappa Coefficients were calculated to measure the degree of classification accuracy (Butt *et al.*, 2015), we did not report in this study as the growing number of literature has criticized it (Foody, 2002; Pontius & Millones, 2011).

Change detection

Change detection is used to quantify land cover transformation over time at a specific geographic location (Biro et al., 2013; D. Lu, P. Mausel, 2004). Although numerous change detection approaches have introduced recently; post-classification comparison, image differencing, and principal component analysis are the most commonly used (D. Lu, P. Mausel, 2004). The post-classification comparison approach was chosen for this study because it generates the size and spatial distribution of changed areas as well as percentage share of individual classes within the change area estimations (El-Hattab, 2016; Yuan *et al.*, 2005). Loss, gain, persistence and net change of each land cover class were calculated in three periods: 2003-2010, 2010-2017 and 2003-2017 using cross-tabulation technique (Pontius *et al.*, 2004).

2.3.3 Climate data

The Bahrdar branch of the National Meteorological Services Agency (NMSA) provided rainfall, maximum and minimum temperatures for eleven meteorological stations over the period between 2001 and 2017 (Figure 1). On average, 4.7% of the data was missing during the study period which was filled with the nearest station's average value (Ferrari & Ozaki, 2014). Prior to commencing the data preparation, the raw data were divided into three periods to get anniversary data with LULC; 2001-2005, 2006-2011 and 2012-2017. Following this, both mean monthly rainfall and temperature as well as mean monthly maximum and minimum temperatures were produced.

The average monthly reference evapotranspiration (ETo) was computed using a modified Hargreaves's equation (Droogers & Allen, 2002). The modified Hargreaves's equation was chosen because it produces better results compared with the Pennman-Montieth method in data-scarce areas (Sharp *et al.*, 2018). After obtaining the mean monthly ETo and rainfall, average annual precipitation and average annual ETo were calculated. Finally, the average annual precipitation and average annual ETo data were interpolated by Inverse Distance Weighted (IDW) with a 30 m spatial resolution over the entire watershed (Hu *et al.*, 2014; Yong *et al.*, 2010).

2.3.4 Site factor data

Soil-related input data like root-restricting layer depth and plant available water content (PAWC) are required for InVEST water yield simulation. The Harmonized World Soil Database, version 1.2, from Food and Agriculture Organization (FAO) under United Nations was acquired to generate root-restricting layer depth and PAWC in this study (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012; Fischer *et al.*, 2012). PAWC and root-restricting layer depth were calculated using weighted average of AWC classes and reference soil depth respectively. Zhang constant is also required to capture the hydrological properties and seasonal patterns of rainfall in the watershed. Despite the existence of three techniques for Zhang constant calculation, we applied calibration to find the best Zhang constant in the area as it was recommended by Hamel & Guswa, (2015).

2.3.5 Tabular data

Root depth, plant evapotranspiration coefficient (Kc), and land cover type (1and 0) are required input parameters in the form of tabular data to calculate potential evapotranspiration from reference evapotranspiration on the basis of the watershed physiological characteristics. We calculated Kc based on Allen *et al.* (1998) and Sharp *et al.* (2018) and root depth following Canadell *et al.* (1996).

2.4. Model Calibration and Validation

The simple production function is the underlying assumption of the InVEST water yield model where all the water reached the outlet of any watershed is the remaining water from evaporative loss. The water yield is calculated at each pixel in the watershed but applied only at the watershed level for practical use. According to Sharp et al. (2018), model calibration should be performed using long term, not less than ten years, streamflow data to get an accurate result from the model. As far as data for validation is available, result validation also increases the trustworthiness of the research findings for practical use. Unlike numerous hydrological models where both calibration of the model and validation of the result are difficult and uncertain, InVEST model calibration and validation is simple, straight forward, and impartial (Belete *et al.*, 2018). We delineated Ribb sub-watershed above Ribb stream gauge and Gummara sub-watershed above Gummara stream gauge, where actual flow measurement has been taken place, for calibration and validation purposes.

We prepared streamflow records for Gummara at Bahir Dar from 1996 to 2006 for InVEST model calibration and streamflow data for Ribb at Addis Zemen from 1996-2008 for model simulation result validation. The streamflow data were aquired from the Ethiopian Ministry of Water, Irrigation, and Electricity (MoWIE) on request. Following streamflow data preparation, water yield calculation and simulation result comparison with the measured streamflow data have been performed. Then consecutive adjustments of root depth, Z parameter, and plant evapotranspiration coefficients were carried out until we got the optimum result from the model simulation based on literature and locally available data in the study area. The value of the abovementioned model input parameters capped through such calibration processes was used for water supply estimation in Ribb-Gummara watershed for our study

The comparison of simulated water yield against measured streamflow data was performed using pairwise comparative statistical methods including Bias, Root Mean Square Error (RMSE) and Mean Error (ME) (Bayissa *et al.*, 2017a; Bitew *et al.*, 2012; Dinku *et al.*, 2007). In the end, the water supply of the whole Ribb-Gummara watershed was estimated. The final estimated water supply was compared with observed streamflow of Ribb sub-watershed with Zonal Statistics in Arc GIS 10.5 environment.

3. RESULTS

3.1.Model Calibration and Result Validation

Water yield model calibration resulted in a Bias of 0.97, a Root Mean Square Error (RMSE) of 0.04 km^3/year and Mean Error (ME) of -0.04 km^3/year, showing near a perfect agreement between estimated and observed annual water supply. The values of ME and RMSE are near to zero and the Bias value is also near to one. The final estimated water supply result has a 0.96 Bias value, which is very close to the perfect score of Bias (1.00). In addition, -0.05 km^3/year and 0.05 km^3/year were recorded for ME and RMSE respectively for the final water supply validation, which are near to the ideal value (0.00).

3.2.Observed Climate Variability

Patterns of rainfall and temperature are reliable indicators of climate change. Therefore, the local patterns of mean annual temperature and annual total rainfall from 2001 to 2017 were analyzed to detect climate change in the Ribb-Gummara watershed. The mean annual temperature of the Ribb-Gummara watershed was 18.78^{o}c during the study period. The year 2002 was the hottest, with an average annual temperature of 19.85^{o}c. Although not significant, the temperature in the study area shows a decreasing trend. The mean annual amount of temperature decreased by about 0.023^{o}c each year over the past two decades (Figure 2). It is contrary to several local and global trends. Hence, further investigation of why this happened is needed in the Ribb-Gummara watershed.

During the past two decades, the Ribb-Gummara watershed has exhibited a significant increasing wetness trend. The annual total rainfall increased by about 12.53mm each year from 2001 to 2017 (Figure 3). However, the amount of annual total rainfall has exhibited inter-annual variability with several dry years, including 2002 (1069mm), 2004 (1091mm) and some wet years such as 2008 (1518mm) and 2010 (1548mm).

3.3.Land Use and Land Cover Change

Table 4 summaries the accuracy assessment report for the 2003, 2010, and 2017 final classified maps. The overall accuracies of 87.01%, 85.38%, and 88.75% were found for 2003, 2010, and 2017 classified images, showing a strong agreement between the observed and the predicted classes.

The LULC dynamics of the Ribb-Gummara watershed are shown in Figure 4 for the periods 2003, 2010 and 2017. The LULC trend analysis of the period 2003-2010, 2010-2017, and 2003-2017 demonstrate that the study watershed has experienced high levels of land use and land cover change.

As shown in Table 1 and Table 2, shrubland, built-up, and bare land increased continuously during the study period. Cropland was the dominant land use type throughout the period, exhibiting the fluctuating trends from period-to-period. Its total area was 2397 km^2 (73.13%) in 2003, rose to 2749 km^2 (84%) by 2010 and dropped back to 2409.05 km^2 (73.61%) by the end of the study period (2017). The growth of cropland (14.71%) in the first period changed to a decline (-12.35%) in the second period. Illegally expanded cropland on marginal areas was also converted to vegetated land after the introduction of SWC in 2010. This result is in agreement with the previous study in the same watershed (Moges & Bhat, 2018), identifying SWC practices as the main reason for cropland reduction.

Grassland and forestland were the third and the fourth dominant land cover types, after cropland and shrubland (Figure 4 and Table 1). Contrary to the other land use types, grassland and forestland areas showed a significant decreasing trend between 2003 and 2017 (Table 2). From 2003 to 2017, there were a decrease in grassland from 556 km^2 (17%) in 2003 to 289 km^2 (9%) in 2017 and forestland from 136 km^2 (4.15%) to 89 km^2 (2.72%). This finding is supported by other empirical results (Biru *et al.*, 2015; Hassen & Assen, 2017; Sewnet, 2016; Teferi *et al.*, 2013; Teklaya *et al.*, 2019) that described the decline of vegetated areas due to conversion to cropland. However, both grassland and forestland areas began to expand after 2010 mainly on farmland because of SWC activities and land reclamation measures. Although its share is very small, water bodies showed an increasing trend which is largely attributed to the Ribb irrigation dam construction on the Ribb River.

From 2003-2017, nearly two-thirds (2,257 km^2) of the watershed remained stable, while one-third (1,016 km^2) of it changed. During this period, the most notable land cover transition was the persistent increment of shrubland in contrast to many previous findings in the Northern Highlands of Ethiopia (Moges & Bhat, 2018; Teklaya *et al.*, 2019; Wubie *et al.*, 2016). In the same period, about 311 km^2 of cropland, 27 km^2 of grassland and 45 km^2 of forestland were converted to shrubland (Table 3). It seems possible that these results are due to area enclosures, cut-and-carry livestock feeding system, eucalyptus plantations, and agroforestry practices on soil bunds of croplands as SWC strategies.

3.4.Water Supply Dynamics

The InVEST annual water yield model result described average annual water supply variation over space and time in the Ribb-Gummara watershed. The average annual water supply was 2461 MCM (Million Cubic Meter) or 752.02 mm in 2003, 3316 MCM or 1013.24 mm in 2010, and 3125 MCM or 954.89 in 2017. The spatial variation of the water supply ranged from 191 mm in Ebnat district to 1470 mm in Estie district. As shown in Figure 5, the southern regions generated higher water yields, whereas the northern areas generated lower water yields in all periods of the study. This implies that the Gummara River generated higher runoff than the Ribb River. This result is in line with previous research findings in the area (Atanaw *et al.*, 2015).

The average annual water supply showed a significant increasing trend between 2003 and 2017. The water supply increased from 752 mm in 2003 to 955 mm in 2017 in the Ribb-Gumara watershed. The water supply, which rose from 752 mm in 2003 to 1013 mm in 2010, was higher during the first period (2003-2010). However, during the second period (2010-2017) it slightly decreased by 58 mm. This implies that water supply in the form of runoff in the watershed decreased since the introduction of SWC practice in 2010.

We produced the maps of water yield for three different periods of 2003-2017, 2003-2010 and 2010-2017 to clearly show the spatial changes in water supply in the watershed (Figure 6). Although there was an overall increase in the water supply (203 mm) between 2003 and 2017, the Ribb dam area and southeastern regions specifically showed a significant decrease. The average annual water supply varies from -240 mm in the Ribb dam area to 762 mm in the southwestern part (Figure 6a). From 2003 to 2010, the average annual water supply increased significantly (261 mm) whereas it slightly decreased (-58 mm) between 2010 and 2017, despite the existence of regional variation. The regional variation pattern between 2010 and 2017 was contrary to the spatial pattern observed between 2003 and 2010 (Figure 6b and c). For example, the average annual water supplies increased (1054 mm) in the northwestern region of the watershed between 2003 and 2010. However, it decreased significantly (-891 mm) between 2010 and 2017 over the same location in the watershed.

In order to differentiate the impacts of LULC change and climate variability on average annual water supply, the water supply scenarios were subtracted from the actual water supply of different periods. Figure 7 shows the residuals of water yield under only land-use change subtracted from the water production at the end of each period. Although the impact of climate variability on the water supply was positive between 2003 and 2017 (192 mm), its positive impact (253 mm) was limited during the first period (2003-2010). The negative impact of climate variability on water supply was observed on the Ribb-Gummara watershed in the second period (2010 - 2017) (-61 mm).

Figure 8 shows the residuals of water yield under only climate variability subtracted from water production at the end of each period. Despite the existence of spatial variation, LULC had a positive impact on the average annual water supply of the study watershed in all periods considered. Its impact was 11mm from the year 2003 to 2017, 8 mm from 2003 to 2010 and 3 mm from 2010 to 2017. This implies that the magnitude of LULC impact on water supply kept decreasing over the last two decades. Although the impact of LULC on the water yield from 2010 to 2017 was positive, its magnitude is insignificant (3 mm).

4. Discussion

4.1. The Relative Impacts of Climate and LULC Changes on Water Production Variation

The study was primarily designed to distinguish the relative impacts of LULC change and climate variability on the water supply variation in the study area. The results of the study suggest that both LULC change and climate variability had a positive contribution to the average annual water supply variation in the Ribb-Gummara watershed from 2003 to 2017 despite spatial differences (Figure 7a and Figure 8a). These results are consistent with the findings of previous studies (Andualem & Gebremariam, 2015; Ayele *et al.*, 2016; Jemberie *et al.*, 2016; Teklaya *et al.*, 2019). However, the impact of both LULC change and climate variability on average annual water supply before and after 2010 was different. The overall water supply change between 2003 and 2017 was 203 mm. It was -58 mm after 2010 and 261 mm before 2010 (Table 4). There are several possible explanations for the negative change of water supply after 2010. One possible explanation could be that the implementation of SWC practices along with land reclamation since 2010 has improved the watershed vegetation cover which reduces surface runoff. Another possible explanation is the occurrence of two severe droughts in 2014-2015 and 2009-2010 (Bayissa *et al.*, 2017b).

One unanticipated finding was that about 94% of the total water supply change was contributed by climate variability from 2003 to 2017, contradicting government reports. The government believes that illegally occupied land reclamation and SWC practices resulted in large water supply increases. However, the relative contribution of LULC to the total water supply variation was only 6% during this period. This finding confirms the association between LULC change and water supply. This finding is in agreement with Pan *et al.*, (2015) findings which showed that the execution of the Three Rivers Source Area Ecological Protection Project has increased the vegetated land area and the water supply. There are two likely causes for the low relative contribution of LULC and the high relative contribution of climate variability to the total water supply variation in the Ribb-Gummara watershed. One is that there was a small change (13 km^2) in the dominant land use type, cropland, between 2003 and 2017 (Table 2). This implies no significant improvement in the capacity of the land to convert runoff into groundwater (Arunyawat & Shrestha, 2016). Another cause is a substantial increasing trend of rainfall (12.53 mm/year) and a decreasing trend of temperature (0.023°c/year) between 2003 and 2017 (Figure 3 and Figure 2). Therefore, increasing rainfall coupled with decreasing temperature resulted in increased water supply in the watershed. This indicates the need for incorporating ecosystem-based climate change adaptation strategies along with SWC practices.

Another important finding was that although the impact of LULC on water supply was positive from 2010 to 2017, its relative contribution to the total water supply decreased from 8 mm before 2010 to 3 mm after 2010 (Table 4). This might be due to the improvement of the water holding capacity of the watershed from ongoing SWC practices commenced in 2010 and indicates the need to strengthen SWC practices in the watershed and to scale these up to community-based watershed management.

4.2.The practical implications of this study

The findings of this study have several important implications for future practices. This study is one of the few, if not the first, to distinguish the relative contribution of LULC change and climate variability to the overall variation of water supply. Therefore, this paper will be a source of scientific information on spatial and temporal water supplies supporting development planners and decision-makers to make informed decisions and to ensure sustainable water supply. The results also clearly show the effect of the ongoing SWC practices on water supply. Thus, the information generated in this study provides a springboard to evaluate the outcome of SWC practices at the watershed level. Contrary to expectations, this study found a significant difference between LULC change and climate variability impact on water supply. Hence, it would help to implement appropriate climate change adaptation strategies along with soil and water conservation practices.

Another important contribution of this study is that the simple and straightforward methodology applied in Ribb-Gummara watershed could be efficiently transferred to other basins across the world in general and in sub-tropical, temperate and alpine climate regions in particular. The method is a combination of InVEST integrated catchment water yield model and Residual Trends analysis. This method could be applied with free and globally available remote sensing data (Sharp *et al.*, 2018; Vogl *et al.*, 2015). Hence, the method could apply in ungauged basins across the world to present complex management issues.

4.3.Uncertainty in this study

There are two sources of uncertainties in this study. Some uncertainties are associated with the InVEST water yield model. This model captures only annual average water supply and ignores extremes and within year variations. The InVEST water yield model does not capture the seasonal variation of the water supply, which is very important in agriculture. The water supply change in the dry season or low flow conditions is associated with LULC, whereas the wet season or high flow conditions is associated with climate change in general and rainfall variability in particular (Dile *et al.*, 2013). The other uncertainties derive from model input parameters. Despite the application of robust classification procedures, it is difficult to generate accurate land use classifications from Landsat images. The spatial resolution of Landsat image is 30m, which does not allow all land cover types to be clearly differentiated. For example, grassland and shrubland demarcation is difficult. In addition, grassland degradation that has an impact on the water supply is hard to detect from Landsat images (Pan *et al.*, 2015). Considered together, these uncertainties do not influence the direction of the results acquired and conclusions drawn. However, this work could be improved further by considering these limitations in the future.

5. Conclusions

This study aimed to separate the relative contribution of LULC change and climate variability to the average annual water supply in the Ribb-Gummara watershed from 2003 to 2017. In order to distinguish the impact of LULC on average annual water supplies from the impact of climate variability, LULC change and climate variability trends were first analyzed. The results showed an increasing trend of annual total rainfall and a slight decrease in mean annual temperatures. The watershed also experienced significant LULC dynamics between 2003 and 2017. For example, cropland, the dominant land use type, increased its area by 15% from 2003 to 2010 and lost 12% of its area between 2010 and 2017.

This study found that average annual water supplies increased over the last two decades. However, changes in the water supply show variation before and after 2010. The average annual water supply change was positive from 2003 to 2010 while negative from 2010 to 2017. The relative contribution of both LULC change and climate variability to the average annual water supply was positive from 2003 to 2017. However, climate variability was found to contribute 94% of the water supply variation, which is much higher than LULC. The impact of climate variability on water supply was negative between 2010 and 2017. Although it is masked by climate variability, LULC change still proved a positive impact on water supply, with a diminishing trend indicating the meaningful impact of SWC and land reclamation practices that commenced in 2010. This implies that SWC practice should incorporate ecosystem-based climate change adaptation strategies and scale up to community-based integrated watershed management to support sustainable land use.

It would be interesting to assess the impacts of LULC change and climate variability on seasonal water supplies. Hence, further study is needed to investigate the present and future impacts of LULC and climate change on seasonal water production in the Ribb-Gummara watershed to sustain freshwater provision services throughout the year.

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References

Allen RG, Pereira LS, Raes D, Smith M, Ab W. 1998. Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56. 1–15

Alphan H, Doygun H, Unlukaplan YI. 2009. Post-classification comparison of land cover using multitemporal Landsat and ASTER imagery: The case of Kahramanmaras, Turkey. *Environmental Monitoring and Assessment* **151**: 327–336. DOI: 10.1007/s10661-008-0274-x

Andualem TG, Gebremariam B. 2015. Impact Of Land Use Land Cover Change On Stream Flow And Sediment Yield : A Case Study Of Gilgel Abay Watershed , Lake Tana. *International Journal of Technology Enhancements and Emerging Engineering Research* **3**: 28–42

Arunyawat S, Shrestha R. 2016. Assessing Land Use Change and Its Impact on Ecosystem Services in Northern Thailand. *Sustainability* **8**: 768. DOI: 10.3390/su8080768

Atanaw F, Collick AS, Mcalister C, Taylor R, Steenhuis TS. 2015. Effects of Physical Catchment Characteristics on River Flow. 1–11

Ayele HS, Li M-H, Tung C-P, Liu T-M. 2016. Assessing Climate Change Impact on Gilgel Abbay and Gumara Watershed Hydrology, the Upper Blue Nile Basin, Ethiopia. *Terrestrial, Atmospheric and Oceanic Sciences* **27**: 1005. DOI: 10.3319/TAO.2016.07.30.01

Ayenew Y. 2008. Rainfall-Runoff Modelling for Sustainable Water Resources Management : The Case of Gumara Watershed , Ethiopia.

Bayissa Y, Tadesse T, Demisse G, Shiferaw A. 2017a. Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the Upper Blue Nile Basin, Ethiopia. *Remote Sensing* **9**. DOI: 10.3390/rs9070669

Bayissa Y, Tadesse T, Demisse G, Shiferaw A. 2017b. Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the Upper Blue Nile Basin, Ethiopia. *Remote Sensing* **9**: 1–17. DOI: 10.3390/rs9070669

Belete M, Deng J, Zhou M, Wang K, You S, Hong Y, Weston M. 2018. A new approach to modelingwater balance in Nile River Basin, Africa. *Sustainability (Switzerland)* **10**: 1–14. DOI: 10.3390/su10030810

Biro K, Pradhan B, Buchroithner M, Makeschin F. 2013. Land Use/Land Cover Change Analysis and Its Impact on Soil Properties in the Northern Part of Gadarif Region, Sudan. *Land Degradation & Development* **24**: 90–102. DOI: 10.1002/ldr.1116

Biru MK, Minale AS, Debay AB. 2015. Multitemporal Land Use Land Cover Change and Dynamics of Blue Nile Basin by Multitemporal Land Use Land Cover Change and Dynamics of Blue Nile Basin by Using GIS and Remote Sensing Techniques , North-Western Ethiopia. *International Journal of Environmental Sciences Vol.* **4**: 81–88

Bitew MM, Gebremichael M, Ghebremichael LT, Bayissa YA. 2012. Evaluation of High-Resolution Satellite Rainfall Products through Streamflow Simulation in a Hydrological Modeling of a Small Mountainous Watershed in Ethiopia. *Journal of Hydrometeorology* **13**: 338–350. DOI: 10.1175/2011JHM1292.1

Butt A, Shabbir R, Ahmad SS, Aziz N. 2015. Land use change mapping and analysis using Remote Sensing and GIS: A case study of Simly watershed, Islamabad, Pakistan. *Egyptian Journal of Remote Sensing and Space Science* **18**: 251–259. DOI: 10.1016/j.ejrs.2015.07.003

Canadell J, Jackson R, Ehleringer J, Mooney HA, Sala OE, Schulze E-D. 1996. Maximum rooting depth of vegetation types at the global scale. *Oecologia* **108**: 583–595. DOI: 10.1007/BF00329030

Chakilu GG, Moges MA. 2017. Assessing the Land Use/Cover Dynamics and its Impact on the Low Flow of Gumara Watershed, Upper Blue Nile Basin, Ethiopia. *Hydrology: Current Research* **08**: 1–6. DOI: 10.4172/2157-7587.1000268

Chawla I, Mujumdar PP. 2015. Isolating the impacts of land use and climate change on streamflow. *Hydrology and Earth System Sciences* **19**: 3633–3651. DOI: 10.5194/hess-19-3633-2015

Congalton RG. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment* **37**: 35–46. DOI: 10.1016/0034-4257(91)90048-B

D. Lu , P. Mausel EB& EM. 2004. Change detection techniques. *International Journal of Remote Sensing* **25**: 2365–2401. DOI: 10.1080/0143116031000139863

Dile YT, Berndtsson R, Setegn SG. 2013. Hydrological Response to Climate Change for Gilgel Abay River, in the Lake Tana Basin - Upper Blue Nile Basin of Ethiopia. *PLoS ONE* **8**: 12–17. DOI: 10.1371/journal.pone.0079296

Dinku T, Ceccato P, Grover-Kopec E, Lemma M, Connor SJ, Ropelewski CF. 2007. Validation of satellite rainfall products over East Africa's complex topography. *International Journal of Remote Sensing* **28**: 1503–1526. DOI: 10.1080/01431160600954688

Donohue RJ, Roderick ML, McVicar TR. 2012. Roots, storms and soil pores: Incorporating key ecohydrological processes into Budyko's hydrological model. *Journal of Hydrology* **436–437**: 35–50. DOI: 10.1016/j.jhydrol.2012.02.033

Dorigo W, De Jeu R, Chung D, Parinussa R, Liu Y, Wagner W, Fernández-Prieto D. 2012. Evaluating global trends (1988-2010) in harmonized multi-satellite surface soil moisture.

Geophysical Research Letters **39**: 3–9. DOI: 10.1029/2012GL052988

Droogers P, Allen R. 2002. Estimating reference evapotranspiration under inaccurate data conditions. *Irrigation and Drainage Systems* **16**: 33–45. DOI: 10.1023/A:1015508322413

Easton ZM, Fuka DR, White ED, Collick AS, Biruk Ashagre B, McCartney M, Awulachew SB, Ahmed AA, Steenhuis TS. 2010. A multi basin SWAT model analysis of runoff and sedimentation in the Blue Nile, Ethiopia. *Hydrology and Earth System Sciences* **14**: 1827–1841. DOI: 10.5194/hess-14-1827-2010

El-Hattab MM. 2016. Applying post classification change detection technique to monitor an Egyptian coastal zone (Abu Qir Bay). *Egyptian Journal of Remote Sensing and Space Science* **19**: 23–36. DOI: 10.1016/j.ejrs.2016.02.002

Evans J, Geerken R. 2004. Discrimination between climate and human-induced dryland degradation. *Journal of Arid Environments* **57**: 535–554. DOI: 10.1016/S0140-1963(03)00121-6

FAO/IIASA/ISRIC/ISS-CAS/JRC. 2012. *Harmonized World Soil Database (version 1.2). FAO, Rome, Italy and IIASA, Laxenburg, Austria*, 1–50

Feng XM, Sun G, Fu BJ, Su CH, Liu Y, Lamparski H. 2012. Regional effects of vegetation restoration on water yield across the Loess Plateau, China. *Hydrology and Earth System Sciences* **16**: 2617–2628. DOI: 10.5194/hess-16-2617-2012

Ferrari GT, Ozaki V. 2014. Missing Data Imputation of Climate Datasets : Implications To Modeling Extreme Drought Events. *Revista Brasileira de Meteorologia* **29**: 21–28. DOI: 10.1590/S0102-77862014000100003

Fischer G, Nachtergaele FO, Prieler S, Teixeira E, Toth G, van Velthuizen H, Verelst L, Wiberg D. 2012. *Global Agro-ecological Zones (GAEZ): Model Documentation*. Rome, Italy

Foody GM. 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* **80**: 185–201. DOI: 10.1016/S0034-4257(01)00295-4

Fu BP. 1981. On the calculation of the evaporation from land surface. *S C IE N TA T M O S P H E R I C A S IN I C A* **5**: 23–31

Hamel P, Guswa AJ. 2015. Uncertainty analysis of a spatially explicit annual water-balance model: Case study of the Cape Fear basin, North Carolina. *Hydrology and Earth System Sciences* **19**: 839–853. DOI: 10.5194/hess-19-839-2015

Hassen EE, Assen M. 2017. Land use / cover dynamics and its drivers in Gelda catchment , Lake Tana watershed ,. *Environmental Systems Research* 1–13. DOI: 10.1186/s40068-017-0081-x

Hu Q, Yang D, Li Z, Mishra AK, Wang Y, Yang H. 2014. Multi-scale evaluation of six high-resolution satellite monthly rainfall estimates over a humid region in China with dense rain gauges. *International Journal of Remote Sensing* **35**: 1272–1294. DOI: 10.1080/01431161.2013.876118

HUANG C, DAVIS LS, TOWNSHEND JRG. 2002. An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing* **23**: 725–749. DOI: 10.1080/01431160110040323

I T T Visual Information Solutions. 2009. Atmospheric Correction Module : QUAC and FLAASH User ' s Guide. 44

Jemberie M, Gebrie T, Gebremariam B. 2016. Evaluation of Land Use Land Cover Change on Stream Flow: a Case Study Ofdedissa Sub Basin, Abay Basin, South Western Ethiopia. *International Journal of Innovations in Engineering Research and Technology* **3**: 2394–3696

Jensen J. 2016. *Introductory Digital Image Processing: A Remote Sensing Perspective*. Pearson Education, Inc: University of South Carolina, USA

Kremen C. 2005. Managing ecosystem services: What do we need to know about their ecology? *Ecology Letters* **8**: 468–479. DOI: 10.1111/j.1461-0248.2005.00751.x

Krysanova V, White M. 2015. Advances in water resources assessment with SWAT—an overview. *Hydrological Sciences Journal* **60**: 771–783. DOI: 10.1080/02626667.2015.1029482

Lü Y, Fu B, Feng X, Zeng Y, Liu Y, Chang R, Sun G, Wu B. 2012. A policy-driven large scale ecological restoration: Quantifying ecosystem services changes in the loess plateau of

China. *PLoS ONE* **7**: 1–10. DOI: 10.1371/journal.pone.0031782

MEA. 2005. *Millennium Ecosystem Assessment (MEA), 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC. World Health*. DOI: 10.1196/annals.1439.003

Moges DM, Bhat HG. 2017. Integration of geospatial technologies with RUSLE for analysis of land use/cover change impact on soil erosion: case study in Rib watershed, north-western highland Ethiopia. *Environmental Earth Sciences* **76**: 1–14. DOI: 10.1007/s12665-017-7109-4

Moges DM, Bhat HG. 2018. An insight into land use and land cover changes and their impacts in Rib watershed, north-western highland Ethiopia. *Land Degradation and Development* **29**: 3317–3330. DOI: 10.1002/ldr.3091

Mountrakis G, Im J, Ogole C. 2011. Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing* **66**: 247–259. DOI: 10.1016/j.isprsjprs.2010.11.001

Mulatu C, Crosato A, Moges M, Langendoen E, McClain M. 2018. Morphodynamic Trends of the Ribb River, Ethiopia, Prior to Dam Construction. *Geosciences* **8**: 255. DOI: 10.3390/geosciences8070255

Munyati C. 2000. Wetland change detection on the Kafue Flats, Zambia, by classification of a multitemporal remote sensing image dataset. *International Journal of Remote Sensing* **21**: 1787–1806. DOI: 10.1080/014311600209742

Pan T, Wu S, Liu Y. 2015. Relative contributions of land use and climate change to water supply variations over yellow river source area in Tibetan Plateau during the past three decades. *PLoS ONE* **10**: 1–19. DOI: 10.1371/journal.pone.0123793

Pessacg N, Flaherty S, Brandizi L, Solman S, Pascual M. 2015. Getting water right: A case study in water yield modelling based on precipitation data. *Science of the Total Environment* **537**: 225–234. DOI: 10.1016/j.scitotenv.2015.07.148

Phiri D, Morgenroth J. 2017. Developments in Landsat land cover classification methods: A review. *Remote Sensing* **9**. DOI: 10.3390/rs9090967

Pontius RG, Millones M. 2011. Death to Kappa: Birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing* **32**: 4407–4429. DOI: 10.1080/01431161.2011.552923

Pontius RG, Shusas E, McEachern M. 2004. Detecting important categorical land changes while accounting for persistence. *Agriculture, Ecosystems and Environment* **101**: 251–268. DOI: 10.1016/j.agee.2003.09.008

Praskievicz S, Chang H. 2009. A review of hydrological modelling of basin-scale climate change and urban development impacts. *Progress in Physical Geography* **33**: 650–671. DOI: 10.1177/0309133309348098

Rodriguez-Galiano VF, Ghimire B, Rogan J, Chica-Olmo M, Rigol-Sanchez JP. 2012. An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing* **67**: 93–104. DOI: 10.1016/j.isprsjprs.2011.11.002

Sahle M, Saito O, Fürst C, Yeshitela K. 2019. Quantifying and mapping of water-related ecosystem services for enhancing the security of the food-water-energy nexus in tropical data–sparse catchment. *Science of the Total Environment* **646**: 573–586. DOI: 10.1016/j.scitotenv.2018.07.347

Setegn SG, Srinivasan R, Dargahi B, Melesse AM. 2009. Spatial delineation of soil erosion vulnerability in the Lake Tana Basin, Ethiopia. *HYDROLOGICAL PROCESSES* **23**: 3738–3750. DOI: 10.1002/hyp.7476

Sewnet A. 2016. Land use/cover change at Infraz watershed by using GIS and remote sensing techniques, northwestern Ethiopia. *International Journal of River Basin Management* **14**: 133–142. DOI: 10.1080/15715124.2015.1095199

Shao Y, Lunetta RS. 2012. Comparison of support vector machine, neural network, and CART algorithms for the land-cover classification using limited training data points. *ISPRS Journal of Photogrammetry and Remote Sensing* **70**: 78–87. DOI: 10.1016/j.isprsjprs.2012.04.001

Sharp, R., Tallis, H.T., Ricketts, T., Guerry, A.D., Wood, S.A., Chaplin-Kramer, R., Nelson, E.

E, D., Wolny, S., Olwero, N., Vigerstol, K., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J. C, D., Arkema, K., Lonsdorf, E., Kennedy, C., Verutes, G., Kim, C.K., Guannel, G., Papenfus, M., Toft, J., Marsik M, Bernhardt, J., Griffin, R., Glowinski, K., Chaumont, N., Perelman, A., Lacayo, M. Mandle, L., Hamel, P., Vogl AL, Rogers, L., Bierbower, W., Denu, D., and Douglass J. 2018. *InVEST 3.5.0 User's Guide*. The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund: Stanford

Soytong P, Janchidfa K, Phengphit N, Perera, Chayhard S, Ranjith. 2016. The Effects of Land Use Change and Climate Change on Water Resources in the Eastern Region of Thailand. **12**: 1695–1722

Teferi E, Bewket W, Uhlenbrook S, Wenninger J. 2013. Understanding recent land use and land cover dynamics in the source region of the Upper Blue Nile , Ethiopia : Spatially explicit statistical modeling of systematic transitions. *"Agriculture, Ecosystems and Environment"* **165**: 98–117. DOI: 10.1016/j.agee.2012.11.007

Teklaya A, Dileb YT, Setegnc SG, Demissiec SS, Asfaw DH. 2019. Evaluation of static and dynamic land use data for watershed hydrologic process simulation : A case study in Gummara watershed , Ethiopia. *Catena* **172**: 65–75. DOI: 10.1016/j.catena.2018.08.013

Turner W, Rondinini C, Pettorelli N, Mora B, Leidner AK, Szantoi Z, Buchanan G, Dech S, Dwyer J, Herold M, Koh LP, Leimgruber P, Taubenboeck H, Wegmann M, Wikelski M, Woodcock C. 2015. Free and open-access satellite data are key to biodiversity conservation. *Biological Conservation* **182**: 173–176. DOI: 10.1016/j.biocon.2014.11.048

Van Griensven A, Ndomba P, Yalew S, Kilonzo F. 2012. Critical review of SWAT applications in the upper Nile basin countries. *Hydrology and Earth System Sciences* **16**: 3371–3381. DOI: 10.5194/hess-16-3371-2012

Vogl AL, Wolny S, Dennedy-Frank PJ, Hamel P, Johnson JA, Rogers M. 2015. *Managing catchments for hydropower services*. Wealth Accounting and the Valuation of Ecosystem Services (WAVES): Washington D.C.

Wessels KJ, Prince SD, Malherbe J, Small J, Frost PE, VanZyl D. 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *Journal of Arid Environments* **68**: 271–297. DOI: 10.1016/j.jaridenv.2006.05.015

Worqlul AW, Ayana EK, Atanaw Bahir F. 2015. Effect of Physical Catchment Characteristics on River Flow: The Case of Ribb and Gumara Rivers in Upper Blue Nile, Ethiopia. *International Soil & Water Assessment Tool Conference June 24-26, 2015*, 87. DOI: 10.13140/RG.2.1.2288.3680

Wubie MA, Assen M, Nicolau MD. 2016. Patterns, causes and consequences of land use/cover dynamics in the Gumara watershed of lake Tana basin, Northwestern Ethiopia. *Environmental Systems Research* **5**: 8. DOI: 10.1186/s40068-016-0058-1

Xu H. 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing* **27**: 3025–3033. DOI: 10.1080/01431160600589179

Yin J, He F, Jiu Xiong Y, Yu Qiu G. 2017. Effects of land use/land cover and climate changes on surface runoff in a semi-humid and semi-arid transition zone in northwest China. *Hydrology and Earth System Sciences* **21**: 183–196. DOI: 10.5194/hess-21-183-2017

Yong B, Ren LL, Hong Y, Wang JH, Gourley JJ, Jiang SH, Chen X, Wang W. 2010. Hydrologic evaluation of Multisatellite Precipitation Analysis standard precipitation products in basins beyond its inclined latitude band: A case study in Laohahe basin, China. *Water Resources Research* **46**: 1–20. DOI: 10.1029/2009WR008965

Yousefi S, Khatami R, Mountrakis G, Mirzaee S, Pourghasemi HR, Tazeh M. 2015. Accuracy assessment of land cover/land use classifiers in dry and humid areas of Iran. *Environmental Monitoring and Assessment* **187**. DOI: 10.1007/s10661-015-4847-1

Yuan F, Sawaya KE, Loeffelholz BC, Bauer ME. 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) metropolitan area by multitemporal Landsat remote sensing. *Remote Sensing of Environment* **98**: 317–328. DOI: 10.1016/j.rse.2005.08.006

Zhang L, Hickel K, Dawes WR, Chiew FHS, Western AW, Briggs PR. 2004. A rational function approach for estimating mean annual evapotranspiration. *Water Resources Research* **40**:

W025021–W02502114. DOI: 10.1029/2003WR002710

Zhang L, Nan Z, Xu Y, Li S. 2016. Hydrological impacts of land use change and climate variability in the headwater region of the Heihe River Basin, northwest China. *PLoS ONE* **11**: 1–25. DOI: 10.1371/journal.pone.0158394

Table 1. *All the input parameters and data sources for InVEST 3.5.0 annual water yield model*

Input Data	**Type or Format**	**Spatial Resolution**	**Sources**
Average annual precipitation (mm)	GIS raster	30m × 30m	NMSA
Average annual ETo (mm)	GIS raster	30m × 30m	NMSA
Soil depth (mm)	GIS raster	30m × 30m	(FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012; Fischer *et al.*, 2012).
PAWC (mm)	GIS raster	30m × 30m	(FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012; Fischer *et al.*, 2012).
LULC	GIS raster	30m × 30m	USGS, (Turner *et al.*, 2015)
Watershed and Sub-watersheds	GIS polygon/Shapefile	-	Delineated by the researchers using Arc Hydro tool in Arc GIS 10.5 from SRTM 30m DEM data
Root Depth	Per LULC class	-	(Canadell *et al.*, 1996)
Kc	Per LULC class	-	(Allen et al., 1998; Sharp et al., 2018)
Z parameter	Integer number	-	(Hamel & Guswa, 2015)

Table 2. *Definitions of land use/land cover classification system in the study area*

Land use types	Description
Crop Land	A land covered with annual and perennial crops frequently found in plains, foot slopes, plateaus, and valley floors
Grass Land	A land covered with grass that found in flat areas and river banks in which water-table is near the surface
Shrub Land	A land dominantly covered by vegetation with lower than one meter height and 50% canopy cover
Forest Land	These include a remnant of high natural forests found in church fence, steep slope areas, and eucalyptus plantations having more than 50% canopy cover
Built up Area	All man-made infrastructures including buildings, roads concrete sports fields etc.
Water Body	Any part of the study area covered with surface water like streams, rivers, ponds, dams, and lakes
Bare Land	Land of limited ability to support life that covered with sand and rocks

Table 3. *Properties of the Landsat images used in this study*

Sensor type	Spatial resolution (m)	Bands used	Path/row	Date of acquisition
Landsat 5 TM	30*30	1, 2, 3, 4, 5,	169/52	2010-01-14
Landsat 7 ETM+	30*30	1, 2, 3, 4, 5,	169/52	2003-01-03
Landsat 8 OLI	30*30	2, 3, 4,5, 6,	169/52	2017-12-19

Table 4. *Classified map accuracy assessment report (2003, 2010, and 2017)*

Land use Classes	2003			2010			2017		
	PA (%)	UA (%)	**OA** (%)	PA (%)	UA (%)	**OA** (%)	PA (%)	UA (%)	**OA** (%)
Crop Land	93.08	79.70	**87.01**	97.39	97.39	**85.38**	88.61	84.36	**88.75**
Grass Land	84.92	80.64		79.05	72.81		87.89	82.98	
Shrub Land	63.57	79.88		35.90	93.33		55.71	79.14	
Forest Land	95.64	93.57		98.87	93.33		99.89	94.71	
Built up Area	48.86	78.18		59.52	100.00		57.65	58.33	
Water Body	96.75	93.70		91.43	94.12		96.72	93.65	
Bare Land	23.44	90.91		67.57	86.21		58.27	87.06	

OA = Overall Accuracy, PA = Producer Accuracies, and UA = User Accuracies

Table 1*.Area coverage of each LULC class (2003-2017)*

Land Use Type	Land use (2003)		Land use (2010)		Land use (2017)	
	Area (km^2)	Percent	Area (km^2)	Percent	Area (km^2)	Percent
Crop Land	2396.57	73.13	2748.99	83.99	2409.50	73.61
Bare Area	0.00	0.00	1.06	0.03	2.51	0.08
Built up Area	4.54	0.14	4.67	0.14	20.74	0.63
Forest Land	135.76	4.15	78.21	2.38	89.02	2.72
Grass Land	556.35	17.00	113.1	3.46	289.24	8.84
Shrub Land	166.81	5.11	320	9.78	442.65	13.53
Water Body	13.15	0.41	7.15	0.22	19.52	0.59
Total	3,273.18	100	3,273.18	100	3,273.18	100

Table 2. *The rate of change for each LULC class (2003-2017)*

Land Use Type	Land Use Change (2003-2010)		Land Use Change (2010-2017)		Land Use Change (2003-2017)	
	Area (km^2)	Percent	Area (km^2)	Percent	Area (km^2)	Percent
Crop Land	352.42	14.71	-339.49	-12.35	12.93	0.54
Bare Area	1.06	-	1.45	136.47	2.51	-
Built up Area	0.13	2.98	16.07	344.04	16.20	357.25
Forest Land	-57.55	-42.39	10.81	13.82	-46.74	-34.43
Grass Land	-443.24	-79.67	176.14	155.73	-267.10	-48.01
Shrub Land	153.17	91.82	122.65	38.33	275.82	165.34
Water Body	-6.00	-45.62	12.37	173.07	6.38	48.51

Table 3. *LULC conversion matrix between 2003 and 2017*

	Initial State (2003)									
Final State (2017)	**Classes**	Crop Land	Grass Land	Shrub Land	Forest Land	Built-up Area	Water Body	Bare Land	Row Total	Gain
	Crop Land	**1952.41**	328.66	88.04	31.40	3.40	5.16	0	2409.50	457.09
	Grass Land	88.53	**189.75**	10.19	0.62	0.13	0.03	0	289.24	99.49
	Shrub Land	311.02	27.39	**56.37**	44.78	0.05	3.02	0	442.65	386.28
	Forest Land	17.97	1.35	10.64	**56.12**	0.00	2.93	0	89.02	32.9
	Built up Area	13.88	4.30	0.79	0.83	**0.90**	0.04	0	20.74	19.84
	Water Body	11.73	3.50	0.77	1.99	0.05	**1.48**	0	19.52	18.04
	Bare Land	1.03	1.40	0.01	0.03	0.01	0.04	**0**	2.51	2.51
	Column Total	2396.57	556.35	166.82	135.76	4.54	13.15	0		
	Loss	444.16	366.60	110.45	79.64	3.64	11.67	0		
	Net Change	**12.93**	**-267.10**	**275.82**	**-46.76**	**16.20**	**6.38**	**2.51**		

Table 4. *The relative contribution of Climate variability and LULC change to average annual water supply*

Periods	ΔY (mm)	ΔY_C (mm)	ΔY_L (mm)	η_C (%)	η_L (%)
2003-2017	203	192	11	94	6
2003-2010	261	253	8	97	3
2010-2017	-58	-61	3	105	-5

Figure 1. *Location map of Ribb-Gummara watershed*

Figure 2. *Inter-annual temperature patterns and trends of change (2001-2017)*

Figure 3. *Patterns of annual total rainfall and trends (2001-2017)*

Figure 4. LULC map of Ribb-Gummara watershed

Figure 5. *Spatial distribution of calculated annual water supply (mm)*

Figure 6. *Average annual water supply variation during the last two decades*

Figure 7. *The impact of climate change on the average annual water supply*

Figure 8. *The impact of LULC on the average annual water supply*