The impact of land-use/land cover changes on water balance of the heterogeneous Buzi sub-catchment, Zimbabwe

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ABSTRACT

The nature of interactions between ecological, physical and hydrological characteristics that determine the effects of land cover change on surface and sub-surface hydrology is not well understood in both natural and disturbed environments. The spatiotemporal dynamics of water fluxes and their relationship with land cover changes between 2009 and 2017 in the headwater Buzi sub-catchment in Zimbabwe is evaluated. To achieve this, land cover dynamics for the area under study were characterised from the 30 m Landsat data, using the eXtreme Gradient Boosting (XGBoost) algorithm. After the land cover classification, the key water balance components namely; interception, transpiration and evapotranspiration (ET) contributions for each class in 2009 and 2017 were estimated. Image classification of Landsat data achieved good overall accuracies above 80% for the two periods. Results showed that the percentage of the plantation land cover types decreased slightly between 2009 (25.4%) and 2017 (22.5%). Partitioning the annual interception, transpiration and ET according to land cover classes showed that the highest amounts of ET in the basin were from plantation where land cover types with tea had the highest interception, transpiration and ET in the catchment. Higher ET, interception and transpiration were observed in the eastern parts of the catchment. At catchment level, results show that 2017 had a higher water balance than 2009, which was partly explained by the decrease in plantation cover type.

1. Introduction

Spatial information on water flux within the soil-vegetation-atmosphere system is critical for water management at catchment level in the face of anthropogenic surface modifications and global change. Land cover change alters the atmospheric carbon and nitrogen cycles, albedo, runoff, soil water holding capacity and biodiversity among others at local, regional and global scales (Devaraju et al., 2018; Duveiller et al., 2018a; Winckler et al., 2018). The nature of interactions between ecological, physical and hydrological characteristics that determine the effects of land cover change on surface and sub-surface hydrology is not well understood in both natural and human-dominated environments. Changes in agricultural land uses are central to environmental change studies because they are situated at the interface between ecosystems and society. With increases in

atmospheric evaporative demand due to global warming against reduced precipitation in many tropical areas, the identification of the drivers of water losses as part of routine landscape management routines is imperative (Huxman and Scott, 2007; Liu et al., 2013). Water balance assessments therefore provide an important basis on which catchment-level decisions on agricultural and forest plantation investments, water resources management and planning, water and carbon accounting, and impact assessments are premised.

Changes in vegetation cover have significant impacts on the surface water budget, especially for evapotranspiration (ET), an important component of the terrestrial hydrological cycle (Aghsaei et al., 2020; Gaertner et al., 2019; Gumindoga et al., 2018). ET is the sum of the evaporation from the land surface and the transpiration from plants into the atmosphere, and links the water budget to carbon sink, and energy exchange (Wang and Dickinson, 2012). It is an important component of

the hydrological cycle that governs interactions between the atmosphere and surface ecosystems (Betts et al., 1996; Liu et al., 2013). Therefore, understanding of the long-term variation of regional ET and its drivers is crucial for monitoring the biophysical processes related to it. Increases in ET may lead to an overall intensification or weakening of the water cycle, with implications for the recycling of precipitation and generation of runoff, which in turn will have impacts on ecological, hydrologic and economic activities depending on water resources availability (Cao et al., 2009; Duveiller et al., 2018a; Odongo et al., 2019).

Agricultural and forestry plantations are important economic activities that contribute to local employment and national development. Plantation forests use more water per unit area per year than agricultural land covers such as grains, pasture and other crops, which lowers runoff and discharge in areas that they are dominant (Lima et al., 2012; Prosser and Walker, 2009). This is so because they are usually large plants with very large leaf areas that consequently transpire more water, their tree canopy intercepts more rain before it reaches the ground, they often have deeper roots and they use water over the whole year, as they are perennial crops (O'Loughlin and Nambiar, 2001; Parsons et al., 2007). Large-scale expansion of plantations is therefore a concern as this would diminish hydrogeological flows and threaten water availability and/or water quality for other subsequent uses (Bosch and Hewlett, 1982; Farley et al., 2005; Gordon et al., 2005; O'Loughlin and Nambiar, 2001; Scanlon et al., 2005). Paradoxically, perennial tree plantations have the potential to improve livelihoods, develop local and national economies, contribute to food security, advance cleaner biofuel energy and provide an array of ecosystems services (Nair, 2010).

It is well established in literature that different vegetation types have different ET, and therefore major changes in land cover have consequent effects on ET (Duveiller et al., 2018b; Han et al., 2018; Jaramillo et al., 2018; Mao et al., 2015). In catchments with plantation crops that are also changing over time, it therefore becomes important to evaluate whether ET is changing with land cover changing or is resilient. In addition, the spatial-temporal dynamics related to land cover change, climate change, human development, vegetation growth, and water cycling have not been simultaneously assessed over agricultural and forest plantations landscapes compared to natural systems, from which results cannot be directly imported. Consequently, little is known about the spatiotemporal dynamics of water flux in the response to land cover change and climate over long periods in these areas.

The substantial extent of plantations as a land cover type in some catchments together with the degree to which they reduce runoff and recharge is sufficient to justify the inclusion of plantations in water resource planning, policy and management (Lima et al., 2012; Parsons et al., 2007). However, there is also evidence that land cover change may not significantly change ET as previously hypothesized. For example, Hamilton et al. (2018) and Abraha et al. (2015), and Blackie and Robinson (2007) observed that land cover/land uses changes between annual and perennial land cover types did not significantly change the ET dynamics of the catchment for the US Midwest and East Africa respectively. It is not clear whether the resilience or lack thereof is related to scale of assessment or specific to a catchment or both. There are very few catchment scale comparisons of water flux due to conversion from annual crops such as maize (*Zea mays*) and sorghum (*Sorghum bicolor*) to perennial crops such as coffee (*Coffea arabica*), tea (*Camelia sinensis*) or pine trees (*Pinus spp.*). This is despite the fact that these conversions are common in many tropical areas pushed by diverse drivers. Projections are that land cover change will continue into the future to meet economic development goals on one hand and humongous commodity appetite on the other hand.

Given the importance of agricultural and forestry plantations as a land cover type in terms of economic importance and provision of environmental service on one hand and catchment hydrology and related water resource management on the other, it is therefore important to understand how land cover change can have an impact on aspects of the water balance in the catchment. We hypothesize that there

is a link between land use/cover and water balance such at catchment level that is modified by land cover change. The objectives of this study were therefore to (1) determine the proportion of agricultural and forestry plantations as land use/cover types in Buzi sub-catchment in 2009 and 2017, (2) establish the quantitative and spatial changes in land cover between the time periods and (3) understand the relationship between changes in land cover and water balance in the catchment level.

2. Materials and methods

2.1. Study area

The Buzi headwaters sub-catchment is located between latitude 32°32′0 E and 32°52′0 E, and longitude 20°20′0 S and 20°08′0 S in Chipinge district in Zimbabwe under the Save Catchment (Fig. 1). It consists of rural communal areas, resettlement areas and large-scale individual and corporate commercial farming areas. The sub-catchment is shared between south-eastern Zimbabwe and central western Mozambique. In rural communal areas and resettlement areas in Buzi sub-catchment, the main economic activities are commercial farming of coffee, tea, macadamia (*Macadamia integrifolia*) and other cash crops (Mupindu et al., 2004). Buzi headwaters sub catchment has an area of 582 km^2. The climate is subtropical with two distinct seasons, divided almost equally between months of the year (October–March is the growing season while April to September is the dry season). Compared to the rest of the Buzi basin, the area receives relatively high mean annual rainfall totals (1200–1800 mm/year) (Nicolin, 2010). The geological setting controls the hydrogeological characteristics and the area is predominantly granitic with the most occurring group of lithology being the paragneiss, quartzite, schist, phyllite, and amphibolite group (Lagerblad, 2010). Elevation ranges from 614 m to 1305 m (Fig. 1). With a complex terrain and high altitude, the catchment is ideal for investigating the response of terrestrial processes to land cover/use change.

2.2. Land cover change assessment

2.2.1. Image data acquisition pre-processing

For the land cover classification, two dry season Landsat images for 2009 and 2017 were acquired. The imagery were obtained with georeferencing, which was sufficient for general land cover classification as was required in the study. To ensure consistency in the atmospheric correction, the analysis ready, atmospherically corrected Landsat Surface Reflectance Level 2 science products were ordered from the earth explorer (https://earthexplorer.usgs.gov). These were 16-bit signed integer data with radiometric and geometric correction and were converted to surface reflectance with a provided scale factor. The dates, sensor types, cloud cover and other characteristic of the images are in Table 1.

Image stacks were made of five bands, that is, blue (B), green (G), blue (B), near infrared (NIR) and shortwave infrared (SWIR1) as Seven land cover types formed the classification scheme used to classify the images. These are described in detail in Table 2. The training points for both 2009 and 2017 classification were obtained from field GPS points (Garmin eTrex with ~3 m accuracy) for all plantations and secondary survey data for plantations classes (tea, coffee and plantation forest) while the other classes were collected from auxiliary secondary sources such Google Earth, catchment plans and knowledge of the area. Since the number of pixels was very small, it was important to implement the region growing method to automatically growth the number of training and validation points. After this process, 60% of the training points were used training set the model and 40% as a validation set. In total, 198 points were used for the 2009 image (119 for training and 79 for validation) and 217 points (130 for training and 87 for validation) for the 2017 image.
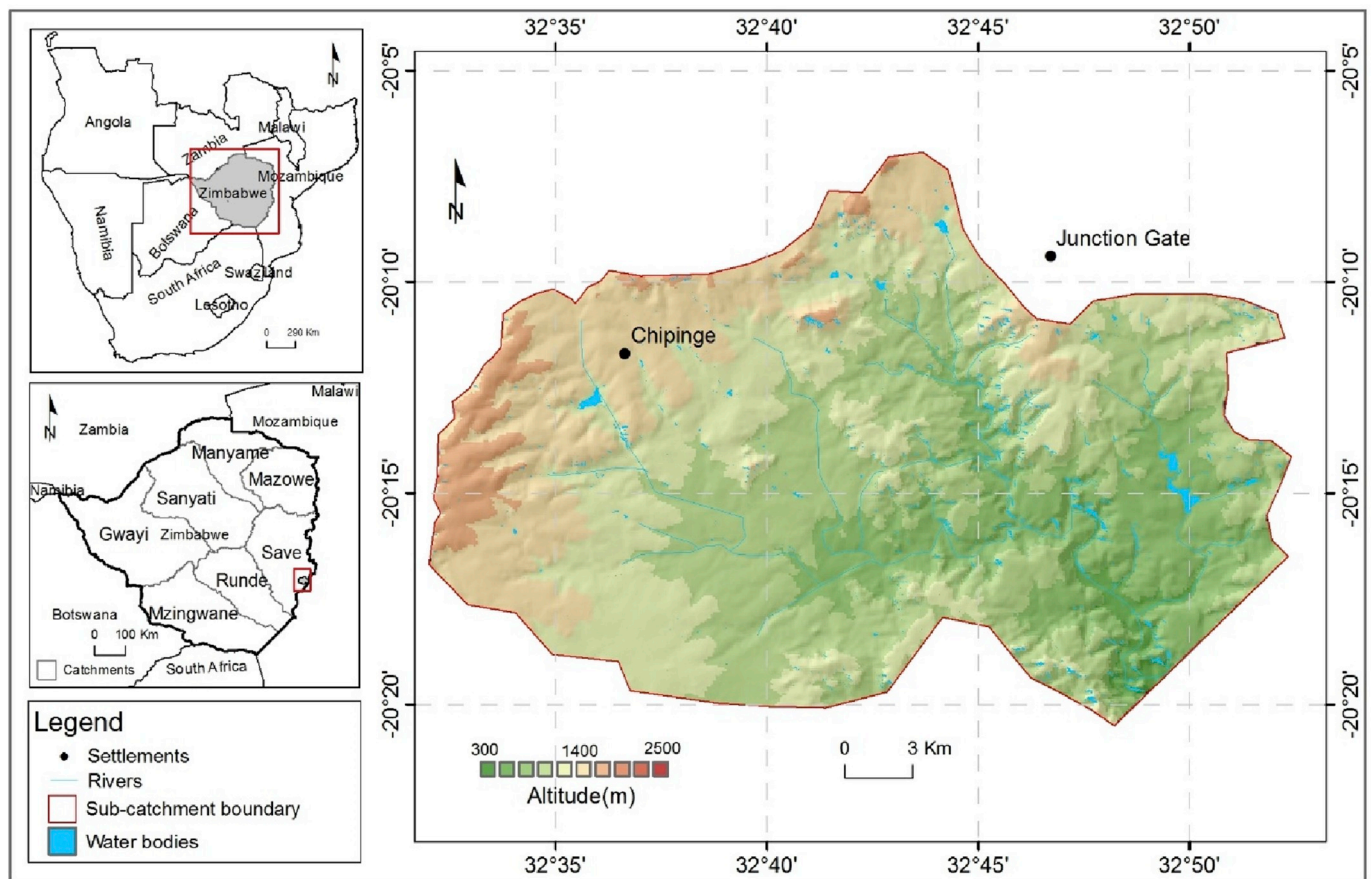
Fig. 1. A map showing the location of the Buzi Headwaters sub catchment in Zimbabwe and the distribution of elevation and major river systems.

Table 1
Description of remote sensing data used in the image classification and spatial analysis.

Description	2009	2017
Acquisition date	5 June	15 June
Sensor type	Landsat 7 TM	Landsat 8 OLI
Path/Row	168/74	168/74
Cloud cover	0.00	6.26
Sun Azimuth	37.80417239	35.71673023
Sun Elevation	37.01035882	38.55711720
Projection	UTM36S	UTM36S
Spatial resolution	30	30
Source	USGS Earth Explorer	USGS Earth Explorer

Table 2
Description of land cover types that were used for the classification scheme.

Land cover/use	Description of land cover/use classes
Tea	Tea is a perennial evergreen shrub managed intensively for its tender leaves, which are periodically lopped to make a beverage, resulting in a flat canopy designed to facilitate plucking either by hand or machine
Coffee	Coffee is a perennial tree crop growing up to 3 m in large and smallholder plantations as a monocrop. Coffee is planted in rows and can reach up to 3 m depending on varieties, with average leaf area index of 6
Plantation forest	Plantation forest are commercial tree species that are grown for their woody parts for use in construction and other industries. These include common gum trees (*Eucalyptus* spp), wattle (*Acacia* spp) and pine trees.
Natural forest	These closed forests have a canopy cover of over 40% and a density of trees and shrubs growing together.
Grassland	Areas with open grasses and shrubs or sparse trees of lower density that cannot be considered as forests
Cropland/Built-up	These fields are ploughed or fallow during the dry season that corresponds with the study. The class also includes bare areas from settlements and other human activities. No major dry season irrigation for annual cropping was identified in the study area.
Water	Open water bodies that are used for different activities that meet the resolution of the data used (30 m × 30 m) in the study.

2.2.2. Image classification algorithm

To classify the four image stacks for 2009 and 2017, we applied the eXtreme Gradient Boosting (XGBoost) approach. Boosting is an ensemble machine learning approach that creates a strong learner from a given number of weak learners. XGBoost is an improved step from the recursive tree-based partitioning method of gradient boosting introduced by Friedman (2001). Gradient boosting builds a sequential series of shallow trees, where each tree corrects for the residuals in the predictions made by all the previous trees. XGBoost uses the sparsity-aware split-finding approach to more efficiently train on sparse data (Gumus and Kiran, 2017; Nobre and Neves, 2019; Sheridan et al., 2016). Variable importance is determined by evaluating the effect of shuffling image bands on the regularized gain. It has been used widely in both regression and classification modes after being developed by Chen and Guestrin (2016). The XGBoost has been widely recognized as one of the most highly performing machine learning algorithms for applications across fields. It is fast, accurate and based on smaller models compared to random forests and support vector machines that are widely applied in classification of remote sensing data. Parameter tuning for automatically determining the number of rounds, maximum tree depth, sigma, was done using the caret package while the XGBoost was implemented with the xgboost package (Chen et al., 2019) using the *multi:softmax* objective in R.

2.2.3. Classification accuracy assessment

We used the confusion matrix to assess the accuracy of the classification process relative to reference data. The overall accuracy (OA), user's accuracy (UA) and producer's accuracy were determined from the confusion matrix. OA is the percentage that indicates the probability that a pixel is classified correctly by the thematic map. PA for is the percentage of a category on the ground that is correctly classified by the on the map, and measures proportion of pixels omitted from a reference classes (omission error). UA expresses the proportion of a category on the ground that is included erroneously in another category (commission error) (Congalton, 1991; Foody, 2002).

2.2.4. Linking land cover changes to water balance in the catchment

The land cover types obtained from the classification were linked to the annual water balance parameters for the catchment that were obtained from the FAO Vapor data portal (https://wapor.apps.fao.org/catalog/1). This was done with the objective of determining the contribtuion of each land cover type to the water flux that are important for catchment boundaly layer processes (Table 2). The used water balance parameters were precipitation, transipiration, interception and evapotransipiration for the year 2009 and 2017 (Table 3). These products are derived from the application of the process-based SEBAL algorithms (Bastiaanssen et al., 1998). In the SEBAL model, water fluxes are computed from satellite images and weather data using the surface energy balance. SEBAL is based on the logic that the incoming net solar radiation drives all energy exchanges on the Earth's surface and therefore all water fluxes require/use energy (Ning et al., 2017). Precipitation used was the Climate Hazards Group Infrared Precipitation Fields (CHIRPS) rainfall at 0.05° (~5 km) resolution (Funk et al., 2015).

The FAO WaPOR datasets were at a lower resolution that the landsat data and therefore majority (modal) resampling was applied on the classified image to bring them to the same resolution of 250 m of the FAO Wapor data. The resampled classes were converted to points and used to extract the values of the water balance parameters for each land cover class for the two periods. In addition, to determine the relationships between the different land cover types and water flux, we calculated three water related vegetation indices from the Landsat bands that have been identified as direct indicators of leaf water content (Du et al., 2018). These were the Land Surface Water Index (LSWI, Eq. (1)), Modified Normalised Difference Water Index (MNDWI, Eq. (2))and the normalised difference vegetation index (NDVI, Eq. (3)). These vegetation indices were then correlated with water flux data.

$$LSWI = \frac{\rho NIR - \rho SWIR1}{\rho NIR + \rho SWIR1} \quad (1)$$

$$MNDWI = \frac{\rho Green - \rho SWIR1}{\rho Green + \rho SWIR1} \quad (2)$$

$$NDVI = \frac{\rho NIR - \rho Red}{\rho NIR + \rho Red} \quad (3)$$

The process of modelling the relationship between land cover types and water flux is summarized in the schematic diagram in Fig. 2.

Table 3
Water baance obtained from the FAO WaPOR dataset for 2009 and 2017.

Data	Precipitation	Transpiration	Interception	Evapotranspiration
Units	mm	mm	mm	mm
Data	CHIRPS data	FAO WaPOR	FAO WaPOR	FAO WaPOR
Resolution	25 km	250 m	250 m	250 m
Temporal scale	Yearly sum	Yearly sum	Yearly sum	Yearly sum
Period	2009 & 2017	2009 & 2017	2009 & 2017	2009 & 2017

3. Results

3.1. Image classification results

The XGBoost achieved an overall accuracy of 83.1% for 2009 and 86.6% for 2017 (Table 4). The highest producers' accuracies were for the class water while for the other classes the results varied depending on the year. The best-classified vegetation classes from the user's accuracy for 2009 were tea and coffee (90.5% and tea 92.3%). For 2017, they were cropland/built-up (92%) and grassland (90%). All land cover types had satisfactory classification accuracies with users' accuracies averages for the two periods exceeding 75% (Table 3). The most important bands in separation of classes for were the SWIR and NIR bands, which for 2009 and 2017 classifications accounted for over 70% of the regularized gain in classification (Fig. 3).

3.2. Land cover/use types and changes between 2009 and 2017

The thematic maps for the two time periods (2009 and 2017) show that grassland and natural forest were the most dominant land cover type in the Buzi headwaters sub-catchment (Fig. 4, Fig. 5). About a third of the sub-catchment had grasslands in both assessment periods. From the 2009 classification, plantations (tea, coffee and forest plantations) occupied 25.4% of the land cover/use types. In 2017, the plantation cover had reduced to 22.5% of the sub-catchment, driven by a 3.3% decrease in the cover class coffee from 5% of the sub-catchment to 1.7% of the catchment in 2017 while other plantation cover types remained relatively unchanged. Coffee is distributed across the catchment, while tea fields were mainly located in the eastern and northern parts of the study area with isolated occurrences in the southern and central parts (Fig. 4).

3.3. Land use based ET in Buzi sub-catchment

The resampled land cover classes for 2009 and 2017 are shown in Fig. 6. The data on precipitation showed that 2017 was a wetter year compared to 2009 but the general distribution of annual precipitation in the sub-catchment remaining the same. There is a general precipitation gradient from the north to the south of the sub-catchment. However, transpiration, interception and evapotranspiration do not follow the precipitation patterns. These are higher on the eastern side of the catchment, where tea and coffee land cover types are more dominant (see Fig. 7).

Using all the pixels in the catchment, the results showed that the greatest amounts of interception in the sub-catchment occur in the cover class tea and plantation forests, followed by natural forest. As expected, water had the least interception and transpiration but high evapotranspiration (Fig. 8). In terms of changes between the periods, coffee areas had an increase in interception between 2009 and 2017, although the transpiration remained the same. In terms of transpiration, all classes had reduced transpiration amounts in 2017 compared to 2009 except for coffee, which remained the same between the two periods (Fig. 8). Through transpiration and total evapotranspiration, the results indicate that the plantation cover types are influencing atmospheric processes more than natural forest and grassland in the sub-catchment (see Fig. 9).

We further determined the correlation between precipitation, interception, transpiration and evapotranspiration losses for all pixels in the catchment, which are shown in Table 5. Overall, correlations between transpiration, ET and interception and LSWI, MNDWI and NDVI were significant (p < 0.05). In general, these correlations were highest for 2009 compared to 2017. Transpiration was higher in 2009 compared to 2017, while total evapotranspiration was higher in 2017 compared to 2009 (Fig. 10). From these results, it is evident that vegetation parameters in the catchment as represented by vegetation indices influence water flux in the catchment in the two periods. The terrestrial moisture
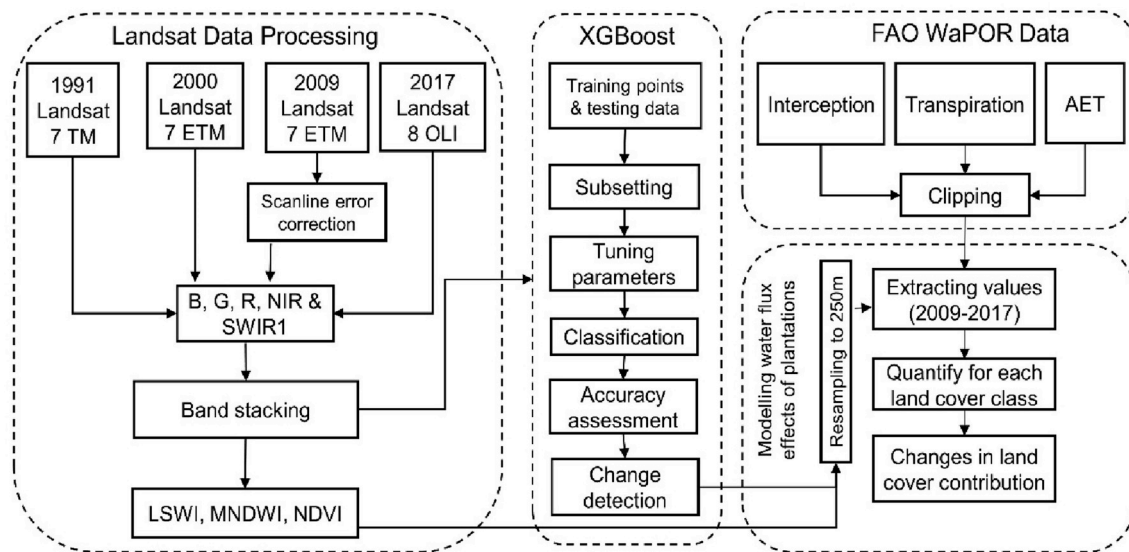
Fig. 2. Flow chart summarising the process for modelling the water balance effects of plantation land cover types in Buzi sub-catchment.

Table 4
Producers, users and overall classification accuracies for the 2009 and 2017 images.

Class	2009		2017	
	Producer	User	Producer	User
Tea	90.5	95.0	86.4	86.4
Coffee	92.3	82.8	78.6	78.6
Plantation forest	72.7	80.0	80.0	83.3
Natural forest	78.3	75.0	77.8	84.0
Grassland	78.9	78.9	96.4	90.0
Cropland/Built-up	81.8	81.8	92.0	92.0
Water	88.9	100	100.0	88.9
Overall	83.1		86.6	
N	142		149	

received. There was a 31% increase in precipitation between 2009 and 2017 and a 33% reduction in catchment transpiration in the same period. 4.6% of the precipitation was lost through interception in 2009 while only 3.8% was lost in 2017 (Fig. 10). The results show that there was a 3% reduction in plantation areas in the catchment, a 31% increase in precipitation, and a 400% increase in the water balance between 2009 and 2017. This means that precipitation alone does not explain the water balance in the catchment but the changes in land cover.

4. Discussion

In this study, we aimed at understanding how land cover change affect aspects of the water balance at sub-catchment level by linking remote sensing image classification with water flux in a heterogeneous tropical catchment. We have presented a catchment-level water balance assessment using remote sensing derived land cover dynamics for 2009 and 2017, which were linked to interception, transpiration and ET. Finally, the water balance for the two periods was calculated to represent long-term spatio-temporal dynamics of terrestrial variables.

4.1. Land cover change assessment

The image classification process determined the spatial and quantitative distribution of the selected land cover classes in the Buzi Headwaters sub catchment as shown by the thematic maps for 2009 and 2017. The accuracies achieved by implementation of the XGBoost algorithm for image classification are satisfactory and comparable to other classification accuracies in similar landscapes. For example, while Chemura and Mutanga (2017) obtained comparable classification using Landsat data, the XGBoost has added advantages that it is fast and produces smaller but more accurate models as it applies the sparsity-aware split-finding approach to more efficiently train the classifier (Sheridan et al., 2016). There is therefore a huge scope in application of the XGBoost in image classification for remote sensing applications as an addition or alternative to exiting methods as shown in this study.

A significant part of the Buzi Headwaters have been modified by human activities as human-induced cover types (cropland, plantation forest, coffee, tea and water) now dominate the landscape of the sub basin accounting for 44.6% in 2009 and 46% in 2017. The high agricultural development potential of the Buzi Headwaters sub catchment makes the area to be in high demand for agricultural land uses at the expense of natural cover types. In 2009 a quarter of the catchment
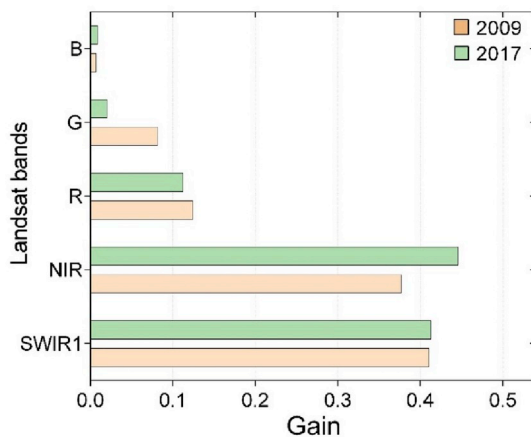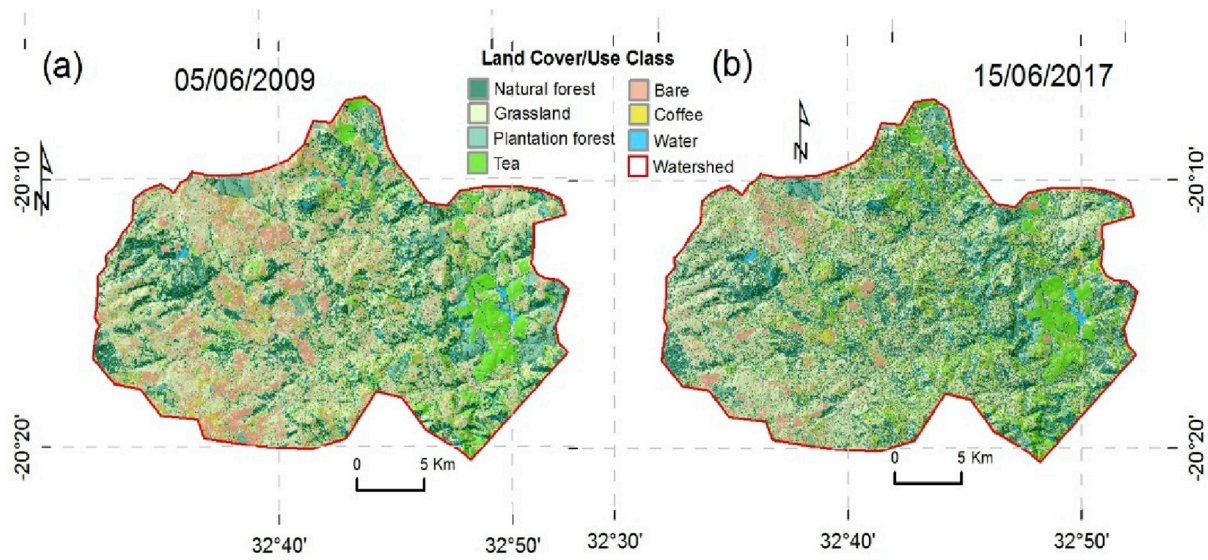

Fig. 3. Variable importance of the five bands used in image classification using XGBoost for 2009 and 2017.

limitation therefore becomes the most significant factor influencing water flux as shown by the positive correlations between vegetation indices and water flux.

The catchment level water balance is shown in Fig. 10. The results indicate that there was a more positive water balance in 2017 compared to 2009. As a ration of the precipitation, the water balance for 2017 was 37% of the precipitation while that of 2007 was only 9% of precipitation

Fig. 4. Spatial distribution of plantation land cover types in Buzi Headwaters obtained from the XGBoost classification of Landsat imagery. Fig. 4a shows the land cover classes for 2009 and 4 b for 2017.
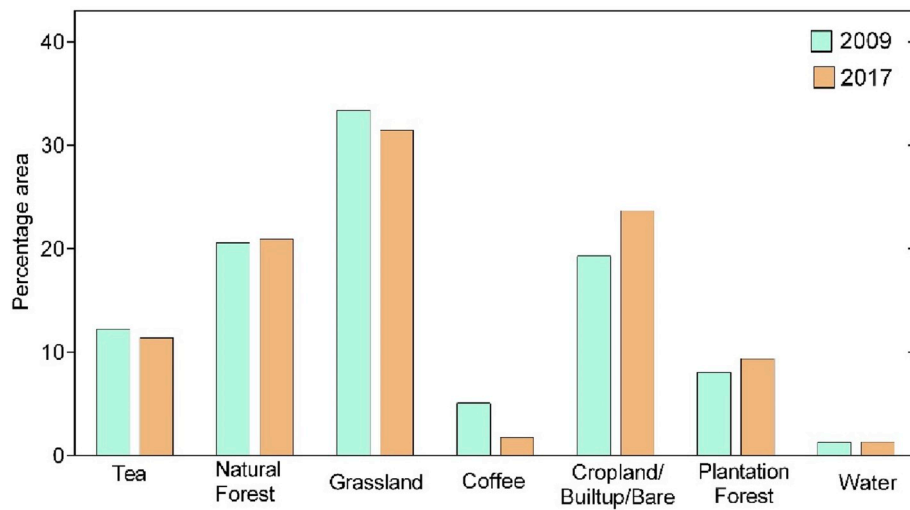

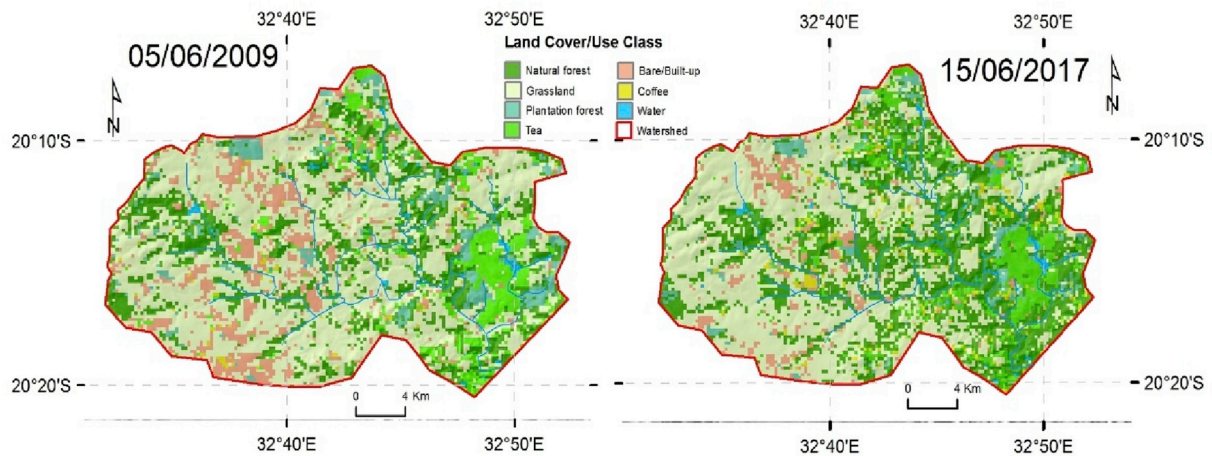**Fig. 5.** Percentage area in each land cover/use type in Buzi sub-catchment in 2009 and 2019.

Fig. 6. Land use classes resampled from 30 m to 250 m using majority filter for 2009 and 2017 images.
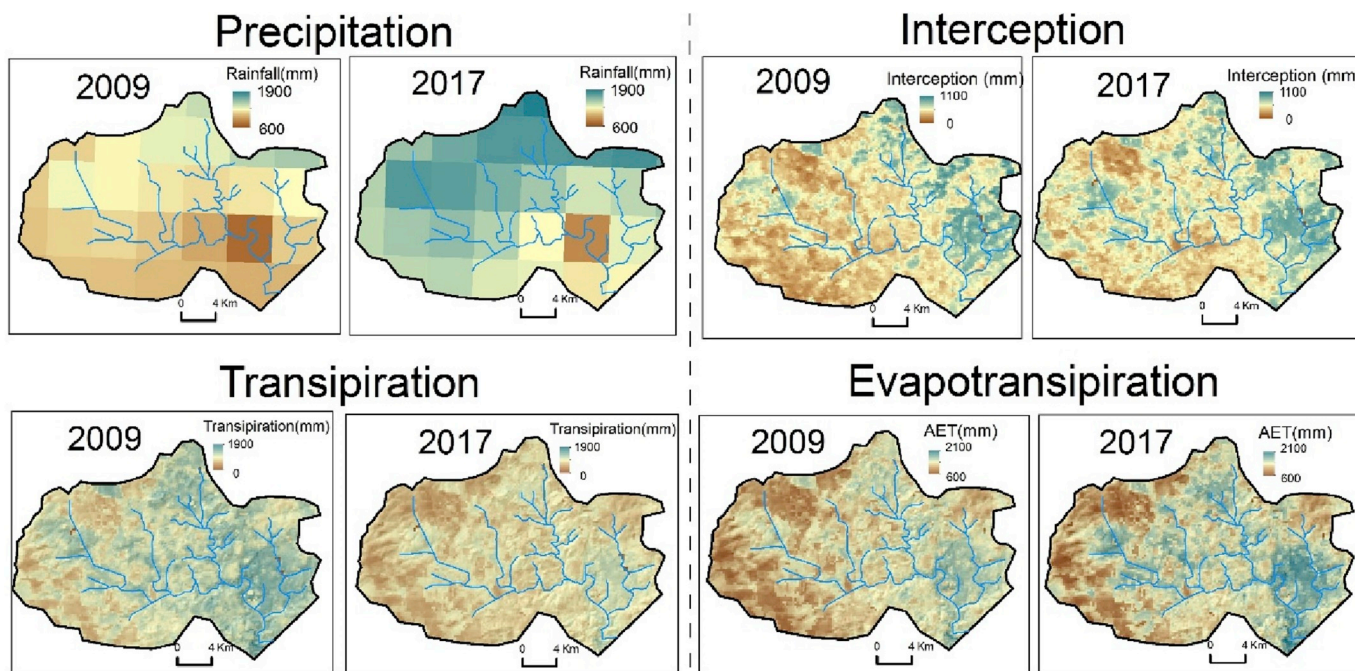
Fig. 7. Distribution of precipitation, interception, transpiration and evapotranspiration in 2009 and 2017 in Buzi sub-catchment.
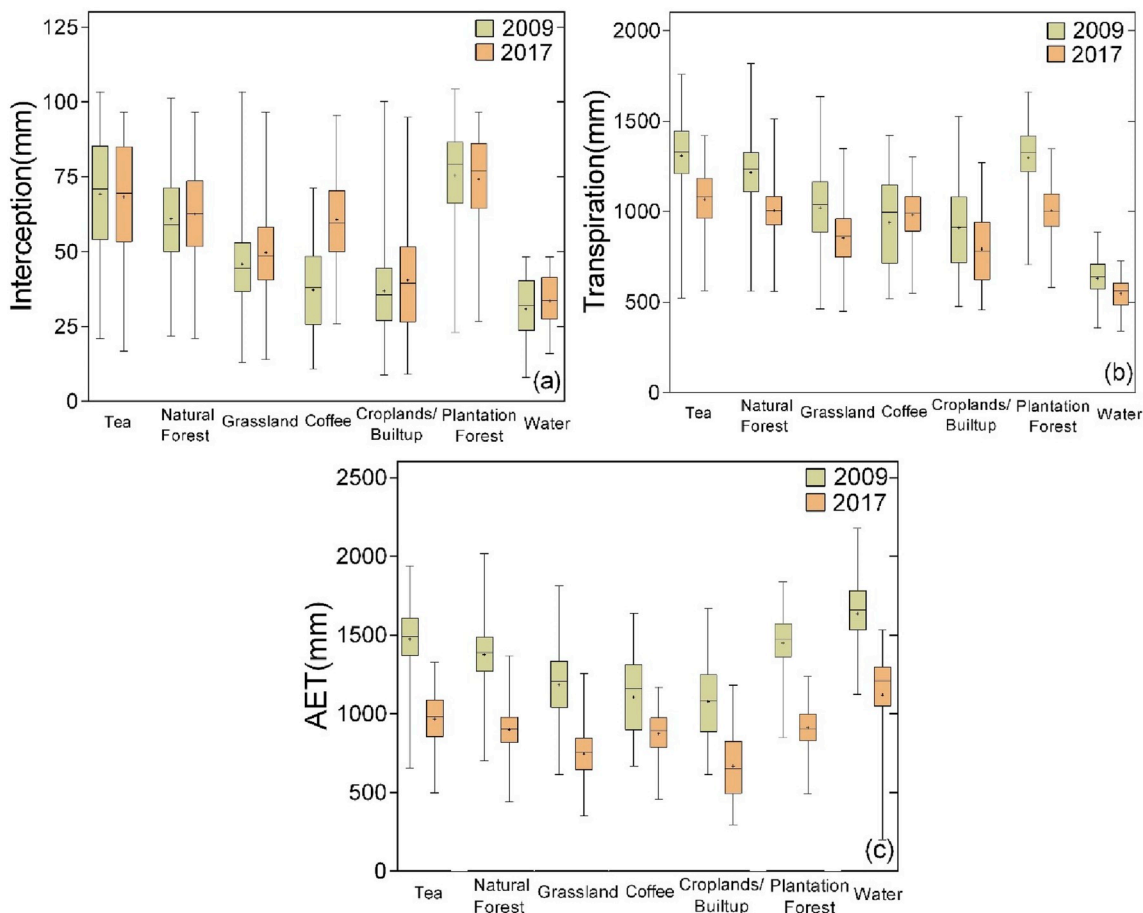

Fig. 8. Amount of interception, transpiration and evapotranspiration from each land cover/use type between 2009 and 2017.
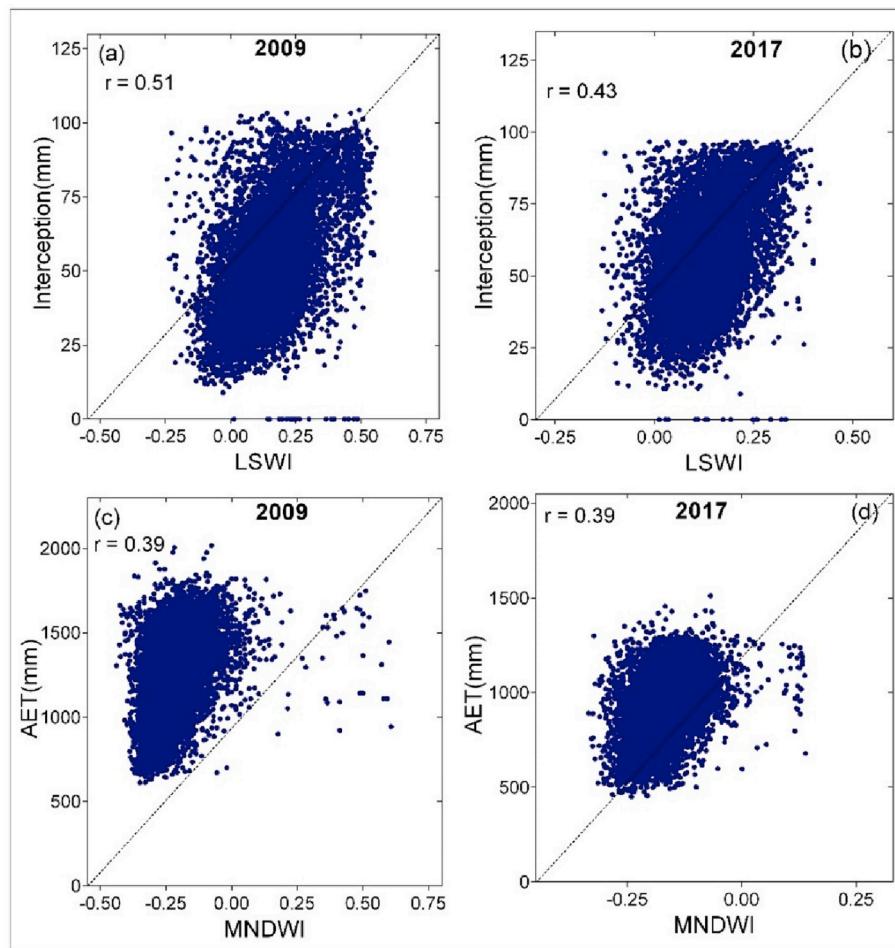
Fig. 9. Relationship between (a) LSWI and interception for 2009, (b) LSWI and interception for 2009, (c) MNDWI and ET in 2009 and (d) MNDWI and ET for 2017.

Table 5
Correlation between water flux (interception, transpiration and ET) with vegetation indices (LSWI, MNDWI and NDVI doe the whole catchment. The bold values are for 2009 while the plain are for 2017.

	LSWI	MNDWI	NDVI	Transpiration	Interception	ET	Precipitation
LSWI	1.00	**0.73**	**0.87**	**0.50**	**0.51**	**0.52**	−0.03
MNDWI	0.68	1.00	**0.36**	**0.35**	**0.34**	**0.39**	−0.02
NDVI	0.85	0.21	1.00	**0.48**	**0.49**	**0.48**	−0.03
Transpiration	0.45	0.35	0.37	1.00	**0.79**	**0.98**	−0.08
Interception	0.43	0.32	0.36	0.71	1.00	**0.75**	**0.19**
ET	0.45	0.39	0.35	0.97	0.64	1.00	**−0.11**
Precipitation	−0.12	−0.08	−0.11	−0.23	0.00	−0.24	1.00

(25.4%) was under plantation cover type which reduced to 22.5% in 2017 but in both years exceeding the recommended maximum threshold of 20% of catchment for plantation cover types (Parsons et al., 2007).

In addition to changes in area for land cover types, co-occurrences of the plantation cover type was also observed especially for tea and plantation forest. Tea and plantation forest cover types have been shown to be concentrated in certain localities compared to coffee, which was scattered in smallholder plots across the sub-catchment. The close association between tea and plantation forest means that these plantation types will take significant areas in particular parts of the catchment, increasing the impact of plantations on the catchment hydrology and other environmental conditions. Parsons et al. (2007) suggested that it is better that plantation cover types be sparsely distributed across a catchment in order to minimise their impacts. Creutzig et al. (2019) observed that activities that affect the biophysical environment tend to co-occur and this has synergistic, additive, or multiplicative effects on

biodiversity and loss of other ecosystem services.

The growth of plantation forests has also been linked to large-scale government initiated reforestation programs elsewhere (Belay and Mengistu, 2019). Conversion to cropland/built-up has reinforced the observations that agriculture and settlements remain the main driver for land cover change in tropical areas (Betru et al., 2019; Phalan et al., 2013; Xu et al., 2019). These findings show that land cover changes are two dimensional, the first being the quantitative changes in area under each class and the second being the spatial re-arrangement of land use/cover types, both of which are important in dealing with land cover change in policy dialogue.

4.2. Land cover change and water balance

Although the plant physiology and management govern negative and positive environmental interactions of plantation land cover types, there
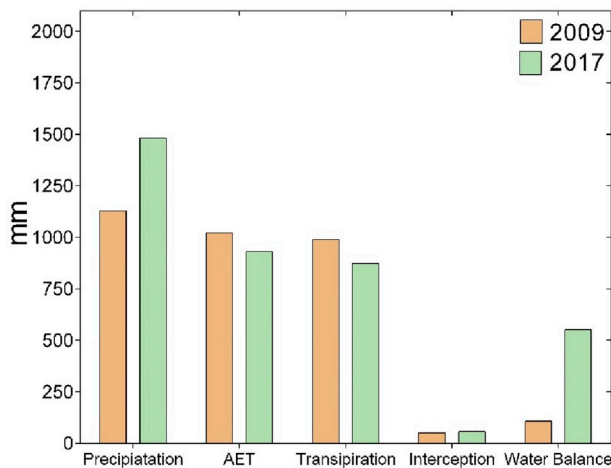
Fig. 10. Water balance calculation for Buzi catchment from water flux for 2009 and 2017.

are significant differences between annual crops and plantations. Tree crops alter the water cycle of catchments, as they are likely to increase interception and increase evapotranspiration, which in both cases reduces runoff (Cao et al., 2009; Farley et al., 2005; Gordon et al., 2005). For example, Parsons et al. (2007) indicated that land conversion from grassland to plantations reduce water yield by as much as 200 mm/year in areas receiving over 1000 mm/year of rainfall. Similar impacts of land use/cover change have been reported elsewhere (Aghsaei et al., 2020; Betru et al., 2019; Eichelmann et al., 2018; Gaertner et al., 2019; Han et al., 2018, 2019). The relationship of tree crops with soil moisture and ground water resources is more complex. This is because it depends on many factors such as the amount, intensity, duration and distribution of rainfall, topography, position of the plantation on the landscape, species and age of the plantations (Lima et al., 2012; Parsons et al., 2007; Prosser and Walker, 2009).

The relatively higher water flux from plantation cover types is explained by higher plant transpiration and canopy conductance of these species. A further supplementary irrigation in the dry period also entails continued water flux in irrigated plantation crops compared to natural systems such as grasslands and natural forests that are dependent of the natural environment. Since these plantations are perennial tree crops, they have higher total root biomass and effective rooting depth accumulated over years that creates a positive transpiration forcing (Parsons et al., 2007; Yang et al., 2016). The ability of this study to provide this understanding without the any near prospects of expensive flux towers provides information on which catchment management can be based, and for similar catchment to adopt such as an approach.

This study has demonstrated that ET sources shift in a catchment with land cover changes, with this also altering the water flux in the catchment. From a catchment management perspective, it shown which areas need focus in term of reducing ET from the catchment in order to maximize water yield and discharge. Thus, depending on the type of changes in land cover at catchment scale, water flux parameters respond accordingly and it is possible to achieve both positive and negative effects on water balance. As such, the suggestion by Odongo et al. (2019) that the effects of land use changes on water balance of a catchment are insignificant in the short-term and only discernible in the long-term concurs with the findings of this study. In some cases, land cover change can have a spatial re-arrangement of land cover types which will cancel out the impacts at catchment scale as losses will be compensated by gains elsewhere in the catchment (Kumar et al., 2017).

It is also important to note that the effects of the changes in land cover may be beyond quantitative water flux but may also include water quality changes and resultant impacts on ecosystems and economic

activities (Jarvie et al., 2002). Similar impacts of changes in plantation cover types on catchment dynamic processes and condition have been reported elsewhere (Gebrehiwot et al., 2014; Le Maitre et al., 2014; Meshesha et al., 2014; Miettinen et al., 2016). The decrease of 28% in AET between 2009 and 2017 points to the significance of plantations in influencing water dynamics as transpiration was shown as the most important water flux activities accounting for between 58% (2017) and 88% (2009) of annual precipitation. Changes in land use/cover explain the changes in water balance that was observed in many ways. For example, Nóbrega et al. (2017) opined that changes in land use can significantly degrade soil hydraulic properties and thus affect the water losses. Some plantation forests such as eucalyptus have been reported to draw as much as 120 mm year^{-1} from groundwater, which is considerable (Swaffer et al., 2020).

4.3. Implications on catchment scale water resources management

The issue of plantations and water resources requires an understanding of several areas of hydrology because forest vegetation cover influences several aspects of water balance in landscapes. This is even more urgent in transboundary basins where activities in one sub-basin have spill over effects in other basins and other countries. According Lagerblad (2010) irrigation is the largest water user in the basin, taking up to 4% of the flows. The expected urban and agricultural development in the Upper Buzi catchment due to population growth and the land reform program respectively are expected to lead to increased demand on water resources in the Buzi basin in eastern Zimbabwe, both for urban water supply and irrigated agriculture (Mupindu et al., 2004). Therefore in addition to current focus on the effects of urbanisation and settlements on catchment processes (Palamuleni et al., 2011), some attention should be placed on the specific dynamics of land cover change as they also influence water flux. It is imperative from this study that a decrease in plantations area increases the water balance, and notwithstanding climatic influences, points to importance in regulating the area under plantations in catchments especially with decreasing precipitation and increased evaporative losses from warming under global environmental change. This is especially so because during dry years, the influence of land use change exceeds that of climate in determining dynamics at catchment scale (Odongo et al., 2019).

5. Conclusions

In this study, we connected land cover changes from satellite remote sensing data to water flux variables data at catchment level to understand the contribution of land cover change to water flux for a tropical catchment. Our approach presents a remote sensing based approach for evaluating and tracking the effect of land use/cover change on water balance that is related to many ecosystem processes. We observed that there were changes in land use/cover in Buzi sub-catchment from 2009 to 2017 with major changes related to human dominated activities such as settlements and croplands with decreases in grasslands. From the results of this study, we conclude that increase in areas under agricultural plantations could threaten water yield as these land cover types increase ET with decreases in their areas being good for positive catchment water balance. We also found that spatial distribution and re-arrangement of plantations within a catchment is an important factor in water balance, as they are some plantations types co-occur and thus are concentrated in specific parts of the catchment. It was noted that plantation cover types are significant in influencing water flux in Buzi sub-catchments that they are significant and water balance changing with land use change. From our findings, we recommend that regular monitoring of development of plantations is important at catchment level given their contribution to water dynamics vis-vis decreasing water availability die to climate change and competing uses. The insights from this study are imperative for catchment managers for related or similar catchments with plantations cover types in terms of understanding, and

projecting impacts from land cover change on water resources for integrated catchment management.

Ethical statement

All ethical practices have been followed in relation to the development, data analysis, writing, and publication of this research article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Abel Chemura: Conceptualization, Formal analysis, Methodology, Writing - original draft. **Donald Rwasoka:** Conceptualization, Formal analysis, Methodology, Writing - review & editing. **Onisimo Mutanga:** Project administration, Supervision, Writing - review & editing. **Timothy Dube:** Formal analysis, Methodology, Writing - original draft. **Terence Mushore:** Formal analysis, Methodology, Writing - original draft, Writing - review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2020.100292.

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