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Mapping Ecological Production and Benefits from Water Consumed in Agricultural and Natural Landscapes: A Case Study of the Pangani Basin

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Abstract: Scarcity of information on the water productivity of different water, land, and other ecosystems in Africa, hampers the optimal allocation of the limited water resources. This study presents an innovative method to quantify the spatial variability of biomass production, crop yield, and economic water productivity, in a data scarce landscape of the Pangani Basin. For the first time, gross return from carbon credits and other ecosystem services are considered, in the concept of Economic Water Productivity. The analysis relied on the MODIS satellite data of 250 m and eight-day resolutions, and the SEBAL model, utilizing Monteith's framework for ecological production. In agriculture, irrigated sugarcane and rice achieved the highest water productivities in both biophysical and economic values. Rainfed and supplementary irrigated banana and maize productivities were significantly lower than the potential values, reflecting a wide spatial variability. In natural landscapes, forest and wetland showed the highest biomass production. However, the transition to economic productivity was low but showed the potential to increase significantly when non-market goods and services were considered. Spatially explicit information, from both biophysical and economic water productivity, provides a holistic outlook of the socio-environmental and the economic water values of a land-use activity, and can identify areas for improvement, and trade-offs in river basins.

Keywords: biomass production; carbon storage; economic water productivity; ecosystem services; SEBAL

1. Introduction

The competition over water resources is escalating in many river basins, worldwide. Population growth and increasing food demands to meet not only local but also global needs imposes high pressures on the world's fresh water resources. More water is also required to provide for the increasing energy demands from hydropower and biofuels [1]. Competition over water is not limited to the agricultural, domestic, and industrial sectors but also includes the natural environment. Ecosystem services provide essential functions that can be grouped in provisioning, regulating, as well as, habitat and cultural services [2,3]. While environmental water uses are fundamental for sustainable economic and social development in river basins, it is becoming clear that the natural environment consumes large amounts of the water resources, and that measures are required to safeguard natural capital [4–6].

The main water flux in a river basin is evapotranspiration, with a large part being consumed by the natural landscape. For example, in the Awash basin, Ethiopia, 49% of all evapotranspiration occurs in mosaic forested shrubland/grassland, and close to the open shrubland [7]. An analysis on the water consumption of different land-use classes for the Nile basin, showed that savannah is the largest water consumer at 38%, followed by pastures (9%), wetlands (7%), and rivers and lakes (7%), of the total evapotranspiration [8]. Of the total evaporative use of the Nile, thus, 61% is explained by environmental systems. Hence, the natural environment consumes large portions of rainfall (i.e., green water), and water from inundations and shallow groundwater tables (i.e., blue water). It is therefore legitimate, if not imperative, to include the economic value of natural ecosystems in the economic water productivity of river basins. So far, most authors have only considered agricultural goods when employing the concept of Economic Water Productivity [9–12]. Valuing the water consumption in a river basin should go beyond the marketable crops and encapsulate financial rewards for the sequestration of atmospheric carbon, heat, and other forms of ecosystem services. Payment for Ecosystem Services (PES) is an emerging topic that is gradually implemented by policy makers, in several basins, both in the developed and the developing countries. Some PES programs involve contracts between the consumers of ecosystem services and the suppliers of these services. However, the majority of the PES programs are funded by governments and involve intermediaries, such as non-government organizations [13].

Natural environments, such as forests and wetlands provide a wealth of ecosystem goods and services, in terms of delayed peak runoff, due to the retention of excess rainfall, sufficient catchment water yield that ensures base flow in the dry season, sustaining rainfall by means of atmospheric moisture recycling, reduced erosion, and improved water quality, from which the downstream societies benefit. Natural ecosystem goods and services also provide a buffer to the local communities, during periods of droughts, in semi-arid African landscapes [14]. Degradation of such environments reduces such benefits, significantly. Similarly, increased withdrawals in upper catchments directly affect the downstream ecosystems, such as wetlands, riparian vegetation, and delta and estuarine ecosystems. Due to the undesirable upstream developments, most perennial tributaries in our study area, i.e., the Pangani River Basin in Tanzania, have actually become seasonal in the last few decades [15].

Costanza et al. [16] estimated the global value of ecosystem services, in 2011, to be US$ 125 trillion a year, with a loss of up-to US$ 20 trillion per year, from 1997, due to land-use change. The study highlighted the magnitude of the ecosystem services and the urgent need for policies that promote environmental conservation. In the United States, farmers are paid an amount of US$ 1.8 billion per year to conserve soil and water on a 1.4 million hectare of "environment-friendly" land, i.e., 1285 US$ ha^{-1} $year^{-1}$ [17]. Similarly, the Chinese government has a program for not clearing forests, which compensates an amount of US$ 50 billion, annually, to the local farming communities [18].

It is clear that optimal water use is indispensable to the river basins that are disappearing due to the prevailing competition over water resources [19]. Ecological and hydrological integrity is central to sustainable water resource use. Crop water productivity expresses the returns per unit of water consumed in river basins, and this can either be expressed biophysically, economically, or socially [20–26]. Therefore, water productivity (kg m^{-3} and \$ m^{-3}) can be a key indicator to assess the effective use of water, although never as a sole purpose [27]. Increasing the water productivity of crops is needed to achieve the broad objectives of increasing food production and, thus, the income and livelihoods of local communities in the river basin. Water productivity gains in agriculture would secure water resources for other landscape uses and the ecosystem services, as more crop is produced with less drops of water [28,29]. Farm practices to increase the physical water productivity are well documented in the literature. They include supplementary irrigation, soil water conservation, deficit irrigation, and the right use of fertilizers and pesticides, amongst other interventions.

Environmental biomass production that has high environmental and social values, often has little or no market price [3,30–33]. The situation is poised to change due to the emerging market of carbon credits. The Kyoto Protocol allows industrial emissions of carbon into the atmosphere to be offset by sequestration, in forests and other forms of permanent green landscapes [34]. Carbon trading appeared as a potential business in the early 21st century, which more recently has been hampered by the economic crisis, since 2008, and fewer industrial activities, resulting in a dramatic drop in carbon prices. Many economists, however, maintain that putting a price on carbon and allowing for carbon trading is a crucial element of the global climate policy [35,36].

There is, however, a systematic lack of data on the water productivity of natural vegetation. Moreover, natural vegetation is highly heterogeneous, with a large spatial coverage. A Measurement-Reporting-Planning-Monitoring (MRPM) system is required to quantify such water productivities. This paper demonstrates that estimates based on remote sensing can achieve this. Much progress has been made recently using remotely-sensed data, in spatial water productivity analysis [37]. In few cases, these have been complemented by modelling approaches to estimate water productivity. Van Dam et al. [38] combined a soil-physical simulation model with SEBAL, and Mainuddin and Kirby [39] used FAO's CROPWAT for their model [40]. At a global scale, water productivity models have been developed, WATPRO (WATer PROductivity) is a model that has been developed for wheat water productivity [41] and GEPIC (GIS-based Environmental Policy Integrated Climate model) is an agro-ecosystem model to assess the global water productivity [42]. Finally, remote sensing data on water productivity has been complemented by using crop-yield statistics [43]. More recently, Yan and Wu [44] and Zhang et al. [45] presented the spatial-temporal crop water productivity for winter wheat, in China, using remotely-sensed estimates of evapotranspiration (ET). Only one study has reported on the economic water productivity, using a combination of remote sensing and economic analysis, for two main market crops, bananas, and sugarcane [12]. So far, few studies have included a valuation, and none have included natural land-use types or non-market-based crops. The objective of this paper is, therefore, to present a basin-wide analysis of the bio-physical (biomass and yield) and economic water productivity of both agricultural and natural land uses in a river basin.

2. Study Area

The Upper Pangani River Basin has an area of 13,400 km^2, which is about 30% of the entire Pangani River Basin, and it is shared by Kenya and Tanzania (Figure 1). The climate is highly varied and mainly influenced by topography. The higher elevation ranges, centered around Mt. Kilimanjaro at 5880 m and Mt. Meru at 4565 m, predominantly have a tropical humid climate and receive nearly 2500 mm year^{-1} of rainfall [46,47]. The area is covered mainly by dense tropical rainforest and afro-alpine natural vegetation. The middle to lower catchments have a sub-humid to semi-arid climate. The rainfall is highly variable and ranges between 1000–2000 mm year^{-1}, in the middle to upper catchments, and 300–800 mm year^{-1}, in the lower catchments of the Upper Pangani River Basin. The middle catchment is dominated by agriculture, while a large expansive area in the lower catchment is dominated by natural shrublands and bushlands. A large part of this area is conserved for wildlife, mainly in the Kenyan part of the basin, in the Tsavo West and the Amboseli National parks.

Rainfall has a bimodal pattern, with a long rain season, during the months of March to May (Masika season) and the short rain season (Vuli season), in the months of November and December. The agricultural seasons follow the rainfall. Rainfed agriculture, in particular the cultivation of maize during the Masika season, is dominant in the middle catchments of the Upper Pangani River Basin. However, rainfed agriculture is unreliable and produces low yields, mainly due to low and unreliable rainfall pattern. Many farming households, therefore, depend on irrigation to supplement rainfall for food production. Irrigation development by smallholder farmers, during the last two centuries, has led to a complex and intricate network of small canals that rely on gravity water flow from springs and streams, in the upper catchments. Presently, about two thousand such irrigation canals exist in the Upper Pangani River Basin, some dating back to the 18th century [48]. Large scale irrigation is located in the lower catchments of the Upper Pangani River Basin, including the Tanzania Plantation Company (TPC) which produces sugarcane, and the Lower Moshi Irrigation scheme, producing rice and maize.

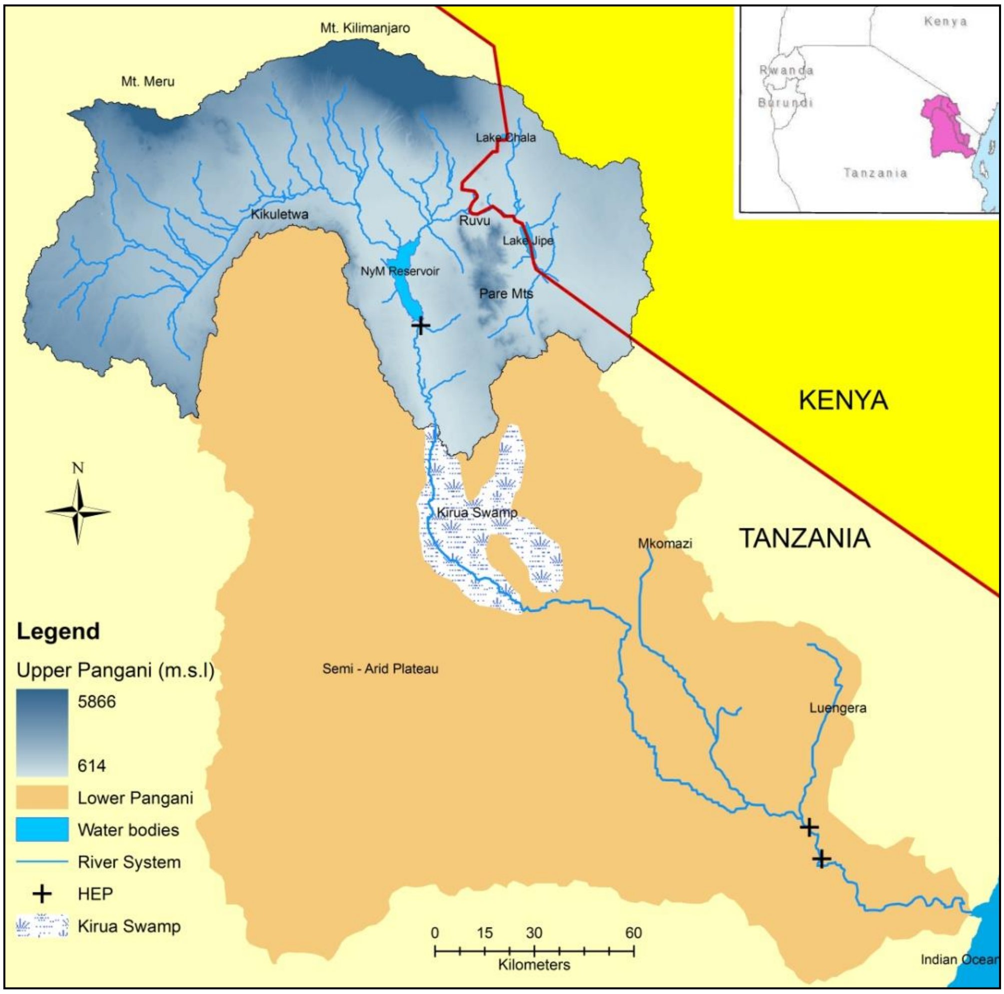


Figure 1. The Upper and Lower Pangani River Basin (HEP = Hydro-Electric Power plant).

The increasing water use for agriculture has resulted in a decrease in the availability of river water and water from the groundwater table is no longer available [49]. Most wetlands and perennial rivers are drying up during the dry seasons, a clear sign that the river basin is closing [19]. This has also increased tensions and water related conflicts between water users [48,50]. It is believed that information on bio-physical and economic water productivity could assist in informing future water allocation or re-allocation strategies that seek to achieve a balance between the optimal social, environmental, and economical uses of the limited water resources, in the Pangani river basin.

3. Materials and Methods

3.1. Remotely-Sensed Data for Assessing Ecological Productivity

3.1.1. Actual Evaporation

Values for actual evapotranspiration (ET) were taken from a study by Kiptala et al. [47] who used the SEBAL algorithm [51]. The SEBAL methodology, including the details of the images and the processing steps, is explained in detail in Kiptala et al. [47]. ET data used for the water productivity analysis were available at 250 m and eight-day resolutions for the period 2008–2010, for the Upper Pangani River Basin.

3.1.2. Biomass Production

Biomass production (B) could be estimated as the dry matter production accumulated during the growing season or a calendar period, under consideration. B could be related to the absorbed photosynthetically active radiation (R_{AP}) expressed in MJ m^{-2}, and the Light-Use Efficiency (B) of plants (g MJ^{-1}), using the relation developed by Monteith [52], Equation (1).

$$B = R_{AP} \cdot \varepsilon \cdot 10 \left(\mathrm{Kg\ ha^{-1}}\right) \tag{1}$$

Plant leaves transmit and reflect solar radiation. Plant chlorophyll responds only to radiation in the 0.4 to 0.7 μm spectral regime, therefore, only a fraction of the total broadband shortwave radiation (K) is available for photosynthesis (R_P). For the average 24 h conditions, the $R_P/K_{24}^{\downarrow}$ fraction is equal to 0.48 [53]. Light interception occurs only in the case of green leaves, filled with chlorophyll. R_{AP} could, therefore, be computed using Equation (2).

$$R_{AP} = f \cdot \left(0.48 K_{24}^{\downarrow}\right)\ (\mathrm{MJ\ m^{-2}}) \tag{2}$$

The fraction f could be estimated directly from the normalized difference vegetation index, (NDVI) [54,55]:

$$f = -0.161 + 1.257NDVI \tag{3}$$

ε for a particular crop is a constant if the environmental conditions are non-limiting [52]. However, water availability and temperature can impact ε, significantly. SEBAL uses the equations first published by Field et al. [56] to correct for the effect of heat variations (T_1, T_2) and soil moisture (W) on ε:

$$\varepsilon = \varepsilon' T_1 T_2 W\ (\mathrm{g\ MJ^{-1}}) \tag{4}$$

where ε' is the maximum light-use efficiency under the optimal environmental conditions (g MJ^{-1}). T_1 and T_2 are heat variations, based on the average temperature (T_{av} in $^{\circ}$C) and the optimum temperature, during a time step, with a maximum leaf area index (T_{opt} in °C). W is a water scalar that is defined by the ratio of actual over potential evapotranspiration to describe the land wetness conditions. Bastiaanssen and Ali [57] adopted the evaporative fraction (Λ), to define the water scalar of land mass.

For crops, the maximum light-use efficiency $\acute{\varepsilon}$ varies with different plant types (C3, C4, and CAM plants) if there is no water shortage [52,58]. The $\acute{\varepsilon}$ values have been provided for various crops, including banana, maize, rice, and sugarcane, from literature sources by Bastiaanssen and Ali [57]. Additional ε' values from the more recent literature that included natural landscapes, have been presented in (see Section 3.3). For natural landscapes, tropical forests have a maximum light-use efficiency range of 1.5–2.6 g MJ^{-1} [59,60]. Shrublands and woodlands, and wetlands (high vegetation grass) have lower values and range between 0.8–1.6 g MJ^{-1} [61,62].

Radiation, water, and carbon fluxes were measured on typical savannah sites, in Niger, as part of the Hydrologic Atmospheric Pilot Experiment in the Sahel (HAPEX-SAHEL) [63]. The non-linear impact of soil moisture and ε appeared to be an essential process. A good synopsis has been provided by Prince [64], for applications with remote sensing.

3.1.3. Crop Yield

The conversion from total biomass development to the actual yield, such as cereal grains, varies with the harvest index (H_i) and the water content of the crop, during the harvest [65].

$$Y_{act} = \frac{H_i}{1 - m_{oi}} \cdot \sum_{t=e}^{t=h} B_{day} = H_i^{eff} . \sum_{t=e}^{t=h} B_{day} \ (\text{Kg ha}^{-1}) \tag{5}$$

where $H^i{}_{eff}$ is the effective harvest index, corrected using the optimal moisture content of the product, after harvest (m_{oi}). Different crops have a specific harvest index range. H_i values for various crops were used in the calibration process (see Section 3.3). The harvest index is also influenced by the crop variety [44,66]. Furthermore, management and agronomic practices, such as the use of fertilizers, can increase crop yield, as well as the harvest index [23].

3.1.4. Carbon Sequestration

The accumulation of biomass is a result of Net Primary Production (NPP). The carbon assimilates are distributed across the various plant organs, including roots, shoots, tubers, stems, branches, leaves, flowers, and grains. This partitioning is plant-specific and the factors are empirically known. The ratio of the above and below ground biomass production, for natural landscapes, has been measured for several biomes. The total biomass will reach a maximum value, after the equilibrium, between photosynthesis and natural decay, due to the seasons and the age of the vegetation. Tropical rainforests with 40 m tall trees and above the age of 150 years, can reach up to 500 to 1000 ton above ground biomass, per hectare [67]. Global maps of above ground biomass for the Pangani basin suggest values in the order of 15 to 40 ton ha^{-1}, depending on the type of ecosystem. A significant amount of biomass is also present in the soil.

Ponce-Hernandez et al. [68] estimated the below ground biomass to be 0.25–0.30 of the above ground biomass, using plant growth simulation models. Litter and woody debris will be formed, due to senescence and the age of vegetation. The decay of biomass will return carbon as carbon dioxide, back into the atmosphere, and partially into the soil organic carbon. The typical carbon pools considered are harvested wood, litter, dead wood, and soil organic matter. This applies to all types of vegetation.

The sequestration of carbon relates to various time scales—while litter and soil organic matter are generally conceived as short-term carbon storage, harvested wood will have much longer time scales. Carbon sequestration can be approximated as:

$$C = \xi \chi \sum B_{day} \tag{6}$$

where ξ [-] relates carbon pools to accumulate above ground biomass production and χ [-] relates total biomass production to above ground biomass production. The carbon pool does not take into account the short-term carbon storage, such as plant leaves and litter that decay and may not change much over the years. The $\xi\ \chi$ factor is essentially the effective harvest index from biomass production for carbon sequestration, which is normally taken as 0.5, (see Section 3.3).

3.1.5. Economic Water Productivity

The biophysical water productivity, $WP_{B/ET}$ (kg m^{-3}) is derived from plant biomass production and the actual evapotranspiration (ET). The approach is widely adopted and has been used in previous studies [41,44].

$$WP_{B/ET} = \sum_{t=e}^{t=h} B_{day} / \sum_{t=e}^{t=h} ET \ (\text{kg m}^{-3}) \tag{7}$$

The crop (yield) water productivity, $WP_{Y/ET}$ (kg m^{-3}) was derived from $WP_{B/ET}$, using the effective harvest index factor, H_i^{eff}, Equation (8).

$$WP_{Y/ET} = WP_{B/ET} \times H_i^{eff} \tag{8}$$

The economic water productivity, $WP_{Ec/ET}$ (US$ m^{-3}) was derived by multiplying the $WP_{Y/ET}$ with the net price of the product (P_n), Equation (9).

$$WP_{Ec/ET} = WP_{Y/ET} \times P_n(i) \tag{9}$$

where $P_n(i) = (P_g(i) - P_c(i))$ (\$ kg^{-1}) was the net farm gate price for crop i, determined by subtracting the total production costs, $P_c(i)$ (\$ kg^{-1}) from the gross farm gate price, P_g *(i)* (\$ kg^{-1}) [12]. The total production costs included both variable and fixed costs, incurred during the crop development. This approach of subtracting the cost of production from the gross production, relies on the fact that the value to a producer is exhausted by the summation of the values of the inputs required to produce it [69].

The production cost was based on estimates provided by the agricultural extension office (Moshi, Pangani, Tanzania) for crops grown in the Lower Moshi irrigation scheme; rice, maize, and vegetables. The farm gate prices for banana were based on field data on the smallholder farms, in the upper catchments of the river basin. The production costs included labor, fertilizers and pesticides costs, seedling, and harvesting and transportation expenses. Family labor and land was also included as variable costs, using the prevailing labor rates and land rent costs. For commercial sugarcane, the economic water productivity was determined from the net benefits of sugar (sucrose), per unit of water consumption. The P_g was based on the wholesale price (2010) for white sugar of Tsh. 941 (US$ 0.67) per kg. The farm gate sugar price was slightly higher than the world average price (2010) for processed sugar (white) of US$ 0.60 per kg [70]. Data on the production costs for TPC sugarcane plantation was not available. The cost of production was, therefore, estimated from the world averages. The production costs ranged between 45–70% and averaged at 58% of the world sugar price for the ten-year period of 2000–2009 [70]. The average value was used, disregarding the returns from bagasse (by-product), which constituted 90% of the total biomass. Table 1 provides the net gates prices for the main crops in the Upper Pangani River Basin.

Table 1. Net farm gate prices for crops under irrigation from 2008–2010 in the Upper Pangani River Basin.

Crop	Gross Gate Price Tsh kg^{-1}	Production Factor	Net Gate Price Tsh kg^{-1}	Net Gate Price US$ [1] kg^{-1}
Rice (rough rice)	500	0.66	170	0.12
Maize	550	0.51	270	0.19
Vegetables (onions)	400	0.38	250	0.18
Bananas	200	0.15	170	0.12
Sugar (white)	941	0.58	395	0.28

[1] Exchange rate of 1US$ to Tsh 1409 (2010).

For natural land cover, the economic productivity may be inferred from the social and economic benefits of carbon sequestration. Here, we assumed that the value of ecosystem services was equal to the value of the net amount of additional carbon sequestered. This was obviously a conservative assumption since there are other ecosystem services, such as erosion control, nutrient recycling, waste treatment, provision of raw materials, habitat (genetic diversity), and cultural services that are provided by natural land cover [3,30]. According to the Interagency Working Group on Social Cost of Carbon [71], the benefits of carbon sequestration varies from \$5 to \$65 per ton of carbon, estimated from the social cost of carbon emission. Coffee farmers in Mexico received an amount of US$ 13 per ton of carbon sequestered [72], while the shadow price of carbon, used by the major global oil and gas companies, such as the Shell Oil Company, ranges between \$28 and \$80 per tC [73]. These values are consistent with the compensation market prices of between US\$ 5 to 30, per ton CO_2 equivalent—on the emerging carbon offset markets [33,74]. A conservative fixed price estimate of US\$ 15 per ton of CO_2 was used in this study.

3.2. Boundary Conditions for Water Productivity Assessment

For the spatial analysis of the economic water productivity, a detailed land use and land cover map was required. This study utilized the land use and land cover (LULC) classification for the Upper Pangani River Basin by Kiptala et al. [75]. The LULC types were derived using phenological variability of vegetation (from MODIS) for the same period of analysis, 2008 to 2010. Sixteen classes (including water bodies) were identified, of which smallholder maize (including supplementary irrigated) and shrublands were the two dominant classes, covering half of the area. The LULC classification achieved an overall accuracy of 85%, with individual classes achieving more than 70% accuracy.

Additional information on irrigation water uses was required to assess the economic water productivity of blue water use. The actual evapotranspiration (ET) comprises of evapotranspiration from precipitation (P) and irrigation water use (Q_b). Q_b was supplied either through river water abstraction and/or groundwater. Q_b was estimated using the STREAM model (Spatial Tools for River basin Environmental Analysis and Management), a hydrological model developed specifically for the Upper Pangani Basin [76]. The STREAM model utilized the remotely-sensed ET, soil moisture, and P to simulate Q_b at 250 m and an eight-day resolution. During low flows, Q_b consumed nearly 50% of the river flow in the river basin. Q_b estimates were comparable to the field estimates of net irrigation, with less than a 20% difference [76].

3.3. Calibration and Validation

The biomass parameters NDVI, evaporative fraction (Λ), and the incoming solar radiation ($K_{24}^{\downarrow}$) were derived from the SEBAL model. The other parameters T_1 and T_2 (Equation (4)), were computed using field-based T_{av} and T_{opt}, derived from the maximum LAI or NDVI in the plant growing season. Only two parameters were, therefore, left for calibration–the maximum light-use efficiency ($\acute{\varepsilon}$ and the effective harvest index ($H^i{}_{eff}$).

The $\acute{\varepsilon}$ values were adjusted within the experimentally-verified parameter ranges, from the literature. The actual yield data were used to derive the field-based harvest index that was compared with the permissible $H^i{}_{eff}$ range for the moisture content of the product, during harvest (moi). The actual yield data were taken from the field measurements and the yield records from the main stakeholders, in the Pangani River Basin.

Table 2 shows the experimentally-verified ranges of $\acute{\varepsilon}$ and $H^i{}_{eff}$ for the four main crops grown in the Upper Pangani River Basin.

Table 2. Crop biomass parameters ranges for calibration.

Crop	Light-Use Efficiency, $\acute{\varepsilon}$ (g MJ^{-1})	Effective Harvest Index $H^i{}_{eff}$ (kg kg^{-1})	Moisture Content, M_{oi} (kg kg^{-1})	Sources
Rice	1.8–2.9	0.35–0.50	0.10–0.15	[77–79]
Sugarcane	3.0–4.0	1.82–2.72	0.63–0.75	[57,80,81]
Banana (Bunch)	3.0–3.5	0.80–1.20	0.80–0.85	[82–84]
Maize	2.7–3.7	0.30–0.47	0.10–0.15	[81,85,86]

Table 3 shows the specific parameter values for the light-use efficiency and the harvest indices from the calibration process for agricultural landscapes. For more information on the calibration and validation process of the specific crops, see Supplementary data, S1.

Table 3. Calibrated crop biomass parameters from calibration against secondary data and their ranges reported in the literature.

Crop	Light-Use Efficiency, $\acute{\varepsilon}$ (g MJ^{-1})	Harvest Index, H_i (kg kg^{-1})	Effective Harvest Index, $H^i{}_{eff}$ (kg kg^{-1})	Moisture Content, M_{oi} (kg kg^{-1})
Rice	2.9	0.39	0.45	0.14
Sugarcane	3.5	0.69	2.20	0.68
Maize	2.7	0.30	0.35	0.14
Banana (Bunch)	3.0	0.15	0.83	0.82

Since there were no actual yield data for the natural land cover, the average values of $\acute{\varepsilon}$, as reported in the literature, were used.

It was expected that the actual light-use efficiency (ε) would be spatially corrected by the spatial environmental factors that were highly variable (due to the large topographical range in the river basin), from the computation of Equation (4). In the natural forest cover (dense forest and afro-alpine), an average $\acute{\varepsilon}$ value of 2.0 g MJ^{-1} was used from the permissible ranges for tropical rain forest. Similarly, average $\acute{\varepsilon}$ values of 1.0 and 1.2 g MJ^{-1} were adopted for the shrublands, the woodlands, and the wetlands, respectively.

The effective harvest index for carbon sequestration were derived from the literature. Carbon quantities were estimated to be 0.43–0.55 of the above-ground biomass production [68,87–89]. An average carbon conversion factor of 0.5 to the annual accumulated dry biomass was, therefore, adopted for this study (Table 4).

Table 4. Maximum light-use efficiency and the harvest index for natural land cover.

Vegetation Type	Light-Use Efficiency, $\acute{\varepsilon}$ (g MJ^{-1})	Effective Harvest Index $H^i{}_{eff}$ (kg kg^{-1})	Sources
Forest (Tropical rain forest)	1.5–2.6	0.5	[59,60]
Shrublands and woodlands	0.8–1.3	0.5	[23,61]
Wetlands (high vegetation grass)	0.8–1.6	-	[90]

3.4. Uncertainty Analysis of Biomass Production

Biomass production is related to vegetation growth and, therefore, has a temporal distribution due to seasonal variability. In remote sensing, the vegetation growth is accounted for by the phenological variability of NDVI over the cropping season or the given time period [47]. Biomass production for a given land-use type does not, therefore, follow a normal distribution. The nonparametric statistical inference is a technique to assess the uncertainty for data that do not follow a normal distribution [91]. The nonparametric bootstrapping technique was, therefore, used to estimate the confidence of mean biomass production. The pixel values of biomass were used as the sample population for the analysis. The bootstrapping method draws random samples with replacement from the original population sample, each time calculating the mean or the variance [92]. The process was repeated a thousand times and a plot of the distribution of the sample means was made. The 95% confidence interval for the mean was determined by finding the 2.5th and 97.5th percentiles on the constructed distribution. The statistical software Minitab Inc [93] was used in the analysis.

4. Results

4.1. Biomass Production

Figure 2a shows the spatial distribution of the mean annual biomass production, in the Upper Pangani River Basin, based on calculations using Equation (1), during a period of three years (2008–2010). The biomass growth covers fifteen land-use types (except water bodies) with the two large (commercial) irrigation schemes, Lower Moshi (rice), and TPC (sugarcane), as shown in Figure 2b,c, respectively. The key drivers of the spatial variability were the biophysical characteristics of different LULC types while the temporal variability was influenced by the precipitation, and the inter-seasonal/intra-seasonal variation of the climate conditions, during the period of analysis, in the river basin (also see Figure S1 and Table S3, in the supplementary data). High biomass production was observed in the mountainous areas and in the main irrigation systems. The lower catchment areas that experienced low rainfall had a lower biomass growth. In the dry year of 2009, the biomass production was suppressed for most of the LULC types, in the lower catchment, while it was enhanced in the land-cover-types, such as irrigated bananas and coffee, afro-alpine and dense forests, and the wetlands that had a sufficient water supply. Further information on the calibration and validation results for different crops is provided in the supplementary materials.

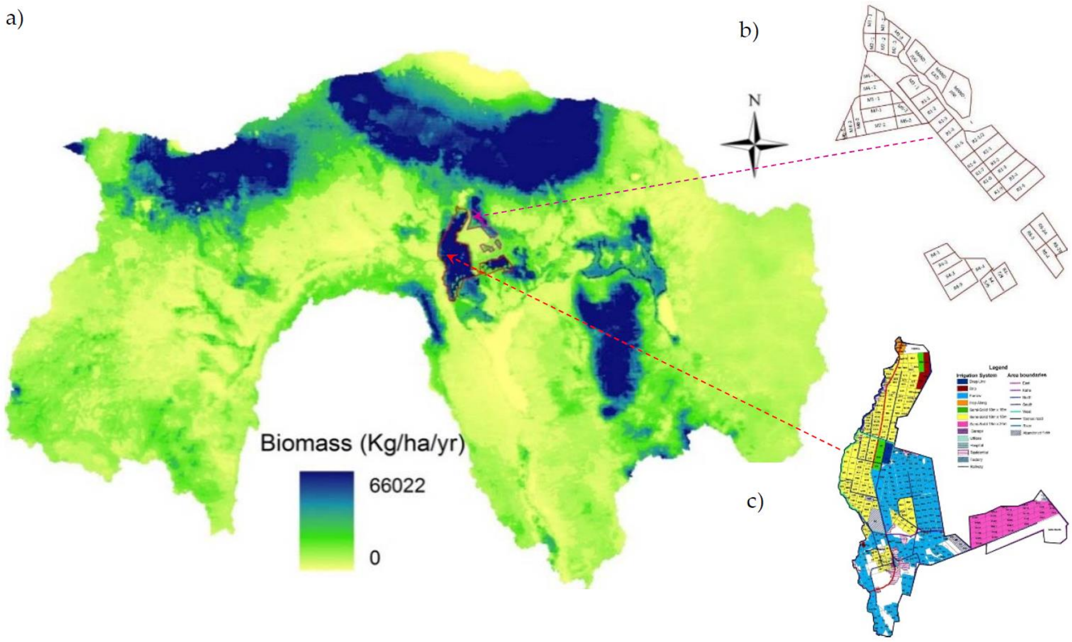


Figure 2. (**a**) Spatial variability of biomass growth in the Upper Pangani River Basin; (**b**) the Lower Moshi irrigation scheme; (**c**) the Tanzania Plantation Company (TPC) sugarcane irrigation scheme.

4.2. Variability in Biomass Production

The uncertainty for biomass production has been assessed through the confidence interval (CI) of the mean for each land-use type. The lower and the upper bound confidence levels were estimated at 95% confidence limits, using the bootstrap non-parametric technique [92]. The uncertainty was greatly influenced by spatial coverage of the land-use types, within topographical or ecological zones. Urban and barelands had the highest uncertainty of 8% and 17%, respectively. The other land-use types had lower uncertainties of less than 2% (Figure 3; also see Section 4.4.1). The results showed that the mean values of biomass production were representative for the given land-use classes.

4.3. Water Yield

The mean annual water yields (P-ET) for the sixteen LULC are presented in Table 5. The water supply is an important ecosystem service, especially for the forest ecosystem [94]. The water yields and snow storage, offers the water regulation services to downstream catchment [2,3]. From Table 5, it can be seen that the ice caps and afro-alpine forests generated significant water yields. The other natural ecosystems with large land masses—dense forest, bushlands, and sparse vegetation, also contributed substantial amounts of water flows to the river basin. The water yields provided essential water flows for irrigation, wetlands and swamps, the water bodies (lakes, reservoirs), and hydropower, in the Pangani river system.

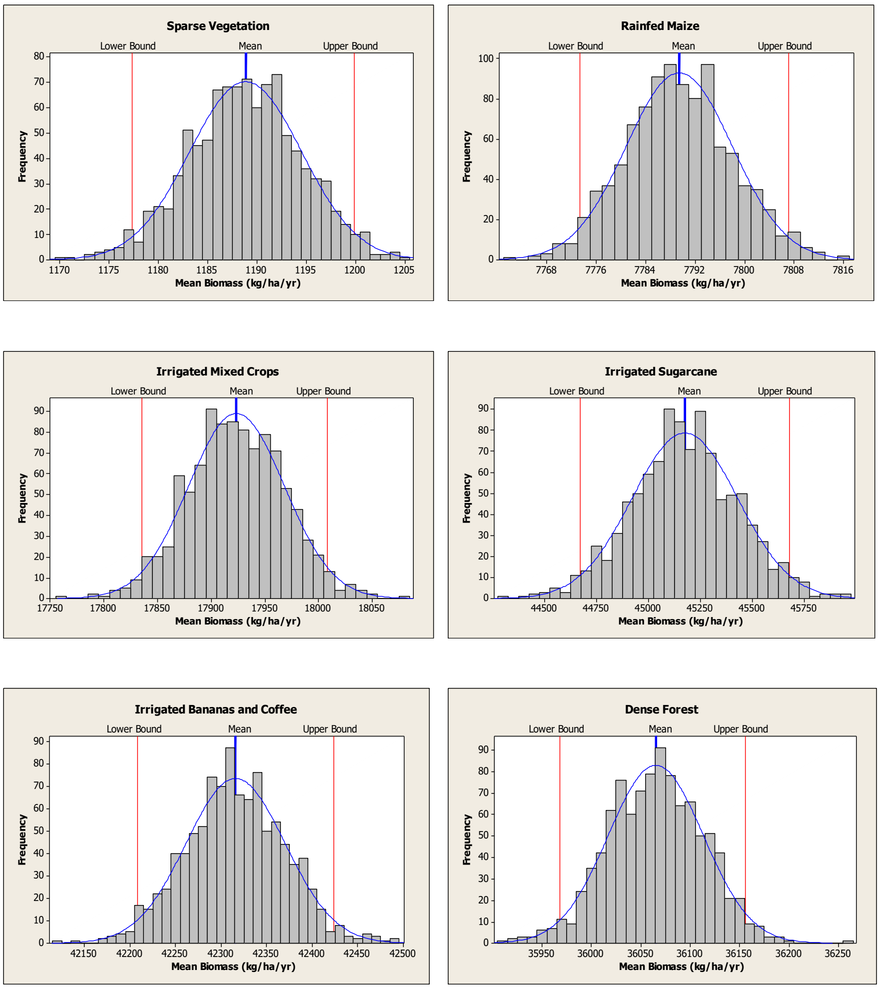


Figure 3. Frequency distribution of the estimated annual mean biomass, from the bootstrap, at 95% confidence limits for the selected land-use types in the Upper Pangani River Basin, for the period of 2008–2010.

Table 5. The water yields for various land use and land cover (LULC) types in the Upper Pangani River Basin, for the period of 2008–2010.

Land Use and Land Cover		Area	Water Yield (P-ET)	
No.		**km^2**	**mm yr^{-1}**	**10^6 m^3 yr^{-1}**
1	Bareland/Ice caps	100	1553	155
2	Sparse Vegetation	445	128	57
3	Bushlands	1152	162	187
4	Grasslands/few croplands	1517	61	93
5	Shrublands/thicket	3509	29	102
6	Rainfed maize	2942	−4	−12
7	Afro-alpine forest	257	871	224
8	Irrigated mixed crops	598	−17	−10
9	Rainfed coffee/Irrig. bana.	723	5	4
10	Irrigated sugarcane	89	−463	−41
11	Forest, Irrig. Croplands	556	−113	−63
12	Irrigated bananas, coffee	607	119	72
13	Dense forest	637	186	118
14	Wetlands and swamps	98	−647	−63
15	Urban, built up	8	202	2
16	Water bodies	100	−1325	−133

4.4. Water Productivity

4.4.1. Biomass and Crop Water Productivity

The water productivity in terms of the above-ground biomass and actual evapotranspiration ($WP_{B/ET}$) was computed based on Equation (7) (Table 6). The highest $WP_{B/ET}$ was realized in irrigated agriculture, with sugarcane providing the highest $WP_{B/ET}$ of 4.4 kg m^{-3}. Dense and afro-alpine forests also attained the high values of 2.4 and 1.4 kg m^{-3}, respectively, due to a high biomass production. Land cover types with low-biomass growth, such as barelands or sparse vegetation, had the lowest $WP_{B/ET}$ values (Table 6).

The coefficient of variation (CV) of the mean (pixel) values of $WP_{B/ET}$ has been presented for each land-use type. For the natural land-use types, a high level of CV (greater than 0.3) was related to high levels of heterogeneity of the land cover. For rainfed and irrigated croplands, the CV was low to moderately high (0.1–0.3), compared to the more homogeneous irrigation systems, which have a CV of 0.05 [21]. The biomass water productivity was converted into crop or yield productivity ($WP_{Y/ET}$), using their corresponding effective harvest indices.

For sugarcane, the estimated $WP_{B/ET}$ of 4.36 kg m^{-3} was within the range reported in literature (3.5–5.5 kg m^{-3}) [12,95–97]. The average $WP_{Y/ET}$ of 9.6 kg m^{-3} sugarcane (1.1 kg m^{-3} sucrose) compared well with the crop water productivity data reported for irrigated sugarcane of between 4.0–11.1 kg m^{-3}, in India, and 7.4 kg m^{-3}, in Thailand [39]. The average yield for sucrose (1.1 kg m^{-3}) was also consistent with the estimates of 1.1–1.3 kg m^{-3}, in the Incomati Basin [12]. There was no significant difference between the water productivities of the furrow and sprinkler irrigation systems. Drip irrigation systems produced lower yields (average of 92 tons ha^{-1}), with a lower actual ET usage, thus, resulting in a statistically similar $WP_{Y/ET}$ (9.6 kg m^{-3}), compared to the other irrigation technologies.

Table 6. Average above-ground biomass (*B*), actual evapotranspiration (ET), and water productivity ($WP_{B/ET}$) in the Upper Pangani River Basin, for the period of 2008–2010.

Land Use and Land Cove		Annual *B* (kg ha^{-1})			Annual *ET* (mm yr^{-1})			$WP_{B/ET}$	
No.		Mean	STDEV	CI [2]	Mean	STDEV	CI [2]	Mean (kg m^{-3})	CV [3]
1	Bareland/Ice caps	319	538	27	643	653	32	0.05	1.3
2	Sparse Vegetation	1189	477	11	586	172	4	0.20	0.6
3	Bushlands	1999	1017	15	669	312	5	0.30	0.4
4	Grasslands/few croplands	2550	652	8	630	223	3	0.40	0.4
5	Shrublands/thicket	4100	1209	10	756	85	1	0.54	0.3
6	Rainfed maize	7789	1870	17	789	221	2	0.99	0.3
7	Afro-alpine forest	19,803	5529	171	1429	309	9	1.39	0.2
8	Irrigated mixed crops	17,923	4133	86	905	207	4	1.98	0.3
9	Rainfed coffee/maize	18,973	4352	80	1022	261	5	1.86	0.2
10	Irrigated sugarcane	45,175	9651	501	1035	212	11	4.36	0.2
11	Forest, croplands	30,612	5250	109	1228	250	5	2.49	0.2
12	Irrigated bananas, coffee	42,316	5239	108	1330	156	3	3.18	0.1
13	Dense forest	36,065	4819	94	1517	144	3	2.38	0.1
14	Wetlands and swamps	20,039	4415	219	1291	267	13	1.55	0.2
15	Urban, built up	1409	327	57	774	80	14	0.18	0.6

[2] CI—confidence interval of mean at 95% confidence limits. [3] CV—coefficient of variation of the mean (pixel) values of water productivity.

$WP_{B/ET}$ for rice of 1.5 kg m^{-3} was within the range (0.6–1.6 kg m^{-3}) reported in the literature [39,98–101]. For irrigated bananas, the average $WP_{B/ET}$ and $WP_{Y/ET}$ was 3.2 and 2.8 kg m^{-3}, respectively. The average $WP_{B/ET}$ for irrigated banana was in the range of 1.4–5.5 kg m^{-3} in the Nico Coelho irrigation scheme, Pernambuco, Brazil [102]. The $WP_{Y/ET}$ was also consistent with estimates of 2.8 kg m^{-3}, for the banana crop, in the Incomati Basin [12]. The water productivity $WP_{B/ET}$ for rainfed maize (with supplementary irrigation) was 1.0 kg m^{-3}, while that for irrigated maize was 2.0 kg m^{-3}. The water productivity translated to $WP_{Y/ET}$ of 0.35 and 0.70 kg m^{-3}, for rainfed and irrigated maize crops. The low productivity for rainfed maize was explained by the low yields that were generally associated with water stress, due to long dry spells during the growing seasons. The result was consistent with a recent study that showed that the water productivity for irrigated agriculture was twice that of rainfed agriculture, in the Indus Basin [21]. In general, the maize productivity $WP_{B/ET}$ was within the range reported in literature of 1.1–2.7 kg m^{-3} [100]. The yield productivity $WP_{Y/ET}$ was also consistent with the range of 0.40 to 0.70 kg m^{-3} for irrigated maize, in Mkoji, Great Ruaha river basin, in Tanzania [20].

For natural landscape, the $WP_{B/ET}$ was high for the natural tropical forest because of the high biomass production associated with the favourable rainfall, throughout the year. $WP_{B/ET}$ for dense forests averaged 2.4 kg m^{-3}, which was within the range of 2–3 kg m^{-3}, for the closed forests, in the Nile Basin, for the year 2007 [103]. The relatively high $WP_{B/ET}$ value for the wetlands and swamps of 1.6 kg m^{-3} was consistent with the values found for natural wetlands, in the Nile Basin of 1.5 kg m^{-3} [104], and could be explained by year round access to water. The $WP_{B/ET}$ for shrublands, bushlands, sparse vegetation, and barelands, located in the lower parts of the Upper Pangani, were lower than 0.5 kg m^{-3}, mainly because of the low rainfall. In natural grasslands, the average biomass production of 2.6 tons ha^{-1} represented a $WP_{B/ET}$ of 0.4 kg m^{-3} (Table 6). The water productivity was low, compared to good pastures or forage (alfalfa), grown for commercial purposes, under irrigation, which ranged between 1.0–2.6 kg m^{-3} [104]. The low productivity might be attributed to low rainfall and could possibly be combined with overgrazing.

The relationship between the average *B* and ET, for various landscapes, is presented in Figure 4.

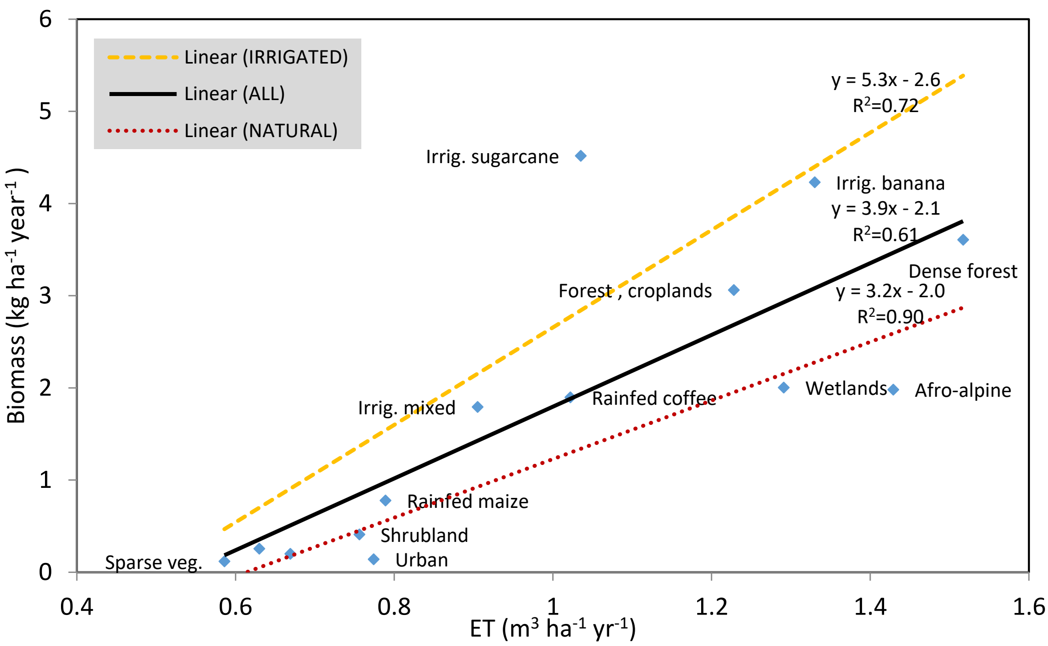


Figure 4. Variation between the biomass and actual evapotranspiration (ET) for agricultural and natural landscapes, using average values, for the period of 2008–2010, in the Upper Pangani River Basin.

There was a strong linear relationship between the *B* and the ET, in irrigated (R^2 = 0.72) and natural (R^2 = 0.90) landscapes. It was observed that biomass production in irrigated agriculture was more enhanced than in rainfed agriculture and natural landscapes. Most of the irrigated crops (maize, banana, and vegetables) were under supplementary irrigation, where only some blue water was added in critical times, to supplement the rainfall. This improves the water availability for the crops. In commercial sugarcane (fully irrigated), irrigation combined with soil fertility management, provides optimal conditions for plant development.

Figure 4 shows the scope for increasing water productivity. Additional water storage (through water harvesting) and the subsequent water use by rainfed systems, would result in a significant increase in the biomass production. This can be observed by comparing rainfed maize and irrigated mixed crops (maize, beans, and vegetables), where the biomass production increases by 130%, with only a difference of 15% in ET. It is noteworthy that the different kinds of plants (C3, C4, and CAM plants) have different water-use efficiency, in terms of B and ET, in their positioning in Figure 4. As such C4 crops, such as sugarcane and maize are more water-efficient, than C3 crops, such as rice [23]. Figure 4 can also implicitly provide (from water use) the shadow value or the opportunity cost of keeping the natural ecosystems in good conditions. These values provide baseline data that can be used for a detailed environmental valuation and modelling.

Figure 5 presents the water productivities (that relates to land use), in the Upper Pangani Basin.

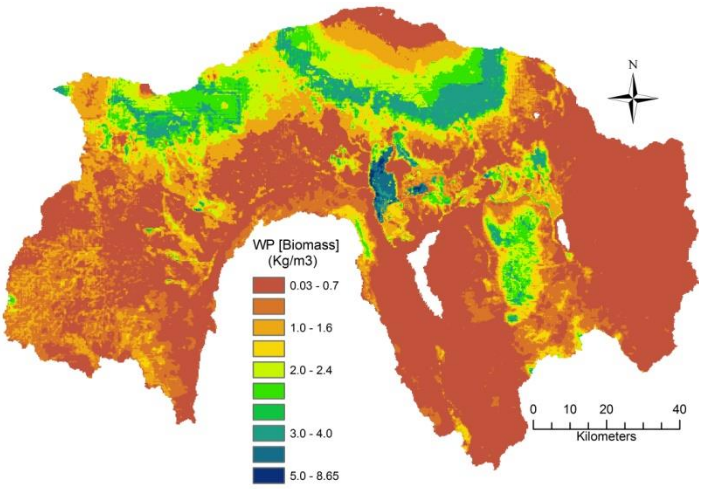


Figure 5. Water Productivity (Biomass) for the period of 2008–2010, in the Upper Pangani River Basin.

4.4.2. Economic Water Productivity

The economic water productivity was computed from the crop yields and the net production values, using Equation (9). Table 7 provides the yield and the corresponding economic water productivity for the main crops in the basin.

Table 7. Crop yield and economic water productivity for main agricultural crops in the Upper Pangani River Basin.

Land Use Land Cover Type	Crops [4]	$WP_{Y/ET}$ (kg m^{-3})	$WP_{Ec/ET}$ (\$ m^{-3})
Irrigated mixed crop	Rice	1.5	0.18
Irrigated mixed crop	Irrigated maize	0.7	0.13
Rainfed coffee/maize	Rainfed maize	0.35	0.07
Irrigated mixed crop	Vegetables	1.6	0.29
Irrigated bananas, coffee	Bananas	2.6	0.31
Irrigated sugarcane	Sugarcane (commercial)	9.6 (1.1 [5] Sucrose)	0.31

[4] The crops were selected from the pixel locations. [5] Biomass to sugar (sucrose) harvest index of 0.24.

$WP_{Ec/ET}$ values for the irrigated crops show that sugarcane and bananas have a higher economic water productivity (0.31\$ m^{-3}), compared to those of vegetables (0.29\$ m^{-3}), rice (0.18\$ m^{-3}), and maize (0.13\$ m^{-3}). The average $WP_{Ec/ET}$ for rice was within the range of 0.10–0.25\$ m^{-3} that has been reported in the literature [23,103]. Rice and maize have relatively stable local markets and are the preferred crops in the Lower Moshi irrigation scheme. The banana and vegetable markets are controlled by middlemen and the market is volatile. The P_g for banana and vegetable crops was about 44% of the retail prices of the produce, at the local markets. The high difference was mainly attributed to the high transport and brokerage costs.

The economic water productivity for the commercial sugarcane of 0.31\$ m^{-3} was higher in 2008/10, compared to that of the Incomati basin (2004/05)—0.20\$ m^{-3} [12]. Since the biomass and crop yield productivities were similar, the difference could be attributed to the high sugarcane prices during the two periods [70].

For pastures (grasslands and scattered croplands), the economic water productivity was assessed using the biomass production that was grazed or harvested mainly for livestock. The assumption here was that the grass consumed by the livestock could otherwise have been purchased as dry feeding forage (hay), in assessing the economic water productivity. Using an effective harvest index of 0.70, for dry grass, at 15% moisture (harvest index of 1 and field moisture of 50%); the $WP_{Y/ET}$ became 0.28 kg m^{-3}. The market price for hay (dry grass) was approx. 0.18\$ kg^{-1} (20 kg hay market price averaged Tsh. 5000). This implied, thus, that the $WP_{Ec/ET}$ could be approximately 0.025\$ m^{-3}, using a cost of production factor of 0.5. The productivity (natural grasslands) was approximately three times less than rainfed maize (0.07\$ m^{-3}), despite the small difference (20% in average) in water usage (ET). However, the grassland's water yield was higher than rainfed maize (Table 5), thus, providing additional ecosystem services to the catchment.

The dense forest and afro-alpine forest, with an annual average biomass growth of 20 tons ha^{-1} yr^{-1} and 36 tons ha^{-1} yr^{-1} (Table 6) had carbon storage of between 10–18 tons C ha^{-1} yr^{-1}. The economic potential for the carbon storage in the forest would, therefore, range between 150–270 US\$ ha^{-1} yr^{-1}. Using the water productivity of carbon yield (from biomass), $WP_{Y/ET}$ (CO_2) of 0.7–1.2 kg m^{-3}, the $WP_{Ec/ET}$ translated to a range of between 0.01–0.02 US\$ m^{-3}. The $WP_{Ec/ET}$ was low (about 15 times less), compared to irrigated agriculture, despite high $WP_{B/ET}$ values (Table 6). This was mainly attributable to the low carbon market prices. The low cost of carbon market prices t has been observed by Batjes [33] was the greatest hindrance for a quicker implementation of the CO_2 mitigation measures, in agriculture. However, there were prospects that the situation was poised to change with emerging markets for carbon trading, where countries (through their industries) trade to meet their CO_2 obligations specified by the Kyoto Protocol.

Shrublands and bushlands also provided for carbon storage. The annual biomass production ranged between 2–4 ton ha^{-1} and the carbon storage would, thus, range between 0.5–1.0 ton C ha^{-1} yr^{-1}. However, other provisioning and regulatory services for these biomes, such as providing grazing fields for wildlife and food for local populations, as well as water regulation, added significant value to this land use [30].

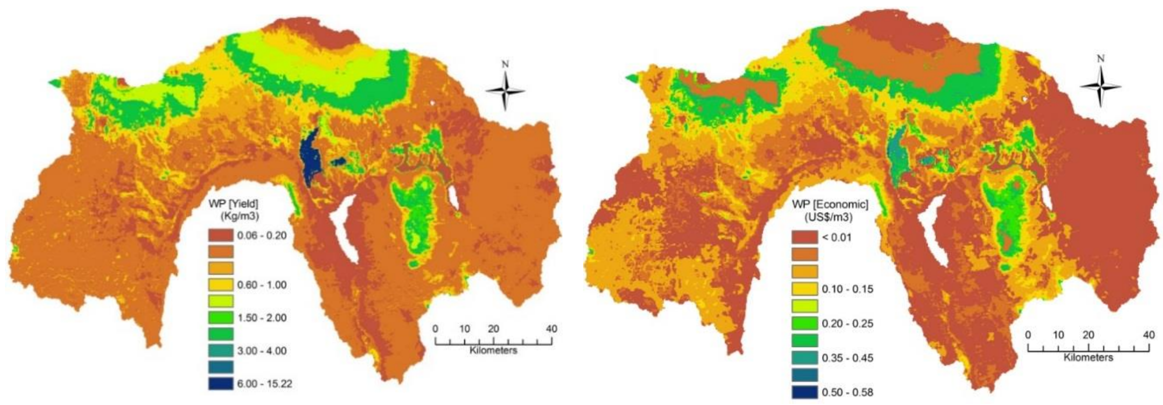
Table 8 presents the yield and economic water productivity for the natural landscapes, based on hay and carbon sequestration. The economic value for carbon was expected to increase by 25–30%, when the below-ground biomass production was considered.

Table 8. Yield and economic water productivity for natural landscapes in the Pangani River Basin.

Land Use Land Cover	Crops [6]	$WP_{Y/ET}$ (Kg m^{-3})	$WP_{Ec/ET}$ (\$ m^{-3})
Grassland	Hay	0.28	0.025
Dense forest/afro-alpine forest	Carbon storage	0.7–1.2	0.01–0.02
Shrublands and bushlands	Carbon storage	0.15–0.27	<0.004

[6] Averaged over the land use land cover type.

Figure 6 presents the spatial crop yield and the economic water productivities, in the Upper Pangani Basin. Both productivities accounted for the CO_2 storage for forest and shrublands, hay for grasslands, and the harvestable yield for irrigated and rainfed agriculture.



(**a**) (**b**)

Figure 6. (**a**) Water Productivity (Yield). (**b**) Water Productivity (Economic) for the period of 2008–2010.

4.4.3. Economic Water Productivity for Irrigation Water Use

Crop water use (actual ET) comprised both precipitation (P) and net irrigation (blue water) withdrawal (Q_b). Table 9 shows the percentage of Q_b to the total actual water use (ET), for the main irrigated crops in the Upper Pangani River Basin, extracted from Kiptala et al. [47]. The economic water productivity, in terms of blue water ($WP_{Ec/ETb}$) was derived by dividing the total economic water productivity ($WP_{Ec/ETb}$) by the blue-water-use factor (Q_b/ET).

Table 9. Economic water productivity for the main irrigated crops expressed in terms of net irrigation water use, for the period of 2008–2010.

Crop	Q_b (%)	$WP_{Ec/ET}$ (US$ m^{-3})	$WP_{Ec/ETb}$ (US$ m^{-3})
Sugarcane	44	0.31	0.70
Rice	36	0.18	0.50
Vegetables	24	0.29	1.21
Bananas	21	0.31	1.48
Maize	17	0.13	0.76

5. Discussion

Apart from carbon storage, natural biomes provide other valuable services that may relate to ecological production, of which some are not monetized. Water yields generated by natural landscapes are consumed in agricultural and urban landscapes, generating economic value, whilst generating some disservices [105,106]. Trade-offs between the natural and anthropogenic landscapes are, therefore, not always clear. Fanaian et al. [107] provided a good and systematic overview of how to undertake local economic valuation of ecosystem services, by way of assessing tradeoffs of alternative resource use, in a river system. In this paper, we argued to infer the extent of the value of the ecosystem services provided by the natural biomes, to go beyond the CO_2 sequestration, alone, and to consider the benefits, as presented in Table 8. The results from this study have been compared to the ranges of economic values (2007 prices), provided by De Groot et al. [3], based on over three thousand peer-reviewed studies, some in the tropical climate. Of interest are the tropical forest, woodlands, grasslands, inland wetlands, and fresh water lakes that constitute much of the natural ecosystems in the Upper Pangani River Basin.

The economic value for provisioning services for tropical forests was estimated to be at 2695 US$ ha^{-1}yr^{-1} from ninety-six case studies, at a standard error rate of 13%. From the water use for dense and afro-alpine forests, in the Upper Pangani River Basin, the water productivity equaled 0.19 US$ m^{-3}, which was ten times greater than the derived value for carbon storage (Table 8). Furthermore, the water value could significantly increase to 0.34 US$ m^{-3} (5264 US$ ha^{-1} yr^{-1}), if the other ecosystem services (water and climate regulation, erosion control, nutrient recycling) were also considered.

The shrublands provided primarily food and pasture to livestock, wildlife, and even local communities, in the form of plant leaves and fruits. This part of biomass was not accounted for in carbon sequestration. From the literature, the economic value of shrublands was estimated at 1305 US$ ha^{-1} yr^{-1}, based on twenty-one case studies, with a standard error of 4%, for which 90% of the value was derived from food [3]. The assessment was consistent with the shrublands areas in the Africa savanna, including Pangani, which hosts a wide variety of wildlife, and pastoralists keeping cattle. Considering the water use for the shrublands in the Upper Pangani River Basin, the water productivity equaled 0.17 US$ m^{-3}. Habitat (genetic diversity) and cultural services of the shrublands further increased the water productivity to 0.38 US$ m^{-3}. On the other hand, bushlands provide ornamental and generic resources, such as medicine to the local communities [30], which was estimated at 253 US$ ha^{-1} yr^{-1} [3], equivalent to a water value of 0.04 US$ m^{-3}, in the Upper Pangani River Basin. Considering habitat services, the economic value of the bushlands would increase to 1588 US$ ha^{-1} yr^{-1} or a water value of 0.24 US$ m^{-3}. These water values, for both the shrublands and bushlands, were much significantly higher than the economic benefits from carbon sequestration (<0.004 US$ m^{-3}), given in Table 8.

Inland wetland is known to provide the greatest value in ecosystem services, in the form of water flow (and disturbance) regulation, water treatment, food production, and recreation. Although most of the functions are not directly related to biomass, its total economic value (2007 prices levels) was estimated to be at 25,682 US$ ha^{-1} yr^{-1} [3]. The valuation was consistent with earlier estimates (1994 price levels) of 15,000 US$ ha^{-1} yr^{-1} [30]. The provisioning services that relate to ecological productions (biomass), such as food, pasture, and raw materials was estimated to be much lower, at 1659 US$ ha^{-1} yr^{-1}. The average value was based on estimates from a hundred and sixty-eight case studies, at an 11% standard error rate. The economic value from the provisioning services was 0.13 US$ m^{-3} from water use (evapotranspiration) of 1300 mm yr^{-1}. The water value would increase to 2.0 US$ m^{-3}, if all the other regulating and habitat services (2007 price levels) were considered.

The fresh water lakes also provide substantially high values, in terms of water supply, water treatment, food (fish and grazing land), and recreation services. The water value from fifteen case studies, at a 17% standard error rate, was estimated to be at 1914 US$ ha^{-1} yr^{-1} [3]. In the Pangani River Basin, the Lake Jipe and Lake Chala provide these provisioning services. Considering the evaporation rate of 2000 mm yr^{-1}, the water value equaled to 0.10 US$ m^{-3}. Costanza et al. [30] argued that additional water regulation services, provided by the wetlands, should also be added to the freshwater lakes. Thus, recreational services would increase the water value of the fresh water lakes to 0.4 US$ m^{-3}. However, these natural biomes are located close to each other in the Upper Pangani River Basin and the water regulation may only be offered by one, or partly, by all.

The comparison of the results for natural landscapes, derived in Table 8 (based on CO_2 and pastures), against the literature reviewed, showed that the biophysical analysis, based on carbon storage and pastures only, significantly underestimates the total economic value of the natural ecosystem services. However, a local ecosystem valuation needs to be undertaken to explicitly derive the total value of ecosystem services, generated by each natural biome. This will reduce the chances of avoiding double counting, especially for parallel ecosystem services supported by nearby natural landscapes. As such the biophysical data and the baseline water values, provided in this study, provide boundary conditions for a further detailed economic valuation.

For irrigated agriculture, the economic (blue) water productivity ($WP_{Ec/ETb}$) showed higher values for smallholder crops (banana, vegetables, and maize) using a less net irrigation, Q_b, compared to the fully irrigated rice and sugarcane (Table 9). This, thus, imply that during periods of physical water scarcity, the opportunity cost for blue water (scarce) resources is much higher than that of precipitation.

6. Conclusions

This paper presented the spatial water productivity in terms of bio-physical (biomass and yield) and economic benefits for different LULC in the Upper Pangani River Basin, in Eastern Africa. In agriculture, irrigated lands achieved the highest water productivity in terms of biomass, crop yield and economic productivity. The productivity for sugarcane and rice is high and within the ranges reported in the literature. In supplementary irrigated and rainfed systems, the productivity was moderate but significantly lower than the potential reported in literature. In natural ecosystems, natural forest and wetland that have access to abundant water resources achieved a relatively high biomass production, compared to the expansive shrublands and sparse vegetation. However, the economic productivity for the natural forest and wetlands was low, when computed using biomass-derived CO_2 storage economic benefits, only. We found a linear relationship between biomass (and yield) and ET, in both agricultural and natural landscapes. As expected, biomass production in irrigated (and supplementary irrigated) agriculture was higher than in rainfed agriculture and natural ecosystems, in the Upper Pangani. This could be explained by better plant water and soil fertility management, in the irrigated landscapes, and a relatively low rainfall, in the rainfed landscapes. The relationship provides a scope for improved water productivity, especially for rainfed systems with supplementary irrigation and good agronomic practices. Molden et al. [23,28] provides the various ways of increasing the productivity of rainfed agriculture and crops, through supplementary irrigation (see also [24,108]).

The pixel results for biomass water productivity of a given land-use class showed large variations. The coefficient of variation (CV) was high for natural and conserved land uses (0.3–1.3). This was mainly due to the large topographical range of the land-use type which influence the environmental factors, such as rainfall and temperature. For agricultural land uses, the CV was lower (0.1–0.3), but nevertheless still higher than those reported for large-scale irrigation systems. The result could be explained by the high levels of intercropping that exists within the land-use types, dominated by smallholder irrigation system. Even so, the spatial analysis provided a further scope for increased water productivity, in agricultural plots that have a low biomass growth.

The economic productivity in terms of irrigation water use (Q_b) was higher for the smallholder banana and maize, under supplementary irrigation, as compared to the fully-irrigated sugarcane and rice. In situations of physical water scarcity, the opportunity cost for blue water (scarce) resources was much higher than that of precipitation. It would, thus, be more prudent to allocate river water to the supplementary irrigated crops than to the fully irrigated crops that are grown during the dry season.

The market price for carbon sequestration was observed to significantly influence the water productivity for the natural forest ecosystems. The market price was observed to be lower than the social costs of carbon emissions, in the global market [33,71]. Nevertheless, the price was expected to increase, significantly, in the near future with the expected carbon trading, following the Kyoto Protocol [109]. Other ecosystem services from natural land cover, inferred from the literature, substantially increased the economic water productivity, especially for the wetlands, natural forests, and the shrublands. Advanced techniques for localized environmental and social ecosystem valuation for the natural environment, exist [110], but these techniques require specific expertise and are quite costly [111]. However, the biophysical data and baseline water values derived here, could therefore, provide boundary conditions for a further detailed economic or environmental modelling.

The social water value to the local populations is also a key factor, for consideration by policy makers, when interpreting the, water productivity indices. Banana, maize and rice provide staple food for local livelihoods and income, thus, enhancing food security and social well-being. On the other hand, sugarcane grown by the large-scale Tanzania Plantation Company that has a relatively high economic productivity and might not provide high benefits to local livelihoods. Trade-offs, therefore, have to be made between attaining high economic water productivities and social benefits in the Pangani river basin.

It is clear from the spatial water productivity maps that biomass production is closely correlated with economic water productivity. Water yields, carbon credits, and other ecosystem services provide insight into the water value that society attaches to a certain cultural and natural land-use activity. Standard payment for environmental services (PES) schemes also relates with efforts to enhance water yields, prevention of soil erosion, and carbon sequestration among others. A holistic approach that involves the improvement of both the biophysical and economic factors, through sustainable basin-wide interventions can, therefore, result into higher economic water productivity at a lower social and environmental cost. Such a comprehensive water productivity analysis will allow policy makers to quantify the foregone economic benefits for allocating water for socio-environmental gains. Moreover, the physical water productivity can inform the long-term basin strategies, based on future market trends and socio-economic scenarios. The remotely-sensed estimate of the economic water productivity that includes natural ecosystems would, therefore, provide vital information for the sustained green growth and socio-economic development, in many African river basins.

Supplementary Materials: The following are available online at http://www.mdpi.com/2072-4292/10/11/1802/s1, further information on the calibration and validation of the specific crops and additional information on biomass production. Table S1. Actual yield to biomass sampling data for rice in the Lower Moshi irrigation scheme; Table S2. Actual biomass to actual yield for sugarcane in the TPC irrigation scheme; Figure S1: Mean annual biomass production in the Upper Pangani River Basin for different land use types for the years 2008–2010; Table S3: Mean annual biomass production for different land use types in Upper Pangani River Basin for 2008–2010

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