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Representation of seasonal land-use dynamics in SWAT+ for improved assessment of blue and green water consumption

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Abstract. In most (sub)-tropical African cultivated regions, more than one cropping cycle exists following the (one or two) rainy seasons. During the dry season, an additional cropping cycle is possible when irrigation is applied, which could result in 3 cropping seasons. In most agro-hydrological model applications such as SWAT+ in Africa, only one cropping season per year is represented. In this paper, we derived dynamic and static trajectories from seasonal land-use maps to represent the land-use dynamics following the major growing seasons, for the purpose of improving simulated blue and green water consumption from simulated evapotranspiration (ET) in SWAT+. This study builds upon earlier research that proposed an approach on how to incorporate seasonal land use dynamics in the SWAT+ model but mainly focused on the temporal pattern of LAI and tested the approach in a small catchment (240 km^2). Together with information obtained from the cropping calendar, we implemented agricultural management operations for the dominant trajectory of each agricultural land-use class for the Kikuletwa basin (6650km^2 area coverage) in Tanzania. A comparison between the default SWAT+ (with static land use representation) set up, and a dynamic SWAT+ model (with seasonal land use representation) is done by spatial mapping of the evapotranspiration (ET) results. The results show that ET with seasonal representation is closer to remote sensing estimations, giving higher performance than default: the Root Mean Squared Error decreased from 181 to 69 mm/year; the percent bias decreased from 20 % to 13% and Nash Sutcliffe Efficiency increased from -0.46 to 0.4. It is concluded that representation of seasonal land-use dynamics produces better ET results which provide better estimations of blue and green agricultural water consumption.

1. Introduction

Representation of land-use dynamics in agro-hydrological models is important due to the numerous impacts of land-use changes on water resources (Wagner et al., 2019; Woldesenbet et al., 2017). LULC changes affect hydrologic processes such as infiltration, groundwater recharge, evapotranspiration, and runoff (Welde and Gebremariam, 2017; Liu et al., 2008; Schilling et al., 2010). Several studies have demonstrated the importance of incorporating dynamic land-use change in models (Chiang et al., 2010;

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Wagner et al., 2016). For instance, Wagner et al., (2016) found a continuous decrease of annual evapotranspiration of up to -53mm (-7%) when dynamic land-use change is implemented per sub-basin scale.

However, most of these studies have implemented annual land-use dynamic. Since land-use refers to manmade socio-economic activities and management practices on the land, these anthropogenic activities may change depending on a season, specifically on cultivated land (Anderson et al., 1976). These changes per season are called seasonal land-use dynamics (Msigwa et al., 2019). Few studies have implemented seasonal land-use dynamic for Nitrogen leaching and plant growth (Glavan et al., 2015) when estimating water withdrawals (Msigwa et al., 2019) and LAI simulation (Nkwasa et al., 2020). Msigwa et al., (2019) found that water withdrawals for irrigated mixed crops increased by 482 Mm^3/year when seasonal land-use maps are used. Also, the implementation of seasonal land-use dynamic in SWAT and SWAT+ models led to an improved vegetation simulation (Nkwasa et al., 2020). The LAI dynamics of the seasonal land-use dynamic implementation showed more realistic temporal advancement patterns that corresponded to the seasonal rainfall within the basin.

Nkwasa et al., (2020) implemented seasonal land-use dynamic in SWAT and SWAT+ through land-use trajectories, and not land-cover classes. Trajectories represent changes of land-use over time by comparing changes between two or several land-use maps at a grid scale. Trajectory analysis has been applied widely to assess the changes and impact of LULC (Feng et al., 2014; Wang et al., 2012), and as a pre-processing tool for LULC (Zomlot et al., 2017). In these studies, change analysis is done pixel by pixel for each year in order to identify land use change (Mertens and Lambin, 2000; Swetnam, 2007; Zhou et al., 2008; Wang et al., 2012; Zomlot et al., 2017). However, none of these studies have analysed pixel by pixel within a year with the aim of identifying the different (cropping) seasons, further referred to as land use dynamics.

Tropical African cultivated areas typically have more than one growing cycle, most of the time ranging between 2 to 3 depending on the sequence of rainy and dry seasons and availability of irrigation water (Msigwa et al.,2019). The right representation and timing of these cropping seasons is important in order

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to quantify the crop water consumption. Agro-hydrological model applications in Africa basins do typically not represent different cropping seasons (Ndomba et al., 2008; Koch et al., 2012; Gashaw et al., 2018). Lack of consideration of the seasonal land-use dynamics in hydrologic modelling studies, especially in African cultivated basins, may be attributed to past constraints of model capabilities, as well as lack of availability of crop-specific and agricultural management practices data (Van Griensven et al., 2012).

The SWAT model incorporates crop rotation and its management at the level of the Hydrological Response Unit (HRU) within a sub-basin (Neitsch et al., 2002). It is represented as a sequence of planting and harvesting operations within the same HRU supplemented with management operations (Gao et al., 2017). The representation of agricultural management is done through a separate management file by specifying the planting, harvesting, tillage, irrigation, fertilizer and pesticide application by heat units or month and date (Arnold et al., 2018). There has been a lot of improvement in how to represent the management operations by utilizing decision tables in the SWAT+ model, which is the revised and improved version of SWAT (Arnold et al., 2018; Bieger et al., 2017). A recent study by Nkwasa et al., (2020) in the Usa catchment with in Kikuletwa basin in northern Tanzania has shown how to represent seasonal land-use dynamics in the SWAT model using the management file and the SWAT+ model using decision tables for accurate hydrologic simulation. Although the SWAT (+) model is capable of representing multiple cropping seasons, this is rarely implemented. By default, SWAT simulates a single growing cycle every year. There is increasing availability of satellite imagery suitable for land-use monitoring with high resolution e.g. Landsat (up to 30m) (Bolton et al., 2020; Al-Hamdan et al., 2017) or Sentinel mission of the European Space Agency (ESA) (up to 5m) (Bergsma and Almar, 2020; Drusch et al., 2012; Berger et al., 2012). After further analysis, these images provide frequent land-use information such as crop types, cropping rotations and irrigation seasons even for small scale agricultural areas in African basins.

This paper builds from previous work that proposed an approach on how to incorporate seasonal land use dynamics in SWAT and SWAT+ models but was only evaluated for the temporal pattern of LAI simulations at a small catchment of 240 km^2 (Nkwasa et al., 2020). This study aims to; (i) investigate the

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effect of implementing seasonal land-use dynamics on the water balance component in Kikuletwa basin (6650 km^2) with focus on the ET using SWAT+ and (ii) estimate blue and green water consumption from simulated ET. Seasonal land-use maps were obtained from remote sensing to derive dynamic and static trajectories at 30m resolution (Msigwa et al., 2019). Together with information obtained from the cropping calendar, we implemented agricultural operations for the dominant dynamic trajectory of each land-use class using the approach proposed by Nkwasa et al., (2020). The paper compares spatial mapping of ET obtained from the default SWAT+ model set up with a static land-use map and a SWAT+ model set up with seasonal dynamic land-use representation. Findings from this study are intended to enhance the understanding of the spatial-temporal variability of water consumption (e.g. expressed as blue and green water uses) through improved ET estimations.

2. Methods

2.1. Study Area

The Kikuletwa basin is a sub-basin of the Pangani basin that covers approximately 6,650 km^2 (Figure 1). Rainfall within the basin is bi-modal, meaning that the area receives long rains (masika) from March to June and short rains (vuli) from November to December, as shown in Figure 2. Annual rainfall ranges between 300-800 mm in the lower part of the basin to 1200-2000 mm in the highlands of Mount Meru and Kilimanjaro. The basin comprises of diverse LULC classes such as agricultural land, dense forest on Mount Kilimanjaro (5880m) and Meru (4562m), grazed land, mixed urban and shrubland/thickets. Shrubland and thickets in the study area are found mainly in the lowlands where rain-fed agriculture is dominant. Urban areas concentrate around Arusha, although there are also emerging small towns. Moreover, grazed land is mainly found in the Maasai land of Monduli and Simanjiro districts. Irrigated agriculture in Kikuletwa is mainly practiced in the highlands and lowlands along the river of Moshi, Moshi urban, Hai, Arumeru, Arusha, and Siha districts. The main crops in the highlands are banana, coffee, and maize, while the lowlands are dominated by mixed vegetable crops such as tomatoes, onions, and beans.

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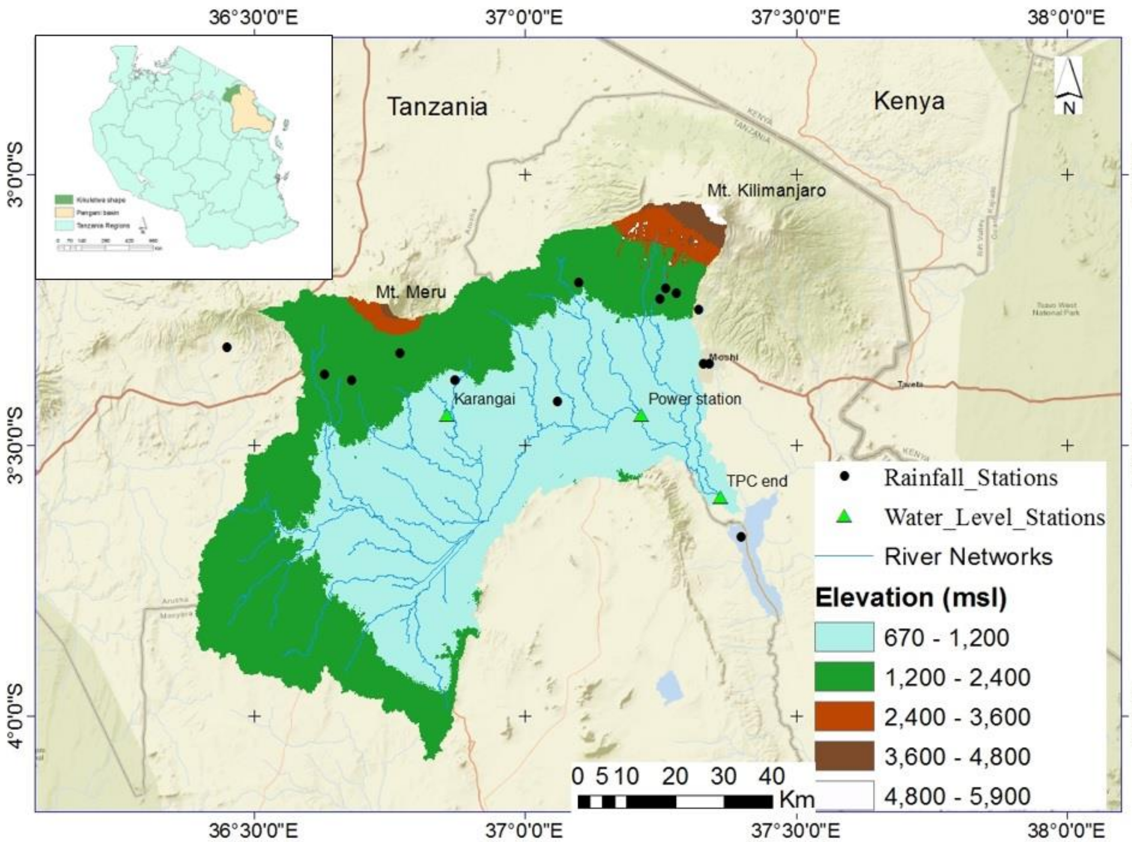

Figure 1. Location and main features of the Kikuletwa basin with google terrain background in Tanzania (by Authors).

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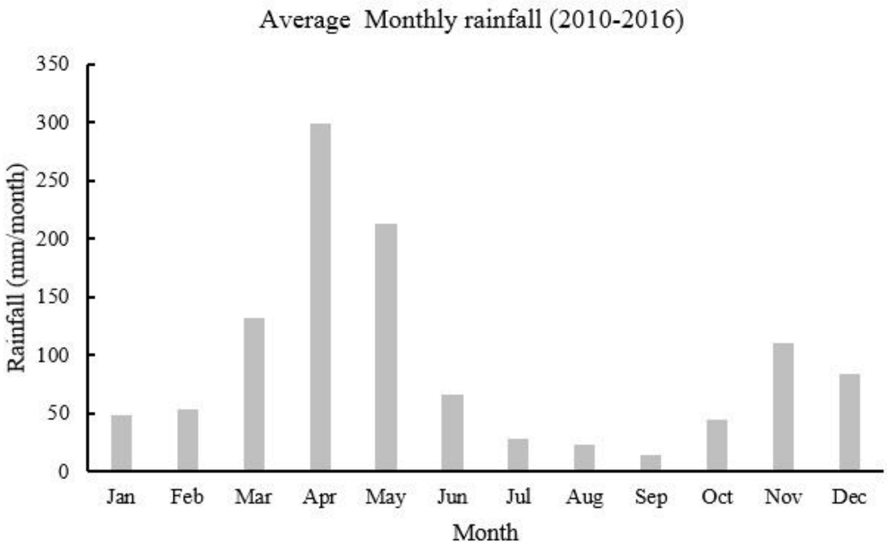

Figure 2. Monthly average rainfall (mm) of Kikuletwa basin ground rainfall stations

2.2 Input dataset for SWAT+

The required rainfall, discharge, climate data, topography, soil map and land-use map were collected from different sources. The 90m resolution Digital Elevation Model (DEM) was obtained from the United States Geological Survey (USGS) website; the soil map was extracted from the African Soil Information Service (AFSIS; Hengl et al., 2015). Daily rainfall records for 10 stations were obtained from the Tanzania Meteorological Agency (TMA) and Pangani Basin Water Office (PBWO). Daily discharge records were obtained from PBWO. The daily climate records of temperature (maximum and minimum) for three stations were obtained from PBWO and TMA. The different data sets had variable record length and quality. However, for the selected 10 rainfall and 4 temperature stations, only good quality data records for the overlapping period (2006 to 2013) were selected.

The LULC maps were created using Landsat 8 (30m resolution) image of three months (March, August and October) representing three seasons in the basin (Msigwa et al., 2019).The March map represents the LULC during the long-wet season (*Masika*), the August map represents the dry season, and the October map represents the short rainy seasons (*Vuli*). The LULC maps were reclassified to match the SWAT

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land-use classification. For instance, the SWAT land-use code 'PAST' was used to represent grazed grassland in the maps.

2.3 Land-use Trajectories

The LULC change trajectory methodology has been widely applied in many areas to assess LULC change and its impact on the environment. Researchers use trajectories to analyse the change happening between two images pixel by pixel (Mertens and Lambin, 2000; Swetnam, 2007; Zhou et al., 2008; Wang et al., 2012; Zomlot et al., 2017).

In this study, we extended the meaning of land-use trajectories from 'land-use change' to 'seasonal succession of land-use types for a given sample unit (pixel) with more than two observations at different times' (Zhou et al., 2008) We applied the method in this study to assess the agricultural seasonal dynamics for the meteorological dry and wet seasons of the Kikuletwa basin.

The land-use change trajectories were obtained by integrating three classified images to represent the three cropping seasons so that pixel-based change trajectories could be found using GIS. A land-use trajectory is the trajectory of a certain pixel in each of the three images. For example, a trajectory of 2→3→0 means for that pixel the land-use in March was rain-fed Maize (2), then in August, irrigated mixed crop (3) and finally, in October, Bare land (0). This type of trajectory is classified as dynamic, whereas a trajectory of 4→4→4 meaning the land-use is irrigated banana and coffee (4) in March, August, and October, is a static trajectory. Thus, the LULC change trajectories were categorized into dynamic and static land-use trajectories. We only implemented the trajectories from all agricultural land-uses except irrigated banana and coffee and irrigated banana, maize and coffee land-uses which were combined as irrigated banana and coffee land-use. About 74% of the trajectories were static while 26% of the trajectories were dynamic. Figure 3 shows the spatial distribution of static and dynamic land-use trajectories found in the study area. Only agricultural land-use and extensive agriculture LULC such as grazed grassland and shrubland were considered when analysing the seasonal changes (dynamic land-uses) and implemented in the SWAT+ model.

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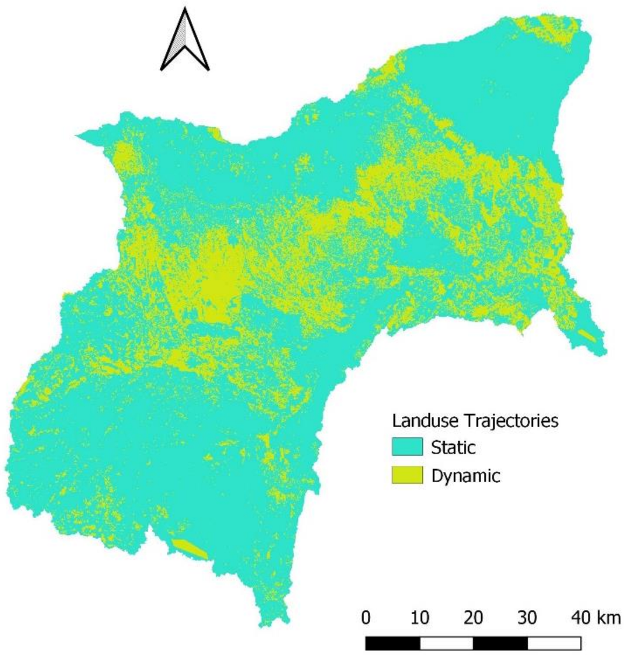

Figure 3. Spatial distribution of dynamic and static land-use trajectories identified in the study area.

2.4. SWAT+ Model

SWAT+ is a physically based, semi-distributed hydrological model and a restructured version of the Soil and Water Assessment Tool (SWAT) designed to face present and future challenges in water resources modelling and management (Bieger et al., 2017). SWAT+ is more flexible in simulating the basin processes such as evapotranspiration, runoff, crop growth, nutrient and sediment transport due to its watershed discretization and configuration. The HRUs are defined as a contiguous area, i.e., a representative field, with an associated user-defined length and width. The actual HRU is calculated based on the DEM, soil and land-use map inputs. Sub basins are delineated during the model construction, but they are divided into water areas and one or more landscape units (LSU) (Bieger et al., 2017).

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Land-use and management representation in SWAT+ can be done through the management file or using decision tables. Decision tables are an accurate yet compact way to model complex rule sets and their corresponding actions (Arnold et al., 2018). Nkwasa et al., (2020) highlighted the greater flexibility provided by decision tables during the representation of agricultural practices in SWAT+. The model gives room for two or more crops growing at the same time by defining the plant community in the specific plant file. The model enables the representation of the reality of cultivated tropical basins.

The ET in the model is estimated at HRU level. There are different methods (Priestley-Taylor, Penman-Monteith and Hargreaves) used to estimate ET in the SWAT+ model. More detailed information can be found in (Abiodun et al., 2017; Neitsch et al., 2002; Alemayehu et al., 2016). Our study adopted the Hargreaves method (Hargreaves and Samani, 1982) to estimate ET due to the limited amount of input dataset such as solar radiation. The method has been tested to be useful in tropical basins such as the Mara basin linking Tanzania and Kenya, rather than using remote sensing climate data which is associated with uncertainties (Alemayehu et al., 2016).

2.5 Land-use Trajectories Implementation in SWAT+

We combine three land-use maps (March, August and October) to obtain the trajectory land-use map. Forty land-use trajectories were produced from the three seasonal land-use maps. Then each trajectory was assigned a placeholder SWAT+ land-use code. For instance, a placeholder SWAT+ land-use code MIXC signifies trajectory CORN→AGRL→AGRL or MIGS signifies CORN →AGRL →BSVG as shown in table 1B of appendix B. Further, the SWAT+ dynamic model was set up with the trajectory land-use map represented with the placeholder SWAT+ land-use codes.

The final model was then implemented by assigning each placeholder SWAT+ land-use codes according to its respective trajectory using the lookup Table 1B, in Appendix B. A python code (Appendix A) was used to first assign trajectories of the placeholder SWAT+ land-use codes, and to create the trajectories' management files such as 'landuse.lum', 'management.sch' and 'hru-data.hru' files. In the 'Landuse.lum' file the trajectories were defined with respect to the plant community. 'Management.sch' file controls the timing of the planting and harvesting of the individual crops in the community. The 'hru-data.hru' file

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links the HRUs to the corresponding land-use management. The irrigation schedules were implemented using decisions tables.

Table 1. An example of a 'management.sch' file input in dynamic SWAT+ model

name	numb_ops[9]	numb_auto[10]	op_typ[11]	Mon[12]	Day[13]	hu_sch[14]	op_data1*	op_data2*	op_data3*
cor_agr_agr_m[1]	8	2							
			irr_toma_soy[2]						
			irr_corn[2]						
			plnt[3]	3	15	0	corn[5]	grain[8]	0
			hvkl[4]	8	15	0	corn	grain	1
			plnt	7	1	0	soyb[6]	grain	2
			plnt	8	20	0	toma	null	3
			hvkl	10	1	0	soyb	grain	4
			hvkl	10	20	0	toma[7]	null	5
			plnt	10	30	0	corn	grain	6
			hvkl	2	28	0	corn	grain	7
agr_agr_agr_m[1]	8	2							
			irr_toma_soy[2]						
			irr_corn[2]						
			plnt	3	15	0	soyb	grain	0
			hvkl	6	30	0	soyb	grain	1
			plnt	7	1	0	soyb	grain	2
			plnt	8	20	0	toma	null	3
			hvkl	10	1	0	soyb	grain	4
			hvkl	10	20	0	toma	null	5
			plnt	10	30	0	corn	grain	6
			hvkl	2	28	0	corn	grain	7

[1] name of the land-use management, [2] points to the irrigation decision tables, [3] planting operation, [4] harvesting operation, [5] rainfed maize, [6] soy bean, [7] tomato, [8] harvest the grain portion of the crop, [9] number of operations, [10] number of auto-operations, [11] operation type, [12] month, [13] day, [14] heat unit schedule, * operations

2.6 Model Configuration

The SWAT+ model was setup using DEM, soil map and land-use map of March 2016 for the static representation scenario and using a trajectory map for the dynamic representation scenario. The ground observations of rainfall and temperature were used (Appendix C, Table 1C). The precipitation stations

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were adjusted manually according to elevation and the potential maximum leaf index was adjusted to correspond to the field measurements of the basin. USDA Soil Conservation Service (SCS) curve number was used to estimate surface runoff and first order markov chain for rainfall distribution and muskingum channel routing.

For the static SWAT+ model, 23 sub-basins, 171 land scape units and 6086hru were generated with 14 land-use classes, while for the dynamic SWAT+ model, 23 sub-basins, 171 land scape units and 9333hru were generated with 40 land use classes representing the 40 different trajectories. The difference in the number of HRUs is related to the higher number of land-use classes in the dynamic land-use mapping.

2.7 Model Evaluation

Both the static and dynamic SWAT+ models were compared on how they simulate the water balance and evapotranspiration estimations as the focus of this study is to estimate the land use fluxes to estimate blue and green water consumption. The ET from both static and dynamic SWAT+ representation scenarios at basin level were compared with the remote sensing ET. The remote sensing ET is an ensemble ET product from six existing global scale ET products (IHE Delft, 2020). The product was evaluated for the study area by comparing the basin water balance at three gauged stations; Karangai, Kikuletwa Power station and Tanzania Plantation Company (TPC) over a period of six years (2008-2013). The comparison of ET calculated using the water balance and remote sensing showed good agreement (NSE= 0.77) for Kikuletwa Power station which covered 86% of the total basin area (Msigwa et al., 2019). Statistical metrices such as Nash-Sutcliffe efficiency (NSE), Root Mean Square Error (RMSE), Percent Bias (PBIAS) and adjusted R squared (R^2) were used to evaluate the both monthly ET from static and dynamic SWAT+ against the remote sensing ET. NSE is a normalized statistic that determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information") (Nash and Sutcliffe, 1970). NSE is computed as shown in Eq. (1):

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{mean})^2}\right] \quad (1)$$

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RMSE is one of the commonly used error index statistics in many models (Kiptala et al., 2014; Jia et al., 2012; Yang et al., 2016; Miralles et al., 2011). RMSE is computed as shown in Eq. (2):

$$RMSE = \left[\sqrt{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}\right] \qquad (2)$$

PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed data (Gupta et al., 1999). The ideal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias (Gupta et al., 1999). PBIAS is calculated with Eq. (3):

$$PBIAS = \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)}{\sum_{i=1}^{n}(Y_i^{obs})} * 100\right] \qquad (3)$$

R^2 describes the degree of collinearity between simulated and measured data. It describes the proportion of the variance in measured data explained by the model. R^2 ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable (Santhi et al., 2001). For more details of statistical matrices, see Moriasi et al., (2007).

2.8 Estimating blue and green ET

The blue ET is a portion of crop evapotranspiration after application of irrigation. The blue ET in this study was estimated as a difference between ET under irrigation and ET without irrigation (Liu and Yang, 2010). The SWAT+ dynamic land-use implementation was run without irrigation and then later irrigation was applied. The green ET is the actual evapotranspiration from precipitation which can be kept in unsaturated soil and absorbed by plants and is then returned to the atmosphere via evapotranspiration. In this study, only the portion of blue water consumed from irrigation was considered and not all the blue water resources like other studies (Xie et al., 2020).

The SWAT+ model was run first assuming that no irrigation was carried out. The computed ET is called ET_{green}. Then the SWAT+ model was run again with irrigation being implemented and the ET computed

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is called ET_{total} as explained in the two scenarios below. ET_{blue} is computed by the difference of ET_{total} from the run with irrigation implantation and ET_{green} "Eq. (4)".

The two scenarios to estimate blue ET

1. The seasonal dynamic SWAT+ is carried out by assuming the soil does not receive any irrigation water. The evapotranspiration computed using this first run is referred to as ET_{green}
2. The seasonal dynamic SWAT+ is carried out by assuming the soil receives sufficient irrigation water. The evapotranspiration computed using this second run is referred to as ET_{total}

Hence, ET_{blue} is computed from the "Eq. (4)" below

$$ET_{blue} = ET_{total} - ET_{green} \qquad (4)$$

It should be noted that the trajectory implementation involves only two of the agricultural land-uses i.e. rainfed maize and mixed crop with exception of irrigated banana and coffee land-use and irrigated banana, coffee and maize land-use.

3. Results

3.1 Comparison of Simulated basin ET from Remote Sensing

Figure 4 shows the average monthly ET at basin scale of Kikuletwa for the two model scenarios of SWAT+ and that from remote sensing. The dynamic SWAT+ model shows higher ET (by 20mm/month) matching remote sensing pattern in the dry seasons (July to October) than the static SWAT+ model implementation. This shows that there are agricultural activities occurring in the dry seasons. In the dynamic SWAT+ model, we implemented irrigation during dry seasons on the growing crops, which led to an increase in ET.

The statistical analysis (Table 2) shows that both the SWAT+ simulations have a correlation (R^2) of above 0.5, when compared with remote sensing monthly ET. However, the monthly average ET value for the dynamic land-use scenario is closer to the remote sensing ET, especially during the dry months from July to November where we implement more than one cropping season.

Unlike the commonly used static land-use scenario where only one cropping season was implemented per year, the monthly ET for the dynamic SWAT+ model implementation shows acceptable PBIAS of 13% whereas, the static SWAT+ model shows higher PBIAS of 30%. Moreover, the dynamic SWAT+ model shows a good NSE of 0.4 while the static SWAT+ shows very low performance with an NSE of -0.46.

Table 3 shows the water balance component for the two scenarios. The notable difference is seen in ET increase (24%) and decrease in other water balance components (lateral flow; 27%, percolation; 42%, surface runoff; 32%). The mass balance in percentage for the static SWAT+ model is higher (1.8%) than the dynamic SWAT+ model (0.5%). The most pronounced differences are found when comparing the dynamic land-use representation on basin scale and the commonly used static land-use approach with remote sensing. Figure 5 shows the spatial distribution of ET from remote sensing, dynamic land-use and static land-use representation.

The average basin ET is 461mm/y, 573mm/y and 642 mm/y for the static SWAT+ model, dynamic SWAT+ model, and remote sensing, respectively. Generally, all the simulated ET from SWAT+ shows lower annual average ET than remote sensing ET. However, the ET from static land-use representation shows a higher difference of 181mm/y whereas with the use of dynamic land-use the difference in ET is only 69mm/y. Spatial distribution of ET from the SWAT+ models is different from remote sensing. However, visually, the spatial distribution of ET from the dynamic land-use scenario is closer and shows similar patches to remote sensing than the ET from the static land-use scenario (Figure 5).

The differences in ET spatial distribution (Figure 5) are vivid mostly in the trajectory implemented areas in the lowlands see Figure 3. However, the pattern of ET in SWAT+ is also influenced by the rainfall pattern. Likewise, the changes seen in the high land areas of irrigated banana and coffee and the forested areas might be due to the increase in the number of HRUs in the dynamic SWAT+ model that contributed to the more accurate results.

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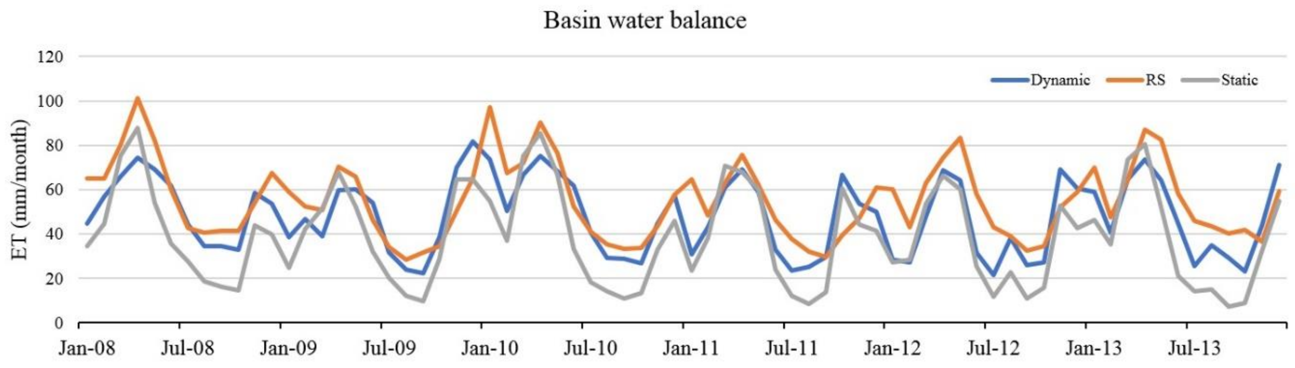

Figure 4. Average monthly ET for basin-scale summarized from remote sensing, dynamic land-use scenario and static land-use scenario.

Table 2. Statistical analysis of ET comparison of SWAT scenarios from Remote sensing

Statistic Parameter	Static SWAT+	Dynamic SWAT+
PBIAS	30%	13%
Nash-Sutcliffe efficiency (NSE)	-0.46	0.4
Adjusted R Square	0.6	0.6
RMSE (mm/month)	20.8	13.3

Table 3. Comparison of water balance component for the basin level

Water balance component (mm)	Static	Dynamic
Precipitation	814	814
Irrigation	0	8.25
Evapotranspiration	461	573
Lateral flow	139	101
Surface runoff	207	140
Percolation	21.7	12.6
%mass balance	1.8	0.53

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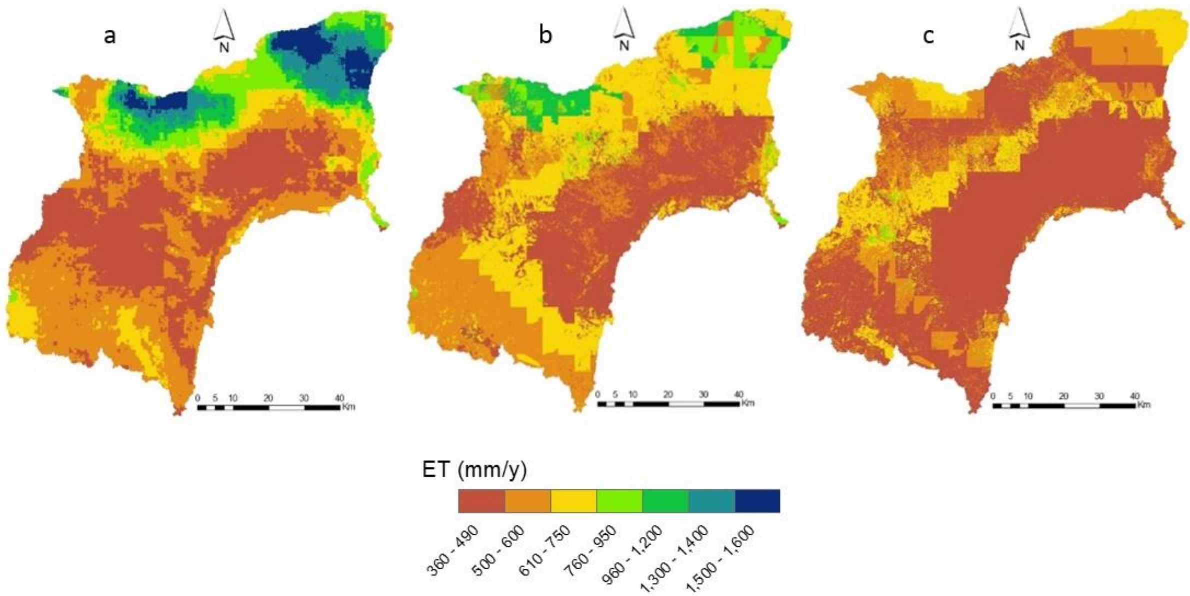

305 **Figure 5**. Spatial distribution of ET from a) Remote sensing b) dymanic land-use scenario and c) static land-use scenario.

3.2 Blue and Green ET

Figure 6 shows the trends of blue and green ET in the Kikuletwa basin for annual (Figure 6) and from 2008 to 2013. The implemented blue and green ET were mainly for irrigated mixed crop land-use due to implementation of trajectories. The annual average blue ET for irrigated mixed crops is 138mm which accounts for 25.5% of the annual average total ET and the annual average green ET is 402mm which accounts for 74.5% of the annual average total ET.

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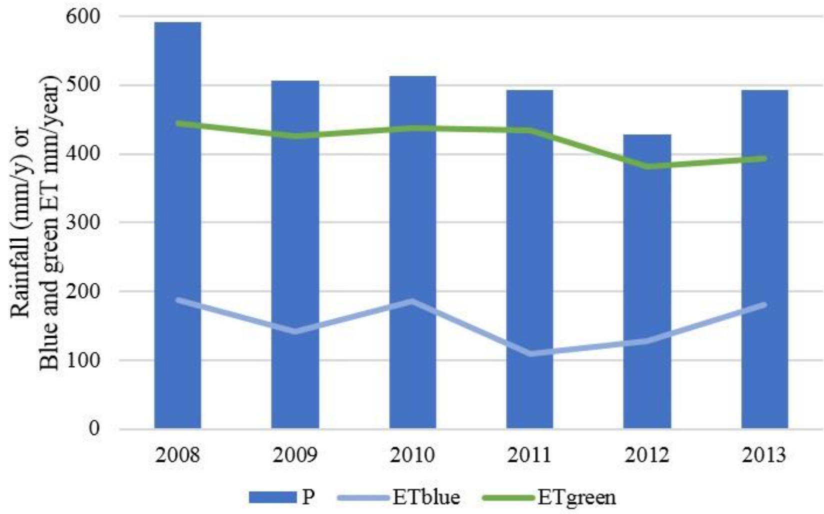


Figure 6. The annual variation of blue and green ET for 2008–2013.

315 Figure 7 shows that the spatial distribution of blue ET for agricultural areas in the Kikuletwa basin for implemented trajectories such as rainfed maize to tomato to irrigated maize. See Appendix 2, Table 2. The blue water is calculated from the irrigated implemented trajectories that mainly include irrigated mixed crops (soybeans, tomato and irrigated maize). Figure 7 shows that more than half of the total area consumes less than 200mm of blue ET. The higher blue ET is seen in the lower right corner where the
320 irrigated sugarcane plantation is found.

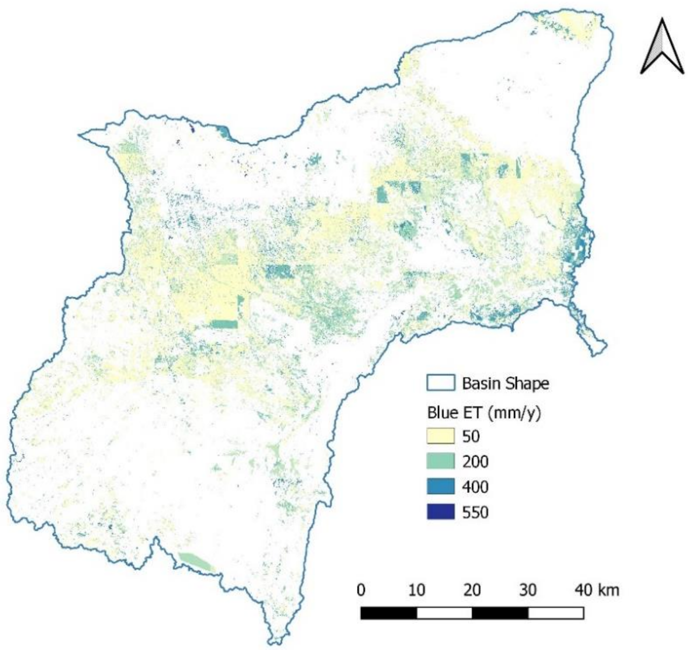
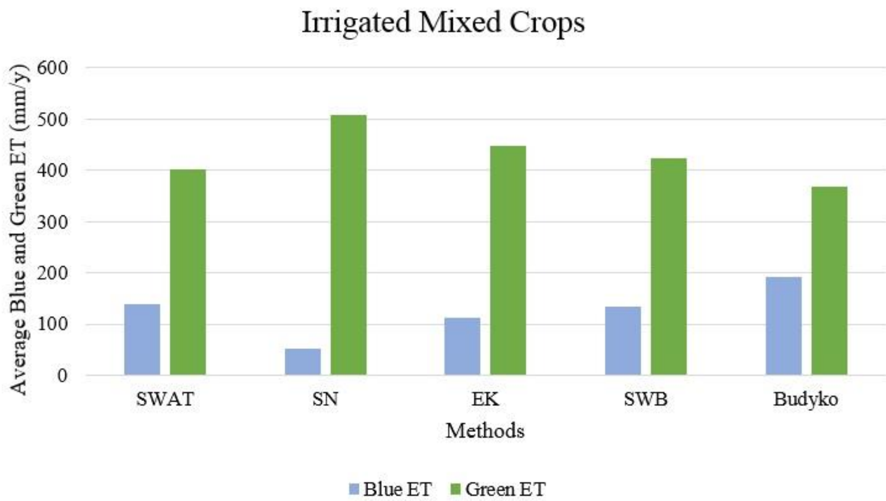


Figure 7. Spatial distribution of Blue ET for the implemented trajectories of rainfed and irrigated mixed crops land-use.

Figure 8 shows the comparison of average blue and green ET from four methods (Msigwa et al 2021
325 forthcoming) with dynamic SWAT+. The value of both blue and green ET is closer to two methods, EK (van Eekelen) and SWB (Soil Water Balance) methods, which were indicated to have realistic values of blue and green ET. Van Eekelen et al., (2015) is the method that analysed P and ET and applied an effective rainfall factor since not all rainfall will infiltrate and be stored in the unsaturated zone to be available for uptake by plants. Both ground data and remote sensing data could be used for data analysis-
330 based approaches on an annual basis. The SWB model is a pixel by pixel vertical soil water balance model that splits green and blue ET by tracking of soil moisture balance and determining if the ET is satisfied only from rainfall or stored in the the soil moisture or additional sources if required (FAO and IHE Delft, 2019).



335 **Figure 8.** Blue and green ET comparison with other four methods from forthcoming publication by Msigwa et al., (2020)

4. Discussion

Some previous studies have represented annual land-use changes in SWAT and found that these have a significant impact on hydrology (Wagner et al., 2016, 2019; Woldesenbet et al., 2017). However, none of these studies has represented the seasonal dynamics of land use within a single year. Nkwasa et al., (2020) incorporated the seasonal land-use dynamic in SWAT and SWAT+ and found that models led to an improved vegetation simulation. This study did not show how the seasonal land-use dynamic improved water balance component such as ET. Our study has compared a common default modelling approach where a static land-use map is used together with its management practices and a seasonal dynamic land-use representation where more than one cropping cycle is represented in a year. The spatial and temporal ET estimates from two model setups were compared with remote sensing ET. An increase of 112mm/y of the ET is seen when seasonal dynamic land-use is implemented to match the remote sensing ET as compared to when a static land-use map is used.

A remarkable difference is seen in the spatial distribution of ET from static and dynamic land-use SWAT+ representation. The dynamic land-use SWAT+ visually is similar to a remote sensing map compared to

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the static land-use SWAT+. This is because of the added management practices such as irrigation in the dry seasons, unlike the default SWAT+ where there were no activities in the dry seasons.

Further, the ET estimates from the dynamic SWAT+ model were used to estimate blue and green ET. The blue and green ET estimates from SWAT+ for the mixed crop land-use show no significant difference in the values from the two methods (EK and SWB) assessed in the upcoming paper by Msigwa et al., (2021).

These findings demonstrate the importance of the representation of seasonal land-use dynamic in modelling hydrological models when quantifying blue and green water consumption. Normally, most models use NDVI to represent seasonal changes (Amri et al., 2011; Ferreira et al., 2003), whereas the use of dynamic land-use leads to improved accuracy of seasonal simulations of the water uses (Nkwasa et al., 2020). Seasonal land-use maps can add information on management practices of changes in temporal crop rotation and irrigation water use at a spatial scale. However, to account for accurate seasonality of land-use, more than 3 maps within a year should be represented, ideally 12 maps each year. This would enable a more complete understanding of the agricultural land-use classes and minimize errors in the trajectory analysis.

The Landsat 8 images used in this study to map seasonal land-use dynamics did not have a revisit time (16-day) that is small enough to acquire an adequate number of monthly images to represent the year. More products are now becoming available (Sentinel-2, 5-day revisit time) that have a higher temporal resolution, which would aid in the collection of more cloud free images to represent seasonality within the year.

Although it appears important to include seasonal land use dynamic, one may claim that the annual land-use implementation is enough when studying the effect of land use in hydrology. Our study shows a significant impact of the representation of seasonal land-use in the SWAT+ model by reducing the errors in water consumption estimations.

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5. Conclusion

Understanding of the spatial-temporal variability of agricultural water consumption in terms of blue water, requires accurate estimates of ET. This study has demonstrated the importance of incorporating seasonal land-use dynamic to improve simulated ET for further blue and green ET estimates in SWAT+. Although the static representation gives equal reasonably good R^2 results of more than 0.5, we found out that the RMSE for the static model result is significant higher compared to the RMSE of the dynamic seasonal model result by about 112 mm per year. Moreover, the ET from the dynamic SWAT+ model gave low PBIAS of 13% and an NSE of 0.4 compared to the ET from static SWAT+ that gives higher PBIAS (20.8%) and a very low NSE of -0.46. The study showed that a dynamic representation in the SWAT+ model gave a closer comparison to remote sensing ET compared to the default model with a static land-use representation. The maps with calculated blue water use from the dynamic SWAT+ model correspond to the known irrigated area and the calculated blue water amount is in line with previous studies. It is concluded that the representation of season land use dynamics is essential to correctly simulate the agricultural (blue and green) water consumption. Also, for land use change studies, it is important to correctly represent the land use dynamics.

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Appendices

Appendix A. Make Management Script

```
import sys
from PIL import Image
import numpy as np

def open_tif_as_array(tif_file):
    im = Image.open(tif_file)
    imarray = np.array(im)
    return imarray


def empty_line():
    print("")

def write_to(filename, text_to_write, report = False):
    '''
    a function to write to file
    '''
    g = open(filename, 'w')
    try:
        g.write(text_to_write)
        if report:
            print('\n\t> file saved to ' + filename)
    except:
        print("\t> error writing to {0}, make sure the file is not open in another program"
.format(
            filename))
        response = input("\t> continue? (Y/N): ")
        if response == "N" or response == "n":
            sys.exit()
    g.close

def show_progress(count, end_val, string_before = "percent complete", string_after = "", ba
r_length = 30):
    percent = float(count) / end_val
    hashes = "#" * int(round(percent * bar_length))
    spaces = '_' * (bar_length - len(hashes))
```

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```
    sys.stdout.write("\r{str_b} [{bar}] {pct}% {str_after}\t\t".format(
        str_b = string_before,
        bar = hashes + spaces,
        pct = '{0:.2f}'.format(percent * 100),
        str_after = string_after))
    sys.stdout.flush()


def read_from(filename):
    '''
    a function to read ascii files
    '''
    try:
        g = open(filename, 'r')
    except:
        print("\t> error reading {0}, make sure the file exists".format(filename))
        return
    file_text = g.readlines()
    g.close
    return file_text

class schedule_data:
    def __init__(self, crop_name):
        self.crop_name = crop_name
        self.oct_plant = ""
        self.oct_harvest = ""
        self.aug_plant = ""
        self.aug_harvest = ""
        self.mar_plant = ""
        self.mar_harvest = ""

base_txt = "C:/Users/james/Desktop/root/anna/new/new_swat_plus_model/kikuletwa/Scenarios/De
fault/TxtInOut"
inputs_path = "trajectory_files"

# read trajectory data
trajectories = open_tif_as_array("{base}/{fn}".format(base = inputs_path, fn = "trajectory_
map_thres.tif"))
legend_raw = read_from("{base}/{fn}".format(base = inputs_path, fn = "trajectory_lookup_fin
al.csv"))
dates_raw = read_from("{base}/{fn}".format(base = inputs_path, fn = "crop_plant_harvest.csv
"))

landuse_lum_raw = """landuse.lum: created for trajectories
name                         cal_group          plnt_com               mgt                 cn
2          cons_prac            urban             urb_ro            ov_mann                tile
               sep                 vfs                grww              bmp
"""
plant_ini_raw = """plant.ini: created for trajectories
```

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```
pcom_name          plt_cnt rot_yr_ini  plt_name  lc_status      lai_init       bm_init
 phu_init      plnt_pop      yrs_init      rsd_init
"""

management_raw = """management.sch: created for trajectories
name                       numb_ops  numb_auto           op_typ       mon       day
 hu_sch          op_data1          op_data2      op_data3
"""

landuse_lum = landuse_lum_raw
plant_ini = plant_ini_raw

trajectories_dictionary = {}
# trajectory_hru_lum_dict = {}
crop_schedule_dictionary = {}
month_dictionary = {'':"None", "Jan": "1", "Feb": "2", "Mar": "3", "Apr": "4", "May": "5",
"Jun": "6", "Jul": "7", "Aug": "8", "Sep": "9", "Oct": "10", "Nov": "11", "Dec": "12"}

for line in dates_raw[1:]:
    parts = line.split(",")
    crop_schedule_dictionary[parts[0].lower()] = schedule_data(parts[0])
    crop_schedule_dictionary[parts[0].lower()].oct_plant = "{0}".format(parts[5]).strip("\n
")
    crop_schedule_dictionary[parts[0].lower()].oct_harvest = "{0}".format(parts[6]).strip("
\n")
    crop_schedule_dictionary[parts[0].lower()].aug_plant = "{0}".format(parts[3]).strip("\n
")
    crop_schedule_dictionary[parts[0].lower()].aug_harvest = "{0}".format(parts[4]).strip("
\n")
    crop_schedule_dictionary[parts[0].lower()].mar_plant = "{0}".format(parts[1]).strip("\n
")
    crop_schedule_dictionary[parts[0].lower()].mar_harvest = "{0}".format(parts[2]).strip("
\n")

for line in legend_raw[1:]:
    trajectories_dictionary[line.split(",")[1].lower()] = line.split(",")[2].strip("\n").lo
wer()

growing_list = ["FRST", "BANA", "SHRB", "SUGC"]

for crop_name in trajectories_dictionary:
    # create lum
    parts = trajectories_dictionary[crop_name].split("-")
    com_mgt_prefix = "{0}_{1}_{2}".format(parts[0][:3], parts[1][:3], parts[2][:3])
    com_mgt_prefix = com_mgt_prefix.lower()
    if True: #not ((parts[0] == parts[1]) and (parts[0] == parts[2])):
        line_ = "{lum_t}                   null        {plt_comm}  {mgt}       rc_strow_g
       cross_slope             null              null    convtill_nores              null
             null              null              null              null  \n".format(
```

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```
            lum_t = trajectories_dictionary[crop_name].lower().replace("-", "_"),
            plt_comm = "{0}_c".format(com_mgt_prefix),
            mgt = "{0}_m".format(com_mgt_prefix),
        )
        landuse_lum += line_
        # print(trajectories_dictionary[crop_name])

    # create comm
    comm__ = "{comm_n}_c            //no         1  \n".format(comm_n = com_mgt_prefix)
    plt_count = 0
    done = []
    for plt in parts:
        if plt == "AGRL":
            for agrl_crop in ["TOMA","CORN","SOYB"]:
                if not agrl_crop.lower() in done:
                    if plt in growing_list:
                        grow_ini = "y"
                    else:
                        grow_ini = "n"
                    plt_count += 1
                    comm__ += "                                        {agrl_crop}
    {growing}       0.00000       0.00000       0.00000       0.00000       0.00000   10000
.00000  \n".format(agrl_crop = agrl_crop.lower(), growing = grow_ini)
                    done.append(agrl_crop)

            continue

        if not plt.lower() in done:
            if plt in growing_list:
                grow_ini = "y"
            else:
                 grow_ini = "n"
            plt_count += 1
            comm__  += "                                        {plt_l}              {growing
}       0.00000       0.00000       0.00000       0.00000       0.00000   10000.00000  \n".
format(plt_l = plt.lower(), growing = grow_ini)
            done.append(plt)

    comm__ = comm__.replace("//no", str(plt_count))
    plant_ini += comm__

    # create_management
    schedule_name = "{0}_m".format(com_mgt_prefix)
    number_of_manual_ops = 0
    number_of_auto_ops = 0

    done_2 = []
```

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```
    management_section_head = "{mgt_name}                        {number_manual}
 {number_auto}  "
    management_section_body = ""
    counter_mgt = 0

    for plant_index in range(0, 3):

        date_day_plant = None
        date_mnt_plant = None

        date_day_harvest = None
        date_mnt_harvest = None
        agrl_list = []

        if plant_index == 0:
            agrl_list = ["soyb"]

        if plant_index == 1:
            agrl_list = ["soyb", "toma"]

        if plant_index == 2:
            agrl_list = ["corn"]


        if parts[plant_index] == "agrl":
            for agrl_crop_mgt in agrl_list:
                if plant_index == 0:
                    date_day_plant = crop_schedule_dictionary[agrl_crop_mgt].mar_plant.spli
t("-")[0]
                    date_mnt_plant = crop_schedule_dictionary[agrl_crop_mgt].mar_plant.spli
t("-")[1]
                if plant_index == 1:
                    date_day_plant = crop_schedule_dictionary[agrl_crop_mgt].aug_plant.spli
t("-")[0]
                    date_mnt_plant = crop_schedule_dictionary[agrl_crop_mgt].aug_plant.spli
t("-")[1]
                if plant_index == 2:
                    date_day_plant = crop_schedule_dictionary[agrl_crop_mgt].oct_plant.spli
t("-")[0]
                    date_mnt_plant = crop_schedule_dictionary[agrl_crop_mgt].oct_plant.spli
t("-")[1]

                management_body_line = "
         {activity}{mnt}{day}       0.00000            {crp}             null       {ord
er}.00000  ".format(
                    activity = "plnt",
                    mnt = month_dictionary[date_mnt_plant].strip(" ").rjust(10),
                    day = date_day_plant.rjust(10),
                    crp = agrl_crop_mgt.lower(),
```

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```
                    order = counter_mgt,
                )
                management_section_body += "{0}\n".format(management_body_line)
                counter_mgt += 1
            for agrl_crop_mgt in agrl_list:
                if plant_index == 0:
                    date_day_harvest = crop_schedule_dictionary[agrl_crop_mgt].mar_harvest.
split("-")[0]
                    date_mnt_harvest = crop_schedule_dictionary[agrl_crop_mgt].mar_harvest.
split("-")[1]
                if plant_index == 1:
                    date_day_harvest = crop_schedule_dictionary[agrl_crop_mgt].aug_harvest.
split("-")[0]
                    date_mnt_harvest = crop_schedule_dictionary[agrl_crop_mgt].aug_harvest.
split("-")[1]
                if plant_index == 2:
                    date_day_harvest = crop_schedule_dictionary[agrl_crop_mgt].oct_harvest.
split("-")[0]
                    date_mnt_harvest = crop_schedule_dictionary[agrl_crop_mgt].oct_harvest.
split("-")[1]

                management_body_line = "
         {activity}{mnt}{day}       0.00000             {crp}              null       {ord
er}.00000  ".format(
                    activity = "hvkl",
                    mnt = month_dictionary[date_mnt_harvest].strip(" ").rjust(10),
                    day = date_day_harvest.rjust(10),
                    crp = agrl_crop_mgt.lower(),
                    order = counter_mgt,
                )
                management_section_body += "{0}\n".format(management_body_line)
                counter_mgt += 1


        elif parts[plant_index] in crop_schedule_dictionary:
            if not parts[plant_index] == "past":

                if plant_index == 0:
                    date_day_plant = crop_schedule_dictionary[parts[plant_index]].mar_plant
.split("-")[0]
                    date_mnt_plant = crop_schedule_dictionary[parts[plant_index]].mar_plant
.split("-")[1]
                if plant_index == 1:
                    date_day_plant = crop_schedule_dictionary[parts[plant_index]].aug_plant
.split("-")[0]
                    date_mnt_plant = crop_schedule_dictionary[parts[plant_index]].aug_plant
.split("-")[1]
                if plant_index == 2:
```

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```
                    date_day_plant = crop_schedule_dictionary[parts[plant_index]].oct_plant
.split("-")[0]
                    date_mnt_plant = crop_schedule_dictionary[parts[plant_index]].oct_plant
.split("-")[1]

                management_body_line = "
         {activity}{mnt}{day}       0.00000             {crp}                 null       {ord
er}.00000  ".format(
                    activity = "plnt",
                    mnt = month_dictionary[date_mnt_plant].strip(" ").rjust(10),
                    day = date_day_plant.rjust(10),
                    crp = parts[plant_index].lower(),
                    order = counter_mgt,
                )
                management_section_body += "{0}\n".format(management_body_line)
                counter_mgt += 1

                if plant_index == 0:
                    date_day_harvest = crop_schedule_dictionary[parts[plant_index]].mar_har
vest.split("-")[0]
                    date_mnt_harvest = crop_schedule_dictionary[parts[plant_index]].mar_har
vest.split("-")[1]
                if plant_index == 1:
                    date_day_harvest = crop_schedule_dictionary[parts[plant_index]].aug_har
vest.split("-")[0]
                    date_mnt_harvest = crop_schedule_dictionary[parts[plant_index]].aug_har
vest.split("-")[1]
                if plant_index == 2:
                    date_day_harvest = crop_schedule_dictionary[parts[plant_index]].oct_har
vest.split("-")[0]
                    date_mnt_harvest = crop_schedule_dictionary[parts[plant_index]].oct_har
vest.split("-")[1]

                management_body_line = "
         {activity}{mnt}{day}       0.00000             {crp}                 null       {ord
er}.00000  ".format(
                    activity = "hvkl",
                    mnt = month_dictionary[date_mnt_harvest].strip(" ").rjust(10),
                    day = date_day_harvest.rjust(10),
                    crp = parts[plant_index].lower(),
                    order = counter_mgt,
                )
                management_section_body += "{0}\n".format(management_body_line)
                counter_mgt += 1

    if counter_mgt == 0:
        continue
```

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```
    management_raw += management_section_head.format(mgt_name = schedule_name, number_manual = counter_mgt, number_auto = number_of_auto_ops) + "\n" +  management_section_body

# fix hrus based on dictionary

hru_data_string = """hru-data.hru: for trajectories
id   name                                   topo             hydro              soil
       lu_mgt   soil_plant_init          surf_stor                snow              field
"""

hru_data_hru_raw = read_from("{base}/{fn}".format(base = base_txt, fn = "hru-data.hru"))

for line in hru_data_hru_raw[2:]:
    for_part = line
    for i in range(0, 20):
        for_part = for_part.replace("  ", " ")
    parts = for_part.split(" ")
    # print(parts[6].split("_")[0])
    hru_data_string += line.replace(parts[6], trajectories_dictionary[parts[6].split("_")[0]].lower().replace("-", "_"))

write_to("{base}/{fn}".format(base = 'model_files\Scenarios\Default\TxtInOut', fn = "landuse.lum"), landuse_lum)
write_to("{base}/{fn}".format(base = 'model_files\Scenarios\Default\TxtInOut', fn = "management.sch"), management_raw)
write_to("{base}/{fn}".format(base = 'model_files\Scenarios\Default\TxtInOut', fn = "plant.ini"), plant_ini)
write_to("{base}/{fn}".format(base = 'model_files\Scenarios\Default\TxtInOut', fn = "hru-data.hru"), hru_data_string)
```

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Appendix B. Trajectories Description

Table 1B. Trajectories for each fake land-use code use for dynamic SWAT+ implementation.

Map_id	Code	Trajectory
1	TUWO	TUWO-TUWO-TUWO
2	GRAS	GRAS-GRAS-GRAS
6	BSVG	BSVG-BSVG-BSVG
11	FRST	FRST-FRST-FRST
78	BANA	BANA-BANA-BANA
110	hmel	SHRB-SHRB-SHRB
121	indn	CORN-BSVG-BSVG
146	lett	CORN-BSVG-PAST
167	PAST	PAST-PAST-PAST
182	SUGC	SUGC-SUGC-SUGC
204	aspn	FRST-BSVG-FRST
224	lima	CORN-PAST-PAST
225	mapl	CORN-PAST-BSVG
243	mesq	CORN-AGRL-PAST
248	migs	CORN-AGRL-BSVG
249	mint	AGRL-AGRL-BSVG
254	mixc	CORN-AGRL-AGRL
262	AGRL	AGRL-AGRL-AGRL

Table 2B. Dynamic agricultural land-use trajectory and their crop or vegetation cover meaning

ID	Trajectory	Crop/vegetation cover Meaning
1	CORN-PAST-PAST	rainfed maize-grass-grass
2	CORN-PAST-BSVG	rainfed maize-grass- sparse vegetation
3	CORN-AGRL-PAST	rainfed maize- tomato-grass
4	CORN-AGRL-BSVG	rainfed maize-tomato-sparse vegetation
5	AGRL-AGRL-BSVG	Beans-tomato-sparse vegetation
6	CORN-AGRL-AGRL	rainfed maize-tomato-irrigated maize
7	CORN-PAST-AGRL	Rainfed maize-grass-irrigated maize

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Appendix C. Data used in this study

Table 1C. Summary of the different data used in the study with description and sources

Data Type	Description	Source/ reference
Climate	Ten station data of rainfall and four stations of maximum/minimum temperature	Tanzania Meteorological Agency (TMA) and Pangani Basin Water Office (PBWO)
Digital Elevation Model (DEM)	Elevation data from at 90m resolution	United States Geological Survey (USGS) website
Seasonal land use maps	Seasonal land use maps at 30m	(Msigwa et al., 2019)
Soil	Africa Soil Information System (AFSIS) at 250m resolution	(Hengl et al., 2015)
Remotely sensed based Actual ET	Ensemble ET from six remote sensing products	(IHE Delft, 2020)
Land management data	Planting dates, harvesting dates and irrigation application dates and frequency	Farmers interview