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Evaluating the grassland NPP dynamics in response to climate change in Tanzania

Azin Zarei *, Abel Chemura, Stephanie Gleixner, Holger Hoff

Potsdam Institute for Climate Impact Research (PIK), Potsdam, Germany

A R T I C L E I N F O

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A B S T R A C T

Livestock is important for livelihoods of millions of people across the world and yet climate change risk and impacts assessments are predominantly on cropping systems. Climate change has significant impacts on Net Primary Production (NPP) which is a grassland dynamics indicator. This study aimed to analyze the spatio-temporal changes of NPP under climate scenario RCP2.6 and RCP8.5 in the grassland of Tanzania by 2050 and link this to potential for key livestock species. To this end, a regression model to estimate NPP was developed based on temperature (T), precipitation (P) and evapotranspiration (ET) during the period 2001–2019. NPP fluctuation maps under future scenarios were produced as difference maps of the current (2009–2019) and future (2050). The vulnerable areas whose NPP is mostly likely to get affected by climate change in 2050 were identified. The number of livestock units in grasslands was estimated according to NPP in grasslands of Tanzania at the Provincial levels. The results indicate the mean temperature and evapotranspiration are projected to increase under both emission scenarios while precipitation will decrease. NPP is significantly positively correlated with T_{max} and ET and projected increases in these variables will be beneficial to NPP under climate change. Increases of 17% in 2050 under RCP8.5 scenario are projected, with the southern parts of the country projected to have the largest increase in NPP. The southwest areas showed a decreasing trend in mean NPP of 27.95% (RCP2.6) and 13.43% (RCP8.5). The highest decrease would occur in the RCP2.6 scenario in Ruvuma Province, by contrast, the mean NPP value in the western, eastern, and central parts would increase in 2050 under both Scenarios, the largest increase would observe in Kilimanjaro, Dar-Es-Salaam and Dodoma Provinces. It was found that the number of grazing livestock such as cattle, sheep, and goats will increase in the Tanzania grasslands under both climate scenarios. As the grassland ecosystems under intensive exploitation are fragile ecosystems, a combination of improving grassland productivity and grassland conservation under environmental pressures such as climate change should be considered for sustainable grassland management.

1. Introduction

Grassland ecosystems as providers of vegetation resource and livestock products cover more than 30% of the earth's surface and about 60% of Africa (Parton et al., 2010). Grasslands are sensitive to environmental change (FAO, 2005; Zhang et al., 2018), on the other side, fire, drought, overgrazing has also contributed to the degradation of grassland (IPCC, 2019). So, it causes difficulties to assess the pure effects of climate change on grassland productivity (Mihretab et al., 2020; Su et al., 2020). As such, the interplay between climate change and grassland ecosystems is considered one of the main issues in global research. Global warming in the future can affect fluctuation in Net Primary Production (Piao et al., 2005). On the other hand, changes in vegetation cover and NPP can, in turn, affect global warming through biogeophysical processes (Wang et al., 2002). Many grasslands ecosystems in different aspects such as phenology, productivity, NPP and plant growth (Gang et al., 2015) are affected by climate change (Su et al., 2020). Net Primary Production (NPP) in grasslands is a substantial indicator of biomass dynamics (Scurlock et al., 2002), fluctuation based on grazing, management, climate change, and human interference such as land-use change (Dangal et al., 2016). So estimation of grassland NPP under climate change is important for sustainable management strategies, available forage for livestock, and the carbon cycle (Schimel et al., 2001; Dangal et al., 2016). Overall, NPP is an essential variable of the ecosystem that simplifies the conception of climate change impacts on grassland ecosystem productivity. As well as NPP is a substantial

* Corresponding author at: Potsdam Institute for Climate Impact Research (PIK), A56 Telegraphenberg, R018, 14473 Potsdam, Germany.
E-mail address: zarei@pik-potsdam.de (A. Zarei).

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indicator for composition, biodiversity (Schuur, 2003). So, many studies have considered the NPP as an indicator to reflect the climate change impacts on vegetation cover (Yin et al., 2020; Jiang et al., 2020; Teng et al., 2020). Generally, NPP value is estimated in different ways such as earth system model, radiation-based NPP estimates, etc. (Del Grosso et al., 2008; Castanho et al., 2013; Cleveland et al., 2015), while uncertainties, concepts, and logic associated with each method are different. Radiation-based NPP estimates have been extensively used, because of adaptability with the high spatiotemporal resolution satellite images. Nevertheless, there are substantial challenges to use this method, especially in tropical ecosystems. Indeed, these methods rely on remote sensing indices to estimate the absorbed solar radiation by vegetated (i.e., FPAR) (Zhou et al., 2014). Whereas, earth system model estimates of NPP are typically based on climate NPP interactions into the future. Given both methods are based on climate data, and meteorological data is available in some areas just at coarse spatial scales, so probably limiting the spatial resolution of NPP (Samanta et al., 2011). Besides, cloud cover mostly limits ground observation by satellite such as MODIS sensor, so may limit the temporal resolution of remote sensing indices (Zhao and Running, 2011).

Climate change will have widespread consequences for local beneficiaries in Africa, the majority of whom depend on livestock productions and grassland for their livelihood. NPP-fluctuation determination can help to inform the improvement of livestock productivity and adaptation of vegetation cover under the future climate. As such, livestock has directly impacts to food security and livelihoods of more than one billion people (FAO, 2011). Specifically, climate change is predicted to have negative impacts on livestock systems in sub-Saharan Africa (SSA), which has a substantial role in the rural livelihoods (Thornton et al., 2009). The negative impacts of climate change are more severe for people most dependent on livestock and crop production (Battisti and Naylor, 2009). Moreover, the world's population is expected to 9.7 billion by 2050 (UN, 2015). So, the demand for crop and livestock products consequently will be increased (Thornton et al., 2007).

Despite the essential role of livestock to food security of people and interaction of climate change, vegetation, and livestock, consideration to this research field in developing countries such as Tanzania as one of the least developed countries is overlooked. Most of the current research on climate change impacts on ecosystems are based on ecosystem monitoring on a regional or local scale and projected change in vegetation in the future are only modeled minimally (Hickler et al., 2011), while this issue promotes powerful motivation for future studies. So, attention to the likely fluctuation in vegetation and NPP induced by climate change under emission scenarios in the future is essential to fill the gaps and the comparison of present and future NPP fluctuation under climate scenarios to identify vulnerable areas. Considering increasing concerns about negative environmental consequences of the increase in greenhouse gas emission, including extreme events (Easterling et al., 2007), addressing climate change impacts have become necessary in terms of mitigation and adaptation perspective (Vermeulen et al., 2013). This study assesses NPP fluctuation and subsequently the number of livestock, affected by climate change by 2050. Overall, the aims of this study are, i) to develop a relationship between the climate variables such as precipitation, temperature, and evapotranspiration as independent variables and NPP as a dependent variable ii) to assess the Spatio-temporal dynamics of grassland NPP under two climate scenarios (RCP2.6 as a best-case scenario and RCP8.5 as a worst-case scenario) iii) to analyze, the number of livestock based on NPP fluctuation in 2050 iv) to identify the vulnerable areas in Tanzania in terms of NPP and the number of livestock in the future. This study holds considerable potential in providing insights into NPP fluctuation in the grassland of Tanzania under climate change in the next decades.

2. Materials and methods

2.1. Study area

The study was conducted in the grassland of Tanzania (1° to 11° S and 29° to 40° E) covering an area of 191,346 km^2. Tanzania is an East African country with the third-largest livestock population on the African continent (TLMI, 2015). Besides, unique biodiversity and natural resources in Tanzania in terms of ecosystem types and richness of ecological communities lead this country to be considered as one of the fourteen-biodiversity hotspots in the world (United Republic of Tanzania (URT), 2009). Also, Mount Kilimanjaro (5895 m) is located in the northeast of Tanzania is the highest point in Africa. The climate is presented in various types: tropical on the coast, semi-temperate in the mountains, and dry in the plateau areas. The average annual rainfall ranges from 200 to 2000 mm, while most parts of the country receive less than 1000 mm. Due to the migration of the Intertropical Convergence Zone, the regions of Tanzania have different rainfall regimes. While the northern and coastal regions experience two rainy seasons (November-January and March-May), most of Tanzania experiences one long rainy season from October to April.

The most serious environmental difficulties are drought, desertification, soil degradation, land-use change, and deforestation (United Republic of Tanzania (URT), 2009). Around 60% of rural households in Tanzania earn income from livestock activities, earning an average of 22% of total household income from livestock rearing (Covarrubias et al., 2012). The number of different livestock types is shown in Table 1 (Fig. 1).

2.2. Datasets

For setting up the regression model, we used gridded observational and reanalysis climate data. We chose the Climate Hazards Group InfraRed Precipitation with Station data rainfall data (CHIRPS) precipitation dataset at spatially high resolution of 0.05° (~5km) in order to capture the spatial variability of Tanzanian rainfall (Funk et al., 2014). CHIRPS precipitation data is based on a variety of data sources including satellite products and in-situ observations and has been shown to perform well shown to perform well over eastern Africa (Dinku et al., 2018; Muthoni et al., 2019). Temperature data was taken from the latest reanalysis dataset, ERA5, which provides hourly data at 0.25° (~25 km) spatial resolution, by combining a numerical weather model with satellite and in-situ observations (Hersbach et al., 2019). ERA5 temperature data has been shown to have good agreement with station-based temperature data in Tanzania (Gleixner et al., 2020). In consideration of the growing season in Tanzania, the monthly sums for precipitation and monthly means for temperature for the month June have been used for the period 2009 to 2019. This period corresponded to the available NPP data and datasets on animal populations (Fig. 2).

ET_0 is defined as an indicator of surface atmospheric evaporation demand over a reference surface and plays a substantial role in the water cycle. It includes soil water evaporation and plant transpiration, while counts about 90% of the total precipitation in semi-arid and arid lands (Wang et al., 2011). Furthermore, the spatial–temporal of ET_0 completely sensitive to global warming and climate change (Mojid et al., 2015). There are various methods to calculate the ET_0, while the Penman-Monteith (FAO-P-M) method is considered the most appropriate model, in a different range of climate conditions (Croitoru et al., 2013; Yu et al., 2016; Chen et al., 2020). The FAO P-M method could solve the availability problems of climatic variables (Jabloun and Sahli,

Table 1
Number of different livestock types in Tanzania (Covarrubias et al., 2012).

livestock	Cattle	Sheep	Goat	Pig	Chicken
	21,125,254	5,714,978	15,085,149	1,581,400	42,666,548

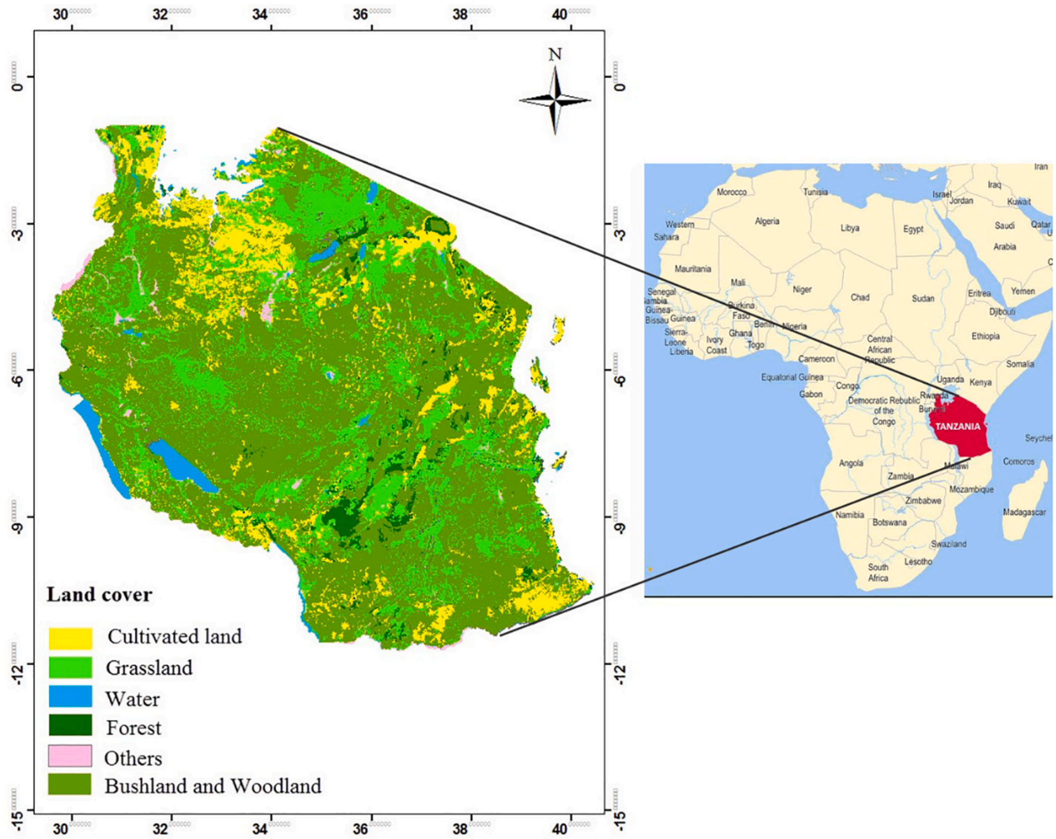

Fig. 1. Map of Tanzania land cover and location in East Africa.

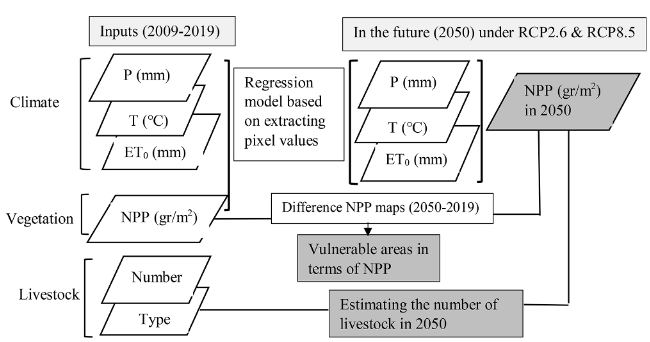

Fig. 2. Flow chart of the research process.

2008), that calculated based on weather data including (mean daily temperature, wind speed at 2 m above ground, humidity), daily incoming solar radiation at the crop surface. ET_0 maps (unit: 1 mm = 10 m^3/ha) which have been prepared according to the FAO P-M method (WaPOR) for the Africa continent are used in this study for the period 2009–2019.

Furthermore, the NPP dataset was used to examine the empirical relationships between NPP as a dependent variable and driving climate variables (precipitation, temperature (max, min and mean), evapotranspiration in June) as independent variables in the grassland of Tanzania. The Food and Agriculture Organization of the United Nations (FAO) provides the NPP maps (unit: gc/m^2) based on satellite imagery and meteorological data such as incoming solar radiation and temperature data (T_{max}, T_{min}) and soil moisture stress (Fig. 3) with a spatial resolution 250 m for Africa and near East countries from January 2009 to the present that were used in this study. The FAO NPP at dekadal time scale is derived from averaged daily input from weather data, solar radiation and dekadal input from fAPAR and soil moisture stress to account for important factors influencing production.

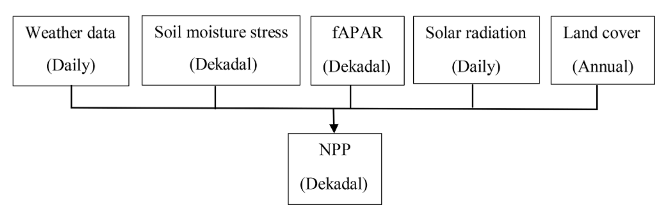

Fig. 3. Net Primary Production in relation to other data components (FAO, 2018).

Primary method to calculate NPP was based on Monteith (1972), which explains NPP in response to solar radiation:

$$NPP = Sc.R_s.\varepsilon_p.fAPAR.\ SM.\varepsilon_{LUE}.\varepsilon_T.\varepsilon_{co2}.\varepsilon_{AR}[\varepsilon_{RES}]$$

where, Sc: scaling factor from dry matter production to NPP; Rs: total short wave incoming radiation (GJT/ha/day); ε_p: fraction of PAR in total short wave (JP/JT); *f*APAR: PAR-fraction absorbed by green vegetation (JPA/JP); SM: soil moisture stress reduction factor; ε_{LUE}: light use efficiency (kgDM/GJPA); ε_T: normalized temperature effect; ε_{co2}: normalized CO_2 fertilization effect; ε_{AR}: fraction kept after autotrophic respiration; ε_{RES}: fraction kept after residual effects. Then, methodologies for estimating NPP were improved within the Copernicus Global Land Component framework which described in detailed by Veroustraete et al., 2002; Eerens et al., 2004. The FAO NPP is downloadable from open-access FAO Wapor database (https://wapor.apps.fao.org/home/WAPOR_2/1). Furthermore, in this study the land cover map was retrieved from http://www.esa-landcover-cci.org with spatial resolution of 300 m.

Eventually, to achieve a consistent spatial resolution for the analysis, the datasets were resampled based on the bilinear interpolation method and interpolation data were unified to 250 m (Chao et al., 2018; Chen et al., 2019; Guan et al., 2020).

2.3. Statistical analysis

The assumption of Fang et al. (2001) and Mohamed et al. (2004) has been adopted in this study, that if the correlation between the coefficients of variation of NPP and climate variables such as T, P, and ET_0 were found significant, the variation in NPP can be attributed to the temporal variability of climate parameters. Correlation coefficient and coefficient form regression are often used to disclose the relationship between NPP and climate variables due to the simplicity of the method (Fensholt et al., 2009). Because of limitations and unreliable results of the linear assumption, methods based on the nonlinear and complicated relations between NPP and climate variables are desired (Zhang et al., 2018). So, the shape (linear or non-linear) of the relationship between the dependent and independent variables was determined based on an analysis of variance by ANOVA test (Cramer and Howitt, 2004). As such, the autocorrelation and amount of multicollinearity was checked by Durbin-Watson and variance-inflating factor (VIF) test respectively. For the next step, the NPP regression equation was developed based on the extracted pixel values of T, P, ET_0, and NPP maps in Tanzania for the period 2009–2019. Then, the accuracy of the model was assessed based on the cross-validation method, such that training (80%) and test (20%) sets were generated from data set by randomly assigned. The following statistical criteria were used to evaluate the accuracy and validation of the prediction the NPP model (Table 2). The equations are as follows:

R^2 shows how close simulated values are to the fitted regression line. RMSE, NRMSE evaluate different aspects of model efficiency (He et al., 2019; Li et al., 2015). RMSE measures the error of predicted values and observed values, while the performance of models with different scales can be compared by NRMSE. Moreover, MSE and MAD were used for error analysis of the model. All statistical analyses were performed using SPSS software.

2.4. Climate projection under climate scenarios

Climate projection from GCMs included monthly average minimum and maximum temperature (℃) and total precipitation (mm) in this study. The projected climate data using the Global Climate Model (GCM) based on HadGEM2-Es (HE) at a spatial resolution of 30-seconds (~1km) in time periods 2050 (average for 2041–2060) were used for two climate scenarios RCP2.6 and RCP8.5 in Tanzania. Indeed, the future projections data was obtained from CMIP5 processed data available on WorldClime data (v.1.7). Notably, HadGEM2 is one of the recommended models used in many projections studies of long-timescale change in climate change variables, ecosystems, etc (Dike et al., 2015; Arsiso et al., 2018; Tindall and Haywood, 2020; Toste et al., 2019; Ahmed et al., 2020; Aziz et al., 2020).

For the estimation of evapotranspiration in the future, the required meteorological dataset for the Penman-Monteith model is not available. Therefore, simple calibrated models of evapotranspiration such as Hargreaves, Thornthwaite method are used instead (Sentelhas et al., 2010; Xystrakis and Matzarakis, 2011). Different forms of the Hargreaves equation, which are a temperature-based estimation, are recommended for calculating reference evapotranspiration and widely used in different studies (Valiantzas, 2018; Shi et al., 2020; Mendes Reis et al., 2019). In this study, the optimization of Hargreaves model was performed by using the generalized reduced gradient method using solver function for Tanzania. Then, the reliability of Hargreaves-adj method was assessed by comparing the simulated Hargreaves-adj with the reference FAO-PM evapotranspiration during 2009–2019.

2.5. Grassland dynamics under climate change

A correction was applied to the ET_0 maps before the pixel data were used as input to develop the regression equation for predictions of NPP values. Based on the implementation of multiple regression models on projected climate variables including P, T, ET_0 as predictors, NPP values were estimated under RCP scenarios (RCP2.6 and RCP8.5) in the future. Therefore grassland dynamic based on NPP was developed as the determined relationship between climate variables and NPP from the previous step. Furthermore, in order to determine the vulnerable grassland regions in terms of NPP to climate change, the NPP maps at present (2009–2019 average) and future (2050 ~ 2041–2060 average) were generated under stringent mitigation scenario (RCP2.6) and very high emission (RCP8.5), then possible NPP variations and vulnerable areas in 2050 was produced based on the difference maps of the current (2019) and future (2050).

In addition, to study the number of livestock units under different climate scenarios, the carrying capacity of grassland was calculated based on the following equation (Arzani 2009) and livestock unit coefficients (LUC) (Table 3). The LUC is a reference unite that simplify the aggregation of livestock from different species/age via the use of special coefficient established on the animal feed requirements (FAO, 2020). Indeed, carrying capacity is the number of livestock units in grassland without depleting resources of vegetation and soil.

$$CC = \frac{ForageSupply \times area}{Foragedemand \times duration}$$

where CC is carrying capacity (AUM) in hectare per month, forage

Table 3
FAO livestock unit coefficients (Sub-Saharan Africa).

	Cattle	Sheep	Goat	Pig	Chicken
Unit	0.8	0.1	0.1	0.2	0.01

Table 2
the statistical indices for model validation.

	Index	Formulate	Model Performance	
MAD	Mean Absolute Deviation	$MAD = \frac{1}{n}\sum_{i=1}^{n}\lvert x_i - m(x)\rvert$	the lower values show a better model	
MSE	Mean Square Error	$MSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}$		
RMSE	Root Mean Square Error	$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}}$		
NRMSE	Normalized Root Mean Square Error	$NRMSE = \frac{RMSE}{\overline{A_t}} \times 100$	Criteria	performance
			≤ 10%	Excellent
			10–20%	Good
			20–30%	Fair
			≥ 30%	Poor
R^2	Coefficient of Determination	$r^2 = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$	≤0.75 (ASHRAE, 2014)	

supply is the total available forage per unit area (g/m^2); area is grassland acres (ha), the duration is grazed period (day), and forage demand refers to forage requirement of an animal unit (AU) per month.

3. Results

3.1. Monitoring of grasslands dynamics

The average grassland NPP in Tanzania was showed from 2009 to 2019 (Fig. 4). The grasslands of Tanzania experienced high productivity in 2018 (7.38 gc/m^2), 2015 (6.76 gc/m^2) and reduction through 2014 (5.57 gc/m^2), from 2009 (5.49 gc/m^2) to 2011 (5.255 gc/m^2). Furthermore, spatio-temporal distribution of NPP is strongly correlated with the spatial distribution of main climate variables including T_{max} (0.934**), P (0.75**) and ET_0 (0.885**). This offers that the combined effects of the main climatic variables are responsible for NPP fluctuation over time (Yili et al., 2014; Wang et al., 2017; Ma et al., 2020). The central regions of Tanzania have less precipitation that causes a lack of water for plant growth. Meanwhile, along with the increase in temperature, evapotranspiration in the central parts of Tanzania intensifies droughts (Slegers 2008). Therefore, T_{max} and P are two important limiting climatic parameters for NPP in areas with low precipitation and high temperature. At the same time, analysis of elevation and NPP patterns show that heights extend in a northeast-southwest direction in Tanzania while in these areas the NPP value is less than other parts. It related to the elevation which reflects the property of vertical zone has the negative impacts on NPP value.

For the next step, to present the relationship between NPP and different predictors, curve fitting regression analysis was proposed specifically for predicting NPP (gr/m^2) as vegetation dynamics indicator in response to climate variables. So the following regression equation was obtained:

$$NPP = -0.833 + (0.123 \times T_{max}) - -\left(0.024 \times ET_0^2\right) + \left(0.006 \times P^2\right) \quad (1)$$

where, ET_0, T_{max}, and P represent evapotranspiration (mm), maximum temperature (℃) and precipitation (mm), respectively. Next, cross validation was performed to evaluate the performance of the statistical model based on the comparison test and train dataset to estimate NPP. The statistical evaluation indicated that the regression model performed well (R = 0.95, R^2 = 0.9, MAD = 0.4, MSE = 0.3, NRMSE = 18, and RMSE = 0.5 (gr/m^2)). According to the results, the model efficiency demonstrated that fluctuations of climatic variables have relatively high explanatory power to justify the NPP changes.

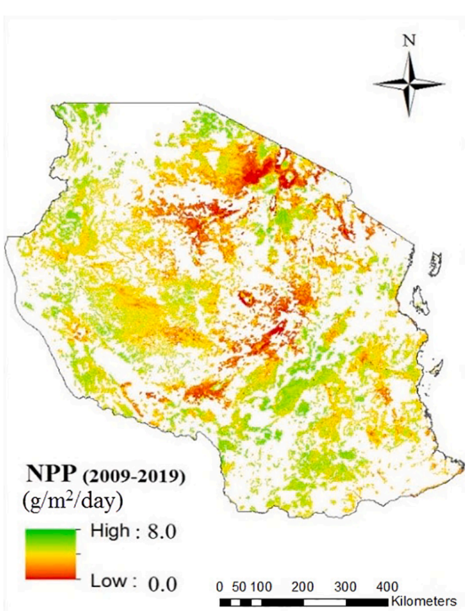

Fig. 4. Spatial distribution of NPP in Tanzania grasslands (2009–2019).

3.2. Projection of climate variables in the future

Given the available dataset, the regression adj-equation in order to estimate ET_0 for Tanzania in the future has the following form:

$$ET_{adj} = 0.0065 \times Ra(T_{mean} + 17.8)\,(T_{max} - T_{min})^{0.015} \quad (2)$$

where Ra is extraterrestrial radiation, T_{mean}, T_{max}, T_{min} are mean, maximum and minimum air temperature (℃), respectively. Based on multiple regression between (T_{max}-T_{min}- T_{mean}) as predictors and predictand ET_0, reference evapotranspiration of period 2009–2019, were used to validate the regression model. According to statistical analysis, validation indicators values for the adj-model had an acceptable range (MAD = 0.45, MSE = 0.3, NRMSE = 12.46, and RMSE = 0.55 mm). Eventually, the spatial distribution of climatic variables such as precipitation, maximum temperature and evapotranspiration under RCP2.6 as an optimistic scenario and RCP8.5 as a pessimistic scenario in 2050 are evident in Fig. 5.

From Fig. 5 it can be seen that mean ET_0 and T_{max} under both scenarios decrease from the northeast to the southwest parts in comparison to the other parts. Indeed, the model results of HadGEM2-Es demonstrate that climate variables patterns T_{max} and ET_0 under emission scenarios have the largest increase from the northwest to the west (Rukuwa, Tabora and Kigoma province) and southeast parts (Pwani, Mtwara, Lindi, and Morogo) of Tanzania. While, the precipitation pattern in the future shows the decreasing trend from the east to the west parts. So that, the precipitation value will decrease by 5–6% under the RCP2.6 scenario and 7–8% under the RCP8.5 scenario in 2050.

3.3. Projection of grasslands dynamics in the future

The general pattern of NPP shows a decreasing trend in the northeast-southwest, while the largest decrease in NPP mainly occurred in the northeast (Arusha, Manyara). This spatial pattern under both scenarios will be maintained in the future (Fig. 6). Furthermore, based on the NPP fluctuation maps in the future, the total amount of NPP in grasslands of Tanzania is estimated to increase until 2050. The NPP value under two emission scenarios show an increasing trend, and increase in RCP8.5 was greater than RCP2.6. Compared with the mean NPP value during 2009–2019 (2.25 gr/m^2/day), the mean NPP of RCP2.6 and RCP8.5 increased by 2.5 and 2.65 gr/m^2/day, respectively.

Overall, the spatial pattern of NPP is mainly consistent with changes in the pattern of T_{max}. As mentioned earlier, under both scenarios, NPP and T_{max} are predicted to decline in mainly the northeast-southwest parts, which can be due to the heights in these areas. While the mean value of the precipitation gradually increases from the western half (<1 mm) to the eastern (>10 mm). The analysis of the temperature and NPP trend showed that an increase in T_{max} probably stimulates NPP. Consequently, the projected NPP showed an increasing trend in response to rising temperatures.

To identify the vulnerable areas in terms of NPP value under RCP scenarios in the future, the difference maps of grassland NPP were prepared in Tanzania at the provincial level (Fig. 7).

The regions showing a relative decreasing trend in the mean NPP value accounted for 27.95% (RCP2.6) such as Ruvuma, Kagera, Mara, Morogoro and Iringa and 13.43% (RCP8.5) in Ruvuma and Iringa Provinces were predominately located in the southwest, whereas the areas showing constant trends accounted for 12.1% (RCP2.6) in Lindi and Kigoma and 14.53% (RCP8.5) in Morogoro, Mara and Kagera Provinces were mostly observed in the northeast. Moreover, the highest decrease would occur in the RCP2.6 scenario in Ruvuma Province, by contrast, the mean NPP value in the western, eastern, and central parts

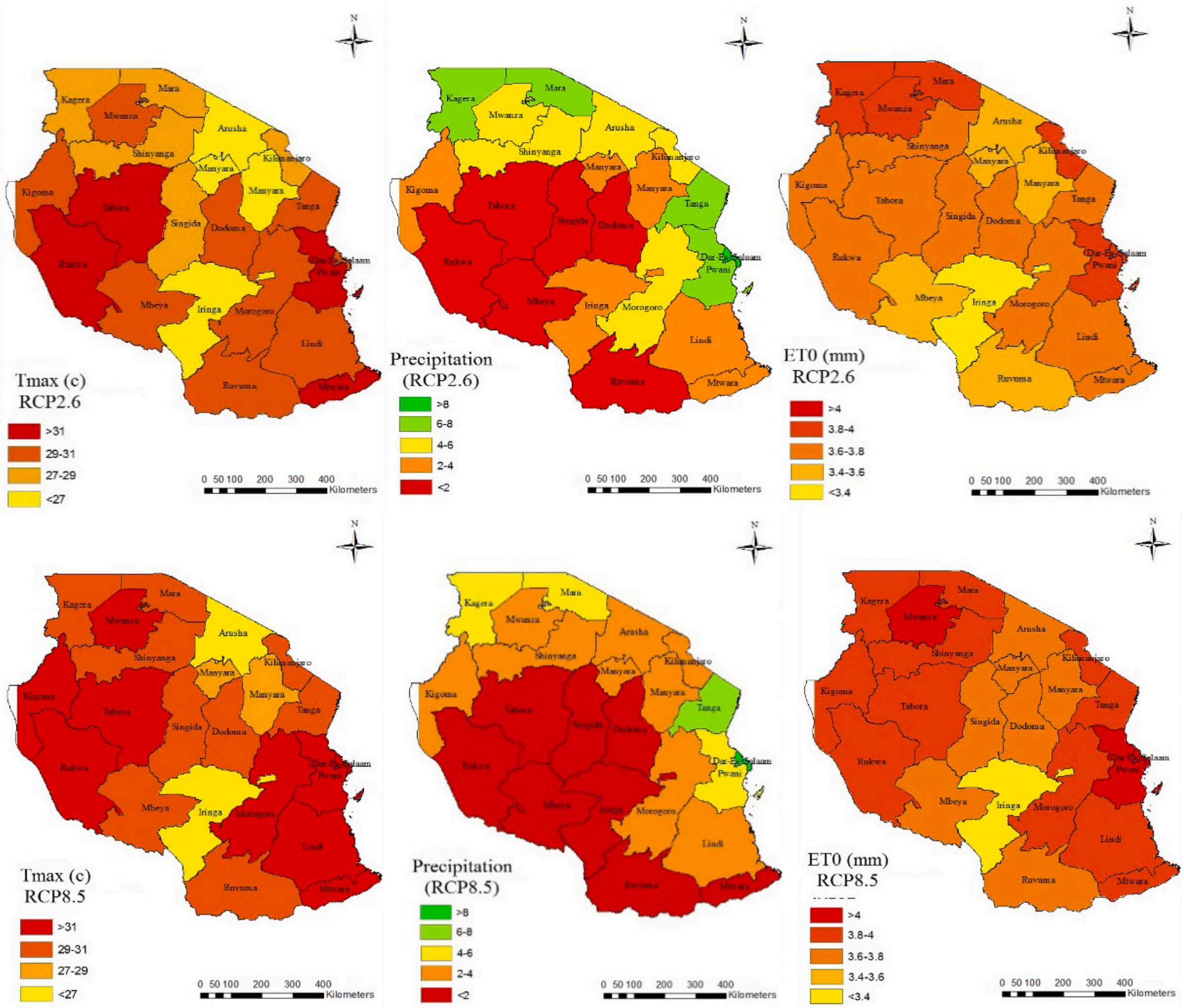

Fig. 5. Projected precipitation, T_{max}, and ET_0 under RCP2.6 and RCP8.5 at the provincial level in 2050.

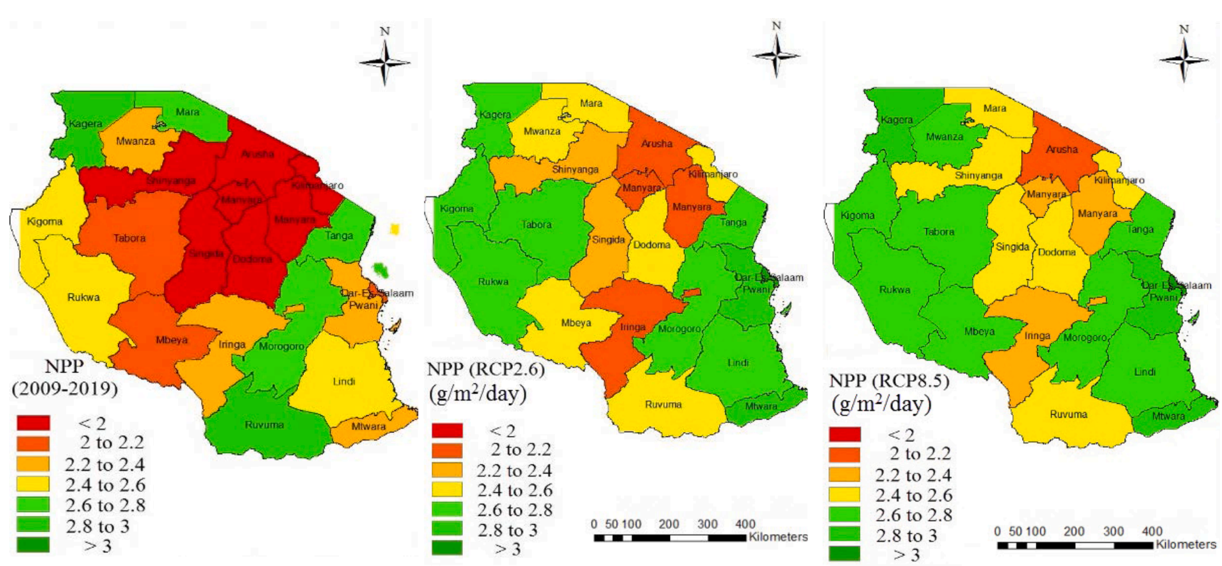

Fig. 6. The mean NPP value at present, and under RCP2.6, RCP8.5 scenarios in Tanzania by 2050.

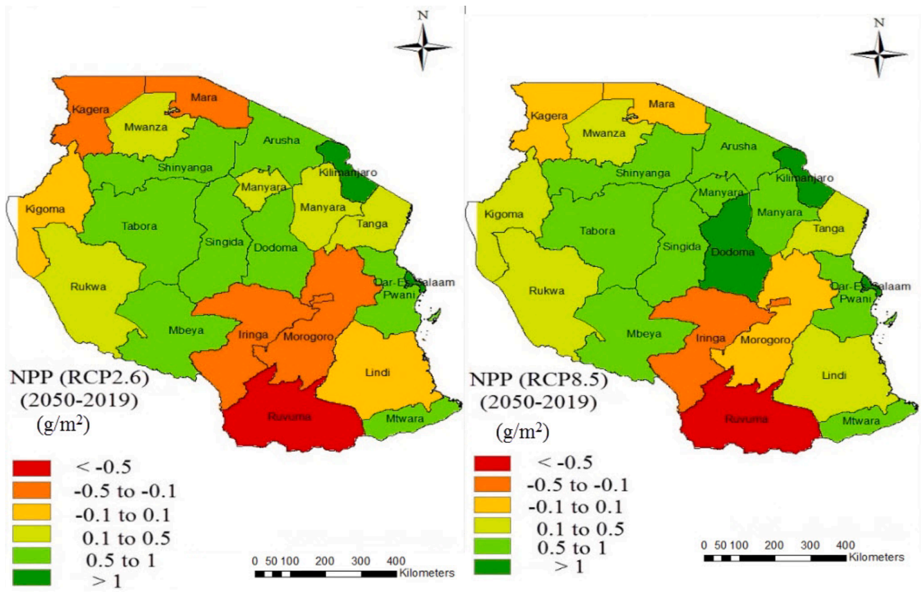

Fig. 7. The vulnerable areas based on the difference map of NPP at present and 2050.

would increase in 2050 in both Scenarios, the largest increase would observe in Kilimanjaro, Dar-Es-Salaam and Dodoma Provinces.

3.4. The changes in livestock in the future

The livestock composition in Tanzania is varied including about 85.7% of the cattle, 2.9% of the sheep, 7.6% of the goats, 1.6%of the pigs and 2.2% of the chicken. The number of livestock based on carrying capacity was estimated in different Provinces in Tanzania under RCP2.6 and RCP8.5 by 2050 (Fig. 8). The number of livestock units based on NPP value will increase by 12.47% and 16% under RCP2.6 and RCP8.5 respectively. There are about 22 million cattle in Tanzania now, while this carrying capacity will increase to more than 13% (RCP2.6) and 18% (RCP8.5) in the future. Furthermore, the number of other grazing animals such as sheep and goats will also increase in the Tanzania grasslands under both climate scenarios.

Generally, the population and the other hand, demand for meat have positive impacts on NPP, so more worker would be invested into efficiency and production of grassland, but in the areas that production and livelihoods rely on livestock production, the increase of economic growth can put pressure more than capacity on the grassland and probably lead to the reduction of the grassland NPP. So, in arid areas, management of the number of livestock is a substantial approach for risk management in grasslands.

4. Discussion

Climatic variables including T, P, and ET_0 are the substantial factors controlling the NPP dynamics in different scales. Therefore, combination of these interactions is of great importance for grassland ecosystem management (Zhao et al., 2019). It is widely acknowledged that Spatio-temporal changes of NPP is a function of climate variable, including precipitation, temperature, and evapotranspiration, many research have been undertaking to analysis the response of NPP to P, T and subsequently ET0 at different scales (Yang et al., 2017; Zhang et al., 2020; Teng et al., 2020). Our results indicated a strong nonlinear relationship between NPP and T_{max}, ET, and P. Thus, the changes in climatic variables had a significant impact on the NPP. Accordingly, the spatiotemporal fluctuation analyses of climatic parameters under different emission scenarios can help clarify the mechanisms driving NPP fluctuation in grassland ecosystems (Piao et al., 2009; Xu et al., 2013). The results of this research imply the temperature and evapotranspiration will increase and precipitation will decrease compared with current climatic conditions, while T and ET increase leads to higher projected NPP growth in Tanzania grasslands. Spatial fluctuations in NPP with solar radiation and consequently ET indicate the rapid rise in temperature has declined the temperature limit for the plant, therefore promoting NPP growth (Piao et al., 2009) on the other side, drought can restrict plant growth. In summary, the optimal temperature and precipitation play an essential role in grassland productivity.

NPP was predicted to increase with increasing T_{max}, ET under both scenarios by 2050. Until 2050, NPP of grassland is projected to increase, at a rate of 0.4 and 0.28 respectively under RCP 8.5 and RCP2.6 scenarios. NPP increasing was primarily due to the impacts of the increase in temperature and consequently elevated CO_2 and ET. The elevated NPP in 2050 projections was consistent with the results of other researchers in different areas (Jin et al., 2015; Gao et al., 2016; Han et al., 2019). The results suggested that NPP fluctuation in the southeast half parts probably primarily controlled by the temperature and precipitation increase. Based on the projection of changing of climatic variables under emission scenarios, it could be concluded that in most parts of the grassland in the south and west, temperature increase leads to the accumulation of dry matter and thus increase NPP values. Similarly, the largest decrease in NPP mainly occurred in the northeast with high precipitation, it is probably due to the fact that increased precipitation in the northeastern region could lead to cloud cover, and therefore have negative impacts on vegetation photosynthesis (Han et al., 2019).

The fluctuations of NPP in grassland ecosystems under warming were presumably to be adjusted by water availability (Zhu et al., 2017). Temperature increase accelerated the rate of evapotranspiration and consequently changed the availability of soil water (Trenberth et al., 2013; Cook et al., 2014). Simultaneously with decreasing soil water availability, NPP might be reduced due to suppressed photosynthesis and even decrease root biomass (Liu et al., 2016; De Vries et al., 2016). Shen et al (2015) demonstrated that precipitation probably regulates the response of soil and vegetation to climate warming in dry areas. Actually, availability of water becomes a substantial factor on NPP as an indicator of vegetation dynamics on Tanzania grasslands, especially under negative scenario as warmer climate condition (Han et al., 2019). These results highlight the essential role of precipitation projection under emission scenarios to estimate NPP fluctuations in the future (Han et al., 2019).

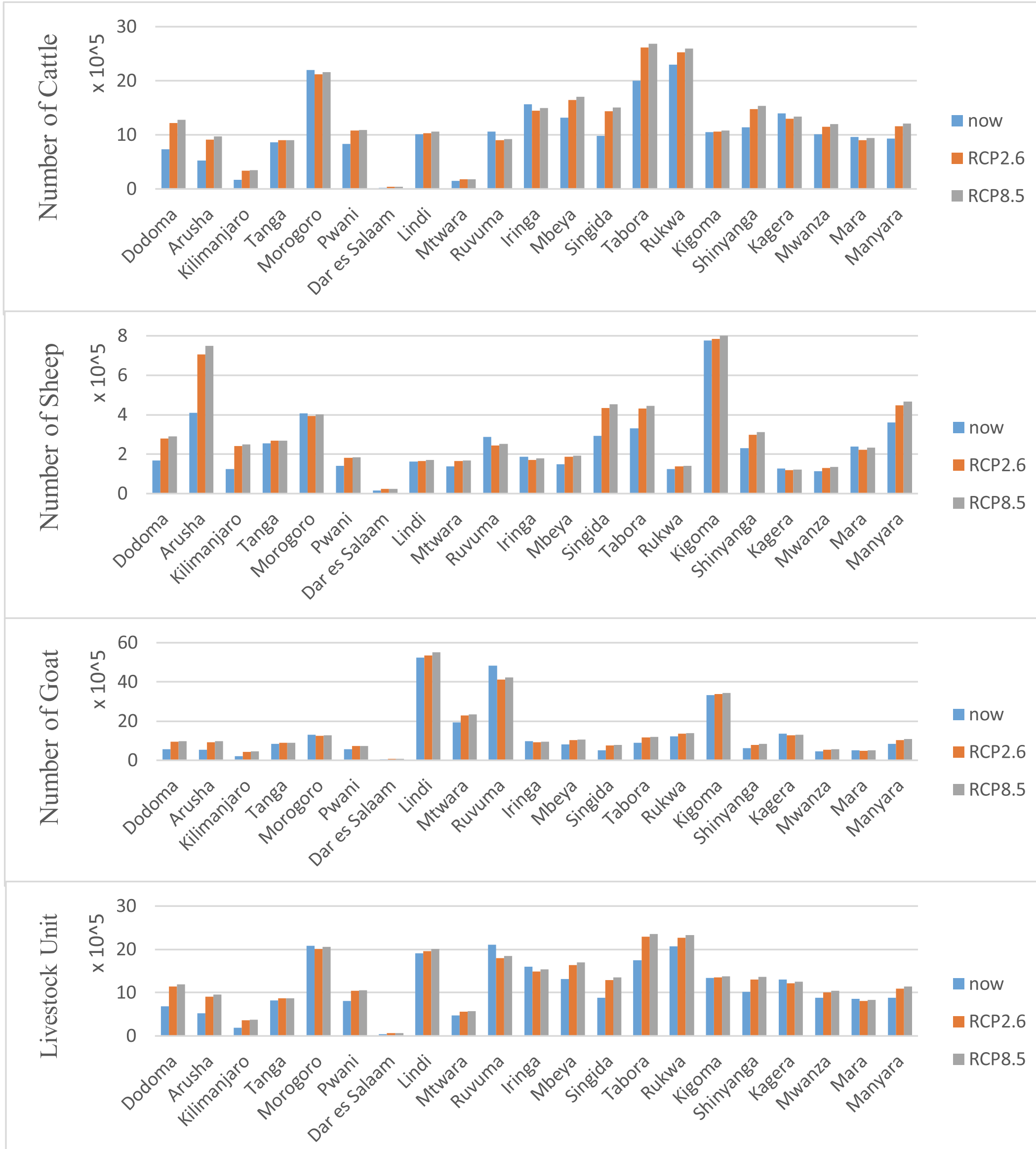

Fig. 8. Projected number of i) cattle ii) sheep iii) goat iv) livestock unit in different provinces in Tanzania by 2050.

It should be emphasized that the results of the projected NPP fluctuations and the number of livestock by 2050 under the assumption of climate variables such as P, T_{max}, and ET have impacts on NPP, meanwhile combination of these changes with anthropogenic pressure such as grassland management, overgrazing will result in worse situations. Specifically, climate change has essential impacts on the livestock sector, undoubtedly changing climate variables will increase the risk of livestock production and decrease the ability of risk management in grasslands. Meanwhile, animal food chains are significant impacts on greenhouse gas emissions (Steinfeld et al., 2006). Studies agree that rising demand for livestock products, due to the growth of population urbanization rate will continue in the future. This rising demand will give an increase to remarkable land-use competition between food and feed, while adaptation to climate change and mitigation greenhouse gas emission approach will enhance the cost of food production (Thornton, 2010). On the other hand, increasing production in the short run by overuse of natural resources reduces long term efficiency. Pastoralists who live at climatic extremes areas with extreme winters or extended droughts causing a high mortality rate of their livestock are vulnerable to climate change (FAO, 2018). Totally, hidden hunger is an obstacle to economic and social development in sub-Saharan Africa (Shikuku et al., 2019). While raising the efficiency of the livestock-agri-food systems, is a substantial solution to achieving food security and sustainable development in underdeveloped countries with food-deficit (FAO, 2011).

Climate change has impacted NPP conditions, while timely action based on risk management can decrease the losses and impacts of climatic extreme on livestock and food security can be improved in vulnerable societies (Matere et al., 2020). Overall, many variables determine whether adaptation approaches are effective and reliable in different locations. It seems more adaptation than currently, is needed to decrease vulnerability to climate change in the future, while adaptation has limits, expense (IPCC, 2007).

5. Conclusion

This study aimed to evaluate the Spatio-temporal fluctuations in NPP and the number of livestock units under climate scenarios in the grassland of Tanzania in 2050. Also, the vulnerable areas in terms of NPP were identified to reduce climate change adverse impacts. According to the results of this study, the temperature and evapotranspiration will rise and precipitation will decrease under both climate scenarios in the future, while T and ET increase will lead to higher projected NPP growth in Tanzania grasslands. On the other side, the number of livestock units based on NPP, carrying capacity, rising demand will increase in 2050. The results will raise our understanding to study the impacts of changes in NPP on grassland productivity, and illuminate the climate change impacts on NPP and consequently livestock units. Considering that the major impacts of climate change will be observed in livestock systems in developing countries that life people depend on grasslands and are very vulnerable, evaluation of NPP fluctuation and developing an early warning system can decrease the loss of grazing animals, increase resilience, and improve the adaptation of grassland. Overall, in the future, food security will increasingly be affected by competition for natural resources between food and feed, especially land, soil, and water, so attention to sustainable development approaches to adaptation of climate change is essential for grassland management. What is more, the pro-active actions based on monitoring data can decrease the potential impacts of climate extreme events and climate change on grasslands and livestock and decrease the losses and enhance food security.

CRediT authorship contribution statement

Azin Zarei: Conceptualization, Methodology, Investigation, Writing - original draft, Visualization. **Abel Chemura:** Methodology, Writing - review & editing. **Stephanie Gleixner:** Resources, Investigation. **Holger Hoff:** Resources, Supervision, Investigation.

Declaration of Competing Interest

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

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