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Biophysical regions of the Southern Highlands, Tanzania: regionalization in a data scarce environment with open geospatial data and statistical methods

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ABSTRACT

Spatially explicit, evidence-based and regionally contextualized data on biophysical landscape characteristics is an essential basis for regionally sustainable landscape management schemes. In many regions of the Global South, the availability of such information is poor, especially at the subnational level, and the spatial management is often based on generic and outdated information, leading to severe threats for land sustainability. We have developed a biophysical regionalization of the Southern Highlands area of Tanzania. The map is based on open-source global datasets depicting climate, soil, topography and vegetation. Through replicable statistical and geospatial analyses, we have identified 7 regions and 18 subsections with biophysically similar and spatially distinctive environmental conditions. The regions provide spatially contextualized support for understanding and managing the landscapes of the Southern Highlands. The applications for such data sets are numerous, from screening suitability areas for e.g. afforestation schemes to evaluating the distinctiveness and vulnerability of landscapes to degradation.

KEYWORDS

Data scarcity; open data; global South; Africa; regionalization; K-means

1. Introduction

Biophysical regionalization methods target the identification of homogeneous biophysical land characteristics for different land assessment needs (Bailey, 2004; Blasi et al., 2014; Leathwick et al., 2003; Omernik & Griffith, 2014; Smiraglia et al., 2013). The regionalization methodology relies on a spatial hierarchy of biophysical factors where macroclimate determines the broad ecological units, and then landforms, soil and vegetation steer the division of the units to more detailed level regions of particular biophysical character (Bailey, 2004; Klijn & Udo de Haes, 1994). The value of the regionalizations lies in their ability to contextualize biophysical variability over geographical space. Thus, regionalizations bring an additional layer of geospatial data into a complex decision-making process of estimating land capacity, resilience, suitability or vulnerability (Gallant et al., 2004; Loveland et al., 2002; Nowak & Schneider, 2017; Sleeter et al., 2013). With the help of semantically and spatially accurate regionalizations, it is possible, for example, to estimate how intensive or extensive are the consequences of land use changes in space and time, or what type of services and benefits landscapes provide to humans (Burkhard et al., 2009; Fang et al., 2015; Willemen et al., 2008; Zomer et al., 2013). When linked into the overall processes of land assessment, regionalizations increase the reliability and practical value of assessments and help establish meaningful region-specific decisions.

During the past decade, open-access geospatial datasets of high spatial accuracy and with global coverage have become widely available, allowing mapping and modeling of environmental factors at rather detailed scales in most parts of the world (Metzger et al., 2013b; Mücher et al., 2016; Sayre et al., 2014). Furthermore, environmental satellite image repositories with abundant and up-to-date image data and access to increased computing power have created new opportunities for the creation of biophysical mapping based on quantitative and repeatable methods (Coops et al., 2009; Song et al., 2017; Xiong et al., 2017). This has changed the ways in which data-scarce regions in the Global South can be studied in terms of their biophysical environment (Egoh et al., 2012; Vrebos et al., 2015). However, the applicability of global data sets directly at the regional level is not straightforward, since the strata of the data sets has been designed for global coverage and may miss essential regional variation. To overcome this type of semantic mismatch, the data sets need rescaling for regional needs.

In Sub-Saharan Africa, sustainable land use planning and management of land resources is challenged due to severe degradation of the environment, rapid population growth and urbanization, combined with

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high expectations on land productivity for better food security and energy demands of the growing cities (Fisher, 2010; Nkonya et al., 2016; Parnell & Walawege, 2011; Salami et al., 2010). The area of the Southern Highlands in Tanzania is a good example of Eastern African rapidly developing landscape regions, where people live on the land in diverse and fragmented settings of montane forests, grasslands, woodlands, bushlands and agricultural land. The area provides Tanzania with some of its most critical elements of food security and especially timber (NBS, 2015, 2016). However, the landscapes of the region are threatened by deforestation of montane and miombo woodlands, land degradation, soil erosion and seasonal water scarcity (Kangalawe & Lyimo, 2010). At the same time, region-wide land improvement schemes both in the sector of agriculture and forestry have been promoted and expectations are set high in terms of their future development opportunities for productivity and well-being (Milder et al., 2013). However, the region lacks data of the variation of biophysical environment and thus any strategic planning, which could address the overall land capacity for ecosystem service provisioning and steer and set limitations and possibilities for land use improvement schemes, is missing.

In this study, we have developed a biophysical regionalization methodology for the area of the Southern Highlands in Tanzania, based on open-source geospatial data sets of global and regional coverage. The method is data-driven and repeatable. The outcome of the methodology is a map of biophysical regions, which visualizes geographical differences in biophysical conditions of climate, topography, soil and vegetation in the Southern Highlands. The map can be used to steer land suitability, risk and vulnerability assessments based on spatially explicit cell-based models. The suggested methodology can be used outside our study area, but since the methodology is based on data-driven statistics, its transfer to other areas needs empirical adjustment in terms of selected variables.

2. Material and methods

2.1. Study area

The Southern Highlands is a socioeconomically valuable area in the regions of Mbeya, Iringa and Njombe with 4.3 million inhabitants (NBS, 2013, Figure 1). Despite the region being among the richest in Tanzania, over 60% of the population is facing poverty (UNDP, 2015). Small-scale, low efficiency agriculture is the main economic activity, with minor cash cropping, livestock and beekeeping and tree planting supplementing local economies. Some 90% of the rural

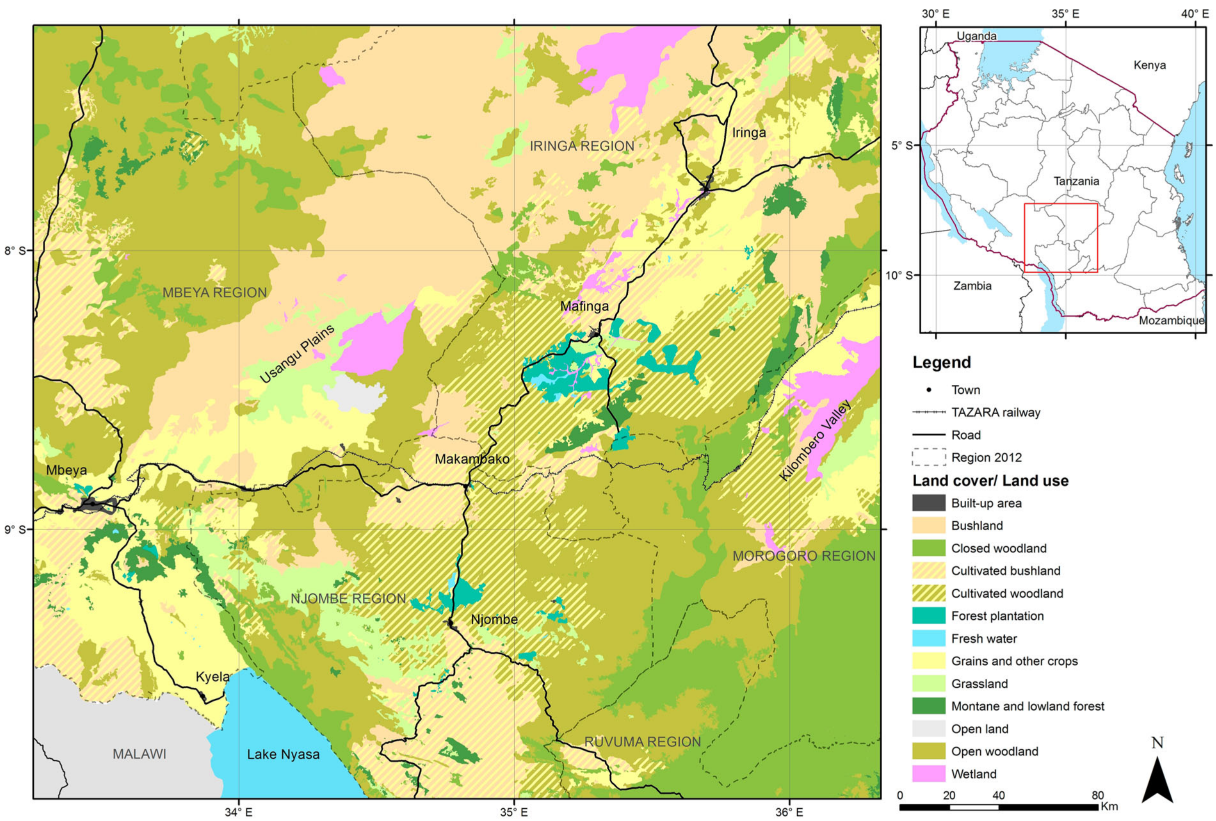

Figure 1. Southern Highlands is a geographically diverse landscape area lying in between 7.3°S and 10°S and 33.3°E and 36.3°E. It is accessible from East through the main roads from Morogoro and Songea and from the West through Mbeya. Largest urban centers in addition to main cities of Iringa and Mbeya are Makambako, Njombe and Mafinga. The land cover is dominated by open and closed woodlands, bushland and cultivated woodland (Naforma land cover/land use map, MNRT, 2013).

population depends on wood fuel for daily energy supply and collects wood extensively also for construction and charcoal production from natural and planted woodlands and forests (Kangalawe & Lyimo, 2010). Population growth accompanied with extensive, low capacity agriculture and high dependency on wood resources increase the demand and pressure for natural resource extraction (Kangalawe, 2012; Kangalawe & Lyimo, 2010). These pose a challenge for sustainable land and natural resource management, especially since the region is already suffering from deforestation, land degradation, soil erosion and seasonal water scarcity (Green et al., 2013; Kajembe et al., 2003; Malley et al., 2009; Sawe et al., 2014; Schaafsma et al., 2012).

Today, the Southern Highlands is the most important production area of grains and potatoes, and its southern and eastern parts are the main source of timber in Tanzania (Kangalawe, 2012). Tanzania has ambitious development plans for the area as a future breadbasket and key timber production region for the country (Milder et al., 2013; PFP, 2016). The government of Tanzania is currently promoting sustainable private forestry to facilitate development and alleviate poverty (PFP, 2016). However, plantation establishment, for example, is not leaning on spatially explicit knowledge of biophysical land conditions since the available information is either completely lacking or is too generic or outdated (De Pauw, 1984; MNRT, 2013). The Southern Highlands needs strategic, science-based, and landscape-level planning practices, as seen in many other resource-rich, extensively used and rapidly developing landscapes in the world.

2.2. Statistical approach for regionalization

Three important issues to consider in developing robust statistical regionalization processes are: (1) the study area extent, (2) the selection of variables and (3) the selection of spatial resolution of the regionalization, also known as the scale issue in Modifiable Areal Unit Problem (MAUP) (Bakkestuen et al., 2008, Dark & Bram, 2007; Jelinski & Wu 1996; Metzger et al., 2005; Wu et al., 2006). In our study, we designed the regionalization only to the Southern Highlands of Tanzania and the demarcations are thus relevant for the Southern Highlands and may change if the extent is changed. For variable selection, we reviewed previous regional and global scale biophysical regionalization studies (Bakkestuen et al., 2008; Chuman & Romportl, 2010; Fairbanks & Benn 2000; Metzger et al., 2013b; Serra et al., 2011) and selected openly available global and regional scale spatial data sets, depicting climate, topography, soil and vegetation conditions (Table 1). To evaluate the effect of MAUP and to develop a robust spatial representation of the biophysical variation within the study area, we developed the regionalization with 1, 5 and 10 km grid cells.

Table 1. Biophysical variables consist of climate (temperature and precipitation related variables), topography (altitude, slope, terrain ruggedness), soil (texture, structure, density), and vegetation (intensity and seasonality), obtained from open access global data sets.

Dataset	Derived variable
Climate, Temperature (CT) Climate, Precipitation (CP) Source: Worldclim2 Spatial resolution 1km	CT1) Annual Mean Temp, CT2) Mean Diurnal Range,CT3) Isothermality, CT4) Temp seasonality, CT5) Max Temp of Warmest Month, CT6) Min Temp of Coldest Month, CT7) Temp Annual Range, CT8) Mean Temp of Wettest Quarter, CT9) Mean Temp of Driest Quarter, CT10) Mean Temp of Warmest Quarter, CT11) Mean Temp of Coldest Quarter, CP1) Annual Prec, CP2) Prec of Wettest Month, CP3) Prec of Driest Month, CP4) Prec Seasonality, CP5) Prec of Wettest Quarter, CP6) Prec of Driest Quarter, CP7) Prec of Warmest Quarter, CP8) Prec of Coldest Quarter, CP9) Global aridity index, CT12) Global reference Evapotranspiration, CP10) Growth days
Topography (T) Source: NASA/SRTMGL1v003 Spatial resolution 30 m	T1) Mean altitude, T2) STD altitude, T3) Mean slope, T4) STD slope, T5) Terrain ruggedness index
Soils (S) AfSoilGrid (ISRIC) Spatial resolution 250 m	S1) Organic carbon, S2) pH, S3) Sand fraction, S4) Silt fraction, S5) Clay fraction, S6) Coarse fragments, S7) Bulk density, S8) Cation exchange capacity, S9) Total N, S10) Exchangeable acidity, S11) Al content, S12) Exchangeable Ca, S13) Exchangeable K, S14) Exchangeable Mg, S15) Exchangeable Na
Vegetation intensity (VI) Vegetation seasonality (VS) MODIS/MOD13Q NDVI, EVI, NDWI 16-day composite and MOD11A2 LST 8-day composite Spatial resolution 250 m–1 km	V1) Mean annual NDVI, V2) STD of annual NDVI, V3) Mean annual EVI, V4) STD of annual EVI, V5) Mean annual NDWI, V6) STD of annual NDWI, V7) Mean annual LST, V8) STD of annual LST

2.3. Creating geodatabase with biophysical variables

We acquired bioclimatic variables related to temperature and precipitation from the WorldClim 2 global climate dataset (Fick & Hijmans, 2017). WorldClim climate variables are especially useful when local weather station data is not available (Li et al., 2017). In addition to the 19 bioclimatic variables available from WordClim2 database, we downloaded Global Potential Evapotranspiration (Global-PET) and Global Aridity Index (Global-Aridity) layers from CGIAR Consortium for Spatial Information (CGIAR-CSI) website (https://cgiarcsi.community/data/). Both Global-PET and Global-Aridity datasets are modeled based on WorldClim2 data (Trabucco & Zomer, 2019) and have been shown previously to be important variables in biophysical regionalizations (Metzger et al., 2013b). Furthermore, we calculated 'number of annual growth days', as this has been shown to be an important variable in South Africa, depicting the soil water balance (see Fairbanks & Benn, 2000).

For topographical variables, we used National Aeronautics and Space Administration's (NASA) Shuttle Radar Topography Mission digital elevation model (SRTM DEM) dataset at 30 m resolution, accessed through Google Earth Engine (GEE) (Google Earth Engine Team, 2015; Jarvis et al., 2008). We calculated mean altitude, STD altitude, mean slope, STD slope and terrain ruggedness index, referring to variables found suitable to depict topographical differences in previous regionalization studies (Bakkestuen et al., 2008; Chuman & Romportl, 2010; Serra et al., 2011).

We obtained soil variables from International Soil Reference and Information Centre (ISRIC) AfSoilGrids250 m database (see details in Hengl et al., 2015). Soil surface (depth 5–15 cm and 0–20 cm) character grids of texture, structure and density were extracted from the database.

We extracted Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation index (EVI), Normalized Difference Water Index (NDWI) and Land Surface Temperature (LST) from GEE MODIS data collection (Google Earth Engine Team, 2015). These indices are frequently used in landscape classification studies as they depict vegetation condition, water content and seasonal changes (Gao, 1996; Jackson et al., 2004). These indices provide composites with 8-day and 16-day intervals adding up to 22–43 composites annually with 250–1000 m spatial resolution. We also calculated annual (2014) mean and annual standard deviations of these composites.

Finally, we resampled all variables and summarized them as means into 1, 5 and 10 km grid cells superimposed over the study area and stored into a geodatabase.

2.4. Establishing biophysical gradients through PCA

We conducted Principal Components Analysis (PCA) in R statistics (package psych (Revelle, 2018)) based on the original variables in order to reduce information redundancy between the variables. Following the Kaiser-Guttman method (Jackson, 1993), we extracted the principal components with greater than average eigenvalue (eigenvalue greater than one). According to the correlations of the 50 variables (see supplementary material for further details), we then identified the components' representative biophysical gradients. We found there to be seven (7) relevant biophysical gradients representing precipitation, temperature, topographical variation, soil fertility, vegetation intensity, vegetation seasonality and temperature variation (Figure 2). These explain 85.6% to 88.4% of the total variance of the data depending on the grid cell size used (Table 2).

2.5. K-means++ clustering and identification of biophysical regions

Through statistical clustering of the extracted components, we formed areas with similar biophysical characteristics. We used *k*-means clustering method for its suitability for post-PCA classification (Ding & He, 2004) and its wide application in regionalization studies (Guitet et al., 2013; Hargrove & Hoffman, 2005; Soto & Pintó, 2010; White et al., 2005; Zhang et al., 2012). *K*-means algorithm divides the data into a set of homogenous clusters by analyzing cell value distances in each individual cell to cluster value centers in Euclidean space and assigning the pixels to the closest cluster. New centroids are calculated for each cluster after each iteration, and pixels are assigned again to the closest cluster. The iterative algorithm continues until thresholds of iteration are met. We applied *k*-means++ algorithm (Arthur & Vassilvitskii, 2007), an augmentation of the k-means algorithm where the random seeding process of ordinary *k*-means is replaced by careful seeding. K-means++ has been shown to produce more robust clusters compared to k-means (Arthur & Vassilvitskii, 2007, Zhang et al. 2012). The clustering was run with 100 initial seeding points and *k*-values ranging from 2 to 30. We used package LICORS (Goerg, 2013) in R statistics.

After clustering, we analyzed the explained variance of each cluster representation in order to evaluate the optimal number of clusters to depict the biophysical regions. Compared to the approaches using a fixed number of clusters (e.g. Metzger et al., 2013b) or spatial aggregation of data sets (e.g. Sayre et al., 2014), the data-driven approach enables statistical evaluation of the significance of the clusters and their explained variances and allows for contextually sensitive cluster

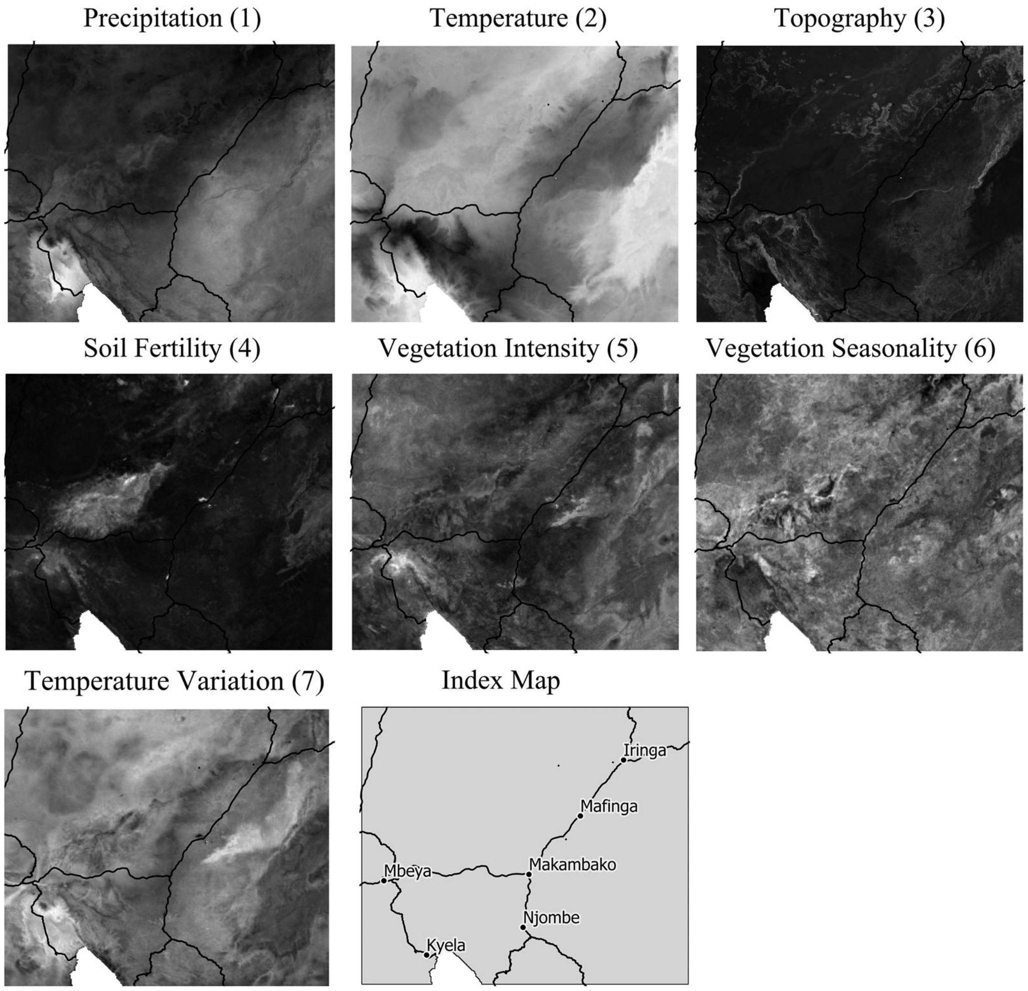

Figure 2. Seven biophysical gradients derived from principal components of the 50 original variables at 1 km resolution.

representation. We plotted the total sum of squares between clusters for each of the 29 regionalization approaches and the optimal number of clusters was chosen visually (see Supplementary). Furthermore, we tested spatial robustness of the clustering approach by calculating spatial goodness of fit (GOF) between the consequent cluster maps using the Mapcurves function (Hargrove et al., 2006) (package sabre (Nowosad & Stepinski, 2018)). The Mapcurves method is not sensitive for the varying amount of categories between the compared maps. We calculated the GOF statistics for map comparisons following the equation given by (Hargrove et al., 2006):

$$\mathrm{GOF} = \sum\left(\frac{C}{B+C} \times \frac{C}{A+C}\right),$$

Where GOF is the goodness-of-fit of a cluster, A is the map to be compared, B is the reference map and C is the overlap between A and B.

We analyzed hierarchical relationships between clusters with Ward's method (Ward, 1963) (package stats (R Core Team, 2019)). The hierarchy of clusters was based on the squared Euclidean distance of each cluster centroid in relation to the biophysical components. We organized cluster distances as a dissimilarity matrix and drew in a dendrogram that shows the scaled distance of each cluster and their hierarchy (Supplementary material). For characterizing the formed homogeneous clusters into biophysical regions, we gathered descriptive information on the clusters on the basis of variables that had high loadings on the principal components.

3. Results

3.1. Biophysical regions in the Southern Highlands

The Southern Highlands comprises seven (7) main biophysical regions (A–G) and 18 subsections (Main map). Each region encompasses distinct biophysical character, as shown in Figure 3. Region A is characterized by high vegetation intensity and low seasonality in vegetation cover, depicting the evergreen montane forests of Eastern Arcs and Southern Rift montane forest-grassland mosaic in the North East and South West, respectively. Region B depicts the fertile flatlands of the Usangu plains with high seasonality in vegetation cover. Region C encapsulates the rugged, topographically variating landscapes, while region D is

Table 2. Principal components 1–7, their eigenvalues, cumulative variance, strongest and weakest correlative variables (high loadings, low loadings) and gradient name based on correlative variables. For all variable loadings, see Supplementary material.

PC	Eig.	Tot var (%)	High loadings	Low loadings	Gradient Name
1 km Resolution					
1	13	26	CP1, CP9, CP10	CP4	Precipitation
2	10.8	47.6	CT1, CT10, CT9	T1	Temperature
3	5.3	58.2	T2, T3, T5		Topography
4	4.9	67.9	S13, S12, S14		Soil Fertility
5	4.1	76.1	VI1, VI2, VI3	CT7	Vegetation Intensity
6	3	82.1	VS3, VS2, VS1		Vegetation Seasonality
7	1.7	85.6	CT3, CT2		Temperature variation
5 km Resolution					
1	14.8	29.6	CP1, CP9, CP10	CP4	Precipitation
2	11.1	51.7	CT10, CT1, CT9	T1	Temperature
3	5.2	62.1	T2, T4, T5		Topography
4	5	72.1	S13, S12, S8		Soil Fertility
5	3.2	78.4	VI1, VI2	CT7, CT2	Vegetation Intensity
6	2.9	84.2	VS3, VS2, VS1		Vegetation Seasonality
7	1.8	87.7	CT3		Temperature variation
10 km Resolution					
1	14.3	28.6	CP9, CP5, CP2	S3, CP4	Precipitation
2	11	50.6	CT10, CT1, CT8	T1	Temperature
3	5.6	61.8	T4, T2, T5		Topography
4	5	71.9	S13, S12, S8		Soil Fertility
5	4.2	80.3	VI1, VI2	VS1, VS2	Vegetation Intensity
6	2.3	84.8	CT2, CT7		Vegetation Seasonality
7	1.8	88.4	CT3		Temperature variation

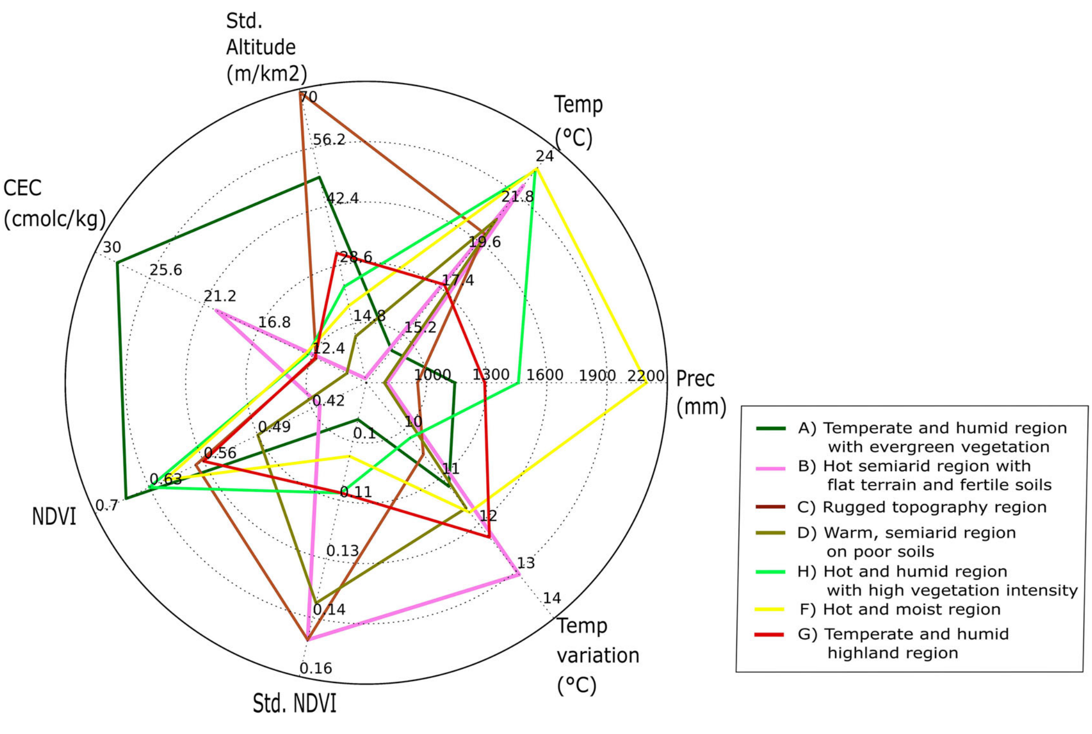

Figure 3. Biophysical regions presented according to the median values of selected biophysical variables. Prec = Yearly precipitation (mm), Temp = Average temperature (°C), Std. Altitude = Standard deviation of altitude (m/km^2), CEC = Cation Exchange Capacity (cmolc/kg), NDVI = yearly average NDVI, Std. NDVI = Standard deviation of NDVI throughout a year, Temp Variation = Mean Diurnal Range of temperature (Mean of monthly (max temp − min temp)).

characterized by poor soils and high vegetation seasonality typical in wooded savannas developed on poor soils of the central African plateau. Region E encapsulates the moist and hot flatlands of the Kilombero valley with high temperature variation caused by the adjacent Udzungwa scarp. Region F encapsulates the very moist flatland of the Kyela valley with a precipitation pattern governed by Lake Nyasa. The region is characterized by high values in precipitation and temperature gradients and low values in temperature variation gradient i.e. stable warm and moist climate. Region G depicts the highland range with low annual average temperatures and high temperature variation.

The subsections are specifications of each main biophysical region and they provide more spatially detailed stratification of the biophysical environment

(Figure 4). For example, the region E consists of three subsections (E1–E3) (Figure 4, graphs 4 and 5). The subsections differ mostly on their topography and vegetation characteristics (NDVI and Std. of NDVI) with E1 having flat terrain and moderate vegetation intensity and seasonality while E2 has high topographic variation and closed and more evergreen vegetation structure.

The created biophysical regionalization map of the Southern Highlands is freely available at PANGAE (https://doi.pangaea.de/10.1594/PANGAEA.909589).

4. Discussion

Our mapping of the biophysical regions shows the practical value of open access global and continental

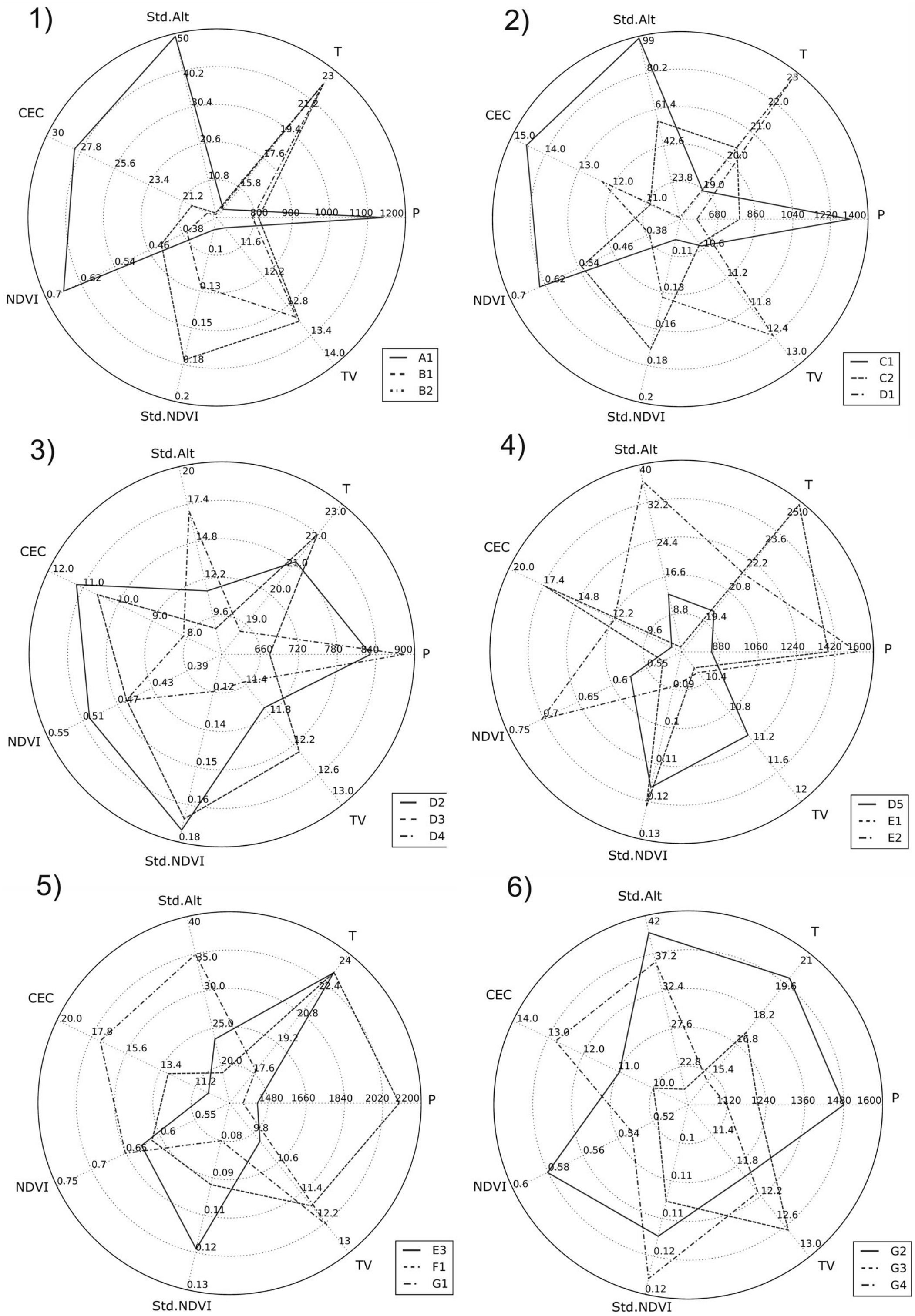

Figure 4. Biophysical subsections presented according to the median values of selected biophysical variables within a subsection. *P* = Yearly Precipitation (mm), T = Average temperature (°C), Std. Alt = Standard deviation of altitude (m/km^2), CEC = Cation Exchange Capacity (cmolc/kg), NDVI = yearly average NDVI, Std. NDVI = Standard deviation of NDVI throughout a year, TV = Mean Diurnal Range of temperature (Mean of monthly (max temp – min temp)).

data sets for regional scale mapping efforts. The 7 biophysical regions and 18 subsections of the Southern Highlands were able to depict regionally important landscape areas such as the Usangu plains and Kilombero valley, and identify essential geographical differences in biophysical conditions over a relatively large geographical area with a data-driven statistical method. The map of biophysical regions will enhance possibilities for regional land use planning and strategic level discussions, since it differentiates the region into unique biophysical areas, which previously have not existed in a map form, and as a digital database (Gallant et al., 2004; Loveland & Merchant, 2004; Metzger et al., 2013a). The map has many other application possibilities. It can be used, for example when planning suitable target areas for agricultural and forestry schemes, which will have a major impact on the success of the region's food security and sustainable forest management (Mücher et al., 2016; Milder et al., 2013; Nijbroek & Andelman 2015; Williams et al., 2008). The biophysical map is a major improvement, considering that at present, the incentive schemes rely on limited knowledge, like rainfall (PFP, 2016) or general environmental classifications (De Pauw, 1984). The map can also have an important role in targeting future discussions of the risks posed by climate change and land degradation to different regions in the Southern Highlands (Zomer et al., 2013).

The additional value of the biophysical map is that as a digital database, it can be analyzed in relation to other spatial data of the region for improved understanding. For example, semantic accuracy and relevance of land use/land cover (LULC) data sets can be enriched with the help of biophysical information (Auch et al., 2011; Bryce et al., 1999; Sleeter et al., 2013). Assessment of LULC patterns in relation to underlying biophysical context, can help to assess which features of the current land cover (e.g forests) are located in a unique biophysical set-up and how rare or abundant are certain critical land assets in each region (Martínez-Harms et al., 2016; Maselli et al., 2009). Thus, the biophysical regionalization can be used to enrich the available geospatial data sets. This is especially vital in Southern Highlands and Tanzania in general, where the generic LULC map demarcations are not capable of depicting the multifunctional land use patterns. The enriching process is inherently spatial since the biophysical conditions are homogeneous and temporally relatively constant within the designated regions.

Despite the advantages of the statistical approach in creating objectively homogeneous biophysical regions, there are still uncertainties and subjectivity in the choice of the input variables. We chose the input variables based on their relevance in depicting biophysical characters (climate, topography, soil and vegetation) according to previous studies (Bailey, 2004; Bakkestuen et al., 2008). Most of the previous regionalizations have used land use data and socio-economic data as input variables (Bernert et al., 1997; Chuman & Romportl, 2010; Coops et al., 2009) but we decided to leave LULC data out from the regionalization since the available data from Tanzania is spatially generic and could steer the regionalization. Furthermore, the spatial accuracy of the global and continental input variables at regional scale may vary (Li et al., 2017) but considerations of the effect of the data quality on the regionalization was not included in our study since they are the only available data sets from the area.

The number of meaningful homogeneous regions and their aggregation remains the most uncertain issue in the regionalization process (Metzger et al., 2005; Metzger et al., 2013b; Serra et al., 2011; Zhang et al., 2012). For a quantitative and statistical approach, this is more important than for qualitative approaches, since the approach is data-driven and thus dependent on the quality of the input variables and the geographical extent of the study. In our case, the biophysical regions and subsections are relative to the area of the Southern Highlands and consequently, the variances of different input variables and the suitable number of clusters are regionally restricted. However, the clustering method provided spatially robust delineations of homogeneous biophysical areas and repetition of the study would result in similar demarcations.

Another crucial step to consider when the regionalizations are based on GIS and data sets derived from remote sensing is the scale issue in MAUP (Dark & Bram 2007). The optimal solution of scale is dependent on the application of the regionalization product. In our case, the smallest common scale was 1 km, governed by the climate data. Nevertheless, the order and loadings of biophysical gradients, derived from the principal components of the original variables were consistent in 1, 5 and 10 km resolutions. This indicates that with the range of 1 km to 10 km the regionalization is not scale-dependent and the aggregation MAUP scale problem is not present. On the other hand, the DEM is available at higher resolution compared to the other biophysical variables and requires significant upscaling from 30 m to 1 km. Thus, some of the topographical variance may have already been averaged out on 1 km resolution and the MAUP aggregation problem is not present when upscaling from 1 km resolution. Applications targeted for local scale should focus on the spatial hierarchy of different biophysical factors (Bailey, 2004; Klijn & Udo de Haes, 1994) and seek ways to combine various datasets with respect to their scale of spatial variance within the landscape.

Tanzania, like many other rapidly growing regions in the world, faces concrete impacts of land degradation due to unsustainable use of lands, increasing demand for natural resources of the growing population and changes in climate patterns (Fisher, 2010; Lambin & Meyfroidt, 2011; Nkonya et al., 2016; Parnell & Walawege, 2011). These challenges require practical solutions to improve planning and management of natural resources. Spatially explicit, real data based assessments are needed at relevant context and resolution to support sustainable regional strategies and planning processes. We have shown through our case study that biophysical regionalization can be statistically established and rescaled to regional context using open access continental and global coverage data sets. Such information reflects the land potential and capacities and offers valuable information to assess and steer human actions, particularly in the rapidly developing areas of the Global South, where global open access data sets may provide an essential source of spatial information to create regional scale landscape assessments (Lu et al., 2015; Sarvajayakesavalu, 2015). Furthermore, such information supports evidence-based decision-making, which is one of the most critical bottlenecks for sustainable land management in rapidly developing countries (Sarvajayakesavalu, 2015).

Software

All the geospatial processing steps and map viaualisations were performed with QGIS 3.4. All the statistical analysis were performed with R Statistics version 3.6.1. The spider diagrams were generated with Python 3.6 and modified with Inkscape version 0.92.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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