

Modeling direct above-ground carbon loss due to urban expansion in Zanzibar City Region, Tanzania

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ABSTRACT

Expansion of urban fabric on carbon storages is estimated to cause loss of 1.38 Pg of Above-Ground Carbon (AGC) in pan-tropics between 2000 and 2030. This would be approximately 5% of all emissions caused by tropical land use changes. Despite the significance of the phenomenon, these emissions are rarely measured, monitored, or addressed in climate change mitigation plans, especially in Sub-Saharan Africa. Therefore, we demonstrated a state-of-the-art approach predicting AGC loss of Zanzibar City Region under multiple alternative urban planning scenarios between 2013 and 2030. The AGC information was modeled based on field measured forest inventory sample plots and RapidEye satellite data from 2013, while the future urban expansion model was calibrated with data of happened expansion between 2004, 2009 and 2013, and geospatial independent variables influencing the expansion patterns. This model was then projected until 2030, while alternative urban planning scenarios were integrated to the model by modifying the geospatial variables. The combination of these two models indicates that 42,000 Mg or 15% of total AGC in Zanzibar City Region can be anticipated to be lost by 2030 due to urban expansion. Majority of the loss will take place in the agroforest and fruit tree plantations surrounding the city, while natural forest face limited impacts. None of the tested alternative urban planning scenarios significantly impact the loss of AGC compared to the business-as-usual scenario. Therefore, alternative policies and plans are seriously needed to address the issue in Zanzibar. These could include promoting urban densification, directing urban expansion to low carbon areas, improving soil carbon management, and preparing an urban forestry and greenery strategy. All in all, the study indicates that data and methods are available for monitoring and predicting the phenomenon in Sub-Saharan Africa. Research based on a comparable methodology should be produced from all the main cities in the region that are surrounded by significant carbon storages and facing high urban expansion rates to support climate change mitigation.

1. Introduction

Cities and urban areas are causing 37–85% of global anthropogenic greenhouse-gas (GHG) emissions indirectly through their energy supply, industry, transportation, waste management and high household consumption (Satterthwaite, 2008; Seto et al., 2014). The direct emissions caused by expansion of urban fabric on forests, vegetation and other carbon storages have been considered insignificant compared to these indirect effects (Seto et al., 2012; Sallustio et al., 2015; Churkina, 2016). However, the ongoing century is facing fastest urban expansion in human history, thus also the direct GHG emission related to spread of

urban fabric will increase (Seto et al., 2011, 2012; United Nations (UN), 2014). It has been estimated that between 2000 and 2030 urban expansion will cause immediate loss of 1.38 Pg of above-ground carbon (AGC) in pan-tropics, which is approximately 5% of total emissions caused by tropical land use changes (Seto et al., 2012). Acknowledging the impacts on other carbon pools, especially on soil carbon, would make these figures even higher (Raciti et al., 2012; Seto et al., 2012).

About a third of urban expansion related pan-tropical AGC loss is estimated to take place in Africa (Seto et al., 2012). Until now, urban expansion has been relatively modest driver of deforestation in the region, but pathways of other continents suggest its importance to increase

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along economic development (Hosonuma et al., 2012). Urban expansion in Africa is happening more at the expense of forests compared to Europe and North America, where cities have expanded more on surrounding agricultural lands (Churkina, 2016; Liu et al., 2019). Average carbon stocks per hectare are generally lower than in other continents, but these low averages are compensated by extreme urban expansion (Baccini et al., 2012; Seto et al., 2012; Mitchard et al., 2013; Spawn et al., 2020). African population is expected to increase from 1.3 to 2.5 billion between 2018 and 2050, while urbanization rate should increase from 43% to 59% simultaneously (United Nations, Department of Economic and Social Affairs, Population Division (UNDESA), 2018). Consequently, urban land cover is estimated to grow almost six-fold between 2000 and 2030, and this is expected to cause rapid decline of terrestrial carbon storages around African cities (Angel et al., 2011; Seto et al., 2012). Furthermore, urban expansion in Africa has generally been more sprawling with little densification and vertical development compared other continents (Xu et al., 2019). It is also associated with loss, degradation and fragmentation of greenspaces, leaving behind cities with very little public greenery (White et al., 2017).

However, there are significant, local-level, factors influencing the direction and severity of carbon changes caused by urban expansion. The pre-urban land cover being the most important aspect; cities expanding to forest areas are subject to higher carbon loss than cities located in dryland, shrubland, grassland or agricultural setting (Hutyra et al., 2011a; Zhang et al., 2012, 2014; Yan et al., 2015). On the other hand, urbanization has been linked to increasing carbon sequestration in certain context. Remaining urban tree and crop species are shown to sequester more AGC than their rural relatives, largely due to cities' higher temperatures and atmospheric CO₂ concentration (Hutyra et al., 2011a; Liu et al., 2019), while soil carbon is shown to increase in residential and agricultural lands after urbanization (Liu et al., 2018). Part of the carbon storage lost during land clearing is also restored as vegetation recovers or new vegetation is planted, especially in landscapes with naturally low AGC content (Hutyra et al., 2011a). Altogether, urban management actions, such as establishment of greenspaces, recovery of vegetation and enhanced forest and lawn management, have potential to compensate up-to one-third of carbon loss caused by initial urban land conversion (Zhang et al., 2014; Yan et al., 2015).

Besides storing carbon, urban forests and greenspaces produce other ecosystem services vital for urban dwellers well-being. These include maintenance of biodiversity, reduction of pollution, regulation of temperatures and water flows, purification of water and air, protection of watershed, prevention of erosion, reduction of noise, moderation of environmental extremes, and provision of food, fuel, materials and health benefits (Dobbs et al., 2011; Susca et al., 2011; Pugh et al., 2012; Wolch et al., 2014; du Toit et al., 2018). Thus, the value of urban forests and greenspaces should be always looked from a broader ecosystem service perspective, instead of focusing solely on their carbon storage functions.

At policy level, direct emissions from urban expansion have been largely disregarded in climate change mitigation in Africa and elsewhere. Strategies for Reducing Emissions from Deforestation and Forest Degradation (REDD+) focus mainly on agricultural intensification, agroforestry, sustainable forest management and other primarily rural interventions, while in urban climate policies the focus has been in waste management, energy supply and efficiency, urban form and transportation (Dhaval, 2010; Castan Broto and Bulkeley, 2013; Salvini et al., 2014). Castan Broto and Bulkeley (2013) assessed 627 climate change mitigation and adaptation experiments of 100 cities and found only 5% to be related to carbon sequestration. The approaches of both urban and forest carbon management might be justified based on current emission sources, but in future more emphasis should be given to mitigation of direct carbon emissions from urban expansion.

Developing effective mitigation interventions requires better measuring, monitoring and predicting of the phenomena, especially in cities surrounded by significant carbon storages with high urban growth

rates. Global studies, such as by Seto et al. (2012), are essential for setting the phenomena to scale, but there is a need for city region level studies as urban planning decisions are made at this scale. This kind of studies have started to accumulate in recent years, but they are heavily focused on cities in high- or middle-income countries within the temperate zone, even though the direct carbon emissions from urban expansion are predicted to mainly happen in low-income countries in the tropics (Table 1) (Seto et al., 2012). Therefore, there is a knowledge gap concerning the cities of the Global South.

On the methodological side, most of the existing studies are measuring already occurred carbon loss (Zhang et al., 2012; Sallustio et al., 2015; He et al., 2016), while only few try to predict potential emission of future urban expansion (Zhao et al., 2013; Jiang et al., 2017; Li et al., 2018). Also, in most cases the used carbon content data are aggregated to land cover classes (Alberti and Hutyra, 2009; Hutyra et al., 2011b; Li et al., 2018), while in only few models, the AGC content is a continuous variable (Ren et al., 2011; Zhang et al., 2012; Zhao et al., 2013). Furthermore, only one of the studies estimated the carbon impacts of alternative urban expansion scenarios (Jiang et al., 2017), although this kind of analysis are routinely performed in urban growth prediction studies (Vermeiren et al., 2012; Abo-El-Wafa et al., 2018).

Therefore, we demonstrate a state-of-the-art approach for predicting future AGC loss under multiple alternative urban planning scenarios for a city region in Sub-Saharan Africa. Zanzibar City was selected as the study area as previous studies imply that the city region has relatively high carbon stock as well as high deforestation and urban expansion rates (Revolutionary Government of Zanzibar, 2013a; Kukkonen and Käyhkö, 2014; Kukkonen et al., 2018). We used the business-as-usual (BAU) and five alternative urban growth scenarios of 2013–2030 developed by Kukkonen et al. (2018) combined with independently developed 2013 AGC model to predict the AGC loss caused by different urban growth scenarios. These results were then used to discuss importance and patterns of urban expansion related AGC loss and possible mitigation measures to reduce it in Zanzibar. Furthermore, we discussed the methodological limitations of the proposed approach, its global significance and future research needs to advance this emerging subfield.

2. Materials and methods

2.1. Study area

The study area consists of Zanzibar City and the administrative region of Mjini Magharibi (hereafter Zanzibar City Region) located in the west coast of Unguja Island in semi-autonomous Zanzibar Archipelago (Fig. 1). The population of Zanzibar City Region has increased rapidly in recent decades (National Bureau of Statistics, 2004, 2013) and it was about 600,000 in the census of 2012 (NBS, 2004, 2013). With current annual population growth rate (4.2%) the city region would exceed one million inhabitants by 2025. The high population growth has been accompanied by extensive and largely informal urban sprawl that has been challenging for land administration and urban planning to control (Myers, 2008; Kukkonen et al., 2018).

This sprawl has had destructive effects on the Island's forest resources and carbon storages. Majority of deforestation in Unguja has taken place in the vicinity of the capital city and urban expansion has been the second most important direct driver of forest clearings after shifting cultivation (Kukkonen and Käyhkö, 2014). The forests in the Zanzibar City Region are mainly fruit tree plantations and agroforests consisting coconut (*Cocos nucifera*), mango (*Magnifera indica*), breadfruit (*Artocarpus altilis*) and jackfruit (*Artocarpus heterophyllus*) trees (RGZ, 2013a) (See Supplementary Materials for forest definition). The most recent forest inventory suggests that majority of Unguja's carbon is actually stored in these non-natural forests and their average carbon stock per hectare are as high as Island's natural forests (RGZ, 2013a). The total carbon stock of Unguja is 1,735,000 Mg, from which 73% is

Table 1
Review of published studies estimating urban expansion related direct loss of above-ground carbon since 2009.

Reference	Study area	Time period	Urban expansion data	Carbon data	Focus
Li et al. (2018)	Xuzhou City, China	2000–2025	LULCC ^a mapping	Existing carbon coefficients of LC ^b classes	Measuring & predicting
Jiang et al. (2017)	Changsha-Zhuzhou-Xiangtan, China	1995–2023	Predictive modeling with alternative scenarios	Existing carbon coefficients of LC classes	Measuring & predicting
He et al. (2016)	Beijing, China	1990–2011	Existing LULCC data	Existing carbon coefficients of LC classes	Measuring
Sallustio et al. (2015)	2 sites in Italy	1990–2008	Point sample-based estimate	Existing carbon coefficients of LC classes	Measuring
Zhao et al. (2013)	USA	1992–2050	Predictive modeling	Modeling (GEMS ^c)	Predicting
Seto et al. (2012)	Pan-tropics	2000–2030	Predictive modeling	Existing global AGC model	Predicting
Zhang et al. (2012)	Southern USA	1945–2007	Existing LULCC data	Modeling (DLEM ^d)	Measuring
Hutyra et al. (2011b)	Seattle, USA	1986–2007	Existing LULCC data	LC class level AGC inventory	Measuring
Ren et al. (2011)	Xiamen, China	1972–2006	LULCC mapping	Modeling based on forest inventory data	Measuring
Alberti and Hutyra (2009)	Seattle, USA	1986–2007	LULCC mapping	LC class level AGC inventory	Measuring
<i>This study</i>	<i>Zanzibar City, Tanzania</i>	<i>2013–2030</i>	<i>Predictive modeling with alternative scenarios</i>	<i>Modeling based on forest inventory data</i>	<i>Predicting</i>

^a LULCC = Land Use/Land Cover Change.
^b LC = Land cover.
^c GEMS = General Ensemble Biochemical Modeling System.
^d DLEM = Dynamic Land Ecosystem Model.

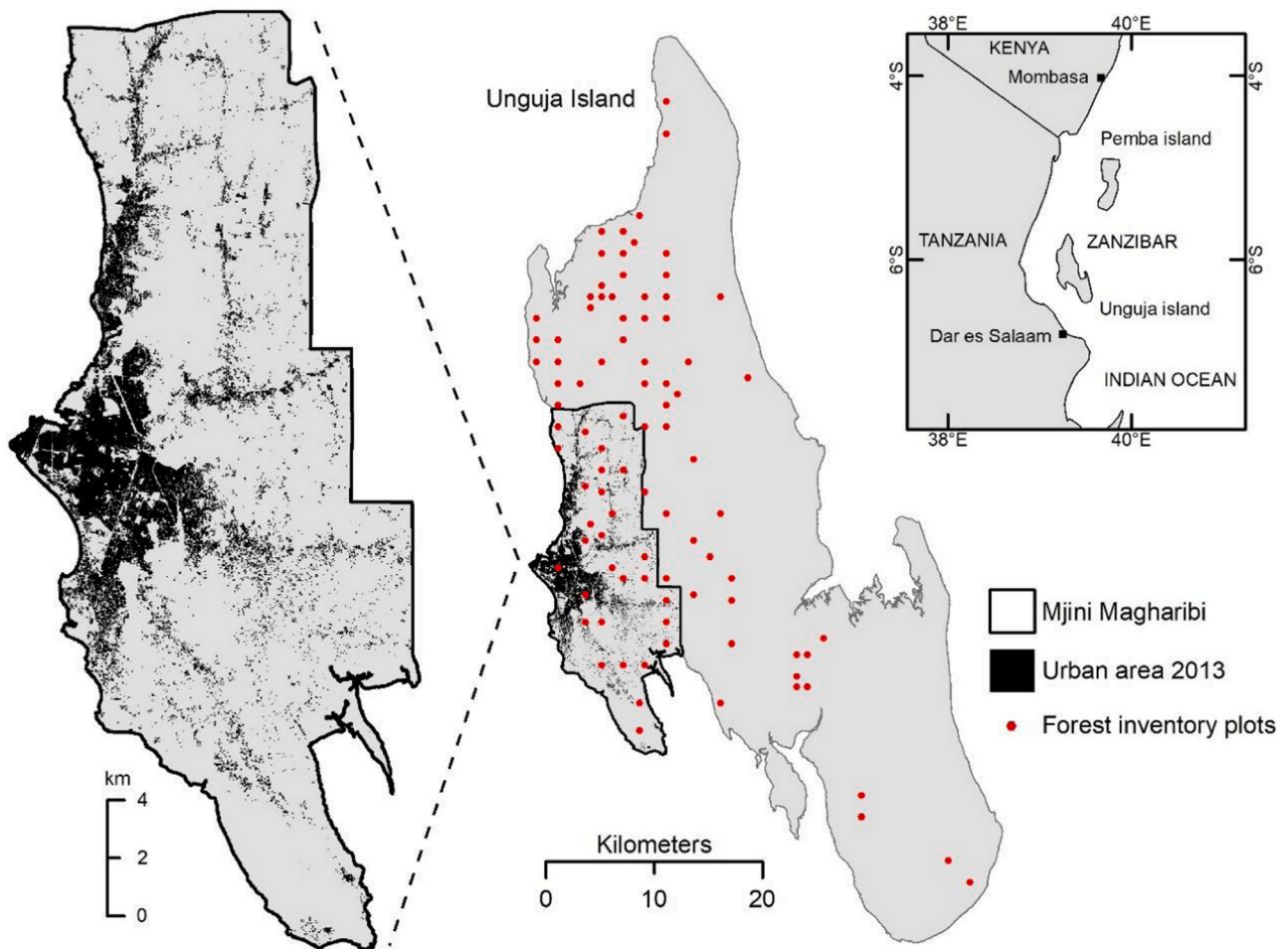


Fig. 1. Zanzibar City is located in Mjini Magharibi region in the west coast of Unguja Island, Zanzibar, Tanzania. The study area, Zanzibar City Region, consists Zanzibar City and its rural hinterlands.

stored in the agroforest and tree plantation systems (RGZ, 2013a). For these reasons, urban expansion is an important, if not the most important, driver behind land use change related GHG emissions in Unguja.

2.2. Workflow

Urban expansion scenarios of Zanzibar City Region produced by Kukkonen et al. (2018) and an independent AGC model were combined to predict the AGC loss due to urban expansion between 2013 and 2030 (Fig. 2). Detailed description of the urban expansion scenario production can be found from Kukkonen et al. (2018), but the main production steps are also described here to provide holistic understanding of the entire process for replication purposes.

Urban expansion between 2004, 2009 and 2013 was mapped using aerial images and high-resolution satellite data. This data was used to estimate the quantity of urban expansion and combined with environmental factors to create business-as-usual Urban Growth Prediction Model (UGPM). Existing spatial plans were adopted to modify the business-as-usual UGPM to produce five alternative urban expansion scenarios for 2013–2030. Simultaneously, forest inventory plot data of Zanzibar Woody Biomass Survey (ZWBS) together with 2012 RapidEye satellite and soil datasets were used to create spatial AGC model, which was then used to produce an estimate of the 2013 above-ground carbon for the study area (Hettige, 1990; RGZ, 2013a). Finally, the six urban expansion scenarios and the AGC estimates were combined to predict the AGC loss caused by future urban expansion between 2013 and 2030.

2.3. Modeling methods

The previously developed UGPMs utilized Generalized Additive Models (GAM), while AGC predictions were based on generally better performing Boosted Regression Trees (BRT). GAMs are extension of Generalized Linear Models (GLM) that allow creation of response shapes that can range from linear to more complex by fitting nonparametric smoothers through range of link functions to the modeled data (Hastie and Tibshirani, 1990; Guisan et al., 2002). Therefore, GAMs can handle nonmonotonic and nonlinear dependencies between the independent and dependent data, which makes the produced prediction accuracies superior to GLMs (Araújo et al., 2005; Luoto et al., 2005; Marmion et al., 2009; Hjort and Luoto, 2011). However, GAMs are prone to overfitting, which needs to be controlled by limiting the degrees of freedom of the smoothed predictors (Wood, 2008). The used GAM models were prepared with ‘mgcv’ package (version 1.8.22) of R software (version 3.2.2), and their degrees of freedom were limited to four.

BRT, on the other hand, is a machine learning method that combines decision trees with boosting (Elith et al., 2008). In decision trees, the dependent variable is predicted by creating multiple binary splits to independent variable values until predefined stopping criterion is achieved (Hastie et al., 2001). Boosting is used to improve the predictive performance of traditional decision trees by combining many simple models (Hastie et al., 2001; Elith et al., 2008). In BRT, boosting is a stagewise process where at each stage a new tree that best reduces the loss of predictive performance is fitted to the residuals of previous results (Elith et al., 2008). The final BRT model will be a combination of

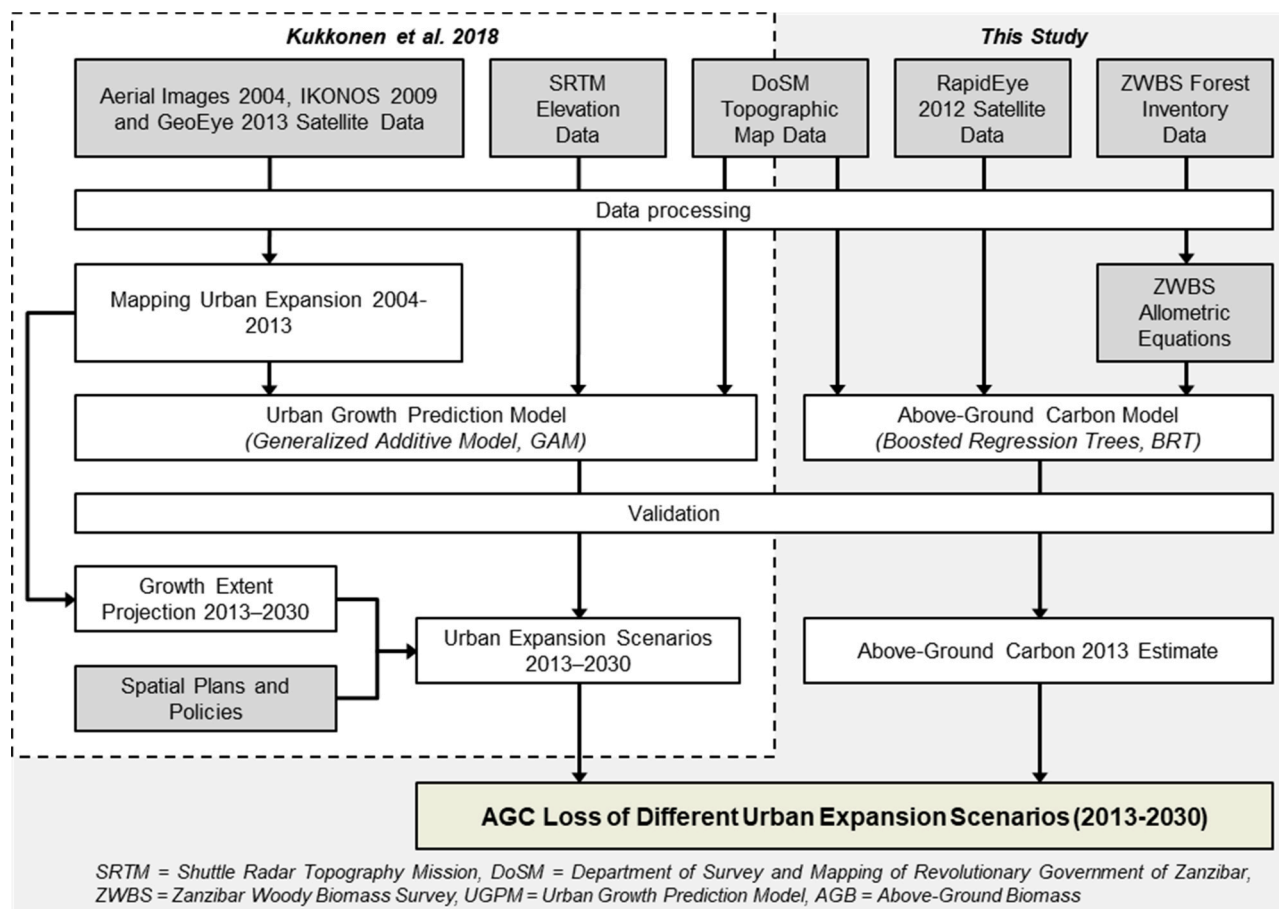


Fig. 2. Simplified workflow chart of the study. The area separated with dashed line and white background are the analysis done in Kukkonen et al. (2018), gray boxes indicate the pre-existing datasets and analysis that were provided for Kukkonen et al. (2018) and this study by various stakeholders, while the white boxes indicate the conducted analysis and the green box the final outcome. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

multiple trees and the predicted values will be calculated as the sum of all trees multiplied by shrinkage. BRT is known for good predictive performance, allowing the use of any type of independent variables and not requiring any data transformation (Leathwick et al., 2006; Elith et al., 2008).

All the BRT modeling of this study was conducted with ‘gbm’ library (version 2.1.1) in R. In ‘gbm’, user must define three parameters: shrinkage, interaction depth and number of trees (Ridgeway, 2007; Elith et al., 2008). Shrinkage defines the contribution of each tree in the final model. Decreasing shrinkage value requires increased number of trees and computational time. Interaction depth determines the amount tree nodes allowed, which controls the interactions between the fitted variables, while number of trees is the total number of trees calculated (Ridgeway, 2007). According to the general guide of Elith et al. (2008) using high interaction depth and very low shrinkage with high number of trees usually provides improved predictive accuracy, but with the trade-off of increased computational time. We determined our parameter values according to these guidelines, while simultaneously keeping the computational time manageable. Eventually, following values were set to the parameters in all BRT models of this study: shrinkage: 0.001, interaction depth: 8 and number of trees: 9000.

2.4. Urban Growth Prediction Model

In UGPMs, cities future expansion is predicted according to previous growth patterns and its relationship with various environmental variables (Vermeiren et al., 2012; Aburas et al., 2016). These models assume that biophysical, social and economic factors together with local spatial policies determine the spatial growth patterns of cities (Poelmans and Van Rompaey, 2010; Aburas et al., 2016). Besides predicting business-as-usual future expansion, UGPMs can be used to produce alternative expansion scenarios based on proposed spatial plans and policies (Vermeiren et al., 2012; Aburas et al., 2016).

As the preparation and results of the used UGPMs are already

described in Kukkonen et al. (2018), they are only summarized here. Urban area expansion mapped from 2004 aerial images (0.5 m resolution), 2009 Ikonos (1 m) and 2013 GeoEye (1.84 m) satellite images was used as the dependent variable in the UGPMs. The 2004 building data had already been digitized by the Department of Survey and Mapping, while expansion of 2004–2009 and 2009–2013 was mapped from the used images in 1:2500 scale with 20 m grid. Grid cells were considered built if they contained or partly covered buildings. Other elements such as roads, parking spaces or yards were not included into the used urban area definition. Based on these results, the urban area was 57.0 km² in 2013 and it had grown 3.8% annually between 2004 and 2013. This pace would mean that the urban area would grow by 88% to 107.4 km² by 2030. Nine independent variables were selected for producing the UGPM from original twelve through stepwise backward selection method where all variables with negative True Skill Statistics (TSS) contributions were removed from the model (Kadane and Lazar, 2004).

The predictive accuracy of the UGPM model was tested by (i) calibrating the model with 2004–2009 expansion data, (ii) predicting expansion from 2009 to 2013 with the created model and (iii) validating the prediction results against real expansion data of 2009–2013. This cross-validation was done in a repeated stratified random subsampling manner, where 5% of positive and equal number of negative samples were selected for calibration and validation, which was then repeated 1000 times (Kuhn and Johnson, 2013). The average area under curve (AUC) and true skill statistic (TSS) for these 1000 repetitions were produced as conclusive results of the model’s predictive accuracy (Allouche et al., 2006; Marmion et al., 2009). The produced model had an average AUC of 0.855 and TSS of 0.568.

The final model was produced by calibrating 1000 GAM sub-models with 5% of positive and equal number of negative sample selected randomly from the full measuring period of 2004–2013. These sub-models were then ensembled with “model.avg” tool of the “MuMIn” package (version 1.43.6) in R, and this ensemble model was used to predict the 2013–2030 urban expansion (Fig. 3A). The extent of urban

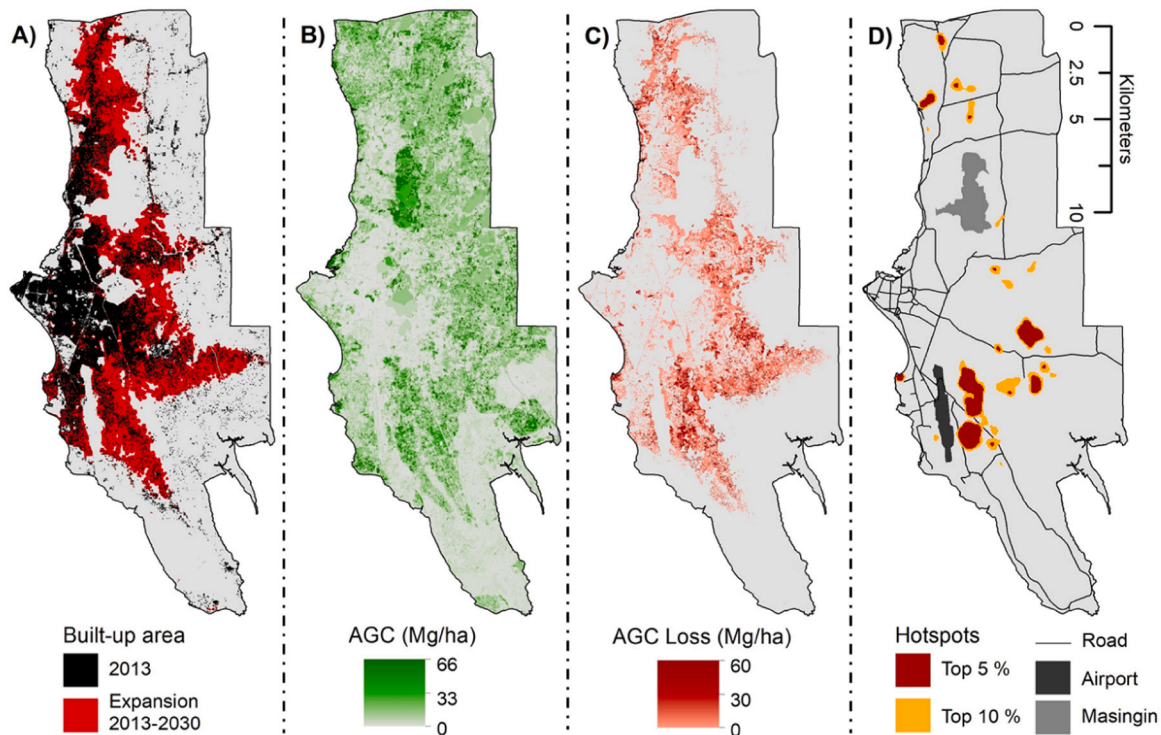


Fig. 3. A) Urban extent of 2013 and predicted business-as-usual expansion between 2013 and 2030 in Mjini Magharibi Region of Unguja Island, Zanzibar, Tanzania, B) Predicted above-ground carbon (AGC) of the study area, C) Predicted AGC loss due to urban expansion in the study area between 2013 and 2030 and D) Hot spots of the predicted AGC loss.

area in 2030 was projected from the expansion of 2004–2013 by assuming that the growth rate remains the same.

Altogether, six scenarios of urban expansion between 2013 and 2030 were produced by altering the model's independent variables based on spatial plans and policies of the Department of Urban and Rural Planning (Kukkonen et al., 2018). "Business-as-usual" (BAU) scenario (i) was the original model without alterations to the independent variables. In "urban nodes" scenario (ii), eight new urban centers are established in the suburbs, while the "infill" scenario (iii) allows urban expansion in certain government and military areas (RGZ, 2014). In "road development" scenario (iv), three new major roads are established in the city, while "airport transfer" (v) scenario relocates the international airport outside the city region (RGZ, 2012). Finally, all the four alternate scenarios (ii, iii, iv & v) were merged into one "combined plans" scenario (vi).

2.5. Above-ground carbon model

Wall-to-wall above-ground biomass (AGB) and AGC models are essential for quantifying land use change related GHG emissions spatially (Saatchi et al., 2011; Castillo et al., 2017; Rodríguez-Veiga et al., 2019). In these models, only the above-ground carbon pool (incl. stem, stump, branches, bark and foliage) is estimated, while below-ground, litter, dead wood and soil carbon pools are excluded. Typically, local AGC models use ground measured AGC estimates of forest inventory sample plots as dependent data and extrapolate this information to a wall-to-wall surface with earth observation and other geospatial variables (Saatchi et al., 2011; Castillo et al., 2017; Rodríguez-Veiga et al., 2019). The used earth observation data can stem from optical, microwave or LiDAR sensors. However, all these sensors are prone to saturation at higher AGC values, meaning that the measured information becomes unable to predict the true AGC content after certain threshold (Rodríguez-Veiga et al., 2019). Rodríguez-Veiga et al. (2019) estimate that all current optical or microwave spaceborne sensors are unable to predict AGB values above 100–150 Mg/ha. Despite these challenges at the upper end of the AGC range, local AGB/AGC models are known to produce reasonable estimates with normalized root-mean square errors (NRMSE) lower than 20% (Rana et al., 2014; Dube et al., 2014).

The AGC modeling of this study was based on the forest inventory conducted by Zanzibar Woody Biomass Survey (ZWBS) project in 2013 (RGZ, 2013a). Altogether, 311 concentric forest inventory plots were established in Unguja based on stratified sampling design using the ZWBS land cover classification, standard deviation of volume/ha per stratum based on previous 1997 forest inventory and allowable error of 10% (RGZ, 2013a) (See Supplementary Materials for land cover classification). Species and breast height diameter (DBH) were recorded for each tree in the inventory plots with 16 m radius, while more information, such as total tree height and bole height, were collected for every fifth tree. Näslund (1936) formula was used to calculate tree height for those trees with only DBH measurement and the tree form factors required for the formula were based on the information measured from every fifth tree. Allometric equation developed for mainland Tanzania was used to convert existing height and basal area information to tree volume estimates for majority of the species, while formulas from previous forest inventory of Zanzibar were used to estimate the volumes for coconut and clove trees (Leskinen et al., 1997; Vesa et al., 2010; RGZ, 2013a). ZWBS adopted an average wood basic density of 0.5 kg/m³ to convert the volume information to AGB estimates, which were then presented as hectare averages of each plot. This above-ground biomass (AGB) per ha data was then provided for this study by the Department of Forest and Non-Renewable Natural Resources (DFRN) of Zanzibar. We used the default carbon fraction of tropical forests, 0.47, to convert the AGB/ha information to AGC/ha (Intergovernmental Panel on Climate Change (IPCC), 2006).

RapidEye (RE) 5-meter resolution satellite images acquired via

tasking operation between October and December 2012 for ZWBS were provided already orthorectified to this study by the DFRM. The images were atmospherically corrected, and haze removed with PCI Geomatica 2014 software's ATCOR tool package (Richter and Schläpfer, 2016). Seven tiles acquired 19th of December created a base for satellite image mosaic, as they were relatively cloud free and covered most of Unguja and all of Zanzibar City Region. Other seven tiles were used to supplement the cloud and shadow areas of the base images. Mosaicking and color balancing was done with PCI Geomatica 2014 software's OrthoEngine module. Color balancing areas were selected manually so that areas with seasonal changes or cloud and shadow coverage were excluded, and the other seven images were then color balanced to the base images. When the final mosaic was compared to aerial images of 2004 and GPS recordings from the field, 20–30 m shift was noticed. This was corrected by orthorectifying the mosaic to the alignment of the 2004 aerial images. The final mosaic had approximately 5% cloud coverage within Zanzibar City Region and about 25% coverage within entire Unguja that could not be removed with the available imagery.

Altogether 212 forest inventory plots with AGC information were selected for the modeling from entire Unguja (Fig. 1). However, 92 plots were removed, because they were either in cloud and shadow areas or forest types not found from Zanzibar City Region (i.e. rubber and clove plantations, mature coral rag forest and evergreen groundwater forest). Information on the RE band values and vegetation indices, used by Dube et al. (2014) in a similar AGB modeling study, were calculated for the plots and used as independent variables (Table 2). As the forest inventory plots covered more than a single pixel, minimum, maximum, mean and standard deviation values were calculated from all the selected independent variables. Only pixels that had over half of their area within the plot were used in these calculations. As soil is known to influence forest type in Zanzibar, this was included as binary independent variable where 1 represented coral scrub soils and 0 other soils (Hettige, 1990; Kukkonen and Käyhkö, 2014).

At this stage, there were 69 partly correlated independent variables. Thus, the model had to be subjected to variable selection to reduce the effects of multicollinearity, while simultaneously maximizing the accuracy of the final model (Dormann et al., 2013). Variable selection was done with a forward stepwise process acknowledging variance inflation factor (VIF) requirements and subjected to 10-fold cross-validation. The first variable included into the model (seed variable) was selected according to the highest Spearman correlation with the dependent variable (Supplementary Materials). In the second step, additional variables were added to the model one-by-one, but first it was tested that neither the seed variable nor the added variable had VIF value above the selected threshold. The threshold was set to relatively low (<3) according to the guidelines provided Becker et al. (2015). All the step two models fulfilling the VIF requirements were passed to the actual testing phase where the modeling was conducted with GBM and previously

Table 2
Vegetation indices used in the above-ground carbon modeling.

Vegetation index	Formula
Simple ratio	NIR/Red
RVI.RE (Ratio Vegetation Index)	Red-edge/NIR
NDVI (Normalized Difference Vegetation Index)	(NIR-Red)/(NIR+Red)
NDVI.RE	(NIR-Red-edge)/(NIR+Red-edge)
DVI (Difference Vegetation Index)	NIR-Red
TVI (Triangular Vegetation Index)	0.5 * [120 * (NIR-Green)-200 * (Red-Green)]
TVI.RE	0.5 * [120 * (NIR-Green)-200 * (Red-edge-Green)]
IPVI (Perpendicular Vegetation Index)	NIR/(NIR+Red)
IPVI.RE	NIR/(NIR+Red-edge)
GI (Greenness Index)	Green/Red
GL.RE	Green/Red-edge
PSSR (Pigment Specific Simple Ratio)	NIR/Red-edge

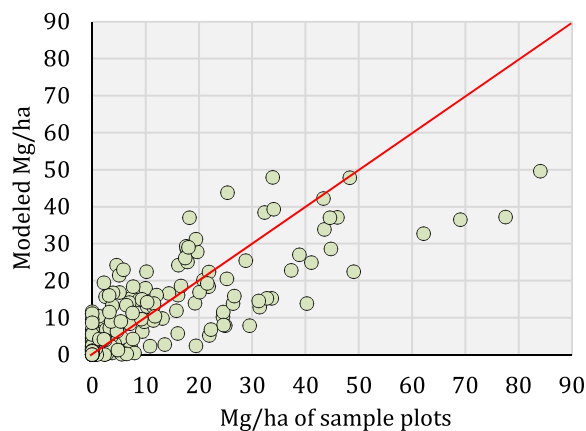


Fig. 4. ZWBS forest inventory plot AGC Mg/ha values plotted against the modeled AGC Mg/ha values of the same plots with line of equality.

defined parameters, while accuracy was measured with 10-fold cross-validation. In the 10-fold cross-validation, the dataset is divided to ten equally sized subsets and in each run nine of the subsets are used in model calibration, while the model is tested against the one held-out subset (Mosteller and Tukey, 1968). This process is then repeated ten times to test all possible permutations of the subsets and average R^2 of the ten runs is reported. The variable providing highest increased R^2 was added to the model and the forward process was then continued until none of the remaining variable would fulfill the VIF requirement or the R^2 would no longer increase (Supplementary Materials).

After selecting the final variables for the model, its accuracy was tested with separate Leave-One-Out Cross-Validation (LOOCV) test. In LOOCV, one observation is left out from the calibration data set and all other observations are used to train the model. The value of the one observation left out is then predicted with the created model and the result is evaluated against the real observed value. This is then repeated for all the observations in the dataset. We used R^2 , Root Mean Square Error (RMSE) and normalized RMSE (NRMSE) to estimate the difference between predicted and observed results in LOOCV and the accuracy of the AGC model in general. The LOOCV predictions are also presented against the forest inventory AGC results in a scatter plot to identify the saturation point of the model.

The final model was calibrated with all sample observations. The 20 m resolution grid that was used for the UGPMs was also used in the AGC predictions. The variables selected for the final model were calculated for each grid cell, which was then used to predict the AGC information for the entire study area. Some errors were corrected from the predicted AGC results. Subzero cell values were converted to zero. Due to lack of observations, wetlands received high AGC predictions, which were then corrected to zero with the assistance of land cover classification of ZWBS (RGZ, 2013a). This classification was also used to assign carbon estimates to remaining cloud and shadow areas in the study area. Average class-level AGC estimates were calculated from all the non-cloud areas of the predicted data. These average carbon estimates were then assigned to the cloud and shadow areas according to their class in the ZWBS land cover classification.

Table 3

Absolute and relative AGC losses associated with the used business-as-usual and alternative urban expansion scenarios.

Scenario	Loss of AGC (Mg)	% of study area AGC	% of Unguja AGC	% difference from BAU
Business-as-usual (BAU)	42,394	15.36%	3.27%	0.00%
Urban nodes	42,159	15.27%	3.25%	-0.49%
Infill	41,768	15.13%	3.22%	-1.23%
Road development	42,473	15.39%	3.27%	0.19%
Airport transfer	41,597	15.07%	3.20%	-1.65%
Combined plans	41,085	14.88%	3.17%	-2.60%

2.6. Final AGC loss estimate

To estimate the direct AGC loss caused by urban expansion, the expansion scenarios and the AGC model were overlaid. The AGC was not considered to decline to zero after expansion, as some vegetation usually remains even after construction of buildings. To estimate an average post-building AGC content, the average AGC of those grid cells already built in 2013 was measured. This average (5.12 Mg/ha) was then subtracted from the AGC content of those grid cells with predicted urban expansion in 2013–2030 to estimate the loss of AGC for each grid cell. However, if the grid cell had AGC content below the average, it was considered that no AGC would be lost in the urban expansion process.

The absolute and proportional AGC losses were reported for each of the six expansion scenarios. The proportional losses were reported against the total AGC of the study area calculated from the produced AGC model and entire Unguja island estimated by ZWBS (RGZ, 2013a). The AGC impacts of different urban expansion scenarios were evaluated by estimating how much the alternative scenarios altered from the business-as-usual scenario in percentages. Also, a hot spot analysis was conducted to identify the main concentrations of urban expansion related AGC loss. This was done with Kernel Density tool of ArcGIS 10.3 with one-kilometer radius setting.

3. Results

Based on the produced above-ground carbon model, there are about 276,000 Mg of AGC in the study area and the average carbon content is 10.6 Mg/ha. AGC is rather evenly distributed, with an exemption of the already established urban area and the coral rag landscapes in the southeastern corner of the study area (Fig. 3B). The main continuous concentration of AGC is in Masingini forest reserve just northeast from Zanzibar City. The AGC model had RMSE of 6.54 Mg/ha, NRMSE of 56.5% and R^2 of 0.68. The AGC model saturated at the upper end of the range, and sample plots with AGC content above 50 Mg AGC/ha were underestimated by the model (Fig. 4).

The BAU predictions suggest that approximately 42,000 Mg of Above-Ground Carbon will be lost in the direct expansion of urban fabric in Zanzibar City Region between 2013 and 2030 (Fig. 3C and Table 3). This will be approximately 15% of the total AGC of the region and 3% of the total AGC of Unguja Island. Average carbon content of cells predicted to be subjected to urban expansion in the BAU scenario is 12.6 Mg/ha. The annual emissions from direct expansion of urban fabric would be about 2500 Mg, which is about 4.2 kg per capita with Zanzibar City Region population of 2012 (NBS, 2013).

The loss concentrates to areas east and southeast from the city center, where high AGC content agroforest and fruit tree plantations are located (Fig. 3D). The largest unfragmented forest area in the study area, Masingini Forest Reserve, in northeast from the city center remains largely uninfluenced as the UGPMs didn't predict urban expansion to officially protected areas.

From the developed alternative scenarios, 'urban nodes', 'infill', 'airport transfer' and 'combined plans' scenarios reduce AGC loss compared to the 'business-as-usual' scenario, while 'road development' scenario increases this (Table 3). However, the magnitude of impacts is low in all alternative scenarios, and only the scenarios 'infill', 'airport

transfer' and 'combined plans' reduce AGC loss over 1% compared to the BAU scenario.

4. Discussion

4.1. Urban expansion caused AGC loss in Zanzibar

Direct expansion of buildings on to the carbon storages is predicted to cause substantial decline in the above-ground carbon content of Zanzibar City Region (15.4%), Unguja Island (3.3%) and entire Zanzibar (2.1%) between 2013 and 2030 (RGZ, 2013a, 2013b). In the official submission to the United Nations Framework Convention on Climate Change (UNFCCC), the total loss of carbon due to deforestation was estimated to be about 17,000 Mg annually in Unguja (The Government of the United Republic of Tanzania (GURT), 2016). Based on this estimate, the carbon loss from expansion of urban fabric in Zanzibar City Region would constitute about 15% of the total annual loss, even though our estimate includes only AGC pool against three carbon pools used in the UNFCCC submission. Furthermore, Kukkonen and Käyhkö (2014) estimated that urban expansion caused 27% of all deforestation happened in Unguja between 1975 and 2009. These figures are substantially higher than the global average prediction by Seto et al. (2012) estimating that only 5% of land use change related carbon emissions would be related to expansion of urban area between 2000 and 2030. However, when compared against the total annual emissions of Zanzibar in 2010, the direct emissions from urban expansion would constitute only 1.2%, which is in line with global findings (Pye et al., 2012; Churkina, 2016). Therefore, it can be said that expansion of urban fabric on carbon storages is highly meaningful source of emissions within the land use sector of Zanzibar, but relatively minor when considering the overall GHG emissions.

The relatively high loss of AGC in urban land conversion of Zanzibar City Region is an outcome of prevalence of high carbon content pre-urban land cover, fruit tree plantations and agroforests, around it. This is in line with global evidence indicating that pre-urban land cover is the main factor influencing urban expansion related carbon loss and that African urban expansion is happening largely at the expense of forests (Hutyra et al., 2011a; Zhang et al., 2014; Liu et al., 2019). Similarly to other studies, the carbon loss is mainly happening at urban fringe instead of the urban core (Li et al., 2018). This is because very little carbon had remained in already urbanized core as is typical to African cities (White et al., 2017). Studies from US and China indicate that post-urbanization recovery of vegetation has potential to compensate significant proportion of carbon storage lost during urban land conversion (Zhang et al., 2014; Yan et al., 2015). However, this is unlikely in Zanzibar City Region due to the dense and unvegetated nature of the expanding residential areas. For the same reason, it is not likely that enhanced carbon sequestration of remaining urban vegetation would significantly compensate the happened loss of storages.

However, the ecological consequences of the urban land conversion are less severe than the high GHG emissions suggest. The loss is taking place mainly in fruit tree plantations and agroforests, while natural forests are less affected as they have been largely cleared in the past and the remaining ones are under official protection (Kukkonen and Käyhkö, 2014). As the fruit tree plantation and agroforests sustain less biodiversity than the natural forests, are the biodiversity impacts substantially lower than in the case where the city would be surrounded by natural forests (RGZ, 2014). However, there is very little information about the importance of these non-natural forests and the impacts of their loss on other regulating ecosystem services, such as purification of water and air and flood protection, in Zanzibar.

Four out of the five tested alternative spatial scenarios suggest reduced loss of carbon storages compared to the business-as-usual scenario. However, only 'infill', 'airport transfer' and 'combined plans' scenarios reduced the loss of AGC more than 1%, but even from these, the 'airport transfer' and 'combined plans' scenarios would be likely to

increase the loss, as they are based on an assumption that the airport is relocated into coral rag forest site outside the study area (RGZ, 2012). Even though these alternative spatial scenarios can quantitatively redirect up-to 10% of the expansion when compared to the BAU scenario, this is not accompanied by significant reductions in AGC loss (Kukkonen et al., 2018). This is because the AGC is quite evenly distributed in the study area and it is challenging to direct expansion away from it.

4.2. Policy-level mitigation efforts

Direct carbon emissions caused by urban expansion are not likely to alter the business-as-usual growth patterns of cities in Zanzibar or elsewhere, as i) the potential market value of this carbon is insignificant compared to the economic return from developing rural land to urban use (Capozza and Helsley, 1989; Cavailhès and Wavresky, 2003; Carbon Pricing Leadership Coalition (CPLC), 2017); ii) urbanization is actively sought after by many decision makers as it is considered to stimulate economic growth, though this causality has been largely questioned (Bertinelli and Strobl, 2007; Turok and Mcgranahan, 2013; Chen et al., 2014); and iii) governments favor rural forest mitigation activities as these are usually more cost-efficient compared to similar efforts in and around urban areas (Salvini et al., 2014; Larjavaara et al., 2018). However, the cumulative value of other ecosystem services provided by the carbon storages may outweigh the economic gains of converting them to urban use. Thus, the protection of carbon storages should be tied to broader benefits of all ecosystem services provided by them.

To mitigate and compensate these emissions and protect ecosystem services in general, urban greenery strategy should be developed for Zanzibar City Region, which would lay out how and where vegetation could be protected and managed. The strategy could be economically justified by cost-efficiency of protecting pre-urban forests and other carbon storages than compensate their loss with restoration (Dumenu, 2013; Jim, 2013; Zhang et al., 2014). Ecosystem services should be at the center of the strategy, but they would need to be tailored towards the needs and values of the communities using them, and acknowledge the plurality of these needs within the urban area (du Toit et al., 2018). The strategy should also clarify the responsibilities of urban greenery management between Zanzibar central government, municipal actors and local communities (Chishaleshalea et al., 2015). It should promote largely participatory management practices, as purely restrictive or statutory policies, such as banning conversion of forest areas or setting minimum greenery requirements for land parcels, are likely to fail in the context of Zanzibar and other cities with weak and under resourced institutions for monitoring and enforcement (Chishaleshalea et al., 2015; Cobbinah and Darkwah, 2016; White et al., 2017; Kukkonen et al., 2018). Finally, the strategy should evaluate the feasibility of different planning tools for urban greenery management. Such approaches as establishment of vegetation corridors to increase connectivity, identifying and maintaining high carbon content trees and stands, establishment of protected urban natural areas, registering individual trees, using trees as fences or parcel boundaries and setback zoning allowing roadside tree corridors have all been suggested in developing country context (Jim, 2008, 2013; Cobbinah and Darkwah, 2016). However, their applicability in settings of rapid, largely informal, urban expansion and limited institutional capacity are uncertain, and thus, their suitability for Zanzibar should be separately assessed.

There are also certain urban planning policies that can have significant implications on the carbon storages. Most importantly, the RGZ (2014) is actively pursuing urban densification through vertical development. The potential for this is enormous as the current building stock consist mainly single-story detached houses (Kukkonen et al., 2018). Densification could significantly reduce the overall expansion of the city, and its negative impacts on carbon storages. The RGZ (2014) is also directing urban expansion to coralline soils to reduce agricultural encroachment. This policy has additional carbon co-benefits, as these

areas have the lowest AGC content in the city region. Thirdly, there are large areas of public lands with high carbon content in the city region. These areas have building restrictions that are enforced with physical barriers, which have been effective in reducing urban expansion (Kukkonen et al., 2018). There are plans to open some of these areas to housing development (RGZ, 2014). However, the carbon emission impacts of these plans should be assessed before their implementation.

Besides the urban planning policies, the direct carbon emissions from urban expansion should also be better addressed in the climate change policies of Zanzibar. Currently, these policies focus on reducing the consumption of wood fuel, promoting tree planting and protecting the natural forest, while in urban realm their focus is on improving public transportation, increasing lower polluting vehicle stock and promoting sustainable building (Pye et al., 2012; RGZ, 2013b). However, considering the significance of these emissions, protection of forest and trees from urban expansion would deserve a recognition in these policies. This kind of overlooking of direct carbon emissions caused by urban expansion is common globally (Castan Broto and Bulkeley, 2013; Salvini et al., 2014).

Despite these policy efforts, it is likely that majority of the predicted AGC loss will take place due to the rapid urban expansion anticipated for Zanzibar City. Therefore, it is essential to start considering the long-term management of urban soil carbon, as soils have the potential to maintain carbon long after it has disappeared from the surface. Use of pervious or semi-pervious instead of impervious surfaces can help to maintain soil carbon after land conversion (Raciti et al., 2012; Wei et al., 2014). Though, the carbon impacts of paving are dependent on the context, and in some cases sealing the soil with an impervious surface may reduce soil decomposition, and thus maintain the carbon storage longer (Lorenz and Lal, 2015; Velasco et al., 2016). Furthermore, certain activities, such as adding organic amendments and re-vegetating bare land, can be done during construction stage to enhance carbon stocks (Lorenz and Lal, 2015). Considering the proportional significance of soil carbon, these dynamics should be investigated within the city region to promote optimal soil carbon management solutions.

4.3. Methodological limitations

There are certain methodological limitations that impacted the results of this study. The ZWBS adopted wood basic density of 0.5 kg/m³ in conversion of volumes to AGB. However, wood densities vary between species and within species based on age (Yeboah et al., 2014; Castillo et al., 2018). Use of a single, universal wood basic density figure distorts the results to some extent. Thus, we recommend using species and age group specific wood densities in similar studies. The developed AGC models saturated at 50 Mg/ha, which decreased both the model accuracy and AGC content predictions at the upper end of the AGC range. This is a general problem in biomass and carbon models based on optical satellite data, which could be overcome with more penetrable, but also significantly costlier, surveying methods, such as LIDAR (Rana et al., 2014; Rodríguez-Veiga et al., 2019). Also, the study estimated all urbanized land covers to have static AGC density of 5.12 Mg/ha. However, studies show significant internal variation in carbon sequestration of urban areas, which could be acknowledged with more detailed classification of the urban areas (Hutyra et al., 2011a; Liu et al., 2019). The AGC prediction is from year 2013, and thus it could not be used for estimating the actual carbon loss of 2004–2013. Measuring the happened AGC loss would have allowed direct statistical validation of the modeled AGC loss, while now the study relies on predicted urban expansion and its independent validation. The used forest inventory plot data and satellite images are from beginning of 2013 and end of 2012, respectively, thus there shouldn't be significant mismatch between the data sources, but it is possible that some of the plots have changed between the acquisition of satellite image and plot information. Also, there might have been significant changes happened since 2013, and the results could be somewhat different if conducted with more recent data.

The study was also limited to only one carbon pool, AGC. However, the typical agroforestry species of Zanzibar City Region contain most of their carbon in other pools. Mango trees (*Magnifera indica*) have approximately 55% of their total carbon stored in soil and 6% in below-ground, while for coconut trees (*Cocos nucifera*) soil carbon constitutes 42–63% and below-ground carbon about 14% of the total carbon (Ranasinghe and Thimothias, 2012; Sundarapandian et al., 2013; Janiola and Marin, 2016). Therefore, acknowledging also these other carbon pools would have increased the total emissions substantially. Altogether, the developed AGC modeling had satisfactory R² and RMSE results. However, the NRMSE was significantly higher than in similar models (Dube et al., 2014; Rana et al., 2014). However, this was merely an outcome of the low average Mg/ha AGC of the forest inventory samples due to numerous zero Mg/ha AGC observations from the urban areas.

The urban expansion models were limited as they estimated only the expansion of buildings. Including other forms of urban fabric would have significantly increased the emissions, as paved surfaces such as roads and parking lots can cover up to 35% of residential and 50–70% of non-residential areas (Akbari et al., 2003). The used UGPM also assumed that expansion will not take place in protected Masingini forest, as this was the case during the measurement period. Unfortunately, recent satellite images indicate encroachment also in Masingini, which may alter the pattern of urban expansion significantly in the study area. Urban expansion has also spillover effects, which are generally far more important than changes happening in the actual urban area (Churkina, 2016). Urban hinterlands are often deforested for agricultural and grazing purposes, while remaining forests are degraded to fulfill the wood fuel and timber needs of the growing city (Ahrends et al., 2010; DeFries et al., 2010; Seto et al., 2012). The study only assessed the AGC impacts of existing spatial plans, while modeling could have been also used to optimize carbon impacts of city expansion. However, this would require a significantly more complex modeling scheme where carbon impacts would be integrated into models optimizing the location of road, urban node and infill development. Finally, the likelihood of occurrence of the used alternative urban expansion scenarios is most likely relatively low, as failure of urban plans have been a chronic problem not only in Zanzibar, but generally in Sub-Saharan Africa (Myers, 2008; UN-Habitat (United Nations Human Settlement Programme), 2014).

4.4. Global considerations

This is the first study predicting future carbon loss caused by urban expansion at a city region scale in Sub-Saharan Africa. It shows an alarming pattern of AGC loss around a secondary city in the region, thus, suggesting that similar processes might be ongoing in other African cities in forested landscapes. It also demonstrates that data for state-of-the-art modeling is available in the region. Global studies, such as Seto et al. (2012), can identify country and continental level patterns of the process, but the relatively low accuracy of their AGC and urban expansion models make them less suitable to guide mitigation actions done at city region or lower administrative levels. Due to the alarming rate of AGC loss detected in this study, we strongly recommend that similar localized models would be developed for all African cities that are surrounded by substantial carbon storages, while simultaneously facing rapid population growth and urban expansion.

The presented study also pushes the boundaries in this emerging field methodologically, despite the challenges described in the previous chapter. Unlike majority of the existing studies, it (i) predicts future loss instead of measuring already happened loss; (ii) uses continuous AGC data instead of generalized land cover estimates; and (iii) uses alternative urban expansion scenarios besides the BAU scenario (Hutyra et al., 2011b; Sallustio et al., 2015; He et al., 2016). However, further methodological developments are needed to make similar models reliably applicable for urban planning and decision-making processes.

The study also suggests few policy tools, such as preparing an urban greenery strategy, urban densification and soil carbon management, that can be adopted in other city regions. However, the impacts of these or other policies have never been quantified even in middle or high-income countries. Thus, there is a need for methodologically rigorous studies evaluating the impacts of policies aiming to reduce AGC loss of urban expansion. Furthermore, more localized studies are needed to tailor the best practices to the context of rapidly growing, largely informal, cities of Global South. All in all, additional research efforts are seriously needed to quantify, predict, understand and address this often overlooked, but growing source of global GHG emissions.

5. Conclusion

This study shows that the direct above-ground carbon loss caused by urban expansion will be a significant source of GHG emissions in the land use sector of Zanzibar City in the future. The loss is significantly faster in Zanzibar City than global averages suggest as the city is surrounded by high carbon content agroforests and fruit tree plantations. For the same reason, the biodiversity impacts of the phenomena are likely to be less severe, however, the impacts to other ecosystem services are unknown and should be studied in the future. To mitigate the loss of these forests, urban greenery strategy should be developed for Zanzibar to identify locations and methods to protect forests from urban expansion, while efforts for urban densification should be also supported. This is the first study measuring and predicting urban expansion related direct carbon losses in Africa. It shows that data enabling such studies exist in the region, which hopefully, paves the way for similar studies in the future. These are seriously needed especially in similar cities that are simultaneously surrounded by carbon storages and facing high urban expansion rates.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.landusepol.2021.105810](https://doi.org/10.1016/j.landusepol.2021.105810).

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