Spatio-Temporal Analysis of the Pattern of Agricultural Land Use Change in Tanzania Using U-net Deep Learning Model

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Abstract

In Sub-Saharan Africa, cropland expansion is expected to increase in the next thirty years to meet the continent’s food needs, which calls for a large-scale agricultural land transformation. To gain insight into these changes, this study aims to analyze the spatial pattern of agricultural land use change in Tanzania over a 6-year (2017-2022) period, using advanced machine learning to map annual cropland cover in high resolution (~5 m) PlanetScope imagery combined with Sentinel-1 radar imagery over the entire country. The study will identify the areas and determine the rate of expansion in cropland during the analyzed time period while identifying temporal patterns in cultivation that indicate variations in cropping/fallow cycles. Ultimately, this study will provide further insights into the nature and extent of agricultural transformation, which can help raise awareness of food security and biodiversity and enable better spatial planning and agricultural policies.

## Introduction

Rapid economic and population growth in Sub-Saharan Africa is expected to increase food needs increase threefold in the next 30 years and is driving a large-scale cropland expansion that has already begun to unfold (Estes *et al.* 2016, Bullock *et al.* 2021, Xiong *et al.* 2022). This large-scale change will have significant social, economic, and environmental impacts (Estes *et al.* 2016). There is, therefore, a pressing need for studies on the pattern of agricultural change within the areas of the region where agriculture is changing most rapidly. This is particularly true in East Africa, which is experiencing the highest rates of cropland change in the region (Bullocks *et al.* 2021), particularly Tanzania (Winmann *et al.* 2020). The global analysis of Curtis *et al.* (2018) shows that 93%–94% of tree cover loss (at >10% tree cover) in Tanzania between 2010 and 2015 was attributed to shifting cultivation. Shifting cultivation occupied 7.6% (66,332 km2) of the total country land area in 2013 (URT, 2015). Similarly, Sekela and Manfred (2019), in their study of land use and land cover change detection in the Wami river basin in Tanzania, show that most of the grassland, bushland, and woodland were intensively changed to cultivated land both upstream and downstream.

Given the size and pace of agricultural change in Tanzania, it is imperative to study the nature and extent of these changes. However, the ability to do so with existing data is limited, given the lack of available and up-to-date agricultural census data and the difficulty of mapping croplands with remote sensing (Xiong *et al.* 2022). This study will address this need by developing a high-resolution time series of cropland maps from 2017-2022 and use that to study the location and nature of agricultural change during the 6-year period. To undertake this work, the project will apply cutting-edge remote sensing to develop the highest resolution set of maps developed to date for Tanzania and the first to do so as an annual time series.

1.1 **Aims and Objectives**

The aim of this study is to understand the spatial patterns and the rate of agricultural transformation in Tanzania over the 6-year study period. Using the developed maps, the study will seek to:

1. Identify the areas of greatest cropland expansion, as well as areas of cropland decline.
2. Analyze the percentages of different land cover types that are converted to agricultural land and vice versa.
3. Distinguish between different forms of croplands based on the frequency of cropping/fallow periods.

## 2. Methodology

To develop maps of Tanzanian land cover, we will use a recently developed method (Xiong *et al.* 2022) that has been used to generate an initial 5 m land cover map of Tanzania. This approach uses two imagery sources. The first comprises Planetscope imagery made publicly available through Norway’s International Climate and Forest Initiative (NICFI). PlanetScope images are collected daily at high spatial resolution (3.7m), making them suitable for delineating crop field boundaries. The data provide 4 multi-spectral bands (Blue, Green, Red, and Near Infra-Red (NIR)) in dimensions that are suitable for developing neural networks (4096×4096). The NICFI program provides PlanetScope imagery processed into cloud-free monthly composites from 2020 to the present, and into 6-monthly composites from 2017-2019, with coverage over the entire tropics. In addition to Planetscope, we will also use Sentinel 1 radar time series, processed using harmonic regression to derive coefficients that describe annual phenological patterns. These image datasets are available in Google Earth Engine (GEE), so image processing will be in GEE. The final images will be exported to high-performance computing resources where model development and prediction will occur.

To map the land cover, we will use a customized version of UNet (Ronneberger *et al.* 2015). To train and assess the model, we will develop labels that combine existing land cover maps into consensus labels to make starter labels, then use a Random Forest model to fill in missing data in the consensus labels, followed by manual editing of the gap-filled labels to develop a full set of labels. Our already developed U-Net model will then be trained with these new labels added to our existing pool of 2018 labels to develop a single model that covers multiple years. The fully trained model will then be fine-tuned (with initial network layers frozen while the last few layers are retrained) using labels for each individual year to generate maps for each year.

2.1 **Independent Validation dataset**

Pixel-based validation dataset needs to be collected to make a validation report for the dataset. Geo-wiki Fritz. *et al*. (2012), or other platforms, or even just in QGIS, will be used to collect the validation dataset for each of the 6 years. Three people will separately collect, compare, and merge the labels based on overall class agreement. The method will follow the workflow of other global datasets, such as Copernicus Global Land Operations and WorldCover.

2.1 **Analysis**

The analysis of the validated maps produced will be done by adopting the approach of Bilintoh *et al.* (2022), using the “Intensity Analysis” method. It will analyze the temporal difference of the agricultural land cover maps for the six-year period. The framework of intensity analysis revolved around three levels of intensities: interval, categorical, and transitional, which show different levels in detail. The categorical level intensity measures the sizes and intensities of each category’s (expansion or rotation) dormant or active, during a given time interval. The transitional level intensity will show which category’s transitions are intensively avoided or targeted during the studied period.

## 3. Expected Outcomes

Upon completion, this research is expected to produce insights into the spatial analysis of agricultural land use patterns (expansion and rotation) in Tanzania during the considered time periods through the agricultural land use maps (digital records of agricultural fields) produced. We will also understand the rate of agricultural land use change in Tanzania and its impact on food security.

## References

Bilintoh TM, 2022, Intensity Analysis to Study the Dynamics of Reforestation in the Rio Doce Water Basin, Brazil. Front*. Remote Sensing*. 3:873341. doi: 10.3389/frsen.2022.873341

Bullock, E.L.; Healey, S.P.; Yang, Z.; Oduor, P.; Gorelick, N.; Omondi, S.; Ouko, E.; Cohen, W.B. Three Decades of Land Cover Change in East Africa. *Land* 2021, 10, 150. https://doi.org/10.3390/ land10020150

Curtis P B, Slay C M, Harris N L, Tyukavina A and Hansen M C 2018 Classifying drivers of global forest loss *Science* 361: 1108–11

Estes LD, T. Searchinger, M, Spiegel, D. Tian, S. Sichinga, M. Mwale, L. Kehoe, T. Kuemmerle, A. Berven, N. Chaney , J. Sheffield, E. F. Wood and K. K. Caylor, 2016, Reconciling agriculture, carbon and biodiversity in a savannah transformation frontier. *Philosophical Transaction*. Royal Society Publishing 371: 20150316. http://dx.doi.org/10.1098/rstb.2015.0316

Fritz S., Ian McCallum, Christian Schill, Christopher Perger, Linda See, Dmitry Schepaschenko, Marijin van der Velde, Florian Kraxner, Michael Obersteiner 2012, Geowiki: An online platform for improving global land cover. *Environmental Modeling & Software*, 31:110-123.

Sekela Twisa and Manfred F. Buchroithner, 2019, Land-Use and Land-Cover (LULC) Change Detection in Wami River Basin, Tanzania. *Land* 8, 136; doi:10.3390/land8090136

van Vliet, J., Magliocca, N.R., Büchner, B., Cook, E., Rey Benayas, J.M., Ellis, E.C., Heinimann, A., Keys, E., Lee, T.M., Liu, J., Mertz, O., Meyfroidt, P., Moritz, M., Poeplau, C., Robinson, B.E., Seppelt, R., Seto, K.C., Verburg, P.H., 2016. Meta-studies in land use science: Current coverage and prospects (eng). *Ambio* 45 (1), 15–28.

Wineman A, Jayne TS, Isinika Modamba E, Kray H. The changing face of agriculture in Tanzania: Indicators of transformation. *Dev Policy Rev*iew. 2020;38:685– 709. <https://doi.org/10.1111/dpr.12491>

Ronneberger, O., Fischer, P., Brox, T. 2015, U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab, N., Hornegger, J., Wells, W., Frangi, A. (eds) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. *Lecture Notes in Computer Science* (), vol 9351. Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4\_28

Xiong, S.; Baltezar, P.; Crowley, M.A.; Cecil, M.; Crema, S.C.; Baldwin, E.; Cardille, J.A.; Estes, L: Probabilistic Tracking of Annual Cropland Changes over Large, Complex Agricultural Landscapes Using Google Earth Engine. *Remote Sensing.* 2022, 14, 4896. https:// doi.org/10.3390/rs14194896

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