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RESEARCH ARTICLE

Detecting level of wetland encroachment for urban agriculture in Uganda using hyper-temporal remote sensing [version 1; peer review: awaiting peer review]

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Abstract

Background: Urbanization is an important indicator of economic growth and social change but is associated with environmental degradation. In Uganda, wetlands cover an area of 11% of the country’s land area, of which half have been converted to industry and residential areas, and urban agriculture. Here, we investigate the extent of wetlands lost in two Ugandan cities, Wakiso and Kampala, in a period of 30 years. Secondly, we demonstrate a simple methodology to monitor agriculture on encroached wetlands.

Methods: Using a field survey and free remote sensing data from Landsat TM 1986 and Landsat ETM 2016 we classified the rate of wetland loss and conversion to agricultural areas has doubled, of which 16,488 ha (23%) were reclaimed from wetlands. Using MODIS NDVI 16-day composites at 500-meter spatial resolution, we generated distinctive crops and crop mixtures in the encroached wetlands for urban agriculture using the ISODATA clustering algorithm.

Results: Over 30 years, 72,828 ha (73%) of the Wakiso wetlands have been lost. Agriculture areas have doubled, of which 16,488 ha (23%) were reclaimed from wetlands. Jatropha cultivated agriculture in Kampala was in the wetlands while in Wakiso, 73% of crop agriculture was in the wetlands. Major crops grown in these urban wetlands were banana (20%), sugarcane (22%), maize (17%), Eucalyptus trees (12%), sweet potatoes (10%).

Conclusions: The Kampala–Wakiso wetlands have been disappearing at a rate of 2,500 ha annually for the last 30 years. At this rate, there will be no wetlands left by 2029. Policy recommendations should promote wetland reclamation programs so as to restore and reconstruct lost and fragmented wetlands; should mandate food security and poverty eradication to convene with ministries regulating wetlands to merge conflicting policies; and should

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Any reports and responses or comments on the article can be found at the end of the article.

Commented [AR1]: In my opinion I prefer “magnitude”, “degree of”, or “rate” over the word level in the title. Also this does not hint at the fact that you performed land cover classification.

This is just a suggestion but it seems to me that a more descriptive title could be: “Detecting wetland encroachment and urban agriculture land classification in Uganda using hyper-temporal remote sensing”

Commented [AR2]: You are starting two sentences back to back with “using”, which is okay but not the best way to describe why you did what you did. I would probably reorder and slightly reword this second sentence to read something like: “To broaden the analysis we used MODIS NDVI 16-day composites at 500-meter spatial resolution to distinguish distinctive crops and crop mixtures in the encroached wetlands for urban agriculture using the ISODATA clustering algorithm.”

Commented [AR3]: These sentences are critical, but they do not flow well. Consider rewording: “Over a 30 year period, 72,828 ha (73%) of the Wakiso-Kampala wetlands have been lost meanwhile agriculture areas have doubled. Of this 16,488 ha (23%) were converted from wetlands.”

Commented [AR4]: I do not prefer this representation of your results because it misleads the reader into thinking that wetland loss has been regular and predictable. I presume you are basing this 2,500 ha/yr rate on the integrated loss between 1986 and 2016. Also the relationship between wetland loss and conversion to ag land seems to be conditional since not all wetland is converted to ag, so there are probably complex socio-economic drivers. I hope that you consider rewording this to do justice to the importance of this work. Perhaps a subtle change like:

“The average rate of loss of the Kampala-Wakiso wetlands over the past 30 years has been nearly 2500 ha annually, although the actual rate of loss has likely been variable from year to year according to economic and policy influences. It is possible however, that by 2029 no wetlands will remain in the Kampala-Wakiso area.”

Commented [AR5]: Is it possible here to draw a connection between wetland conservation and the long-term interests of people in the Kampala-Wakiso area? My concern with these last few sentences is that they do not explain or hint at “why”. People should change. These last few sentences could tie this work together better with a simple change if for example you noted that policy recommendations should shift to include a long-term sustainability focus that allowed for conservation of the Kampala-Wakiso wetlands, which provide (presumably) critical ecosystem services to the urban residents and without which ecosystem services will decline and ultimately impact critical factors such as the availability of clean, abundant drinking water.
develop polices that are inclusive of challenges faced by the urban poor while at the same time minimize the pressures on urban environments.

Keywords

Environmental degradation, Papyrus wetlands, Lake Victoria, Urban growth, Sustainability

This article is included in the Climate collection.

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Introduction

While global urbanization is stipulated to increase to 67% by 2050, Africa’s urban population is predicted to triple (UN-HABITAT, 2012). Although urbanization is an important indicator of economic growth and social change, this fast growth is associated with environmental degradation, which threatens sustainable growth of African cities. One of the most vulnerable ecosystems in urban areas is wetlands. Wetlands of the world cover 9% of the global land area (Zedler & Kercher, 2005). Human induced activities driven by population pressure, expansion of agricultural land area, land degradation and poor policies have led to the loss of at least 50% of the global wetlands (Chapman, 2001; Harper & Southworth, 2009; IUCN, 1996). As a result ecosystem services performed by wetlands, such as water quality improvement, flood abatement, carbon sequestration, biodiversity ecological units of wild life and medicinal plants, have been reduced (Dugan, 1993; Jooosten, 2009; Saunders et al., 2012; Schuyt 2005b; Zedler & Kercher, 2005).

In Uganda, wetlands cover an area of 11% of the country’s land area, with seasonal wetlands covering 7.7%, while permanent wetlands and swamp forests cover 3.4% and 0.1%, respectively (e.g. WETLANDS-ATLAS, 2016). A recent study in Kampala by Ahebe (2013) showed that 658 hectares of permanent wetlands in Kampala, Uganda’s capital, had been converted to built-up areas between 1989 and 2010. However, there exists limited information on the extent of wetland conversion or utilization for urban agriculture. There is evidence that former rural farmers who migrate to urban areas transfer rural livelihood strategies by engaging in urban agriculture. There is evidence that agricultural expansion in urban areas has improved food security but has placed pressure on the wetlands. With projected changes in climate and population increase, wetland encroachment for urban agriculture requires quantitative and reliable agricultural statistics of the productivity of these wetlands. Knowing the exact location and seasonal utilization of these wetlands for agriculture is fundamental for their sustainable use. Periodic information concerning urban agriculture in wetlands can inspire the development of policies that are more inclusive of challenges faced by the urban poor, while at the same time minimize the pressures on urban environments. In addition, protection of these wetlands needs to be intensified to abate negative impacts.

In recent years, monitoring agriculture from space has been effective using remote sensing techniques. Crop characteristics are described in remote sensing using vegetation indices that describe the condition of vegetation in terms of seasonality and land cover change (Murthy et al., 2007). Vegetation indices are calculated from spectral differences in absorption, transmittance, and reflectance of energy by vegetation in the red and near-infrared regions of the electromagnetic spectrum (Jensen, 1996). These spectral differences change with the condition of the vegetation in terms of growth or stress, making these indices useful in monitoring agriculture. The normalized difference vegetation index (NDVI), is a commonly used index that is associated with greenness and above ground dry matter by revealing crop photosynthetic activity (Goward & Hueni, 1992; Sarkar & Kató, 2004). Agricultural crops exhibit characteristics that are detectable by

and Environment, who call for eviction of wetland encroachers (Isunju et al., 2016a; MWE, 2001). Nevertheless, despite these policy interventions, half of the wetland areas in Ugandan cities have been converted to industry and residential areas, and crop land (MWE, 2014; UBOS, 2009). The presidential initiative of Operation Wealth Creation (OWC, 2017) and Uganda’s Vision 2040 policies (NDPII, 2015) include increasing the ability of the poor to raise incomes and improve the quality of life of the poor. Wetlands in Ugandan cities are a key source of livelihood for the urban poor and yet over exploitation can lead to land degradation and risk of food shortages. This implies that there lies a dilemma in implementing these wetland conservation policies in the same framework as Operation Wealth Creation (OWC, 2017), Sustainable Development Goal 11 (Sustainable cities and communities) and Uganda’s Vision 2040 policy (NDPII, 2015), in regards to urban areas. Twenty years ago, 35% of Kampala households engaged in agriculture within the city (Maxwell, 1995). Agriculture land in Kampala comprised of a total of 11,942 hectares which was 56.1% of the total land area of the city (Maxwell, 1995). A recent study observed that currently the population of Kampala engaged in agriculture has dropped to 5.1%, and yet 38% of household income was from crop production (UBOS, 2016). In another urban district, Wakiso, 50% of household income is derived from crop production, with 56% of the population engaged in agriculture (UBOS, 2016). This implies that while the population engaged in agriculture in Kampala has reduced, in Wakiso this has increased. In this study, we demonstrate that agricultural expansion in urban areas has improved food security but has placed pressure on the wetlands. With projected changes in climate and population increase, wetland encroachment for urban agriculture requires quantitative and reliable agricultural statistics of the productivity of these wetlands. Knowing the exact location and seasonal utilization of these wetlands for agriculture is fundamental for their sustainable use. Periodic information concerning urban agriculture in wetlands can inspire the development of policies that are more inclusive of challenges faced by the urban poor, while at the same time minimize the pressures on urban environments. In addition, protection of these wetlands needs to be intensified to abate negative impacts.

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temporal patterns of NDVI profiles that can be distinguished from other vegetation types through analysis of their respective phenologies (Guo et al., 2008).

A vegetation sensor aboard the MODIS (moderate resolution imaging spectroradiometer) Terra satellite launched by NASA in 1999 has been used for vegetation monitoring. The National Aeronautics and Space Administration (NASA). MODIS NDVI temporal sequences of regularly acquired data (hyper-temporal NDVI image data) have been used to monitor drought, vegetation anomalies, vegetation phenology, land cover characteristics, and estimation of crop yields (Guo et al., 2008; Murthy et al., 2007). Hyper-temporal image analysis was first used in the study of monitoring changes in arctic sea-ice by Piwowar et al. (1998). A hyper-temporal image analysis involves acquisition of a series of several satellite images of the same area over a period of time. These images are batched together in a self-organising data technique algorithm known as ISODATA clustering. It is followed with a divergence statistical analysis that evaluates signature separabilities, that are used to select the best number of classes present in the NDVI data set, and the correlation between those classes with field data, to develop an informative and user-friendly map (Nguyen et al., 2012). The objective of this study was to investigate the extent of wetland loss in two Ugandan cities, Kampala and Wakiso, between 1986 and 2016. Secondly, we demonstrate a simple methodology to monitor agriculture on encroached wetlands. The method uses free remote sensing data from Landsat TM and MODIS NDVI 16-day composites at 500-meter spatial resolution to map wetland exploitation, and distinctive crops and crop mixtures in the encroached wetlands.

**Methods**

**Study area**

The study area was in Kampala and Wakiso districts with a land area of 176 km² and 1906.7 km², respectively. Kampala (0°05′N–0°16′N and 32°30′E–32°38′E) is the capital city of Uganda. Wakiso (0° 24′ 0″ N and 32° 29′ 0″ E), at 59.2% urbanisation level, is the largest urban district and surrounds Kampala in all directions (Figure 1). The population of Kampala and Wakiso is approximately 1.5 million and 2 million individuals.

![Figure 1. Map of Uganda showing the study area. Kampala the capital city of Uganda (dark colour) and Wakiso district (light colour).](image-url)
respectively (UBOS, 2016). Rainfall data for the year 2016 was obtained from Uganda National Meteorological Authority (UNMA, 2016) (Figure 2).

Landsat TM remote sensing data set
Remote sensing data were downloaded from https://earthexplorer.usgs.gov. Landsat image scenes (path 171, row 60, 30m resolution) were acquired for 1986 and 2016. The 1986 scene was from Landsat 5 Thematic mapper (TM), while that of 2016 was from Landsat 7 Enhance Thematic Mapper (ETM). The two images were geo-rectified with topographic maps and with 25 Ground Control Points (GCPs). GCPs are defined as points on the surface of the earth of known location used to georeference Landsat Level-1 data. These were identified from https://landsat.usgs.gov/gcp. ERDAS IMAGINE 9.3 software was used for geo-rectification (alternative free software that can perform this task is BEAM, an open-source toolbox and development platform for viewing, analysing and processing of remote sensing raster data: https://earth.esa.int/web/sentinels-user-guides/software-tools/article/beam). Labels of classes used in this study included broad categories of land use and land cover, including agriculture, forest, wetlands and agriculture in wetlands (Figure 3), built up and bare ground:
- Agriculture area: small plots of land or broad tracts of mechanized land areas;
- Forest classification: used training samples from Mabira forest (a natural forest), which was away from the study area on the satellite image, as there were no natural forests within the study area.
- Wetlands: marsh land and seasonal ephemeral areas.

Since a previous data set for the 1986 scene was not available, classification was dependent on the cover types observed and the ground points (109) taken during field work in 2016.

![Figure 2](image2.png)

**Figure 2**: Rainfall pattern of Kampala and Wakiso district during the year 2016 (UNMA, 2016).

![Figure 3](image3.png)

**Figure 3**: Landsat satellite images showing wetlands converted to agriculture plots in the study area.

Commented [AR6]: Is it necessary to have the “Total” line? I do not yet see what its significance is and it seems like redundant information.

Commented [AR7]: It is difficult to see the amount of wetland area in the 1986 scene due to the red saturation. Also, what is the spatial scales of this scene? Please provide a scale bar or list what the vertical and horizontal dimensions are.
Using ERDAS IMAGINE 9.3 software, the 13 NDVI images were derived for the effects of atmospheric gases and heavy aerosols. They are masked for water, clouds, and cloud shadows. MODIS data was accessed as 16 km resolution. Each pixel encompasses the best observation values within ever 16-day periods. The stacked images were then batched to create one image that was subset to create a sub-area of Wakiso and Kampala. MODIS unsupervised classification was carried out with ERDAS IMAGINE. The unsupervised classification was then performed using an ISODATA batch run calculated using the divergence distance measure to assess the clustering signature separability (Asilo et al., 2014). A total of 50 classes from the stratified random sampling were derived. To generate the digital NDVI numbers (DN), linear stretching was applied. The minimum NDVI value, -1, was assigned 0 while the maximum NDVI value, 1, was assigned values from 1 to 255. The extraction of 50 classes provided an ideal stratification for the NDVI time series. The NDVI ISODATA image was polygonised in ERDAS IMAGINE software and plotted as a map in ArcGIS software version 10.3 (alternative software that can perform this task is QGIS, a free and open source software: https://www.qgis.org/en/site/).

Field work
All the 50 class polygons were given a unique identifying colour and located on a boundary map of both Wakiso and Kampala. The data was input on ArcPad 10.3 on a Trimble GPS system that was used in the field (in addition to QGIS, Google maps App on an android phone can also perform this task). In the period between April and December 2016, the sites on the maps were visited through a mobile GIS approach, which consisted of a sensitive hand held Gramin Global Positioning System (GPS) and Trimble GPS system running ArcPad to locate the ground truth points. Due to rough terrain and inaccessibility of some wetland areas, sample points that were near roads were selected. The ground truth points were saved in ArcPad for later use. For all 50 classes, 5 sites of each class were visited giving a total of 250 sites in Kampala and Wakiso. The sampling frame consisted of 20 clusters of five sampling units. Each sampling unit within a cluster had a 15-meter radius of sampling area whose centres were 100 meters apart within each cluster. The data collected included 250 ground truth points (X, Y coordinates), cover percentage of vertical vegetation, dominant species, land cover and land use. These gave an indication of types of crops growing on the site and the associated wetland encroachment. Data collected from field work was checked for completeness and was organized using Excel for analysis.

Accuracy assessment
Accuracy assessment of the MODIS-derived urban agriculture was based on the kappa coefficient and confusion matrix assessing classified pixels with reference to ground-truth points. The urban agriculture maps generated from MODIS was evaluated using 109 randomly sampled ground truth points, obtained from the fieldwork explained above. To identify homogenous classes based on NDVI characteristics, similarity measures between the 50 classes were generated from hierarchical cluster analysis using Pearson’s correlation as the proximity procedure. The clustering analysis was conducted in SPSS version 20.0 (SPSS, 2011).

Results
Rainfall
Usually Kampala and Wakiso district location around the Lake Victoria basin is characterized by two rainy seasons. However, 2016 had one prominent rainy season that started in February peaked in April (940 mm) and gradually dropped in July, which is a usual rain pattern in the first season of the study area. In the second half of the year, the rainfall pattern was more erratic with the amount of rainfall barely attaining 400 mm between September and December of 2016. This prominently dry season resulted in one of the worst droughts Uganda has faced in recent years.

Current state of urban wetlands in Uganda

(Commented [AR1]: Which sites on which maps?)

(Commented [AR2]: I would not mention the blue channel if it’s not being used in your NDVI calculation. People may think you’re calculating EVI.)

(Commented [AR3]: Exactly what did you do? “batched” does not describe to me the steps you took. Please describe your process simply and unequivocally. I do not understand how you went from a multi-temporal raster stack to an integrated scene. To develop and integrated scene did you take the average over all time points, the mode, or something else?)

(Commented [AR4]: You will need to justify why 50 classes were used/determined (and not 60 or 70). Are there 50 different kinds of urban crops in the area? Or were these 50 classes known a priori? Or was the number 50 determined based on expert knowledge? Or by your clustering algorithm? Please state which. Also if you used an algorithm to determined that 50 was a suitable level of division then please briefly explain why it stopped at 50 (e.g., this maximizes within cluster similarity but also between centroid distance.)
The overall classification accuracy and Kappa coefficient for 1986 and 2016 land cover maps of the Wakiso-Kampala study area was 83.1% and 0.87, and 87% and 0.85, respectively. We found that over the 30-year period, 72,828 ha of the Wakiso-Kampala wetlands have been lost (Figure 4 and Figure 5). Agriculture on the other hand doubled in cultivation area. Of the new cultivation area, 73% of the crop agriculture segregated in Kampala using hyper temporal remote sensing was in wetlands, while 25% of the wetland encroachment by a crop agriculture in the wetlands was 92% and 0.93, respectively. Our results showed that all crop agriculture segregated in Kampala using hyper temporal remote sensing was in wetlands, while 73% of the crop agriculture segregated in Wakiso was in the wetlands.

**Characterization of crop agriculture in wetland:**

Temporal signatures of the 50 NDVI classes were obtained. These were plotted in a spread sheet to give profile curves of NDVI DN values for each 16-day composite from April to September 2016 (Extended Data). Hierarchical cluster analysis yielded a dendrogram (Figure 6) that segregated the 50 NDVI classes into 10 clusters (Figure 7). Five of the clusters (cluster 1–5) showed sigmoid curves of NDVI values as the year progressed. These five clusters appeared similar but differed in values at the beginning of the year and at the levelling off points. The NDVI profiles in cluster 1 (classes 22–25), started off at 2000–3000 values and levelled off between 7000–6000 values, while the profiles in cluster 2 (classes 16, 17, 21 & 20), also started off at 2000–3000 values but levelled off between 6000–5000 values but were more erratic in shape. The NDVI profiles in cluster 3 (classes 37–39 & 41), started off at 3500–5500 values, levelled off below 8000 while the NDVI profiles in cluster 4 (classes 34–36) started off at 5000 values, also levelled off below 8000 values but had a smoother sigmoid growth than cluster 3. Cluster 5 (classes 29, 31–33) was similar to cluster 3 but differed by starting off at 3000 values and had steeper growth than cluster 3. Clusters 6, 7 and 8 were similar but differed in their exhibition of prominent peaks during the course of the year. The NDVI profiles in cluster 6 (classes 19, 26, 28 & 30) started off at 3000 values but peaked in early May just above 6000 values, dipped deeply in early July (just above 4000 values) and peaked again in September (about 7000 values). The NDVI profiles in cluster 7 (classes 27, 40, 42 & 43) started off between 4000–6000 values but peaked in early May just above 6000 values, slightly dipped in early June (just below 6000 values) and peaked again in late July (about 6500 values). The NDVI profiles in cluster 8 (classes 12–15, & 18), on the other hand, started off between 2500–5000 values, prominently peaked in early May (just above 6000 values), strongly dropped in early July (just below 6000 values) and conspicuously peaked again in mid-August but at lower values (below 6000) than they did in May. The NDVI profiles of cluster 9 (classes 44–50) were flatter throughout the year except the NDVI profile of class 46, that prominently dipped in early July but rose gradually during August.

**Figure 4:** Landsat TM images showing 30-year land cover, revealing wetland encroachment by agriculture in Wakiso and Kampala. Wetlands, 1986 (A), wetlands, 2016 (B) and wetlands converted to agriculture (1886–2016) (C).

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**Commented [AR12]:** I am not sure which data these accuracy scores refer to. Based on the “Accuracy assessment” section above I thought you would be reporting on the accuracy of your MODIS crop classification relative to your field surveys. However, a few sentences below you list the “overall accuracy... for the MODIS based stratification”. So does this mean these first numbers refer to any land cover classification of the MODIS phenology data (ag and non-ag) whereas the lower numbers are for ag only? In any case what I am suggesting is a simple fix. I think it would benefit your paper to specifically list what each of these two results are relative to (all land cover or just ag) and also please specifically mention if the first set of results are also based on MODIS classification.

**Commented [AR13]:** You will need to go through this section with a fine toothed comb in order to provide a clearer description of exactly what you did. Here is what I believe you did in this study:

1) Extracted the NDVI profiles (Apr-Sep) of each pixel within the study domain.
2) Assigned each pixel to 1 of 50 NDVI classes (I am guessing about this step and am very unsure because it is not actually described in the text, at least that I saw. If that is true, please fix that and give a detailed description of where these 50 NDVI profile classes come from)
3) Assigned each

**Commented [AR14]:** Obtained from where?

**Commented [AR15]:** Is “Extended data” left in here intentionally? Not sure what this means.

**Commented [AR16]:** A little “nit picky” here but I would use any one of grouped, classified, partitioned, or clustered rather than the word segregated.

**Commented [AR17]:** As mentioned below in the Figure 7 caption these units are not NDVI. NDVI ranges from -1 to 1, so please scale your numbers down to standard NDVI units. I assume you are using raw data file integers, which I think need to be divided by 10^4 to obtain actual NDVI values.

**Commented [AR18]:** Please add a scale bar.
Figure 5. The 30-year change in area of wetlands in the study area and the state of encroachment for agriculture and built-up areas in Wakiso and Kampala.

Figure 6. Dendogram showing grouping of 50 NDVI classes segregated by hierarchical cluster analysis.

Commented [AR19]: Your area estimates in 1986 sum to... whereas in 2016 your numbers sum to 96,357. I am sure this is because some of the 1986-wetland land went to some other land cover type not included in this figure. I would suggest reworking this figure or maybe making a Figure 5(a) and 5(b) so that it is clearer and more complete in describing where that 96,139 hectares of 1986-wetland went. Without that, the true impact and importance of this figure is diminished.
Figure 7: Respective profile curves of NDVI plotted from clusters produced by the dendogram in Figure 6. Numbers 1 to 15 in the legend refer to the chronology of dates of the satellites taken every 16 days in the two 2016 growing seasons of Kampala and Wakiso.

Commented [AR20]: NDVI values should only range from -1 to 1. But to save file size space NASA converts them to integers, which have a different range in the raw NASA data files (I think -10,000 to +10,000). I assume that is why your axes here in Figure 6 range from 0 to 10,000. To avoid confusion you will want to correct this to a 0 to 1 range on the plot axes.
the last quarter of the year. The NDVI profiles of cluster 10 (classes 1-10) were conspicuously different from all the other nine clusters in that the first quarter of the year started off with flat profiles ranging between 1800-3800 values (except class 1). However, in late March the profiles rose drastically to just above 6000 values and peaked in late April and then gradually dropped to early July and then remained flattened out for the rest of the year.

Ground observations found that 50 classes were represented in the 10 clusters, 13 of them representatives of the wetlands. The wetland classes included classes 6, 10, 14, 28, 34, 36, 37, 39, 41, 30, 43, 45 and 50. These were represented in all clusters except clusters 1, 2 and 5. The major crops grown in these urban wetlands in order of frequency were banana (20%), sugarcane (22%), maize (17%), Eucalyptus (12%) and sweet potatoes (10%), while ornamental nurseries, pine trees, vegetables and passion fruits were each at 5%. Using visual interpretation, the 13 classes in the wetlands were grouped using similarity of the shape NDVI profiles, which yielded 4 types of phenology types. Type 1 included NDVI classes 34, 36, 37, 39 and 41, while Type 2 included 14, 43, 45 and 50. Type 3 included classes 28 and 30 while Type 4 included classes 6 and 10. The crops and crop mixtures that each of these classes represent are shown in maps in Figure 8.

Discussion

Our results clearly show that wetlands in Uganda’s urban areas have been the prime target for agricultural expansion in the last 30 years. The results reveal that 76% of wetlands in the Wakiso-Kampala study area have been lost. Of the lost wetlands, 23% have been converted to agricultural cultivation area. Using The MODIS-based classification of urban agriculture we showed that monitoring agriculture in these wetlands using ISODATA analysis, is a worthwhile approach to manage, monitor and control the effectiveness of wetland encroachment. The normalised difference vegetation index (NDVI) from MODIS revealed crop characteristics that were detectable by temporal patterns of NDVI profiles distinguishing crops and crop mixtures through analysis of their respective phenologies. The NDVI profiles were sensitive to the rainfall pattern, which in 2016 consisted of one rainfall season and an erratic second season. This anomaly was rather unsurprising as in recent years Uganda has shown high vulnerability to rainfall variability and climate change (MoWE, 2010). Many studies have observed and validated a linear relationship between NDVI and precipitation, an association that is highly sensitive to climatic fluctuations (Nicholson et al., 1990; Nicholson & Farrar, 1994; Wang et al., 2003). Our results show that at the peak of the rainy season in April, the NDVI profiles started rising irrespective of the category of the NDVI classes, confirming the linearity of the NDVI-precipitation relationship, mentioned above. We also observed that some NDVI profiles in wetland classes levelled off during the month of July and plateaued through the rest of the year. This implied that the crops grown in the wetlands responded strongly to the rainfall season but also remained thriving during the prolonged drought. Although most of the country suffered an acute food insecurity situation, which saw Uganda lose its food secure status (OPM, 2017), crops in these urban wetlands exhibited resilience, owing to the moisture retained in these wetter ecosystems; wetlands are linked to accumulation of fertile sediment during floods and long periods of water retention (Dixon & Wood, 2003).

The 13 classes of NDVI profiles identified in the wetlands seemed to be determined by the type of agriculture practiced in these wet ecosystems. The vegetation in Type 1 was prominent in western Wakiso in the sub counties of Kakiri, Masulinda, Gombe and Kasanje whose wetlands are made of swampy flora, which is the natural wetland vegetation. The NDVI profiles in this type had sigmoid curves that rose in early April at the peak of the rainy season, depicting a crop phenology that followed the rains or one that responded strongly to high moisture. This assertion was confirmed by ground data that observed that Phenology Type 1, was dominated by perennial crops (bananas: *Musa* spp; sugarcane: *Saccharum officinarum*), seasonal crops (specifically maize: *Zea mays*), fruit farming (specifically passion fruit: *Passiflora edulis*) and silviculture (pine trees: *Pinus* spp. and *Eucalyptus* spp.). The vegetation in Type 2 was prominent in Wakiso in the sub counties of Busukuma, Kiira, Shagabo-Makindye and Kasanje which are more peri-urban sub counties with a large influence of Kampala city in terms of urban markets. The profiles in Type 2 were flatter curves depicting a continuous crop phenology that can either represent uninterrupted crop growth or perennial crops. Field observations found that Type 2 was dominated by high value vegetables (radish: *Raphanus* spp.; broccoli: *Brassica oleracea*; lettuce: *Lactuca sativa*; sweet potatoes: *Ipomoea batatas*), which are constantly cropped, and perennial crops such as banana and sugarcane. This finding is indicative of the advantage of the constant moisture supply provided by these wetlands. The vegetation in Type 3, was prominent in Wakiso in the sub counties of Kasanje, Wakiso Town council, Kakiri and Gombe. The profiles in Type 3 rose sharply in early April, depicting vegetation response to rainfall and fell in early July portraying harvest, but rose sharply again in late July, representing the commencement of a second cropping season. Field observations found that Type 3 was a mixture of crops found in both Type 1 and Type 2 that were perennial, annual, silviculture and horticulture, still indicating the extent of which urban wetland ecosystems offer a substantial supply of moisture to carry two cropping seasons. Type 4 was prominently in the wetlands of the Greater Kampala metropolitan division of Nakawa, Rubaga, Makindye and the Central city area. The most prominent crops were banana, maize, sugarcane and tree nurseries.

Some studies have shown that urban wetlands in Uganda contribute approximately US$432 per year to local communities practicing subsistence agriculture (Turyahubwe et al., 2013). Moreover, the type of crops grown in the urban wetlands are important Ugandan staple crops that have a high economic value in urban markets but are also a reflection of urban nutritional combinations. It is not surprising that bananas dominated urban wetland agriculture, as these are the country’s staple crop. Sugarcane and fresh roasted maize are enjoyed by urban dwellers as snacks and are sold along road sides. In other countries in sub-Saharan Africa, an increasing population...
The significant policy implications from this study depict that the
Policy implications
combination with efforts to increase food security has intensified
pressure to expand agriculture in wetlands. For instance, in many
parts of eastern and central Africa, it has been observed that up to
tres per year can be grown in wetlands significantly
contributing to food security. For example, in Tanzania, the
Kilombero wetland was found to contribute up to 98% of food
intake for all households surveyed irrespective of the
socioeconomic status (Rebelo et al., 2010).

It has been suggested that wetlands can be converted to include
intensification of a specific wetland strategy, such as the complete
reclamation or commercial agriculture or industrial development,
which are considered to be more economically viable (Holnis,
1998). Conversely, it has been a matter of debate whether
quantifying the economic value of wetlands in Africa undervalues
their importance for their future utilization (Schuyt, 2005a; Seyam
et al., 2001). For example, already, the essential role that wetlands
play in regulating the flow of water into the Lake Victoria has been
lost (Olindo, 1992). A couple of decades ago, agriculture was
responsible for 80% and 75% riverine phosphorus and nitrogen
entering Lake Victoria (Odada et al., 2004; Scheren et al., 2000).
Papyrus wetlands play a significant role of filtration and protection
of the lake from eutrophication acting as sediment traps and buffer
discharges (Ryken et al., 2015). Whereas short term impacts are
already visible, studies on longer term impacts of such massive
wetland encroachment at both local and regional scales are limited.
The danger is that the current wetland exploitation for food security
may be a trade-off between the provision of food in the short-term
and the loss of important ecosystems services in the long-term.

Policy implications
The significant policy implications from this study depict that the
Kampala-Wakiso wetlands have been disappearing at a rate of 2500
ha annually for the last 30 years, implying that at this rate, there will
be no wetlands left by 2029. In this respect, it means that ecosystem
services of these urban wetlands have been lost. It could be that the
main challenge in implementation of policies that effectively
protect these wetlands is that legislative and policy provisions have
lagged behind growing scientific knowledge and understanding.
Marching policy to cutting edge science can minimize and mitigate
the impacts on ecosystems resulting from over exploitation
(MacKay, 2006). Government environmental protection bodies
have access to widely applied and tested methods of assessing
wetland encroachment at larger scales, such as remote sensing data
(WETLANDS-ATLAS, 2016). These institutions can integrate regional and local databases
to identify potentially vulnerable wetland dependent ecosystems.
Scientists on the other hand can develop the scientific knowledge
on understanding wetland dependent ecosystems at both local and
regional scales. When these two levels of understanding are
merged, this information can be useful in implementation and
strengthening of already existent but poor policies. For example
modelling scenarios of threatened and vulnerable ecosystems to
policies, can be used to predict the future of wetland encroachment
as evidence based data to strengthen weak policies (Odgard et al.,
2017). In addition, the ability to address multiple approaches that
identify the various ecosystem services provided by wetland
cosystems through rapid assessment of wetland ecosystem
services is required. These can provide an output of a range of
ecosystem services through a rapid and comprehensive overview of
the various benefits provided by wetlands (Everard & McInnes,
2013; McInnes & Everard, 2017). The Rapid Assessment of
Wetland Ecosystem Services (RAWES) approach interactively
involves all stakeholders and equips wetland managers to address
data constraints in relation to the magnitude and extent of
beneficiaries. The benefits are linked through three scales: local
benefits (at household and individual level), regional benefits (at
wider catchment levels), and global benefits (those beyond national
boundaries) (McInnes & Everard, 2017). Such an approach could
sufficiently increase the ability to recognize the importance of
ecosystem services, monetary valuation and multiplicity of social
economic benefits of these urban wetlands.

The second policy implication from this study indicates that a large
population of urban dwellers are utilizing these wetlands for
survival and therefore confirming the observation that poverty
eradication policies are in conflict with wetland conservation
policies. This study could not ascertain the fraction of commercial
from subsistence farming that was provided by these urban
wetlands as it was not easy to identify owners of the crops in the
wetlands. It is possible that urban dwellers farming in wetlands are
aware that it could be illegal, but do not understand the framework
of the improperity; they take care of crops very early in the morning
and then have other occupations during the day. Policy regulators
on the other hand observe growing crops but cannot identify the
owners or whether the agricultural practice used is suitable for
wetlands. This indicates that there lacks sensitization of simple but
precise indicators of what wetland encroachment for agriculture is
to lay persons. In addition, government protection dialogue with
relevant stakeholders may be rather high handed, with reports of
destroying food crops grown in wetlands or forcefully evictions
(DISPATCH, 2019; Monitor, 2017). The tendency to emphasize
discipline-bound legislations could easily have demoralized
citizens from recognizing potential economic and ecosystem
services of these urban wetlands. This has in turn undermined
conservation of biodiversity and weakened protection laws. At the
same time wetlands are seen as an easy option for the construction
of infrastructure. For instance, in recent years, to avoid
compensation to evacuated urban settlements on road reserves,
major roads have been constructed in the middle of papyrus
wetlands. In return, flood events have increased in adjacent areas
that are hazardous to the most vulnerable urban poor (African
Development Fund, 2008; Isunju et al., 2016b). Already, in Wakiso
district, wetland encroachment for settlement and agriculture has
changed the local area climate in terms of increasing drought,
reductions in rainfall seasons and increasing day and night
temperatures (WDLG, 2017). This may have far-reaching
consequences to local communities dependent on these wetlands
but have significantly contributed to the environmental crisis at the
Lake Victoria basin.

Policy recommendations
We recommend that the Government of Uganda needs to promote wetland reclamation programs so as to restore and reconstruct lost and fragmented wetlands. Secondly, ministries mandated to food security and poverty eradication need to convene with ministries regulating wetlands to merge these conflicting policies. Thirdly, there is need for the development of polices that are inclusive of challenges faced by the urban poor while at the same time minimize the pressures on urban environments.

Conclusion
The level of wetland degradation revealed by this study shows that protection of urban wetlands has been relatively low pointing to poor policy implementation over the years. Despite the existence of seven policies protecting wetlands, enforcement and compliance systems have not been suited for the dynamism of urban change. This study has demonstrated that despite environmental data being scarce and heterogeneous landscapes in Africa being difficult to map, wetland regulators in Uganda can utilize free remote sensing data to monitor wetlands. In the present study, the MODIS Collection 5 land cover datasets at high resolution processed with the ISODATA clustering algorithm was a useful choice of remote sensing data for monitoring wetland encroachment by crop agriculture. The necessity of collecting training datasets of individual crops grown in the wetlands during field work was key to ascertain the results of ISODATA clustering of NDVI profiles. This greatly improved the accuracy of our maps. The NDVI time series from ISODATA clustering algorithm have been shown to capture crop phenologies (crop calendars) and thus represents a good relationship with the cropped areas.

The dynamic situation of these urban wetlands requires informed understanding of the ecological and socio-economic benefits that they provide. There is a need to recognize the longer-term degradation threats and more spatially extensive impacts of these changes. This calls for coordinated adaptation strategies between scientists, policy makers and urban dwellers for equitable utilization of wetlands without compromising their ecosystem services and economic benefits.

Data availability
Underlying data
Remote sensing data: https://earthexplorer.usgs.gov

References
MODIS remote sensing data: https://modis.gsfc.nasa.gov/data/dataset/mod13.php
1. Satellite imagery from LAND SAT (1986 and 2016):
   b. Pangaea: Detecting level of wetland encroachment for urban agriculture in Uganda using hyper-temporal remote sensing - ground truth points of wakla. https://doi.pangaea.de/10.1594/PANGAEA.913486. (Kabiri et al., 2020b).
   c. Pangaea: Detecting level of wetland encroachment for urban agriculture in Uganda using hyper-temporal remote sensing - classifiedland2016. https://doi.pangaea.de/10.1594/PANGAEA.913480. (Kabiri et al., 2020c).
3. ISODATA clustering of NDVI profiles for 10 cluster and wetland class types:
   a. Pangaea: Detecting level of wetland encroachment for urban agriculture in Uganda using hyper-temporal remote sensing. https://doi.pangaea.de/10.1594/PANGAEA.915587. (Kabiri et al., 2020e).
4. GIS shape files for wetland encroachment for the last 30 years:
   a. Pangaea: Detecting level of wetland encroachment for urban agriculture in Uganda using hyper-temporal remote sensing, https://doi.pangaea.de/10.1594/PANGAEA.915586. (Kabiri et al., 2020f).

Data are available under the terms of the Creative Commons Attribution 4.0 International license (https://creativecommons.org/licenses/by/4.0/).
I was surprised that I did not find many of the papers I expected on clustering and remote sensing phenology. This could be due to my bias in North American and European research. If relevant I have these papers to recommend that the authors consider (not necessarily to cite them but to use the themes and progression of work described in them to broaden their discussions in the Discussion section).

Don't worry about the details but consider the big picture of what these papers describe, which is how one can classify pixels in MODIS scenes using clustering and obtain meaningful land cover information. This list is simply a primer of relevant articles, at least one of which, I was surprised did not appear in the references. There are many more recent examples (2018-2020) of this kind of work being published, which would also be useful context for this paper.

