Planetary Scale Monitoring of Urban Growth in High Flood Risk Regions

Climate change is increasing the incidence of flooding. Many areas in the developing world are experiencing strong population growth but lack adequate urban planning, representing a significant humanitarian risk. We explore the use of high-cadence satellite imagery and a deep learning-based computer vision approach to determine flood-related humanitarian risk in cities in Africa.

1. Introduction

By 2050, more than two-thirds of the world's population will live in cities, with the majority of urbanization occurring in developing countries (United Nations & Social Affairs, 2018). Rapid urbanization in developing countries is often unplanned and carries substantial risk for critical infrastructure, public health and clean water provision. More frequent and severe flooding caused by climate change is further inflaming this. National, state, and local government officials need access to a new suite of tools to better plan their cities. High cadence geospatial imagery, coupled with advances in Deep learning, offer transformative potential to provide such tools. Inspired by studies in Africa (Butterfield, 2017) and (Lall, 2017), we monitor building development in 5 African cities, and use flood risk data to quantify the humanitarian risk from flooding.

2. Methodology

Our workflow (Figure 1) to monitor urban growth in regions of high flood risk starts with daily optical imagery produced by Planet - Planet operates the largest constellation of Earth observation satellites, imaging nearly all of Earth's landmass daily at 3-5 meter resolution. To avoid cloudy images, we consume Planet's monthly 'basemap' images compiled from multiple days, which are nearly cloud-free.

Figure 1. Workflow for monitoring urban growth in flood risk regions using daily geospatial imagery

We use a variant of U-Net (O. Ronneberger, 2015) - a deep learning architecture for semantic segmentation of images, used widely by the remote sensing community - to map building footprints in the Planet RGB imagery. The training dataset is compiled from a globally diverse set of geographies, seasons, and terrains, enabling our model to generalize well.

(FMGlobal, 2019) provides a global map of high-hazard flood zones derived from a combination of historic flood data, hydrology, hydraulic science, and up to date environmental monitoring data from rainfall, snowmelt and terrain. Intersecting the building segmentation masks with the high flood risk zones enables quantitative flood risk analysis of urban regions.

Figure 2 illustrates an example of how our process can observe urban sprawl in Bangui, the largest city in the Central African Republic. We compute change in building footprints based on the U-Net outputs at multiple time points. In this example the higher density of red pixels - the final timepoint - on the leading western edge shows the urban 'sprawl' away from the city center.

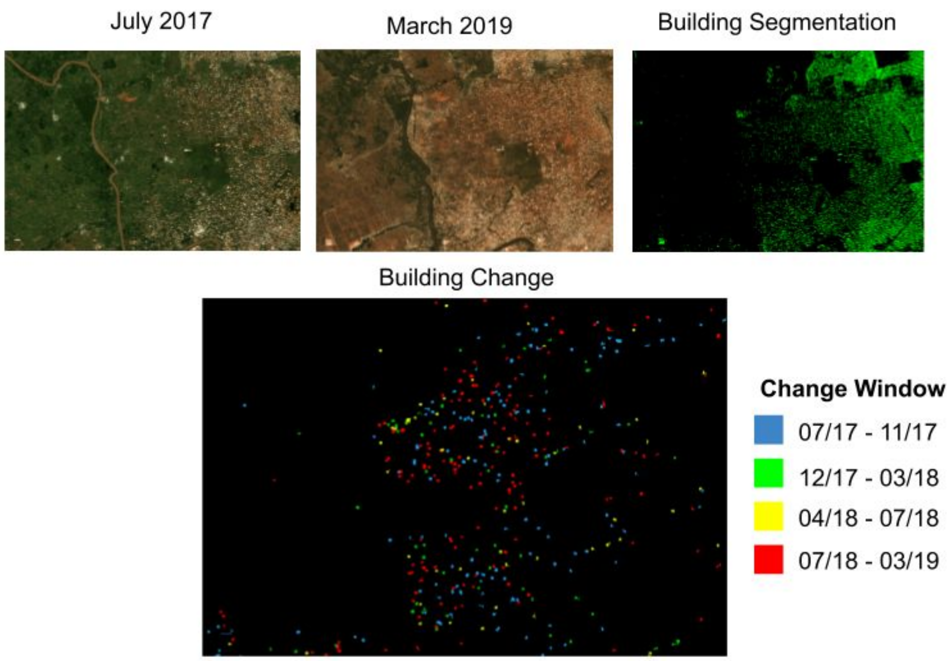

Figure 2. Top left and middle, example of urban growth in satellite imagery in a high flood risk area on the Western edge of Bangui, Central African Republic. Top right, a building segmentation output from our U-Net model. Bottom, change in building footprint area at multiple time-points, mapped to different colors.

3. Results

3.1. Change in Urban area in 5 Cities

We computed change in urban area from mid-2017 to early 2019 for 5 cities: Addis Ababa in Ethiopia, Bamako in Mali, Bangui in Central African Republic, Casablanca in Morocco, and Ouagadougou in Burkina Faso. We selected cities in Africa with varied terrains and climates, which intersected high-risk flood zones, and had monthly, cloud-free satellite imagery available from the middle of 2017 to early 2019 (the time of writing). Table 1 shows the percentage of the urban area - the area classified as building by our model - for each of the 5 cities within high flood risk zones, as of March 2019. Errors in these values are derived solely from the Poisson pixel count, but our future analysis will include additional error terms stemming from geographical variability. We also show the absolute growth since July 2017, calculated as the difference of the first 6 versus last 6 monthly area values in the interval of July 2017 - March 2019. In all of the cities, we observe growth of buildings in flood risk zones.

Country	City	% Urban Flood Risk	% Growth
C.A.R	BANGUI	57.0+-1.4	2.5+-2.0
MALI	BAMAKO	18.70+-0.2	0.1+-0.3
MOROCCO	CASABLANCA	13.7+-0.1	0.3+-0.1
BURKINA FASO	OUAGADOUGOU	7.0+-0.2	0.3 +-0.2
ETHIOPIA	ADDIS ABABA	2.1+-0.1	0.6+-0.2

Table 1. Percentage of urban area within high flood risk zones in March 2019 for 5 African cities. Growth represents the differential increase from October 2017 to March 2019.

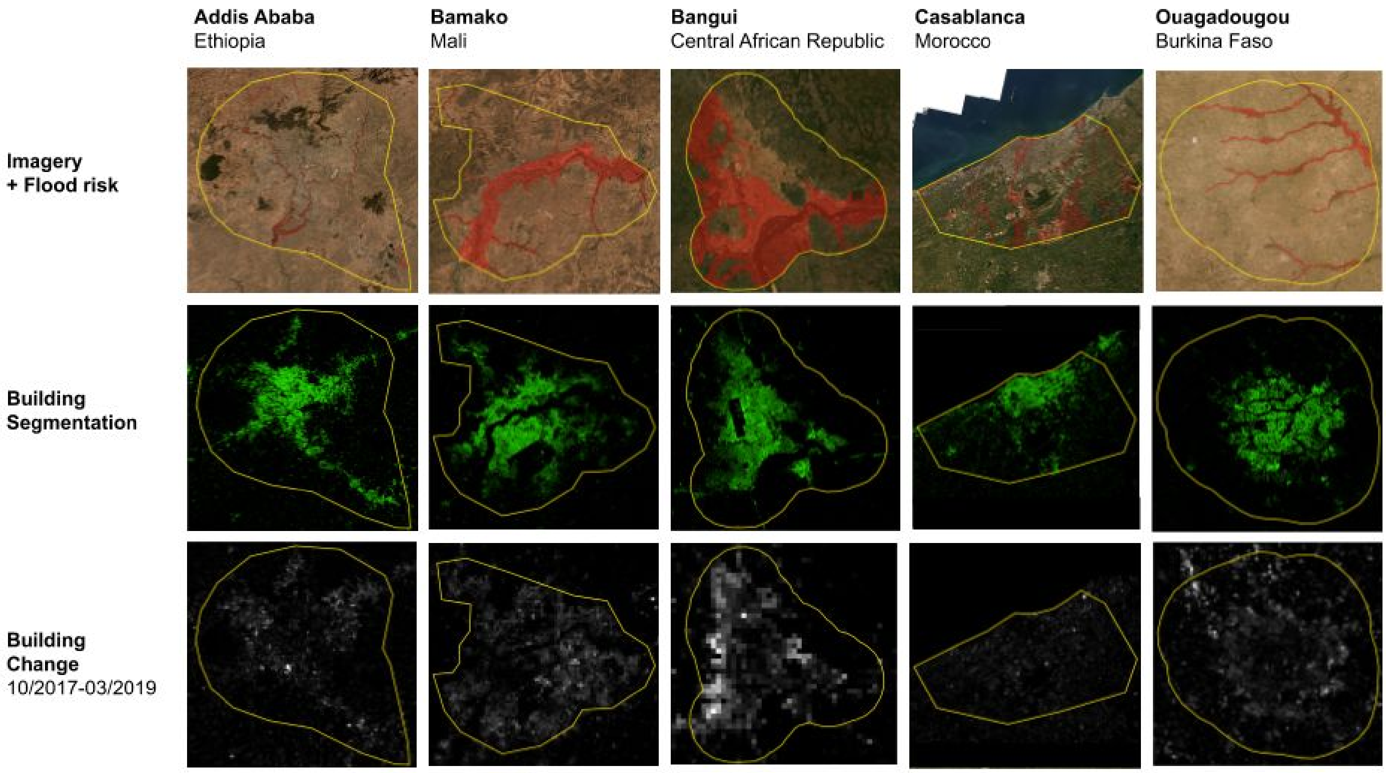

Figure 3. Change in urban area 2017-2019 for 5 cities in Africa. Top row, satellite images of each city from March 2019, overlaid with city extent and high flood risk area. Middle row, U-Net building segmentation maps. Bottom row, Change in buildings 10/2017-03/2019, aggregated at a 0.5km2 spatial grid.

3.2. Spatio-temporal Analysis of Bangui, Central Africa Republic

In this section we perform a deeper analysis on Bangui - the city with the highest proportion of urban area classified as high flood risk. Visual inspection of the urban change map for this city suggested that growth was concentrated in the city outskirts. Thus, we conduct a comparative analysis between the inner and outer city. We took the Administrative Level 4 city boundary (HumData, 2016) to define the inner city. We defined the outer city as 5km buffer beyond the inner city-limit (Figure 4 (A)). The outer city area was intersected with the high risk flood area map (Figure 4 (C)).

For the outer city we plotted urban area for every month from October 2017 to March 2019 (Figure 5 (A)), and measured change by taking the mean of the first and last 6 months in the period. As expected the growth observed was larger in the outskirts than in the city area as a whole in Table 1, with a growth of 9.1%. The majority of the urban area detected was within the high risk flood area in March 2019 (65.2%). We further observed that the urban area in the high flood risk zone grew by 7.9%, over the period of study. Note: the months of July, August, September in 2017, and August and September in 2018 were removed due to high cloud cover.

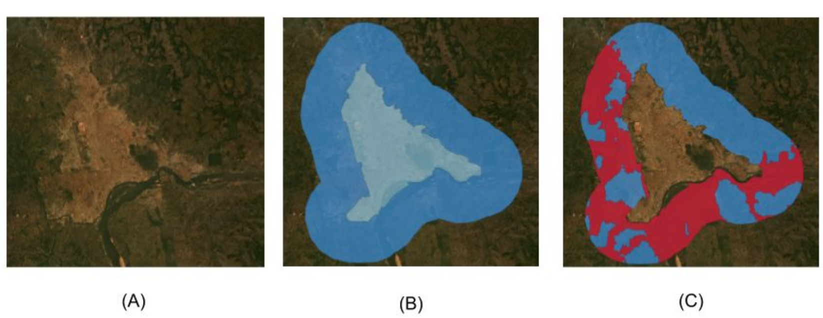

Figure 4. Bangui's (B) inner city (light blue), outer city (dark blue), and (C) high flood risk zone in the outer city (red).

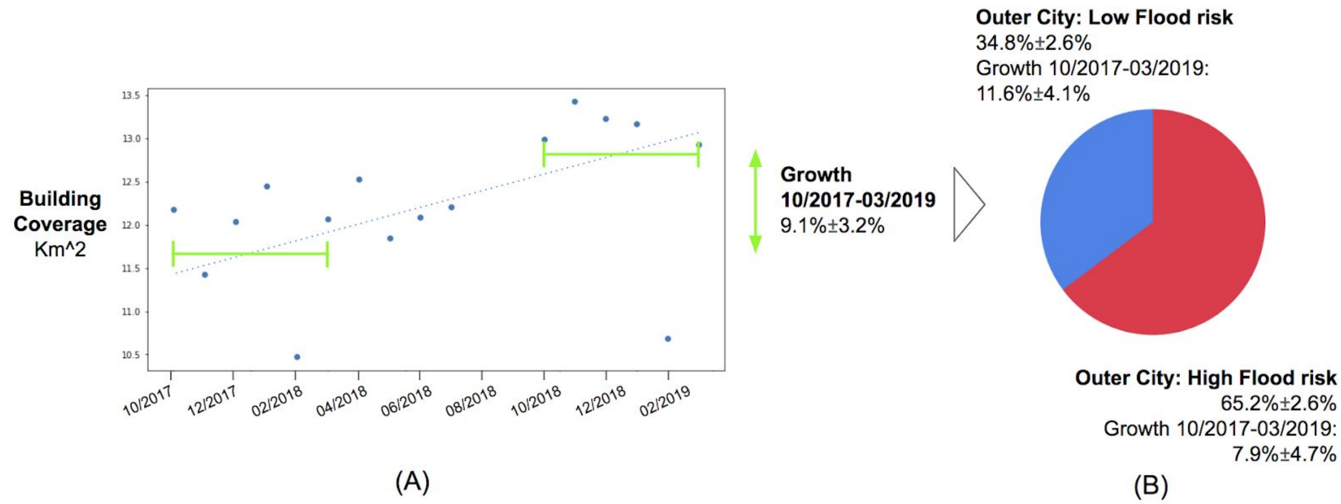

Figure 4. Urban area measurements within Bangui's outskirts. Left, Urban area plotted monthly for 15 months 10/2017-03/2019. Note: total city area is ~410km2. Right, break down within the outer city of high and low flood risk areas. Error values are the standard error.

4. Conclusion

Using automated analysis of up-to-date satellite imagery we quantified urban area growth in 5 cities in Africa. We found buildings in high flood risk zones, and that these areas e.g. in Bangui and Burkina Faso, were growing at an alarming rate. These data are valuable to urban planners for these cities to deter growth in the future, and provision infrastructure to mitigate climate risk from flooding.

Our approach can be applied to address growing flood risks induced by climate change. In particular:

- High cadence results enables analysis of trends on shorter timescales than previously possible, to better inform urban planning and flood response.
- The spatial resolution of this imagery allows for aggregation across multiple dimensions, including correlation with external flood risk maps and separation of inner urban cores from city outskirts.
- Global availability of satellite imagery, and deep learning-based models which generalize across diverse terrain, mean approach can be applied across widely varied environments.

References

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