Planetary Scale Monitoring of Urban Growth in High Flood Risk Areas

Christian Clough [1] **Ramesh Nair** [1] **Jesus Martinez Manso** [1] **Matt George** [1] **Gopal Erinjippurath** [1]

Abstract

Climate change is increasing the incidence of flooding. Many areas in the developing world are experiencing strong population growth but lack adequate urban planning. This represents a significant humanitarian risk. We explore the use of high-cadence satellite imagery provided by Planet (PlanetSpec, 2019) (Planet, 2019) who's flock of over one hundred 'Dove' satellites image the entire earth's landmass everyday at 3-5m resolution. We use a deep learning-based computer vision approach to measure flood-related humanitarian risk in 5 cities in Africa.

1. Introduction

By 2050, more than two-thirds of the worlds population will live in cities, with the majority of this growth 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. Proper measurement and monitoring enables e.g. better resource allocation for critical infrastructure, commercial zoning interventions which increase tax revenue, and make viable insurance markets that incentivize growth in lower risk areas.

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 work flow is shown in Figure 1. Monitoring 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 the Earths landmass daily at 3-5 meter resolution. To avoid cloudy images, we consume Planets monthly nearly cloud-free 'basemap' images compiled from multiple days.

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, which has lead to our model generalizing 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, snow melt and terrain. Intersecting the building segmentation masks with the high flood risk zones enables quantitative urban flood risk analysis.

3. Results

3.1. Change in Building Coverage in 5 Cities

We computed the change in urban area from mid-2017 to early 2019 (the time of writing) 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 climates and terrains, which intersected high-risk flood zones, and had low cloud coverage. 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 - in future analyses we 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 the last 6 monthly area values in the period. In all 5 of the cities we observe urban growth in high flood risk zones.

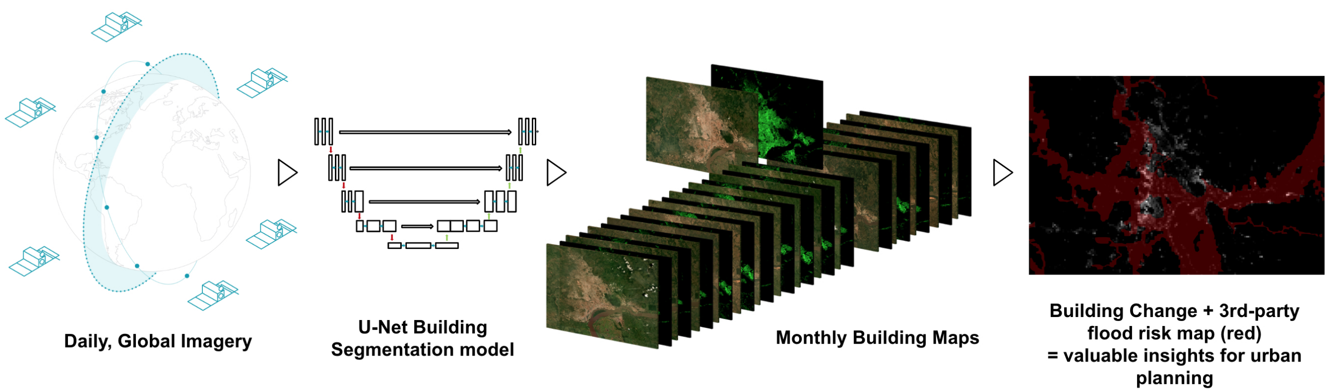

Figure 1. Work flow for monitoring urban growth in flood risk regions using daily geospatial imagery

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.

COUNTRY	CITY	% URBAN FLOOD RISK	% GROWTH
C.A.R.	BANGUI	57.0±1.4	2.5±2.0
MALI	BAMAKO	18.7±0.2	0.1±0.3
MOROCCO	CASABLANCA	13.7±0.1	0.3±0.1
BURKINA FASO	OUAGADOUGU	7.0±0.2	0.3±0.2
ETHIOPIA	ADDIS ABABA	2.1±0.1	0.6±0.2

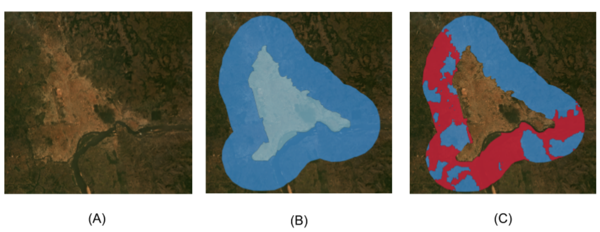

Figure 2. Bangui's (B) inner city (light blue), outer city (dark blue), and (C) high flood risk zone in the outer city (red).

3.2. Spatio-temporal Analysis of Bangui

In this section we perform a deeper analysis on Bangui - the city with the highest proportion of urban area within the high flood risk zone. 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 2 (A)). The outer city area was intersected with the high risk flood area map (Figure 2 (C)).

For the outer city we plotted urban area for every month from October 2017 to March 2019 (Figure 4 (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.

4. Conclusion

Using automated analysis of up-to-date satellite imagery we quantified urban area growth in 5 cities in Africa. We found that alarmingly large areas of these cities were in high flood risk zones, and that these areas were growing. Our approach can be applied to address growing flood risks driven by climate change. In particular,

- High temporal cadence results enables analysis of trends on shorter timescales than previously possible.
- 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.
- The global availability of satellite imagery, and power of deep learning-based models which generalize across diverse terrain, mean this approach can be applied across widely varied environments, at planetary scale.

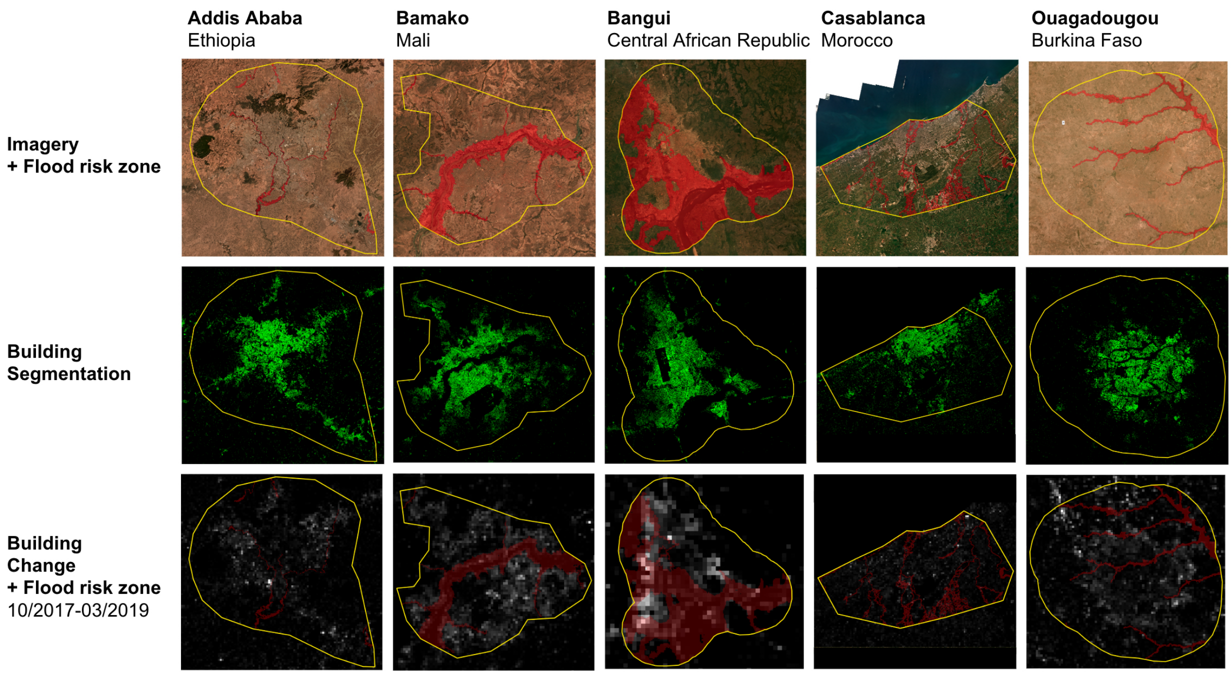

Figure 3. Change in urban area 2017-2019 for 5 cities in Africa. Top row, satellite images of each city from March 2019, overlaid with city extent and high flood risk area. Middle row, U-Net building segmentation maps. Bottom row, Change in buildings 10/2017-03/2019, aggregated at a 0.5km^2 spatial grid, intersected with high flood risk area showing growth 'hot spots'.

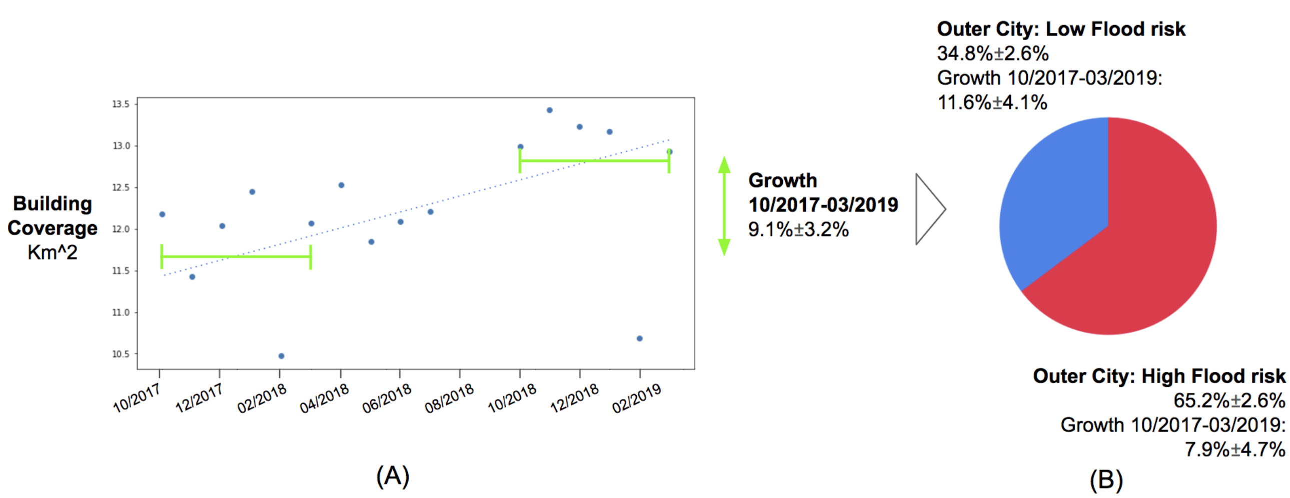

Figure 4. Urban area measurements within Bangui's outskirts. Left, Urban area plotted monthly for 15 months 10/2017-03/2019. Note: total city area is 410km^2. Right, break down within the outer city of high and low flood risk areas. Error values are the standard error.

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[*]Equal contribution [1]Planet Labs Inc, San Francisco, California, USA. Correspondence to: Christian Clough <christian.clough@planet.com>.

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