Application of Open-access and 3rd Party Geospatial Technology for Integrated Flood Risk Management in Data Sparse Regions of Developing Countries

"Preparedness, Response and Recovery"

By

Ekeu-wei Iguniwari Thomas (M.Sc., B.Eng.)

This thesis is submitted in partial fulfilment of the requirement for the award of the degree of

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Supervised by:

Prof. George Alan Blackburn

Dedication

To the Almighty God

and

To the Memory of Nom Habu

Former. Regional Officer, West Africa, Lancaster University, UK.

“Data can help you make a good design great, but it will never make a bad design good”

Margaret Gould Stewart

Declaration

I declare that, except where explicit reference is made to the contribution of others, that this thesis is the result of my work and has not been submitted for any other degree at the Lancaster University or any other institution.

Signature

Mr Ekeu-wei Iguniwari Thomas

ABSTRACT

Floods are one of the most devastating disasters known to man, caused by both natural and anthropogenic factors. The trend of flood events is continuously rising, increasing the exposure of the vulnerable populace in both developed and especially developing regions. Floods occur unexpectedly in some circumstances with little or no warning, and in other cases, aggravate rapidly, thereby leaving little time to plan, respond and recover. As such, hydrological data is needed before, during and after the flooding to ensure effective and integrated flood management. Though hydrological data collection in developed countries has been somewhat well established over long periods, the situation is different in the developing world. Developing regions are plagued with challenges that include inadequate ground monitoring networks attributed to deteriorating infrastructure, organizational deficiencies, lack of technical capacity, location inaccessibility and the huge financial implication of data collection at local and transboundary scales. These limitations, therefore, result in flawed flood management decisions and aggravate exposure of the most vulnerable people.

Nigeria, the case study for this thesis, experienced unprecedented flooding in 2012 that led to the displacement of 3,871,53 persons, destruction of infrastructure, disruption of socio-economic activities valued at 16.9 billion US Dollars (1.4% GDP) and sadly the loss of 363 lives. This flood event revealed the weakness in the nation's flood management system, which has been linked to poor data availability. This flood event motivated this study, which aims to assess these data gaps and explore alternative data sources and approaches, with the hope of improving flood management and decision making upon recurrence. This study adopts an integrated approach that applies open-access geospatial technology to curb data and financial limitations that hinder effective flood management in developing regions, to enhance disaster preparedness, response and recovery where resources are limited.

To estimate flood magnitudes and return periods needed for planning purposes, the gaps in hydrological data that contribute to poor estimates and consequently ineffective flood management decisions for the Niger-South River Basin of Nigeria were filled using Radar Altimetry (RA) and Multiple Imputation (MI) approaches. This reduced uncertainty associated with missing data, especially at locations where virtual altimetry stations exist. This study revealed that the size and consistency of the gap

within hydrological time series significantly influences the imputation approach to be adopted. Flood estimates derived from data filled using both RA and MI approaches were similar for consecutive gaps (1-3 years) in the time series, while wide (inconsecutive) gaps (> 3 years) caused by gauging station discontinuity and damage benefited the most from the RA infilling approach. The 2012 flood event was also quantified as a 1-in-100year flood, suggesting that if flood management measures had been implemented based on this information, the impact of that event would have been considerably mitigated.

Other than gaps within hydrological time series, in other cases hydrological data could be totally unavailable or limited in duration to enable satisfactory estimation of flood magnitudes and return periods, due to finance and logistical limitations in several developing and remote regions. In such cases, Regional Flood Frequency Analysis (RFFA) is recommended, to collate and leverage data from gauging stations in proximity to the area of interest. In this study, RFFA was implemented using the open-access International Centre for Integrated Water Resources Management–Regional Analysis of Frequency Tool (ICI-RAFT), which enables the inclusion of climate variability effect into flood frequency estimation at locations where the assumption of hydrological stationarity is not viable. The Madden-Julian Oscillation was identified as the dominant flood influencing climate mechanism, with its effect increasing with return period. Similar to other studies, climate variability inclusive regional flood estimates were less than those derived from direct techniques at various locations, and higher in others. Also, the maximum historical flood experienced in the region was less than the 1-in-100-year flood event recommended for flood management.

The 2012 flood in the Niger-South river basin of Nigeria was recreated in the CAESAR-LISFLOOD hydrodynamic model, combining open-access and third-party Digital Elevation Model (DEM), altimetry, bathymetry, aerial photo and hydrological data. The model was calibrated/validated in three sub-domains against *in situ* water level, overflight photos, Synthetic Aperture Radar (SAR) (TerraSAR-X, Radarsat2, CosmoSkyMed) and optical (MODIS) satellite images where available, to access model performance for a range of geomorphological and data variability. Improved data availability within constricted river channel areas resulted in better inundation extent and water level reconstruction, with the F-statistic reducing from 0.808 to 0.187 downstream into the vegetation dominating delta where data unavailability is pronounced. Overflight photos helped improve the model to reality capture ratio in the vegetation dominated delta and highlighted the deficiencies in SAR data for delineating flooding in the delta. Furthermore, the 2012 flood was within the confine of a 1-in-100-year flood for the sub-domain with maximum data availability, suggesting that in retrospect the 2012 flood event could have been managed effectively if flood management plans were implemented based on a 1-in-100-year flood.

During flooding, fast-paced response is required. However, logistical challenges can hinder access to remote areas to collect the necessary data needed to inform real-time decisions. Thus, this adopts an integrated approach that combines crowd-sourcing and MODIS flood maps for near-real-time monitoring during the peak flood season of 2015. The results highlighted the merits and demerits of both approaches, and demonstrate the need for an integrated approach that leverages the strength of both methods to enhance flood capture at macro and micro scales. Crowd-sourcing also provided an option for demographic and risk perception data collection, which was evaluated against a government risk perception map and revealed the weaknesses in the government flood models caused by sparse/coarse data application and model uncertainty.

The C4.5 decision tree algorithm was applied to integrate multiple open-access geospatial data to improve SAR image flood detection efficiency and the outputs were further applied in flood model validation. This approach resulted in F-Statistic improvement from 0.187 to 0.365 and reduced the CAESAR-LISFLOOD model overall bias from 3.432 to 0.699. Coarse data resolution, vegetation density, obsolete/non-existent river bathymetry, wetlands, ponds, uncontrolled dredging and illegal sand mining, were identified as the factors that contribute to flood model and map uncertainties in the delta region, hence the low accuracy depicted, despite the improvements that were achieved.

Managing floods requires the coordination of efforts before, during and after flooding to ensure optimal mitigation in the event of an occurrence. In this study, and integrated flood modelling and mapping approach is undertaken, combining multiple open-access data using freely available tools to curb the effects of data and resources deficiency on hydrological, hydrodynamic and inundation mapping processes and outcomes in developing countries. This approach if adopted and implemented on a large-scale would improve flood preparedness, response and recovery in data sparse regions and ensure floods are managed sustainably with limited resources.

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CHAPTER 1: INTRODUCTION TO RESEARCH, AIM AND OBJECTIVES DEFINITION

1. Background

1.1. Flood Hazard and Impact

Floods are arguably one of the most devastating disasters known to man, accounting for approximately one-third of global natural disasters, and impacting more people than any other natural or man-made phenomenon (Smith, 1998). Over the past decades, the impact of floods has been on the rise (Di Baldassarre et al., 2010, Aerts et al., 2014), resulting in the death of approximately 100,000 persons and affecting over 1.4 billion of the global populace in the last decade of the 20th century (Jonkman, 2005). Flood events are strongly linked to climate-change triggered weather variations, resulting in more severe and frequent storms (Yukiko et al., 2013). As the global population continue to increase, pushing people to settle in flood-prone regions (Burby et al., 2001), the exposure to flooding and its impact is expected to rise accordingly. The Global map of flood occurrences between 1985 to 2016 is presented in Figure 1, showing the spread of flooding across developed and developing regions.

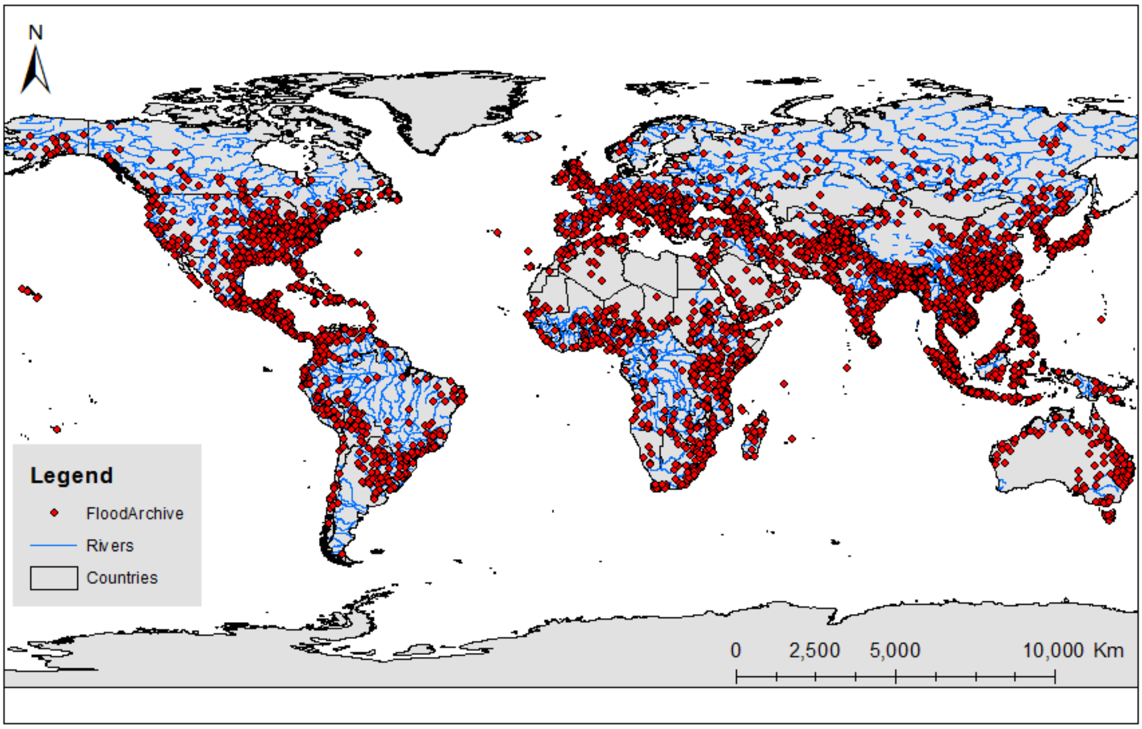


Figure 1 Global Distribution of flood occurrences 1985 – 2016 (Source: Dartmouth Flood Observatory)

Usually, floods transit political boundaries, affecting both developed and developing countries alike (Biancamaria et al., 2011, Nkwunonwo et al., 2016). However, vulnerability varies widely from high to low-income regions, as the ability to cope with and mitigate flood impact varies with economic capacity (Brouwer et al., 2007, Adelekan, 2011). Godschalk (1999) argued that the low-income populace is naturally inclined to reside in high-risk regions due to the low cost of settling within such regions, thereby limiting their capacity to cope with and recover from disastrous events. Nigeria has experienced increased flooding in recent years (Brakenridge, 2016), with impact aggravated due to the high number of the vulnerable populace living within floodplains (Nkeki et al., 2013, Agada and Nirupama, 2015, Daura and Mayomi, 2015). Locations of flood occurrences in Nigeria are presented in Figure 2, while global and local (Nigerian) flood impacts are presented in Table 1 (Brakenridge, 2016), and provides details of impact for occurrences greater than or equal to 1-in-100-year flood.

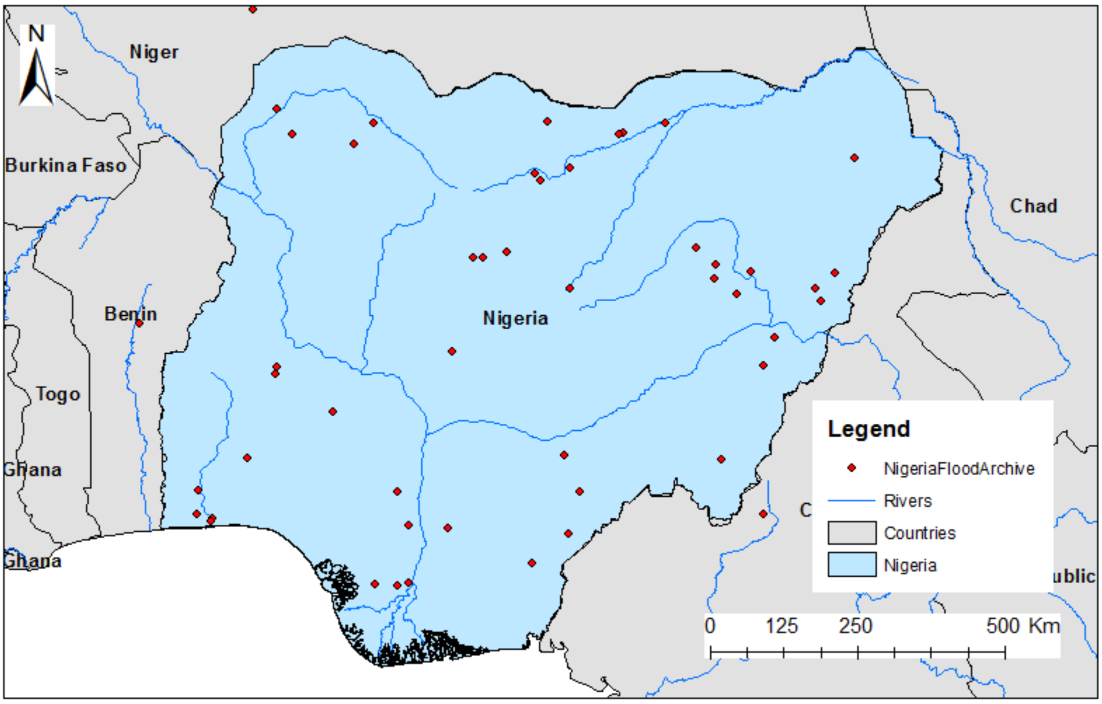


Figure 2 Distribution of flood occurrences in Nigeria 1985 – 2016 (Source: Dartmouth Flood Observatory)

Table 1 Estimated global and local (Nigeria) flood impacts from 1985 – 2016 (Source: Dartmouth Flood Observatory)

Location	Occurrence	Deaths	Displaced	Damage ('USD)	Affected populace	≥ 100 year floods
Global	4387	661295	638196277	$8.01*10^{11}$	$4.62*10^{8}$	725
Nigeria	58	1444	1881957	$1.01*10^{8}$	$4.64*10^{6}$	6

Recent reviews on flood risk assessment in Nigeria categorised the causes of flooding in terms of initiation and exacerbation factors (Nkwunonwo et al., 2016, Ugonna, 2016, Egbinola et al., 2015). Figure 3 shows a flowchart of the causes of flooding in Nigeria, including climate change, poor urban planning, urbanisation and anthropogenic activities. Climate change affects ocean-atmospheric patterns, thus initiating heavy storms that consequently cause pluvial (rainfall), fluvial (river) and coastal (ocean) floods (Nkwunonwo et al., 2015). Poor developmental blueprints, policies and implementation result in the violation of building regulations and settlement of persons within high-risk floodplains, thereby increasing impervious land surface, run-off and exposure to flooding. Also, anthropogenic activities such as poor waste management, upstream dam water releases, poorly designed hydraulic structures, blockage of waterways and drainages exacerbate flooding (Adeaga et al., 2008, Olukanni and Alatise, 2008, Etuonovbe, 2011, Raheem 2011, Agbola et al., 2012, Komolafe, 2015, Nkwunonwo et al., 2016). Although most floods occur independently, in some instances flood causes criss-cross, resulting in complex flood scenarios and associated risk. Nevertheless, this study is focused solely on fluvial (river) flooding.

Managing flood disasters sustainably requires the coordination of efforts before (preparedness), during (response) and after (recovery) flooding (APFM, 2011), to enable integrated flood management at variable paces to minimize flood effects. Courteille, (2015) highlighted components of the disaster risk management cycle:

1. Pre-disaster (Preparedness): involves expected risk assessment, mitigation, prevention, recovery planning and preparedness.

2. During disaster (Response): includes warning/evacuation, saving people, providing immediate assistance, and assessing damages to critical infrastructures.
3. Post-disaster (Recovery): encompasses reconstruction (resettlement and relocation), economic and social recovery, and risk assessment (lessons for recurrence mitigation and prevention).

Implementing these flood management strategies requires some form of data. Pre-and Post-flood management measures are usually deliberately paced, adapting existing methods that require available data. For instance, pre-flood measures can be accomplished by identifying locations susceptible to flooding based on knowledge of past flood trends from which annual flood exceedance probabilities are estimated (Reed, 1999). Flood estimates are then propagated through hydrodynamic models to route flood spread and quantify hazards (i.e. flood depth, velocity, and inundated area) (Sarhadi et al., 2012). Post-flood measures, on the other hand, entails identifying impacted locations, people and critical infrastructure within inundated areas to quantify damage and impact for reconstruction and rehabilitation purposes (Eyers et al., 2013, Thorne, 2014). Responding to floods in the heat of the event is particularly challenging, as real-time data processing and information are needed for a prompt response (Muller et al., 2015, Temimi et al., 2004, García-Pintado et al., 2013).

Although several structural and non-structural steps have been taken by various stakeholders to combat flooding in Nigeria, the results have been poor, judging from recent flood impacts (Ugonna, 2016, Tami and Moses, 2015, Ojigi et al., 2013). This failure is attributed to the ad-hoc nature, ineffective and poorly coordinated nature of flood management efforts (Obeta, 2014a); shortage of quality data, poor stakeholders flood risk perception and poor citizen inclusiveness; lack of funding, technological know-how and political will by the government (Maxwell, 2013, Ugonna, 2016).

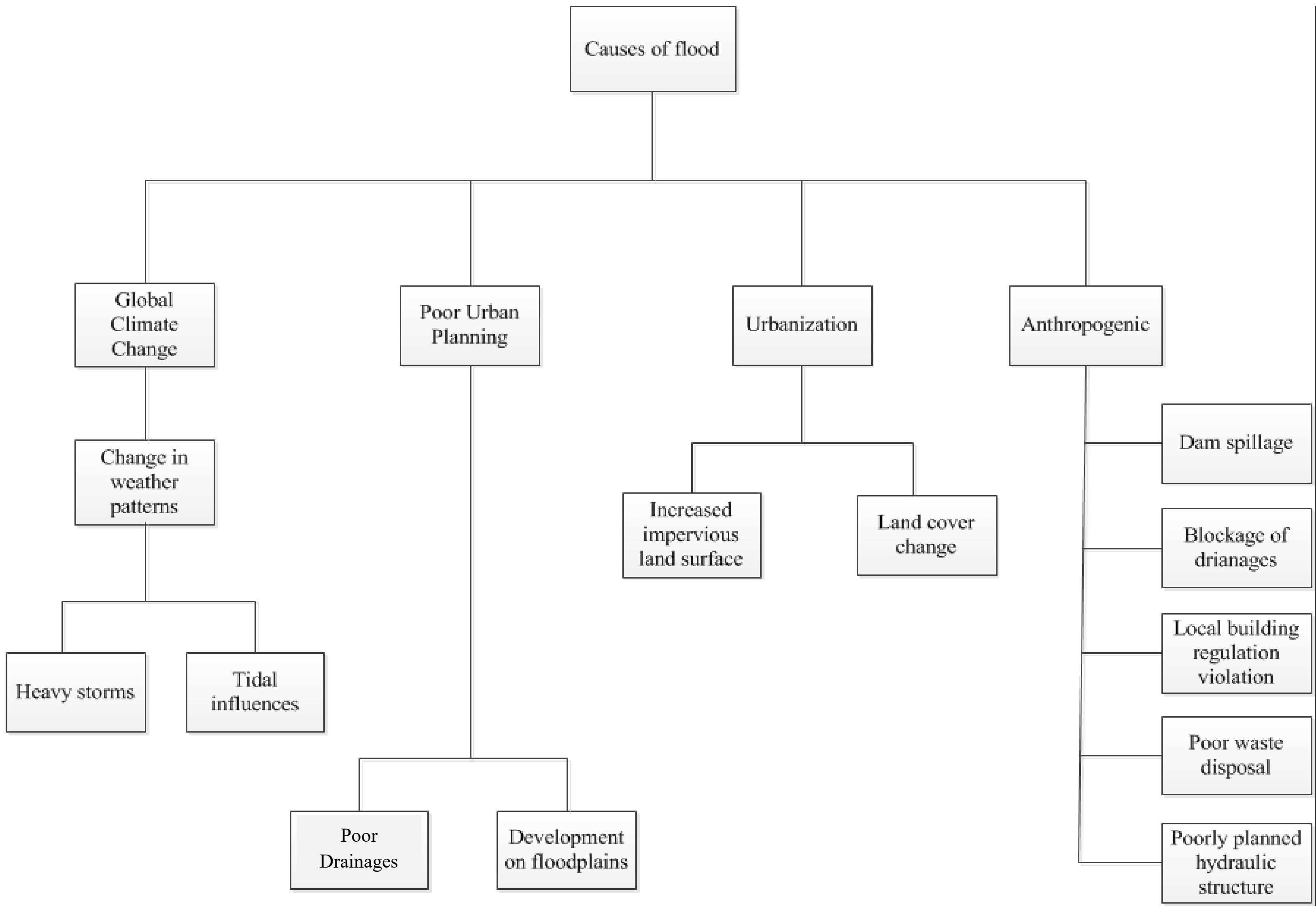


Figure 3 Classification of common causes of flooding in Nigeria

1.2. Aim

The aim of this study is to overcome data and resources limitations in developing regions to adequately model and map flooding, using alternative open-access geospatial technology within an integrated flood management framework that enhances preparedness, response and recovery.

1.3. Objectives

1) Identify the causes of data limitations in flood management and alternative open-access data sources available to fill the data gap.

2) Investigate varying hydrological data filling approaches to curtail missing data effect on flood frequency estimates.

3) Explore methods by which identified open-access, 3rd party and citizen acquired data can be integratively applied to improve hydrodynamic modelling and flood mapping in data sparse regions.

4) Assess the limitations of alternative open data application and apply known concepts to improved flood delineation.

1.4. THESIS STRUCTURE

This thesis is structured following the alternative format, composed of eight chapters, with Six (6) chapters (2-7) drafted to focus on specific research objectives.

Chapter 1: INTRODUCTION TO RESEARCH, AIM AND OBJECTIVES DEFINITION

Introduces the research problem of flood risk and the need for flood management, highlighting the key issues and rationale at global and local scales. The research aim and objectives of the research are also outlined.

Chapter 2: APPLICATIONS OF OPEN-ACCESS REMOTELY SENSED DATA IN FLOOD MAPPING FOR DATA SPARSE REGIONS: A REVIEW AND CASE STUDY OF NIGERIA

This chapter presents a review section that focuses on the data challenges and uncertainties associated with sparse data application in hydrological modelling, hydrodynamic modelling and flood mapping at global, transboundary and local (Nigerian) scales. The core causes of data limitations in developing regions are disclosed, and available alternative open-access remote sensing and third-party data sets that compensate for ground data deficiency in flood mapping are highlighted. Flood mapping processes including flood frequency estimation, hydrodynamic modelling, and inundation mapping are discussed, and ways radar altimetry, digital elevation model, bathymetry, optical, radar images, and satellite consortium data can be applied to curb data sparsity for each of these processes. Transboundary flood management challenges are also emphasised with the prospect of effective flood management through current and future open - access remote sensing data application.

Chapter 3: INFILLING MISSING DATA IN HYDROLOGY: SOLUTIONS USING SATELLITE RADAR ALTIMETRY AND MULTIPLE IMPUTATION FOR DATASPARSE REGIONS

One of the causes of data deficiency disclosed in Chapter 2 is gaps within hydrological time series, which results in uncertain flood estimates. Chapter 3 explores the use of radar altimetry and multiple imputation techniques to fill missing data in hydrological time series, consequently reducing flood estimates uncertainties. These approaches were aimed at reconstructing missing annual peak river discharges distorted due to destructive floods, discontinued gauging stations or inaccessibility to remote locations during flooding. The magnitudes of the 2012 and 2015 flood events at gauging stations along Niger and Benue rivers in Nigeria were also evaluated from distinctly filled time-series, and the application of these techniques in practice discussed.

Chapter 4: ACCOUNTING FOR CLIMATE VARIABILITY IN REGIONAL FLOOD FREQUENCY ESTIMATES FOR WESTERN NIGERIA

Logistical and financial challenges make it difficult to establish gauge stations at all required locations, hence the hydrological monitoring networks are often sparse, and several locations left ungauged (Chapter 2). Also, the increasing influence of climate change on floods as discussed in Chapter 1 and Chapter 2 annuls the assumption of stationarity in flood frequency estimation. Chapter 4 presents findings that assess the effect of climate variability on regional flood frequency estimates in the sparsely gauged Ogun-Osun River basin in Nigeria. Freely available International Centre for Integrated Water Resources Management–Regional Analysis of Frequency Tool (ICI-RAFT) that aids the integration of the National Oceanic and Atmospheric Administration (NOAA) climate indices into flood frequency estimation was applied, thereby supporting flood management in regions with limited resources.

Chapter 5: INTEGRATING CROWD-SOURCING AND OPEN-ACCESS REMOTE SENSING FOR FLOOD MONITORING IN DEVELOPING COUNTRIES

Monitoring flooding at the peak of occurrence is required to identify flooded locations to deploy resources to mitigate flood impact. Integrated Near-Real-Time remote sensing MODIS flood maps and crowdsourcing (Volunteered Geographic Information System) were applied for flood monitoring during the peak flood season of 2015 (Chapter 5), and data on the past flood event of 2012 was collected in retrospect. The VGIS crowdsourcing approach was based on a revised disaster communication model by the

UN Office for Disaster Risk Reduction (UNISDR), focused on impacted persons communicating disaster reality to management agencies. Citizen and government perception of flood risk is evaluated, and citizen risk perception in relation to flood risk indicators such as Awareness, Worry and Preparedness is also assessed from supplementary data collected.

Chapter 6: HYDRODYNAMIC MODELLING OF EXTREME FLOODS IN DEVELOPING REGIONS USING MULTIPLE OPEN-ACCESS REMOTE SENSING DATA SOURCES

Chapter 6 portrays an integrated flood modelling and mapping approach applied in the Niger-South river basin of Nigeria (i.e. from Niger river at Baro and Benue river at Umaisha to the Niger Delta through Nun and Forcados tributaries). The hydrodynamic model incorporates open-access remote sensing, airborne (overflight), hydrographic and bathymetric data from multiple sources and third-parties. 2-D CAESAR-LISLFOOD model is applied using 2012 hydrograph and modified SRTM to recreate the unprecedented flood event hydraulically. The model was calibrated using a combination of satellite images (i.e. TerraSAR-X image, MODIS Near-Real-Time flood map, RadarSat-2, CosmoSkyMed), overflight geotagged photos and water levels available for three sub-domains. 1-in-100-year flood frequency estimates were modelled and compared in retrospect to the 2012 flood event to improve planning and management of subsequent events.

Chapter 7: IMPROVING RADAR IMAGERY FLOOD DETECTION CAPACITY USING MULTI-CRITERIA DECISION TREE ANALYSIS TECHNIQUE BUILT ON OPEN-ACCESS DATA

Chapter 6 revealed the deficiency of Synthetic Aperture Radar (SAR) image in delineating flooding in the vegetation covered Niger Delta using overflight geotagged photos, due to SAR inability to penetrate vegetation covers and discrepancies in built-up areas. Chapter 7 combines multiple open-access data sets using a C4.5 algorithm driven decision-tree to delineate flood extent within the Niger Delta for improved hydrodynamic flood evaluation.

Chapter 8: CONCLUSION, CONTRIBUTIONS, LIMITATIONS AND RECOMMENDATIONS

Concludes the thesis, summarising the main findings and discussing the implications in regard to flood management. It also Synthesises previous chapters, aligning them within the integrated flood management framework of preparedness (pre-flood), response (during the flood) and recovery (post-flood). The contributions of this thesis in filling the data sparsity gap in developing regions with limited resources are highlighted. The limitations and recommendations for improvement and future research direction is also presented.

CHAPTER 2: APPLICATIONS OF OPEN-ACCESS REMOTELY SENSED DATA IN FLOOD MAPPING FOR DATA SPARSE REGIONS: A REVIEW AND CASE STUDY OF NIGERIA

Abstract

Flood mapping generally entails flood frequency estimation, hydrodynamic modelling and inundation mapping, which requires specific data sets that are sometimes unavailable especially in developing regions due to financial, logistical, technical and organisational challenges. This chapter reviews flood modelling and mapping processes, outlining the data requirements and how open-access remote sensing can supplement for ground and high-resolution space-borne commercial data. The merits, demerits and application cases of data sets such as radar altimetry, DEM, optical and radar images are also discoursed for global, transboundary and local flood risk management. Also, the role of collaborative satellite information sharing and service delivery in flood disaster monitoring and management is disclosed.

Keywords: Open-access remote sensing, flood management, Altimetry, Synthetic Aperture Radar, Optical Satellite, Digital Elevation Model (DEM), Transboundary floods.

1. Introduction

1.1. Flood modelling and mapping

Managing flood effectively requires a good understanding of historical flood trends, future expectations, and identification of locations likely to be impacted by flooding. Flood mapping provides the baseline for acquiring such information, to ensure prevention, protection and management are efficiently undertaken (Plate, 2002). Flood mapping is a process that defines the expected extent of water inundation into dryland as a result of intense precipitation or river water level rise driven by natural or anthropogenic factors (Merwade et al., 2008). Flood mapping process differs considerably from project to project, or country to country, depending on specific project requirements and country-specific guidelines. Also, the scale of flood risk assessment, available data, resources, technical knowledge and delivery timeline influences the approach deployed (Moel et al., 2015, Klijn et al., 2008, Büchele et al., 2006, Ologunorisa, 2004). Nevertheless, the sequence of activities that lead to risk map outcome is fundamentally the same, and involves flood frequency estimation (probability of occurrence of a flood of specific magnitude over a certain period); hydrodynamic modelling (routing of river discharge or catchment runoff over landscape to determine water depth and inundation extent); and risk assessment (determining landscape properties impacted within flooded regions) (ISDR, 2004, Els, 2013, FME, 2005b, Aerts et al., 2009, Martini and Loat, 2007).

Table 1 highlights Flood mapping processes, basic data requirements, expected outcomes and some case studies. These processes aid flood management by providing the necessary information needed for planning, flood defence structure design, disaster response and recovery to mitigate flood effect.

Going forward, this review highlights the scarcity of data needed for mapping processes (Table 1), detailing how advancements in open-access remote sensing can compensate for ground monitoring deficiencies in local and transboundary river basins. Remote sensing data sets such as altimetry, digital elevation models, radar and optical images application in each flood mapping process are discoursed. To further demonstrate the usefulness of open-access remote sensing in developing regions, a case study of Nigeria is presented, emphasising on local and transboundary flood management developments, data limitations, current role and future prospect of remote sensing.

Table 1 Flood mapping process and fundamental data requirement

Process	Data	Outcomes	Cases
Flood frequency estimation	▪ Historical data: River discharge, water levels and rating curves/equations.	▪ Flood magnitude at specific return periods (Direct and regional).	(Awokola and Martins, 2001, Kjeldsen et al., 2002, Leclerc and Ouarda, 2007, Ahn et al., 2014)
Hydrodynamic model	▪ Flood frequency outcome ▪ River discharge ▪ Digital elevation model ▪ Land use and cover map Historical flood extent, and marks	▪ Inundation Extent ▪ Water depth ▪ Flood velocity and travel time	(Sarhadi et al., 2012, Di Baldassarre et al., 2010, Muncaster et al., 2006, Neal et al., 2011a)
Flood risk assessment	▪ Hydrodynamic model outcomes, demographic, socio-economic and infrastructure data.	▪ Exposure maps ▪ Vulnerability maps ▪ Evacuation plan	(Taubenböck et al., 2011, Eyers et al., 2013, Neal et al., 2011a)

2. Data limitations, Prediction of Ungauged Basins (PUB) and Remote sensing advancement

In recent decades, floods have been perceived to be increasingly frequent, widespread and more devastating. As such, the spatial network of existing hydrological gauging stations has become inadequate for optimal data collection (NIHSA AFO, 2014). In other cases, obsolete equipment, financial and technical challenges hamper sufficient data collection for flood mapping and management (Olayinka et al., 2013, Maxwell, 2013). Due to increasing global data deficiency and uncertainty associated with sparse data application for hydrological and hydrodynamic modelling, the International Association of Hydrological Sciences (IAHS) launched the Prediction of Ungauged Basins (PUB) initiative to explore alternative data and techniques for improved Ungauged basin modelling (Sivapalan, 2003). One of the core objectives of the PUB is to "Advance the technological capability around the world to make predictions in ungauged basins firmly based on local knowledge of the climatic and landscape that controls hydrological processes, along with access to the latest data sources, and through these means constrain the uncertainty in hydrological predictions." (Sivapalan et al., 2003). This objective aligns seamlessly with remote sensing, considering that it provides an alternative data source to improve our understanding of local hydrology and associated uncertainties in flood mapping for data-sparse regions (Hrachowitz et al., 2013).

Remote Sensing (RS) has advanced to the stage whereby, in many places, data is now freely available at a global scale, enabling developing countries to explore its potential at little to no data acquisition cost (Yan et al., 2015a). This review focuses solely on open-access (freely available) satellite data integration into flood mapping processes to compensate for data sparsely faced in developing regions, then emphasises on a Nigerian cases study, assessing the possibility of leveraging global geospatial technology for local flood management. Inferences are drawn from previous reviews on low-cost Geographic Information System (GIS) and remote sensing application in hydrology, hydrodynamic modelling and flood mapping (Yan et al., 2015a, Schumann et al., 2009a, Mason et al., 2011, Dano Umar et al., 2011). However, a wider range of freely available datasets and sources needed for every step listed in Table 1 are explored in this review, with case studies of application for flood management improvement discoursed.

3. Alternative open-access remote sensing data for flood modelling and management

3.1. Radar Altimetry Water Level and Elevation

River water levels are an essential data input for hydrology and hydrodynamic modelling, and advancement in remote sensing has improved the way changes in water surface elevation and slope can be measured since the early 90's (Alsdorf et al., 2007). Several radar altimetry missions routinely measure freshwater surface despite being originally designated to measure ocean water surfaces (Koblinsky et al., 1993, da Silva et al., 2010). Radar altimetry data is acquired via a process that measures the distance between the orbiting satellite and water surface in relation to a reference datum, using satellite sensor echo pulse return intervals from when emitted to when reflection by water surface and return to satellite (Sulistioadi et al., 2015, Belaud et al., 2010), Figure 1 (A). Altimetry water levels are measured at virtual stations located intermittently where altimetry satellite tracks cross path with rivers (Birkinshaw et al., 2014b, Musa et al., 2015); when altimetry tracks pass over dry land, the elevation of the surface intersected is measured. Figure 1 (B) and (C) shows a sample virtual station and extracted altimetry time series (Crétaux et al., 2011) along the Niger River in Nigeria. The water level at a river of interest with reference to a predefined datum (such as Earth Gravitational Model (EGM 2008)), is expressed as:

$$h = H - R_{Cor} \quad (1)$$

$$R_{cor} = R - \left(c\frac{\Delta t}{2}\right) - \sum \text{cor} \quad (2)$$

Where, h = water surface elevation in relation to the reference ellipsoid, H = altitude of satellite (from satellite orbit to reference ellipsoid), R = range (distance between satellite and open surface water body), R_{cor} = corrected range, c = speed of light, $\frac{\Delta t}{2}$ = the dual direction travel time of radar signal, and ∑cor = the sum of ionospheric, tidal, wet and dry tropospheric corrections.

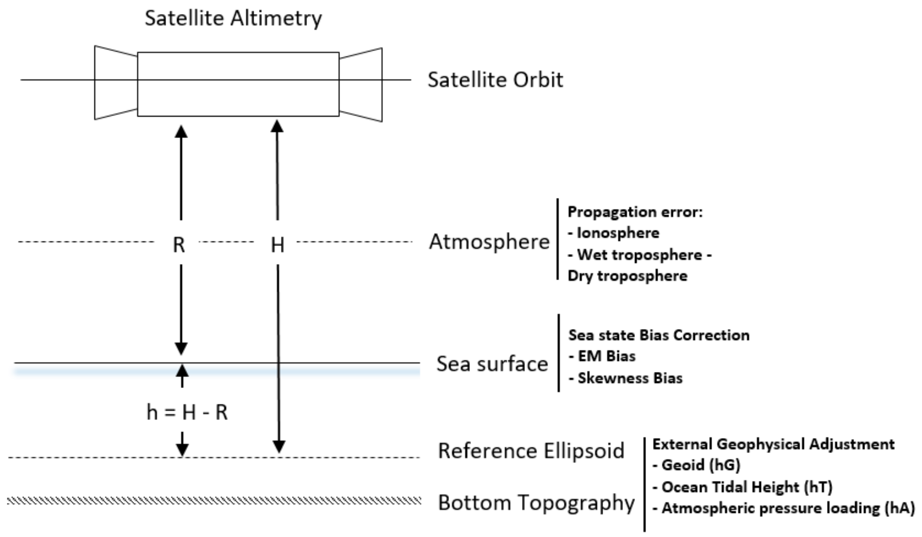


Figure **1 (A)** Graphic illustration of satellite altimetry height measurement principle (adapted from (Musa et al., 2015)

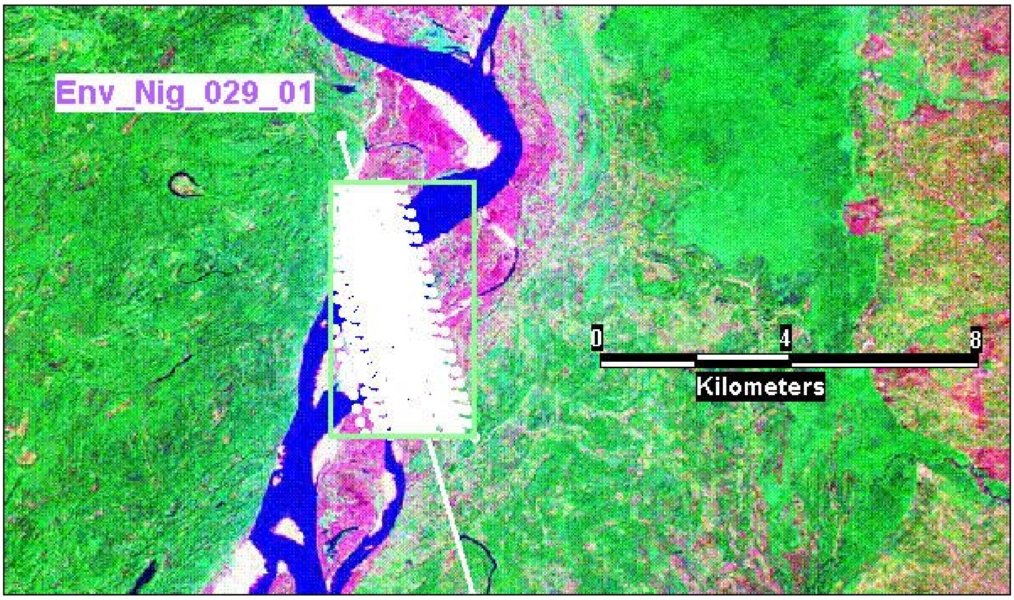


Figure 1 (B) Illustration of a virtual station, where altimetry satellite tracks intersect river Niger

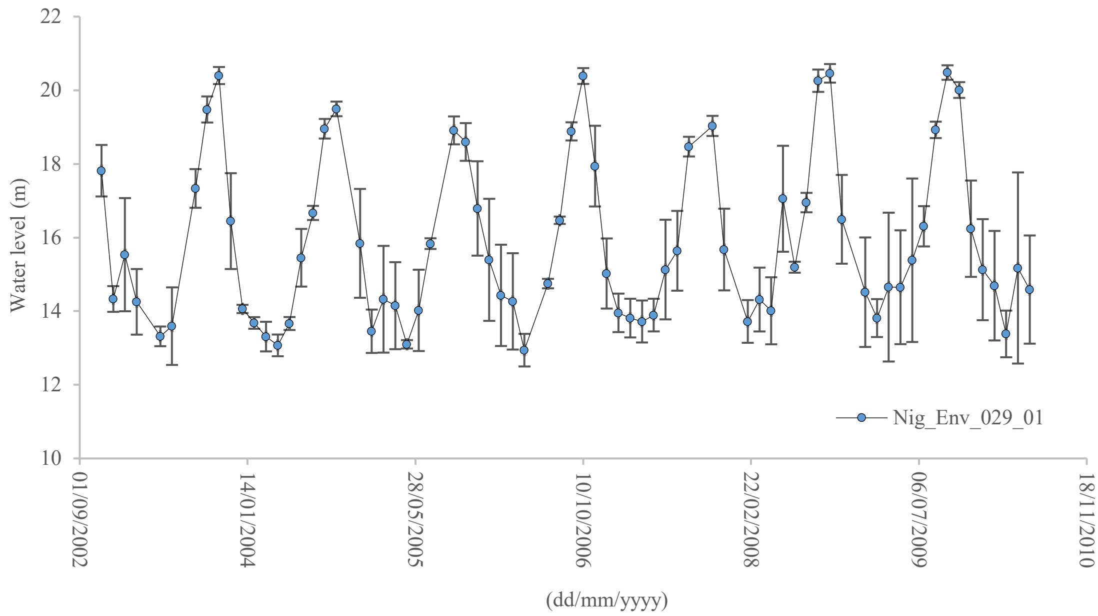


Figure 1 (C) Typical water level time-series, derived from an altimetry virtual station

The vertical accuracy of altimetry water levels directly affects the results derived from its application (O'Loughlin et al., 2016a). In comparison to ground (*in situ*) measurements, altimetry water level vertical accuracy ranges from approximately 0.01 to 0.05 metres, and Root Mean Squared Error (RMSE) from 0.003 to 0.004 metres for watershed areas up to 100 km^2 (Birkett, 1995, Birkett et al., 2002, da Silva et al., 2010, Frappart et al., 2006). In some cases, the difference between altimetry and *in situ* water levels can be as high as 2 metres (Birkinshaw et al., 2010). Variations of altimetry water level accuracies are presented in Table 2 and are attributed to varying sensor types, the distance between *in situ* and virtual station, and location of altimetry track intersection with the river (Yan et al., 2015a). Other factors that affect altimetry accuracy include ionosphere, troposphere, instrument noise, geoid, tidal and water surface variations (Ponte et al., 2007, Chelton et al., 2001, Belaud et al., 2010). River width and tributaries discharging into main rivers upstream of the virtual station have also been identified as the external factors that contributed to altimetry water level discordancy from *in situ* measurements (Sulistioadi et al., 2015, Pandey and Amarnath, 2015).

The application of radar altimetry has been largely documented, especially in hydrodynamic modelling in data sparse regions. Four (4) aspects of altimetry application in data sparse regions are discussed below (Sections 3.1.1 to 3.1.4) include Altimetry discharge estimation, Altimetry Digital Elevation Model (DEM) accuracy assessment, Altimetry Bathymetry definition, and Altimetry hydrodynamic model calibration and validation. Table 2 Altimetry characteristics Adapted and modified from (O'Loughlin et al., 2016a)

S/N	Mission	Ground footprint (m)	Revisit time (days)	Operation timeline	Accuracy (m)	References
1	TOPEX/Poseidon	~600	9.9	1993-2003	0.35	(Frappart et al., 2006)
2	ERS-1	~5000	35	1991-2000	N/A	(da Silva et al., 2010)
3	ERS-2	~400	35	1995-2003	0.55	(Frappart et al., 2006)
4	ENVISAT	~400	35	2002-2012	0.28	(Frappart et al., 2006)
5	Jason-1	~300	10	2002-2009	1.07	(Jarihani et al., 2015a)
6	ICE Sat/GLAS	~70	-	2003-2009	0.10	(Urban et al., 2008)
7	Cyrosat-2	~300	369	2010*	< SRTM	(Schneider et al., 2016)
8	Jason-2	~300	10	2008*	0.28	(Jarihani et al., 2015a)
9	SARAL/Altika	~173	35	2013*	0.11	(Schwatke et al., 2015c)
10	Sentinel 3 SRAL	~300	27	2016*	0.03	(ESA, 2016)
11	Jason-3	~300	10	2016*	0.03	(NASA, 2016)
12	SWOT	~10 -70	21	2020^{+}	0.10	(Fu et al., 2009)

Current = *, Future = +

3.1.1. Altimetry discharge estimation

River discharge and stage are typical initial/boundary conditions needed in hydrodynamic modelling and are usually seldom unavailable at remote locations of most developing regions due to factors previously highlighted in Section 2 (Birkinshaw et al., 2014b, Olayinka et al., 2013). Radar altimetry has been explored in several studies to curb data limitation challenges and reduce the uncertainty associated with modelling ungauged rivers, and are discussed in detail below.

Papa et al., (2010) utilised TOPEX/Poseidon, ERS-2, ENVISAT and Jason 2 altimetry water levels in combination with *in situ* rating curve to estimate discharge along Ganga and Brahmaputra river from 1993-2011to accuracy levels of 0.17 (mean error) and 0.28 (standard error) in comparison to *in situ* discharge at gauging stations. River discharge along Godavari river from 2001 to 2014 was derived by combining ENVISAT (2002-2010), Jason-2 (2008-2014) and SARAL/Altika (2013-2014) radar altimeter water levels with *in situ* rating curves at nearby gauging stations, and validated against hydrodynamic model to a correlation coefficient (R^2) value of 0.9 and standard error varying from 0.15 to 0.40 metres (Sridevi et al., 2016). In an Amazon River basin study, Getirana and Peters-Lidard, (2013) explored the potential of estimating discharge at 135 gauging stations using altimetry data from 475 ENVISAT virtual stations (2002 – 2005). Using the relationship between *in situ* water level and discharge, Getirana and Peters-Lidard, (2013) successfully estimated discharge at 90 virtual stations with mean relative errors varying from 15 to 84% for large and small river basins respectively. Discharge was estimated at transboundary rivers including Danube (Austria, Romania, Bulgaria, Slovakia, Hungary, Ukraine, Croatia, Germany, Serbia, and Moldova), Mekong (Thailand, Cambodia, Laos, China, Myanmar (Burma and Vietnam), Amazon (Ecuador, Colombia, Peru, and Brazil), Brahmaputra (India), Amur (China and Russia), Ob (Russia), Vistula (Poland) and Niger (Nigeria, Mali, Niger, Benin, and Guinea), using quantile function algorithm approach that exploits ENVISAT altimetry data (Tourian et al., 2013). This approach resulted in discharge outcomes similar to those derived from conventional Forecast Rating Curve (FRC) approach.

Typically, estimating river discharge from altimetry water level depends on rating curve or river geometry availability (Michailovsky et al., 2012). However, several studies have been able to demonstrate direct river discharge estimation from altimetry water levels in the absence of *in-situ* measurements, using supplemental remote sensing data or models. ENVISAT altimetry data from six virtual stations along Brahmaputra River from 2008 to 2010 were assimilated into a Muskingum routing model driven by outputs of a calibrated Budyko type rainfall-runoff model derived from Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) 3B42RT real-time products. This integrated approach improved the model's discharge derivation accuracy (Nash-Sutcliffe efficiency) from 0.78 to 0.84. Also, using a different hydrodynamic modelling approach, Tarpanelli et al., (2016) combined Moderate-resolution Imaging Spectroradiometer (MODIS) Terra and Aqua satellite images with ENVISAT altimetry using a pixel to water level detection approach to estimate discharge with a correlation coefficient of 0.96 and Nash-Sutcliffe efficiency of 0.91 when compared to *in situ* discharge along the Niger and Benue rivers. Sichangi et al., (2016) similarly integrated MODIS satellite derived river width and altimetry water levels into Manning's equation to estimate discharge at a Continental scale. The derived discharge Nash-Sutcliffe efficiency varied 0.60 to 0.97.

Other than a few studies including Getirana and Peters-Lidard, (2013), Tarpanelli et al., (2016) and Sichangi et al., (2016) that have demonstrated direct river discharge estimation in the absence of *in-situ* data, river discharge estimation from altimetry is usually based on the establishment of an empirical relationship with *in situ* gauging stations available at proximity to virtual stations. Although discharge estimates derived from altimetry are usually with acceptable levels of uncertainty, factors such as the distance between virtual and ground stations, contributing tributaries and the width of the river affect the efficacy of such estimates (Pandey and Amarnath, 2015). The discussed discharge estimation approaches also reveal that the availability of multiple supplementary remote sensing data at an ungauged river basin integrated into empirical formulas and hydrodynamic models can improve discharge estimates.

3.1.2. Altimetry Digital Elevation Model (DEM) accuracy assessment

Once discharge and/or flood magnitude is estimated, it is propagated longitudinally along river channels and laterally across floodplains in hydrodynamic models governed by continuity and momentum equations (Casas et al., 2006). The accuracy of DEM that defines the river channel and floodplain terrain upon which flow is propagated influences model outcome accuracy (Cook and Merwade, 2009). Therefore, in several flood modelling studies the accuracy of the primary DEM is assessed prior to usage against a higher accuracy DEM such a Light Detection and Ranging (LiDAR) or Differential Global Positioning System (GPS) elevation points (Patro et al., 2009, Wang et al., 2012, Sanyal et al., 2013, Ullah et al., 2016). Acquiring such data sets for accuracy assessment is cost intensive and in other instances impossible due to terrain complexity and weather conditions that hinder logistics for effective data collection (Amans et al., 2013, Isioye and Yang, 2013). ICE Sat/GLAS altimetry data acquired by the National Aeronautics and Space Administration (NASA) between 12 January, 2003 and 11 October, 2009 using geoscience laser altimeter system (GLAS) onboard the Ice Cloud and Land Elevation Satellite (ICE Sat) provides a worthy alternative to ground elevation due to its high accuracy in comparison to Kinematic GPS measurements (Zwally et al., 2002). The absolute accuracy of ICE Sat is recorded to be as low as 0.002 and 0.005 meters in Bolivia (Fricker et al., 2005) and French Lake (Jean Stéphane et al., 2011) respectively, and depend on the slope of the terrain under scrutiny (Satgé et al., 2015). Over the years ICE Sat/GLAS has been applied in assessing various DEM accuracies including SRTM (Carabajal and Harding, 2005, Kon Joon Bhang et al., 2007, Du et al., 2016), ASTER GDEM (Zhao et al., 2010, Satgé et al., 2015), GPS elevation (Braun and Fotopoulos, 2007), Carto DEM (Rastogi et al., 2015), Canadian DEM (Beaulieu and Clavet, 2009), InSAR DEM (Yamanokuchi et al., 2006), TANDEM (Mirzaee et al., 2015) and modified/corrected DEMs (Jarihani et al., 2015a, Sampson et al., 2015, O'Loughlin et al., 2015).

The 70-metre ground footprint of ICE Sat (Zwally et al., 2002) coupled with its ability to penetrate gaps in vegetation canopy to capture underlying bare earth elevation (Heyder, 2005) makes it a more accurate and useful alternative to ground survey for DEM accuracy assessment.

3.1.3. Altimetry Bathymetry definition

Accurate digital elevation models combined with detailed river bathymetry delineation provides the best terrain data for flood routing (Trigg et al., 2009, Casas et al., 2006). Nevertheless, acquiring such data for remote locations is usually difficult as earlier discussed. Hence, flood modellers have resorted to exploring alternative options to compensate for such deficiency. In the Amazon and Napo Rivers in Peru, Chávarri et al., (2012) examined the applicability of altimetry (ENVISAT) in constraining river cross-section of a one-dimensional hydraulic model. The results showed reduced model uncertainty, mostly for rivers with widths less than or equal to 2.5 km. The proposed Surface Water and Ocean Topography (SWOT) scheduled for launch in 2020 is expected to provide one of the best altimetry data for water resource monitoring and management at a global scale (Fu et al., 2009, Bates et al., 2014). Few studies have experimented on SWOT derived bathymetry for hydrodynamic modelling to improve outcome accuracy. For example, Durand et al., (2008) experimented on the SWOT mission, applying data assimilation technique to estimate bathymetric depth and slope at five points along a 240 km reach along the Amazon river to within 0.50 m and 0.30 cm km^{-1} of accuracies respectively. Both derivatives were then integrated into LISFLOOD-FP hydrodynamic model (Bates and De Roo, 2000) to improve inundation extent and downstream water surface elevation (WSE). The relationship between river width and depths established using ENVISAT altimetry was combined with SRTM, Landsat, MODIS and satellite rainfall data to derive updated river network and adjusted bed profile was applied in the development of Ganges, Brahmaputra, and Meghna (GBM) model suitable for large ungauged watersheds (Maswood and Hossain, 2016). The GBM model data integration resulted in a reduced RMSE from 3.0 to 1.0 metres. In another study by Yoon et al., (2012), SWOT WSE was assimilated into LISFLOOD-FP hydrodynamic model using a local ensemble batch smoother (LEnBS) method, resulted in the generation of bathymetry, depth and discharge estimates. Bathymetry extracted from SWOT had a RMSE of 0.56 metres, improving with the inclusion of more SWOT observations in the modelling process.

The proposed SWOT and recently launched Sentinel-3 provides a huge dataset prospect for future of hydrodynamic studies, and integration into hydrodynamic models can improve flood extent, discharge and water levels outcomes, particularly when multiple altimetry data are available along a modelled reach as Yoon et al., (2012) suggested.

3.1.4. Altimetry hydrodynamic model calibration and validation

Hydrodynamic model validation helps reveal how well a model represents what is expected in reality (Stephens et al., 2014), and is directly linked to the confidence in the flood management measures implemented as a result of the model outcome. Calibration is usually undertaken by adjusting various model parameters such as floodplain roughness, channel roughness, river channel depth, and river width while comparing flood model outcomes (water level, discharge and/or inundation extent) to what is expected in reality, derived from *in situ* or remote sensing measurements (Belaud et al., 2010, Sun et al., 2012, Van Wesemael et al., 2016, Neal et al., 2015). Commercial high-resolution optical and radar satellites images, aerial images and hydrological data have been largely established as the optimal data sources for hydrodynamic model calibration and validation (Jung et al., 2012, Dung et al., 2011, Pasquale et al., 2014, Wood et al., 2014). However, the high cost of acquiring such data hinders their application in developing countries (Andréfouët et al., 2006). Hence, radar altimetry over the past decade has been explored globally as an alternate source of data for model calibration and validation (Domeneghetti, 2016).

Typically, in developing regions river measurements are manually collected using staff gauges and later converted to discharge using an established rating curve. At the peak of floods, measurement equipment are usually damaged and access roads inundated, thus impeding the observation process (Olayinka et al., 2013, Dano Umar et al., 2011). Therefore, remote sensing radar altimetry provides an alternative river measurement option that supports hydrodynamic model calibration and validation in the absence of observed records (Domeneghetti, 2016).

Water level data from three ENVISAT altimetry virtual stations along a 150km reach of Danube river were applied in the calibration a 2-D LISFLOOD-FP model to reconstruct the 2006 transboundary flood occurrence (Yan et al., 2015b). Yan et al., (2015b) realised a Mean Average Error (MAE) of 1.53 m and 1.37 m for altimetry and *in situ* model calibration approaches respectively, suggesting that both data sets can be used interchangeably to improve flood modelling in sparsely gauged river basins. Domeneghetti et al., (2014) performed hydrodynamic model calibration for a 140 km reach along the Po river using ERS-2 and ENVISAT altimetry data, resulting in RMSE of 0.85 m and 0.73 m respectively, and improved Nash–Sutcliffe efficiency (NS) when altimetry is combined with *in situ* data for model calibration. Soil and Water Assessment Tool (SWAT) rainfall run-off model for the sparsely gauged Okavango transboundary river of Angola, Namibia and Botswana were calibrated using total water storage derived from Gravity Recovery and Climate Experiment (GRACE) altimetry satellite and *in situ* data (Milzow et al., 2011). Also, Sun et al., (2012) assessed the uncertainty associated with HYdrological MODel (HYMOD) along the Mississippi River, calibrated against *in situ* and altimetry data. NS efficiencies of 79.05 and 64.50 were reported for *in situ* stream flow and radar altimetry (TOPEX/Poseidon) respectively, showing reduced uncertainty bounds for stream flows calibration in comparison to altimetry calibration.

From these instances highlighted above, it is evident that radar altimetry can serve as an alternative to ground observation, especially in data sparse regions. While hydrodynamic models driven by SRTM DEM have been seen to result in comparable outcomes when calibrated with altimetry water levels, models driven by LiDAR and river survey cross-section embedded terrain result in hugely discordant accuracies when calibrated with similar datasets (Domeneghetti et al., 2014). This thereby raises the question of altimetry uncertainty in model calibration and accuracy assessment. Belaud et al., (2010) applied TOPEX/Poseidon (T/P) and ENVISAT altimetry satellites data in calibrating a propagation model and disclosed that inherent altimetry uncertainty effect on the model outcome.

Residual altimetry uncertainties are expected to affect flood model accuracy as Tommaso et al., (2013) further demonstrated and further emphasised by Domeneghetti et al., (2014), where ENVISAT proved to provide better accuracy than ERS-2 (See Table 2 for altimetry accuracy differences).

Despite these deficiencies, the importance of altimetry data in model calibration and validation in ungauged basins cannot be dismissed. However, it is advised that altimetry is applied in combination with *in situ* data when available (Domeneghetti et al., 2014), or *in situ,* data should it takes priority over altimetry as suggested by Sun et al., (2015) and Sun et al., (2012).

3.2. Open-access Digital Elevation Model (DEM), Modifications and applications in flood modelling

Topographical data is an essential requirement in hydrological and hydrodynamic modelling (Yan et al., 2015a), and accounts for a substantial portion of the uncertainty that propagates through to model outcomes (Cook and Merwade, 2009, Jung and Merwade, 2015). The effect of terrain accuracy on hydrodynamic models and the need for accuracy assessment have been discussed briefly in sections 3.1.2., and 3.1.3, showing how improved river channel definition using altimetry improved flood model outcomes (Chávarri et al., 2012, Yoon et al., 2012, Durand et al., 2008). High-resolution topographical data such as LiDAR, TanDEM, bathymetry and differential GPS survey provides the best terrain characterization with reduced uncertainty and error (Neal et al., 2011a, Mason et al., 2016, Trigg et al., 2009, Bates et al., 2006). However, the cost of acquiring such data is enormous (Sanyal et al., 2013) and in other cases, remote locations are inaccessible for *in situ* data collection (Jarihani et al., 2015a).

Freely available digital elevation model provides a suitable alternative to commercial data in data sparse developing regions where resources are limited (Patro et al., 2009, Lewis et al., 2013).

Shuttle Radar Topography Mission (SRTM) DEM is arguably one of the most widely used topographical data in developing regions, applied mostly in improving flood modelling in data-sparse regions (Sanyal et al., 2013, Domeneghetti, 2016, Jarihani et al., 2015a, Neal et al., 2012). The 30 and 90 metres resolution SRTM was collected during an 11-day mission in February 2000, through a collaborative effort among the National Aeronautics and Space Administration (NASA), the National Geospatial-Intelligence Agency (NGA) and the German Aerospace Centre (DLR), and provides near-global scale (80%) DEM (Farr et al., 2007, Farr and Kobrick, 2000). The 15 metre Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) acquired by a joint mission of the U.S. National Aeronautics and Space Administration and Japan's Ministry of Economy, Trade, and Industry is also widely used in flood modelling and mapping (Gichamo et al., 2011, Demirkesen, 2016, Ullah et al., 2016). However, ASTER GDEM is argued to be less accurate than SRTM due to inherent elevation pixel voids (Wang et al., 2012, Bates et al., 2014).

Other open-access topographic data sets such as Altimeter Corrected Elevations 2 (ACE2) GDEM, Global 30 Arc-Second Elevation (GTOPO30) and Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) are generally coarse in resolution and are therefore employed in large-scale models only (Neal et al., 2012, Schumann et al., 2013). Recently released Advanced Land Observing Satellite (ALOS) DEM (Tadono et al., 2014) has been evaluated and confirmed to provide more accurate elevation in comparison to SRTM and ASTER (Santillana et al., 2016), but its application in hydrodynamic modelling is yet to be seen. Various open-access DEMs, properties and case studies are presented in Table 3.

Table 3 Some open source digital elevation models

DEM	Spatial resolution (m)	Vertical error (m)	Case study	Reference
SRTM	30, 90	± 16	Damoda River, India.	(Rodriguez et al., 2006, Sanyal et al., 2013)
ASTER GDEM	30	± 25	Lake Tana, Ethiopia.	(Tarekegn et al., 2010, Tachikawa et al., 2011)
ACE 2 GDEM	1000	>10	Balkan Peninsula, Croatia.	(Varga and Bašić, 2015)
GTOPO30	1000	9-30	Balkan Peninsula, Croatia.	(Varga and Bašić, 2015)
Bear-Earth SRTM (Veg/Urban)	90	6.05- 12.64	Belize, Honduras.	(Sampson et al., 2015)
Bare-Earth SRTM (Veg)	90	4.85- 8.667	Global	(O'Loughlin et al., 2015)
EarthEnv-DEM90	90	4.13-10.55	Johor River Basin, Malaysia.	(Tan et al., 2015, Robinson et al., 2014)
ALOS	30	± 5	Sindh and Balochistan, Pakistan.	(Tadono et al., 2014, Jilani et al., 2007)
GMTED2010	250	26-30	Shikoku, Japan.	(Danielson and Gesch, 2011, Pakoksung and Takagi, 2016)

The discrepancies between open-access DEM and ground surveyed elevation data that results in diverse vertical accuracies (Table 3) is attributed to inherent systemic and external factors (Farr et al., 2007). SRTM system noise coupled with the C and L-band sensors reflection off forest canopies, water bodies and rooftops in urban areas are the causes of noisy and poorly estimated terrain properties (Yamazaki et al., 2012, Baugh et al., 2013, Cook and Merwade, 2009, Kon Joon Bhang et al., 2007).

Over the years, various methods have been adopted to curb these deficiencies and reduce the uncertainty associated with open-access SRTM DEM application. Baugh et al., (2013) reduced STRM uncertainty by combing vegetation canopy heights (Simard et al., 2011, Lefsky, 2010) and MODIS image to reduce vegetation height effect. Betbeder et al., (2015) reduced SRTM bias by 64 percent by adopting a systematic approach that combines vegetation height (Simard et al., 2011), Landsat land cover map and radar altimetry to produce hydrologically corrected DEM. SRTM derived river cross-sections were adjusted using limited bathymetric surveys and applied in the one-dimensional MIKE11 model (Patro et al., 2009) and LISFLOOD-FP two-dimensional model (Sanyal et al., 2013) to reduce model uncertainty. Neal et al., (2012) adopted an approach that reduced SRTM uncertainty by characterising hydrodynamic model parameters (i.e. channel width and depth) as calibratable parameters in a sub-grid LISFLOOD-FP model, thereby improving simulated water levels, wave propagation and flood extent. Biancamaria et al., (2009a) experimented by varying river channel depth by 5, 10 and 15 metres when modelling Obi river, and identified 10 meters as the optimal average river channel depth for the best outcome. In a recent study in Australia, Jarihani et al., (2015a) adopted Hydrological Correction (HC) and Vegetation Smoothening (VS) (Gallant, 2011) approaches to reduce SRTM and ASTER DEM error and deduced that HC DEM outperformed VS DEM for flood modelling. Though the above described DEM modification techniques resulted in reduced DEM and flood model uncertainty, they require specific skill sets, computational power and supplementary data that are not always readily available. Hence, there is a need to explore globally available off-the-shelf modified DEM that can be readily applied in developing regions where such resources are seldom available. At a global scale, errors emanating from satellite system noise, and sensor beam reflection off vegetation canopy, water surfaces and urban rooftops have been treated with different techniques, resulting in the development of freely available new data sets. O'Loughlin et al., (2016b) reduced average vertical bias from 14.1 m to 5.9 m by systematically combining ICESat Geoscience Laser Altimeter System (GLAS) ground elevation (Zwally et al., 2002), vegetation height (Simard et al., 2011), MODIS-derived forest canopy density and climate regionalization maps (Peel et al., 2007, Broxton et al., 2014). Sampson et al., (2015) reduced SRTM sensor noise irregularities, urban landscape and vegetation canopy elevation overestimations using a moving window filtering technique (Gallant, 2011). Their approach reduced RMSE from 10.96 m to 6.05 m when compared to LiDAR, and overall flood model bias from 15.08 m to -0.1 m. EarthEnv-DEM90 was developed by Integrating ASTER GDEM2, CGIAR-CSI SRTM V4.1 and Global Land Survey Digital Elevation Model (GLSDEM) using a combined Delta surface filling (Grohman et al., 2006) and adaptive DEM noise smoothing (Gallant, 2011) methodology, resulting in minimised error in comparison to raw SRTM and ASTER GDEM2 (Robinson et al., 2014).

Since no study currently presents a comparison of all available modified SRTM DEM for a specific region, this is undertaken for the Niger-South river basin of Nigeria and presented in Table 4, revealing EarthEnv90 to be the most improved modified open-access DEM when evaluated against ICE Sat altimetry SPOT heights. The results presented in Table 4 will later inform the choice of DEM selected for hydrodynamic modelling in Chapter 6.

Table 4 SRTM and Modifications comparison with ICE Sat SPOT elevation

Elevation	**Min**	**Max**	**Mean**	**Std. dev.**	**R^2**	**RMSE**
Bare-Earth SRTM (Urban and Veg)	36.00	68.00	47.28	9.09	0.95	2.94
Bare-Earth SRTM (Veg)	34.45	69.44	47.21	9.22	0.95	2.94
EarthEnv90	36.00	65.00	47.40	8.91	0.95	2.85
Raw-SRTM	36.00	63.00	47.34	8.95	0.94	3.08
ICE Sat	35.62	64.33	47.74	8.01	-	-

Std. dev = standard deviation, R^2 = Correlation coefficient

3.3. Open-access Optical and Radar Satellite Images application in Flood Modelling and Mapping

Optical and Radar images also play a crucial role in flood modelling and mapping, used for a range of applications including (i) manning's roughness derivation (Medeiros et al., 2012), (ii) river width estimation (Andreadis et al., 2013), (iii) geomorphological properties extraction (Khadri and Chaitanya, 2014), (iv) inundation extent mapping (Bates et al., 2006), (v) river discharge estimation (Tarpanelli et al., 2013, Gleason and Smith, 2014), (vi) land use/cover derivation (Sanyal et al., 2014), (vii) bathymetry estimation (Karimi et al., 2016) and (viii) hydrodynamic model calibration and validation (Wood et al., 2016). Remote Sensing (RS) application in flood management has been well established, with open-access images including Landsat, MODIS, and ASTER widely used in developing regions (Dano Umar et al., 2011). Until the launch of the C-Band Sentinel-1 SAR mission by the European Space Agency (ESA) in 2014, radar imagery application has been limited in developing regions due to the high cost of acquisition (Townsend and Walsh, 1998, Qasim, 2011).

Optical and Radar Remote sensing data provides unique merits and demerits, and are characterised based on the source of energy employed during data collection. Optical (passive) remote sensing relies on solar energy, while radar (active) remote sensing uses inbuilt energy source onboard the satellite (Dano Umar et al., 2011). Passive RS data can only be captured in the day-time and depends on cloud-free skies (Asner, 2001). However, its multispectral characteristics make it a suitable for land use/cover classification, inundation delineation, drainage mapping, and flood impact assessment (Musa et al., 2015, Stephen et al., 2015, Alexakis et al., 2013). Active RS beam ability to penetrate clouds cover and water discrimination potential makes it the optimal data type for flood mapping when available (Schnebele and Cervone, 2013, Townsend and Walsh, 1998).

Despite SAR advantages, sensor noise, vegetation and built-up radar backscatter have been identified as factors that hamper SAR effective flood discrimination (Long et al., 2014, Lamovec et al., 2013, Giustarini et al., 2013). SAR imagery flood maps are usually extracted by pixel discrimination, given that flooded pixels tend to have lower values of back-scatter, due to the weak return signal associated with waters smooth surface (Henderson and Lewis, 1998); the discrimination method applied can also grossly impact on the accuracy of the derived flood extent (Veljanovski et al., 2011b).

Some SAR flood extent mapping techniques include statistical active contouring, radiometric thresholding, histogram thresholding, pixel-based segmentation, fractal dimensioning of multi-temporal images, neural networks in a grid system, Image segmentation and decision tree analysis (Long et al., 2014, Im et al., 2008).

Optical image flood extent, on the other hand, are derived mostly from the discriminating between the spectral signatures of water surface and the surrounding landscape in single or multi-temporal images, using classification or spectral indices approaches (Zhang et al., 2014, Stephen et al., 2015). The properties of some open-access optical and radar RS images applied in flood modelling and mapping are presented in Table 5.

Table 5 Optical and Radar Satellite imageries case studies

Sat. Imagery	Res. (m)	Case study	References
Landsat	30	Floodplain inundation delineation for 2 and 1 – dimensional model calibration and validation, Inner Niger and	(Neal et al., 2012, Seung Oh et al., 2013)
MODIS	200	Hydrodynamic model calibration and validation.	(Sanyal, 2013, Lewis et al., 2013)
Terra ASTER	15	Urban sprawl and flood management Dhaka, Bangladesh.	(Franci et al., 2015)
Sentinel - 1	10	Sentinel-1 and Landsat-8 combination in mapping flooding at river Evros, Greece.	(Kyriou and Nikolakopoulos, 2015)
Sentinel - 2	10	Water bodies delineation	(Herve et al., 2013)

Sat. = Satellite, Res = Spatial resolution

4. Open-access remote sensing application for flood monitoring and management in Nigeria

Previous sections highlighted flood modelling and mapping processes, data requirements, and detailing available open-access remote sensing data sets and application prospects in several locations. Nigeria is located downstream of the Niger Basin (Figure 2) that collects run-off from a 2156000 km^2 area through the Niger and Benue rivers (Aich et al., 2014b). Thus, Nigeria is prone to fluvial flood, exposing floodplain dweller to diverse negative consequences (Nkeki et al., 2013, Akinbobola et al., 2015, Agada and Nirupama, 2015, Tami and Moses, 2015). Nigeria recently experienced unprecedented levels of flooding attributed to poor dam water release management and risk communication attributed to data unavailability (Ojigi et al., 2013).

This section focuses on identifying the causes of data deficiencies in Nigeria and reviewed the literature on applications of open-access applications in Nigeria to identify gaps and opportunities for research improvement based on global trends discussed in the preceding sections. This review section builds of previous reviews on flood risk management in Nigeria (Komolafe, 2015, Ugonna, 2016, Opolot, 2013, Adeaga et al., 2008, Ologunorisa and Abawua, 2005), then incorporate data challenges, solutions and prospect for regional and national flood management using open-access remote sensing.

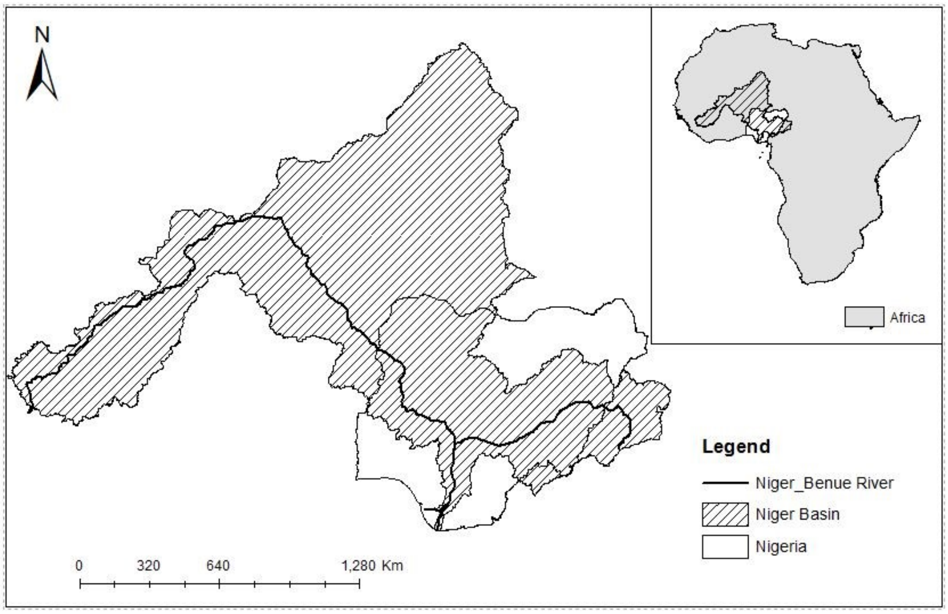


Figure 2 Map showing Nigeria, Niger Basin, Africa and the main inflow rivers (Niger and Benue)

4.1. Data limitations for hydro-meteorological studies in Nigeria

Like in many developing countries, the lack of hydro-meteorological data in Nigeria has been widely documented, consequently resulting in poor flood management decisions (Ngene et al., 2015). Currently, existing hydrological and meteorological gauge distribution are below World Meteorological Organization (FMWR, 2013) and Ngene, (2009) recommendations, i.e. (237 out of 384) and (291 out of 970) respectively. Also, several of the established stations have been reported to be inactive, decommissioned or discontinued (Figure 3), contributing to the data sparsity in the country (Ngene et al., 2015, FMWR, 2013).

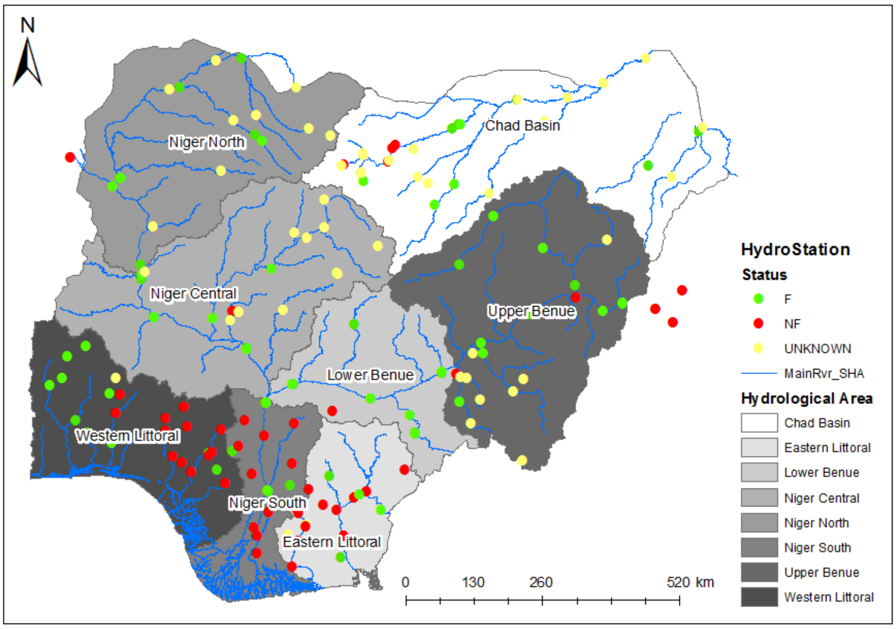


Figure 3 Status of some hydrological gauging stations in Nigeria (F= Functional, NF = Non-Functional, Unknown)

Lack of financial support, technical deficiency, poor organisational structure and obsolete equipment/infrastructure have been identified as the factors responsible for data shortage in Nigeria (Olomoda, 2012, Izinyon and Ehiorobo, 2014, Olayinka et al., 2013, Ertuna, 1995). Also, Maxwell, (2013) and Ononiwu, (1994) attributed data inconsistency to poor hydrological data management systems and lack of standards, resulting in unreliable, fabricated and data format inconsistency. Furthermore, Maxwell (2013) and Olayinka (2012) argued that even when data is available, custodians store data in paper formats, thus reducing transferability, applicability and long-term/sustainable data availability.

Hydro-meteorological data are essentially applied in estimating expected flood magnitudes based on past trends, and the length of available historical data contributes to the uncertainty in the derived flood estimates (Merz and Blöschl, 2005, Reed, 1999). Extended historical data result in more accurate estimates and vice versa (Kjeldsen et al., 2002).

Meta-analysis of river and rainfall estimation studies (Figure 4) shows that rainfall data sets are generally longer in duration than those of streamflow data. In 2016, a search was conducted within the peer-reviewed literature on the google scholar (https://scholar.google.com/[1]) database spanning the years 2000 to 2016. A combination of the search terms and keywords including "hydrology", "flood modelling", "hydrodynamic modelling", "flood frequency analysis", "vulnerability assessment", "rainfall frequency analysis", "flood mapping", and "GIS and Remote sensing of flooding", were used, with the results further refined with keywords such as "Nigeria", representing the country of interest.

Majority of hydrological modelling studies are based on historical data of lengths ranging from 10 to 20 years, hence there is a need for adaptation of an approach that leverages on data from multiple gauging stations to reduce flood estimate uncertainty and improve flood management decision making (FME, 2005a).

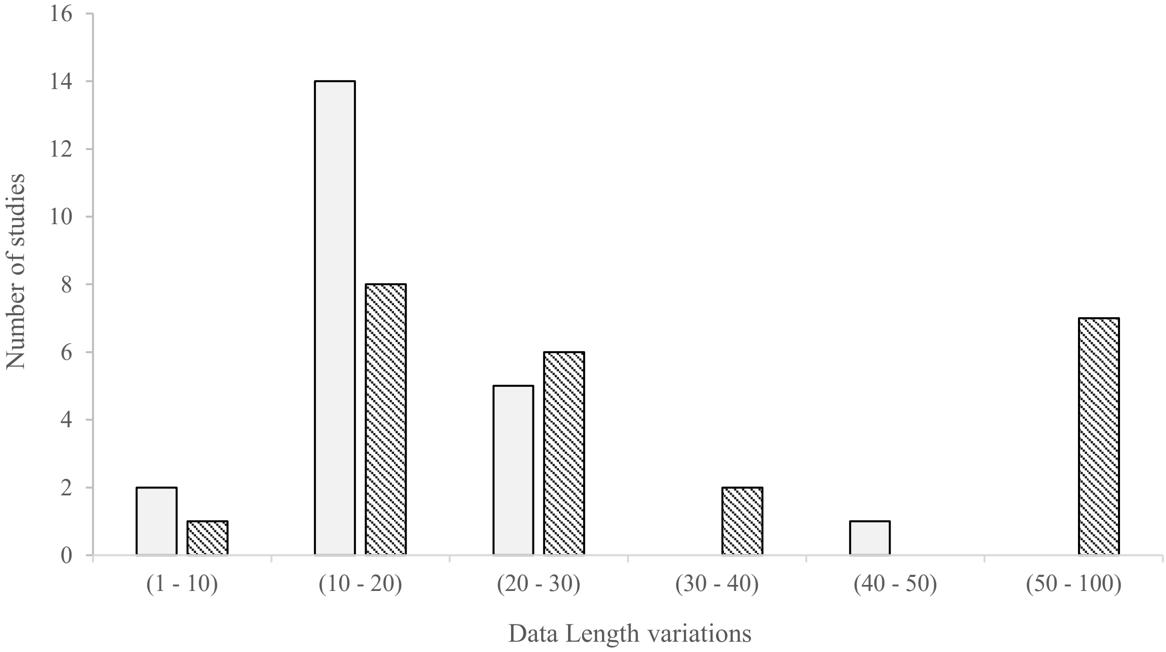


Figure 4 Rainfall and streamflow data length variation from previous studies in Nigeria

4.2. Remote sensing application for flood management in Nigeria

Remote sensing (RS) in past three decades has played a crucial role in flood management globally, regionally and Nigeria in particular (Adeaga et al., 2008, Hughes et al., 2015, Hrachowitz et al., 2013). Remote sensing allows for the collection of data without being in direct contact with the object under investigation (Smith, 1997, Kite

[1] https://scholar.google.com/

and Pietroniro, 1996), thereby providing an alternative to ground data collection hindered by factors previously discoursed (Nwilo et al., 2012, Musa et al., 2015). The spatiotemporal capacity of remote sensing, ease of manipulation of digital data and the advantage of radar sensors images has enhanced inundation mapping tremendously (Musa et al., 2015, Ritchie and Rango, 1996). Despite these advantages, RS is not without limitations, as the time lapse between satellite image captures, high cost associated with acquisition of high-resolution images, cloud cover, vegetation canopy and terrain roughness have been reported in several instances to hamper RS application (Chen et al., 2005, Lewis et al., 2013, Sanyal et al., 2013).

Integrated flood mapping mainly involves flood magnitude estimation, hazard modelling and impact assessment (Aerts et al., 2009). Seven sub-categories of RS flood application areas have been identified in Nigeria, including Vulnerability assessment, Flood frequency analysis, Flood risk mapping, Rainfall frequency (intensity) analysis, Hydrodynamic modelling, Water resource management and Floodplain encroachment analysis. Vulnerability analysis entails integrating socio-economic and biophysical factors to ascertain a regions' coping capacity in relation to flood exposure (Musa et al., 2014a, Adelekan, 2011, Tamuno et al., 2003). Flood frequency analysis involves estimating expected flood magnitudes by fitting historic flood time series to a suitable probability distribution to or combining hydrological data from regions of physiographic similarity (Izinyon and Ehiorobo, 2014, Izinyon and Ajumka, 2013, Fasinmirin and Olufayo, 2006). The rainfall frequency (intensity) analysis applies rainfall data to estimate expected rainfall intensity and expected runoff (Isikwue et al., 2012, Ologunorisa and Tersoo, 2006). Once flood estimates are determined, the outcomes are routed in 1/2 dimensional models in combination with terrain data to derive flood hazard information such as inundation extent, depths and /or velocity (Olayinka et al., 2013, Adewale et al., 2010). Other than hydraulically modelling flood hazard, flood depths and inundation extent for a particular point in time can be directly determined using satellite images and digital elevations models (Eyers et al., 2013, Akinbobola et al., 2015). The increasing development of industries and settlements within the floodplain is directed related to exposure and vulnerability (Padi et al., 2011, Tamuno et al., 2003). Remote sensing and GIS approaches are usually used to identify floodplain encroachment, to ensure adherence to, and enforcement of flood management policies (Oyinloye et al., 2013, Ndabula et al., 2012). Figure 5 illustrates flood management application areas mostly focused on in Nigeria, showing high levels vulnerability mapping, flood frequency assessment and risk assessment.

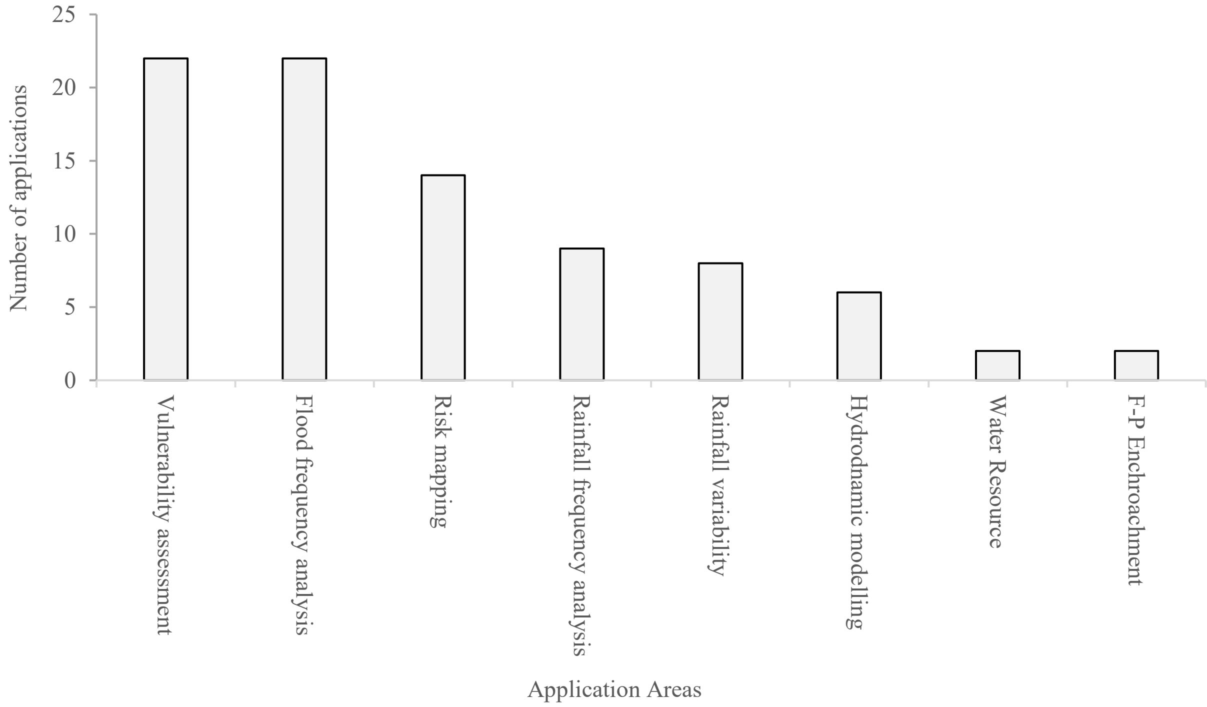


Figure 5 Flood studies in Nigeria showing specific application areas

4.3. Open-access remote sensing application in flood management Nigeria

Meta-analysis of 100 flood research journal articles focused on Nigeria shows the range of data applied in flood management studies (Figure 6), revealing high reliance on Landsat and SRTM. Various data sets provide contrasting levels of accuracy and uncertainty (Jung and Merwade, 2015), therefore high spatial resolution data such as LiDAR and SAR are mostly recommended for flood modelling processes due to the advantages of terrain complexity detailing and effective water surface discrimination capacity (Qasim, 2011, Hunter et al., 2008). Figure 7 further shows the variation between TerraSAR-X (radar) digitized from the flood map derived using histogram thresholding approach by the Disaster Charter consortium and MODIS (optical) flood extents automatically generated as Modis Water Product through a collaborative effort between NASA and Dartmouth Flood Observatory, University of Colorado, USA, using algorithm that uses a ratio of MODIS 250-m Bands 1 and 2, and a threshold on Band 7 to provisionally identify pixels as water (Nigro et al., 2014).

Nevertheless, such highly detailed satellite data are costly and therefore seldom applied in developing countries like Nigeria. However, the constellation of global satellites for disaster management through the International Charter "Space and Major Disasters" initiative (Bessis et al., 2004) and other emergency services makes high-resolution data available for disaster response if activated during flooding. Also, multinationals companies with large financial capacities such as Shell Petroleum Development (SPDC) and others operating in the Niger Delta region of Nigeria acquire high-resolution images for operational purposes, and sometimes use such data for disaster management (Eyers et al., 2013). Nigerian Satellite images are also seldom available as bureaucratic bottlenecks and poor data management infrastructure hinder data availability for flood management and other applications (Agbaje, 2010, Akinyede and Adepoju, 2010). Other data types and techniques widely applied in Nigerian flood management studies are presented in Figure 8.

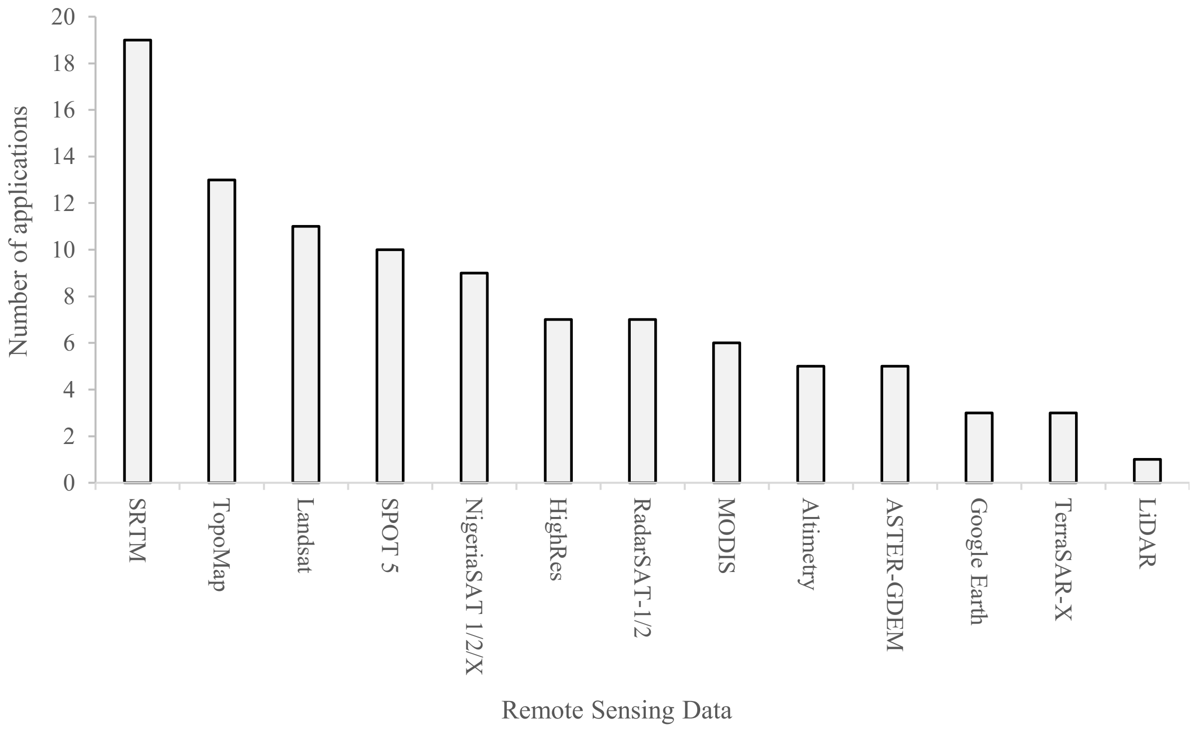


Figure 6 Remote sensing data application in flood studies in Nigeria

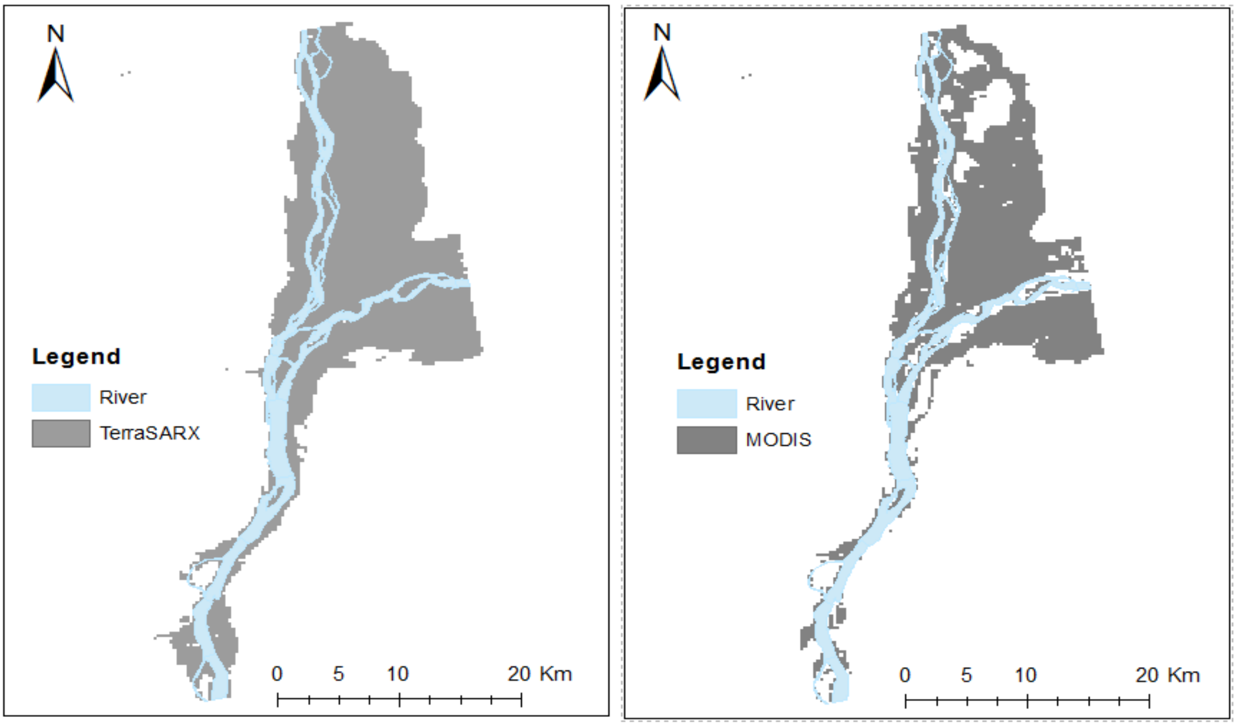


Figure 7 Radar (TerraSAR-X) and Optical (MODIS) flood extents comparison at Lokoja, Nigeria

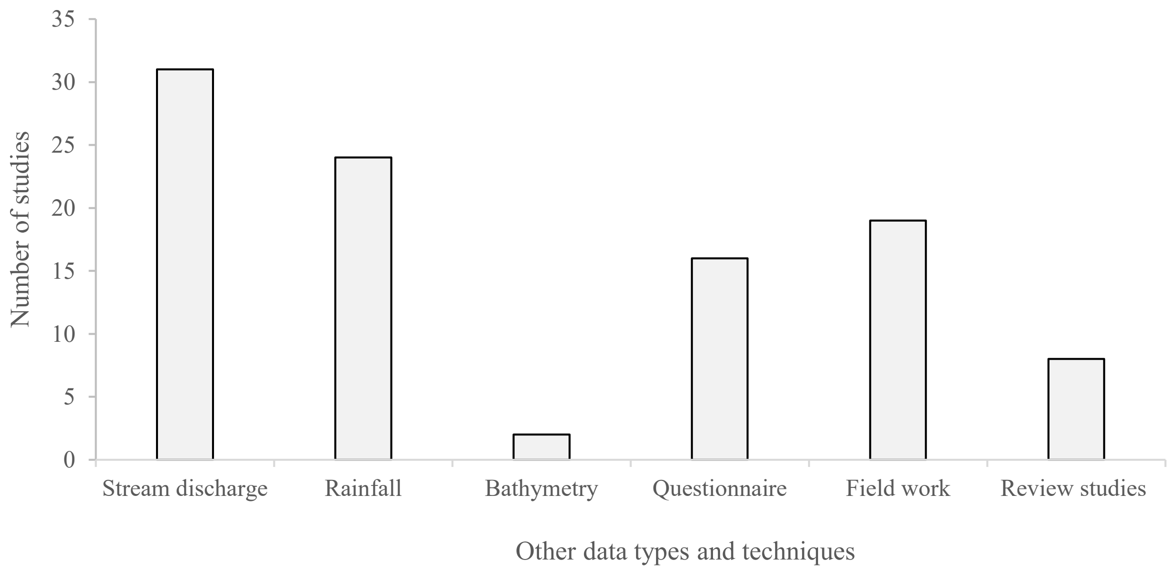


Figure 8 Flood studies in Nigeria showing other non-Remote sensing methods

5. Open-access remote sensing in transboundary flood management

Managing flood occurrences in a sovereign nation is challenging enough; the complexity is increased when flood transcends borders. Floods sometimes originate from one country, and if hydraulically connected to another country within a single catchment area, travels downstream (Bakker, 2009), hence transboundary flooding. Poor management of excess water releases from dams triggered by climate change and other anthropogenic factors have been identified as some of the leading causes of transboundary flooding (Angelidis et al., 2010, Clement, 2012, Zeitoun et al., 2013, Cooley and Gleick, 2011). In such situations, efforts need to be coordinated between flood origination and destination countries to ensure effective flood management. Approximately 2286 transboundary river basins exist globally (Figure 9), encircling 42% of the world's population within a 62 million km^2 area, and is responsible for approximately 50% of global river discharge (Wolf, 2002, TWAP, 2016).

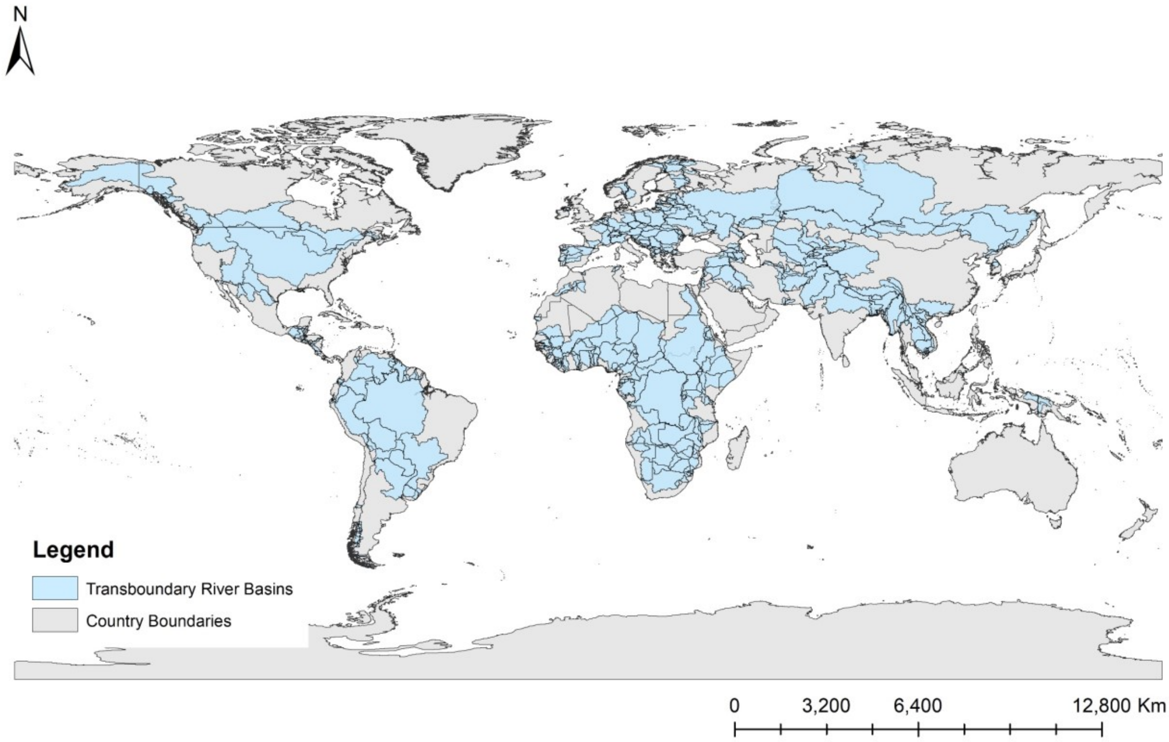


Figure 9 Global Transboundary River Basins (source: Transboundary Freshwater Dispute Database)

Coordinating the activities of individual countries within a transboundary water resource management organisation is particularly challenging due to the diverse interests, policies and activities of riparian (ECOWAS-SWAC/OECD, 2008, Hooper and Lloyd, 2011, Chikozho, 2014), thus prompting the need for a shift to remote sensing approaches that aid independent data collection by riparian countries without administrative protocols violation (Klemas, 2015).

Several remote sensing studies have been undertaken in this regard, using radar altimetry, optical/radar imageries, and hydrodynamic models to solve the data limitation challenges associated with poorly coordinated transboundary flood management efforts. Mallinis et al., (2013) delineated transboundary Evros river (Bulgarian/Turkey) flood extent and damage caused by upstream dam water release using ENVISAT ASAR and post-flood multi-temporal LANDSAT TM images. The effect of varying flood magnitudes released from upstream Ivaylovgrad dam (Bulgaria) on the connecting Ardas River (Greece) was modelled using HEC-HMS, using *in situ* gauge measurements and digital terrain data (Serbis et al., 2013), thereby enabling effective downstream flood planning and management. Mati et al., (2008) investigated changing land use/cover impact on the Mara transboundary river (Kenya/Tanzania) hydrological regime, using remote sensing (Landsat MSS, TM/ETM, and SRTM), ground-collected land use/cover data, meteorological and streamflow data integrated within the Geospatial Streamflow Model (GeoSFM). Biancamaria et al., (2011) established an empirical relation between downstream altimetry (TOPEX/Poseidon) water levels (India) and upstream *in situ* measurements (Bangladesh) for forecasting purpose along the Ganges and Brahmaputra transboundary river. Hossain et al., (2014) in the same study area applied a forecasting rating curve approach combined with HEC-RAS hydraulic model to forecast downstream water levels using upstream JASON-2 altimetry, *in situ* water levels and rating curve. Seyler et al., (2008) further demonstrated the value of remote sensing altimetry and SAR satellite missions in transboundary water resource management, as remote locations along the Beni-Madeira river in the Amazon was monitored using ENVISAT altimetry and JERS-1 radar images.

The case studies discussed above illustrates the wide range of open-access remote sensing application in transboundary flood management, with radar altimetry, DEM, SAR and optical images identified as alternatives to ground survey distorted by bureaucratic challenges. Remote sensing makes it possible to forecast expected floods, estimate flood exceedance probabilities and monitor riparian country changes to land use/cover effect on downstream hydrology.

5.1. Transboundary flood management Nigeria (Niger Basin)

The unprecedented flood event of 2012 in Nigeria was attributed to (i) excess water release from dams within and outside Nigeria due to intense precipitation; (ii) inadequate risk communication; and poor stakeholder collaboration (Ojigi et al., 2013, Olojo et al., 2013). The lack of transboundary stakeholder collaboration is evident for instance in Nigeria's inability to uphold part of the 1980 agreement by Nigeria and Cameroon to establish Dasin Hausa dam to buffer the effect of Lagdo dam built by Cameroon along the Benue River (Erekpokeme, 2015, Daura and Mayomi, 2015).

The Niger transboundary river basin (Figure 10) encompasses 12 countries including Senegal, Guinea, Côte D'Ivoire Mauritania, Mali, Burkina Faso, Algeria, Niger, Benin, Nigeria, Cameroon and Chad. The basin encircling 93,617,850 persons within a 2156000 km^2 area(TWAP, 2016, Aich et al., 2014b).

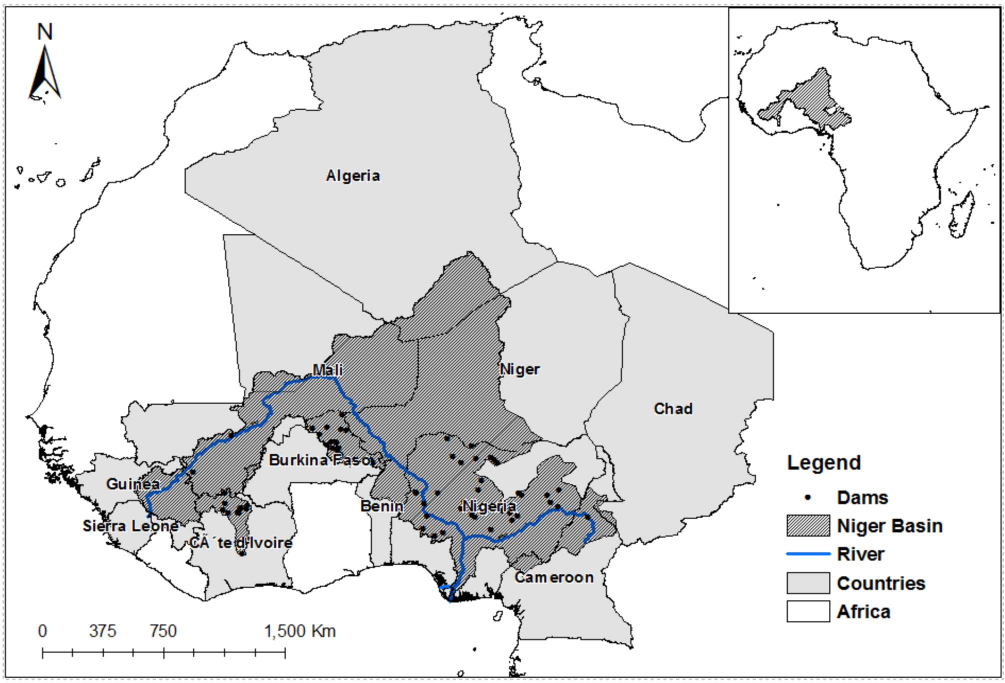


Figure 10 Map of Transboundary Niger River Basin, showing constituting countries and Dams

Figure 10 also highlights the transboundary nature Niger River Basin, constituent countries and characteristics. The Niger basin is largely regulated by dams, housing approximately 69 Dams (Lehner et al., 2011) conceived mostly as national and local projects, but have transboundary impacts (GRP, 2016). To effectively manage transboundary water resource and impact on riparian countries, the Niger River Commission (NRC) was established in 1963, now the Niger Basin Authority (NBA) as reconstituted in 1980 to promote co-operation between member states and ensure sustainable Integrated Water Resource Management (GWP, 2016). The Niger basin is presently controlled by several post-colonial agreements presented in Table 6.

Table 6 Niger River Basin Agreement, Nigeria. Adapted from (Bossard, 2009, International Waters Governance, 2016, Wolf, 2002)

S/N	Treaty	Function	Location	Year
1	Act regarding navigation and economic co-operation between the states of the Niger Basin.	Navigation and Joint management	Niamey, Niger.	1963
2	Agreement concerning the River Niger Commission and the navigation and transport on the River Niger.	Navigation, Joint management, information exchange	Niamey, Niger.	1964
3	Agreement Revising the Agreement Concerning the Niger River Commission and the Navigation and Transport on the River Niger.	Navigation, Joint management, information exchange	Niamey, Niger	1973
4	Convention Creating the Niger Basin Authority (NBA)	Water resource mgt. coordination	Faranah, Guinea	1980
5	Protocol relating to the Development Fund of the Niger Basin	Planning funds for NBA	Faranah, Guinea	1982
6	Agreement between Nigeria and Mali	Co-operation on water resource use in the Niger	-	1988
7	Agreement Nigeria and the Republic of Niger concerning the equitable sharing in the development, conservation and use of their common water resources	Environmental conservation and water resource management	Maiduguri	1990
8	Nigeria-Cameroon Protocol Agreement	Coordinate dam water release.	-	2000
9	Niger Basin Water Charter.	NBA review and update.	Niamey, Niger.	2008
10	African Risk Capacity	Weather financial risk management	Pretoria, South Africa.	2012

Despite these various cooperative frameworks, several factors including (i) Poor and fragmented data collection, (ii) Lack of co-ordination between riparian countries and organizations, (iii) Poor communication and knowledge of legal and institutional frameworks, (iv) Funding deficiency, (v) Lack of clear objectives, (vi) Lingual differences, and (vii) Technical limitations (Morand and Mikolasek, 2005, Olomoda, 2002, IWG, 2016), have been identified as the core issues hindering effective water resource management in the Niger Basin. Grossmann, (2006) also lamented the deplorable state of the 65 gauging stations set-up by NBA through the "Hydro Niger Project" initiative. Although the emergence of the Niger-HYCOS (Hydrological Cycle Observing System) program is expected to restore river monitoring networks to optimal capacity (Olomoda, 2012, Pilon and Asefa, 2011), the process is currently in progress. Nigeria, however, further faces specific challenges such as poor engagement, varied risk perception, lack of interest, poor communication and commitment within the Nigeria Basin Authority, which hinders effective coordination and integrated water resource framework implementation (Olomoda, 2012).

5.2. Open-access remote sensing application in Transboundary flood management, Nigeria

As transboundary floods become more prevalent and intense due to increased storms triggered by climate change and anthropogenic factors (Earle et al., 2015), sufficient hydrological data is required for planning, to mitigate flood impact. Also, considering that transboundary flood management institutions are facing recurring challenges that limit its functionality and sufficient data acquisition, open-access remote sensing provides a low-cost and viable alternative that allows transboundary flood monitoring and management without disrupting any sovereign nation's autonomy.

Open-access satellite imageries such as Landsat and MODIS have been proven to provide an easy to visualize the extent of flood transiting from a country of origin to another downstream, enabling impact quantification needed for prompt response, risk assessment and evaluation (Mallinis et al., 2013, Skakun et al., 2014). Radar altimetry, on the other hand, can be applied independently or with satellite images to support planning, forecasting and flood management in riparian countries.

Tarpanelli et al., (2016) explored the potential of integrating MODIS image and ENVISAT radar altimetry to predict and forecast discharge along the Niger-Benue river. The discharge was derived from daily and 8-day 250m resolution MODIS AQUA (BAND 2-NIR) by establishing an empirical relationship between water-free land pixels during peak flood, permanent water pixels within the river and known discharge values. Pandey and Amarnath, (2015) applied a combined forecasting rating curve approach (Hossain et al., 2014) and hydraulic (HEC-RAS) model techniques to estimate discharge from ENVISAT, Jason-2 and AltiKa altimetry virtual station water levels along the Niger and Benue rivers, resulting in NS and R^2 of 0.7 and 0.97 respectively.

In other closely related studies in the region, Salami and Nnadi, (2012) monitored Kainji Lake using TOPEX/Poseidon and ENVISAT altimetry, revealing stronger correlation between altimetry and *in situ* measurements in the wet season ($R^2 = 0.93$) than the dry season ($R^2 = 0.77$), and RMSE varying from 0.50 m to 0.83 m for TOPEX/Poseidon and ENVISAT respectively. Sparavigna, (2014) studied the variability of Nasser, Tana, Chad and Kainji lakes using TOPEX/POSEIDON and Jason-1 altimetry, and Cretaux et al., (2011) combined TOPEX / Poseidon (T/P) and ENVISAT altimetry with 8-day MODIS Near Infrared band images to monitor water level variations and inundation along the Niger inner delta, Lake Tchad and Ganaga river delta.

The high accuracy of water level estimation from radar altimetry during the wet season along the Niger river (Salami and Nnadi, 2012), suggests that altimetry can potentially be used in flood monitoring and management in Nigeria and the Niger Basin, and the varying accuracies of different altimetry missions imply that altimetry data must be applied cautiously, due to residual uncertainty. With current radar altimetry tracks, such as Jason-2 (Figure 11), Sentinel 3A/B (Figure 12) and future SWOT (Figure 13) passing across the Niger basin, the potential for long-term data collection from spaceborne altimetry for flood management is huge.

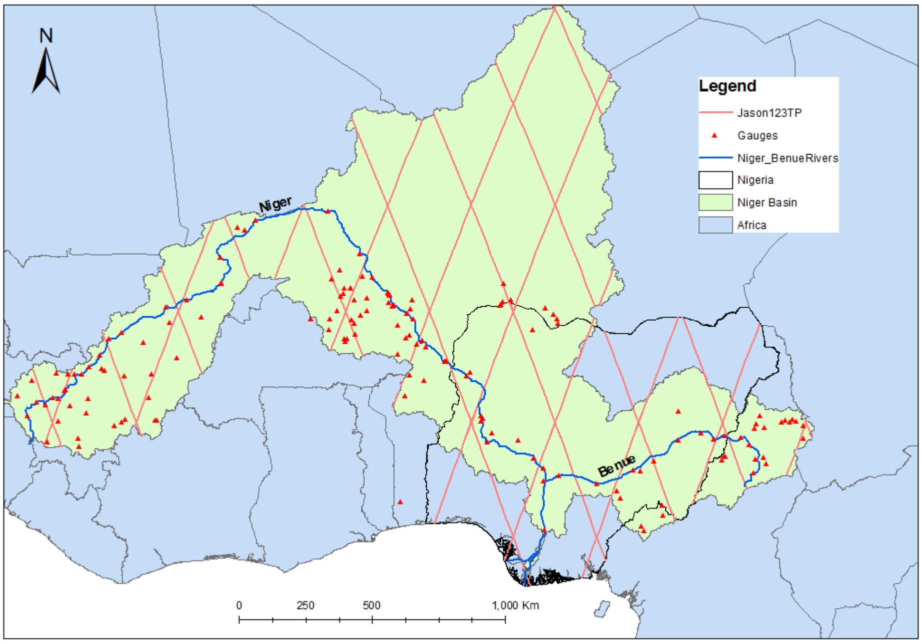


Figure 11 Jason-1/2/3/TP Altimetry Tracks within the Niger River Basin

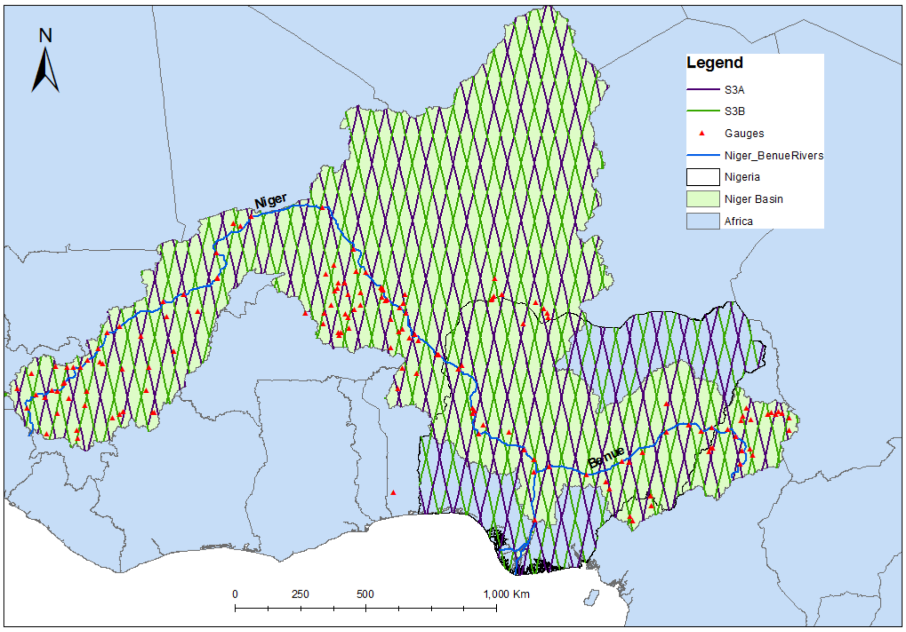


Figure 12 Sentinel 3A/B Altimetry Tracks within the Niger River Basin

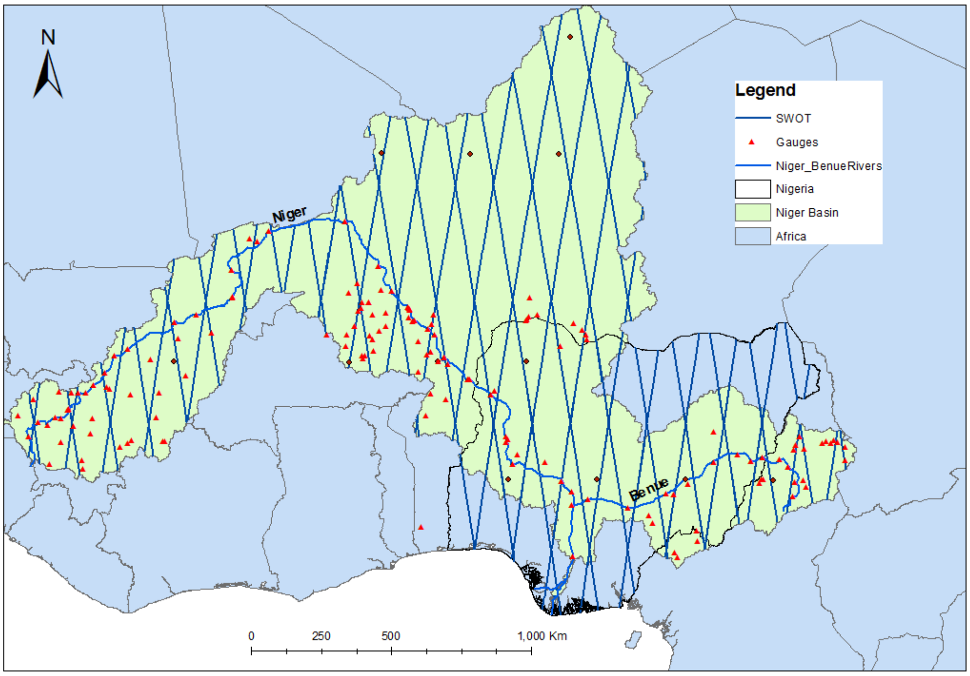


Figure 13 SWOT Altimetry Tracks within the Niger River Basin

6. Consortium of satellites for flood emergency management

Other than open-access remote sensing data, in some instances, commercial, regional and national satellite organisations collaborative deliver high-resolution images and services to support flood response and mitigation efforts. This section discusses some of the available satellite consortiums, disaster support services and cases of application in Nigeria and hydraulically connected rivers in the Niger Basin.

6.1. International charter "space and major disasters" (ICSMD)

The international charter "space and major disasters" (ICSMD) was established by the European Space Agency (ESA) and the Centre National d'Etudes Spatiales (CNES) following the UNISPACE III conference held in Vienna in 1999, and was co-signed by the Canadian Space Agency (CSA) in 2001 (Bessis et al., 2004). The objective of the Charter is to provide data to enable critical decision making during environmental or technological disasters such as flooding, oil spills, fires, earthquake, volcanoes, hurricanes, landslides and ice hazards, thereby ensuring minimized the impact on people and infrastructures is minimized (ICSMD, 2015). Between 2001 and 2012, several satellite agencies including Japan Aerospace Exploration Agency (JAXA), Indian Space Research Organisation (ISRO), United States Geological Survey (USGS), National

Oceanic and Atmospheric Administration (NOAA), Argentinean National Commission on Space Activities (CONAE), Exploration of Meteorological Satellite (EUMETSAT), German Space Agency (DLR), National Institute for Space Research (INPE) of Brazil, China National Space Administration, Disaster Monitoring Constellation International Imaging (DMCii) and Korean Aerospace Research Institute (KARI) joined the Consortium, thus enhancing the Charter's prompt high resolution optical and SAR images acquisition and availability (UNOOSA, 2013).

Between 2000 and 2015 the ICSMD charter has been activated 447 times by more than 110 countries for various disasters (ICSMD, 2015, UNOOSA, 2013). As at 1 August 2016, 500 disaster Charter activations have been recorded (ICSMD, 2016). Up to date overview of disaster Charter activations for flood monitoring and management is presented in (Figure 13), with South America, Africa and Asia showing the highest activations.

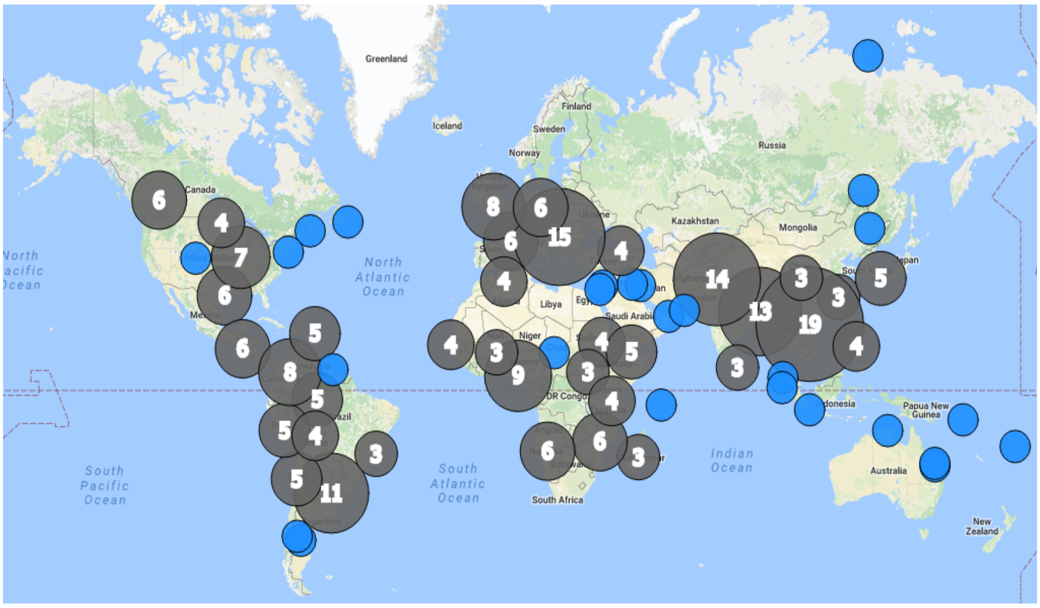


Figure 13 Map showing International Disaster Charter Flood Activations (2000 – 2016) (Source: Disaster Charter)

6.2. Disaster Charter activations in Nigeria

In Nigeria, the charter is usually activated by the National Emergency Management Agency (NEMA) designated project manager. The activation follows the following five steps: (1) requisition by authorised person, (2) requestor identification and request verification by a 24/7 operator, (3) request analysis and satellite tasking for data capture, (4) data acquisition and delivery, and (5) support in data processing throughout the emergency (James et al., 2013). In Nigeria, activation of the disaster charter is relatively new, and only 6 activations have been made between 2010 and 2012 to monitor flooding events at Sokoto in 2010 (calls: 324 and 326), Ibadan in 2011 (call: 370), and in 2012 at Adamawa, Kogi and Bayelsa, (calls: 407, 415 and 416) respectively (James et al., 2013). Some of the images collected over the course of the activations in Nigeria include RADARSAT-2, SPOT-5, TerraSAR-X/TanDEM-X, Landsat ETM, KOMPSAT, ENVISAT, UK-DMC, and NIGERIASAT (ICSMD, 2016, Olojo et al., 2013). One of the lingering challenges of the Disaster Charter images is the strict license and copyright policies that prohibit re-use and distribution of the data (James et al., 2013), thus limiting the prospect of further data application in research. Nevertheless, finished products are available via the Charter Activations web page as high-resolution maps and can be used for flood mapping processes.

6.3. International Water Management Institute (IWMI) Emergency response products for water disasters

This is a space-based information and rapid mapping platform for emergency response aimed at providing support for disaster management in Africa and Asia. The platform was developed from a collaboration amongst the International Water Management Institute (IWMI), Asia-Pacific Regional Space Agency Forum (APRSAF), European Space Agency (ESA), the United Nations Office for Outer Space Affairs (UNOOSA) and the United Nations Platform for Space-based Information for Disaster Management and Emergency Response (UN-SPIDER). This platform channels an impacted country's data request to the Disaster Charter, and also directly processes and applies open-access remote sensing images (i.e. Landsat, Sentinel 1, MODIS and Global Precipitation Measurement) to deliver products needed for decision making during a disaster (Backhaus et al., 2010). So far, the platform has supported five countries including Sri Lanka, Myanmar, India, Bangladesh, and Nigeria (IWMI, 2016). Also, a total of 37 flood support information has been deployed from open-access satellites, as well as TerraSAR-X, Radarsat-2, RISAT-1, ALOS-2 PALSAR-2, and JAXA-2 ALOS-2 (IWMI, 2016).

6.4. IWMI Emergency response application, Nigeria

This Space-based information and rapid mapping for emergency response platform between 27th September – 4th October 2015 has delivered 10 Sentinel-1 flood maps to support flood management efforts along Niger and Benue rivers in Nigeria. This emanated from a collaborative effort amongst IWMI, European Space Agency (ESA), Federal Ministry of Agriculture and Rural Development (FMARD) and Consortium of International Agricultural Research (CGIAR).

6.5. Copernicus Emergency Management Service

The European Union Copernicus Emergency Management (EMS) provides rapid (i.e. hours or days) free satellite-based maps to inform decision-making before, during and after natural and man-made disasters (Copernicus, 2016). Although European nations are considered a priority for support provision, other countries through an authorised user can activate the Copernicus EMS. So far, between 1st April 2012 and 19th August 2016, the Copernicus EMS has been activated 175 times (Table 7), with flooding identified as the highest cause of activation (40%), resulting in 68% of delineation maps generated.

Table 7 Summary of the Copernicus EMS - Mapping Activations

Type of Disaster	Number of Activations	Number of Reference Maps	Number of Delineation Maps	Number of Grading Maps
Earthquake	9	83	31	67
Flood	**71**	**358**	**692**	**61**
Forest fire, wildfire	21	47	98	79
Industrial accident	5	12	3	1
Other	55	218	143	127
Wind storm	14	80	45	53
Total	175	798	1012	388

6.6. Copernicus Emergency Management Service (EMS) application, Nigeria region

The Copernicus Emergency Management Service (EMS) has not been activated for Nigeria yet, but have been activated twice (EMSR018 and EMSR019) for Niger (Niamey) and Cameroon (Lake Maga, Garoua-Benue River) respectively in 2012, and could prove useful for transboundary flood monitoring in Nigeria. Authorised users France|Centre Operationnel de Gestion Interministeriel de Crises (C.O.G.I.C) and EC Services|DG JRC activated the Copernicus EMS for the respective countries, providing Radarsat-2, Rapid Eye, COSMO-SkyMed, and SPOT-5 satellite images flood extent maps.

6.7. Digital Globe Open Data Program

More recently, Digital Globe, a commercial satellite company launched the "Open Data Program (ODP)" initiative aimed at providing high-resolution satellite imagery to support recovery from large-scale natural disasters such as flooding (Price, 2017). ODP provides pre and post-disaster images, including support via the Tomnod and Humanitarian OpenStreetMap Team (HOT) crowdsourcing platforms for damage assessment. (Baruch et al., 2016) So far, the ODP has been activated six times by Haiti, Nepal, Mexico, Ecuador, Caribbean/United States, and Madagascar, to manage disasters including earthquakes, hurricanes, and cyclones. The prospect of this initiative is enormous, as high-resolution imagery will largely improve risk and damage assessment in remote locations that are usually unobserved in coarse images. Though the ODP is yet to be deployed in Nigeria, it was deployed for post-disaster assessment of the 2017 Sierra Leone Mudslide disaster. This is its first application case in the African continent.

7. Conclusion

Flood disasters are becoming more frequent, intense and destructive, owing to climate change and anthropogenic factors. Managing floods requires effective decision making based on up-to-date and reliable hydrological information (Els, 2013). Typically, data needed for flood management includes river discharge, water levels, precipitation, terrain, and land use/cover characteristics collected through the establishment of ground monitoring stations and field observations/surveys (Kite and Pietroniro, 1996). In situations where flood transcends administrative boundaries due to natural catchment delineations or river network connectivity, transboundary corporations are set up to enable collaborative data collection, co-operation, risk communication, information sharing and planning to effectively manage flood impact in riparian countries (Bakker, 2009, Chikozho, 2014). Nevertheless, both independent and transboundary data collection systems for flood management are usually flawed by organisational, technical, Institutional, infrastructural and financial challenges that limit inter and intra organisational co-operation (Olomoda, 2012, Bakker, 2009, Chikozho, 2012, Zeitoun et al., 2013, Tilleard and Ford, 2016).

The role of remote sensing in supporting transboundary flood monitoring, planning and management is enormous, as it allows data collection at upstream flood origination countries by downstream impacted country without the need for bureaucratic authorization (Angelidis et al., 2010, Sridevi et al., 2016). In independent countries, remote sensing mostly enables data collection in remote, inaccessible and data sparse locations to improve flood management practices (Musa et al., 2015).

Advancement in remote sensing has immensely improved flood management, particularly by making data available free geospatial data to improve flood practices in data sparse regions of developing countries where ground monitoring network is limited and the cost of obtaining commercial satellite data is particularly high (Biancamaria et al., 2011, Yan et al., 2015a). Open-access remote sensing improves flood modelling and mapping when data sets such as radar altimetry, digital elevation model, optical and radar satellite imagery are applied independently, in combination with *in situ* measurements or integrated into hydrodynamic models as initial or boundary conditions, thereby reducing flood estimation uncertainty in ungauged river basins (Birkinshaw et al., 2014b, Sanyal et al., 2013, Jung et al., 2012, Trigg et al., 2009).

It is worth noting that various freely available RS data sets provide varying accuracy levels, depending on multiple factors. Altimetry Mission accuracies depend on the satellite ground footprint, virtual station location, river width, tributaries discharging into the main river and satellite sensor properties (Yan et al., 2015a). Digital elevation model spatial resolution results in elevation approximation, due to C and X-band radar inability to penetrate vegetation canopies, and reflection off rooftops and water surfaces, resulting in elevation over-estimation (Cook and Merwade, 2009, Musa et al., 2015). Optical imagery applications are hampered by atmospheric conditions and spatial resolution (Asner, 2001), while one of the core deficiencies of radar images is the inconsistency in delineating floods in urban and forested areas (Veljanovski et al., 2011a).

Despite these deficiencies, the role of individual and collective RS sensor images application in flood management is huge, especially in developing regions, as it allows for the estimation and quantification of hydrological parameters at previously undetected locations once a concept has been proven at a location where *in situ* data is available (Tarpanelli et al., 2016).

With remote sensing technology continuously advancing and becoming more freely available, the reliance on ground observation data is expected to decline, especially where ground data is unreliable and scanty as evident in Nigeria. Also, with commercial satellites companies such as Digital globe and other satellite consortiums making available high-resolution images for disaster management (ICSMD, 2015, Price, 2017), flood mapping processes will benefit hugely. Despite this obvious advantage of remote sensing, the role of ground-collected data cannot be disregarded and must take priority or applied in combination with remote sensing data for enhanced flood mapping (Domeneghetti et al., 2014, Sun et al., 2012).

7.1. Future research direction for improved flood modelling and mapping in Nigeria

1. Planning for flood management usually requires flood magnitude estimates at varying return periods based on historical flood data. In developing regions, such data are typically short if the gauging station is newly established or discontinued, and contain gaps (missing data points) caused by equipment malfunction or poor data collation practices (Maxwell, 2013, Olayinka, 2012). Altimetry can aid historical river data reconstruction where newly established and old discontinued gauging stations exist at proximity to virtual stations (Escloupier et al., 2012). Nevertheless, the low revisit time of altimetry satellites (O'Loughlin et al., 2016a) can result in the non-capture of peak floods needed for flood magnitude estimation (Domeneghetti et al., 2014, Yan et al., 2015b) and in other instances, altimetry data is unavailable at certain locations (Papa et al., 2010). Therefore, it is essential that the effect of altimetry application is evaluated against another that statistically infills missing hydrological data to ascertain the influence of both approaches on

flood frequency estimates, and to understand when these individual approaches can be used.

2. The potential of individual satellite data such as altimetry, DEM, optical and radar images has been demonstrated in this review, with the unique merit, demerit and application prospect clearly highlighted. In very remote locations of developing regions, data sparsity is so widespread that uniform data is seldom available for a whole catchment area. Therefore, a combination of all available open-access RS data in such unique data-sparse location is recommended, leveraging on merits of individual data sets to improve all phases of flood mapping processes, i.e. hydrological modelling, hydrodynamic modelling and inundation mapping.
3. Satellite consortium images have been proven to be useful in flood risk assessment when a flood occurs, as pre and post-flood images are provided for comparative analysis (Olojo et al., 2013). However, strict license and copyright policies prohibit re-use and distribution of the data (James et al., 2013), thereby restricting a shift in focus from flood recovery to planning. Nevertheless, end products (i.e. high-resolution inundation maps) are available via the Charter Activations web page and can be applied to support flood modelling processes and inform decision making before, during and after a flood event.
4. The deficiencies of space-borne images application in flood modelling and mapping are quite pronounced in various landscapes, irrespective of the sensor type and their particular advantages (Long et al., 2014, Corcoran et al., 2012). The private sector has played a vital role in advancing geo-informatics in developing regions (AARSE and EARSC, 2016), investing hugely in high-resolution satellite and airborne data needed for operational and disaster management purposes (Eyers et al., 2013, Nwilo and Osanwuta, 2004). A unique opportunity for collaboration is identified here, as privately sourced data can be integrated with open-access remote sensing and crowd-sourcing (Degrossi et al., 2014) to improve flood mapping in data sparse regions.
5. Though this literature review focused on fluvial flood modelling and mapping, it is important to note that precipitation data (*in situ* and satellite) could also vital in this process, and has been widely applied, especially in data-sparse regions from flood modelling and hazard mapping (Yoshimoto and Amarnath, 2017, Komi et al., 2017,

Yu et al., 2016, Revilla-Romero et al., 2015a). However, this is beyond the scope of this thesis.

7.2 Summary of thesis methodologies for analytical chapters 3 - 7

Chapter	Gaps address using method	Method description	Available data
3	This chapter attempts to fill the gap in hydrological data evident during flooding, that emanates from restricted access to remote locations to acquire river measurements manually, as well as the destruction of measuring equipment during peak floods that deter continuous data acquisition.	Two approaches, empirical and statistical are applied to assess the prospect of estimating peak flows needed for direct flood frequency estimation, as well as ascertain the variation in the flood frequency estimates derived using both approaches. The empirical (Radar Altimetry) and statistical (Multiple Imputation) are respectively applied to curtail missing data deficiency at locations where supplementary data available and unavailable.	Annual peak flow time series with gaps varying from 1 to 3 years (consecutive) and > 3 years (inconsecutive).
4	In situations where gauging stations are non-existent or data collected is short in length, regional flood frequency can enable	Regional flood frequency is adopted and considers climate variability effect. The analysis is executed using the International	Annual peak flow time series for gauging stations within the Ogun-Oshun river basin of Nigeria, SRTM DEM, and

	hydrological data agglomeration from nearby stations with similar hydrological parameters.	Centre for Integrated Water Resources Management–Regional Analysis of Frequency Tool (ICI-RAFT) software with inherent climate indices database to enable climate variability assessment. Climate variability is accounted for due to the significant trends and homogeneity observed in the available historical data.	global climate indices time series from the National Oceanic and Atmospheric Administration (NOAA).
5	During flooding, swift response is expected, therefore disaster management authorities require Real or Near-Real-Time (NRT) information on exposure to respond, to mitigate flood impact. Such datasets are seldom available in many developing countries. Typically, government agencies develop	To deliver the required NRT flood information, twice daily overpass (Terra and Aqua satellites) MODIS Water Product (MWP) is combined with crowd-sourcing in this chapter. The MWP flood extent is generated automatically by a NASA through an algorithm that uses a ratio of MODIS 250 m resolution Bands 1 and 2, and a threshold	Inundation extent derived from the MWP; georeferenced crowdsourcing data points of responses from citizens on knowledge of flooding around their surrounding (flooded or non-flooded) and supplementary information that infer preparedness, response and recovery; and the Annual Flood

	maps of perceived flood risk before a flood occurs, to inform flood management decisions. However, if such flood risk maps are developed from coarse and inaccurate data, the perception of flooding will differ considerably from reality, resulting in flawed decision making.	of Band 7 to provisionally identify pixels as water. Crowdsourcing data is acquired using web GIS application developed by the author using ArcGIS GeoForm platform. The discrepancy between government and citizen flood risk perception is also evaluated using data acquired from crowdsourcing is also assessed, as well as factors that affect citizen preparedness, response and recovery.	Outlook of Nigeria (2015).
6	Hydrodynamic models provide a viable approach to estimate known or expected flood extent and water level needed for flood management decision making. These models typically require hydrological, topographic and calibration (known historical flood extent, water levels, discharge or	Variable degrees of data availability was evident in the model domain (i.e. Niger-South, Nigeria). Therefore, the whole study domain is modelled and calibrated using CAESAR-LISFLOOD, due to the availability of input hydrological data upstream of the domain, while validation is segmented into	**Whole domain**: Hydrological input data (Umaisha and Baro gauging stations, along Benue and Niger rivers respectively), and SRTM DEM (with Urban and Vegetation elevations reduced). **Lokoja**: River bathymetry (acquired in

	watermarks) data, which as seldom available in many developing regions.	sub-domains to reflect the variable data availability. The three (3) sub-domains are named Lokoja, Onitsha and Niger Delta.	2011), NRT MWP, TerraSAR-X, water level measurement at Lokoja gauging station. **Onitsha**: River bathymetry (acquired in 2001), NRT MWP, and water level measurement at Onitsha gauging station. **Niger Delta**: NRT MWP, Geotagged overflight photos, CosmoSkyMed and RADARSAT-2.
`7	Flood extents extracted from passive and active satellite images such as MODIS, RADARSAT 2, and TerraSAR-X are usually impaired by environmental conditions including reflectance from vegetation cover, urban land-use and cloud cover. These	Decision tree based algorithm is adopted and applied here using WEKA data mining software. This approach integrates various open -access datasets including hydrology (river), geology, soil composition, land use/cover, DEM and its derivatives to	CosmoSkyMed, RADARSAT-2, Landsat-8, soil composition, geology map, SRTM DEM, DEM derivatives (Topographic Wetness Index, and Stream Power Index), geotagged overflight images.

	conditions are particularly evident in the Niger delta region.	improve radar flood detection potential in the mangrove dominated Niger delta region.	

Further details of specific methodologies are presented in individual chapters

CHAPTER 3: INFILLING MISSING DATA IN HYDROLOGY: SOLUTIONS USING SATELLITE RADAR ALTIMETRY AND MULTIPLE IMPUTATION FOR DATASPARSE REGIONS

Abstract

Floods are undoubtedly one of the most devastating natural disasters on earth, triggered mostly by climatic activities and aggravated by anthropogenic factors. Due to the disastrous consequences of flooding, it is important that proper structural and non-structural measures be put in place to manage the effects of flooding, and the first step towards this is the estimation of expected flood magnitude and the probability of occurrence. Gaps in hydrological data, particularly in developing countries increases the complexity of flood frequency analysis and could contribute to flood estimates uncertainty, consequently resulting in poor flood management decisions.

In this study, two methods for filling hydrological data gaps are deployed, (i) incorporating river level data derived from satellite-based Radar Altimetry and (ii) Multiple Imputation technique, and the impact of these approaches of derived flood estimates are quantified. The approaches presented here were applied along the Niger and Benue rivers in Nigeria to assess scenarios of supplementary data availability and unavailability, to fill data gaps at specific gauging stations.

The study revealed that Radar Altimetry missing data infilling approach outperformed Multiple Imputation, especially for widely gapped time series (> 3 years), but did not differ significantly for data sets with gaps of 1-3 years. Also, previously unquantified 2012 and 2015 flood events in Nigeria were quantified as 1-in-100 and 1-in-50 year floods respectively, suggesting that the impact of these flood events would have been mitigated considerably if such information was available, having filled the historic data gaps.

This study demonstrates the potential of altimetry and statistical computation for providing information to support flood management in developing regions where *in situ* data is sparse, especially where gauging stations have been destroyed, discontinued or are newly established.

Keywords

Hydrology, Missing data, Radar Altimetry, Multiple Imputations, Uncertainty, Flood Frequency Analysis

1. Introduction

Flooding is one of the most devastating natural hazards, increasing in frequency, magnitude and impact due to changing climatic conditions and anthropogenic triggers/factors (Lavender and Matthews, 2009). Reliable flood information is required by flood risk managers and stakeholders when deploying measures to effectively counter the impacts of floods. Typically, networks of hydrologic gauging stations are established for this purpose (Hipel, 1995, Herschy, 2008), distributed across several locations of interest to collect long-term hydrological data. However, operating such *in situ* measurement systems, especially in developing regions are often problematic due to underfunding of implementation agencies by governments (Starrett et al., 2010), inaccessibility and security challenges at some locations (Ampadu et al., 2013b), lack of commitment by gauging station operators, and equipment malfunction, replacement, damage, modification and discontinuity (Olayinka et al., 2013).

These factors contribute to hydrological network inadequacy, and decline of functional stations and gaps in available records that flood modelling processes can result in uncertain estimates. Even when data is available, in many cases for developing regions, these records are usually short, and river water level measurements and discharge estimation processes further subjects the available hydrological data to aleatory and epistemic uncertainties (Merz and Thieken, 2005, Baldassarre and Montanari, 2009, Beven and Hall, 2014). This paucity of data is particularly severe in developing countries, further limiting their capacity to mitigate and cope with the impact of flooding on people, infrastructure and socio-economic activities.

Researchers have explored several techniques to compensate data deficiencies to estimate flow for ungauged or sparsely gauged river basins, including remote sensing applications (Bjerklie et al., 2005, Tarpanelli et al., 2013, Birkinshaw et al., 2014a, Gleason and Smith, 2014), hydrodynamic modelling (Biancamaria et al., 2009a, Neal et al., 2012, Sanyal et al., 2014), combined remote sensing and hydrodynamic models (Pereira Cardenal et al., 2010, Tarpanelli et al., 2013, Yan et al., 2015a), catchment geomorphological and meteorological data applications (Jotish et al., 2010, Grimaldi et al., 2012, Rigon et al., 2015), and hydrological regionalization (Saf, 2009a, Smith et al., 2015, Kumar et al., 2015, Rahman et al., 2014). These techniques provide varying advantages and challenges and are applicable in different scenarios depending on available data. Furthermore, all of these approaches require some form of ground data for verification, given that *in situ* observations provides better insight into local hydrological processes and catchment response to changing climatic conditions (Hrachowitz et al., 2013), and the output of each technique is strongly dependent on the input data accuracy.

Irrespective of the method adapted for flood magnitude estimation, missing data within the hydrological time-series increases the uncertainty in the estimate, resulting in flawed flood management decisions (Jung and Merwade, 2015). To curtail this deficiency, hydrologists have devised several means to fill gaps in hydrological time-series using both statistical and empirical methodologies (Campozano et al., 2014). Statistical techniques are centred on filling missing data by simulating missing data using trends/patterns from available data using methods such as regression analysis (Westerberg and McMillan, 2015, Olayinka et al., 2013), interpolation (Lee and Kang, 2015, Hasan and Croke, 2013) and artificial neural networks (Steven et al., 2010, Starrett et al., 2010).

Traditional missing data infilling approaches generally involve removal of incomplete data or single data imputation methods such as arithmetic mean or median imputation, regression-based imputation and principal component analysis-based imputation (Peugh and Enders, 2004). Though the deletion method is usually convenient (King et al., 1998), this approach reduces sample size, thereby introducing statistical bias and reducing the statistical power and precision of standard statistical procedures (Little, 2002). Single imputation approaches contrastingly replace missing data while retaining the original sample size. However, single imputation techniques lead to distorted parameter estimates, reduced data variability (Baraldi and Enders, 2010, Little, 2002), predictable bias, high variable correlation (Donders et al., 2006), and dimensional subjectivity (Jolliffe, 2002).

To curtail the limitations of the single imputation approach, Multiple Imputation (MI) has been proposed; an approach that fundamentally replaces missing time series values using two or more plausible values derived from a distribution of possibilities (Graham et al., 2007, Graham and Hofer, 2000). Multiple imputation is widely used in hydrological studies (Asian et al., 2014, Khalifeloo et al., 2015, Graham et al., 2007, Yozgatligil et al., 2013, Tyler et al., 2011, Lo Presti et al., 2010, Li et al., 2015), as it provides the unique advantage of accounting for missing data uncertainty, and do not overestimate correlation error (Lee and Carlin, 2010).

Empirical methods on the other hand fill missing data using supplementary data sets from upstream or downstream gauging stations close to the location of interest, as well as other data sets such as digital elevation model (Pan and Nichols, 2013), bathymetry (Tommaso et al., 2013) and/or satellite imagery data sets (Tarpanelli et al., 2013, Gleason and Smith, 2014, Birkinshaw et al., 2014b) and radar altimetry (Dubey et al., 2015, Asadzadeh Jarihani et al., 2013). Of all listed empirical approaches, only altimetry provides direct water level estimates that can be integrated seamlessly into existing hydrological time series without complex computation (Pandey and Amarnath, 2015, Silva et al., 2014, Papa et al., 2010). Given that altimetry virtual station networks are globally distributed (See Figure 11 – 13, Chapter 2), a unique opportunity for infilling hydrological time series gaps is presented, especially in developing regions during peak flood seasons when *in situ* stations are usually disrupted or damaged. Notwithstanding radar altimetry's advantages, its application is not without limitation, as factors including atmospheric state during data acquisition, satellite sensor properties, temporal resolution, water surface characteristics and altimetry ground footprint contribute to the measurement variability and uncertainties (Belaud et al., 2010, Jarihani et al., 2015b, Clark et al., 2014). Furthermore, considering the recent launch of Jason-3 (NESDIS, 2016) and Sentinel-3 (ESA, 2016) in early 2016, and the prospective launch of Surface Water and Ocean Topography (SWOT) in 2020 (Avisio, 2016), altimetry data collection is expected to continue, and dominate sustainable water resource management for years to come.

The objectives of this chapter are detailed as follows:

I. Explore the prospect of filling missing hydrological timeseries using radar altimetry and multiple imputation.

II. Estimate flood frequency and magnitude using contrastingly filled hydrological time series and the effect of the gap length.

III. Assess the accuracy and discordancy of derivatives from both approaches

IV. Quantify the magnitude of the recently experienced flood in 2012 at the location of interest (Nigeria), using data filled by both approaches, to demonstrate the practicality of this study.

2. Study region

The Niger south Hydrological Area (HA5) (Figure 1A) is the focus of this study and encircles 22,170,300 persons within a 54000km^2 area. The hydrology of the region is defined by Niger Basin water inflow from Niger and Benue rivers (Figure 1B) travelling downstream to the Atlantic Ocean through Nun and Forcados distributaries in the Niger Delta (Figure 1C), and to the Anambra-Imo river basin through Anambra river. Annual rainfall in the Niger Basin varies from 1100 mm to 1400 mm, while the land cover/use along the Niger and Benue is comprised of built-up areas, cultivated land, plantations, wetlands, mixed land use, grasslands, vegetation and bare surfaces (Odunuga et al., 2015). HA-5 encompasses sections of some of the most impacted states (i.e. Kogi, Anambra, Imo, Delta Bayelsa and Rivers) during the 2012 and 2015 flood events, of which the 2012 flood was reported to have caused the greatest impact/damage in 40 years (Ojigi et al., 2013, Tami and Moses, 2015). The impacts include disruption of socio-economic activities, damage to properties and infrastructure, and sadly deaths (FGN, 2013, Erekpokeme, 2015). Both events were triggered by intense precipitation which resulted in the release of excess water from dams in Nigeria (Kainji, Shiroro and Kiri) and Cameroon (Lagdo), with the impact exacerbated by poor planning due to insufficient data and poor communication (Ojigi et al., 2013, Olojo et al., 2013, FGN, 2013). Hence, this study site is valuable as it explores the challenges and opportunities associated with hydrological data acquisition, the potential of alternative data sources and their applicability. Figure 1A also shows *in situ* gauging stations, radar altimetry tracks and virtual stations along the Niger and Benue rivers.

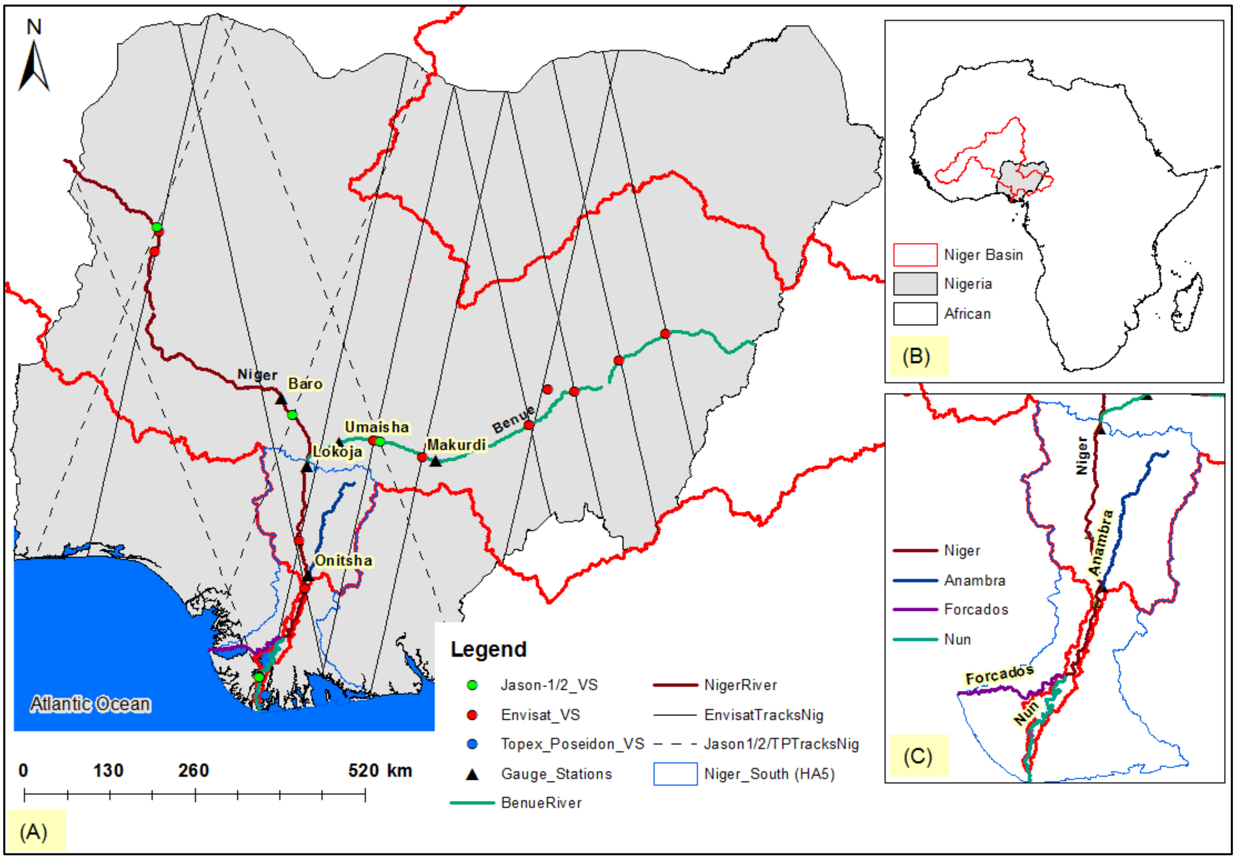


Figure 1: (A) Map of Nigeria showing *in situ* gauging stations, altimetry virtual stations and tracks along Niger and Benue Rivers. (B) Map of Africa showing Niger Basin imprint on Nigeria. (C) Niger South hydrological area showing tributaries (Niger and Anambra) and distributaries (Nun and Forcados).

3. Materials and Methods

3.1. *In-situ* hydrological data

Hydrological data (Discharge, Water level and Rating curve) for the five (5) *in situ* stations (Table 1) used in this study were acquired from the Nigerian Hydrological Service Agency (NIHSA), National Inland Waterways Authority (NIWA) and the Niger Basin Authority (NBA). Daily mean water level data is manually collected using staff gauges, then converted to discharge using pre-defined and up-to-date rating curves (i.e. the relationship between *in-situ* discharge and water levels), see Appendix 3. The respective gauging stations were established before the establishment of upstream dams that alter the Niger and Benue river hydrological regimes (Abam, 2001b), i.e. Baro (1915), Lokoja (1915), Umaisha (1980), Onitsha (1955) and Taoussa (1954). Therefore, post-dam establishment hydrological time series is applied to eliminate hydrological heterogeneity caused by dam creation. Hydrological data for Taoussa gauging station located in Mali was acquired from the Niger Basin Authority (NBA) for validation purpose, as none of the datasets available within the area of interest was without gaps (Supplementary Figure 1 – 3). Only annual maximum flow time series data are used in this study.

Table 1 *In situ* gauge station characteristics

Station Name	River	Lat. (º)	Long. (º)	Area (km^2)	Period of record	GBM (m)	River Width (km)	Missing annual peak data
Baro	Niger	8.6066	6.4170	730,000	1985 - 2011	57.22	0.64	12
Lokoja	Niger	7.8167	6.7333	752,000	1989 - 2012	45.77	1.65	6
Umaisha	Benue	8.0000	7.2333	335,000	1985 - 2012	18.87	0.61	19
Onitsha	Niger	6.1667	6.7500	1,100,000	1989 - 2011	24.14	1.03	16
Taoussa	Niger	16.9500	-0.5800	340,000	1985 - 2015	N/A	0.47	0

* GBM: Gauge Bench Mark above Mean Sea Level, N/A: Not Applicable (Source: NISHA, NIWA and NBA)

3.2. Radar altimetry data collection and application for missing filling data gaps

Radar altimetry data is acquired via a process that measures the distance between the orbiting satellite and water surface in relation to a reference datum (Earth Gravitational Model (EGM) 2008), using satellite sensor echo pulse return intervals from when emitted, to when received upon reflection by the water surface (Sulistioadi et al., 2015, Belaud et al., 2010). Altimetry water levels are measured at virtual stations located intermittently where altimetry satellite tracks cross path with rivers (Birkinshaw et al., 2014b, Musa et al., 2015). Off-the-shelf Topex/Poseidon (T/P), Envisat, Jason-1 and Jason-2 altimetry missions (See Table 2 for properties) data from the Centre for Topological studies of the Ocean and Hydrosphere (CTOH) (Crétaux et al., 2011) database are applied in this study.

Altimetry water level data downloaded from CTOH are pre-processed using the Virtual Altimetry Stations (VALS) software and takes into cognizance the distance between the satellite and water body, and uncertainty contributing factors such as the ionosphere, humid and dry atmospheric conditions, polar tide, and solid earth tide (da Silva et al., 2010).

Table 2 Radar Altimetry mission and characteristics

S/N	Mission	Ground footprint (m)	Return period (days)	Operation timeline	Vertical Accuracy (m)	References
1	Topex/Poseidon	~600	9.9	1993 - 2003	0.35	(Frappart et al., 2006)
2	Envisat	~400	35	2002 - 2012	0.28	(Frappart et al., 2006)
3	Jason-1	~300	10	2002 - 2009	1.07	(Jarihani et al., 2015a)
4	Jason-2	~300	10	2008 –	0.28	(Jarihani et al., 2015a)

The EGM 2008 vertical datum for altimetry data used in VALS was converted to MSL which corresponded with the *in-situ* gauge station datum. This conversion was performed using datum correction parameters derived from the geoid calculator GeoiedEval (http://geographiclib.sourceforge.net/cgi-bin/GeoidEval[2]).

[2] http://geographiclib.sourceforge.net/cgi-bin/GeoidEval

3.3. Missing Data Imputation, Pre-processing and Flood frequency analysis

3.3.1. Missing Data Imputation

Missing data is a regularly occurring phenomenon in hydrological analysis, depicted by gaps within hydrological time series that emanate due to poor data management, equipment damage/malfunction and un-acquired data due to inaccessibility, thus resulting in poor flood magnitude estimates and management decisions. Two approaches, Radar altimetry and Multiple imputation are explored in this study, aiming to reduce the uncertainty associated with applying gapped in historical hydrological datasets.

3.3.1.1. Radar Altimetry Missing Data Imputation

This approach involves establishing a correlation relationship between upstream or downstream altimetry virtual station datasets those of a nearby *in-situ* gauging station when water level data exist at both stations. The established relationship is then applied to estimate missing *in-situ* data when only altimetry data is available. At locations where data is not available at similar dates for *in-situ* and altimetry virtual stations to establish an empirical relationship, previously established relationship from a nearby altimetry station can be adopted, provided the distance between both virtual stations is minimal, the change in river width is negligible, no hydraulic structure or tributary exist between both virtual stations (Papa et al., 2010, Pandey and Amarnath, 2015). This approach is consistent with previous studies (Papa et al., 2010, Michailovsky et al., 2012, Dubey et al., 2015), where the rating curve for a nearby gauging station was adapted for another station where data was unavailable. The newly estimated water at *In-situ* station is then converted to discharge using a pre-defined rating curve/equation. Figure 1 showed the altimetry virtual stations chosen for this study which was along Niger and Benue rivers located upstream and downstream of the *in-situ* gauging stations. The framework presented in Figure 2 describes the methodology for infilling missing data using altimetry, while the characteristics of altimetry virtual stations are presented in Table 3.

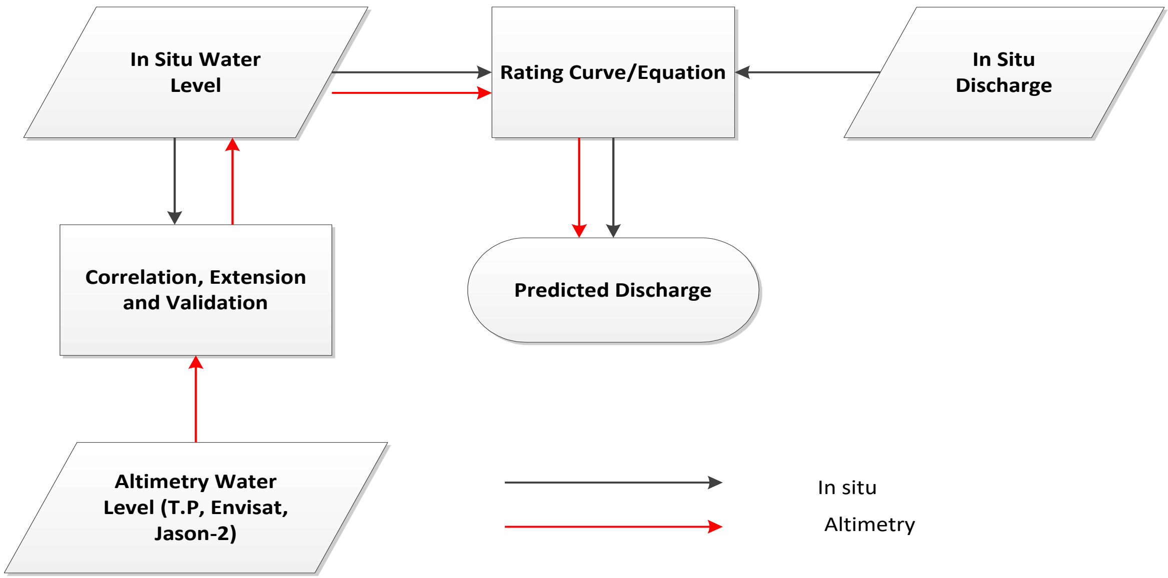


Figure 2 Methodology for estimating missing discharge data using radar altimetry, *in situ* water level and rating curves

Table 3 Characteristics of the altimetry virtual stations within the study area

Name	**Mission**	**River**	**Temporal coverage**	**Latitude**	**Longitude**	**Distance from GOI (km)**	**Data match points (Alt vs *In situ*)**	**R^2**
Env_702_01	Envisat	Niger	2002-2010	6.6500	6.6500	115.4 (Lokoja)-DS	42	0.59
Env_029_01	Envisat	Niger	2002-2010	5.9900	6.7200	23.7 (Onitsha)-DS	9	0.95
Env_158_01	Envisat	Benue	2002-2010	8.0200	7.6700	54.3 (Umaisha)-US	15[!]	0.934[!]
tp198_4_moy	T/P	Nun	1993-2002	6.0981	4.7563	234.7 (Onitsha)-DS	88	0.66
j2_020_1	Jason-2	Benue	2002-2011	8.0082	7.7540	62.9 (Umaisha)-US	15	0.95
j2_211_3	Jason-2	Niger	2002-2011	8.3675	6.5570	33.8 (Baro)-US	20	0.94
j2_161_1	Jason 2	Niger	2002 - 2015	17.0107	-1.5247	112.5 (Taoussa) -US	14	0.92

GOI: Gauge of interest, DS = Downstream of in situ gauge, US = Upstream of in situ gauge, R^2 = correlation coefficient, (!) denotes that the correlation relationship at the J2_020_1 virtual station was adopted for Env_158_01 due to the absence of *in situ* measurements near that virtual station. The distance between the two virtual stations was limited (9.3 km).

Table 3 (R^2) indicates that the correlation between RA-derived and *in situ* stage data was higher as the distances between virtual and *in situ* gauge stations reduce and vice versa. Also, the reduced correlations between virtual stations (Env_702_01 and tp198_4_moy) and *in situ* stations water levels at Lokoja and Onitsha respectively are attributed to tributaries discharging into the main rivers. These findings are consistent with other studies at Brahmaputra river (Dubey et al., 2015), Lake Argyle (Asadzadeh Jarihani et al., 2013) and Lake Victoria (Crétaux et al., 2011, Asadzadeh Jarihani et al., 2013, Dubey et al., 2015) and Benue river (Pandey and Amarnath, 2015).

3.3.1.2. Missing Data Multiple imputation

Multiple imputation (MI) allows for the infilling of missing data in situations where supplementary data such as radar altimetry is unavailable and is widely applied in hydrological studies (Gill et al., 2007, Schneider, 2001, Lo Presti et al., 2010, Graham et al., 2007). MI has also been found to outperform traditional techniques such as mean imputation, missing indicator and complete case analysis (Roderick, 2011, Schafer, 1997, van der Heijden et al., 2006). MI fills data gaps by generating a plausible number of values after fitting the existing data to a distribution based on the statistical parameters such as mean and standard deviation of the dataset, while accounting for uncertainty about the supposed true value (Li et al., 2015, Rubin, 1987, Yozgatligil et al., 2013). The term "Multiple imputation" implies the missing data is simulated multiple times, in this case (5 times) using XLSTAT Ms Excel add-in, thus quantifying the uncertainty in the simulation process and reducing false precision attainable with single imputation (Li et al., 2015). The MI algorithm is implemented in XLSTAT which adopts the Markov Chain Monte Carlo approach (van Buuren, 2007), whereby missing values are estimated by random sampling from a distribution of plausible values derived from multiple simulations undertaken using mean and standard error parameters similar to that of the original dataset under the assumption of normal distribution.

3.3.2. Pre-processing

3.3.2.1. Preliminary Analysis Prior to Flood Frequency Estimation

Preliminary analysis is an integral part of flood frequency estimation, as it ensures the applied dataset meets the required prerequisite to ensure the data sets applied does not contribute additional uncertainty to probability distributions and flood frequency estimates (Lamontagne et al., 2013). These include test for outliers, trends, homogeneity and serial correlation

- Grubbs and Becks (Grubbs and Beck, 1972) and multiple Grubbs and Becks outlier test: applied to identify Potentially Influential Low Floods (PILFs).
- Mann-Kendall test (Mann, 1945, Kendall, 1975): applied to assess trends in the time-series.
- Pettit's test (Pettitt, 1979): assess historical data homogeneity
- Lag-1 correlation coefficient statistics (Kendall and Stuart, 1969): test the serial correlation between the independent observations of a time-series.

All data pre-processing except the multiple Grubbs and Becks test (mGBt) was undertaken using XLSTAT MS Excel Add-in. The mGBt was performed in Flike flood frequency analysis software (Kuczera, 1999, Lamontagne et al., 2013). mGBt assesses the anomaly of the (k^{th}) smallest sample in comparison to the peak flood population dataset (n) and uses a threshold to remove this anomaly. Nonetheless, Pedruco et al., (2014) warned on the need to be cautious when removing PILFs to ensure data that significantly affects the quantile estimate is not eliminated. Other uncertainties factors that contribute to hydrological data uncertainty include changes in land cover, catchment geomorphological, river channel, and the construction of hydraulic structures; these are somewhat curtailed by consistently updated rating curves (Dubey et al., 2015).

3.3.2.2. Simple Rating Curve extrapolation uncertainty assessment

In addition to the impact of missing peak flow data on flood frequency estimates, the rating curve from which discharge is derived can contribute to design-flood uncertainty (Baldassarre and Montanari, 2009, Di Baldassarre et al., 2012, Kuczera, 1983). Rating curves present the relationship between *in-situ* stage and discharge at gauging station (Haddad et al., 2014). This, therefore, allows for the estimation for discharge from river water level measurement acquired using staff gauge, which is usually the case in most developing countries due to the absence of sophisticated equipment (van Meerveld et al., 2017). Typically, rating curves are developed from data collected within river boundaries. However, during flooding rivers rise above known boundaries used in rating cures derivation, resulting in extrapolation uncertainty (Herschy, 2008). Other factors that contribute to rating curve uncertainty include rating curve overfitting (Haque et al., 2014, Baldassarre and Montanari, 2009), river cross-section changes due to erosion or aggradation, land cover change, hydraulic structure design (Jalbert et al., 2011), and measurement errors (Baldassarre and Montanari, 2009).

A simple Ratings Ratio (RR) approach is applied to identify stations with a high degree of extrapolation uncertainty (Haddad et al., 2010). RR is ascertained by dividing the maximum discharge for each year (Q_F) by the maximum measured discharge applied in the ratings curve development (Q_M). The equation below defines RR as:

$$\mathrm{RR} = \frac{Q_F}{Q_M} \qquad (2)$$

If the RR value is less than 1, the corresponding Q_F value is assumed to be free from extrapolation uncertainty and the presence of extrapolation uncertainty is pronounced if RR is much greater than (>>) 1 (Haque et al., 2014).

3.3.3. Flood frequency estimation

Flood frequency estimation is a process that entails establishing a relationship between flood quantile and the probability of occurrence. "Flood frequency" generally refers to the likelihood of a flood of specific magnitude/threshold being met or exceeded at any given point in time, and "time" being expressed as return period (Reed, 1999). This is undertaken by fitting a predefined probability distribution to historic Annual Maximum Series (AMS) or partial series data from a single or combination gauging stations, thus capturing the probability of a peak flood occurrence (Stedinger and Griffis, 2008).

The length of available data also contributes to flood estimates uncertainty, thus the availability of more historical data implies improved flood estimates and confidence in the decision made from such estimates. The Reed (1999) Flood Estimation Handbook (FEH) 5T rule of thumb for length of data required for flood estimation is adopted, i.e. the historical data should be at least five times the target return periods, thus providing acceptable uncertainty limits.

Varying probability distributions including Generalized Extreme Value (GEV), Generalized Logistic (GLO), Extreme Value (type 1 – 3), Generalized Pareto (GPA), and Log-Pearson type 3 (LP3) have been applied to fit Annual Maximum time series, and providing contrasting levels of flood estimates, even for the same dataset (Laio et al., 2009). Typically, a suitability analysis is undertaken to access the best probability distribution (Peel et al., 2001), but GEV is adopted to estimate flood frequency and magnitude in this study, due to its robustness, flexibility (Komi et al., 2016, Hailegeorgis and Alfredsen, 2017, Papalexiou and Koutsoyiannis, 2013) and wide applicability in the area of interest, for consistency (Izinyon and Ehiorobo, 2014, Garba et al., 2013b, Fasinmirin and Olufayo, 2006). GEV probability distribution estimates are however affected by tropical cyclones and extratropical weather systems that results in extremely large shape parameters (Smith et al., 2011, Villarini and Smith, 2010), and these events do not manifest in Nigeria. Furthermore, GEV like other probability distributions is affected by short hydrological time series, resulting in uncertain flood estimates (Ragulina and Reitan, 2017, Botto et al., 2014).

GEV is expressed as thus:

$$F(x|\tau,\alpha,\kappa) = \begin{cases} \frac{1}{\alpha}\exp\left\{-\left[1-\frac{\kappa(x-\tau)}{\alpha}\right]^{\frac{1}{\kappa}}\right\}\left[1-\frac{\kappa(x-\tau)}{\alpha}\right]^{\frac{1}{\kappa}-1} & \text{when}\kappa>0, x<\tau+\frac{\alpha}{\kappa}; \text{when}\kappa<0, x>\tau+\frac{\alpha}{\kappa} \\ \frac{1}{\alpha}\exp\left[-\frac{(x-\tau)}{\alpha}\right]\exp\left\{-\exp\left[-\frac{(x-\tau)}{\alpha}\right]\right\} & \text{if}\,\kappa=0 \end{cases} \quad (3)$$

where, τ, α, and k represents location, scale and shape parameters of the distribution function.

Once the GEV parameters were fitted to the peak flood historical data for each station, the uncertainty limits (i.e. upper and lower boundaries) are ascertained by a bootstrap approach that samples the original dataset to create random data series with similar parameters as the original dataset, then applies the pre-defined distribution function to estimate various flood magnitudes at different return periods (Efron, 1979a, Efron, 1979b, Kuczera, 1999, Hu et al., 2013).Flood frequency analysis was undertaken in the Flike flood frequency analysis software.

3.3.4. Comparative Analysis (Permutation test and Kolmogorov-Simonov test):

Permutation and Kolmogorov-Simonov tests are applied to ascertain the significance of the missing data imputation approaches on the flood estimates and variation in the quantile distributions respectively. Permutation test is the non-parametric alternative to parametric t-test, used in ascertaining the difference between two treatments (Good, 2000), i.e. Multiple Imputation and Radar Altimetry Imputation in this case, while the Kolmogorov-Simonov test (Kolmogorov, 1991) assesses if two distributions are the same or if a distribution differs from a reference distribution. Both analysis was undertaken in R.

3.3.5. Infilling method evaluation for contrastingly gapped data at Taoussa, Mali:

To further evaluate the effect of the infilling approaches applied on flood estimates, complete hydrological time series available at Taoussa gauging station in Mali (See location map in Supplementary Figure 1) was acquired from the Niger Basin Authority Database: http://nigerhycos.abn.ne/user-anon/htm/[3], due to the absence of gap-free data in Nigeria. Historical water levels were converted to discharge using ratings curve presented in Supplementary Figure 2. Flood estimates derived from data filled using Multiple Imputation (MI) and Radar Altimetry (Alt) for both consecutively (≤ 3 years) and inconsecutively (> 3 years) gapped data are then compared to estimates derived from complete data using Permutation and Kolmogorov-Simonov tests.

[3] http://nigerhycos.abn.ne/user-anon/htm/

4. Results and Discussion

4.1. Missing Data Infilling: Radar Altimetry (RA) and Multiple Imputation (MI)

Figure 3 (a-d) shows the Annual Maximum Series data for each of the four gauging stations, with gaps filled using RA and MI data infilling approaches. Both approaches respectively address situations of supplementary data (i.e. remote sensing) availability and unavailability and provides options for hydrological data gaps infilling, considering that altimetry tracks and virtual stations are not present at every river.

Points of data overlap between the MI and RA time-series depicts points where historical data exist, and the space between time-series represents peak flood estimated by the varying approaches. The RA derived discharge is higher its MI counterpart at Umaisha, compared to any other station. At Baro, Lokoja and Onitsha gauging stations, RA peak flood estimates were mostly lower than those estimated by MI, and higher only in 1993 at Baro and Onitsha, and 1995 and 2001 at Baro only. The consistently low peak flood estimates displayed at Umaisha reveals the deficiency of MI, especially when estimating missing data for time series with wide gaps (Tyler et al., 2011). The higher Altimetry peak flood estimates at Baro and Onitsha is also consistent with historical flood events reported by the Dartmouth Flood Observatory (DFO) Archive. The high discharge values estimated from the RA infilling method compared to MI were most evident for data sets with inconsecutive (>3 years) missing data.

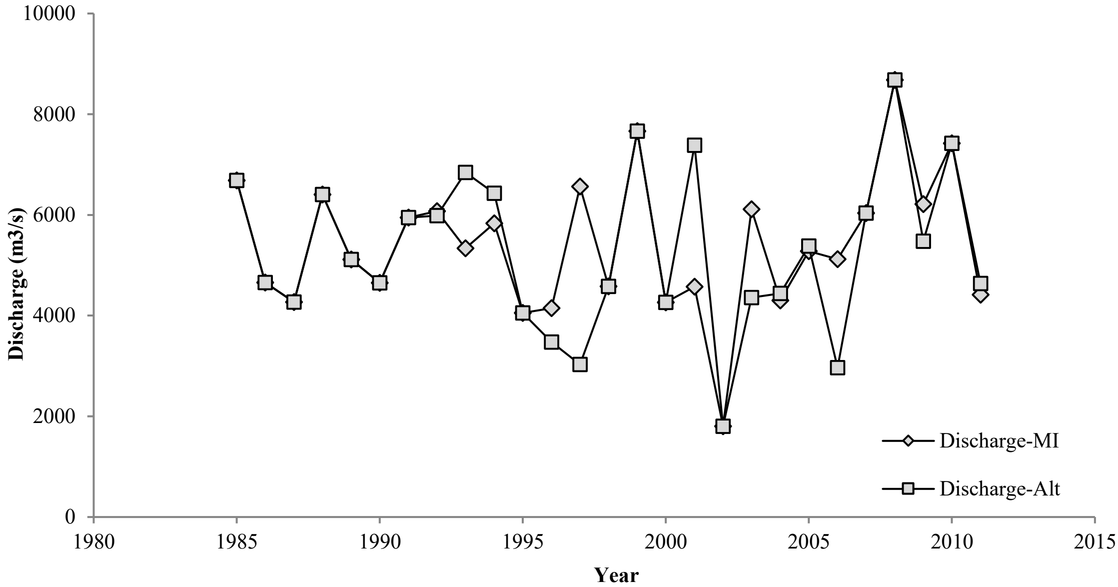


Figure 3 (a) Baro station MI and RA Infilled time series

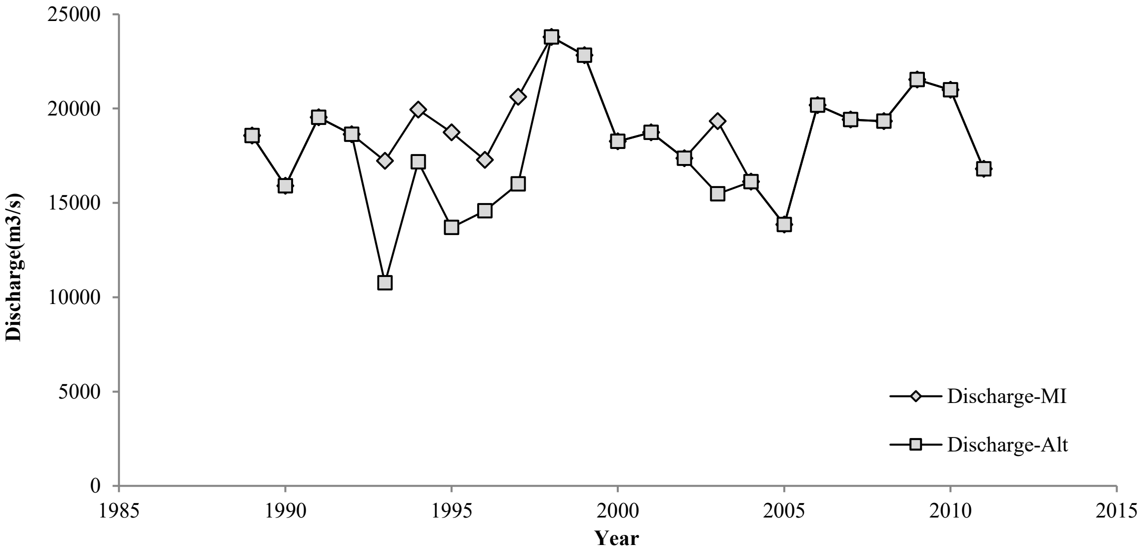


Figure 3 (b) Lokoja station MI and RA Infilled time series

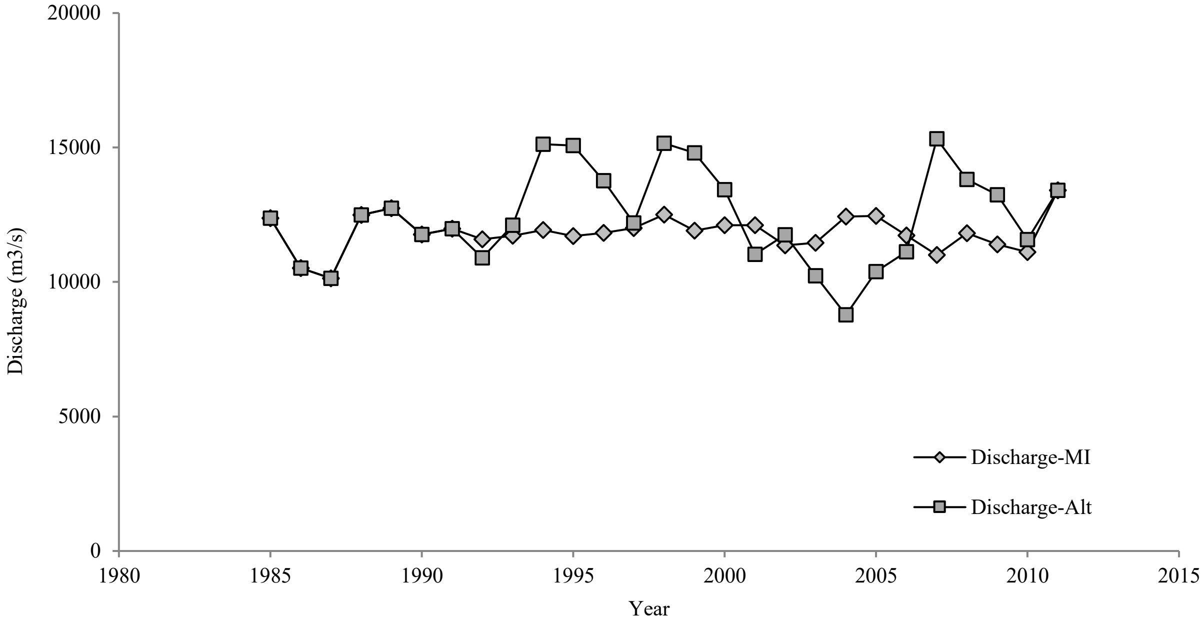


Figure 3 (c) Umaisha station MI and RA Infilled time series

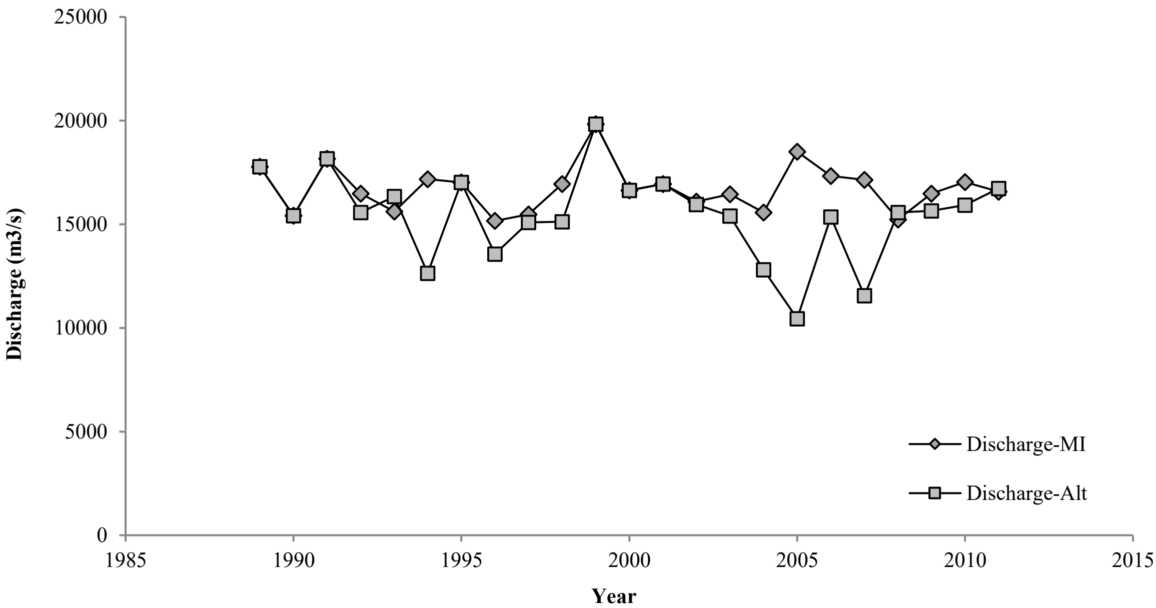


Figure 3 (d) Onitsha station MI and RA Infilled time series

Figure 4 (a - b) shows the time series for Taoussa reference station in Mali, used as the validation station for the methods applied in this study for consecutively and inconsecutively spaced historical time-series. Both figures generally reveal that estimated peak discharge discordant from the real values, but RA estimates were closer to the *in-situ* measurements, compared to MI estimates, especially for consecutively gapped data. Results from the further quantitative analysis are presented and discussed in section 4.6, and more information on the exacted figures of these outcomes are presented in Supplementary Figure 1.

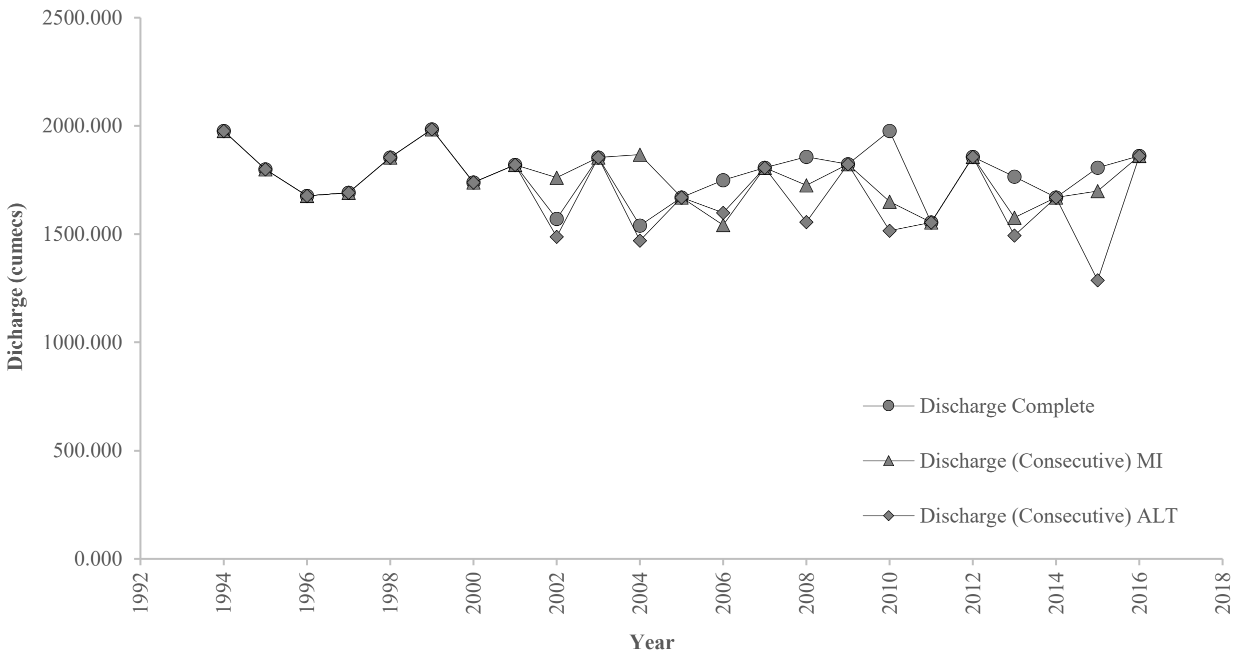


Figure 4 (a) Taoussa Complete and Consecutive missing data

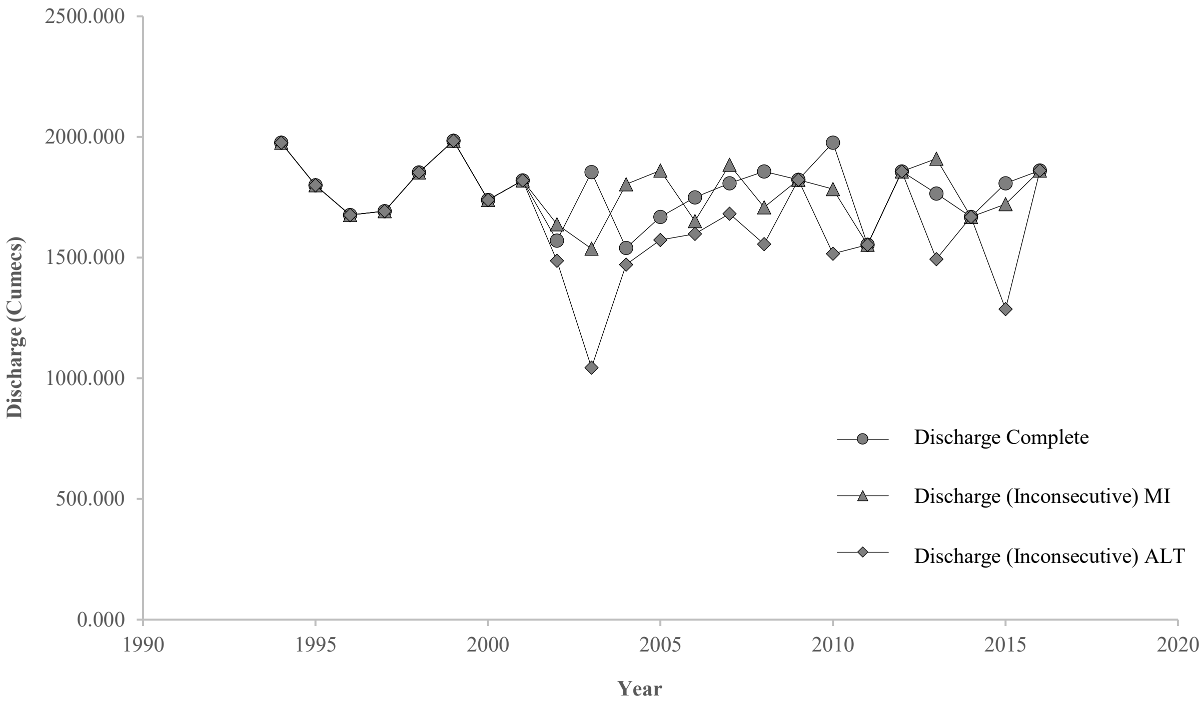


Figure 4 (b) Taoussa Complete and Inconsecutive missing data

4.2. Preliminary data analysis

Results of the preliminary analysis, i.e. outlier, trend, homogeneity and serial (lag1) correlation for each gauging station is presented in Table 4. P-values greater than (>) 0.05 implies that significant outliers do not exist within the dataset, inferring that high and low flood levels captured in the historical series are consistent with years of recorded flood events. The results of the outlier test further suggest the historical data sets responded to real flood events rather than of equipment faults. Table 4 also shows the results of the (i) Mann-Kendall trend test demonstrated the absence trends for all gauge stations at 5% significance level, (ii) Homogeneity (Pettit) test which assesses the variability in the hydrological data is specified in the homogeneity (p-value) and (iii) Serial (Lag 1) correlation within gauge records results ranging from -1 to 1, where 1 infer perfect correlation and -1 perfect non-correlation. Mann-Kendall and Homogeneity p-values vary from (0.170 - 0.917) and (0.052 - 0.963) respectively, suggesting the absence of significant hydrological trends and homogeneity (breakpoints), indicating stationarity. These results indicate the long-term consistency of environmental and physical conditions within the catchment at the time of data collection (Kang and Yusof, 2012). Although dams upstream of the gauge stations have altered the hydrological regime of the Niger and Benue rivers when established (Abam, 2001b, Olayinka et al., 2013), this study used data sets acquired after dam construction, thus sudden changes in discharge were not observed. Also, average serial correlation of all sites ranging from (-0.044 – 0.519) suggests the absence of statistically significant correlation between peak floods for each site.

Table 4. Preliminary analysis results (Mean, Homogeneity, Trend, Outlier, Serial correlation)

Station	n	Mean		Homo. (P-Value)		Trend (P-value [+/-])		Outlier LO - UO (P-Value)		Lag1 correlation	
		MI	RA	MI	RA	MI	RA	MI	RA	MI	RA
Baro	27	5414.464	5282.514	0.568	0.567	0.680 [+]	0.967 [+]	1805.638 - 8679.583 (0.149)	1805.638 - 8679.583 (0.664)	-0.044	-0.021
Lokoja	23	18912.48	17805.802	0.663	0.142	0.433 [+]	0.228 [+]	13846.000 - 23797.980 (0.415)	10752.972 - 23797.980 (0.364)	0.26	0.291
Umaisha	27	11838.31	12416.21	0.887	0.525	0.869 [-]	0.680 [+]	8775.407 - 15318.597 (0.209)	10138.233 - 13408.253 (0.893)	0.05	0.519
Onitsha	23	16742.22	15457.1	0.963	0.29	0.917 [-]	0.403 [-]	15161.802 - 19829.556 (0.063)	10451.462 - 19829.556 (0.286)	-0.103	0.119
Taoussa[1]	23	1759.316	1697.879	0.208	0.284	0.256 [-]	0.132 [-]	1542.080 - 1984.615 (0.208)	1286.796 - 1984.615 (0.352)	0.060	-0.113
Taoussa[2]	23	1774.456	1652.969	0.129	0.052	0.791 [+]	0.170 [-]	1536.970 - 1984.615 (0.980)	1044.185 - 1984.615 (0.054)	-0.072	0.191

MI = Multiple Imputation, RA = Altimetry, LO = Lower Outlier, UO = Upper Outlier, n = Number of data points, (-) = negative trend, (+) = positive trend, Taoussa[1] = Consecutively gapped, Taoussa[2] = Inconsecutively gapped.

4.3. Rating Ratio: rating curve extrapolation uncertainty

Figure 5-9 shows plots of Rating Ratios (RR) of peak flood data derived from the two infilling approaches (MI and RA), in relation to the threshold value of 1. As suggested by Haque et al., (2014), a RR much greater than (>>) 1 implies the presence of residual uncertainty in the discharge estimates due to ratings curve extrapolation.

From the results presented, the maximum RR values are observed at Baro (1.0172) and Taoussa (1.045) gauging stations, and are slightly greater than (>>) 1, suggesting minimal rating curve extrapolation uncertainty. Therefore further analysis is not undertaken to integrated rating curve extrapolation effect into the flood frequency estimation procedure using approaches such as Coefficient of Variation (CV), Likelihood framework and Bayesian framework suggested by Haque et al., (2014), Petersen-Øverleir and Reitan, (2009) and Lang et al., (2010).

Figure 5 Baro ratings ratio (RR)

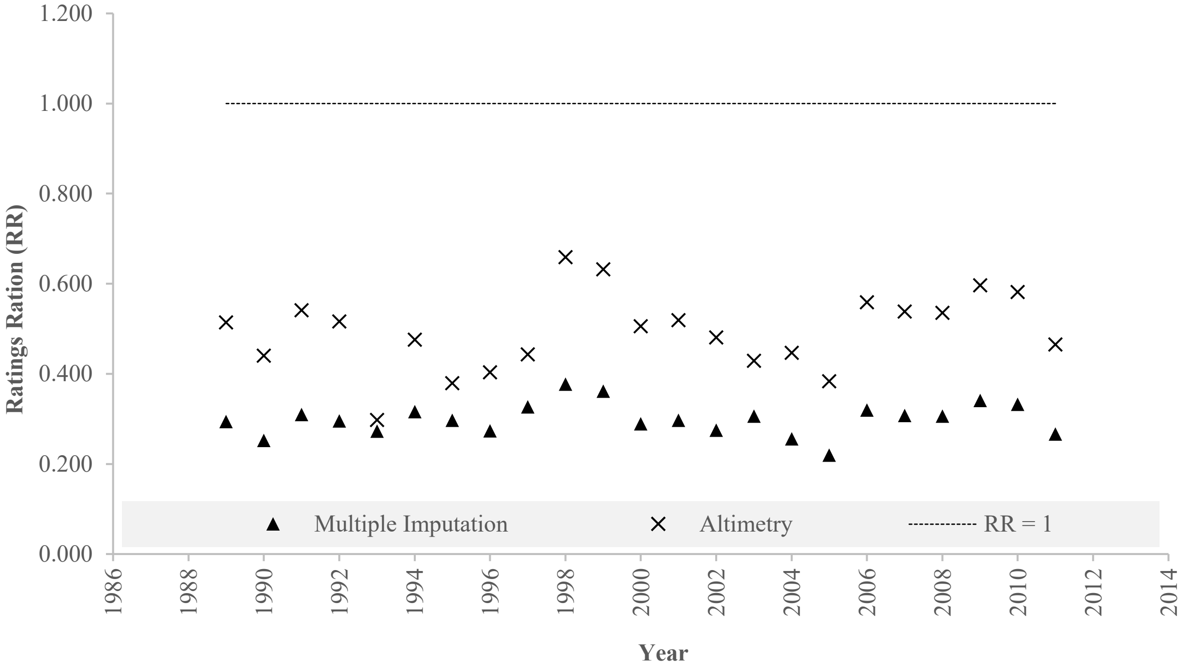


Figure 6 Lokoja ratings ratio (RR)

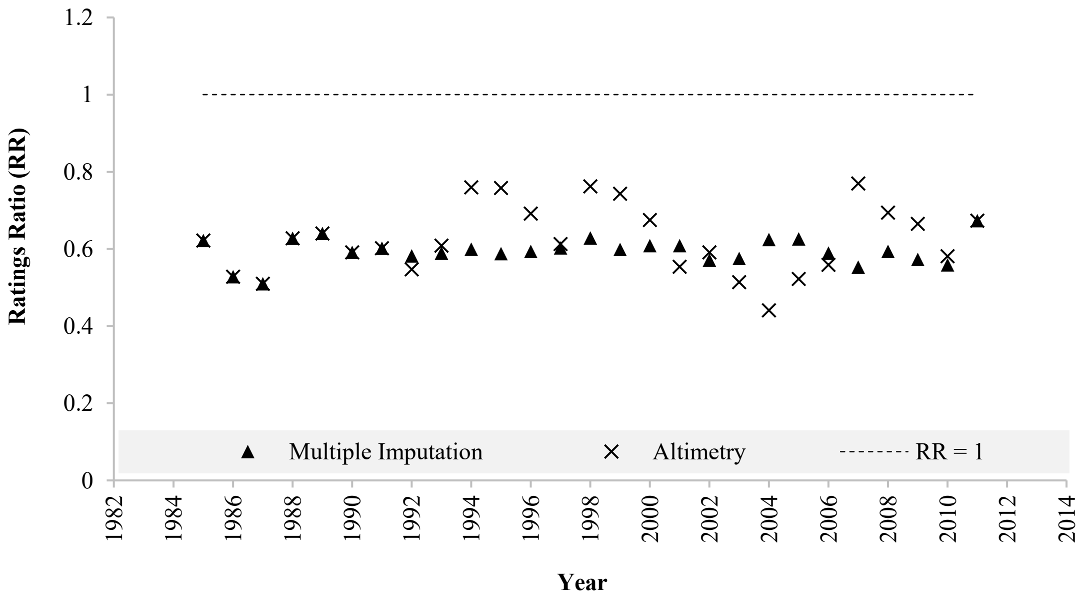


Figure 7 Umaisha ratings ratio (RR)

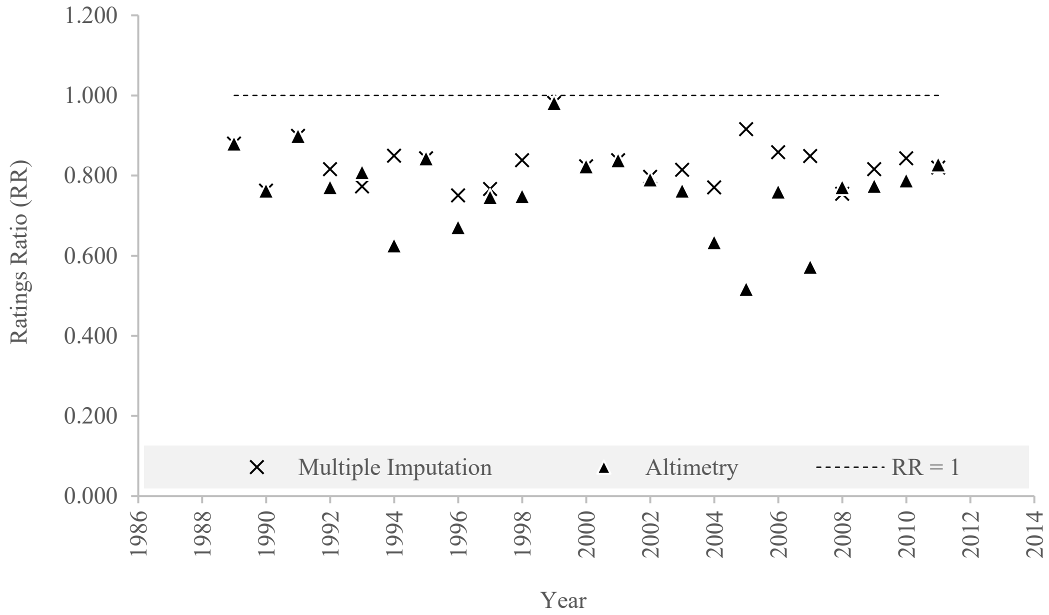


Figure 8 Onitsha ratings ratio (RR)

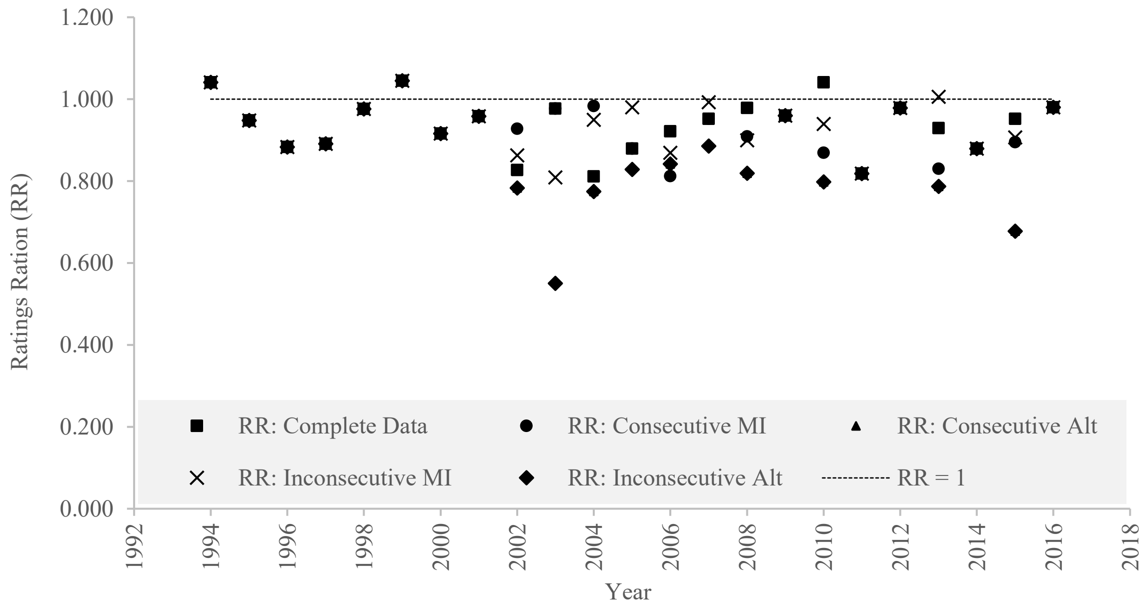


Figure 9 Taoussa ratings ratio (RR)

Figure **5 -9** ratings ratio (RR) for all stations, Multiple Imputation (MI) and Radar Altimetry (RA) comparison

4.4. Flood frequency estimation, uncertainties and application

Flood quantiles estimates, upper and lower confidence limits based on 90% confidence interval for five return periods (1-in-2, 1-in-5, 1-in-20, 1-in-50 and 1-in-100 year flood events) are presented in table 5 - 8, and the flood frequency plots for Lokoja and Umaisha gauging stations are presented in Figure 10 (a-d). At Lokoja, an equal number of missing data were filled with radar altimetry and Multiple Imputation, while Umaisha has the most missing data (gaps). Presenting the results from these stations with varying gaps allowed for the assessment of the effect of the two missing data infilling approaches for datasets. The dash lines above and below the expected quantile line (Figure 10 a-d) represent the upper and lower uncertainty boundaries, and the area within the uncertainty boundaries defines the confidence or credibility limits of the derived estimates, i.e. the smaller, the better and vice versa. Flood frequency curves of other sites are presented in Supplementary Figure 4 – 8.

The difference between MI and RA infilled flood estimates generally tend to increase with increasing return periods, and these differences are more pronounced for inconsecutively gapped historic time series such as Umaisha (Table 7), where MI approach resulted in much lesser flood estimates than RA. MI is typically known for its ineffectiveness in filling inconsecutive missing data points (Tyler et al., 2011), thus this result was expected. At Baro, Lokoja and Onitsha gauging stations that exhibited consecutive gaps, the MI flood estimates were higher than those of RA (Table 5, 6 and 8). These results imply that both methods can be applied interchangeably for consecutively gapped time-series. Nevertheless, the statistical significance of these results is further evaluated by permutation and Kolmogorov - Simonov tests and presented in section 4.5.1.

Table 5 Baro flood quantile estimates and uncertainty boundaries for MI and RA filled datasets

Return Period (1-in-Year)	Expected quantile (m^3/s)		Lower Uncertainty Limit (m^3/s)		Upper Uncertainty Limit (m3/s)	
	MI	RA	MI	RA	MI	RA
2	5415.9	5244.3	4906.3	4676.8	5770.9	5858.3
5	6753.9	6741.0	5949.4	6090.3	7444.5	7565.0
20	8018.9	8267.1	7209.9	7408.6	11870.9	10194.6
50	8614.7	9039.3	7845.3	7971.0	17085.9	12145.3
100	8980.1	9536.3	8229.0	8271.4	23207.5	13887.6

Table 6 Lokoja flood quantile estimates and uncertainty boundaries for MI and RA filled datasets

Return Period (1-in-Year)	Expected quantile (m^3/s)		Lower Uncertainty Limit (m^3/s)		Upper Uncertainty Limit (m^3/s)	
	MI	RA	MI	RA	MI	RA
2	19006.2	17934.5	17947.2	16529.0	20198.5	19479.5
5	22200.2	22013.5	20653.9	20115.6	24413.6	24548.2
20	26592.40	27139.4	23856.4	24056.5	32051.6	33002.4
50	29529.4	30294.0	25698.7	26172.6	39055.4	39780.8
100	31812.1	32611.4	26987.0	27559.2	45774.8	45710.1

Table 7 Umaisha flood quantile estimates and uncertainty boundaries for MI and RA filled datasets

Return Period (1-in-Year)	Expected quantile (m^3/s)		Lower Uncertainty Limit (m^3/s)		Upper Uncertainty Limit (m^3/s)	
	MI	RA	MI	RA	MI	RA
2	11868.8	12409.9	11540.7	11723.9	12232.2	13140.8
5	12995.2	14478.52	12489.1	13573.6	13672.2	15642.9
20	14676.3	17019.0	13718.3	15580.5	16370.9	19756.0
50	15887.6	18549.5	14497.5	16615.7	18832.8	23108.6
100	16878.1	19657.8	15071.1	17269.6	21156.0	25951.1

Table 8 Onitsha flood quantile estimates and uncertainty boundaries for MI and RA filled datasets

Return Period (1-in-Year)	Expected quantile (m^3/s)		Lower Uncertainty Limit (m^3/s)		Upper Uncertainty Limit (m^3/s)	
	MI	RA	MI	RA	MI	RA
2	16575.0	15649.5	16167.9	15110.1	17029.2	16229.4
5	17723.2	17110.0	17151.4	16419.0	18565.1	18063.1
20	19302.0	18901.5	18272.96	17806.3	22009.8	21251.1
50	20357.7	19979.5	18840.6	18508.7	25557.4	24003.6
100	21178.3	20759.5	19194.3	18947.0	29506.5	26585.8

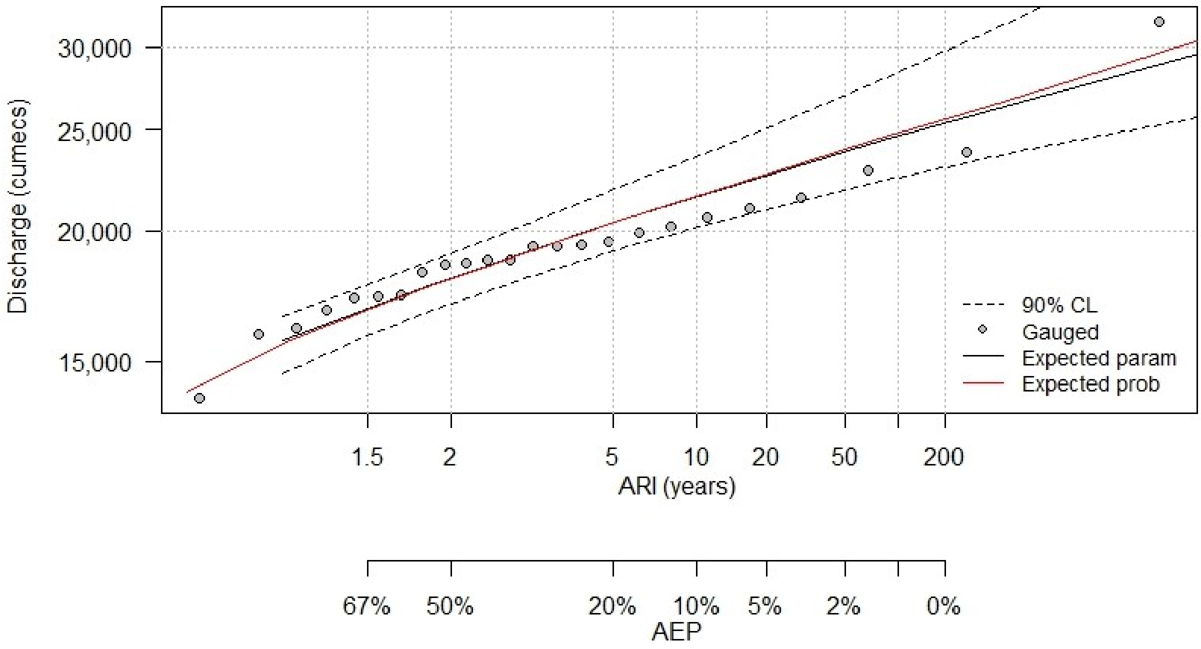


Figure 10 (a) Lokoja-MI flood frequency plot

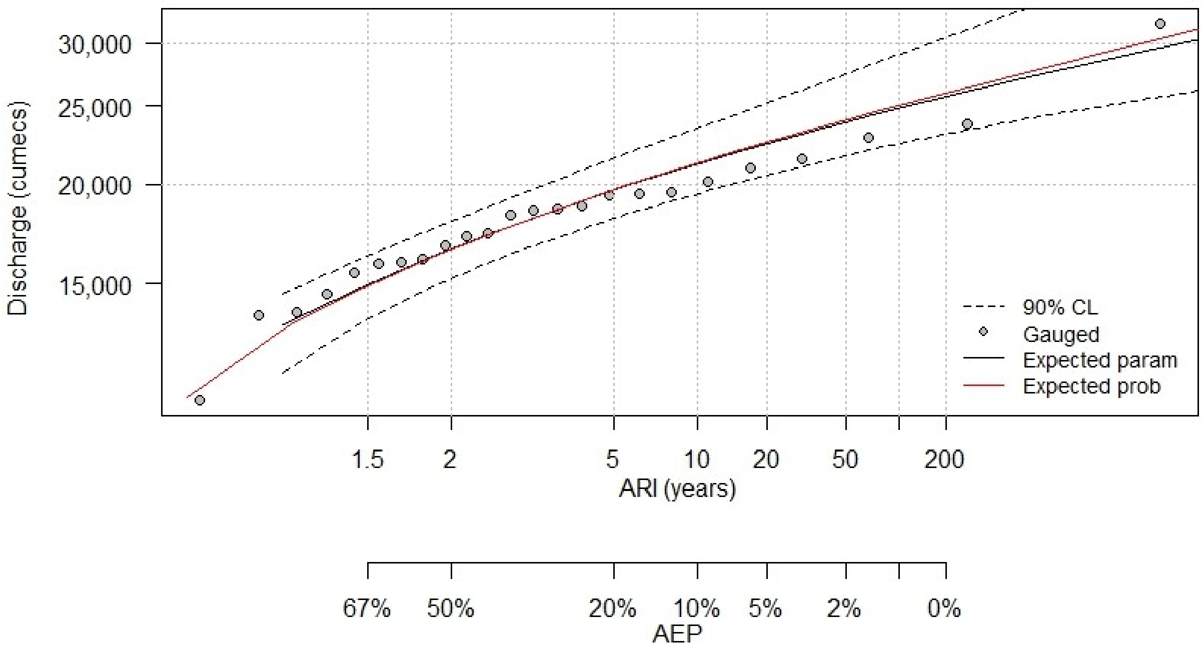


Figure 10 (b) Lokoja-RA flood frequency plot

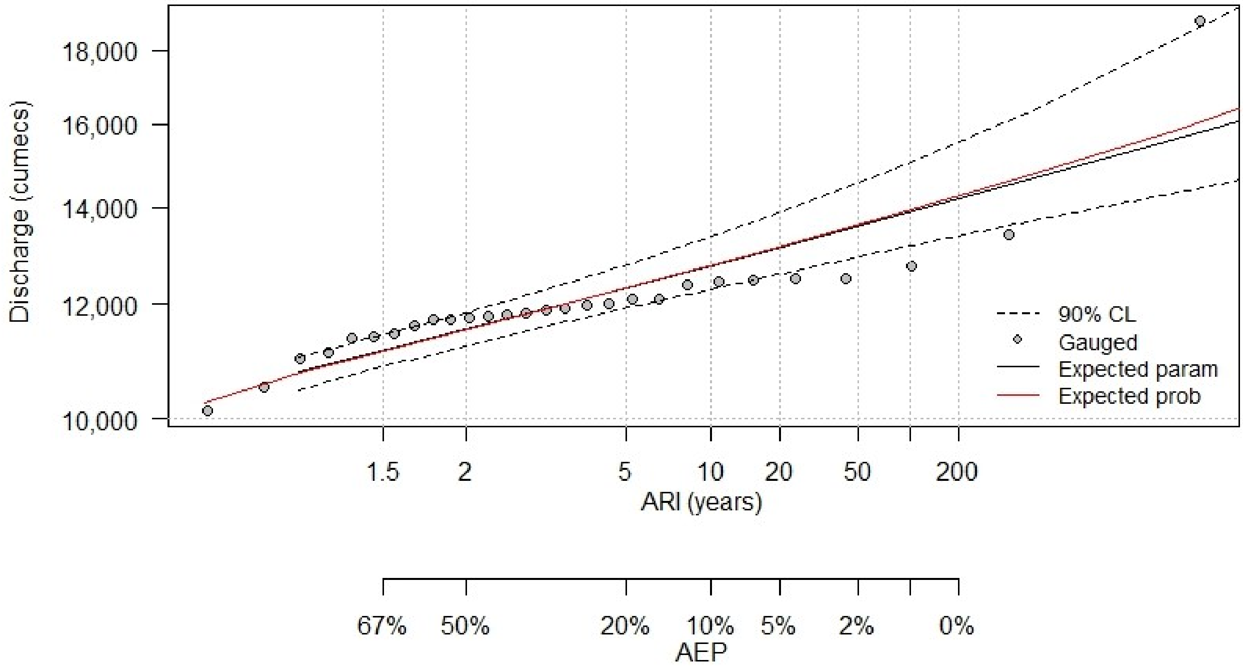


Figure 10 (c) Umaisha-MI flood frequency plot

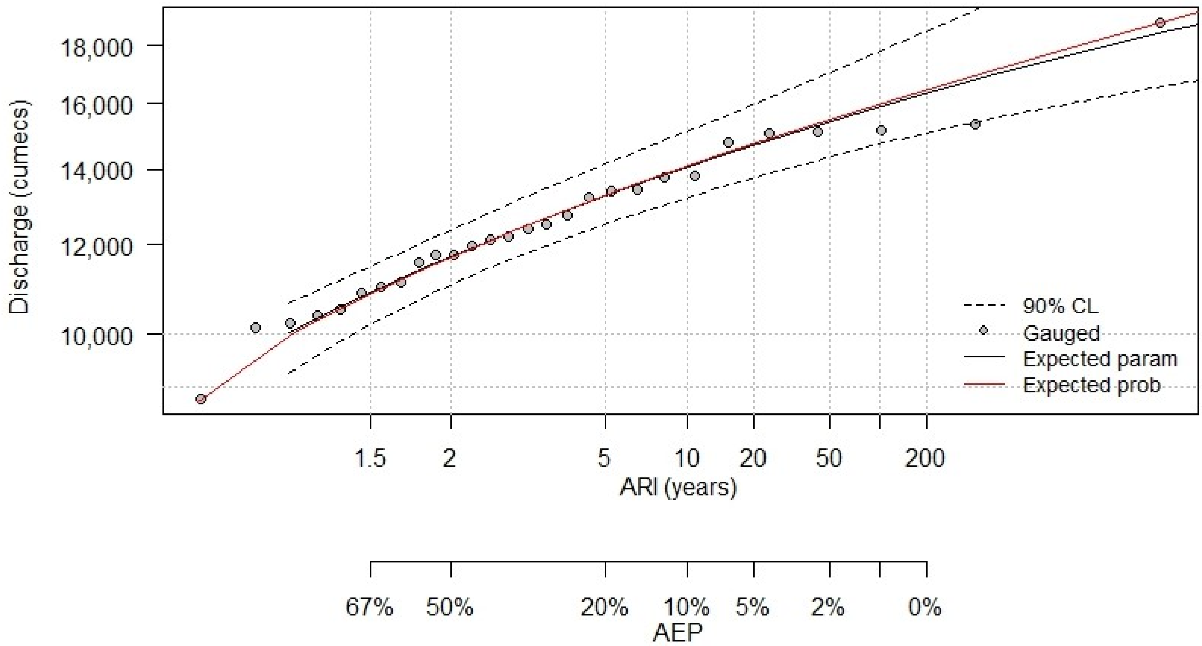


Figure 10 (d) Umaisha-RA flood frequency plot

Figure 4 (a-d): Probability distribution plots (PDP) of flood quantiles based on Multiple Imputation (MI) and Radar Altimetry (RA) filling methods.

4.5. 2012 and 2015 floods return period estimations

The unprecedented flood of 2012 was reported as one of the most devastating floods in Nigeria in 40 years, followed by subsequent flood event of 2015. The post-flood need assessment report (FGN, 2013), revealed (i) economic and infrastructure loss worth 16.9 billion US Dollars, (ii) displacement of 3.8 million people, and (ii) loss of 363 lives.

A retrospective approach was undertaken in this study to categorise the flood magnitude that resulted in these devastating impacts having filled the data gaps. The results are presented with better details in Table 6 and 7 revealed that the peak flood magnitudes of 2012 (31700 m^3/s at Lokoja; 18800 m^3/s at Umaisha) and 2015 (22700 m^3/s at Lokoja) detailed in the Nigerian Flood Outlook (NIHSA, 2016) were within the 90% confidence level bounds of 1-in-50 and 1-in-100-year flood events. This implies that radar altimetry application in filling gaps in hydrological datasets can be instrumental in improving flood management decisions in data-sparse regions through the provision of substantial information that would enhance mitigation efforts to reduce the impact of flooding on the potentially exposed populace.

At Baro (Niger River), the 2012 and 2015 flood events were captured as 1-in-100 year flood events i.e. 13200 m^3/s and 13000 m^3/s respectively from data derived from both missing data infilling methods. Furthermore, the upper uncertainty boundaries of the quantile estimates derived from MI was greater than RA's, depicting the possibility of design over-estimation in practice, if MI flood estimates are implemented for flood risk management.

4.6. Assessment of missing data infilling method effect on flood quantile estimates

4.6.1. Assessment of Radar Altimetry and Multiple Imputation infilling, Niger and Benue rivers, Nigeria

The results of the Permutation and Kolmogorov - Simonov tests presented in Table 9 assesses statistical significance of the difference between flood quantiles estimated using multiple imputation and radar altimetry infilling approaches. Radar altimetry data was not available for all the missing data years, hence the Missing /infilled-RA column of Table 9 shows the number of missing data points and available altimetry data points. Umaisha gauging station had the most missing data (19), of which (14) radar altimetry data points where available to fill the gaps, and the remaining (5) filled with multiple imputation. At Lokoja, the 6 missing data points where equality filled with multiple imputation and radar altimetry approach, thus providing a reference station for equal comparison of both approaches.

Permutation test results (P_{perm} = 0.02) at Umaisha station with inconsecutively gapped data suggests that flood frequency estimates derived from MI and RA imputation approaches differed significantly, and the D_{ks} statistic = 0.571 and P_{ks} = 0.017 for the Kolmogorov - Simonov test further reveals the difference in the quantile distribution for both estimates. This deviation is attributed to the high number of missing data filled by the contrasting techniques i.e. 14 out of 19 missing data, and MI inability to accurately fill inconsecutively gapped datasets (Graham et al., 2007, Rochtus, 2014, Tyler et al., 2011). At Lokoja station where an equal number of missing data were filled by both techniques, the difference between derived flood frequency estimates and distributions was not statistically significant (P_{perm} = 0.713, D_{ks} = 0.143, and P_{ks} = 0.98). Similarly, at Onitsha and Baro, the estimated quantiles and probability distribution were not statistically different ($P > 0.05$), implying that the application of altimetry in filling missing data did not result in any viable change in the quantile estimates and distributions when compared to MI. Therefore, both approaches can be applied interchangeably depending on the number of gaps and spread within the historical time series.

Table **9**: Kolmogorov-Simonov and Permutation test results

Stations	Missing/infilled-RA	Permutation test	Kolmogorov - Simonov test	
		P_{perm}-Value	K-S Statistic (D_{ks})	P_{ks}-Value
Umaisha	19 (14)	0.020	0.57143	0.0017
Onitsha	16 (9)	0.407	0.19048	0.8531
Lokoja	6 (6)	0.713	0.14286	0.9870
Baro	12 (1)	0.063	0.38095	0.0948

4.6.2. Assessment of Radar Altimetry and Multiple Imputation infilling at Taoussa, Mali

Flood frequency estimates and the upper and lower uncertainty bounds for a 1-in-2 to 1-in-100year flood events are presented in Table 10 to capture varying scenarios of gaps (consecutive and inconsecutive) and infilling approaches (Radar Altimetry and Multiple Imputation). The results show that flood estimates for both infilling approaches are within the uncertainty bounds of the complete data flood events for all return periods, except the 1-in-2year flood derived from inconsistently gapped data filled with radar altimetry. Permutation and Kolmogorov - Simonov test results (Table 11) further revealed that though flood estimates did not significantly differ (P_{perm}> 0.05), the D_{ks} and P_{ks}-Values for the radar altimetry estimates for both consecutive and inconsecutively gapped time series showed significant differences in distribution when compared to complete data. The observed difference in distribution suggests that the two complete and RA imputed flood estimates are not drawn from the same distribution despite not being significantly different (Ewemoje and Ewemooje, 2011). Therefore, an assessment of the optimal probability distribution for fitting the historical time series derived infilling the varying infilling approaches is suggested, rather than using a predefined distribution such as GEV as was the case in this study, given that varying probability distribution can result in very different flood estimates even for the same dataset (Laio et al., 2009).

Table 10: Taoussa flood quantile estimates and uncertainty boundaries for complete historical data and consecutively and Inconsecutively gaped missing data filled with MI and RA approaches

Return Period	Discharge Complete	Lower Limit (Complete)	Upper Limit (Complete)	Discharge (Consecutive) MI	Discharge (Consecutive) RA	Discharge (Inconsecutive) MI	Discharge (Inconsecutive) RA
2	1787.79	1734.88	1842.2	1760.15	1709.32	1779.18	1669.77
5	1898.39	1850.91	1954.0	1874.26	1861.13	1887.62	1835.12
20	1983.25	1938.07	2087.7	1978.07	1984.19	1976.08	1986.4
50	2015.89	1967.17	2170.6	2025.17	2034.14	2012.2	2055.43
100	2033.39	1978.96	2229.2	2053.36	2061.89	2032.35	2096.89

Table 11 Kolmogorov-Simonov and Permutation test results, Taoussa gauging station

Data gap infilling comparison	Permutation (P_{perm}-Value)	Kolmogorov - Simonov test	
		K- S Statistic (D_{ks})	P_{ks} - Value
Complete Vs Consecutive (MI)	0.731	0.381	0.095
Complete Vs Consecutive (RA)	0.870	0.429	0.041
Complete Vs Inconsecutive (MI)	0.997	0.238	0.603
Complete Vs Inconsecutive (RA)	0.873	0.476	0.016

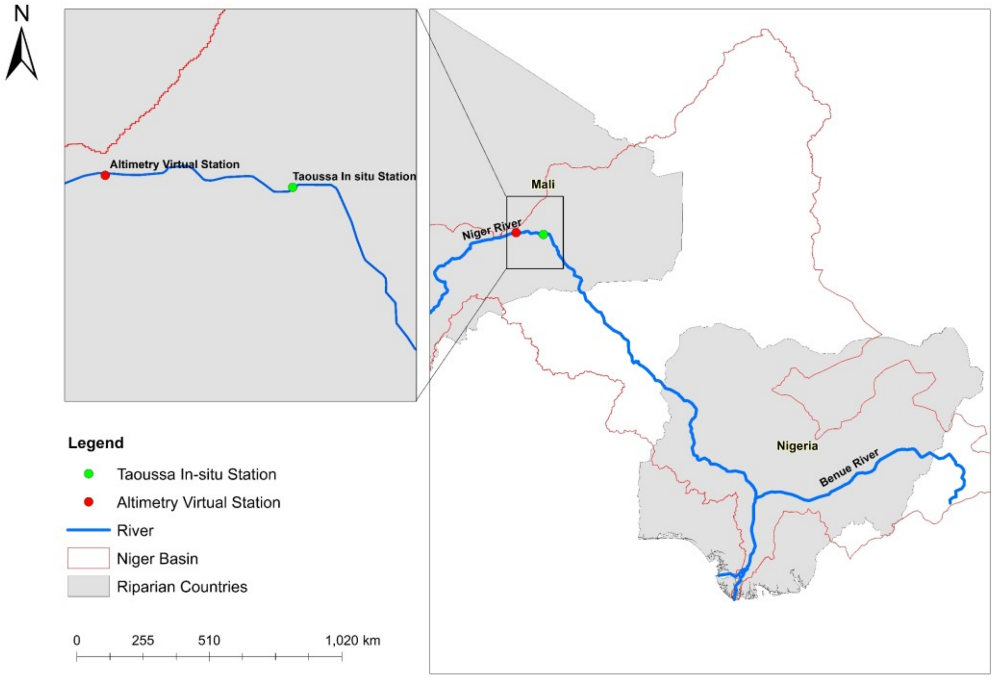
5. Conclusion

Missing data in hydrological time series is an unavoidable part of ground monitoring and emanates due to varying factors that include natural, technical, physical, procedural and financial constraints. These challenges consequently result in uncertain design flood estimates (Tyler et al., 2011, Starrett et al., 2010), thus increasing flood exposure and/or cost of flood control and management measures implementation based on such results. Advancement in open-access radar altimetry provides reasonably accurate continuous water level measurements not hampered by gaps as evident in *in situ* measurements (Escloupier et al., 2012), especially during extreme flood events. Also, advances in computational hardware and software have reduced the challenges associated with undertaking complex statistical imputations to estimate missing data (Little, 2002).

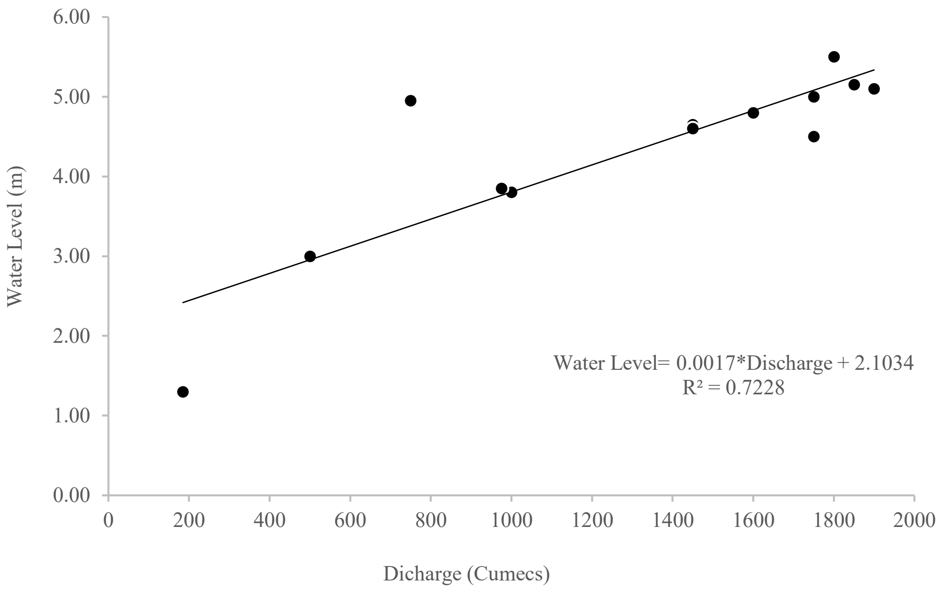
This study applies Radar Altimetry and Multiple Imputation to fill gaps in hydrological historical time-series and flood frequency estimations, thereby capturing scenarios of supplementary data availability as unavailability respectively, as usually, the case along several rivers in developing regions. Furthermore, the effect of both approaches on flood frequency estimates was evaluated for gauging stations along the Nigeria and Benue rivers, accounting for the variation in missing data apparent in the study area, i.e. consecutive (1-3 years) and inconsecutive (> 3 years). To further evaluate the most suitable infilling approach, data was deliberately removed from complete dataset to depict these missing data variations.

Results from this study revealed (i) improved correlation between *in situ* water level measurements and radar altimetry as the distance between them reduce and vice versa, (ii) the size of the gaps in the hydrological time series (consecutive and inconsecutive) determines to a large extent the missing data imputation approach applied; (iii) Radar Altimetry missing data infilling approach outperformed Multiple Imputation, especially for widely gapped time series (> 3 years), but did not differ much for data sets with gaps of 1-3 years, hence can be applied interchangeably for datasets with consecutive gaps; and (iv) the previously unquantified 2012 and 2015 flood events in Nigeria were quantified as 1-in-100 and 1-in-50year floods respectively, and can be applied to inform flood management decisions having filled the historic data gaps. Despite the progress and potential portrayed in this study, the outcome could contain residual uncertainties that have propagated from in situ and altimetry hydrological data collection process, rating curve extrapolation, probability distribution and methodology selection. The quantification of these uncertainties is however beyond the scope of this study. Furthermore, hydrodynamic flood modelling and mapping of flood depth and extent based on the outcome of this section will be undertaken in Chapter 6.

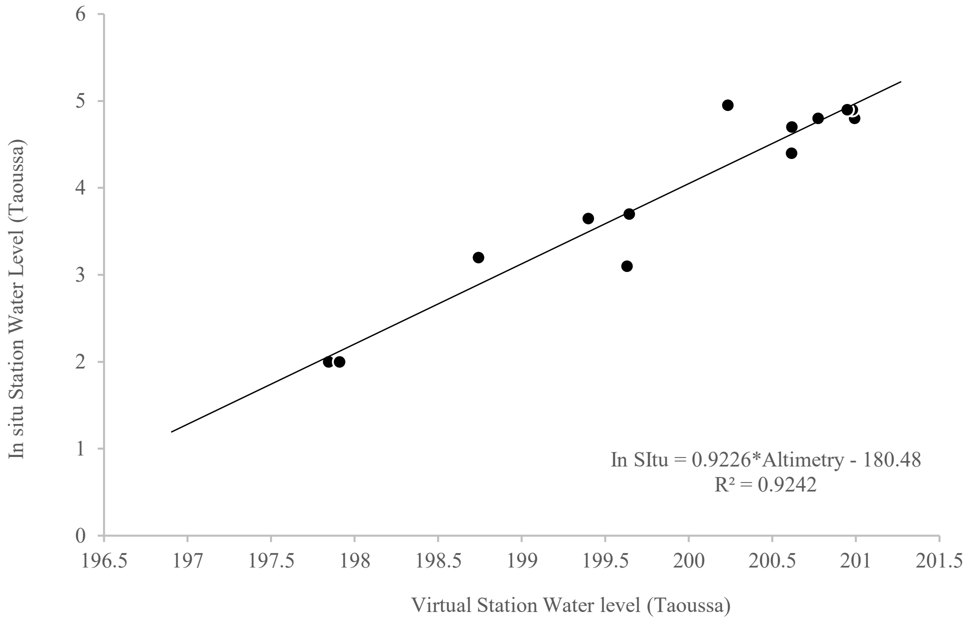
Chapter 3 Supplementary Figures and Tables



Supplementary Figure 1. Approach validation *in-situ* and Altimetry virtual station locations



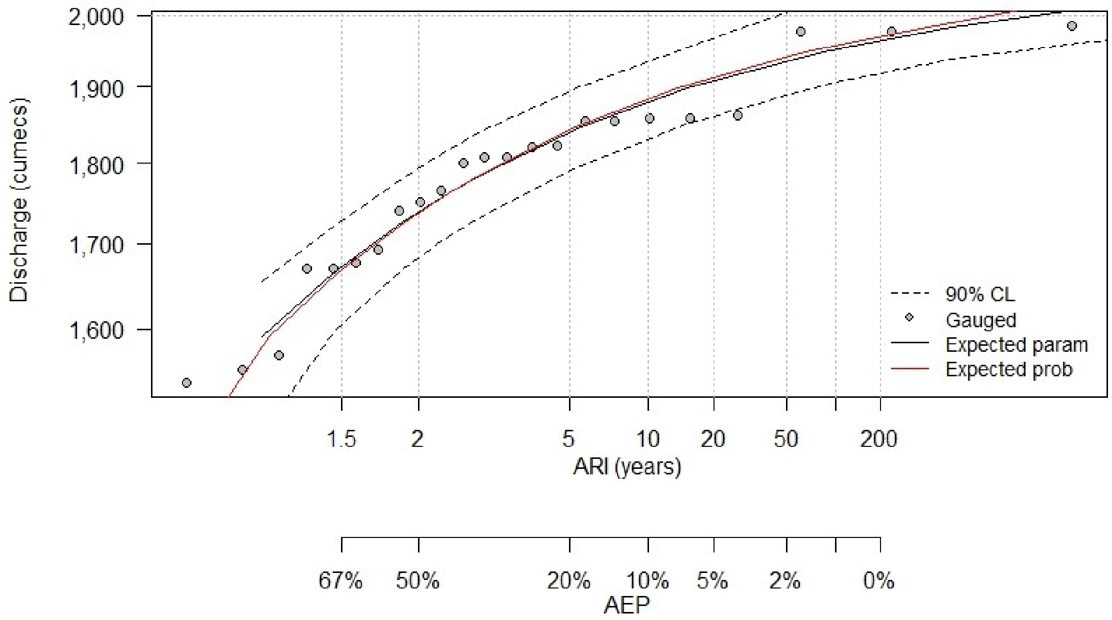
Supplementary Figure 2. Taoussa Rating Curve



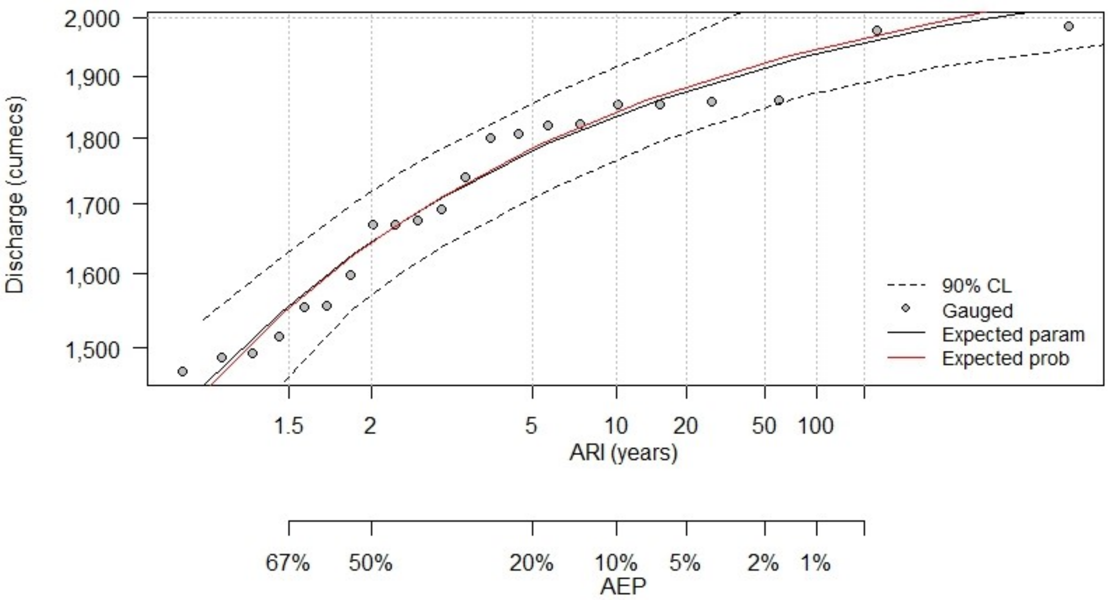
Supplementary Figure 3. In situ Station (Taoussa) vs Virtual Station (Taoussa)

Supplementary Table 1. Radar Altimetry Missing data filling outcome

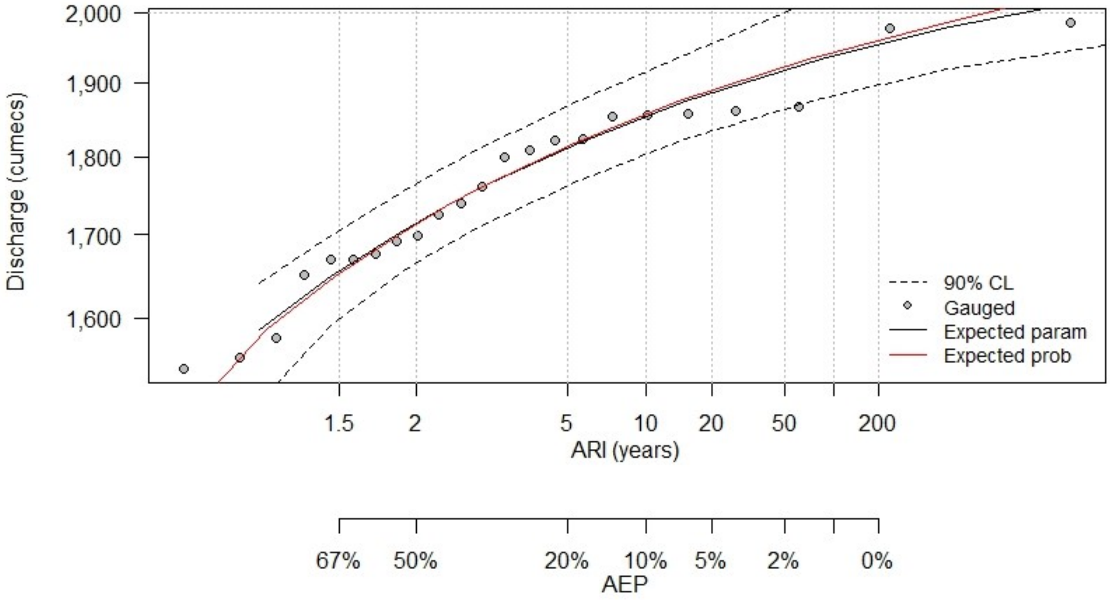
S/N	Year	Altimetry Water level (m)	Filled Water level (m)	Filled Discharge (m3/s)
1	2002	200.773	4.754	1487.468
2	2003	199.642	3.710	1044.185
3	2004	200.730	4.714	1470.615
4	2005	200.992	4.956	1573.303
5	2006	201.056	5.015	1598.387
6	2007	201.268	5.210	1681.478
7	2008	200.947	4.914	1555.666
8	2009	201.205	5.152	1656.786
9	2010	200.846	4.821	1516.080
10	2013	200.790	4.769	1494.131
11	2014	200.743	4.726	1475.710
12	2015	200.261	4.281	1286.796



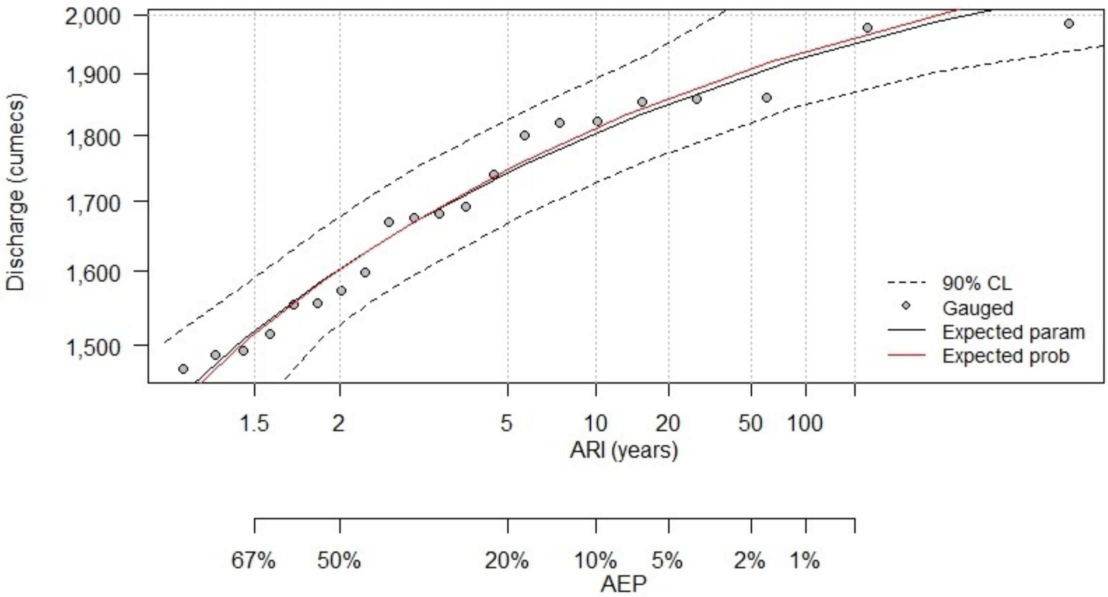
Supplementary Figure 4 Taoussa Complete flood frequency plot



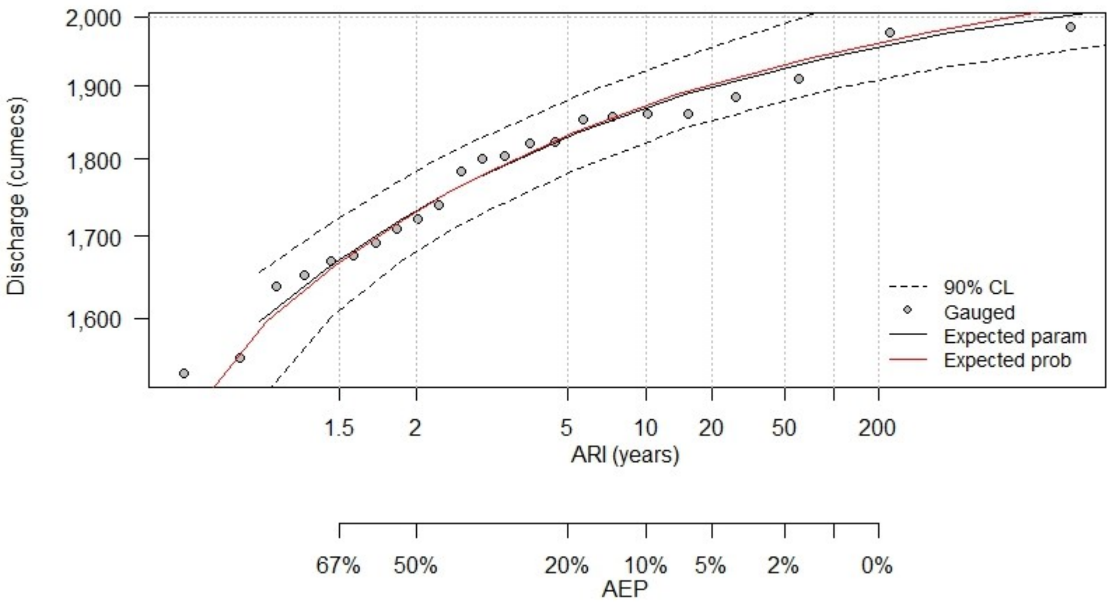
Supplementary Figure 5 Taoussa Consecutive Altimetry flood frequency plot



Supplementary Figure 6 Taoussa Consecutive Multiple Imputation flood frequency plot



Supplementary Figure 7 Taoussa Inconsecutive Altimetry flood frequency plot



Supplementary Figure 8 Taoussa Inconsecutive Multiple Imputation flood frequency plot

CHAPTER 4: ACCOUNTING FOR CLIMATE VARIABILITY IN REGIONAL FLOOD FREQUENCY ESTIMATES FOR WESTERN NIGERIA

Abstract

Extreme flood events are becoming more frequent and intense, owing to climate change and other anthropogenic factors. Nigeria recently has been impacted immensely, resulting in damage to infrastructures, displacement of people, and loss of lives. To reduce such impacts in the future, effective planning is required, underpinned by analytical work based on reliable data and information. Such data is however sparse in developing regions, owing to financial, technical and organisational drawbacks. Regional Flood Frequency analysis (RFFA) is applied in this study to curtail data unavailability and short record deficiency challenges, by agglomerating data from various sites with (i) similar hydro-geomorphological characteristics, (ii) governed by a similar probability distribution, and (iii) differ only by an "index-flood" that can be estimated using proxy information. Using ICI-RAFT tool to implement the RFFA, climate indices are integrated to account for climate variability effect.

Data from seventeen gauging stations within the Ogun-Osun River basin in western Nigeria were analysed, resulting in the delineation of three sub-regions delineated, of which two were homogeneous and one non-homogeneous. Generalized Logistic (GLO) distribution was fitted to the annual maximum flood series for the two homogeneous regions to estimate flood magnitudes and probability of occurrence while accounting for climate variability. The influence of climate variability on flood estimates was linked to Madden-Julian Oscillation (MJO) and resulted in an increased probability of high return period flood (i.e. 1-in-100year) occurrence. The results reiterate the importance of taking climate variability into account in flood frequency estimation and suggests a review flood management measures based on the assumption of stationarity.

Keywords: Climate variability; Regional flood frequency; climate-indices; L-moment, Madden-Julian Oscillation (MJO); Generalised Logistic (GLO)

1. Introduction

Floods are natural hazards aggravated by anthropogenic factors and result in the destruction of agricultural landforms, livestock and crops, disruption of socio-economic activities, damage to properties and infrastructures, loss of lives and financial loss (FGN, 2013). In Nigeria (the case study of this research), the recent unprecedented levels of flooding and impact resulted in increased public, government and other stakeholders concern and curiosity about the probability of flood recurrence, in order to plan and implement appropriate mitigation measures to reduce flood impact (Agada and Nirupama, 2015). Knowledge of flood frequency estimates is crucial in ensuring that socio-economic activities and infrastructural development are planned appropriately (Hosking and Wallis, 1997). Accurate estimates of flood frequency estimates, also known as Annual Exceedance Probabilities (AEP) are also important for design of flood defence structures (dykes, levees, dams, etc.), construction of hydraulic structures (Bridges and culverts), development for floodplains and urban land-use regulations, emergency management and insurance policy development (Kjeldsen et al., 2002, Saf, 2009b). Under-estimation of the design flood can lead to increased flood risk with potentially damaging consequences, while overestimation can lead to resource wastage and flood aggravation upstream or downstream (Mishra et al., 2009).

To accurately estimate AEP, networks of gauging stations are established to collect hydrological data over a long period (Herschy, 2008). However, it is logistically difficult due to harsh topography and cost intensive to establish gauging stations at every location of interest. Hence, some locations are usually left ungauged or with short data for newly established stations. In several developing regions many catchments are poorly/sparsely gauged, due to (i) lack of commitment by station operators, (ii) deteriorating conditions of observation equipment, (iii) insecurity challenges, and (iv) inaccessibility to remote locations (Ampadu et al., 2013a, Olayinka et al., 2013). The absence of quality and sufficient data leads to poor flood predictions, as often the case in developing regions (Dano Umar et al., 2011). Therefore, It is essential to explore techniques with the capacity to extract the maximum value from any available data, to develop reasonable flood frequency estimates (Oyegoke and Oyebande, 2008).

Generally, the choice of techniques for flood frequency estimation depends on the availability of historical flood records at/or around the specific site of interest (Reed, 1999). When sufficient historical flood data are available, AEP is estimated by the application of direct (at-site) flood frequency analysis which involves fitting predefined probability distribution to the annual maximum flood or partial flood time series (Herschy, 2008). Where data is insufficient, indirect flood estimation procedures are used which includes (i) the adoption of hydro-meteorological data from other locations similar in characteristics to the site of interest (Hrachowitz et al., 2013, Wagener, 2007, Gupta et al., 2008) and (ii) the incorporation of data from other sources such as remote sensing (Smith et al., 2015, Owe and Neale, 2007). In the present study, the former approach is adopted while in our ongoing related work the merits of the latter approach are being investigated.

A major factor that affects future flood regimes and must be considered when estimating flood magnitudes is the changing climatic conditions, which results in more intense and frequent flooding (Kunkel, 2003). Estimating frequencies under climate variable conditions require the incorporation of non-stationarity effects defined by statistically significant breakpoints (Pettitt, 1979) and trends (Kendall and Stuart, 1969) within historical time series. While stationary flood frequency methods entail directly fitting predefined probability distributions to historical data, non-stationary approaches are not as straight and requires the integration climate variability using climatic indices - a mechanism for depicts climatic influence (O'Brien and Burn, 2014, Kochanek et al., 2013, Hounkpè et al., 2015b). Several studies have demonstrated the benefits of incorporating climatic variability into flood frequency estimation procedures (Kochanek et al., 2013, Li and Tan, 2015, Machado et al., 2015, O'Brien and Burn, 2014), and emphasized the need for a paradigm shift in approach to enable the development of robust and resilient predictions (Hounkpè et al., 2015b, Solecki and Rosenzweig, 2014). Also, recent evidence from studies in West Africa (Mouhamed et al., 2013, New et al., 2006, Diatta and Fink, 2014) and Nigeria (Salau et al., 2016) further supports this argument and provides evidence of strong correlations between climatic variability and hydro-meteorological events in these regions (Aich et al., 2014a, Hounkpè et al., 2015b, De Paola et al., 2013).

Therefore, this study aims to tackle the problem of data sparsity and limited resources to estimate flood frequency while taking into consideration climate variability effect, as often the case in developing countries. In subsequent sections, (2) describes the study area and data sources; (3) details preliminary analysis and L-moment based regional flood frequency techniques, taking climate variability effect into account; (4) presents the results of preliminary analysis, direct and regional L-moment based flood frequency estimates; and (5) concludes one the findings and implication of the results on flood management.

2. Study Area and Data Sources

The Ogun-Osun River Basin (OORB) is in western Nigeria (6°30′ - 8°20′N latitude and 3°23′- 5°10′E longitude), and encompasses four states including Ogun, Osun, Oyo and Lagos, within a 66,264 km^2 area. The basin is drained by two major tributaries, Ogun and Osun, and other minor tributaries including Yewa, Ibu, Ona, Sasa and Ofiki Rivers. The climate of OORB is influenced by tropical continental and maritime air masses (Adeaga et al., 2006), and experiences an annual rainfall of 1400 mm to 1500 mm; mean annual air temperature between 25.7°C and 30°C; and relative humidity varying from 37% – 85% for dry and wet seasons respectively (Adeleke et al., 2015). OORB has experienced recurring flooding recent years, caused by factors such as intense precipitation; poor urban planning and waste management; and failure of upstream hydraulic systems, resulting in socio-economic, infrastructural, ecological and environmental impacts (Jinadu, 2015, Komolafe, 2015).

Hydrological data (discharge, water levels and rating curves) used for this study were provided by the Ogun-Osun River Basin Development Authority (OORBDA), the agency responsible for the collection and management of data in the basin. Additional data sets for two hydrological station, i.e. Yewa Mata and Ona River/Sala village were extracted from published research Olukanni and Alatise (2008) and Ewemoje and Ewemooje (2011) respectively, using the WebPlotDigitizer (Rohatgi, 2014). The catchment area for each station was delineated from 30 m Shuttle Radar Topography Mission (Farr et al., 2007) using Arc Hydro in ArcMap. The properties of the gauging stations for OORB is presented in Table, and the spatial distribution of gauges is presented in Figure 1, showing the spread and sparsity of the hydrological monitoring network. Climate indices were provided by the National Oceanographic and Atmospheric Administration (NOAA) (GCOS-AOPC/PPOC, 2016), available within the International Centre for Integrated Water Resources Management (ICIWaRM) Regional Analysis of Frequency Tool (ICI-RAFT) database, and includes multi-decadal meteorological events such as Pacific Decadal Oscillation, El Nino/Southern Oscillation, Madden–Julian Oscillation (MJO), North Atlantic Oscillation and others.

Table **1** Gauge stations properties

S/N	Station ID	Years	Data	Lat.	Long.	Missing	Cat. Area (km^2)
1	Eggua	1980-2012	26	7.05	2.92	0	0.64
2	Idogo	1980-2012	24	6.83	2.92	0	0.923
3	Ajilete	1980-2012	29	6.70	2.92	0	2.89
4	Oba/Oyo-Obgbomoso	1966-1988	23	6.70	2.92	0	2.90
5	Ebute Igboro	1980-2012	25	6.90	2.90	0	7.92
6	Yewa Mata	1982-1994	14	6.95	2.92	0	24.05
7	Ijaka-Oke	1980-2012	27	7.18	2.90	0	63.15
8	Ogun/Oyo-Iseyin road	1966-1988	23	7.85	3.94	0	578.00
9	Ofiki/Ofiki town	1966-1988	23	7.63	3.21	1	715.00
10	Ogun/Shepeteri	1966-1988	23	8.63	3.65	0	1190.00
11	Oyan/Ilaji-Ile	1982-2009	26	7.98	3.00	1	1460.00
12	Ofiki/Iganna-Ilere road	1966-1988	23	7.95	3.23	0	3978.00
13	Ofiki/Igangan	1966-1988	23	7.68	3.18	0	2732.00
14	Oshun/Iwo railway	1965-1988	24	7.85	3.93	0	4325.00
15	Ona river/Sala Village	1982-1999	18	7.01	3.015	0	8500.00
16	Ogun/Olokemeji	1966-1987	22	7.45	3.09	0	9140.00
17	Ogun/Ibaragun	1965-1988	24	6.77	3.33	0	21660.00

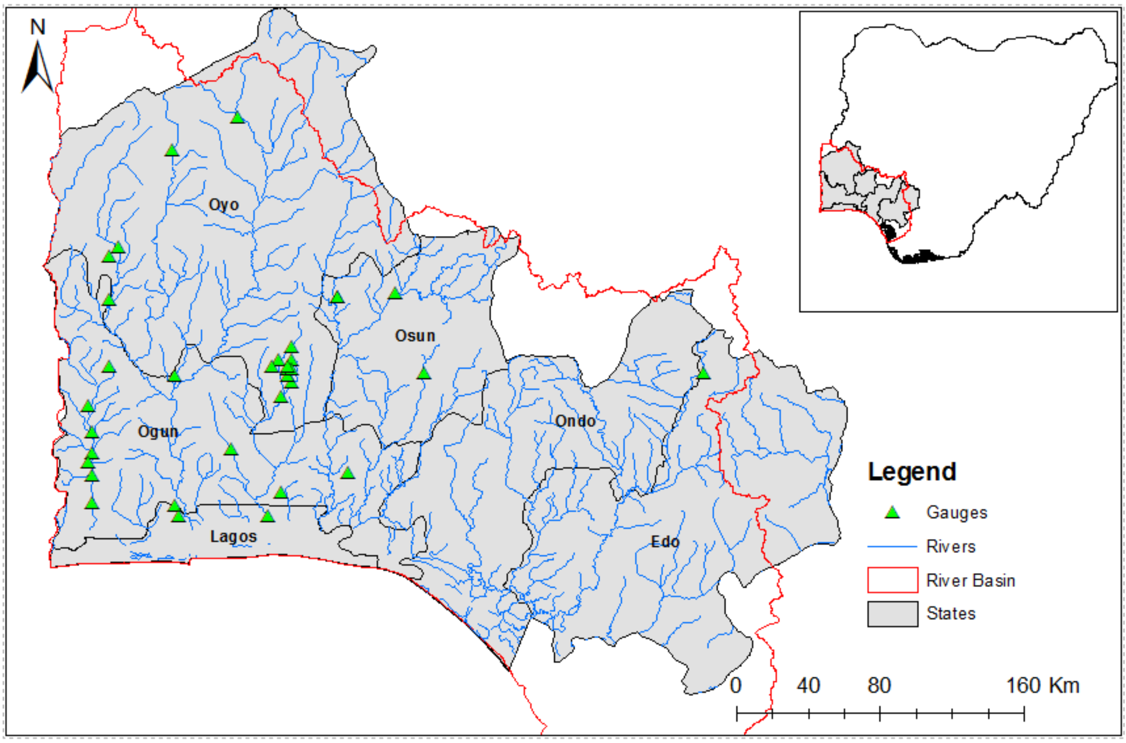


Figure **1**: The OORB study region.

3. Methodology

3.1. Data Preparation and Preliminary analysis

Data preparation is a prerequisite for RFFA, and entails data formatting, filling of missing data gaps and statistical test analysis. River water levels were converted to discharge using rating curves provided by the OORBA. Multiple imputation techniques (van Buuren, 2007) was applied to fill the gaps in the hydrological data due to the consecutive gaps of 1-3years inherent in the hydrological data (Khalifeloo et al., 2015). Multiple imputations were executed using Microsoft Excel XLSTAT add-on that implements a coupled Markov Chain Monte Carlo and ordinary least squares regression approach to estimate missing annual peak flows (van Buuren, 2007).

RFFA application is also based on the assumption that the data used satisfies the conditions of randomness, serial non-correlation, outliers absence and homogeneity, to reduce the inherent data uncertainty (Kang and Yusof, 2012).

The randomness of hydrologic data points at each station was estimated using the trend identification function Mann-Kendall (M-K) test (Mann, 1945). The M-K test assesses the upward and downward trends in the time series (Yue and Wang, 2002). Serial correlation within hydrological records at a particular site results in discrepancies in regional variance and increased data skewness (Stedinger, 1983), thus contributing to uncertainty in regional flood frequency estimates (Kuczera, 1983, Hosking and Wallis, 1997). To assess the magnitude of the serial correlation, Lag1 correlation coefficients (Kendall and Stuart, 1969) was applied to derive values ranging from -1 (perfect non-correlation) to 1 (perfect correlation). The presence of outliers also affects data quality, and consequently flood estimates. Outliers are attributed to gauge failure, sampling inconsistencies, typo errors, or gauge disruptions, and are not considered part of the real flood population data set (Pedruco et al., 2014). Outliers were identified by using the Grubbs and Beck test (Grubbs and Beck, 1972). Finally, breakpoint analysis (Pettitt, 1979) was applied to assess significant homogeneity within the hydrological time series, attributed to changing climatic conditions.

3.2. Climate indices - climate variability effect

Climate variability affects the frequency and magnitude of extreme flood events (Kwon et al., 2008, Gutiérrez and Dracup, 2001). Warmer climate implies increased evaporation and atmospheric water moisture, resulting in persistent precipitation and consequently flooding (CEDEAO-ClubSahel/OCDE/CILSS, 2008). While in the past hydrologic models have assumed stationarity, current climate change conditions imply that the future is expected to vary despite what is known of the past (He et al., 2006, Sayers et al., 2015). Processes in the ocean-atmosphere system that influence precipitation, atmospheric pressure and temperature can be defined by climatic indices and is useful in tracking long-term hydrological changes (Li and Tan, 2015, Machado et al., 2015, López and Francés, 2013, Giovannettone, 2015). Some key climate indices that characterize the frequency, intensity and duration of extreme climatic events include the Arctic Oscillation (AO), North Pacific Oscillation (NPO), North Atlantic Oscillation (NAO), Pacific Decadal Oscillation (PDO), Pacific/North American Index (PNA), El Nino/Southern Oscillation (ENSO), and Madden–Julian Oscillation (MJO) (Mouhamed et al., 2013).

In this study, the correlation between the annual maximum series and climatic indices are evaluated, and the influence of these indices on the hydrologic time-series are accounted for within the flood frequency estimation process (Hounkpè et al., 2015b, Giovannettone, 2015). The International Centre for Integrated Water Resources Management (ICIWaRM) Regional Analysis of Frequency Tool (ICI-RAFT) developed by Giovannettone and Wright, (2011) embeds various climate indices, including those previously mentioned to enable analysis and inclusion of climate variability for the estimation of Annual Exceedance Probability (AEP). ICI-RAFT tends to correlate peak flood values with each climate indices, to determine that with the highest correlation coefficient (R^2) (Giovannettone, 2015), thus inferring the influence of climate indices.

3.3. L-moment - Index Flood Regional Flood Frequency Analysis (RFFA)

Regional flood frequency analysis is based on the agglomerate hydrological data in regions characterised by similar physiographical parameters including catchment area, catchment slope, stream length, precipitation, and/or elevation. Hydrological data available at the sites within the defined region are used to estimate the regional flood quantile based on the assumption that they are defined by the same probability distribution, and differ only by the index flood (Hosking and Wallis, 1997). This process therefore reduces the inconsistencies associated with data shortage (Mishra et al., 2009).

The Index flood technique developed by Dalrymple (1960) has been applied widely in determining flood estimates for catchments of varying sizes, gauged and ungauged, applied at global, regional and local scales (Smith et al., 2015, Padi et al., 2011, Izinyon and Ajumka, 2013). The general assumption for this technique is that the probability distributions of the annual maximum floods across sites in the region are similar, and differ only by a site-specific scaling factor termed the “index flood – mean or median” (Hosking and Wallis, 1997, Reed, 1999, Dalrymple, 1960).

The flood quantile (Q_T) for a T-year return period at a site of interest (i), given a regional probability distribution factor (X_T), common to all sites, can be mathematically expressed as:

$$Q_{T(i)} = (Q_{\text{index}})X_T \tag{4}$$

Index-flood (Q_{index}) for an ungauged site of interest is usually derived from an established relationship between available catchment characteristics information such as catchment area and the index-flood of gauged sites within the homogeneous region (Stedinger and Griffis, 2008). The regional probability distribution is a dimensionless parameter determined using a best-fit statistical approach discussed in a later section of this study.

L-moment based flood frequency analysis was undertaken using ICI-RAFT (Giovannettone and Wright, 2011), and the procedure includes (i) data screening of clustered sites using the discordancy measure (D), based on Wards hierarchical clustering approach, (ii) regional homogeneity testing using the heterogeneity measure (H), (iii) selection of the appropriate distribution using the goodness-of-fit measure (Z), for the estimation of the frequency distribution using the index flood procedure (Hosking and Wallis, 1997). L-moment is a widely-preferred method for RFFA due to the robustness of Linear (L) - moments in comparison to ordinary moments in handling extreme values over a wider range of probability distributions, and its reduced susceptibility to bias. The components of L-moment analysis are detailed in Hosking and Wallis (1997) and other studies (Izinyon and Ehiorobo, 2014, O'Brien and Burn, 2014, Kjeldsen et al., 2002, Saf, 2009a, Peel et al., 2001). The individual L-moment components and processes are not explained in details but summarised below.

Data screening: The discordancy measure is based on L-Moments (L-Mean, L-Covariance, L-Kurtosis and L-Skewness), and identifies sites whose L-Moment ratio are discordant from that of the whole group, denoted by a critical value of ($D \geq 3$). **Homogeneity testing:** Heterogeneity measure (H) compares the variation between L-moments for a group of sites and what is expected of a homogeneous region to justify that the group of sites are defined by a similar probability distribution. The region is deemed acceptably homogeneous if $H < 1$, possibly heterogeneous if $1 \leq H < 2$, and $H \geq 2$ if the region is definitely heterogeneous (Hosking and Wallis 1997). **Probability distribution selection:** The Z-Statistic is a goodness-of-fit measure that assesses the probability distribution that best fits the weighted-average regional L-moment parameters of each site in a homogeneous region (L-Skewness and L-Kurtosis) (Borujeni and Sulaiman, 2009). An optimal probability distribution can also be visualised using L-moment diagram (L-Kurtosis vs. L-Skewness), with the best distribution is approximated as the distribution curve closest to the majority of the sample data points (Komi et al., 2016).

4. Results and Discussion

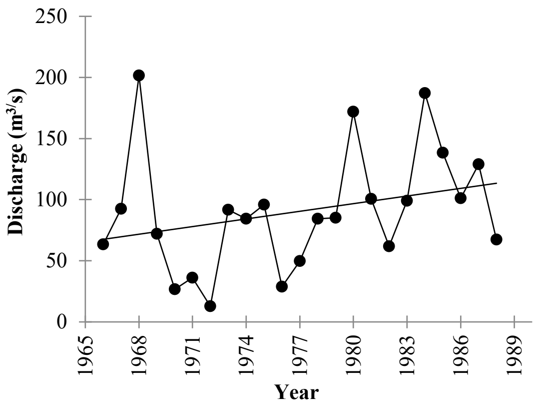
4.1. Data characteristics and preliminary analysis

Data preparation results for this study are presented in Table 2. Lag1 correlation results show that the serial correlation between data sets at each site varied from -0.002 to 0.516 (-1 = perfect non-correlation; 1 = perfect correlation), suggesting the absence of a strong relationship among peak floods at each site. No low outlier was detected from the Grubbs and Beck test, and high outliers identified at Oba/Oyo-Obgbomoso, Ofiki/Ofiki town, Ofiki/Iganna-Ilere road, Ofiki/Igangan, Ogun/Shepeteri, Ogun/Oyo-Iseyin road, and Ogun/Ibaragun gauging stations were consistent at each site, as well as with flood events recorded in past literature (Olukanni and Alatise, 2008). The trend and breakpoint analysis (homogeneity test) result revealed that significant upwards trends were evident at Ijaka-Oke, Oyan/Ilaji-Ile, and Oba/Oyo-Obgbomoso stations, while no significant trends were identified at the remaining sites. These trends were consistent with those of the neighbouring Oueme River Basin in the Benin Republic (Hounkpè et al., 2015b), influenced by similar climatic conditions. The time series plots presented in Figure 2 (a - d) show the annual maximum discharge of the four stations selected for further analysis. These selections capture the varying spectrum of trends displaying spikes and troughs that represent peak flood variability at Ijaka-Oke and Ofiki -Igangan (Figure 2 (a-b)), while changes in hydrologic regimes defined by the breakpoints analysis are for Ofiki/Iganna-Ilere road and Oba/Oyo-Obgbomoso stations are presented in Figure 2 (c-d). Changes in the hydrological regime are evident in the breakpoint analysis plots from 1965 to 1957 and 1979 to 1988, corresponding to documented years of changes in precipitation patterns in Nigeria and West Africa that depict dry to wet (intense drought to rainfall) zone transition (New et al., 2006, Oguntunde et al., 2011, Ogungbenro and Morakinyo, 2014, Adeaga, 2006).

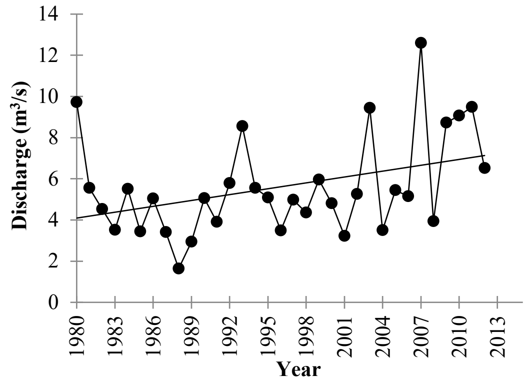
Table 2 Preliminary test results

S/N	Station ID	N	Missing	Outlier	Trend	(+/-)	Homogeneity	Lag1 cor.
1	Ijaka-Oke	33	6	0.464	0.001	+	0.081	0.516
2	Eggua	33	7	0.017	0.721	+	0.149	0.083
3	Ebute Igboro	33	8	0.005	0.420	+	0.193	0.083
4	Idogo	33	9	0.001	0.768	+	0.776	0.330
5	Ajilete	33	4	0.016	0.457	-	0.290	-0.025
6	Yewa Mata	14	0	0.049	0.518	-	0.885	-0.209
7	Oyan/Ilaji-Ile	26	0	0.838	0.000	-	0.548	0.319
8	Ona river	18	0	0.955	0.654	-	0.439	0.019
9	Oshun/Iwo railway	24	0	0.061	0.132	+	0.189	0.305
10	Oba/Oyo-Obgbomoso	23	0	0.298	0.016	+	0.001	0.272
11	Ofiki/Ofiki town	23	1	0.128	0.566	+	0.659	-0.254
12	Ofiki/Iganna-Ilere road	23	0	0.370	0.057	+	0.013	0.302
13	Ofiki/Igangan	23	0	0.398	0.057	+	0.047	0.274
14	Ogun/Shepeteri	23	0	0.079	0.172	+	0.183	-0.164
15	Ogun/Oyo-Iseyin road	23	0	0.312	0.566	+	0.444	0.125
16	Ogun/Ibaragun	24	0	0.279	0.472	+	0.463	-0.018
17	Ogun/Olokemeji	22	0	0.000	0.617	-	0.170	0.077

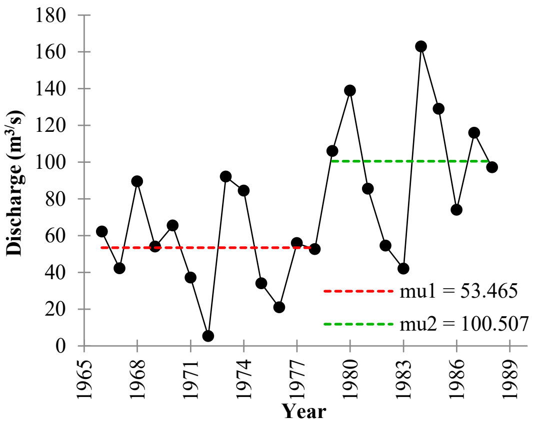
Trend-direction (+/-), Outlier, and Homogeneity depicted by p-values, Lag1 correlation varies from -1 to 1



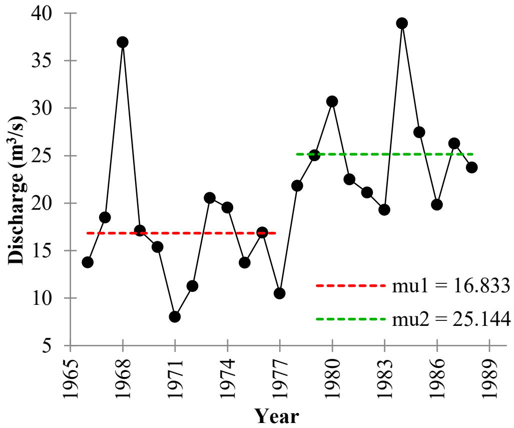
(a) Ijaka-Oke



(b) Ofiki-Igangan



(c) Ofiki/Iganna-Ilere road



(d) Oba/Oyo-Obgbomoso

Where: mu_1 (---) and mu_2 (---) represent the mean discharge of both break points, representing the average difference in hydrological regimes.

Figure 2 (a-d) Trends and breakpoints plots for some of the non-stationary gauging stations

4.2. Identification of homogeneous regions and determination of discordancy measure

Regional L-moment statistics, discordancy (D) and heterogeneity (H) statistics are presented in Table 3, while site-specific results of same statistics are presented in Table 4. An H statistic value of 8.89 (i.e. H>1) reported for the entire catchment area reveals the variable land cover, hydrologic and catchment characteristics over the Ogun-Osun River Basin (Oyegoke and Oyebande, 2008). Consequently, the region was divided into three sub-regions and tested for homogeneity (Table 3), and the L-moment statistics of sites constituting each sub-region are presented in Table 4. The H-Statistics for sub-regions 2 and 3 showed homogeneity (H<1), while sub-region 1 was heterogeneous (Table 3). For the H and L-statistics of all defined regions are presented in Table 4, only Idogo was discordant (D = 4.2232) and was removed from further analysis. All other sites within the homogeneous sub-regions were within the prescribed critical limit for discordancy (D<3). The combination of gauging station historic data within the homogeneous sub-regions provides a means to improve long-term flood magnitude estimation by using a combined data set record of 126 years (sub-region 2) and 141 years (sub-regions 3), thus satisfying in excess the Nigerian guideline of time series length for RFFA of 30 years in Nigeria (FME, 2005b).

Table 3 Regional Average L-Statistics and H-Statistic for defined regions

Region	No of Stations	Mean	L-CV	L-Skew.	L-Kurt.	Dis. (D)	H	Homogeneity
All	17	66.144	0.252	0.146	0.198	3.000	8.89	Heterogeneous
1	6	35.458	0.224	0.112	0.226	0.165	12.42	Heterogeneous
2	5	70.680	0.248	0.180	0.172	1.333	0.62	Homogeneous
3	6	98.865	0.275	0.175	0.171	1.648	0.87	Homogeneous

L = Linear, CV = Covariance, Skew = Skewness, Kurt = Kurtosis, Dis = Discordancy, H = Heterogeneity

Table 4 L-Moments and Discordancy Statistics for the Sites in the three Sub-regions

Region	Station ID	Mean	L-CV	L-Skew.	L-Kurt.	LM-ratio	Dis (D)
1	Eggua	7.965	0.456	0.449	0.296	0.134	1.587
1	Ebute Igboro	17.312	0.219	0.189	0.235	0.114	0.279
1	Ajilete	31.219	0.120	0.176	0.229	0.129	0.854
1	Idogo*	11.905	0.049	-0.434	0.276	-0.211	**4.223**
1	Yewa Mata	10.203	0.461	0.352	0.159	0.143	1.264

1	Ona river/Sasa Village	189.723	0.137	0.053	0.033	0.016	0.667
2	Ijaka-Oke	5.613	0.234	0.236	0.178	0.021	0.633
2	Oshun/Iwo railway	200.474	0.218	0.169	0.163	0.111	0.808
2	Oba/Oyo-Obgbomoso	20.808	0.209	0.132	0.198	0.058	0.532
2	Ogun/Shepeteri	17.822	0.261	0.128	0.238	-0.018	2.09
2	Ogun/Oyo-Iseyin road	131.331	0.322	0.213	0.078	-0.022	1.462
3	Oyan/Ilaji-Ile	13.691	0.293	0.026	0.125	-0.034	1.3635
3	Ofiki/Ofiki town	16.270	0.253	0.185	0.159	0.032	0.3348
3	Ofiki/Iganna-Ilere road	73.918	0.303	0.116	0.129	0.001	0.4341
3	Ofiki/Igangan	90.501	0.305	0.142	0.203	0.059	1.3824
3	Ogun/Ibaragun	190.916	0.216	0.041	0.187	-0.044	0.975
3	Ogun/Olokemeji	218.108	0.359	0.455	0.346	0.188	0.667

4.3. Regional Distribution and Goodness of Fit Measures

Z Statistics provides a more viable statistical approach that quantifies individual probability distributions. Table 5 shows the Z Statistics for all distributions for each sub-region and demonstrates that GLO is significant at the 10% confidence interval ($Z \leq |1.64|$as prescribed by Hosking and Wallis (1997) for regions 2 and 3, while Generalised Extreme Value (GEV) provides the second best distribution for these regions. The L–Moment ratio diagram on the other hand (Figure 3), displays the relationship between regional average L-skewness and L-kurtosis fitted to varying probability distributions for all three regions. The 3-parameter distribution line/curve closest to L-moment ratio points of sub-regional sites portray the optimal distribution

(Peel et al., 2001, Reed, 1999), and in this case, Generalized Logistic (GLO) curve satisfies this approximation. Three (3) parameter were selected due to their robustness and optimal representation of probability distribution parameters (Hailegeorgis and Alfredsen, 2017). This optimal probability distribution corresponds with those applied in previous single-site and regional studies in proximity to our study area (Komi et al., 2016, Izinyon and Ehiorobo, 2014). The insignificance of the probability distribution for the combined sites and region 1 (Z >1.65) shows that all individual sites within this region are not defined by a particular distribution, hence the heterogeneity.

Table 5 Z Statistics for different probability distributions for the sub-regions

Region	LNO	GEV	GLO
All	-3.97	-3.44	-1.45
1	-4.69	-4.58	-3.13
2	-1.83	-0.50	0.49[a]
3	-3.27	-1.31	-0.23[a]

a = optimal distribution

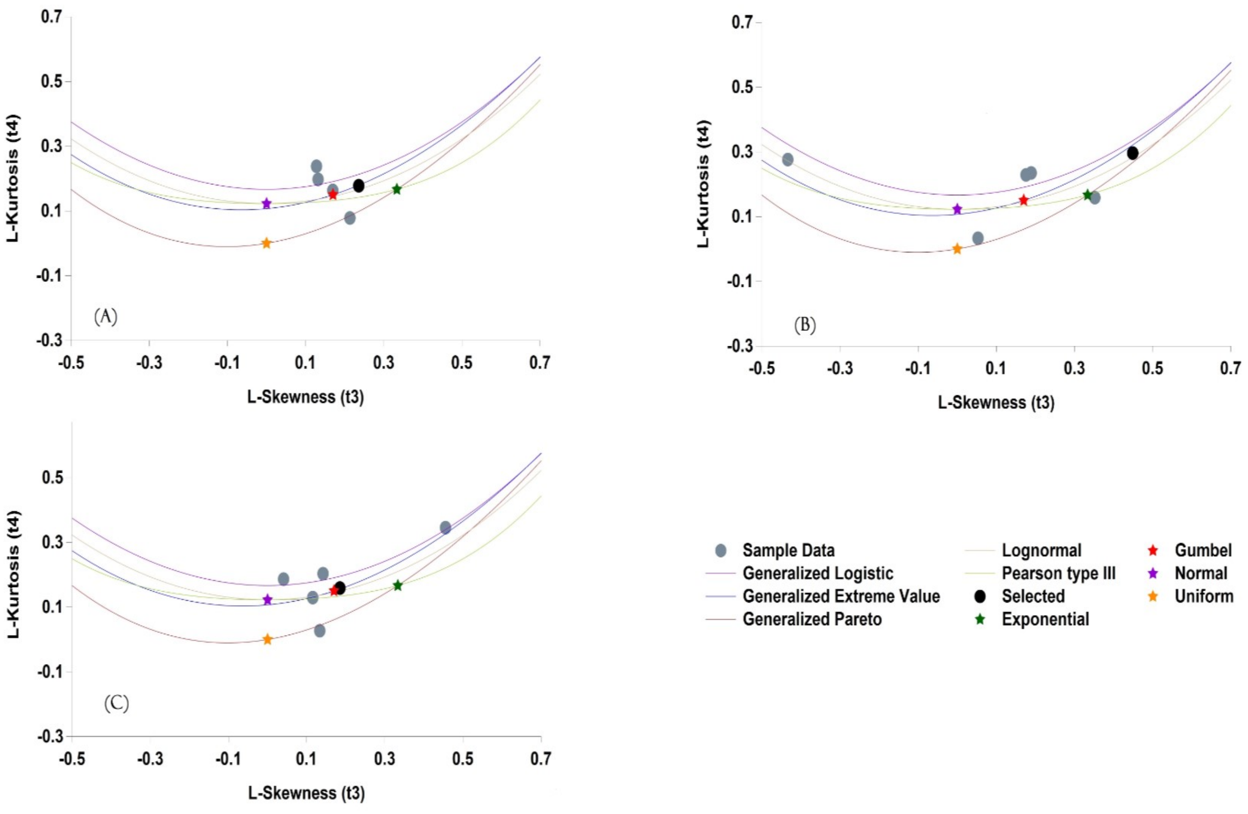


Figure 3 L-Moment ratio diagram for the three (3) sub-regions

4.4. Regional flood frequency and parameter estimation:

After identifying GLO as the optimal probability distribution for regions 2 and 3, a flood frequency relationship was established to derived flood magnitudes. The GLO probability density function is given by:

$$f(x) = \frac{\alpha^{-1}\exp(-(1-k)y)}{(1+\exp(-y))^2}, \; y = \begin{cases} -k^{-1}\ln\left(1-\frac{k(x-\xi)}{\alpha}\right) & k \neq 0 \\ \frac{x-\xi}{\alpha} & k = 0 \end{cases} \qquad (2)$$

where ξ, α and k are location, scale and shape parameters, respectively (Hosking and Wallis, 1997).

The range of x is defined as$-\infty < x \leq \xi + \frac{\alpha}{k}$ If $k > 0 - \infty < x < \infty$; If $k = 0$; $\xi + \frac{\alpha}{k} \leq x < \infty$ If $K < 0$.

The location parameter (ξ) dictates the position of the distribution about a symmetric axis, the scale parameter (α) defined the distribution spread, and the shape parameter (k) indicates the behaviour of the upper tail of the distribution. Theses parameters were derived from L-moments, and applied to derive T-year flood exceedances based on the GLO (X_T) is defined by:

$$\boldsymbol{X_T = \xi + \frac{\alpha}{k}(1-(T-1)^{-k} = \xi\,[1 + \frac{\beta}{k}(1-(T-1)^{-k}]} = \xi \boldsymbol{Z_T} \qquad (3)$$

where $\beta = \alpha/\xi$, T is the return period and Z_T is the growth curve of T.

GLO distribution parameters estimated for each sub-region using L-moments were substituted into equation (3) to estimate the sub-regional growth factor for ungauged and sparsely gauged basins and presented in Table 6.

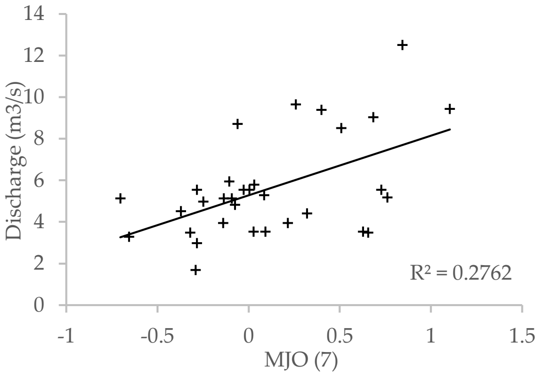
Table 6 Regional distribution parameters for the sub-regions

Region	Distribution	ξ	α	k	Sub-region Growth Factor
1	GLO	0.959	0.219	-0.112	$0.959 + \frac{0.2197}{-0.1123}(1-(T-1)^{-(-0.112)}$
2	GLO	0.928	0.235	-0.180	$0.928 + \frac{0.2345}{-0.1803}(1-(T-1)^{-(-0.180)}$
3	GLO	0.922	0.261	-0.175	$0.922 + \frac{0.261}{-0.175}(1-(T-1)^{-(-0.175)}$

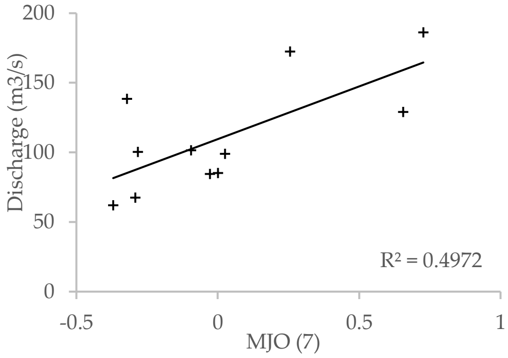
4.5. Climate Indices and flood relationship

Ijaka-Oke, Oba/Oyo-Obgbomoso, Ofiki/Igangan-Ilere road and Ofiki-Igangan were identified by break points and trends to be heterogeneous, and further investigated to ascertain the influence of climate variability by the correlating peak annual flood and global climate indices, then regional flood frequency estimates were determined in ICI-RAFT using the highest correlated indices.

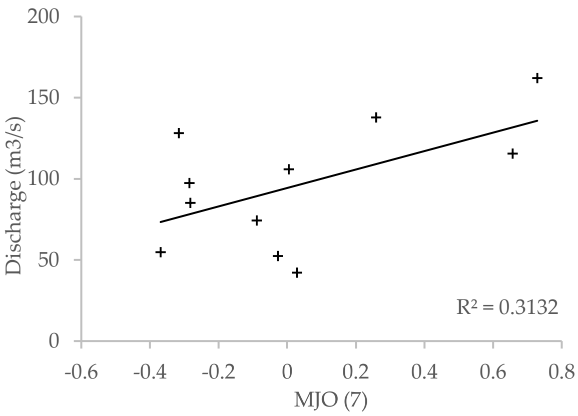
Madden–Julian Oscillation (MJO) demonstrated the highest correlation with annual maximum time series for the four sites (Figure 4), using an optimal lag time of 1 month selected in ICI-RAFT, considering that only single peak flood for each year was applied. Correlation coefficients (R^2) based on MJO (7) (i.e. longitude 40W) were 0.27, 0.50 0.31 and 0.45 for Ijaka-Oke, Ofiki Igangan, Ofiki/Iganna-ilere road and Oba/Oyo-Obgomoso, respectively, suggesting the presence of evidence that shows that between 27 to 50 percent of the variability in the annual maximum flood series was induced by climate dynamics. The correlation values derived in this study were consistent with those revealed in other studies (Li and Tan, 2015, Liu et al., 2015), considering that, local catchment properties, land use/cover changes and hydraulic factors also contribute to changes in hydrological regimes (Leclerc and Ouarda, 2007, Hall et al., 2014). These other contributing factors are beyond the scope of this study. MJO is known to be a strong driver of rainfall variability in tropical regions (Madden and Julian, 1971, Ventrice et al., 2011, Schreck et al., 2013), governing atmospheric pressure and temperature around the equator. The MJO is also reported to significantly influence regional rainfall (Mohino et al., 2012, Lavender and Matthews, 2009, Janicot et al., 2009), and prompted the 2012 flood event in Nigeria (ACMAD, 2012). Arnold et al., (2015) and Caballero and Huber, (2010) further suggested in their study that, due to the dependence of MJO on Sea Surface Temperature (SST) and Outgoing Longwave Radiation (OLR), MJO activity may increase in response to global warming, resulting in more frequent MJO influenced events.



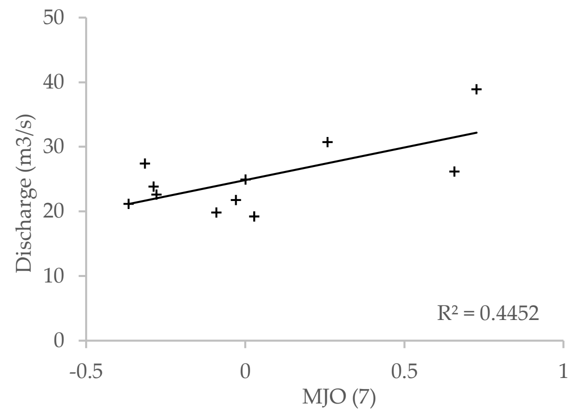
(a) Ijaka-Oka



(b) Ofiki-Igangan



(c) Ofiki/Igangan-Ilere road



(d) Oba/Oyo – Obgbomoso

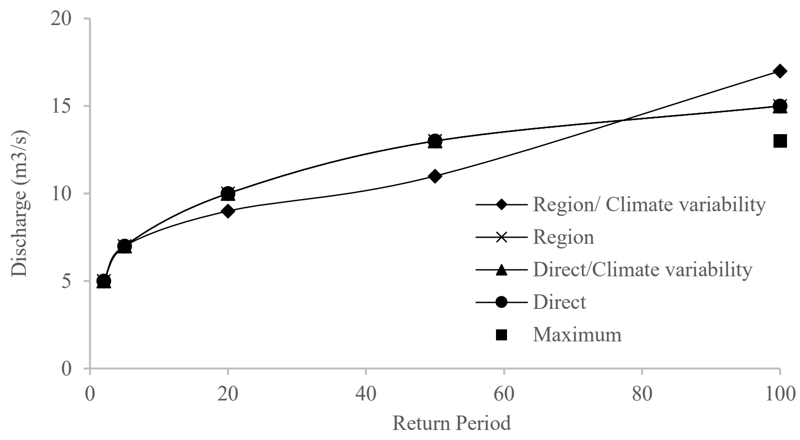
Figure 4 (a-d) relationship between climate indices and stations Peak Annual Flood Time series

4.6. Climate Variability effect and flood quantile estimation

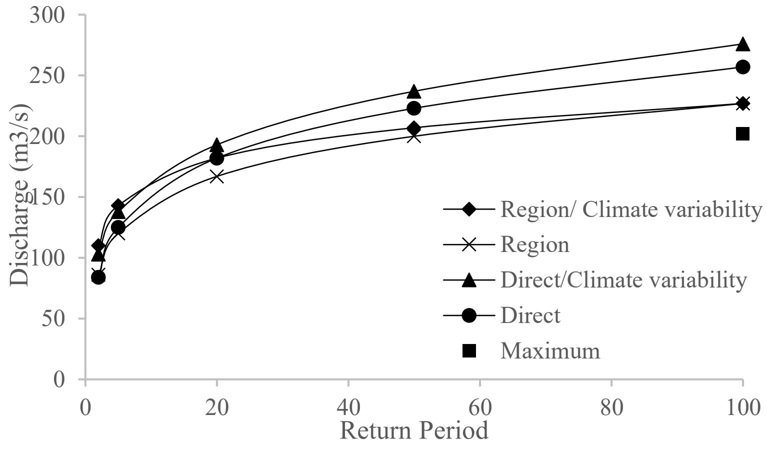
Results capturing climate variability inclusion and omission are presented in Table 7 and Figure 5, and reveal that climate variability effect on flood quantile estimates increases with a return period, thus demonstrating the time dependence of the climate (Hounkpè et al., 2015b, Machado et al., 2015). Also, climate variability influence was evident at sites that exhibited high correlation with climate indices (i.e. Ofiki Igangan and Oba/Oyo-Obgomoso). Criss-cross plot patterns observed at Ijaka-Oke for climate variability inclusion for regional flood frequency estimation, suggests that caution must be taken when accounting for climate variability effect in FFA (López and Francés, 2013), especially when the relationship between climate indices is low (R^2 = 0.28). Also, the significance of the homogeneity (0.081) rather than trends (0.001), is identified as the key indicator of nonstationarity, as evident at Ijaka-Oke gauging station.

Table 7 Flood frequency estimates (Non-Stationary, Stationary regional and at-site) – m^3/s

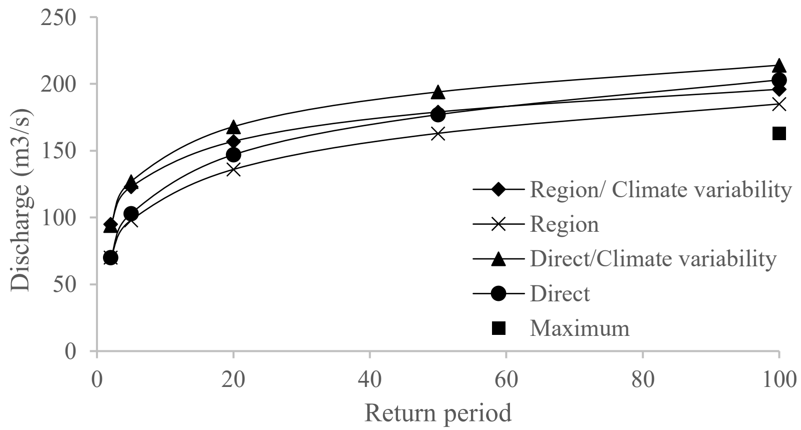
Ijaka-Oke	2	5	20	50	100
Regional/ Climate variability	5	7	9	11	17
Regional	5	7	10	13	15
Direct/Climate variability	5	7	10	13	15
Direct	5	7	10	13	15
Oba/Oyo – Obgbomoso	2	5	20	50	100
Regional/ Climate variability	24	31	41	47	52
Regional	19	27	38	47	54
Direct/Climate variability	24	28	36	44	52
Direct	20	26	35	41	47
Ofiki/Igangan-Ilere road	2	5	20	50	100
Regional/ Climate variability	95	123	157	179	196
Regional	70	98	136	163	185
Direct/Climate variability	94	127	168	194	214
Direct	70	103	147	177	203
Ofiki-Igangan	2	5	20	50	100
Regional/ Climate variability	110	143	182	207	227
Regional	86	120	167	200	227
Direct/Climate variability	103	138	193	237	276
Direct	84	125	182	223	257



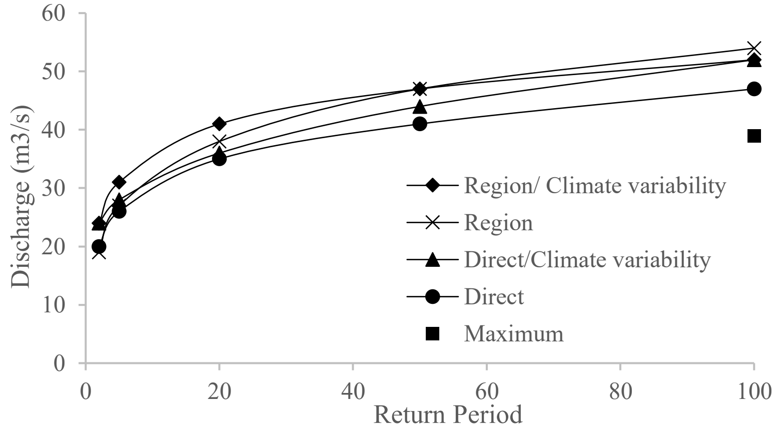
(a) Ijaka-Oke



(b) Ofiki-Igangan



(c) Ofiki/Igangan-Ilere road



(d) Oba/Oyo – Obgbomoso

Figure 5 Probability plots of regional and direct (at-site) flood frequency analysis taking climate variability into account.

At Oba/Oyo-Obgomoso, the regional flood estimates were similar for both climate variability inclusion and omission, for 50-year flood, but differed slightly (by 2 m^3/s) for a 100-year flood, and were higher than the direct flood estimates. For Ofiki/Igangan and Ofiki/Igangan-Ilere road, the opposite was detected, regional flood estimates for both climate variability inclusion and omission were less than that of direct flood estimates. Furthermore, Figure 4 revealed that for each approach, the maximum flood experienced at each sample site in the OORB was less than the 1-in-100year stipulated for flood management planning in Nigeria (FME, 2005b). This suggests that even at locations where climate variable regional flood estimates were less than direct and regional counterparts when climate variability is not taken into account, flood management measures (structural and non-structural) based on such estimates would substantially curtail flood impacts, even with reduced capital investment.

The variations exhibited among sites when climate variability was taken into account is generally similar to those revealed by O'Brien and Burn (2014), where varying trends at different sites resulting in varying quantile estimates when climate variability was accounted for. Also, In Spain, López and Francés (2013) observed that flood estimates that accounted for climate variability were higher than those predicted under the assumption of stationarity, while in a different study in Canada (Cunderlik et al., 2007), the reverse was the case.

5. Conclusions

Managing flooding is particularly challenging when historical hydrologic data is sparse or short, due to administrative, logistics, financial and technical drawbacks. This increases the complexity of flood frequency estimation, thus prompting the need for a shift in focus from direct to regional flood frequency that combines data from various stations to improve data availability and consequently reduce flood estimates uncertainty associated with poor data usage (Izinyon and Ajumka, 2013). By combining regional flood frequency analysis with climatic indices using the open-access ICI-RAFT tool in this study, climate variability effect was accounted for in the flood frequency estimation process, thereby capturing the mechanism of climate responsible for rainfall or flow behaviour and variation in the region (Adeaga, 2006).

This study evaluated hydrological data from 17 gauging stations in the Ogun-Osun river basin, Western Nigeria, and identified significant trends and breakpoints in the hydrological time series that negates the assumption of homogeneity often employed for flood frequency estimation in the region (Izinyon and Ajumka, 2013, Izinyon and Ehiorobo, 2014, Awokola and Martins, 2001). Three (3) sub-regions were delineated from the river basin, two homogeneous and one heterogeneous, based on L-moment regionalization, and four (4) sample sites of varying trends and break-points selected from the two homogeneous regions to assess the impact of climate variability and data agglomeration in flood frequency estimation.

Madden-Julian Oscillation (MJO) was identified as the most influential climate indices, especially at gauging stations where high climate indices to peak flood correlation were observed, and the effect of climate variability increased with return period. This revealed the time dependency of climate variability, as well as resulted in more realistic flood estimates that were still higher than the maximum flood experienced in the OORB.

The outcome of this study further iterates the need to integrate climate variability into flood frequency analysis and suggests the need for a review of flood management measures based on the obsolete assumption (Solecki and Rosenzweig, 2014, Izinyon and Ajumka, 2013, Sayers et al., 2015), and given that MJO driven events are expected to be more frequent as average global temperature trends continue to rise. Nevertheless, it is important to note that the outcome of this section could likely inhabit uncertainties that have propagated from in situ hydrological data collection process, rating curve extrapolation, probability distribution and methodology selection. The quantification of these uncertainties is however beyond the scope of this study.

CHAPTER 5: INTEGRATING CROWD-SOURCING AND OPEN-ACCESS REMOTE SENSING FOR FLOOD MONITORING IN DEVELOPING COUNTRIES

Abstract

Managing floods effectively requires the efficient coordination of efforts before, during and after flooding, i.e. planning, response and recovery respectively. Planning and recovery are usually undertaken at a controlled pace, while the response is undertaken rather swiftly to mitigate the immediate effect of the flood event on people, resources, critical infrastructures and socio-economic activities. Hence, during flooding real/near-real-time flood management data and information is required to inform decision-making and actions to minimize immediate flood impact.

These datasets are usually sparse in developing regions, therefore hampering effective flood management. Hence, remote sensing and crowd-sourcing provide an alternative to *in situ* data collection, as it enables flood delineation and information gathering for flood management in several remote locations.

This study was undertaken in 2015 during the peak flood season (September and October) in Nigeria (a typical developing country). An integrated remote sensing and crowd-sourcing approach are adapted to (i) optimise recurrent flood delineation, (ii) assess the factors that contribute to citizen flood risk perception and (iii) analyse the discrepancy between government and citizen risk perception.

The results from this study revealed from MODIS NRT Water Product flood images that 76% of locations flooded in 2015 were previously affected in 2012, and the integrated remote sensing (MODIS Water Product) and crowd-sourcing approach adopted resulted in improved flooded detection in comparison to each independent approach, as the methodology enabled the capture of macro and micro scale floods. Statistical analysis suggests that the relationship between flood risk perception and flood risk indicator (i.e. awareness, worry and preparedness) was insignificant. This is contrary to previous studies and is likely as a result of the limited data collected during the peak flood season to enable a statistically valid conclusion. Nonetheless, qualitative analysis of individual themes of indicators revealed an understanding of the (i) causes of flooding, (ii) varying flood management responsibility, (iii) lack of knowledge of the

existing flood risk maps, displacement camp locations and (iv) poor flood insurance subscription.

Furthermore, the discordance between government and citizens flood perception was apparent, suggesting the need for improved flood data collection, modelling, and synergy between government and citizens to enhance flood management and risk communication.

Keywords: Crowd-sourcing, Volunteer-GIS, MODIS Water Product, Near-Real-Time, Flood monitoring, Flood Risk Perception

1. INTRODUCTION

With flood events becoming increasingly frequent and intense due to climate change and anthropogenic factors, hydrological and inundation extent information are needed to make informed flood management decisions and deployment of measures such as early-warning communication, relief materials, evacuation planning and rehabilitation (Lo et al., 2015, Maxwell, 2013). Typically flood management efforts are coordinated before, during and after the flood to enhance preparedness, response and recovery respectively, thus ensuring reduced exposure of people, damage to infrastructure and impact on socio-economic activities from flooding (APFM, 2011).

Pre and Post-flood management activities are usually deliberately paced, adapting existing methods supported by available data (Ekeu-wei and Blackburn, 2016). For instance, Annual flood exceedance probabilities and flood magnitude estimates require knowledge of past flood trends (Reed, 1999), which is propagated through hydrodynamic models to route floods and quantify hazards (Sarhadi et al., 2012). Pre-flood plans can be implemented based on flood estimates and hydrodynamic model outcomes to reduce exposure when flood occurs, while post-flood measures, on the other hand, entails identifying impacted locations, settlements and critical infrastructure to quantifying the damage/impact for reconstruction and rehabilitation purposes (Eyers et al., 2013, Thorne, 2014).

Responding to floods in the heat of the event is particularly challenging in developing regions, as real-time data processing and information required are usually unavailable. Floods are unexpected occurrences, thereby making it difficult and impractical to monitor large-scale floods using ground-based (*in situ*) approach (Temimi et al., 2004). Nevertheless, technological advancements such as remote sensing satellite and telemetry provide alternatives to *in situ* data collection, as they enable data acquisition from remote locations (Li et al., 2006, Pereira Cardenal et al., 2010) and hydrological information transfer (Sene, 2010, Sene, 2012) in real and near-real-time to enable early warning and flood response.

The cost of acquiring such timely data is usually high, and in some instances turbulent floods disrupt *in-situ* gauges, thereby impeding high flow measurements (Olayinka et al., 2013, Yan et al., 2015a). Open-access remote sensing makes available alternative free satellite data (Imagery and Altimetry water levels) including Landsat, MODIS (Terra and Aqua), Sentinel 1/2, ENVISAT, Topex/Poseidon, Jason 1/2, etc. (Musa et al., 2015). Also, the consortiums of satellites for global disaster monitoring and management (Bessis et al., 2004) when activated provides member nations with free high-resolution satellite data in Near-Real-Time (James et al., 2013).

Despite the wide application of open-access satellite data in flood modelling and mapping in several regions, certain challenges persist, including coarse spatial resolution, low temporal resolution and data processing delivery time frame, inherent system properties and external landscape characteristics which result in poor flood detection in vegetation and urban landscape dominated regions (Yan et al., 2015a, Musa et al., 2015, Veljanovski et al., 2011b). Due to these deficiencies, alternative data acquisition approaches are required to capture the true state of inundation in poorly detection locations, and persons living in remote locations can help fill such data gaps.

1.1. Crowdsourcing and Volunteered Geographic Information (VGIS)

Citizen involvement in science has been proven to be an invaluable source of data in inaccessible locations for flood management processes that include (i) flood impact assessment (Werritty et al., 2007, Verger et al., 2003), (ii) exposure evaluation (Riggs et al., 2008), (iii) vulnerability analysis (Ologunorisa, 2004, Kron, 2005), (iv) risk perception evaluation (Siegrist and Gutscher, 2006), (v) resilience capacity assessment (Brouwer et al., 2007) and (vi) flood model validation (Yu et al., 2016). Crowd-sourcing is particularly useful in populated regions and aided by wide-coverage mobile telecommunication and internet systems (Wang et al., 2017). The global population and internet users are currently estimated at 7,300,000,000 and 3,378,588,043 respectively (Haub et al., 2011). In Nigerian (the proposed case study for this study), the population is approximately 186,987,563, of which 46 % have access mobile internet and 8 % are active social media users (Kemp, 2015, Facebook, 2016, NBS, 2016). Figure 1 shows the Nigerian population, telephone subscribers and internet users growth in Nigeria (Doghudje, 2016).

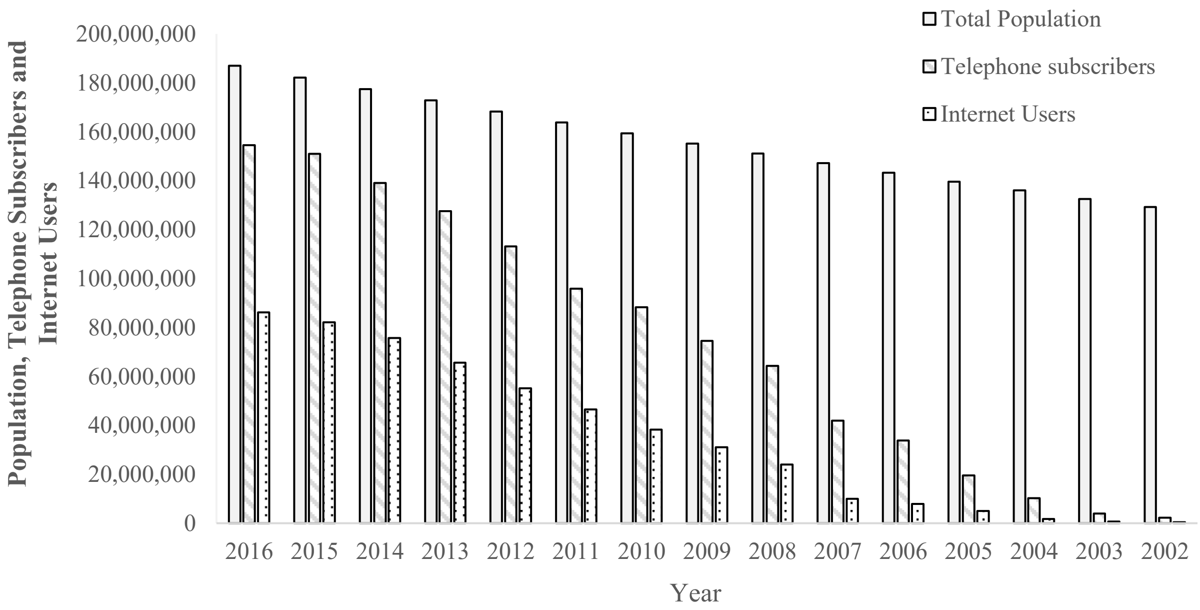


Figure 1 Population, Telephone subscribers and Internet users growth in Nigeria (Sources: NBS, Internetlivestats and Nigerian Communication Commission)

Crowd-sourcing (CS) integrates “crowd”, “outsourcing” and “internet technology” (Saxton et al., 2013) in a system whereby a virtual crowd (citizens) perform an organizational task such as data collection during an emergency using internet driven technology. Crowd-sourcing can be active or passive, depending on the information collection structure (Meek et al., 2014); active CS to refer surveys completed directly by respondents, while passive CS involves social media mined information.

With advancement in telecommunication, increasing internet coverage and growing population, near-real-time data gathering during disaster events can be undertaken over a large spatial extent. Various social media platforms have been used in acquiring crowd-sourced data (passive crowdsourcing), including Twitter, Facebook, Flickr, and YouTube, which allows victims of disaster to report first-hand details of on-ground situation, thus improving situational awareness data for informed decision making by policy makers and first responders (Huiji Gao et al., 2011). Some instances of social media application in flood monitoring include (i) Assessment of road damage due to flooding using Twitter hashtags (#flood) and crowdsourced images and videos (Schnebele et al., 2014); (ii) Community need assessment using Facebook feeds and updates in the cities of City of Calgary, Canada and Boston, United States (Magnusson, 2014, Franks and Evans, 2015); and (iii) Disaster monitoring using combined social media data sources (Musaev et al., 2014). Further literature on social media application in emergency management is entailed in Simon et al., (2015).

Despite this progression, the practicality of harnessing, validating and leveraging crowd-sourcing data to inform flood management is being hampered by the complexities arising from the variable data structure, formats and multi-sourced nature of the data. Volunteer Geographic Information system (VGIS) provides a platform that curbs these deficiencies, as it enables the collection, coordination and management of location-based data in the required format (Goodchild, 2007). VGIS also enables thorough disaster impact assessment, considering that the respondents are victims of disaster and reside within the impact zones at the time of the event (Triglav-Čekada and Radovan, 2013, Poblet et al., 2014). Additionally, VGIS aids crowd-sourced data quality assurance, which is one of the most predominant issues associated with crowdsourced data collected from anonymous (non-expert) sources at various locations (Foody et al., 2013, Miorandi et al., 2013, Foody et al., 2014).

1.2. About Risk Perception and Indicators

The perception of flooding directly influences flood mitigation actions and depends on flood risk awareness, worry and preparedness, linked to past exposure experiences, socio-economic and demographic characteristics (Raaijmakers et al., 2008, King, 2000).

Understanding the cause of flooding (awareness) is essential for flood management. Climate change, poor urban planning/enforcement, improper drainage systems, poor waste disposal, excessive rainfall and excess water released from upstream dams have been identified as some of the major causes of flooding in several developing regions (Olayinka et al., 2013, Nkwunonwo et al., 2016, Ologunorisa, 2004). Unique management measures are required depending on the flood type/cause. For instance, poor waste management results in the blockage of drainage systems and a reduction in drainage hydraulic capacity (Parkinson, 2003), therefore, managing flood caused by poor waste management requires the clearing of solid waste trapped in drainage systems and awareness campaigns for behavioural change to improve waste management practices (Momodu et al., 2011). Managing excess water releases from dams, on the other hand, require improved reservoir planning, preparation from scenario-based event models, risk communication and learning from experiences (Olojo et al., 2013, Vanguard, 2015, Ramirez et al., 2016).

Worry depends on the awareness of the frequency of exposure to flood hazard, severity and concern for individual or community welfare, and therefore prompts preparedness (Tapsell et al., 2004). This consequently impacts on the coping capacity to manage expected flood hazard (Raaijmakers et al., 2008, Harvatt et al., 2011). Worry is usually based on previous experience of flooding, social responsibility (e.g. family size) and economic capacity (e.g. employment status) (Boamah et al., 2015), therefore a person or group of persons would perceive flood risk as high if they have previously experienced flooding, have a large family size, and have less economic capacity to cope with flood consequence/recovery and vice versa (Brilly and Polic, 2005, Siegrist and Gutscher, 2006, Adelekan and Asiyanbi, 2016).

Preparedness is built on the awareness of expected flood hazard and sufficient worry which therefore prompts planning and resilience improvement before a flood event (Veen and Logtmeijer, 2005). Preparedness can be categorized as technical, social, economic or institutional; where (i) Technical preparedness entails putting in place structural measures that modify the environment or building/properties to reduce potential impact and exposure (e.g. flood walls, dykes, dredging, etc.); (ii) Social preparedness refers to personal skill development and knowledge gathering to manage expected flood impact (e.g. awareness campaigns) (Buckland and Rahman, 1999); (iii) Economic preparedness denotes the financial capacity to cope with flood impact, or measures put in place to reduce financial loss and risk transfer (e.g. insurance); and (iv) Institutional preparedness involves the design, communication and implementation of a disaster management plan to reduce flood risk and impact through measures such as evacuation and emergency staff capacity development (Raaijmakers et al., 2008). Flood risk maps are also essential for preparedness, as it enables town planners and residents understand infrastructural development and socio-economic activities exposure to flood hazard and management measures required to mitigate disaster effect (Porter and Demeritt, 2012).

1.3. Study Objectives

This study is aimed at leveraging open-access remote sensing and crowd-sourcing data for flood monitoring in developing countries in Near-Real-Time, with the specific objectives of:

- Compare recurring flood events and impact to assess management measure efficiency
- Explore the feasibility of applying crowd-sourcing for Near-Real-Time flood monitoring.
- Integrate crowdsourced and open-access remote sensing data to enhance near-real-time flood monitoring and mapping.
- Analyse flood risk elements; Awareness, Worry and Preparedness in relation to flood risk perception using crowd-sourcing data.
- Evaluate citizen and government flood risk perception using crowd-sourcing data and government flood model respectively.

2. STUDY AREA

Nigeria is located at the downstream end of the Niger Basin (Figure 2). The Niger Basin drains a 2,111,475 km^2 area and encircles 93,617,850 persons from 12 countries (TWAP, 2016). Multi-decadal climatic variation intensifies precipitation in the region, resulting in frequent flooding (Adeaga, 2006). In the past decade, Nigeria has experienced severe flood events arising from extreme precipitation and excess water releases from upstream dams within Nigeria (i.e. Kainji, Jebba, Shiroro, Kiri, etc.) and Cameroon (i.e. Lagdo) along Niger and Benue river respectively, with the 2012 event reported to have caused the greatest flood impact/damage in 40 years (Tami and Moses, 2015, Ojigi et al., 2013). These high magnitude floods have resulted in the damage to properties and infrastructures, displacement of people, disruption of socio-economic activities and loss of lives (FGN, 2013).

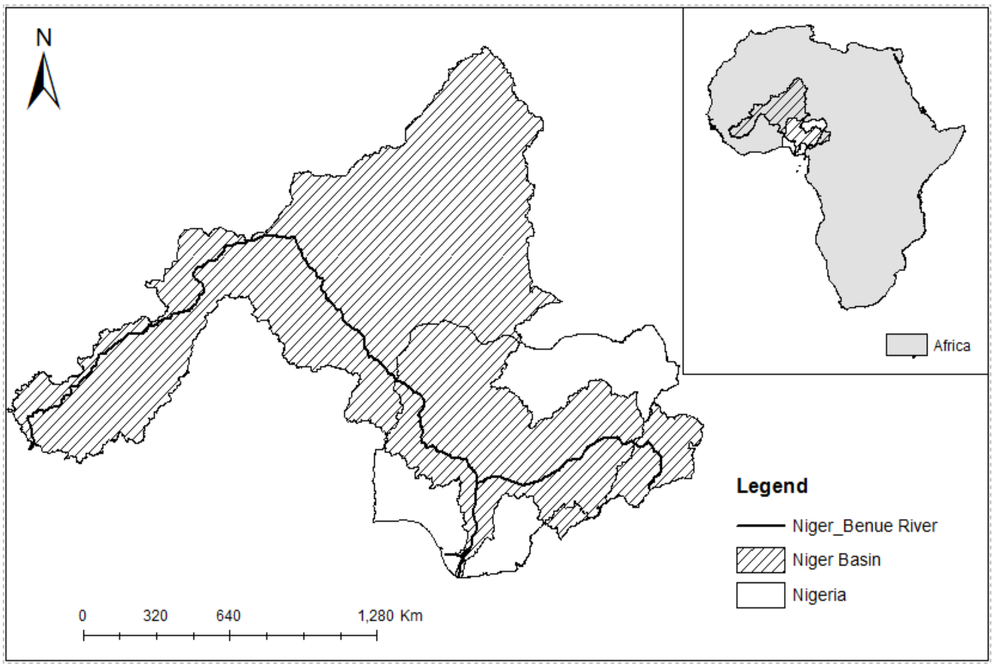


Figure 2 Map of the Niger River Basin within Africa and across Nigeria

The recent flood events in Nigeria coupled with the growing vulnerable population, internet subscribers and social media users trend presents a unique opportunity for crowd-sourcing exploration in Nigeria as will be demonstrated in this study. Although citizen science has been previously explored in Nigeria, the focus has been on pre and post-flood data gathering using questionnaires (Eguaroje et al., 2015, Raheem 2011, Jinadu, 2014, Adelekan and Asiyanbi, 2016, Adelekan, 2011). This study proposes to apply crowd-sourcing for near-real-time flood data gathering in Nigeria, to inform flood management during flooding (Schnebele and Cervone, 2013, Schnebele et al., 2014, de Brito Moreira et al., 2015).

3. METHODOLOGY

3.1. Research framework for crowdsourcing

The United Nations Office for Disaster Risk Reduction (UNISDR) disaster communication framework developed to communicate disaster warning at a local scale to inform decision/response is adapted for this study. The communication framework comprises of five components including (i) a credible **source**; (ii) a duly designed **message;** (iii) an efficient communication **channel;** (iv) a specific **Audience**; and (v) a **feedback** process to enable message scrutiny and local input.

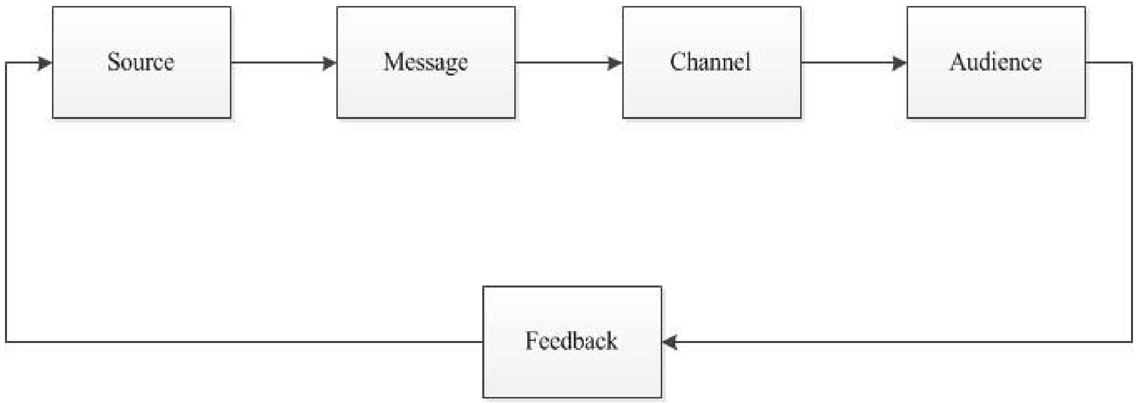


Figure 3 UNISDR Disaster Communication Model adapted for this study

This study applies the UNISDR Disaster Communication Model (Figure 3) in reverse, with a source of information being the people and audience depicting the responsible agencies (government), hence "crowd-sourcing". The message is whether a location is flooded or not, and the channel is a Geographic Information System (GIS) (i.e. Volunteered GIS), while the feedback refers to the action by the agencies, such as resources distribution, rescue, or evacuation during a flood event.

3.2. Data and Analysis

Data for this study were simultaneously acquired using remote sensing and crowd-sourcing techniques during the peak flood season (between September and October) of 2015 in Nigeria.

3.2.1. Questionnaire Survey

Quantitative and qualitative data on hazard impact/awareness, demographic and socio-economic characteristics used as indicators for flood risk perceptions were acquired using a custom designed ESRI GeoForm web application (Appendix 4). The platform allows for the collection of Geocoded alpha-numeric and photo data that can be extracted for spatial analysis in ArcMap. The offline submission option was enabled within the GeoForm setting to allow for data collection and storage without internet coverage. The GeoForm accessible through the link: http://arcg.is/1sn5CXG[4] was shared on Facebook within different social groups encompassing members from the various states in Nigeria. 50 responses were collected for analysis in this study during the peak flood season.

3.2.2. MODIS Near-Real-Time (NRT) Flood Maps

Global 250 metres resolution Near-Real-Time binary flood maps derived from Moderate Resolution Imaging Spectro radiometer (MODIS) Bands (1, 2 and 7) using Dartmouth Flood Observatory (DFO) algorithm (Nigro et al., 2014) was applied in this study. MODIS instrument onboard the National Aeronautics and Space Administration (NASA)'s Terra and Aqua satellites acquires optical satellite images for 1 to 2 days that are automatically processed by the Dartmouth Flood algorithm to produce MODIS Water Product (MWP), and can be downloaded through the webpage http://oas.gsfc.nasa.gov/floodmap/[5] (Revilla-Romero et al., 2015b). The algorithm uses a ratio of MODIS 250-m Bands 1 and 2, and a threshold on Band 7 to provisionally identify pixels as water. Nigro et al. (2014) further disclosed that the performance of the NRT MWP varies from 40% to 66% for clouded and cloud-free conditions respectively, for good, excellent, almost perfect flood detection that captures from half to almost all flooded surfaces. Also, poor and fair flood detection that captures no flood, poorly classify flooded surfaces and less than half the flooded area, vary from 23% to 34% for clouded and cloud-free conditions respectively.

A combination of the MWP time series for September and October of 2012 and 2015 that corresponds with the peak rainfall and river flow season in Nigeria were applied to delineate NRT flood extent. MODIS imagery has been widely applied in similar respect for flood monitoring and mapping (Nkeki et al., 2013, Zhang et al., 2014, Revilla-Romero et al., 2015b) and is known for wide-coverage flood delineation and high temporal resolution. Nevertheless, MODIS flood maps are usually distorted by spatial resolution, cloud covers, and rugged terrain (Nigro et al., 2014), resulting in inundation underestimation, and consequently flawed decision making. By integrating MODIS and

[4] http://arcg.is/1sn5CXG

[5] http://oas.gsfc.nasa.gov/floodmap/

Crowd-sourcing in this study, we hope to leverage on the merits of both approaches to improve NRT flood monitoring and mapping.

3.2.3. Government Flood Risk Perception: The Annual Flood Outlook (AFO), Nigeria

Communicating flood risk to the general public is an important and integral part of flood management, to ensure precautionary measures are put in place to mitigate flood impact (Hagemeier-Klose and Wagner, 2009). In Nigeria (the case study for this research), the technical guideline on flood management (Federal Ministry of Environment, 2005b) stipulates the need to prepare and publish flood risk maps to sensitise the public. The aftermath of the unprecedented flood in 2012 resulted in the initiation of the Annual Flood Outlook (AFO) through a collaboration between the Nigerian Hydrological Service Agency (NIHSA) and the Nigerian Meteorological Agency (NiMET), with the aim of providing flood hazard information to mitigate the impact of flood on the populace, socio-economic activities and infrastructure (NIHSA AFO, 2013). This information is used by the government to plan for flood events and advise citizens at risk of flooding to relocate.

The AFO is generated based on the Geospatial Stream Flow Model (GeoSFM) and Soil and Water Assessment Tools (SWAT), using data sets such as the previous flood extent of 2012, Nigerian Meteorological Agency (NiMET) Seasonal Rainfall Prediction (SRP), SRTM DEM, Land use/cover, stream and rain gauge historical data and satellite precipitation data, to categorize state and local government scale flood risk exposure as high, medium and low (NIHSA AFO, 2014, NIHSA AFO, 2015, NIHSA AFO, 2013). Furthermore, the AFO exist as paper-based maps and reports and was converted to a digital format compatible with ArcMap for spatial analysis and comparison with citizen flood risk perception. In this study, government's flood risk perception is evaluated against that of the citizens, to assess whether government flood management measures are effectively deployed as required by the affected populace.

3.2.4. Geo-Spatial data and Analysis

Administrative shapefiles that outline national, state, local government and settlement boundaries were downloaded from the DIVA-GIS database (Hijmans et al., 2004), while population density estimates were acquired as Gridded Population (GPW: v4), from the Socioeconomic Data and Applications Centre (SEDAC) database. The combined MODIS Water Product (MWP) composites were mosaic to extract inundated areas and spatial analysis (overlay and zonal statistics) undertaken to identify flooded states, local government, settlements, and the inundated populace. All spatial analysis was performed in ArcMap 10.2, after importing GeoForm data from ArcGIS online.

Chi-square test and Mann-Whitney U statistical analysis were undertaken in SPSS (Nie et al., 1975) to assess the relationship between flood risk perception and risk elements. Chi-square test evaluates the relationship between two categorical variables (Laerd Statistics, 2016a), while Mann-Whitney U test assesses the relationship between categorical and continuous variables (Laerd Statistics, 2016b). The 50 crowd-sourced data responses (flooded/non-flooded) were compared with MODIS flood extracts and later combined to assess possible improvements flood detection. Flooded locations from both approaches were also compared to media reports i.e. online newspapers, bulletins, blogs, and post from established outlets such as Vanguard, Independent, Today, Tribune, and Nation as some form of validity check.

4. RESULTS AND DISCUSSION

4.1. NRT-MODIS Flood River Niger and Benue flood extents of 2012 and 2015

In this study, a retrospective approach is also applied to quantify flood extent and impacts of the 2012 and 2015 flood events using remote sensing and GIS technology. At the national level, 35 out of the 36 states in Nigeria were flooded in 2012, with the exemption of Borno, while in 2015 Borno, Enugu and Yobe were the states not flooded. Similarly, 58% and 41% of the 774 Local Government Areas in Nigeria were affected in 2012 and 2015 respectively, corresponding to 8,876 and 4,884 settlements (towns) for the respective years, out of 56012 settlements (towns). Further details of both impacts are presented in Table 1. Comparative spatial analysis of 2012 and 2015 flood events showed that 76% of the locations affected in 2015 were previously impacted in 2012, despite the reduced flood extent in 2015 as a result of the agreement between Nigeria and Cameroon in 2013 to manage excess water release from Lagdo dam (Jinadu, 2015). The recurrent flood affected 400,181 persons, thus reiterating the need to manage recurring flood risk despite the agreements that resulted in reduced flooding originating from riparian countries. Figure 4 shows the extent of flooding in 2012 (Red), 2015 (Green), and recurrent flood in both years (Blue), and corresponding crowd-sourced data points with similar colour codes for the respective years.

In 2015 the United Nations Office for the Coordination of Humanitarian Affairs (OCHA, 2015) reported reduced levels flooding, owing to the agreement between Nigeria and Cameroon to collaboratively manage dam subsequent water releases and communicate risk effectively (Jinadu, 2015). This study portrays the effect of that agreement and decision, evident in the reduced extent of inundated area in 2015 when compared to 2012 despite the less than 1 metre water levels variation between both years along the Benue river Kainji Lake (Schwatke et al., 2015a) from which flow contributed to both flood events (See Supplementary Figure 1 (a-b)).

Table 1 Quantitative flood risk assessment based on MODIS NRT Flood Data

Flood Event	**Flooded Area (km^2)**	**States**	**Local Govt.**	**Settlements**	**Impact Population**
2012	12,050.80	35	446	8,876	1,927,390
2015	4,337.57	33	321	4,884	528,803
2012 & 2015	3,716.57	33	174	3511	400,181

Settlement based on 5 km buffer. The total number of states = 36, Local Governments = 774, Settlements = 56012.

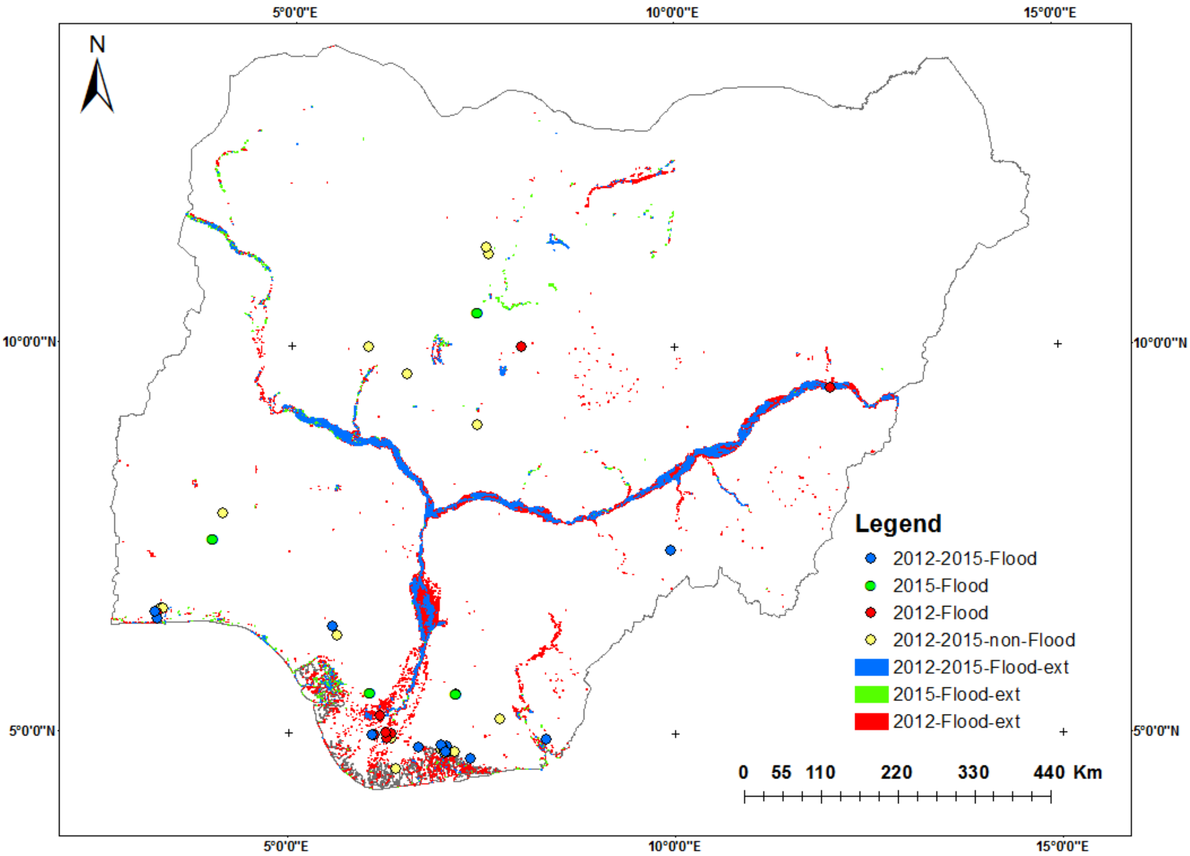


Figure 4 Overlay map of Flood extents (ext.) and crowdsourced data (Map) for 2012 and 2015 flood events

4.2. NRT-MODIS and Crowd-sourcing VGIS Integration

Crowdsourced data was compared with MODIS NRT flood maps as presented in Figure 4 for 2012 and 2015 flood events, then combined to access improvement in flood detection in relation to media report. Table 2 shows higher levels of remote sensing flood detection than crowd-sourcing in 2012 and 2015 (i.e. the percentage of flooded data points). Integrating both approaches resulted in an increase in flood detection percentage for both years. This result aligns with the resolve that crowdsourced data allows for the capture of micro-scale flood, while the 250m resolution MODIS satellite image enables macro scale flood detection (Moel et al., 2015, Penning-Rowsell, 2014). The microscale approach (crowd-sourcing) provide the unique advantage of usability for specific need/damage assessment, while macro flood outcome enables large-scale planning at the national or state levels. The Integrated approach was further compared to online media reports, and the results showed a 75% and 53% agreements in 2012 and

2015 respectively. The high level of online media agreement with the integrated remote sensing and crows-sourcing flood detected areas in 2012 is likely due to the wide extent and impact of the 2012 flood event which resulted in intense media publicity. Some of the locations identified by media reports as well as this study are presented in Figure 5, including Ughelli, Patani, and Amassoma (Alamy, 2012, Voice of America, 2012, Koriake, 2015).

Table 2 Percentage of flood detection points from respondents - MODIS and VGIS Integration

Year	MODIS	VGIS	VGIS and MODIS	(VGIS and MODIS) vs Media
2012	53.1	49.0	81.6	75.5
2015	32.7	20.4	71.4	53.1

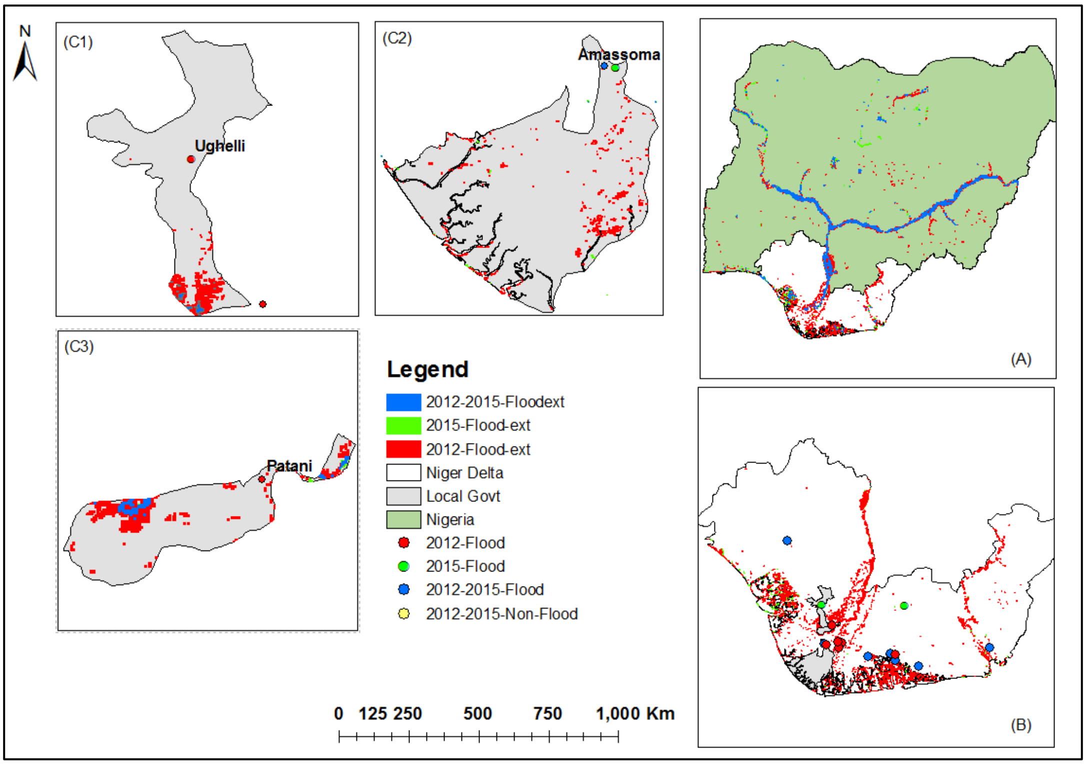


Figure 5 Zoomed-in flooded locations (Ughelli (C1), Amassoma (C2) and Patani (C3)) in the Niger Delta (B).

The crowd-sourcing platform was designed to enable photo collection as evidence of flooding to enable validation, as well as provide flood hazard, impact and socio-economic information. Figure 6 (A-B) shows flood scenario at Amarata in Yenagoa, Nigeria captured at the point of crowd-sourcing data collection, showing rainfall and urban flood resulting from local conditions, thereby revealing the advantage of crowd-sourcing to capture micro-climate phenomenon (Muller et al., 2015). More photos could not be captured due to technical challenged experienced using the VGIS platform. Figure 6 (C-D) shows evidence of fluvial flood at Amassoma highlighted by media reports (Koriake, 2015), which resulted from Nun river overflow due to the release of excess dam water along upstream Niger and Benue rivers. The flood scenario in Amassoma was captured by both MODIS and crowdsourcing, due to large-scale extent and localized impact (Akintoye et al., 2016, Ohimain et al., 2014).

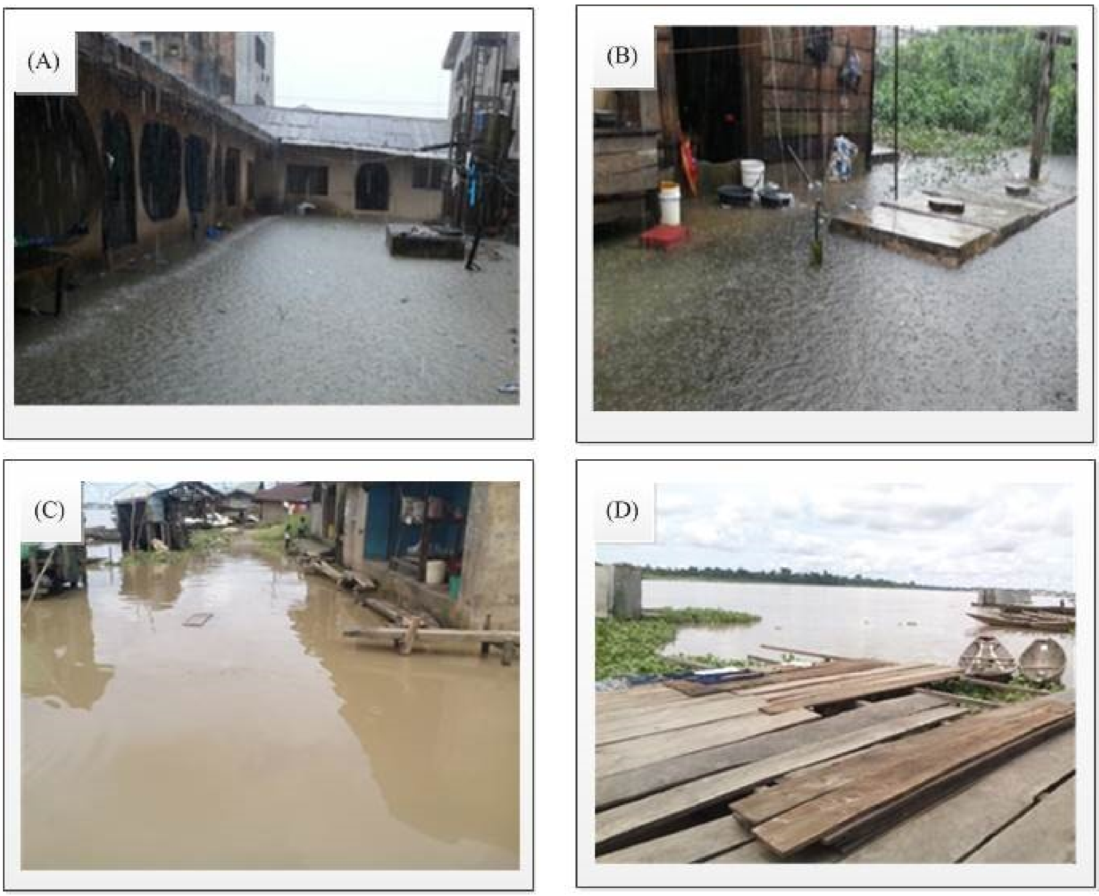


Figure 6 (A-B) Amarata, VGIS detected flood in Yenagoa, Bayelsa state (2015), and (C-D) Media reported flood in Amassoma, Bayelsa state (2015).

4.3. Flood Risk Indicator Analysis

Outcomes of the flood risk indicators analysis are presented in Table 3, encompassing flood risk elements of awareness, worry and preparations as the key themes that infer flood risk perception as earlier disclosed. A total of 50 responses were recovered, covering 11 out of the 37 Nigerian states.

Table 3 Descriptive Statistics Summary of Flood Risk Indicators

Themes	Variables	Responses to questions			
		option (1)	option (2)	option (3)	option (4)
Awareness	Flood Cause	Heavy Rain (14)	Poor Drainage & Waste (60)	Dam Release (12)	All causes (14)
	Rivers Proximity	No (30)	Yes (70)	-	-
	Flood Management responsibility	Federal Govt. (20)	State Govt. (34)	Local Govt. (20)	Individual (26)
Worry	Risk perception	Low (44)	Medium (44)	High (12)	-
	Previously Affected	No (24)	Yes (76)	-	-
	Family size	1 (6)	2-4 (30)	5-Above (64)	-
	Employment status	Unemployed (18)	Employed (56)	Student (26)	-
Preparedness	Aware of Flood Map	No (86)	Yes (14)	-	-
	Property Insurance	No (88)	Yes (12)	-	-
	Displacement Camp	No (72)	Yes (28)	-	-

Results presented as percentage of recipients (%)

4.3.1. Flood Risk Awareness

The awareness elements assessed in this study are (i) the knowledge of flood causation factors, (ii) nearness to hazard and (iii) flood management responsibility, given that the understanding of the cause of flooding influences the management measure deployed by the responsible authority.

4.3.1.1. Flood Cause

Intense precipitation is the underlying cause of flooding globally, aggravated by changing climatic and anthropogenic conditions that result in more frequent and intense storms (Hounkpè et al., 2015a, Giustarini et al., 2015). Flooding in Nigeria has been attributed to factors including climate change, poor drainage planning, urbanisation and other anthropogenic activities such as dam water releases and hydraulic structures design failure (Nkwunonwo et al., 2016). Results presented in Table 3 reveals that 60% of the respondents identified poor drainage and waste management as the primary cause of flooding, 14% heavy rainfall, 12 % dam water release and the 14% suggested a combination of factors. The results reveal a recognition of a broad range of flood-causing factors in Nigeria as previously highlighted by Shabu and Tyonum, (2013) and Agbola et al., (2012), where intense rainfall, drainage blockage due to poor waste disposal, and dam breakage were also identified as the leading causes of flooding.

4.3.1.2. Distance from River

The rise in river water level as a result of precipitation runoff that consequently causes fluvial flooding has been documented in the EM-DAT: International disaster database (Guha-Sapir et al., 2014) to account for 80% of flood events in Nigeria. Therefore, the distance from hazard source (i.e. river) contributes to people's perception of flood risk (Tehrany et al., 2013). Usually, the further the person lives from a hazard source, the less exposed they are and vice versa (Heitz et al., 2009). Although 70% of the respondents specified knowledge of residing close to the river, Mann-Whitney statistics indicated otherwise when knowledge of exposure to flood hazard was compared to the actual distance from the river estimated from google earth ($U = 135.5$, $Z = -2.690$ and $P = 0.007$). This evidence suggests that people's knowledge of hazard source (river) and actual distance from river differed significantly, indicating a poor sense of hazard source identification from respondents.

4.3.1.3. Flood Management and Stakeholder Responsibility Mapping

Flood management is usually undertaken at an individual, local or central government (White et al., 2016, Porter and Demeritt, 2012, Box et al., 2013), depending on the scale of flood impact, the resource required or urgency of intervention needed. In this study, 74% of the respondents maintain that the flood management is solely the responsibility of the government, operating at the local, state or federal levels. In the early 1960's in Nigeria, individuals were solely responsible for flood management, prior to the establishment of government parastatals for organised flood management (Obeta, 2009, Obeta, 2014b). The Government of Nigeria through several federal, state and local government parastatals are now responsible for data collection, flood prediction, planning and flood management strategy implementation (FMWR, 2013, FME, 2005a). These duties highlighted in the Action Plan for Erosion and Flood Control (FME, 2005a) were divided based on risk management cycle components stipulated in the Associated Programme on Flood Management (APFM, 2011), i.e. Preparedness; Response; Recovery and Rehabilitation (Table 4) to show the role of specific agencies in an integrated flood management framework and further foster collaboration between key stakeholders.

Flood management at a national scale is mostly handled by the Federal Government, including cost-intensive projects such as dams establishment (FMWR, 2016), and recovery implementation such as the deployment of relief materials and the establishment of displacement camps (NEMA, 2012). State and Local scale flood management efforts are focused on small-scale structural and non-structural measures such as river channelization, dredging (Chisa et al., 2015), city Masterplan development and response to local flood hazards (Adejuwon and Aina, 2014).

The results in table 3 also revealed low levels (12%) of subscription to property insurance against flooding. Lack of societal awareness, lack of incentives to insurance companies and poor flood data availability have been cited as the factors that contribute to poor insurance policy in Nigeria (Nkwunonwo et al., 2015).

Table 4 Flood Risk Cycle and Stakeholder Mapping

Risk Management Cycle	Content	Federal	State	Local
Preparedness	Data collection, Early Warning Systems, Planning, Prediction, Education, Code Enforcement, Flood Risk Mapping.	FMENV, FMI, NIMET, FMWR, NIWA, NEMA, NIHSA, RBDA, NIOMR, NASRDA, FMP, FMARD.	SG, SEMA	LG
Response	Infrastructure protection (Dams, Levees, Dikes), Evacuation, Channels, Displacement camp establishment.	CBO, NGOs, NEMA, FMWR, RBDA, FMP.	SG, SEMA	LG
Recovery and Rehabilitation	Repair and Reconstruction of critical infrastructures (Water supplies, Electricity, Roads, Post Risk Assessment, telecommunication, etc.).	NDDC, NEMA, FMHUD, FMW, FMP, FMARD.	SG, SEMA	LG

See Supplementary Table 1 for acronym definitions

Adapted from (Ologunorisa, 2004, Federal Ministry of Environment, 2005a).

4.3.2. Flood Hazard Worry

4.3.2.1. Flood Risk Perception and Worry element

Bradford et al. (2012) and Raaijmakers (2008) discussed the relationship between flood risk perception and worry, suggesting that persons afraid (worried) of flood risk are more likely to take preventive actions. Flood risk perception was therefore used as an indicator for worry, as the question of "level of worry" was not directly asked in the survey. High-risk perception is expected to indicate a high degree of worry and vice versa. (Table 5). Results from the analysis of flood risk perception in relation to worry elements (Table 5) revealed no significant evidence to support the argument of a strong relationship between flood worry elements and risk perception, contrary to other studies (Adelekan, 2011). This lack of relationship is likely due to the bias caused by limited responses (Ronald et al., 2015). Nevertheless, the results revealed that 76% of the respondents have previously been affected by flooding, and corresponds with the results from the remote sensing MODIS approach, where 76% of the populace affected in 2015 had experienced the 2012 flood (Table 1).

Table 5 Flood worry elements analysis

Worry	Citizen (P-value)
Previously Affected	0.850
Family Size	0.925
Employment status	0.428

4.3.3. Flood Management Preparedness

4.3.3.1. Flood Management Preparedness and Risk Perception

How an individual or community perceives and prepares for flood risk also depends on knowledge of exposure, which informs the instigation of mitigation actions for expected impact (Miceli et al., 2008). The preparedness elements assessed were knowledge of flood risk map for planning, awareness of displacement camp location for relocation during flooding and subscription to flood insurance to enhance recovery (Ologunorisa, 2004, Agada and Nirupama, 2015, Nkeki et al., 2013). Results from Table 6 shows that there was no statistically significant relationship between preparedness elements and risk perception, contrary to the proven concept that high perception of flood risk instigates preparedness for future flood occurrences (Miceli et al., 2008, Wachinger et al., 2013). This is likely due to the limited data collected and skewed nature of the responses (Choi and Pak, 2004, Ronald et al., 2015). The results, however, indicate that 86% of the respondents are unaware of the availability of flood risk maps, 72% oblivious of displacement camp locations and 88% are not subscribed to flood insurance, thus revealing gaps in communication, institutions and the national flood management strategy (Obeta, 2014a).

Table 6 Flood Risk Perception Relationship with Preparedness Elements

Preparedness	Citizens (P value)
Aware of Flood Map	0.148
Property Insurance	0.354
Displacement Camp	0.417

4.4. Government and Citizens Flood Perception Analysis in Nigeria

The role of the Nigerian government in flood management has been well established at all levels in table 4, which includes flood management plan implementation; structural and non-structural mitigation measures deployment; and resource prioritisation and distribution during flooding. These actions rely on their perception of flood risk in a particular region of the country, that is based on the annual flood map developed bases using combined GeoSFM and SWAT model (Kellens et al., 2011, NIHSA AFO, 2013), to designated a region as high, medium or low flood risk area. Figure 7 shows individual flood risk perception overlaid on local government scale government risk perception, and it revealed the discordancy in risk perception by both parties. Comparative analysis also showed that 34% of the risk perceived by the government was same as the citizens', while the remain 66% differed considerably. Furthermore, 30% of citizens perceived higher risk than the government, and 34% of the citizen's responses indicated the reverse, suggesting that risk perception variability mostly influenced by localized flood experiences. Chi-square statistical analysis further supported this finding ($X^2 = 2.037$, $P = 0.729$), revealing the absence of significant similarity between government and citizen flood risk perception at corresponding locations.

The NIHSA AFO identified mostly regions hydraulically connected to river systems as high and medium risk flood risk zones, hence accounting mostly for fluvial flooding (Adetunji and Oyeleye, 2013, Nkwunonwo et al., 2016). Crowd-sourcing contrastingly capture micro-environmental flooding caused by localised climate and anthropogenic conditions (Muller et al., 2015, Muller et al., 2013), thereby providing the advantage of identifying flood caused by factors that are seldom captured by models developed from coarse data. Also, given that citizens have first-hand flood experiences, personal risk perception is mostly based on empirical knowledge (Jacobs and Worthley, 1999), while government risk perception is based on flood models likely affected by inherent model and data uncertainties (Rowe and Wright, 2001, Beven and Hall, 2014, Siegrist and Gutscher, 2006).

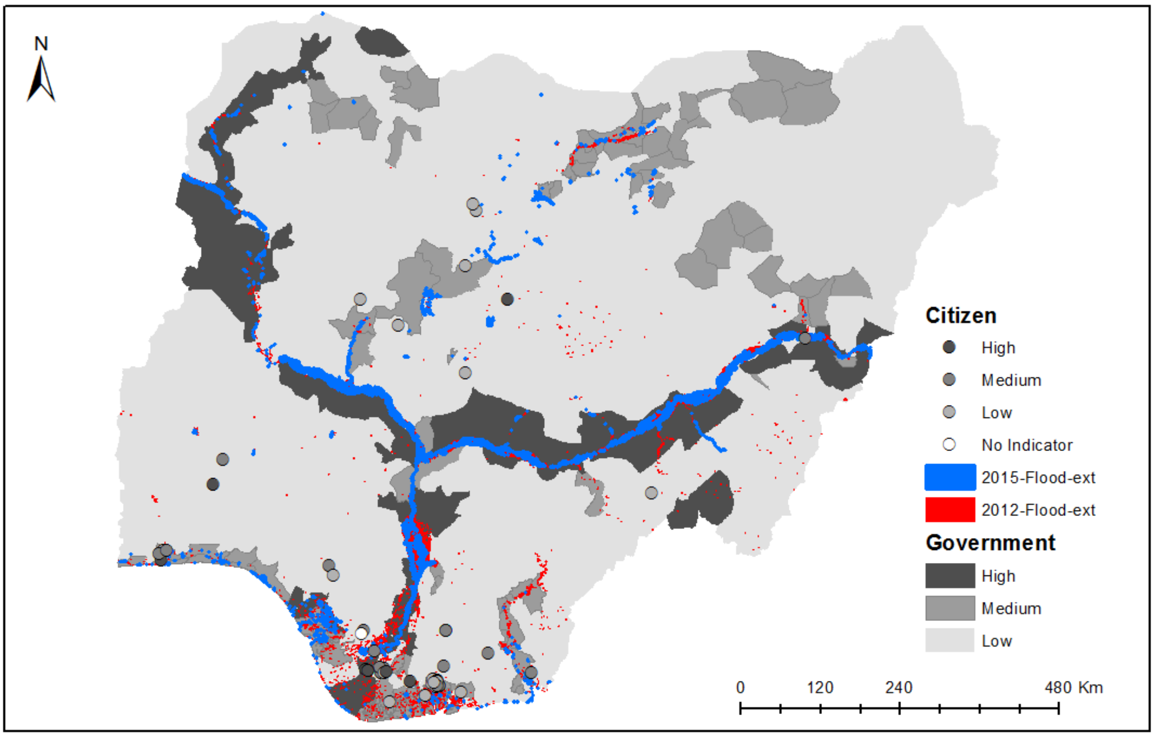


Figure 7 Overlay map of NIHSA 2015 Annual Flood Outlook (AFO), crowd-sourcing risk perception, and MODIS NRT flood overlay (2012 and 2015).

5. CONCLUSION

Understanding flood hazard exposure and impact is essential in flood management, especially during flooding to improve response and mitigate immediate flood impact. Ground-based flood monitoring and assessment are largely incapable/insufficient of efficient flood data gathering due to the logistical challenges that emanate when flood hits peak and inundates transport infrastructure that links remote locations. Remote sensing becomes particularly useful in such cases, as it enables large scale flood risk assessment without being in direct contact with the region of interest. Remote sensing is however hampered by financial, technical temporal, spatial, satellite sensor and environmental drawbacks (Musa et al., 2015, Yan et al., 2015a, Wood et al., 2014). Also, considering that flood events sometimes occur rapidly with little or no notice (especially in riparian countries), estimating the schedule time for satellite devices capture the event can be particularly challenging. Citizen involvement in data collection (crowd-sourcing) to support scientific research and decision making has been found to be one of the compensatory approaches that allow data collection at a wide spatial scale and even in vegetated and rugged locations where satellite technology is deficient (Goodchild, 2007, Baruch et al., 2016). This has been proven to provide first-hand empirical evidence to enhance and validate scientific models and predictions over the years (Yu et al., 2016, Goodchild and Glennon, 2010).

This study evaluated the feasibility of integrating open-access remote sensing and crowd-sourcing for Near-Real-Time flood monitoring, to draw from the strength of both approaches during the peak flood season of 2015 in Nigeria to improve flood detection. This study also collected retrospective data on a past 2012 flood event, to enable comparison with the current 2015 flood event, to enable the assessment the riparian flood management agreement effect on downstream flooding and other flood management efforts by the government. Flood risk indicator effects on citizen flood risk perception were assessed, and citizen flood risk perception is further evaluated against government's flood risk perception that is based on annual flood risk maps, upon which flood management decisions are based.

From the results of this study, the following conclusion has been drawn:

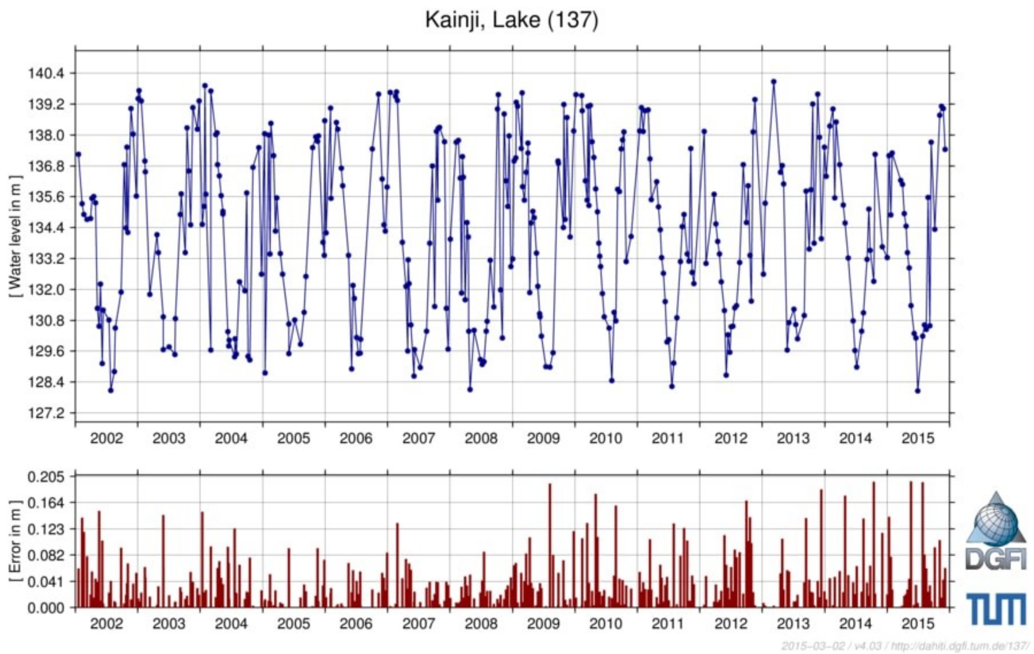
1. This study highlighted recurrent flooding in several locations using both remote sensing and crowd-sourcing methodologies, despite reduced flooding in 2015 due to the riparian dam water release agreement between Nigerian and Cameroon in 2013. This, therefore, suggests the need for a revised flood management approach in these regions (Egbinola et al., 2015), with a focus on repeatedly flooded locations, to improve flood mitigation and recovery.

2. Combining remote sensing (MWP) and crowdsourcing resulted in increases flood detection compared to when individual approaches were applied individually, especially in 2012 when high magnitude flood was experienced. This improved flood detection took advantage of the spatial resolution of both approaches, which allows for the capture of macro and micro scale flooding caused by a combination of regional and local factors (Muller et al., 2015, Revilla-Romero et al., 2015b), i.e. fluvial and urban flooding. Therefore, an integrated remote sensing and crowd-sourcing approach is recommended, given that it provides the best approach to flood detection especially in mangrove dominated, urban areas, rugged terrains and cloud covered areas where individual approaches could be deficient.
3. The relationship between flood risk perception and flood risk indicator elements (Worry, Awareness and Preparation) was statistically insignificant, and owing to the limited data collected, no decisive conclusion can be made. Nevertheless, the responses obtained revealed an appreciation of the diverse causes of flooding and flood management responsibility designations, while knowledge of existing flood maps, displacements camps and flood insurance was limited.
4. Citizen and government flood risk perception varied considerably, owing to inherent model and data uncertainties, and in the integrated SWAT and GeoSFM model (Yang et al., 2008, Daggupati et al., 2015, Tan et al., 2015) from which government flood perception is based. Also, the government flood model is biased towards fluvial flood risk detection, while crowdsourcing's is capable of capturing flooding caused by local factors such as intense precipitation in poorly drained urban areas and drainages clogged by poor waste management practices. As such, an integrated approach is suggested for effective flood risk assessment, incorporating citizen risk detection and improved flood models based on sufficient *in situ* and satellite remote sensing data (Renschler and Wang, 2017).
5. A unique challenge of reluctance to divulge socio-economic information in combination with flood impact during active crowd-sourcing is revealed in this study, peculiar to developing regions, owing to experiences and perception of internet fraud in recent years (Jegede, 2014).
6. Although the prospect of crowd-sourcing for improving flood detection is clearly evident in this work, the responses received and used in the analysis presented are

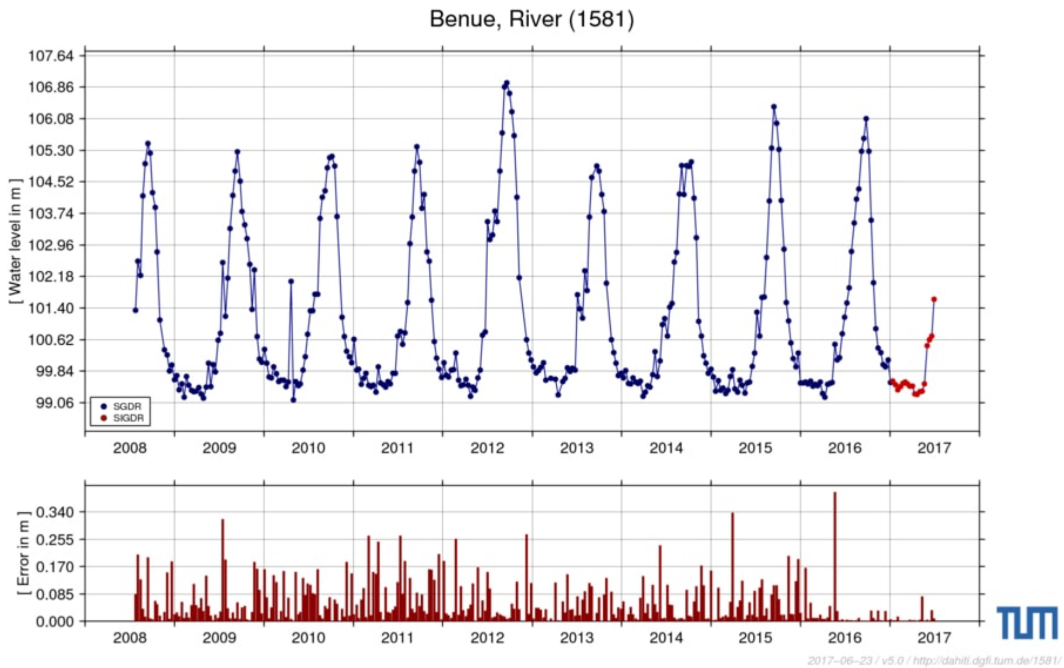
quite limited, as such the outcomes of this section are not definitive due to this limitation.

Having understood the potential of integrated crowdsourcing and remote sensing for near-real-time flood monitoring, going forward it is expected that such an approach if coordinated by a designated disaster management agency such as the National Emergency Management Agency (NEMA) in Nigeria would improve citizen participation, and can aid large-scale flood detection, damage impact assessment and resource prioritization and distribution to alleviate immediate flood impact and inform rehabilitation activities (Dashti et al., 2014, Roxanne and Andrej, 2014).

Chapter 5 Supplementary Figures and Tables



Supplementary Figure 1 (a) Kainji Lake Water Levels and Variations



Supplementary Figure 1 (b) Benue River Water Levels and Variations

Supplementary Table 1. Definition of acronyms

S/N	Name of Ministries	Acronyms
1	Federal Ministry of Water Resources	FMWR
2	Nigerian Meteorological Agency	NIMET
3	Nigerian Inland Waterways Agency	NIWA
4	River Basin Development Authorities	RBDA
5	Nigerian Hydrological Service Agency	NIHSA
6	Federal Ministry of Environment	FMENV
7	National Emergency Management Agency	NEMA
8	Federal Ministry of Housing and Urban Development	FMHUD
9	Federal Ministry of Works	FMW
10	State Government	SG
11	Local Government	LG
12	Niger Delta Development Commission	NDDC
13	National Institute of Oceanography & Marine Research	NIOMR
14	Federal Ministry of Information	FMI
15	Community Based Organisation	CBO
16	Non-Governmental Organisation	NGO
17	Federal Ministry of Agriculture and Rural Development	FMARD
18	Federal Ministry of Power	FMP

CHAPTER 6: HYDRODYNAMIC MODELLING OF EXTREME FLOODS IN DEVELOPING REGIONS USING MULTIPLE OPEN-ACCESS REMOTE SENSING AND 3RD PARTY DATA SOURCES.

Abstract

The sparsity of hydrological data hampers flood modelling in many developing regions, due to the logistical, administrative and financial challenges associated with the data collection processes. As floods become more frequent and increase in magnitude, alternative data sources need to be explored in order to provide reliable information required for managing known and expected flood impacts. This study explores the contribution of open-access remote sensing datasets in all stages of fluvial flood modelling and mapping including (i) flood frequency estimation, (ii) hydrodynamic modelling, and (iii) inundation mapping.

It uses a case study of Niger South region of Nigeria and integrates radar altimetry, digital elevation model, optical and Synthetic Aperture Radar (SAR) images, 3rd party (independent organization) acquired bathymetric survey data and aerial geotagged photos in the CAESAR-LISFLOOD-FP 2D hydrodynamic model to simulate flooding. The model was calibrated/validated by varying the Manning's roughness from 0.01 to 0.045, with 0.04 established as the optimal roughness value for maximum accuracy. A combination of SAR and optical satellite images was found to improve the model predictive accuracy in comparison to when only optical imagery was used, due to the presence of cloud cover during the wet season in the Niger Delta section of the study domain. Breaking the study domain into three sections for validation showed how hydrodynamic model prediction varied with data availability and geomorphology, resulting in F-Statistics of 0.81, 0.53 and 0.19 at Lokoja, Onitsha and Niger Delta respectively for combined SAR and optical images, decreasing with reduced data availability. The RMSE of modelled water levels evaluated against *in Situ* measurements at Lokoja and Onitsha were 0.56, 3.65 m respectively. Geotagged overflight photos showed an improved model to reality accuracy, revealing SAR inundation delineation deficiency in the Niger Delta dominated by mangrove cover. Incorporating the 1-in-100 year AEP flood into the study at Lokoja where less error was evident revealed that the 2012 flood event was the 90% confidence level bounds of the 1-in-100-year. This implies that open-access remote sensing and 3rd party data can be instrumental in improving flood management decisions in data-sparse regions through

the provision of substantial information that would enhance mitigation efforts to reduce the impact of flooding on the potentially exposed populace.

Keywords: Open-access remote sensing; hydrodynamic model; 2012 Flood Nigeria; Radar Altimetry; Digital Elevation Model; Optical and Radar Satellite images.

1. Introduction

The magnitude and frequency of flood events are continuously increasing, and with climate change altering long-term climate and short-term weather patterns this scenario is not expected to change in the foreseeable future (Balbus et al., 2013). The total global cost of flood damage stands at a staggering 46 trillion US Dollars and is projected to increase to 158 trillion Dollars by 2050, based on growing population and GDP rates (Jongman et al., 2012). Population increase and urban sprawl typically result in the migration of people towards settling in floodplains, which are flooded annually during peak flow periods (Yukiko et al., 2013, McGranahan et al., 2007, Syvitski et al., 2012). Hallegatte, (2014) documented a 170% increase in the number of floodplain dwellers between 1970 and 2010 globally. As a typical example of a developing country, Nigeria has seen a substantial increase in population inhabiting floodplains over the recent decade (Mahmoud et al., 2016, Komolafe, 2015, Daura and Mayomi, 2015, Mayomi et al., 2013, Tamuno et al., 2003). Thus there is a need for the development of measures to reduce flood exposure as the upward trends in urbanization and population continue.

To manage floods and their impacts efficiently, accurate information that depicts the extent of the hazard (i.e. inundation extent, flood depth and propagation velocity) is essential (Els, 2013). However, deriving such information requires detailed data inputs for flood modelling procedures such as flood frequency estimation, flood routing and hazard mapping (Aerts et al., 2009). Flood frequency estimation requires the approximation of the magnitude of flood at a certain return period by fitting a defined probability distributions to the annual maximum or partial discharge time series (Kuczera, 1999, Reed, 1999) when enough data is available. For ungauged rivers , alternative methods based on runoff estimation (Merz and Blöschl, 2005, Rogger et al., 2012), empirical altimetry forecast rating curve extrapolation (Pandey and Amarnath, 2015, Clark et al., 2014) and regionalization techniques (Haddad et al., 2014, Izinyon and Ajumka, 2013, López and Francés, 2013, O'Brien and Burn, 2014) can be applied. Flood routing models (1 and 2 – Dimensional) utilise topography data (river channel and floodplain terrain details), hydrographic data, and river channel and floodplain roughness that define terrain resistances, in order to derive water depth, velocity, propagation timeline, and inundation extent (Aerts et al., 2009, Seung Oh et al., 2013, Skinner et al., 2015). Lastly, flood maps communicate the outcomes of hydrology and hydrodynamic models in an easy to assimilate and implementable format (Kron, 2005), and have recently become interactive, allowing public involvement via volunteer geographic information systems and crowd-sourcing (Degrossi et al., 2014, Bordogna et al., 2016). Flood maps can be presented in probabilistic or deterministic forms, depending on the type of flood information and accompanying uncertainty to be communicated (Di Baldassarre et al., 2010, Domeneghetti et al., 2013).

In many developing countries, flood modelling and mapping are hampered by a lack of sufficient *in situ* hydrological data (Sanyal, 2013, Yan et al., 2015a). This data sparsity challenge results in uncertain outcomes used in flood management (Sanyal et al., 2013, Yan et al., 2015a), consequentially causing aggravated exposure and socio-economic loss when planning is based on poorly derived information (Mishra et al., 2009).

River gauge stations are usually set-up to collect hydrological data (Bshir and Garba, 2003), however logistical and financial challenges in developing countries restrict spatial coverage of gauge networks (Ngene, 2009). Where gauge stations do exist they often collect insufficient data due to disruption of infrastructure due to intense floods, poor planning and organization (Izinyon and Ehiorobo, 2014, Olayinka et al., 2013, Ngene et al., 2015). Likewise, detailed high-resolution ground survey or satellite data that capture terrain details are cost-intensive, hence researchers have recently shifted focus to open-access remote sensing data to curb the cost associated with such data collection (Patro et al., 2009, Yan et al., 2015b, Yan et al., 2015a).

There have been advancements in open-access remote sensing over the past decade, with applications in many different aspects of flood modelling and mapping having been demonstrated. Brief reviews of the application of open-access remote sensing are presented later in Section (2.1), with emphasis on optical and Synthetic Aperture Radar (SAR) satellite images, radar altimetry, Digital Elevation Models (DEMs), and bathymetry. In this chapter, the use of multiple open-access geospatial technologies (data and model) is explored, complemented by 3rd party (independent organization) collected datasets with the aim of modelling flood dynamics, simulating the extent and depths of a high magnitude flood event at the chosen study site and assessing in retrospect the extent in comparison to a 1-in-100-year Annual Exceedance Probability (AEP) flood for management purposes. The Limitations associated open-access data usage in flood modelling are addressed, including the implications of missing *in situ* data in hydrological flood magnitude estimation, the accuracy of the Shuttle Radar Topography Mission (SRTM) derived DEM used in hydrodynamic modelling, and the discrepancies associated with flood extent mapping based on optical and SAR Images.

1.1. Study area

The study area Figure 1(A) is located within hydrological area 5 (Niger South) in southern Nigeria, encompassing a substantial part of the Niger and Benue rivers, which meet at Lokoja and travel downstream to discharge into the Atlantic Ocean via Nun and Forcados rivers (Abam, 2001a). The Niger basin covers a large proportion of West Africa (2,170,500 km^2) and is represented in Figure 1 (B). The Niger Basin drains into the Niger South hydrological area, collecting an average discharge of 6000 m^3/s from 11 riparian countries (Gaston, 2013). Due to these high flows, many rivers within the basin have been dammed for hydroelectric power generation, irrigation and flood control (Aich et al., 2014b, Andersen and Golitzen, 2005).

In recent years the Niger and Benue rivers have been heavily influenced by excess water released from upstream reservoirs in Nigeria, Niger and Cameroon (Ojigi et al., 2013, Olojo et al., 2013), resulting in flooding of the low-lying settlements within floodplains (FGN, 2013, Agada and Nirupama, 2015, Odunuga et al., 2015). The annual average rainfall in the region varies from 750 to 1600mm, and the average temperature from 18 to 28°C.

The flood model domain used in this study is represented by the DEM area in Figure 1, while subdomains defined by the red rectangles in Figure 1 (Lokoja, Onitsha and Niger Delta) were selected for subsequent analysis and accuracy assessment given the differences in data availability and geomorphological characteristics i.e. River confluence, Canyon and delta.

The three sub-domains were among the most affected when Nigeria experienced unprecedented levels of flooding in 2012 (Ojigi et al., 2013, Tami and Moses, 2015, Nkeki et al., 2013, Olojo et al., 2013). The interflow of water from the Niger and Benue rivers initiated flooding at Lokoja (Odunuga et al., 2015), the Onitsha/Asaba floodplain was flooded due to constricted channels and high upstream flow (Efobi and Anierobi, 2013); and the Niger Delta region was flooded as a result of its low-lying topography and the influx of rising upstream water levels (Tami and Moses, 2015, Olojo et al., 2013).

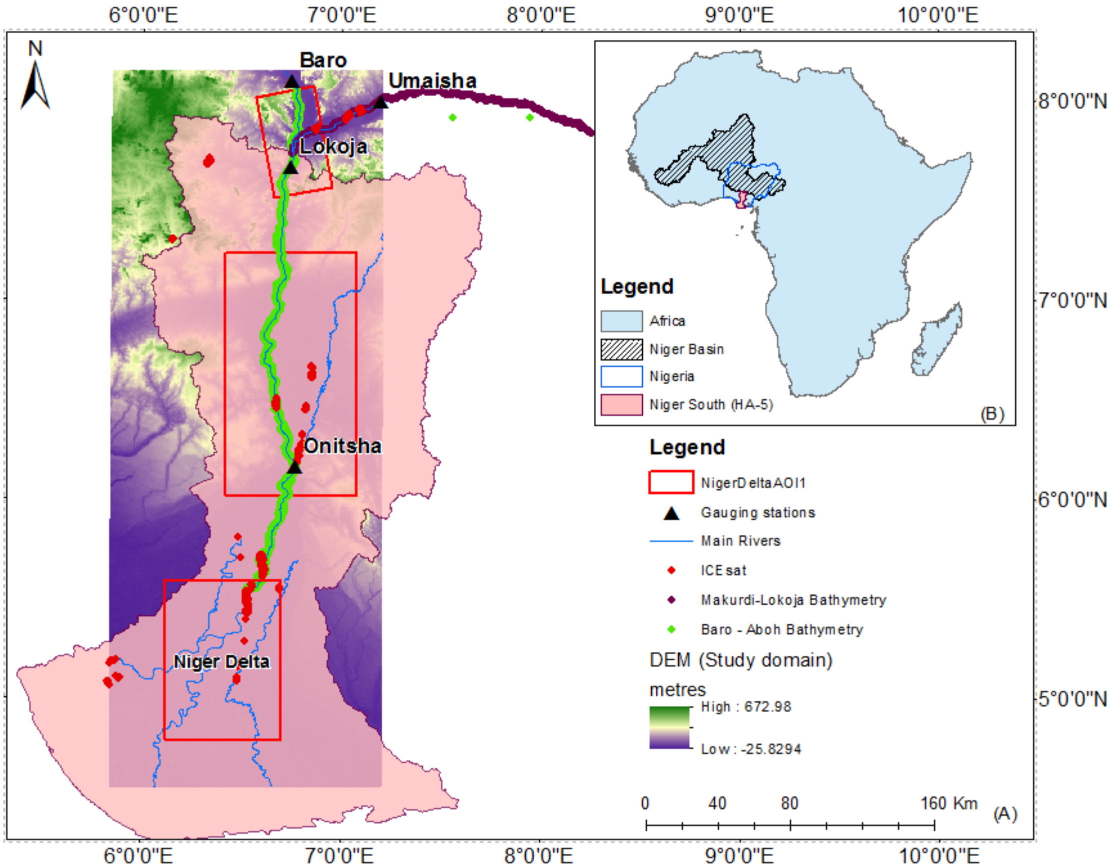


Figure 1 (A) Map of study area, showing the Niger-South river basin (hydrological area 5), gauging stations, ICESat elevation points, bathymetry points, DEM/Model domain and sub-domains. Figure 1 (B) Map of Africa showing the Niger Basin that discharges through the HA-5 into the Atlantic Ocean.

2. Methodology

2.1. Data sources and their application

The flowchart of the overall study methodology is presented in Figure 2, detailing how the various datasets were integrated for flood modelling and risk evaluation in the

Niger-South Basin of Nigeria. Further details are presented in subsequent sections 2.1.1 to 2.4.

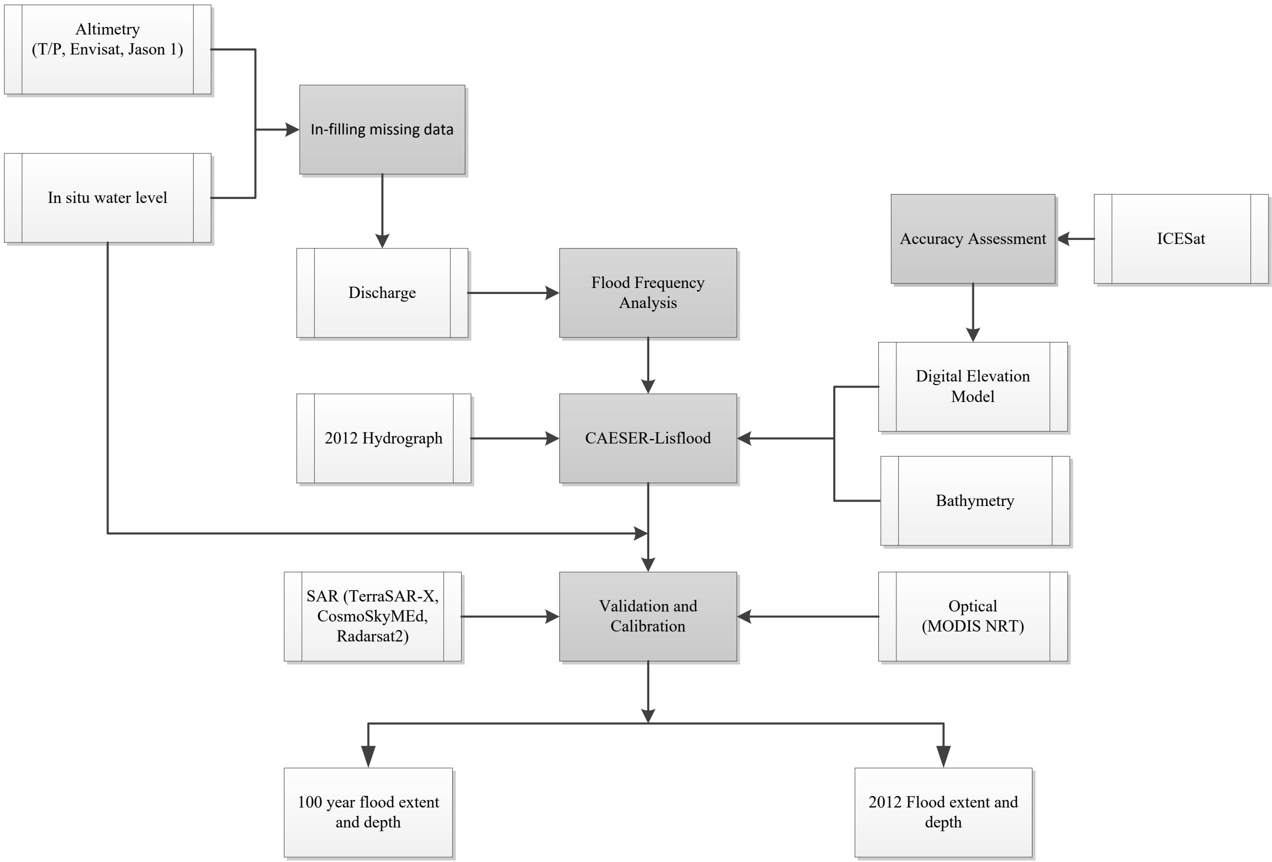


Figure 2 Conceptual flowchart of integrated flood modelling and mapping in the Niger South

2.1.1. Optical and Radar Satellite Images, and their application

The passive remote sensing Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat and the recently made open-access Advanced Spaceborne Thermal Emission and Mission Radiometer (ASTER) images have been the most widely applied satellite data in flood management processes (Forkuo, 2011, Qi et al., 2009, Gareth et al., 2015, Nigro et al., 2014). The high temporal resolution of MODIS (1-2days) and the high spatial resolutions of Landsat and ASTER (i.e. 30 and 15 meters respectively) provides unique advantages for varying scales and frequencies of flood mapping (Ojinnaka et al., 2015, Ojigi et al., 2013, Jeb and Aggarwal, 2008, Tarpanelli et al., 2013). Nevertheless, optical satellite data application is hampered by cloud cover, especially during the wet season when cloud formation leads to rain and consequently runoff and flooding (Asner, 2001, Musa et al., 2015, Revilla-Romero et al., 2015b). To minimise these deficiencies and improve optical imagery application, several techniques have been proposed and applied, including imagery fusion to leverage the best features of combined images. For example, Zhang et al. (2014) combined MODIS and Landsat to map inundation extent in urban regions of New Orleans, thus improving the spatial and temporal resolution of the outputs. Phuong and Yuei-An (2015) employed MODIS and Landsat-8 in mapping inundation over rice paddies downstream of the Mekong River in Cambodia. MODIS and ASTER were also combined and applied in validating the Coupled Routing and Excess Storage (CREST) hydrologic model in the ungauged basin of Nzoia (Khan et al., 2011). Trigg et al., (2013) developed and applied a gap filling approach that improved the hydraulic connectivity of the MODIS flood water extent for large-scale flood detection by accounting for spatial uncertainty, using geostatistical connectivity approach that quantifies the probability of a location being flooded given a known flood location and specified distance (Pardo-Igúzquiza and Dowd, 2003).

Active sensor SAR, on the other hand, allows for day and night image acquisition and penetrates cloud cover, thus allowing for an effective inundation extent delineation process (Musa et al., 2015). Commercial SAR satellite data has dominated flood mapping studies for decades, due to their high spatial resolution and capacity for water discrimination. Some examples include low-cost ERS SAR/Envisat ASAR, CosmoSkyMed, Radarsat 1 and 2, TerraSAR-X, and ALOS PALSAR (Betbeder et al., 2015, Frappart et al., 2006, García-Pintado et al., 2013, Yan et al., 2015a). Although open-access 10-metre resolution SAR Sentinel-1is now available for flood mapping in several developing regions (Kyriou and Nikolakopoulos, 2015, Donato et al., 2014), at the time of the flood event of interest for this study occurred in 2012, Sentinel 1 was yet to be launched. Hence, the emphasis in this study is on commercial satellites made freely available by independent organizations (3rd parties) operating in the flood-prone region of interest. Despite the advantages associated with SAR imagery, the inability of C and X-band sensors to penetrate vegetation cover and the misinterpretation of imagery over different land use types have been identified as significant limitations (Bruce et al., 2015), and must be considered when applying SAR data.

In the context of the present study, remotely sensed data will be used to assess the capacity of a hydrodynamic model to depict the observed extent of flooding. A combination of TerraSAR-X, MODIS Near-Real-Time flood maps, Radarsat2 and

CosmoSkyMed images acquired at the time of the 2012 flood event in Nigeria were used in mapping the inundation extents. Optical and radar images were combined to capture the alignment of flood extents with hydrographic changes throughout the flood event (rise, peak and fall), thereby compensating for the deficiencies in inundation extent derived from both sensors (Wood et al., 2014, Mason et al., 2016, García-Pintado et al., 2013). Details of the images used, dates of acquisition and discharge measured at upstream gauging stations (which are mapped in Figure 1) are presented in Table 1. MODIS coverage was deficient in the Niger Delta due to high cloud cover in the region (Uchegbulam and Ayolabi, 2013), hence the SAR data compensated for this gap. SAR images with Horizontal-Horizontal (HH) polarisation only were used as they provided good discrimination between flooded and non-flooded area pixels (Mason et al., 2016). The MODIS Near-Real-Time (NRT) Water Product was developed by the National Aeronautics and Space Administration (NASA) and available via https://oas.gsfc.nasa.gov/floodmap/, TerraSAR-X from the disaster charter activated in 2012, while Radarsat2 and CosmoSkyMed provided by the Shell Petroleum Development Company (SPDC) Nigeria (Appendix 5), acquired on the 18th, 19th and 20th of October 2012. The SAR images flood extent was extracted by histogram thresholding approach (Long et al., 2014). In addition to the MODIS and SAR imageries which covered specific locations of the study domain, Landsat 8 Operational Land Imager (OLI) was acquired for the whole study area. This was used to derive land use maps following similar maximum likelihood supervised classification approach employed by Butt et al., (2015), in order to determine the built-up area inundated, based on satellite and modelled derived flood extents.

Furthermore, given the deficiencies of optical and SAR satellite images previously highlighted, this study took a further step by incorporating geotagged overflight photos acquired from a helicopter over the Niger Delta region during the peak of flooding in 2012 using NIKON D7000 camera. Geotagged photos points (287) were manually classified as flooded and non-flooded, and applied in extracting corresponding values for the model and observed flood extents for comparative analysis (Section 3.3). The geotagged photos were captured at an average distance of 2 km from focus on the helicopter (see Supplementary Figure 5), thus a 2 km buffer was created and spatial zonal statistics applied to select the dominant (majority) cell value (flooded/Non-flooded) contained within the buffer area, to identify flooded areas detected by the model and SAR imagery in 2012.

Table 1 Satellite imagery used in the study with acquisition dates and corresponding upstream gauge station discharge values and Annual Exceedance Probability (AEP).

Dates [YYYY-MM-DD]	Images				Baro Gauge (m^3/s)	AEP	Umaisha Gauge (m^3/s)	AEP
	TSX	MDS	R2	CSKD				
2012-09-03	-	X	x	-	5,187	2	12,303	2
2012-09-25	x	x	-	-	8,533	50	20,328	100
2012-10-09	-	x	x	-	6,969	5	17,378	50
2012-10-11	-	x	x	-	6,696	5	16,771	20
2012-10-12	-	X	X	-	6,504	5	16,520	20
2012-11-06	-	x	x	x	3,270	2	7,955	2

TSX = TerraSAR-X, MDS = MODIS, R2 = Radarsat2, CSKD = CosmoSkyMed

2.1.2. Radar Altimetry and application in study

Recent advancements in open-access remote sensing have led to the availability of high temporal and spatial resolution radar altimetry data sets (European Space Agency (ESA), 2016, NESDIS, 2016, Donato et al., 2014). This means that hydrological data (water levels) can now be captured in remote and inaccessible locations that have previously been ungauged or with newly established gauges with short records. Altimetry is applicable in several aspects of hydrodynamics modelling and flood mapping, discharge estimation at ungauged or data sparse river basins (Papa et al., 2010, Sridevi et al., 2016, Getirana and Peters-Lidard, 2013, Tarpanelli et al., 2016), digital terrain data accuracy evaluation (Carabajal and Harding, 2005, Fricker et al., 2005, Kon Joon Bhang et al., 2007), river bathymetry characterisation and assimilation (Chávarri et al., 2012, Yoon et al., 2012) and hydrodynamic model calibration and validation (Domeneghetti et al., 2014, Sun et al., 2012, Sun et al., 2015).

Gaps in hydrological time series due to intermittent gauging station recording or disruption to the station network, which frequently occurs in most developing countries, resulting in uncertain flood frequency estimates (Gill et al., 2007, Lee and Kang, 2015). In the present study, altimetry data sets (Topex/Poseidon, Envisat, Jason 1, and Jason 2) were used to fill missing data for flood frequency estimation, using the method described in Chapter 3 (Section 3.1.1.1).

Ice, Cloud, and land Elevation Satellite (ICESat)/Geoscience Laser Altimeter System (GLAS) SPOT points were applied in this study to assess the accuracy of the SRTM DEM in the absence of ground surveyed elevation (again a typical situation in developing countries). Also, for the Niger Delta region where bathymetry data is unavailable, the average elevation difference between the two systems was deducted from the DEM river channel delineated from Landsat OLI, based on the Patro et al. (2009) approach, to compensate for SRTM C-band radar inability to penetrate water surface.

Altimetry datasets were downloaded from the Database for Hydrological Time Series of Inland Waters (DAHITI) (Schwatke et al., 2015b, Schwatke et al., 2015a), the Centre for Topographic studies (CTOH) of the Ocean and Hydrosphere archive (HYDROWEB) and ICESat-derived inland water surface spot heights (IWSH) data was downloaded from the recently developed database (O'Loughlin et al., 2016a). All digital elevation models were directly compared to ICESat spot height "n05e005_GLA14", as all data sets were on the same vertical datum WGS96-Geiod and projected to WGS_1984_UTM_Zone_32N. The properties of the altimetry missions used in this study are listed below (Table 2):

Table 2 Altimetry data and properties for sources used in this study (O'Loughlin et al., 2016a)

Mission	Ground Footprint (m)	Vertical Accuracy (m)	Frequency (days)	Operation timeline
Jason-2	~ 300	0.28	10	2008 - active
Jason-1	~ 300	1.07	10	2002 - 2009
Envisat	~ 400	0.28	35	2002 - 2012
ICESat	~ 70	0.10	-	2003 - 2009
T/P	~ 600	0.35	9.9	1993 - 2003

2.1.3. Digital Elevation Model (DEM), Bathymetry, accuracy assessment and application

DEMs are essential in hydrodynamic modelling as they provide a continuous topographical surface upon which the flood is routed. Shuttle Radar Topography Mission (SRTM) DEM (Farr et al., 2007) is one of the most widely applied open-access terrain datasets for hydrological and hydrodynamic modelling globally (Biancamaria et al., 2009a, Neal et al., 2012, Sanyal et al., 2013, Gleason and Smith, 2014, Smith et al., 2015) and Nigeria in particular (Bas van de et al., 2012, Olayinka et al., 2013, Adeaga et al., 2006). Despite the wide applicability of SRTM, the C and X-band radar cannot penetrate the water surface to detect channel geometry, therefore resulting in an overestimation of the bed elevation and consequently flawed flood model outcomes (Yan et al., 2015a). Other challenges linked to SRTM usage are its inability to completely penetrate vegetation cover in forested areas and reflections of radar signals off the top of building in urban areas, resulting in positively biased elevation estimates (Brown et al., 2010, Neal et al., 2012) and consequently biased outcomes when applied in hydrological and hydrodynamic modelling studies (Yamazaki et al., 2012).

Several studies have adopted various techniques to curb this deficiency at local scales. In Baugh et al., (2013), 50 to 60 percent of the vegetation height estimated from MODIS, ICESat vegetation canopy height, as well as the Simard et al. (2011) and Lefsky (2010) global vegetation height data sets were reduced from SRTM DEM. This resulted in SRTM vegetation correction and improved model accuracies when compared to Topex/Poseidon and JERS (Japanese Earth Resources Satellite) observations. Betbeder et al., (2015) reduced vegetation bias by adopting a systematic method in the Amazon that harnesses vegetation height (Simard et al., 2011), Landsat land cover and Radar altimetry to deliver a hydrological corrected DEM, thereby reducing SRTM DEM bias by 64 percent. Patro et al., (2009) and Sanyal et al., (2013) refined SRTM DEM-derived channel cross-section used for one-dimensional MIKE 11 and two-dimensional LISFLOOD-FP flood models respectively. This was done by subtracting the average errors derived from comparing STRM DEM cross sections and Differential GPS survey data sets. Neal et al., (2012) adopted a hydrodynamic model approach that reduces channel and floodplain elevation overestimations by defining calibratable hydraulic geometry parameters (i.e. channel depth and width) within the two-dimensional sub-grid LISFLOOD-FP model. This led to significant improvements in water level, wave propagation and inundation extent accuracies. In Siberia, Biancamaria et al., (2009a) applied a simple approach that reduced the SRTM derived channel elevation by 5, 10 and 15 metres to determine an appropriate assumption for optimal flood modelling for Obi Rivers. This resulted in 10 metres being identified as the optimal river depth estimates for efficient hydrodynamic modelling for Obi rivers.

At a global scale, a few studies have derived hydrologically corrected SRTM DEMs, aimed at reducing elevation errors caused by voids, vegetation non-penetration and urban rooftop bounce-off. O'Loughlin et al. (2015) systematically combined SRTM, MODIS vegetation canopy (DiMiceli et al., 2011), ICESat GLAS and varying percentages of satellite-derived vegetation (Simard et al., 2011) to produce the Global Bare-Earth SRTM DEM (BARE) with reduced uncertainties in various climatic zones (Broxton et al., 2014, Peel et al., 2007). This approach resulted in the reduction of average vegetation bias from 4.94 to 0.4 m, and standard deviation from 7.12 to 4.80 m in comparison to ICESat and cross-sections of LiDAR respectively. Sampson et al.(2015) applied an alternative approach to correct SRTM bias caused by vegetation and urban land use/cover to generate the Bare Earth SRTM Terrain (BEST). This approach uses a moving window filter algorithm (Elvidge et al., 2007) to reduce urbanization elevation bias, while similar algorithm adopted by O'Loughlin et al. (2015), i.e. adaptive smoothing (Gallant, 2011) is applied to reduce vegetation bias. The BEST model resulted in a RMSE reduction from 10.96 to 6.05 m in comparison to local LiDAR-derived validation data and an overall bias reduction from 15.08 to -0.1 m. Robinson et al. (2014) developed a global DEM from a combination of CGIAR-CSI SRTM version 4.1, ASTER GDEM and Global Land Survey Digital Elevation Model (GLSDEM) to fill voids in the DEM data and systematically reduced noise by applying an adaptive smoothing approach by (Gallant, 2011), thereby reducing SRTM vertical error to between 4.13 and 10.55 m.

In the present study, the BARE and BEST DEMs covering the study domain were combined using the ArcGIS 10.2 mosaic “minimum” function that outputs the minimum cell value of two overlapping cell, based on the assumption that the lowest DEM value represents bare earth elevation. This approach is intended to curb overestimation bias that results from unremoved vegetation and urban areas heights from individual DEMs. Mean Error (M.E.) and Root Mean Squared Error (RMSE) was used for accuracy assessment and were applied in this study, defined by:

$$\mathrm{RMSE} = \sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \acute{y}_i)^2\right]} \tag{1}$$

Where "n" is the total data points, "y_i" the ICESat elevation, "$\acute{y}_i$" the SRTM DEM-extracted elevation points, "$\sum$" summation and $\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \acute{y}_i)^2\right]$is the Mean Error (ME).

M.E informs us of the vertical bias in the DEM, quantifying the consistency in elevation underestimation (negative M.E) and overestimation (positive M.E) in relation to the reference (ICESat elevation) value. RMSE on other hand characterizes the overall DEM surface error by a single quantity (Patel et al., 2016).

In the Niger Delta region where river bathymetry data is unavailable, the vertical bias was applied in correcting the offset between ICESat and DEM elevations. The mosaiced and river channel adjusted DEM was then converted to contour points and combined with bathymetric survey data points, then interpolated at a 90-metre grid spacing using the nearest neighbour method (Sibson, 1981). This resulted in a hydrologically smoothed DEM (Arun, 2013), that was then converted to ASCII format for use in the CAESAR-LISFLOOD model.

Surveyed bathymetry enables improved river geometry detailing, leading to improved hydrodynamic model outputs with reduced uncertainties (Sanyal et al., 2013). In Nigeria, most bathymetry data are restricted and subject to confidentiality, thus creating artificial data scarcity. For this study, bathymetric data were obtained from two companies after signing confidentiality documents that the data would be used for research purposes only. Digital Horizon Co. is a private company contracted to survey from Lokoja (Confluence) to Makurdi (Benue River), over a 240km distance. The survey was undertaken between 8th March to 16th April 2011 using HYDROSTAR ELAC 4300 DUAL Echo-sounder and C-Nav 2050 differential GPS systems. The bathymetric data were projected in Clarke 1880 Minna datum and UTM Zone 32. Bathymetric survey data from Jamata to Aboh – 300km along the Niger river was obtained from Royal Haskoning. These data were collected on-behalf of Nigerian Inland Waterways Authority (NIWA) in 2002 using an Ashtech Z12 Real Time Kinematics (RTK) GPS, Navisound 210, Navisound 50 and Raytheon 210Kc digital and analogue echo sounders. The bathymetric surveys were based on a Mean Sea Level (MSL) vertical datum and WGS84 spatial reference.

2.1.4. Hydrological Data, Flood Frequency Estimation and application

Flood magnitude for a specific return period is essential in planning for flood events and designing hydraulics structures to mitigate flood impact (Reed, 1999). In this study a Generalised Extreme Value (GEV) probability distribution was fitted to annual maximum flood series (Jenkinson, 1955), an approach that has been widely adopted in hydrological studies in several regions (Leclerc and Ouarda, 2007, Kochanek et al., 2013, El-Jabi et al., 2015, Smith et al., 2015, O'Brien and Burn, 2014). See supplementary material and Chapter 3 for more details.

Hydrological data from Baro, Umaisha, Lokoja and Onitsha were obtained from the Nigerian Hydrological Service Agency (NIHSA) and the National Inland Waterways Authority (NIWA), the agencies responsible for hydrographic data collection and management in Nigeria. Discharge values at Baro and Umaisha were used as input boundary conditions for the model (Di Baldassarre, 2012) for simulating floods for the hydrological year of 2012 (See Supplementary Figure 6 for the input hydrographs), and those at Lokoja and Onitsha were used in the model calibration and validation downstream (See Figure 1A or Figure 1 in Chapter 3). The maximum flood quantile (upper uncertainty bound) for the 1-in-100 Year AEP flood obtained from Chapter 3 was modelled for comparison with the 2012 hydrograph. Flood frequency plots from Chapter 3 are further presented as supplementary materials in this study (Supplementary Figure 1 - 2). The choice of upper uncertainty bound application is supported by the fact that the high discharges are often underestimated when using the rating curve (Di Baldassarre and Claps, 2011), coupled with the need to plan for the worst-case scenario.

2.2. CAESAR-LISFLOOD (CL) Hydrodynamic Model Description and Setup

CAESAR-LISFLOOD hydrodynamic and geomorphological (erosion and deposition) modelling tool (Van De Wiel et al., 2007) embeded with the LISFLOOD-FP code

(Bates et al., 2010) was selected for this study due to its effectiveness and applicability for fluvial flood modelling in data sparse regions, using coarse resolution terrain data sets (Biancamaria et al., 2009b, Trigg et al., 2009, Neal et al., 2012, Sanyal et al., 2013, Yan et al., 2015a, Seenath, 2015, Luke et al., 2015, Skinner et al., 2015). The CAESAR-LISFLOOD 2-Dimensional grid discretized flood plain model calculates fluxes flow between two Cartesians coordinates (X and Y) driven by gravity as a result of the free surface height between two elevation cells, given by the equation:

$$Q = \frac{q - gh_{flow}\Delta t \frac{\Delta(h+z)}{\Delta x}}{(1 + gh_{flow}\Delta t n^2 |q| / h_{flow}^{10/3})}\Delta x \tag{2}$$

where Q is defined as the flow between neighbouring cells, q is the flux between cells from previous time steps, g is the acceleration due to gravity, n is the manning's roughness coefficient, h is the water depth, z is the bed elevation, h_{flow} Is the maximum flow depth between cells, Δx is the grid resolution, and t is time. The depth of water within each cell is defined by:

$$\frac{\Delta h^{i,j}}{\Delta t} = \frac{Q_x^{i-1,j} - Q_x^{i,j} + Q_x^{i,j-1} - Q_x^{i,j}}{\Delta x^2} \tag{3}$$

Where i and j are the cell coordinates. The model time step controlled by the shallow water Courant-Friedrichs-Lewy (CFL) conditions is defined by:

$$\Delta t_{max} = \alpha \frac{\Delta x}{\sqrt{gh}} \tag{4}$$

Where α is a coefficient factor (courant number) that varies from 0.3 to 0.7 depending on the cell size, and influences the model stability (Almeida et al., 2012, Bates et al., 2010). High values of α increase model time-step and reduced model run time, but can result in more unstable models. For this study, α was approximated as 0.7 based on suggestions by Coulthard et al., (2013) for cell size greater than 50 metres.

In the present study, DEM was resampled from 90 to 270 metres, reducing the number of cells to 1,793,400 (active = 1,256,656) within a 9,1610 km^2 domain area, thus reducing the computational cost and SRTM DEM noise (Neal et al., 2012, Craig et al., 2012), to meet CAESAR-LISFLOOD cell computation limit of fewer than 2 million cells (Seoane et al., 2015). The river channel width within the study area varied from 0.3 to 1.5 km, represented by 1 to 6 cells after resampling. Final model outcomes were post-processed in ArcMap using the model presented in Appendix 6. The model parameters and sediment input grain sizes and distribution adapted from Olayinka (2012) are presented in Appendix 8.

2.3. Model Calibration and Validation

Flooded model calibration is usually undertaken by adjusting the manning's roughness (n) coefficients for the river channels and floodplains corresponding to input discharge parameters, while comparing the resultant outputs (Inundation extent and water depth) to observations from other data sources such as radar altimetry (Belaud et al., 2010), optical and radar satellite imagery (Sanyal et al., 2013, Trigg et al., 2009, Lewis et al., 2013, García-Pintado et al., 2013), aerial photography (Neal et al., 2011b) and/or *in situ* river measurements (Skinner et al., 2015, Luke et al., 2015, Jung et al., 2012). The aim is to ensure the model is capable of predicting reality within acceptable uncertainty limits fit for a particular purpose (Di Baldassarre, 2012, Hunter et al., 2007); in this case flood risk assessment. Usually, a range of roughness coefficient is predetermined based on existing literature (Chow, 1959, Arcement and Schneider, 1989, Kalyanapu et al., 2010), assigned to represent the degree of flow resistance caused by varying land use/cover types (Medeiros et al., 2012). Depending on the level of details required, spatially distributed or static roughness values can be assigned to the model (Seenath, 2015). In this study static manning's roughness was applied, which varied from 0.01 to 0.045 to capture the roughness that defines the Niger South region broadly (Olayinka, 2012).

Several test statistics including Root Mean Squared Error (RMSE) (Lewis et al., 2013), F-Statistics (Amarnath et al., 2015, Horritt, 2006, Md Ali et al., 2015), Nash-Sutcliffe efficiency (Sanyal et al., 2013, Neal et al., 2012), P-error, Skill value (Skinner et al., 2015), and R-Squared (Lewis et al., 2013, García-Pintado et al., 2013) have been used as goodness-of-fit measures for flood models. In the present studies, the F-Statistic (Critical Success Index), BIAS, percentage (%) flood capture and RMSE were adopted as the validity measures, to enable the comparison of model output comparison with independent data on flood extent and water surface elevation (Di Baldassarre, 2012).

The RMSE equation used was similar to that previously presented in Equation 1 (Section 2.1.3), with "y_i" depicting *in situ* water levels and "$\acute{y}_i$" The simulated value.

The F-Statistics was defined as:

$$F = \frac{A}{A + B + C} \tag{5}$$

Where A = (Simulated wet and observed wet), B = (Simulated wet but observed dry), C = (Simulated dry but observed wet) and D = (Simulated dry and observed dry) are defined in Table 3, and F can range from 0 to 1, increasing in levels of accuracy. The F-measure applied herein does not apply D, as a different measure would be needed and its inclusion is known to result in bias in the flood fit, as model domains usually contain larger dry areas than flooded (Wood et al., 2016). Stephens et al., (2014) however highlighted the limitations of this performance measure, as it tends to be biased towards high magnitude floods. Nevertheless, for this study, the measure is suitable as it was applied for relative comparison of flood extents only.

To assess the BIAS and percentage of observed flood correctly captured, both indices are stipulated as:

$$\text{BIAS} = \frac{A + B}{A + C} \tag{6}$$

$$\%\ \text{Flood Capture} = \frac{A}{A + C} \tag{7}$$

Table 3 Parameter definition for performance indices

	Observed wet	Observed dry
Simulated wet	A	B
Simulated dry	C	D

2.4. Evaluating model outcome and Flood Management Implications

To access the flood management implications of this study, overlay analysis was performed in order to identify the population, settlements (villages), built-up areas and road networks affected by the observed, modelled (2012) and 1-in-100 year floods. The population data (Gridded Population of the World (GPW), v4) was acquired from the SEDAC database, settlements points obtained from SPDC Nigeria Limited, land use (built-up area) derived from Landsat 8 OLI (Path:189/Row:55) image, using similar approach as Bhatti and Tripathi (2014), while Road networks were acquired from the Socio-Economic Data and Application Centre (SEDAC) database (Global Roads Open Access Data Set (gROADS), 2010 update).

3. Results and Discussion

3.1. Floodplain DEM Accuracy assessment with ICESat

River channel and floodplain elevation statistics extracted from corresponding ICESat and DEMs points, and the descriptive statistics, ME and RMSE are presented in Table 4, while the correlation between ICESat and the combined BARE and BEST DEMs is displayed in Figure 3. Combining these DEMs by their minimum values, reduced the ME (and RMSE) from 14.51 m (3.81 m) and 15.28 m (3.91 m) for BARE and BEST DEMs respectively, to 12.16 m (3.49 m), thereby improving the vertical accuracy when compared with ICESat data. The spatial distribution of ICESat elevation correlated better with the merged DEM, resulting in a slight improvement of the correlation coefficient of (R^2 = 0.994) (see Supplementary Figure 3 for others DEMs). The difference in elevation between ICESat and the corrected DEM was consistent with the average error levels records from previous studies in Nigeria that evaluated SRTM DEM against differential GPS elevation data (Isioye and Jobin, 2012, Isioye and Yang, 2013, Menegbo and Doosu, 2015, Ozah and Kufoniyi, 2008). To compensate for riverbed elevation overestimation in the SRTM DEM at the Niger Delta sub-domain where bathymetric data was unavailable, the average difference between ICESat and DEM elevation of 1.053 meters was subtracted from the SRTM river channel elevation using raster calculator function in ArcMap.

Table 4 Digital Elevation Model Comparative statistics (units [m])

DEMs	Points	Min	Max	Mean	Std. Dev.	ME	RMSE
BARE	694	1.30	302.65	33.64	45.95	14.51	3.81
BEST	694	2.00	306.00	33.93	45.63	15.28	3.91
SRTM90	694	2.00	309.00	34.44	45.36	17.03	4.13
BARE+BEST	694	1.38	302.65	33.28	45.59	12.16	3.49
ICEsat	694	0.297	290.45	33.39	45.51		

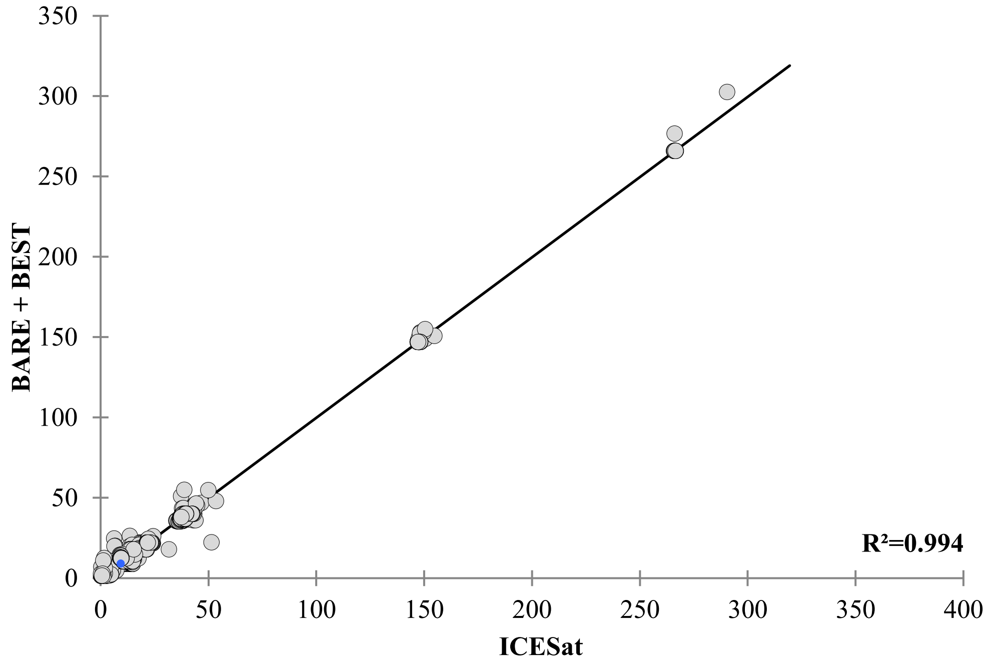


Figure 3 Correlation between ICESat and BARE + BEST DEM points. (see Supplementary Figure 3 for others DEMs)

3.2 Model Calibration and Validation

The modelled flood extent was quantitatively evaluated against combined MODIS Near-Real-Time (NRT) Water Product, TerraSAR-X, Radarsat2 and CosmoSkyMed, where available (See Supplementary Table 1), to reduce the effect of optical imagery limitations. The model F-statistic was found to decrease as cloud cover, and forested land use increased downstream of the study domain. A similar decrease in model performance away from domain input was also observed in (Skinner et al., 2015), as uncertainty increases with data ambiguity. To compare evaluation criteria based on varying imagery types (optical and SAR), static roughness parameters was varied from 0.01 to 0.045 (Figure 4) at an interval of 0.05 to determine the optimal manning's roughness (n = 0.04), at Lokoja, Onitsha and the Niger Delta sub-domains respectively. The TerraSAR-X imagery flood extent at Lokoja was applied for comparison with MODIS analysis, while RADARSAT2 and CosmoSkyMed images in the Niger Delta region to improve inundation mapping given the limitations of MODIS (Figure 4 and Table 5). For simplicity of comparison, the uncertainties associated with flood extent delineation from satellite image were not considered in this study, but are understood and highlighted in image integration for improved inundation delineation.

The overall F-statistics is observed to be generally low in Figure 4 and Tables 5 and 6, owing to the variation in available topographic, bathymetric and calibration datasets (Supplementary Table 1), that contributes to the overall uncertainty of the model outcome. This also goes to reveal the value of and need for improved data collection. This is further demonstrated in the sub-domain division predictiveness assessment revealed the effect of spatial and data disparity.

The adoption of TerraSAR-X imagery resulted in an insignificant change in the (F = 0.7884) acquired when compared to MODIS (F = 0.7869), varying only by 0.0015. This is attributed to the low degree of cloud cover at Lokoja (James et al., 2013). The F-Statistic in the Niger Delta region changed from 0.02864 to 0.1562 because of the switch from MODIS to SAR imagery validation data sets, an 81.7% improvement in model prediction capacity. The BIAS and % flood capture accuracy also improved substantially, especially in the Niger Delta region (See Table 5 and 6). In a previous study within the region based on a 1-D SODEK model (MUSA et al., 2015), optimal channel and channel over bank roughness were 0.01 and 0.04 respectively, when comparing simulated and *in situ* water levels at a cross-section at Onitsha. Some description of roughness parameters within the channel and floodplain include matured crops, scattered bush, heavy weeds, short grass, early growth vegetation and meandering channel (Arcement and Schneider, 1989, Chow, 1959). At Onitsha, this model appears to be steady for manning's roughness above 0.025, owing to the dish-like geomorphology of the terrain that supports continuous water intake and gradual propagation despite increased inflow and higher manning's roughness. The BIAS presented in Tables 6 is also consistent with F-Statistic performance measure, increasing downstream, while the % Flood capture is high at locations where SAR flood extent was available.

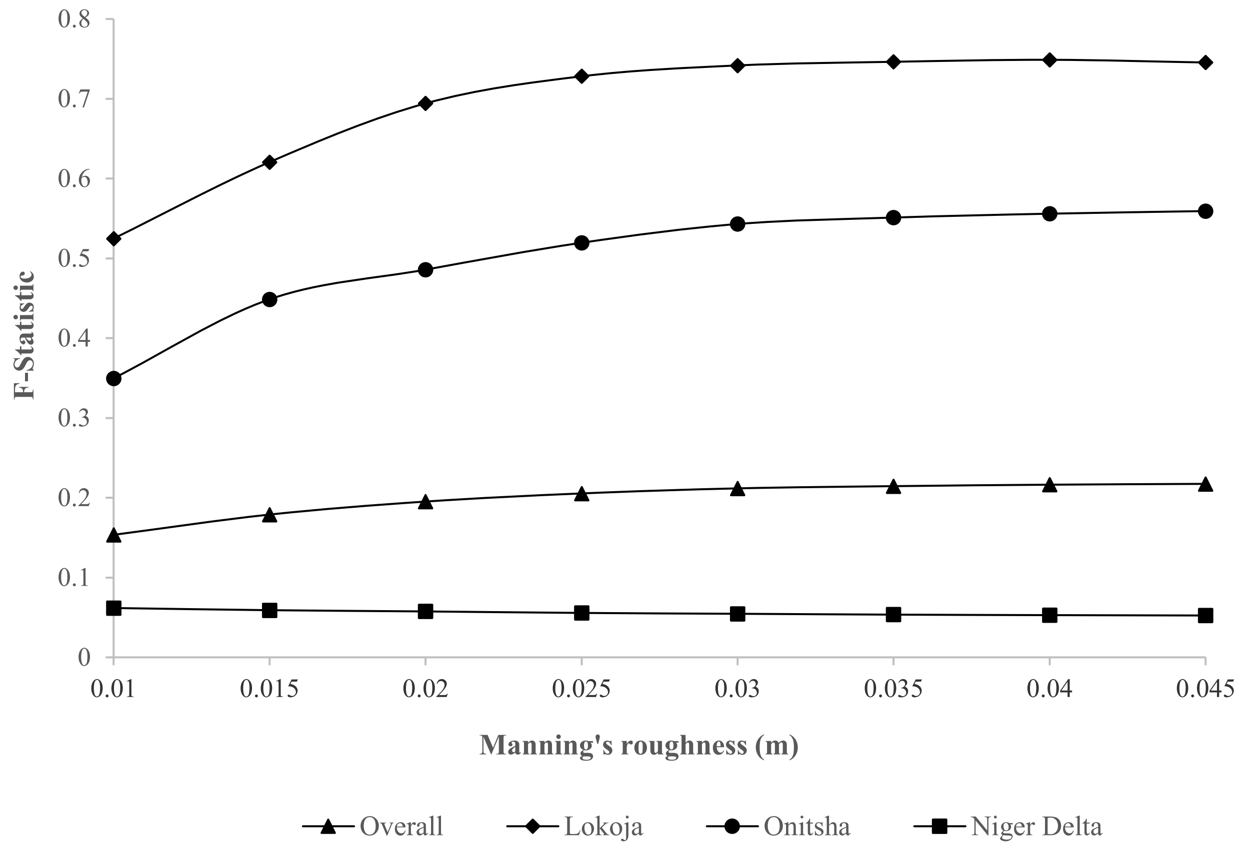


Figure 4 F-Statistic (Critical Success Index) versus Manning's roughness (n)

The reduced model accuracy in the Niger Delta region can be attributed to the lack of bathymetry data in the flat terrain area, resulting in flood over-estimation due to ease of eater conveyance from shallow rivers to adjacent floodplains Also, undocumented levels sand mining activities, water-saturated mangrove and poor dredging practice are identified as factors contributing to the model uncertainty within the region. An undocumented amount of dredging has been reported in Niger Delta, beginning in the late 1990s till date (Lubke et al., 1984, Abam, 2001a, Tamuno et al., 2009), resulting in hydrological changes (Fagbami et al., 1988, Okonkwo, 2012, Agunwamba et al., 2012). Dredging of the delta is aimed at deepening the river to alleviate flooding effects and improve river transportation (Ohimain, 2004, Okonkwo, 2012), thereby resulting in socio-economic benefits and improved operational logistics for oil producing companies in the region. Nevertheless, heaps of dredged and sand-mining materials along river banks and floodplains complicate terrain and river channel properties, altering mangrove characteristics and act as barriers/levees along the river over banks that reduce inundation, drainage and river overtopping (Ohimain, 2004, Ohimain et al., 2004).

Table 5 Performance Matrices for optimal manning's roughness calibration (MODIS)

Performance	Overall	Lokoja	Onitsha	Niger Delta
F	0.235	0.729	0.534	0.095
BIAS	4.245	1.183	1.140	9.661
% Flood Capture	99.972	92.012	74.545	92.186

Table 6 Performance Matrices for optimal manning's roughness calibration (TerraSAR-X/MODIS/RADARSAT2/CosmoSkyMed)

Performance	Overall	Lokoja	Onitsha	Niger Delta
F	0.273	0.808	0.529	0.187
BIAS	2.511	0.918	1.132	3.432
% Flood Capture	75.308	85.679	73.802	69.946

3.3. CAESAR-LISFLOOD Model outputs: evaluation of inundation maps and water levels

The modelled flood extent patterns derived from the CAESAR-LISFLOOD model were similar those observed from satellite (Figure 5 (A-C)). *In situ* gauging station water levels at Lokoja and Onitsha were also compared to model water levels during the rainy season (June till September) defined by the hydrography of 2012 figure 6 (A) and (B) to supplement the inundation extent evaluation.

These patterns in Figure 5 (A-C) shows (i) flooding spreading out at the confluence in Lokoja where the Niger and Benue rivers meet, (ii) extended flooding at Onitsha resulting from the constricted river channel at Asaba that causes backwater filling of the upstream dish-like floodplain, (iii) the Niger Delta inundation spread resulting from excess upstream water spreading over the low-lying topography, and overflow from the Nun and Forcados distributaries. The overall inundation coverage pattern at Lokoja, Onitsha and the Niger Delta are similar to those previously simulated in the region using global flood models (Trigg et al., 2016, Sampson et al., 2015), with the model agreement index (MAI) decreasing downstream from the narrowly confined floodplain into the wetland of the Niger Delta due to DEM and model limitations resulting from the flat terrain and channel bifurcation in the delta (Trigg et al., 2016).

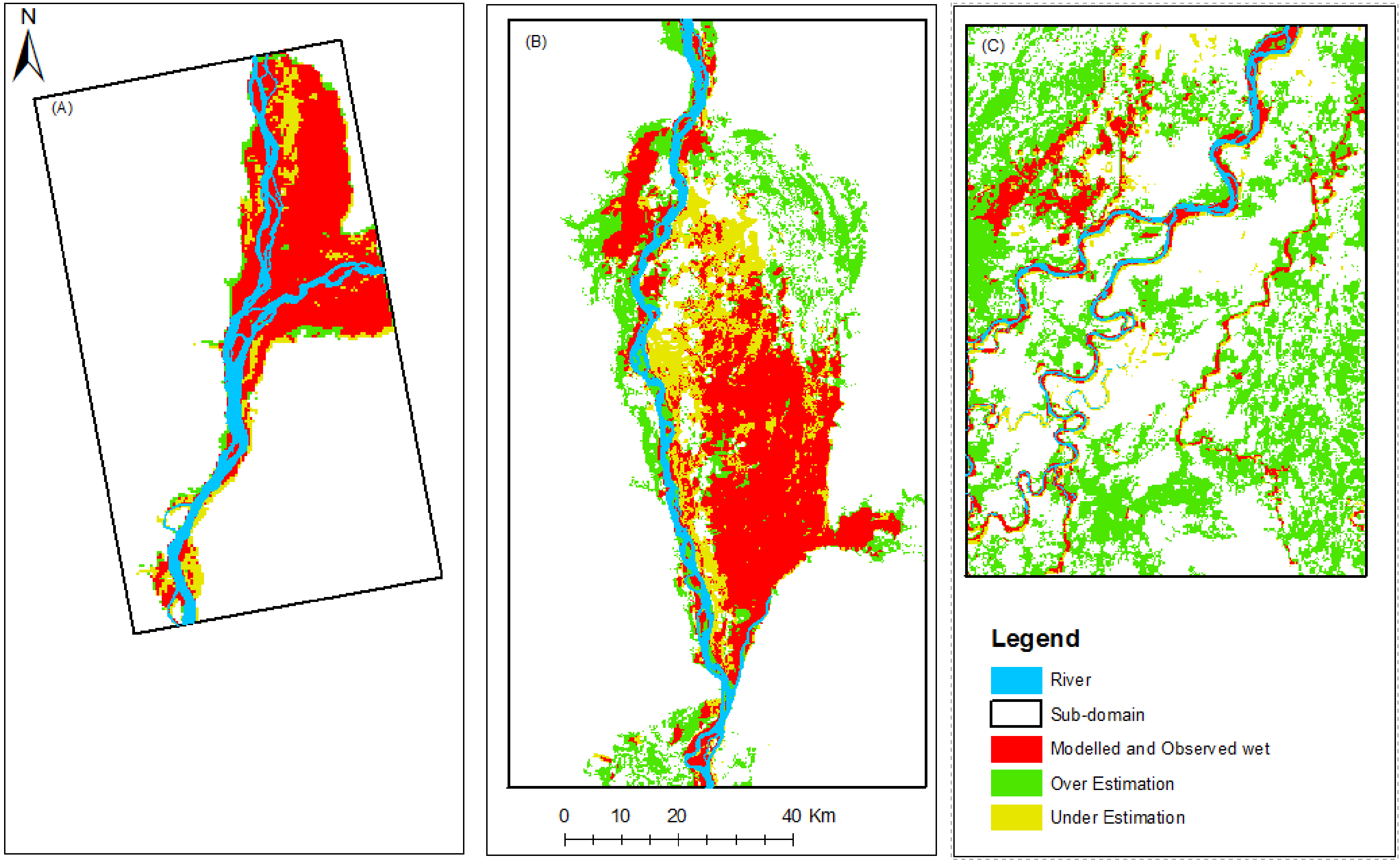


Figure 5 Lokoja (A), Onitsha (B) and Niger Delta (C) CAESAR-LISFLOOD Model outcome and satellite (Combined MODIS and SAR) observation comparison

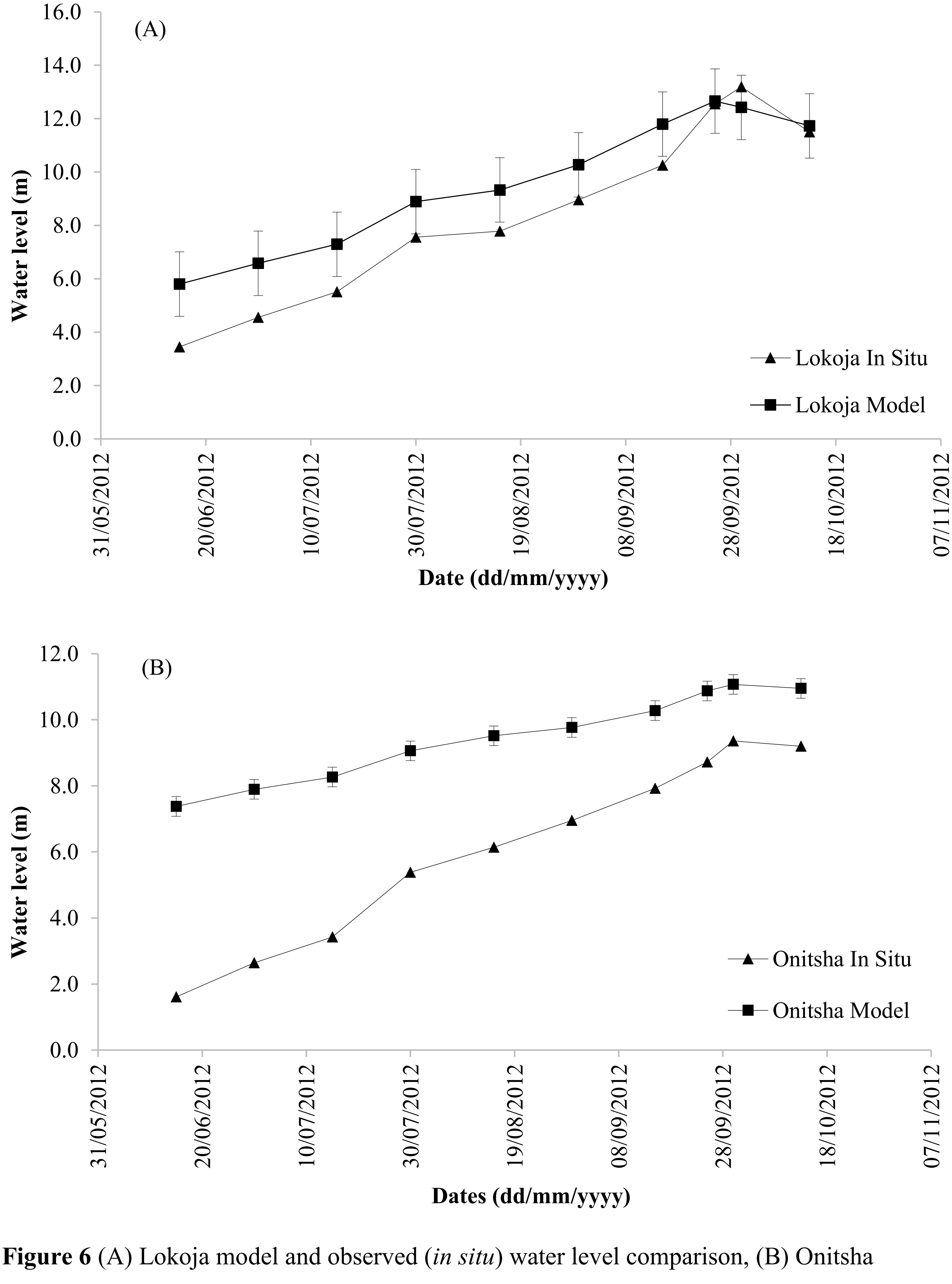


Figure 6 (A) Lokoja model and observed (*in situ*) water level comparison, (B) Onitsha modelled and observed (*In situ*) flood water level comparison

Water levels extracted from the CAESAR-LISFLOOD model results at river sections (2-D cells) around the gauge location was applied in assessing the accuracy of the model at *in situ* gauging stations (see Supplementary Figure 4 and Table 2, for location coordinates and map), showing a rising limb from June until peak rainfall in September and beginning to fall in October. The RMSE and Coefficient of determination (R^2) at Lokoja and Onitsha gauging stations were (0.564, 3.653 m) and (0.987, 0.998) respectively. Given the residual error in the data (discharge, DEM, Satellite image) as well as model uncertainty, the RMSE at Lokoja was within reasonable uncertainty limits, similar to other studies in data-sparse regions (Komi et al., 2017, Neal et al., 2012, Trigg et al., 2013). Figure 6 indicates that the optimal value of manning's roughness determined through calibration was high for water level estimation, owing to the poor river channels defined by obsolete bathymetric data in the model (Niger (2001), Benue (2011)). Also, the RMSE of this study was within the limit observed by Baugh et al., (2013) LISFLOOD-FP model study using Bare-Earth SRTM floodplain DEM and validated against TOPEX/POSEIDON altimetry water level. The discrepancy between model and observed water levels at Onitsha can be attributed to the absence of downstream bathymetry in the Niger Delta regions and obsolete upstream bathymetry data applied in the modelling process (Gautier, 2002), which was acquired prior to dredging activities in 2010 (Van Der Burg, 2010). This is likely to result in backwater propagation and water level overestimation due to low downstream river slope (Paiva et al., 2013). This was expected as the locations where hydrographic data were available was modelled using DEM with channel bathymetry embedded, resulting in improved outcomes as seen in other studies that integrated river bathymetry/cross-section surveys (Casas et al., 2006, Sanyal et al., 2013, Seenath, 2015). The results presented in Figures 5 and 6 further suggests that water level estimations within the river channel is more sensitive to hydrologic, bathymetric and topographic uncertainties than inundation extent across the floodplain. This consistent overestimation of water level by the model (Figure 6 (A and B)) could also be because of the simplified river characterization within the applied DEM at 290 m resolution as well as the hydrodynamic modelling process, which does not capture explicitly details such as river anabranches and meandering that would likely attenuate water released from the main river channel.

The improvement in flood delineation using SAR imagery resulted in the improved model to observation alignment (Table 5 and 6, Figure 5 (A-C)). However, SAR is not without its limitations, especially in mangrove, swamps and built up areas (Long et al., 2014, Phuong and Yuei-An, 2015, Musa et al., 2015). To assess the variation in accuracy assessment due to SAR deficiencies in the Niger Delta region, model accuracy was compared with SAR flood extracts and classified overflight geotagged photo points (Figure 7 (A-D)). The geotagged photos were not captured as orthophotos, hence could not be applied to extract the geometric extent of flooding. The quantitative outcomes of the comparison are presented in Table 7, with the overall accuracy (i.e. percentage match) of the model performing better when compared to overflight data points (69%) than SAR observations, which was a 13% match. Figure 8 shows the typical environmental/physical variation in the Niger Delta region: (A) mixed land use (built-up area greater than vegetation); (B) mixed land use (vegetation greater than built-up); (C) bare land, sparsely built and vegetated lands; and (D) matured mangrove vegetation. These variations influenced the CAESAR-LISFLOOD model and SAR flood inundation capacities, as seen in Table 7, with sections (A) and (B) revealing the highest alignment with model and SAR outcomes respectively when compared to overflight data. High level of alignment between model outcome, SAR inundation and overflight photos was observed in section (C), while flooded locations within the mangrove dominated section (D) known to hamper SAR and coarse DEM driven flood model outcomes were mostly identified by overflight photos only. This provides a novel approach to ascertaining the deficiencies of hydrodynamic models and SAR images in complex terrains using third-party data collected by organisations operating in the study area.

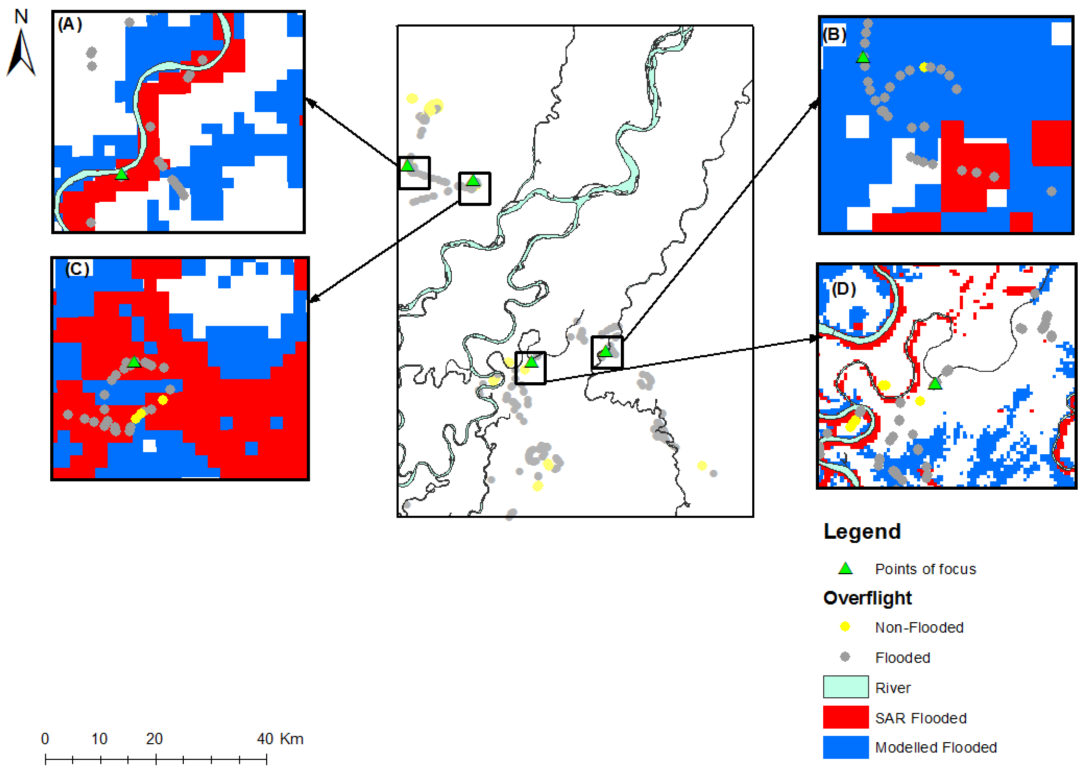


Figure 7 Niger Delta overflight geotagged photo points comparison with model and SAR observation outcomes (Photos for green points of focus shown in Figure 8)

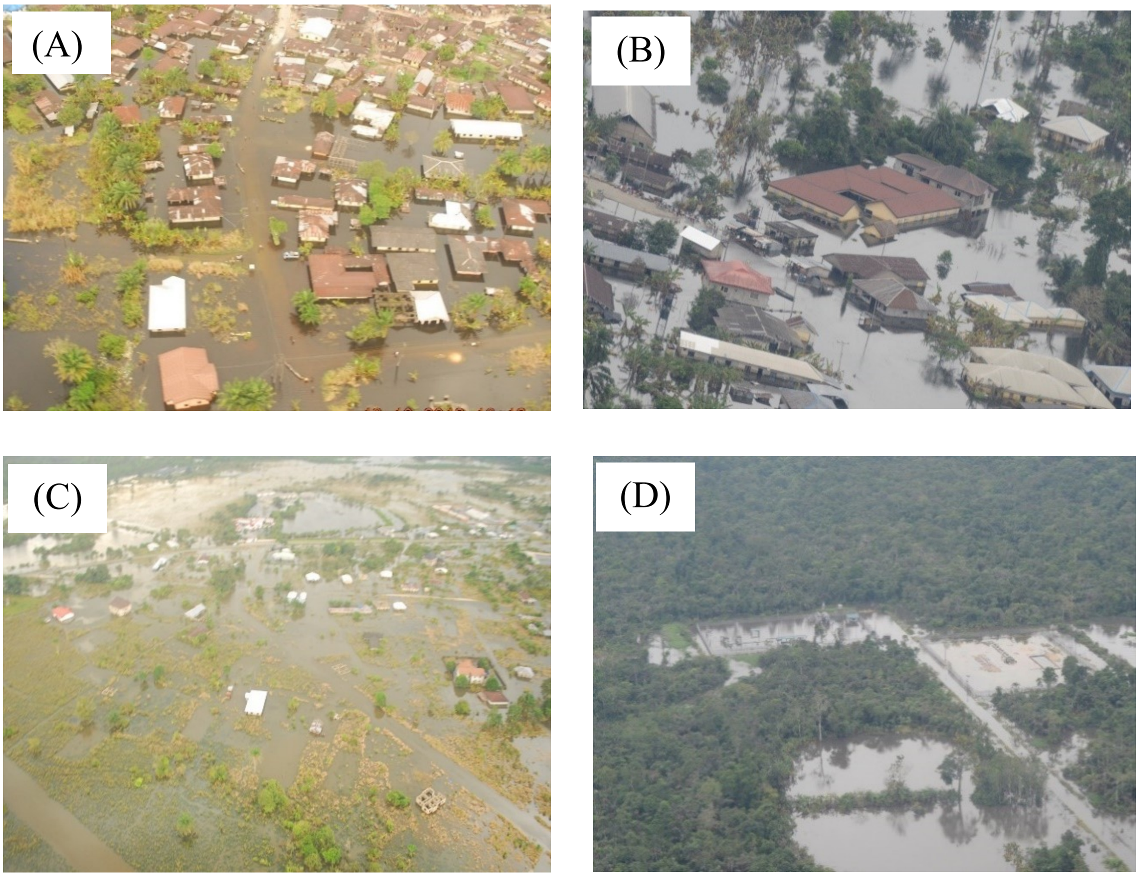


Figure 8 Sectional examples of overflight photos of flooded areas compared to observed and modelled flood in the Delta region, showing points of focus (Figure 7). (A) = match between model and photo, (B) = match between SAR and photo, (C) = match between model, SAR and photo, (D) = only the overflight showing flooding.

Table 7 Comparative analysis of overflight data points, model and SAR observation flood extents

Points of focus	Data Points (n = 287)	Hits	Miss	% Accuracy
A	Overflight and Model flooded	196	91	69
B	Overflight and SAR flooded	37	250	13
C	Overflight, Model and SAR flooded	43	244	15
D	Overflight only flooded	62		

3.4. Model extent and Flood Management Implications

Estimates of 1-in-100 year flood peak at Baro and Umaisha gauging stations were estimated as 13,887 and 19,589 m^3/s respectively Chapter 3. The 1-in-100 year flood event is stipulated as the AEP for planning and infrastructural development purposes in Nigeria by the Ministry of Environment (FME 2005b). The estimated flood magnitude is essential in understanding the Niger-South exposure to upstream dam water release as was the case in 2012, to inform policy implementation. The 1-in-100-year event was simulated and compared with the 2012 flood event to ascertain whether the actions/plans based on a 1-in-100 Year flood as stipulated in the National Flood Management guideline would have likely mitigated the impact of the extreme flood event. Actual (2012) and expected (1-in-100year) flood exposure was assessed by land area, population, settlements, Built-up areas and roads impacted and presented in Table 8 and Figure 6. The emphasis of this assessment is at Lokoja where the highest agreement between modelled outputs and observation was imminent due to optimal data availability for flood modelling and mapping. Ninety-seven (97) percent of the flooded area identified from satellite image was captured as a 1-in-100 year flood event; nevertheless, the model could likely be exaggerated, given the possible propagation of river discharge, DEM and calibration uncertainties unto the final model outcome. Notwithstanding, the results are promising and prove the value of open-access and 3rd data integration for flood modelling and mapping in developing regions. The inundated area and exposure estimates for impacted population, settlements, built-up areas and roads for the observed and modelled flood extent, and are presented in Table 8 and Figure 9 for visualization.

Table 8 Model, Observed and 1-in-100-year flood exposure comparisons

Flood	Area (km^2)	Population	Settlements	Built-up (km^2)	Roads (km)
1-in-100 year modelled	427.2	32,867	14	12.834	32.987
2012 Model	425.8	32,703	14	12.648	34.573
2012 Observed	440.2	34,391	21	12.326	37.287

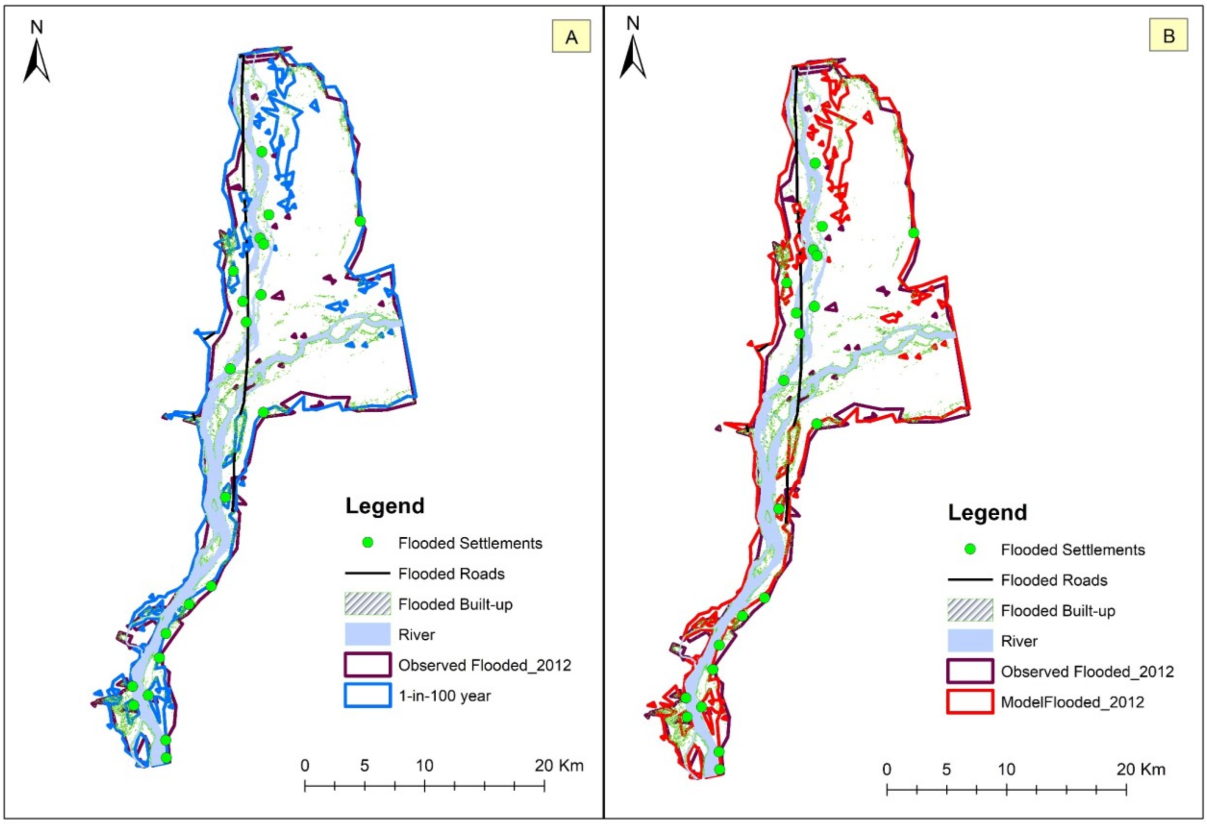


Figure 9: (A) comparison of SAR observed 2012 and 1-in-100 year modelled flood extents, and(B) comparison of SAR observed 2012 and modelled flood extents for the same period, as well as impacted settlements, roads and built-up areas in both A and B at Lokoja.

4. Conclusion

In order to fill data gaps that hinder effective flood modelling, mapping and consequently flood management decisions, this study presents an approach that incorporates multi-source open-access geospatial and remote sensing for hydrodynamic modelling of extreme flooding in the Niger south hydrological area of Nigeria, with the aim of reducing model outcome uncertainties in the region. The approach applied here systematically fills missing data gaps for flood procedures of flood modelling and mapping including (i) flood frequency estimation, (ii) hydrodynamic modelling, and (iii) inundation mapping, most pronounced in developing countries. Multiple geospatial data sets were used including MODIS NRT flood map, Landsat 8 OLI, vegetation and urban areas elevation corrected SRTM DEM, Radar Altimetry (ICESat, Envisat, Jason 2 and Topex/Poseidon) and 3rd party captured, TerraSAR-X, Radarsat2, CosmoSkyMed, bathymetry and geotagged overflight photos. These data were applied at various stages of the flood modelling and mapping process as follows: (i) based on the outcome of Chapter 3, radar altimetry was applied to fill missing data in the hydrological time series in flood frequency estimation, (ii) ICESat data were used to assess the DEM accuracy due to the lack of ground elevation data and to improve river channel elevation where bathymetry data was unavailable, (iii) bathymetry data were merged with Bare-Earth SRTM DEM for routing upstream hydrography, and (iv) geotagged photos, optical, and SAR images were used for hydrodynamic model calibration, validation and comparative analysis.

The following conclusions are drawn from this study:

1. Other than flow data being one of the predominant sources of uncertainty in hydrodynamic models, DEMs, especially those with a low or medium resolution that average out terrain properties can result in flawed model outcomes, especially in built-up and mangrove dominated areas. Nevertheless, where recent bathymetric data is available as was the case in Lokoja, within a constricted river channel, improved model accuracy is expected and this should be the basic data required for flood routing in developing regions.
2. The role of remote sensing in modern-day hydrology, hydrodynamics and flood mapping cannot be over-emphasized, especially in developing regions where access to *in situ* data is limited. Evidence from this study suggests the availability of data in even very remote locations of Nigeria (a typical developing country), though segmented and in varying formats and resolutions. A conscious effort must be made to scout for and integrate multiple datasets when mapping flooding in developing regions. We conclude that data is always available in most remote locations, however, accessibility, validity and accuracy remains a challenge.
3. When modelling floods in large catchments using multiple remote sensing data, an understanding of the landscape, climate and seasonal variability are essentials, considering their effect on optical and SAR imagery efficiency and usability. Upstream of the Niger south catchment (Lokoja) for instance is mostly sparsely vegetated and cloud-free during the wet season, hence the negligible difference between SAR (TerraSAR-X) and optical (MODIS) inundation extent when used for the model calibration and validation. Contrastingly in the Niger Delta region, the

mangrove vegetated and cloudy atmosphere resulted in very limited MODIS flood capture and even affected SAR inundation delineation capacity. This thereby prompted an alternative measure (overflight photos) that enabled flood detection within pockets of the mangrove and built-up areas where SAR imagery was deficient.

4. The value of baseline data availability was evident at Lokoja, where the 2012 flood event was quantified as a 1-in-100 year flood event, and the effect of the modelled and observed flood on the populace, built-up areas and road infrastructure simulated. The deteriorating effect of data quality was also evident at Onitsha and the Niger Delta regions respectively. These outcomes further suggest the need for improved data collection by agencies such as the National Inland Waterways Agency (NIWA), Nigerian Hydrological Service Agency (NISHA) and the Niger Basin Authority (NBA) for improved flood management.
5. Modelling the Niger Delta region of Nigeria is a complex task that requires detailed and up-to-date bathymetric survey, high-resolution terrain, landscape information and *in situ* river measurements. The complexity of the region is further exacerbated by the wetland nature of the region that promotes attenuation, and anthropogenic activities such as sand mining and dredging activities (Okonkwo, 2012, Ohimain et al., 2004, Ohimain, 2004, Awelewa, 2016) that alters the hydrological regime and hydraulic connectivity of the region.
6. Throughout the modelling process, it is evident that quality hydrological input, digital elevation model, bathymetry, and calibration datasets contain uncertainties that propagate onto the model outcome. Although because to simplicity and the huge computational cost of combined hydrological and hydrodynamic simulations, the effects of these uncertainties are not quantified, the calibration process curtails the uncertainties to a reasonable extent, through the definition of an optimal manning's roughness parameter to enable the simulation of a known flood extent.

Chapter 6 Supplementary Materials

In this study Generalized Extreme Value (GEV) probability distribution is fitted to annual maximum flood series (Jenkinson, 1955), widely adopted in hydrological studies in several regions (Leclerc and Ouarda, 2007, Kochanek et al., 2013, El-Jabi et al., 2015, Smith et al., 2015, O'Brien and Burn, 2014). GEV is expressed as thus:

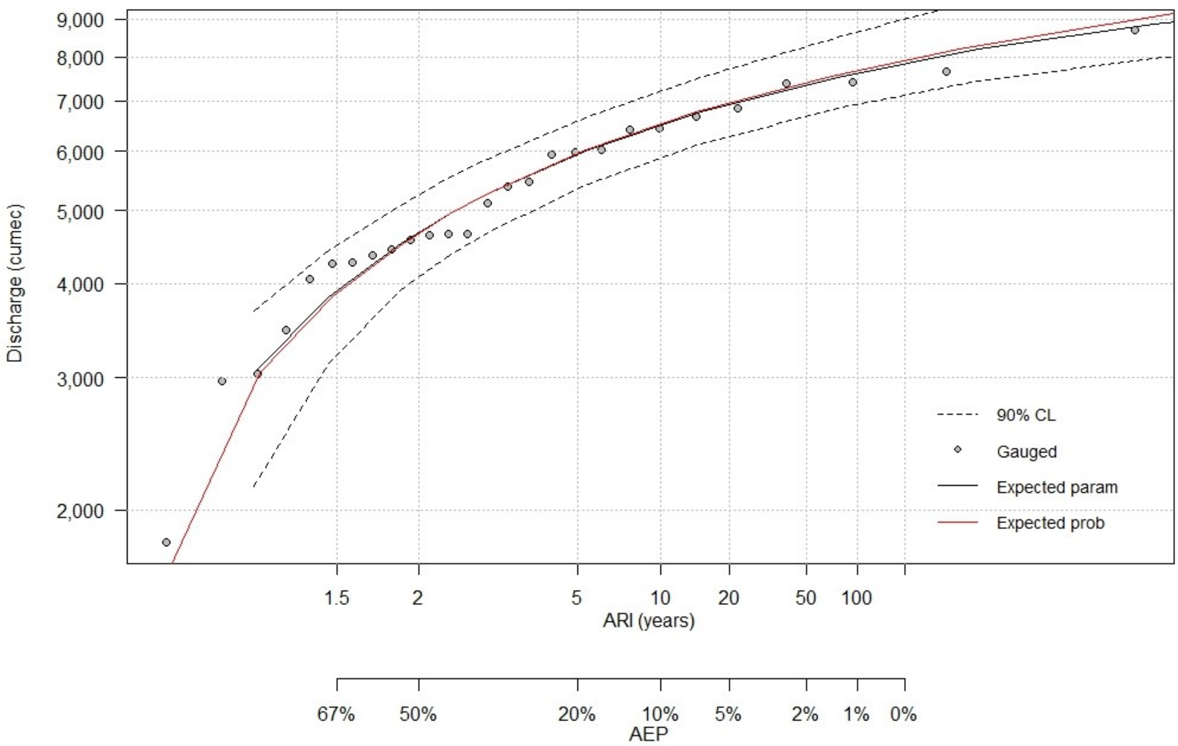
F (x| τ, α, and k) =

$$\begin{cases} \frac{1}{\alpha}\exp\left\{-\left[1-\frac{\kappa(x-\tau)}{\alpha}\right]^{\frac{1}{\kappa}}\right\}\left[1-\frac{\kappa(x-\tau)}{\alpha}\right]^{\frac{1}{\kappa}-1} & \kappa>0, x<\tau+\frac{\alpha}{\kappa}; \kappa<0, x>\tau+\frac{\alpha}{\kappa} \\ \frac{1}{\alpha}\exp\left[-\frac{(x-\tau)}{\alpha}\right]\exp\left\{-\exp\left[-\frac{(x-\tau)}{\alpha}\right]\right\} & if\, \kappa=0 \end{cases}$$

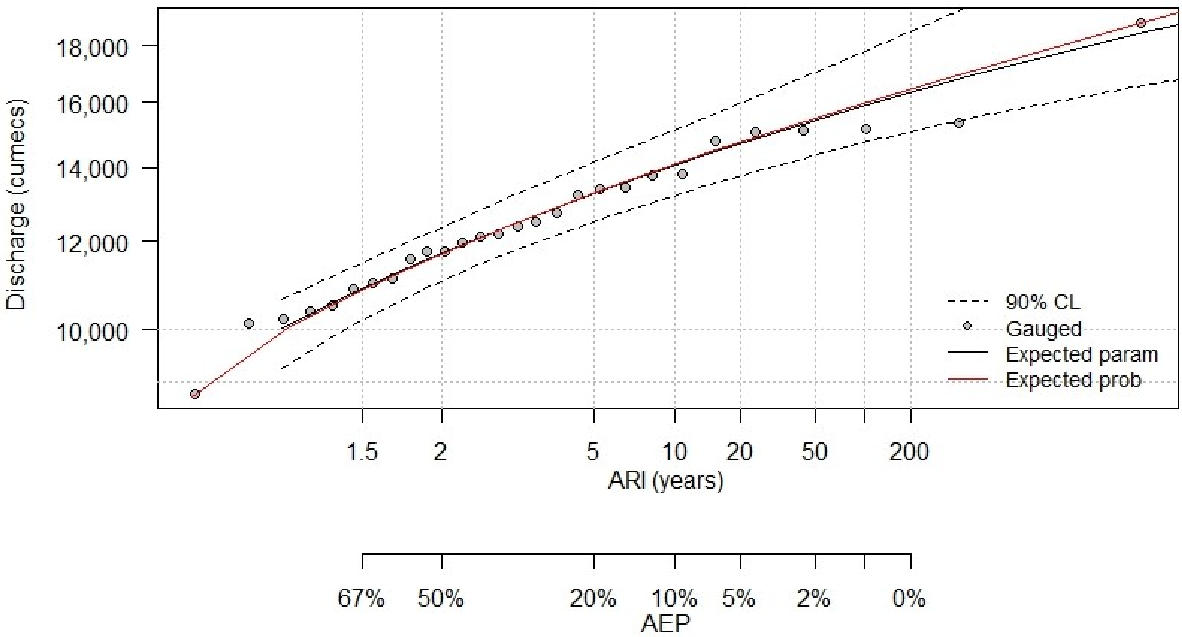
Where: τ, α, and k represent location, scale and shape parameters respectively of the distribution function.

Supplementary Table 1: Spatial data availability matrix for sub-domains

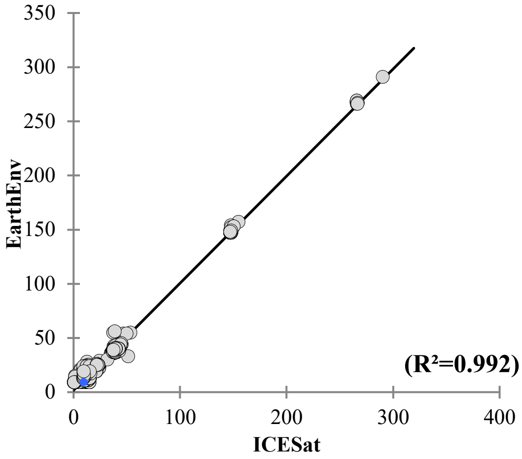
Spatial Data (Imagery and Survey)	Locations		
	Lokoja	Onitsha	Niger Delta
MODIS	√	√	×
TerraSAR-X	√	×	×
Radarsat-2	×	×	√
Cosmo-SkyMed	×	×	√
Geotagged Photos	×	×	√
Bathymetry	√	√	×
Radar Altimetry	√	√	√
SRTM DEM	√	√	√



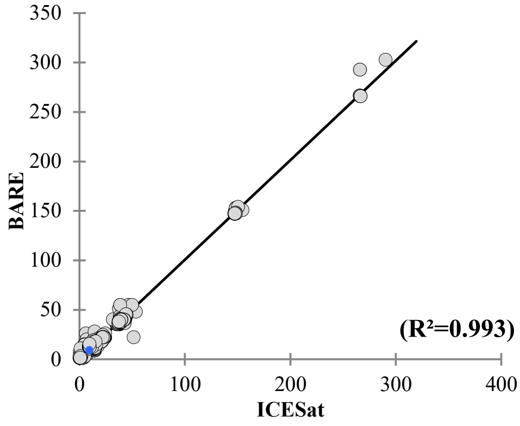
Supplementary Figure 1 Baro flood frequency plot



Supplementary Figure 2 Umaisha flood frequency plot



(a)



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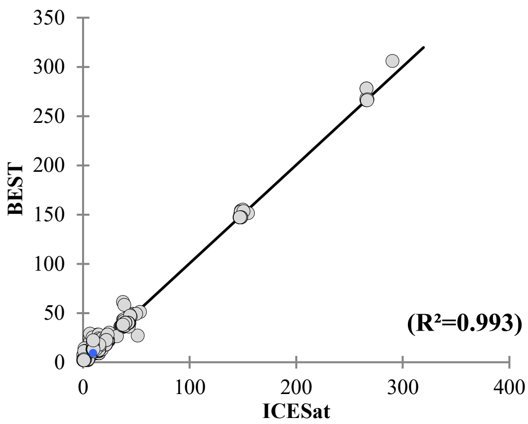

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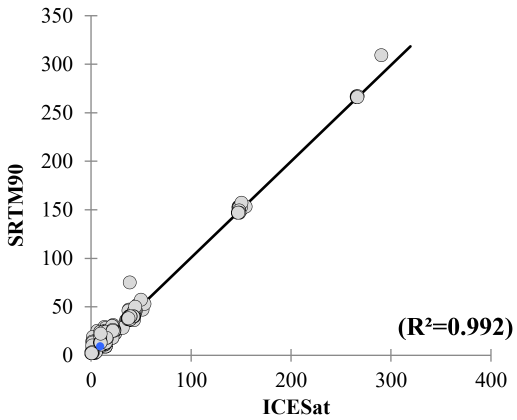
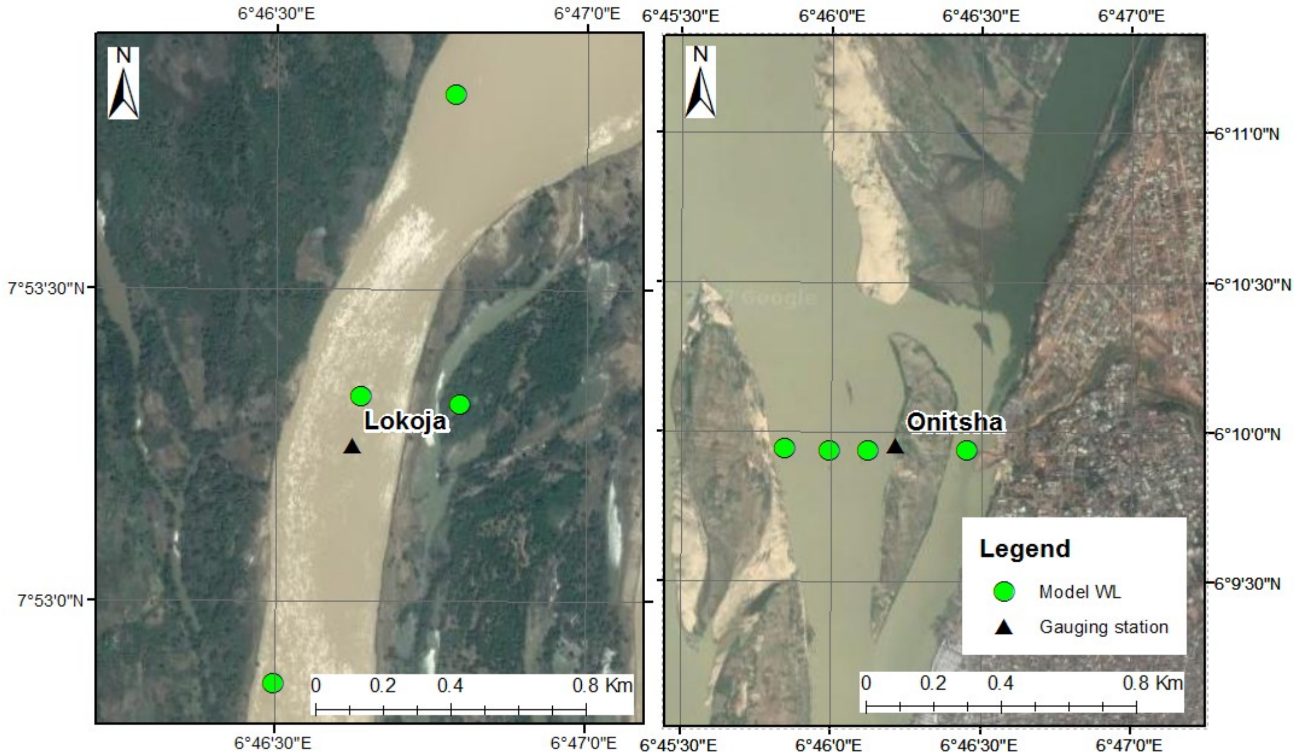


(d)

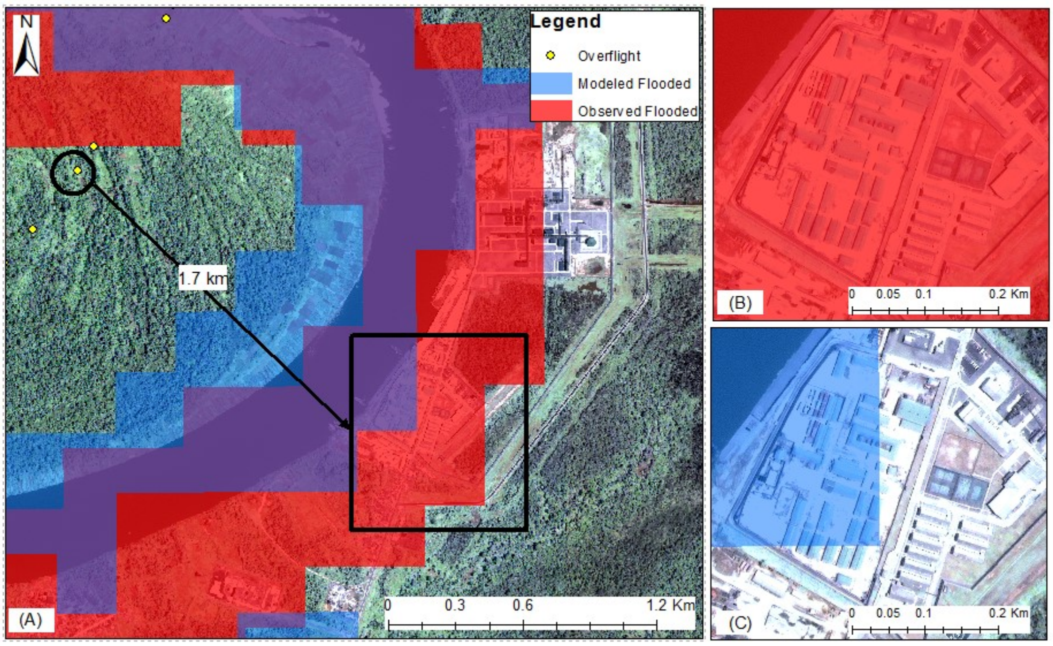
Supplementary Figure 3 Correlation between ICESat points and DEM extracts EarthEnv (a), BARE (b), BEST (c), SRTM90

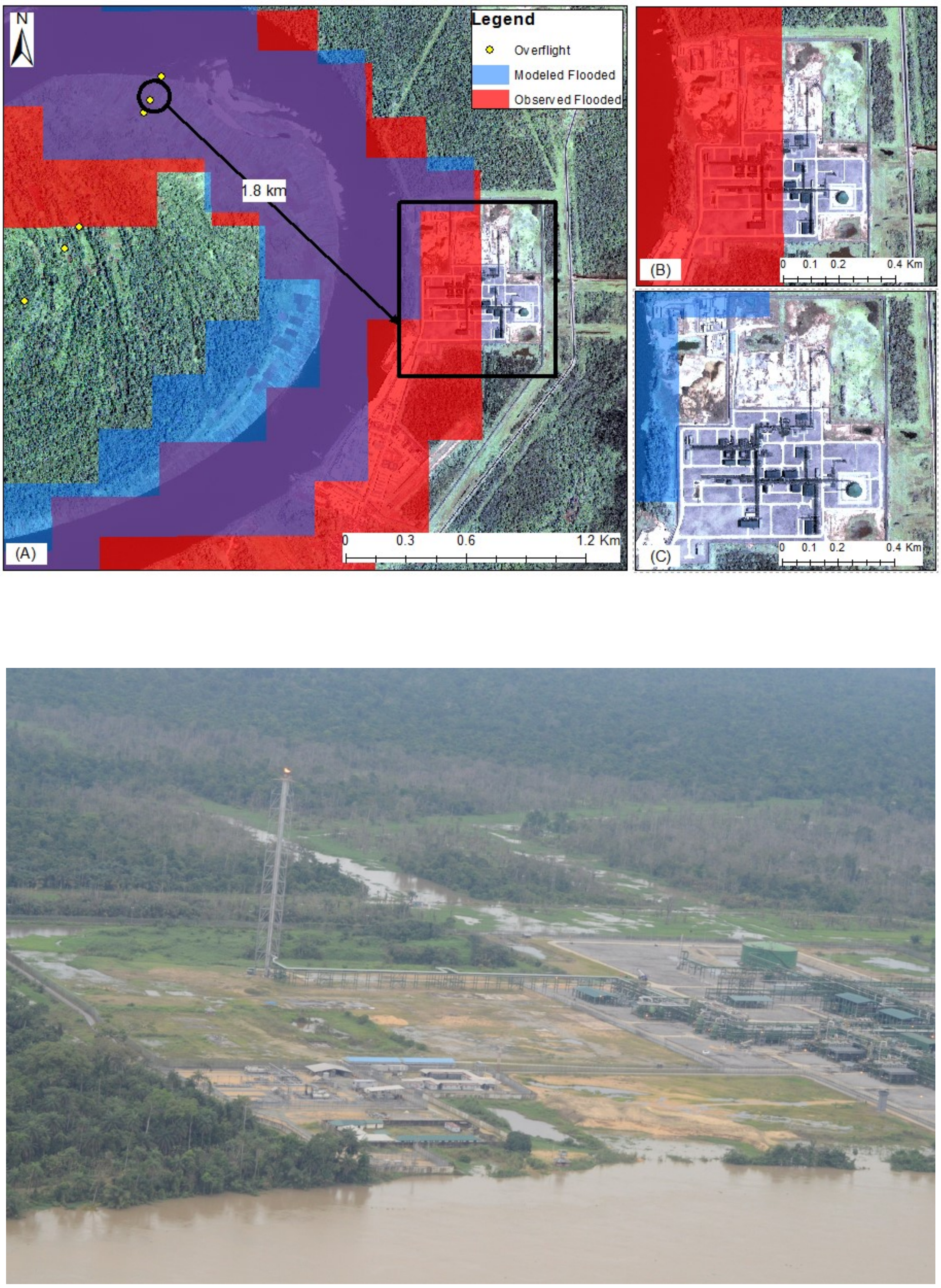


Supplementary Figure 4 Water level points for accuracy assessment

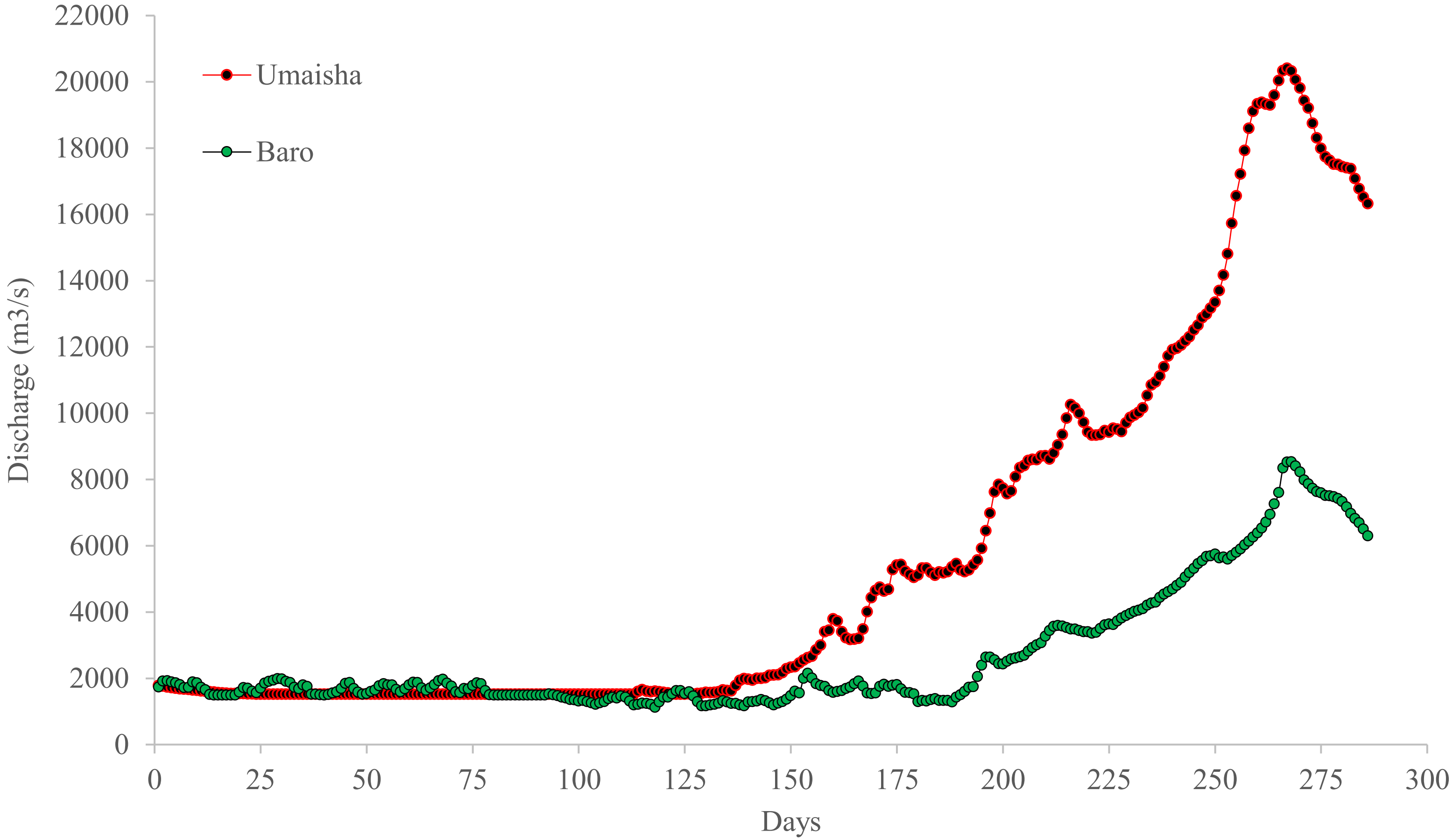
Supplementary Table 2 Coordinates of Water level points for accuracy assessment

	Lokoja		Onitsha	
S/N	Northing (X)	Easting (Y)	Northing (X)	Easting (Y)
1	255224.796577	873550.54681	252253.53001	683194.262142
2	254945.095998	872659.407754	252961.522103	683089.984237
3	872659.407754	872633.389095	253458.21423	682958.264778
4	254684.909412	871807.296685	253996.068688	683188.773831


N
Legend
Overflight
Modeled Flooded
Observed Flooded
1.7 km
(A)
0 0.3 0.6 1.2 Km
(B)
0 0.05 0.1 0.2 Km
(C)
0 0.05 0.1 0.2 Km



Supplementary Figure 5 Model, Observation and Overflight line of sight overlaid on high-resolution GeoEye Imagery.



Supplementary Figure 6. Input hydrographs at the upstream boundaries of Umaisha and Baro

CHAPTER 7: IMPROVING RADAR IMAGERY FLOOD DETECTION CAPACITY USING MULTI-CRITERIA DECISION TREE ANALYSIS TECHNIQUE BUILT ON OPEN-ACCESS DATA

Abstract

Remote sensing has become one of the most widely used data set for flood modelling processes due to the challenges associated with acquiring *in situ* data for hydrodynamic and flood mapping studies, particularly in developing regions. Active sensor Synthetic Aperture Radar (SAR) is one of the primarily used satellite images in flood mapping due to the advantages of cloud-free imagery capture, day and night operationality and ease of flooded and non-flooded areas discrimination. Despite these advantages, SAR image flood detection capacity is limited by inherent (system) and external (landscape properties) factors.

This study aims to reduce external deficiency effect on SAR extracted inundation maps by combining multiple open-access data sets using J48 (C4.5) decision tree algorithm to enhance SAR flood discrimination capacity in the vegetation dominant Niger Delta region, Nigeria. This approach is intended to improve the flood map used for CAESAR-LISFLOOD hydrodynamic model evaluation in the region. Historic flood extent derived from histogram thresholding approach, land use/cover maps, hydrologic parameter (rivers), and Digital Elevation Model (DEM) derivatives were trained using overflight geotagged photos that capture real flooded locations even within pockets of the mangrove where SAR could not penetrate.

The results show improved inundation extent in comparison to histogram threshold (only) technique when evaluated against crowd-sourcing and overflight data sets. Also, the overall hydrodynamic model accuracy (F-Statistic) improved by 51%. Nevertheless, high levels of model to flood extent mismatch was still evident, and this can be attributed to model uncertainty due to the coarse DEM and poorly defined river bathymetry data used for the modelling, as well as several hydro-morphological activities within the region such as uncontrolled dredging activities and permanent wetlands, that contribute to the complexity of modelling the Niger Delta terrain.

Keywords: Decision Tree (DT), Flood mapping, Synthetic Aperture Radar (SAR), Niger Delta, CAESAR-LISFLOOD and Open-access Remote Sensing.

1. Introduction

Remote sensing has gained considerable influence in flood mapping, hydrology and hydrodynamic applications in recent years, mostly due to the lack of spatially sufficient ground data (Musa et al., 2015). Data limitations emanate from a combination of factors including (i) technological and cost challenges (Sanyal et al., 2013, Seung Oh et al., 2013), (ii) inaccessibility to rugged and remote terrains (Quinn et al., 2010, Isioye and Jobin, 2012), and (iii) organizational and capacity drawbacks in developing countries (Olayinka et al., 2013). Therefore, remote sensing (open-access) provides an alternative which allows for capture of aerial images that infers land properties and composition without being in direct contact with the object of interest (Dano Umar et al., 2011), thereby overcoming the aforementioned deficiencies. Depending on the source of energy during the data capture process, remote sensing can be classified as passive or active. Passive remote sensing depends on natural energy (solar) source resulting in optical imagery that measures landscape reflectance properties along various electromagnetic spectrums. Hence optical images can only be captured in the daytime and depend on cloud-free skies for optimal imagery acquisition (Musa et al., 2015). Active remote sensing contrastingly uses satellite built-in energy source and quantifies the properties of target objects by measuring the return signal (backscatter) intensity, hence Synthetic Aperture Radar (SAR) sensors have the ability to penetrate cloud to capture underlying objects and provide day/night coverage (Grandoni, 2013).

1.1. SAR flood mapping challenges

Despite the obvious advantages of SAR, its application is not without challenges. Most notable in hydrological applications is the difficulties associated with discriminating between water and other smooth surfaces such as wetlands, roads and radar shadows in mountainous regions, that shows similar reflectance characteristics as flooded surfaces, which results in inundation over-estimation (Qasim, 2011, Long et al., 2014). Urban, forested and cultivated regions, on the other hand, pose the challenge of under-estimation as features such as trees, plants, rails tracks, houses and traffic lights inhibit SAR beam penetration and emit high-intensity reflectance hamper optimal flood delineation (Veljanovski et al., 2011b). Other factors that contribute to poor SAR imagery flood delineation potential is the system inherent deficiency that results in the generation of granule pattern features called speckle noise (Sheng and Xia, 1996, Qiu et al., 2004).

Recent reviews by Musa et al., (2015) and Hong et al., (2015) highlighted the impact of meteorological conditions such as wind and rainfall on SAR imagery, as well as vegetation cover, urban landscape, topography, satellite inclination angle and the satellite polarization mode at the time of image acquisition on SAR derived inundation extent. These factors distort the return pulse efficiency and consequently reduce the discriminating potential of the imagery in flood mapping applications.

Polarization mode which defines the direction of radar wave oscillation employed during imagery acquisition i.e. Horizontal-Horizontal (HH), Vertical–Horizontal (VH) and Vertical–Horizontal (VH) and Vertical–Vertical (VV) also impacts flood delineation. HH polarization acquired SAR images are known to be more efficient for flood extent delineation than its VH and VV polarization counterparts, especially in vegetation covered and wetland areas (Wood et al., 2014). HH polarization provides a higher backscatter ratio of flooded to non-flooded areas than VV under similar conditions of wavelength and angle of inclination (Wang et al., 1995, Wood et al., 2014). Nonetheless, VV polarization mode image is valuable in highlighting vertical features such as vegetation (Schumann et al., 2007), while the horizontal profile of VH polarization mode is useful in delineating smooth flood surface due to its low sensitivity to waves (Henry et al., 2006). Peter et al., (2013) also highlighted the possible challenge of misidentifying other items such as mud and debris during as flood rapid floodplain water outflow.

1.2. Some challenge compensation approaches

System inherent deficiencies such as Speckle noise are usually reduced using appropriate filter modules available in image analysis software such as ERDAS Imagine, ENVi, and e-cognition, while incident angle defects and shadow reflections can be managed by ortho-rectification that incorporates auxiliary digital elevation model data (Veljanovski et al., 2011b). Discriminating surface water from other features is somewhat straightforward also, but depending on the method applied, the accuracy of flood extent varies (Qasim, 2011, Veljanovski et al., 2011b, Long et al., 2014, Gala and Melesse, 2012). Some commonly applied SAR processing approaches include visual interpretation (Schumann et al., 2009b), multitemporal image differencing, histogram thresholding (Long et al., 2014), image segmentation (Phuong and Yuei-An, 2015), multi-polarized image combination, statistical active control model (Horritt et al., 2001), radiometric thresholding (Giustarini et al., 2013), artificial neural network (Kussul et al., 2011) and decision tree analysis (Corcoran et al., 2012). Also, combining SAR Imagery with supplementary data sets such as optical images, and derivatives digital elevation models have been found to improve flood delineation in urban, forested and wetland regions (Corcoran et al., 2012, Phuong and Yuei-An, 2015, Malinowski et al., 2015).

1.3. Study Description

A previous chapter using overflight geotagged photos in the Niger Delta region of Nigeria (Chapter 6), revealed the deficiency of SAR imagery in delineating flooding in the mangrove dominated regions. To overcome this deficiency, a Decision Tree (DT) approach is proposed in this study, combining multiple open-access data sets to improve SAR flood delineation capacity in the region. The DT flood extents are then compared to that derived from Histogram Thresholding (HT) technique in a previous chapter (6) and applied in the evaluation of hydrodynamic model accuracy in the Niger Delta region of Nigeria based on three performance measures F-Statistic, BIAS and percentage flood capture.

2. Methodology

2.1. Study Area

This study focuses on a section of the Niger-South hydrological area within the Niger Delta region of Nigeria (Figure 1), covering a 5671 km^2 area. The section constitutes of three states (Delta, Bayelsa and Rivers) in the oil-producing region of Nigeria that was part of the most impacted during the 2012 flood event (FGN, 2013, Ojigi et al., 2013). The low-lying topography of the region makes it vulnerable to flooding, coupled with the settlement of persons and development of infrastructure within floodplains that further aggravates and compounds flood risk and exposure in the regions (Tamuno et al., 2003, Eyers et al., 2013). These challenges and the recurrent exposure to flooding has raised genuine concerns and the need for improved flood mapping.

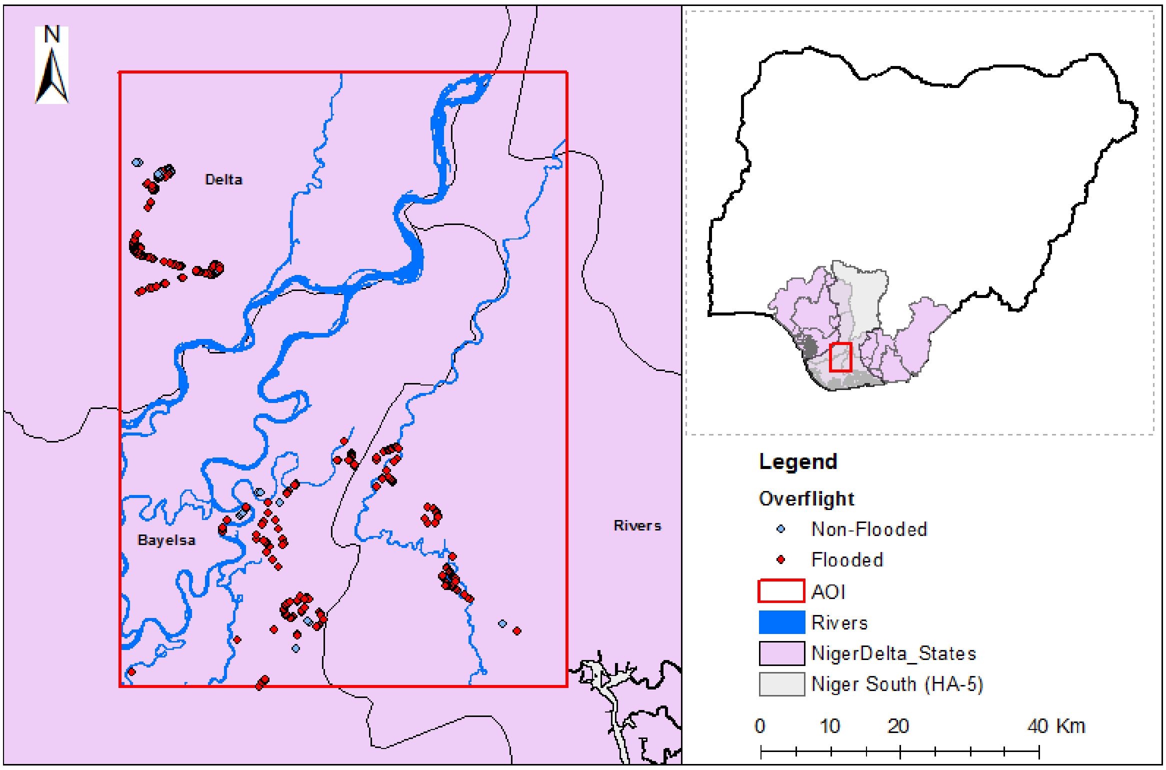


Figure **1** Map of study area showing Location in Nigeria, the Niger South river Basin and States.

2.2. Data requirements

2.2.1. Flood Inventory and Overflight geotagged photos

Accurate maps of historical floods play a crucial role in delineating flood extent in susceptible locations (Merz et al., 2007, Rahmati et al., 2016), as past flood occurrences provide the baseline for assessing future expectations under similar or heightened hydrological conditions. Flooded locations were identified from overflight geotagged photos and radar images acquired by Shell Petroleum Development Company (SPDC), Nigeria during the peak flood season of October in 2012. This flood experience was reported to have caused the greatest impact/damage in 40 years (Ojigi et al., 2013, Tami and Moses, 2015), affecting people, settlements, infrastructures and distorting socio-economic activities in the Niger Delta region (Jinadu, 2015, Eyers et al., 2013). Overflight geotagged photo data points (325) were visually assessed and assigned binary codes “0” and “1” to indicate non-flooded and flooded locations respectively, and used for training the flood conditioning factors. Radar flood extent derived by histogram thresholding was assumed to underestimate inundation due to vegetation cover in the region and was applied as the historic flood maps to be improved upon.

2.2.2. Flood Conditioning Factors

Besides radar derived inundation extent that directly depicts actual flood at the time of image acquisition, other factors contribute to flooding and can be applied in combination with other landscape properties to indirectly infer the presence or potential of flood where SAR imagery is deficient. Furthermore, radar images are sometimes insufficient in delineating flood extent in vegetated, built-up and rugged terrain (Long et al., 2014).Therefore, the combination of factors that contribute to flood susceptibility, such as Geology, Soil type, Distance from water bodies, Land use/cover types, Topography and DEM derivatives such as Topographic Wetness Index (TWI), Stream Power Index (SPI), curvature and slope (Pradhan, 2009, Dano Umar et al., 2014, Tehrany et al., 2014, Rahmati et al., 2016, Siddayao et al., 2014), will further enhance flood delineation.

2.2.2.1. Geological Formation

Geology contributes to flooding because various lithological units respond differently to hydrological processes, thus influencing the spatial extent of the river basin hydrology and sedimentation over time (Rahmati et al., 2016). Reijers, (2011) disclosed the geological formation of the Niger Delta, revealing the effect of lithological variability on flooding and erosion within the region. Geological structures impacts on landscape erodibility and permeability, consequently defining river channels and drainage density (Reynolds et al., 2013, Celik et al., 2012). Geological data was acquired from the nationwide geological map (1: 2,000,000) obtained from the Nigerian Geological Survey Agency (NGSA). Lithological composition, percentage coverages and descriptions are presented in Table 1.

Table **1** Study area geology, Adopted from (Reijers, 2011)

Geological Age	Lithology	Description	%
Quaternary	Freshwater swamp	Sands, gravel and clays	46
	Sombreiro Deltaic Formation	Sands, clay and mangrove swamps	19
	Mangrove Swamp	Sands, clay and mangrove swamps	10
	Abandoned beach ridges	Sand and Pebbles	1
	Coastal plains sands	Sand and clays	21
Tertiary	Lignite Formation	Clays, lignite and shales	3

2.2.2.2. Soil Type

The ability of a landscape to hold, retain and transport water depends strongly on soil properties (Shi et al., 2007, Pradhan, 2009, Yahaya et al., 2010), consequently influencing surface run-off and inundation extent. Soil dataset was downloaded from the International Soil Reference and Information Centre (ISRIC) soil repository (Hengl et al., 2014), and comprises of various soil classes. Gleysols class which counts for 51% of the soil composition in the study area is known for its prolonging wetness due to its nearness of groundwater. The main components of dominant soils in the region are loamy, clay, sand, gravel and humus. Percentages of all major soil compositions are presented in Table 2.

Table **2** Study area soil constituents, Adapted from (Hengl et al., 2014)

ISRIC Soil Reference	**Class**	**Composition**	**% composition**
CN 019, CN 017	Acrisols	Loamy Sand	20
CN022, CN028	Alisols	Loamy Sand	8
IT 016	Andosols	Volcanic deposits	1
CN 018	Ferralsols	Water-dispersible clay	6
TH 001	Fluvisols	Sand and Gravel	9

DE 006	Gleysols	Humus, sand, and Clay	51
CN 046, CN 003	Luvisols	Clay	5

2.2.2.3. Distance from Waterbodies

Other than the location with permanent water bodies, rivers overflow its boundaries during peak flood seasons, resulting in inundation at locations that are usually dry (Okoye and Ojeh, 2015). Hence distance from rivers is an important hydrological factor in flood mapping as locations nearest to water bodies are more likely to be flooded than those farthest when overbank flow route across adjacent landscapes (Kazakis et al., 2015). River locations were derived from the Landsat8 image acquired during a low flow season in 2015 using Normalized Difference Water Index (NDWI) and Euclidean distance outcome from rivers generated using the spatial analyst toolbox of ArcMap.

2.2.2.4. Digital Elevation Model (DEM) and derivatives

Topography influences hydrodynamic modelling and inundation mapping to a large extent and controls the dynamics of water from rivers to adjacent floodplains (Cook and Merwade, 2009). However, the DEM accuracy significantly influences the accuracy of flood outcomes (Jung and Merwade, 2015). DEM and its derivatives such as Stream Power Index (SPI), Topographic Wetness Index (TWI), Slope, and Curvature were applied in this study. The TWI was developed by Beven and Kirkby, (1979) to quantify the effect of local runoff on flood generation, and supports evidence of moisture within the landscape as a result of surface water accumulation (Qin et al., 2011, Kopecký and Čížková, 2010, Gokceoglu et al., 2005). SPI supports flooding conditions as it describes the catchment water flow and erosion (Jebur et al., 2014, Cao et al., 2016). Slope and curvature also affect catchment hydrology and flow accumulation as run-off generally flows from high regions to accumulate in low-lying areas (Kazakis et al., 2015). Slope and curvature were generated from DEM using ArcMap Spatial Analyst Surface Toolbox, SPI derived using ArcMap raster calculator and TWI using the Topography Tool developed by Tom Dilts of the University of Nevada Reno.

2.2.3. Land use/cover classification

Land use/cover characterizes landscape roughness that is directly linked to run-off dynamics resistance and eventual flow accumulation (Arcement and Schneider, 1989, Medeiros et al., 2012). Bare soils tend to allow swift flow compared to vegetated or croplands (Tehrany et al., 2013), while built-up areas covered with impervious surfaces aggravate run-off (Zhou et al., 2015, Miller et al., 2014). Land use/cover was extracted from Landsat 8 OLI Imagery composites presented in Table 3, and classified into Built-up, Bare Land, Water Bodies, Matured Vegetation, Tampered Vegetation, Swamp and Cultivated land, using similar maximum likelihood supervised classification approach employed by Butt et al., (2015).

Table **3** Landsat 8 Imagery properties

Scene Name	Path	Row	Date Acquired
LC81880562015353LGN00	188	56	2015-12-19
LC81880572015353LGN00	188	57	2015-12-19
LC81890562015360LGN00	189	56	2015-12-26
LC81890572015360LGN00	189	57	2015-12-26

2.2.4. Synthetic Aperture Radar (SAR) Imagery Data: RADARSAT-2 and CosmoSkyMed

RADARSAT-2 and CosmoSkyMed SAR images were applied in this study acquired by Shell Petroleum Development Company operating within the study are for operational purpose (i.e. oil spill detection). The RADARSAT-2 images were captured in FineWide (F0W1) and Wide (W1 and W2) beam modes with swath widths of 170 km and 150 km respectively, corresponding to incident degrees of 20º to 45º (Canadian Space Agency, 2015). Properties of Radarsat 2 images are presented in Table 4.

Table **4** RADARSAT-2 Imagery properties

Satellite	**Beam Mode**	**Polarization**	**Date of Acquisition**	**Res (m)**
Radarsat-2	W2	HH	2012-10-09	12.5
Radarsat-2	F0W1	HH	2012-10-16	12.5

The CosmoSkyMed data sets were acquired as Detailed Ground Multi-look (DGM) Geocoded level 1 products (e-GEOS, 2009). The incidence angle of both products varies from 20º to 60º, while the swath widths were100 km and 200 km respectively, acquired in Wide Region instrument mode. CosmoSkyMed image properties are presented in Table 5.

Table **5** CosmoSkyMed Imagery properties

Satellite	Product standard	Instrument Mode	Polarization	Date of Acquisition	Res (m)
CosmoSkyMed	DGM	Wide Region	HH	2012-10-11	25
CosmoSkyMed	DGM	Wide Region	HH	2012-10-15	25

Both SAR Images were preprocessed using European Space Agency (ESA) Sentinel Application Platform (SNAP) tool, i.e. Calibration, Geometric correction and Speckle filtering (Jong-Sen, 1983), and reprojected to UTM Zone 32N. Flood extents were derived using the density slice histogram thresholding approach (Long et al., 2014) in Erdas Imagine.

2.3. Flood Delineation using Decision Tree (DT) Analysis

Decision Tree (DT) provides a powerful statistical approach that is widely applied in predictive and cluster/classification analysis (Song and Lu, 2015). DT generally follows a hierarchical structure that categorizes flood conditioning factors (Section 2.2.2.) in relation to a pre-determined set of classes (i.e. flooded and non-flood). The aim of DT is to establish a relationship between dependent and independent variables in a robust way using training data sets (Corcoran et al., 2012, Hogg and Todd, 2007). Some DT algorithms widely applied in flood mapping and vulnerability assessment studies include (i) Chi-squared Automatic Interaction Detection (CHAID) (Tehrany et al., 2013, Althuwaynee et al., 2014), (ii) Quick, Unbiased and Efficient Statistic Tree (QUEST), (iii) CRUISE (Classification Rule with Unbiased Interaction Selection and Estimation) (Panuju and Trisasongko, 2008), (iv) Classification and Regression Trees (CART) (Malinowski et al., 2015), (v) Exhaustive CHAID, (vi) C4.5 (J4.8) (Peter et al., 2013, Veljanovski et al., 2011b), (vii) Random Tree, and (vii) Random Forest (Quanlong et al., 2015). Various DT algorithms are known to result in varying accuracies, depending on the data composition, spatial distribution and algorithm complexity (Donglian Sun et al., 2011, Malinowski et al., 2015, Veljanovski et al., 2011b). Therefore, selecting an optimal DT is a difficult task (Grąbczewski, 2014). In several instances, studies compare different DTs and choose to apply the one that provides the most accuracy (Song and Lu, 2015).

In this study, the C4.5 algorithm (Quinlan, 1986) is adopted to develop a decision tree and execute the flood mapping process using the Waikato Environment for Knowledge Analysis (WEKA) open-access Machine learning and Environment for Visualising Images (ENVi) software respectively.

The C4.5 algorithm is implemented using the concept of information entropy/gain (Shannon, 1948), starting from the DT root node which is the variable with the most influence on the dependent variable, and classifying (splitting) downward while including subsequent variables according to their levels of importance. The model is iterated and pruned to remove redundant variables and overfitting in the decision-making process to improve predictive accuracy (Hssina et al., 2014, Singh and Gupta, 2014, Pooja et al., 2011, Patel and Upadhyay, 2012). The C4.5 algorithm provides the unique advantages of (i) accommodating continuous and categorical such as the conditioning factors, (ii) is capable of handling missing data and (iii) iterates through the tree to remove unwanted branches (Singh and Gupta, 2014).

Images of six priority conditioning factors are presented in Figure 2 and the hierarchical structure of the DT generated in WEKA is presented in Figure 3, showing the most important conditioning variables in descending order of significance automatically generated from WEKA using the trainng datasets and pruned to eliminate redundance.

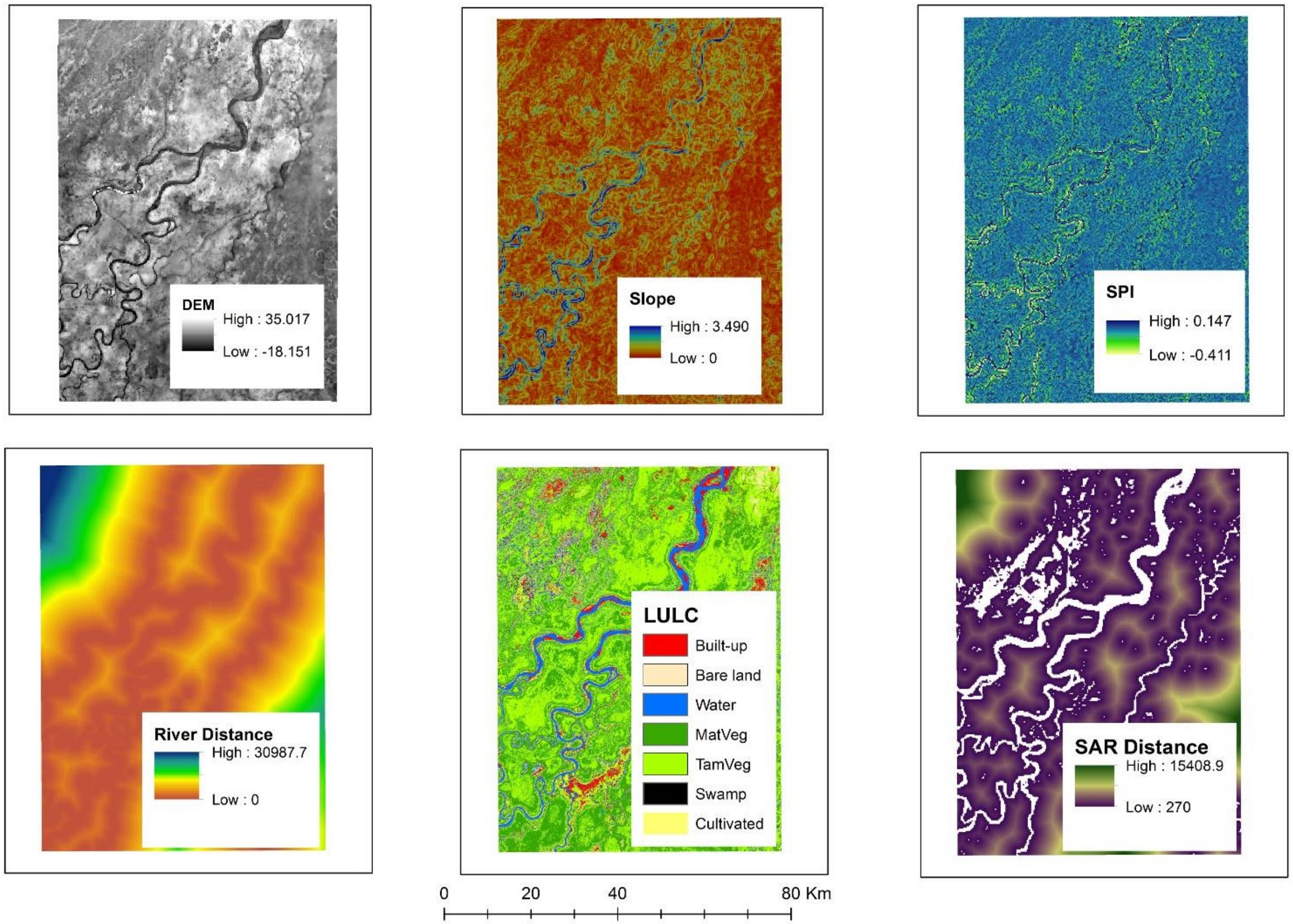


Figure 2 Six priority condition factors determined by decision tree presented in Figure 3.

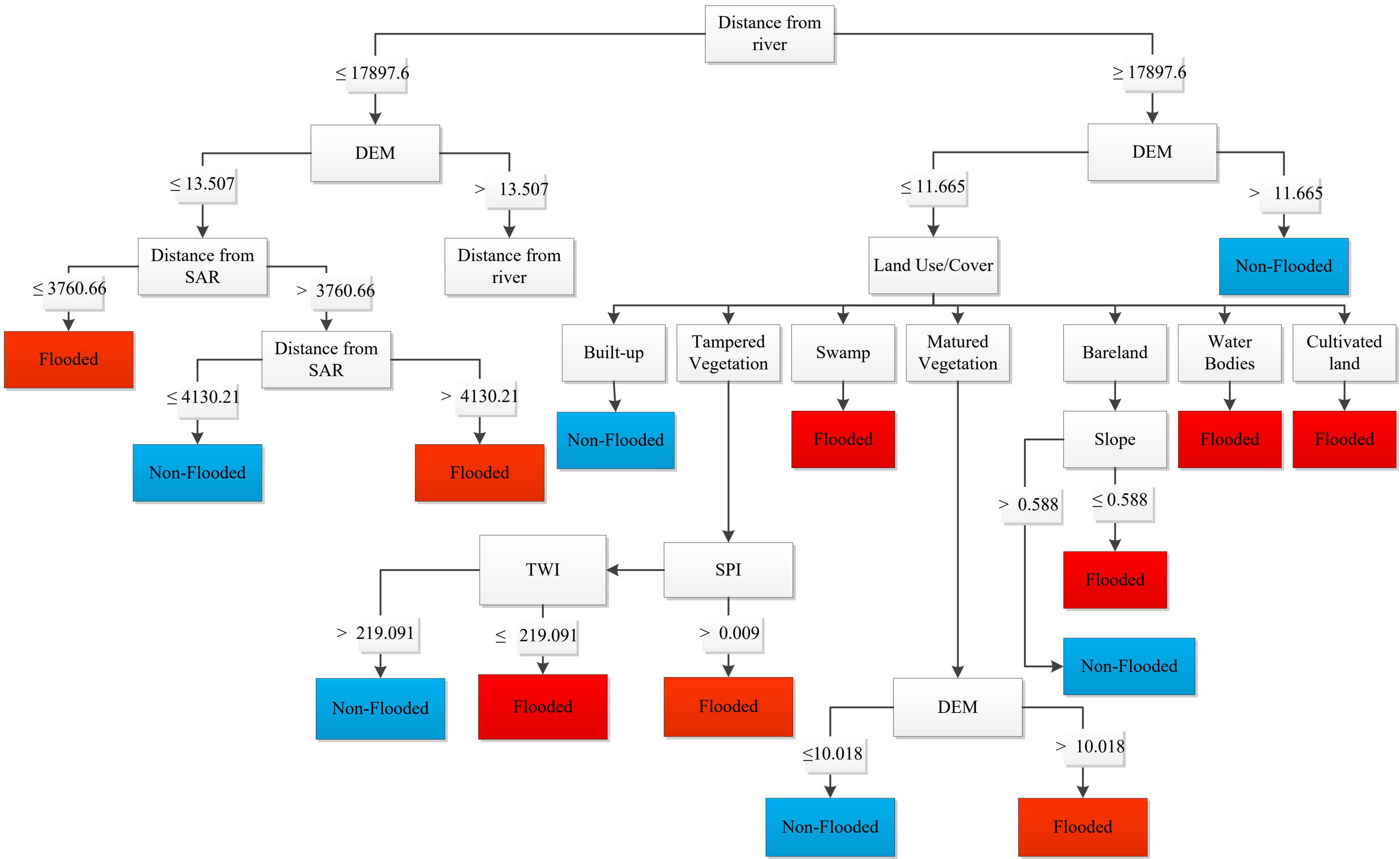


Figure 3 Decision Tree flood delineation based on influential factors

3. Results and Discussion

3.1. Decision Tree evaluation

DT (C4.5) algorithm outcome showed that of the 12 conditioning factors tested, distance from the river, DEM, distance from SAR flood extent, land use, SPI and slope had the most influence in flood classification (See Appendix 7 for more details). These were consistent with factors such as the cause of flood, hydraulic connectivity, historically flooded locations, land use roughness characteristics and flow direction (Tehrany et al., 2013, Tehrany et al., 2014, Peter et al., 2013). The accuracy of the DT algorithm is presented in Table 6, disclosing the F-measure, Receiver Operating Characteristic (ROC) area, the percentage of correctly classified independent variables and Kappa Statistic, suggesting that the DT algorithm is within reasonable limits of acceptability.

Table **6** Decision Tree Accuracy Assessment

Class	F-measure	ROC Area	Correctly classified (%)	Kappa Statistic
Flooded	0.973	0.917		
Non-Flooded	0.814	0.917		
Weighted average	0.951	0.917	95.27	0.7872

1 and 100% = perfect accuracy for decimal and percentage-based measures respectively.

3.2. Flood map accuracy assessment

The accuracy of the inundation map derived using a C4.5 algorithm, and that previously derived using histogram thresholding were assessed using five crowd-sourced data points that fell within the AOI (Ekeu-wei and Blackburn, 2016) – Chapter 5 and overflight data applied in the training process. The percentage of correctly classified data points are presented in Table 7, and evidence of improvement is seen in DT when compared to HT flood extracts. Visually, the highest flood spread is seen in the DT model outcome (Figure 4A) in comparison to HT (Figure 4B). DT flood extent showed increased hydraulic connectivity along the river over banks and continued within the floodplain. However, some disconnectivity exists within the floodplain, suggesting the capture flood susceptibility regions (Trigg et al., 2013), given that DT technique takes into account locations that would likely be flooded, but may not necessarily be flooded during the 2012 flood season (Tehrany et al., 2013).

Table **7** Flood Map accuracy assessment: Histogram Thresholding (HT) and Decision Tree (DT)

Data Type	Correctly estimated HT SAR (%)	Correctly estimated DT SAR (%)
Crowd-sourcing	40	80
Overflight	30	68

3.3. CAESAR-LISFLOOD evaluation in the Niger Delta

Inundation extent extracted from satellite, especially SAR provides the baseline for evaluation flood model accuracy in data-sparse regions (Di Baldassarre et al., 2011, Van Wesemael et al., 2016). A previous study at the same study area using HT flood extent (Chapter 6), revealed the limited accuracy of SAR image in delineating flood in the mangrove dominated Delta, due to C-band radar inability to penetrate vegetation and bounce of rooftops in urban regions. Results of the CAESAR-LISFLOOD model evaluation presented in Table 8 shows that the decision tree approach improved the F-Statistic by 51% and reduced the overall BIAS from 3.432 to 0.669. However, the overall percentage flood capture reduced by 25% due to increased inundation by the DT approach which captured susceptible but not likely flooded areas. The DT and HT flood maps both revealed modelled flood extent over-estimation over the delta region (Figure 4), owing to the uncertainties arising from coarse data inability to represent the complex terrain (Abam, 2001b, Syvitski et al., 2012), as well as landscape characteristics such as wetlands that are usually waterlogged over the dry and wet season (Powell, 1997), and activities such as dredging and sand-mining (Ohimain et al., 2004, Tamuno et al., 2009) which contributes to the complexity of the region's geomorphology.

Table **8** CAESAR-LISFLOOD evaluation based on Histogram Thresholding and Decision Tree

Performance	Histogram Threshold	Decision Tree
F-Statistic	0.19	0.37
BIAS	3.43	0.70
% Flood Capture	69.95	45.41

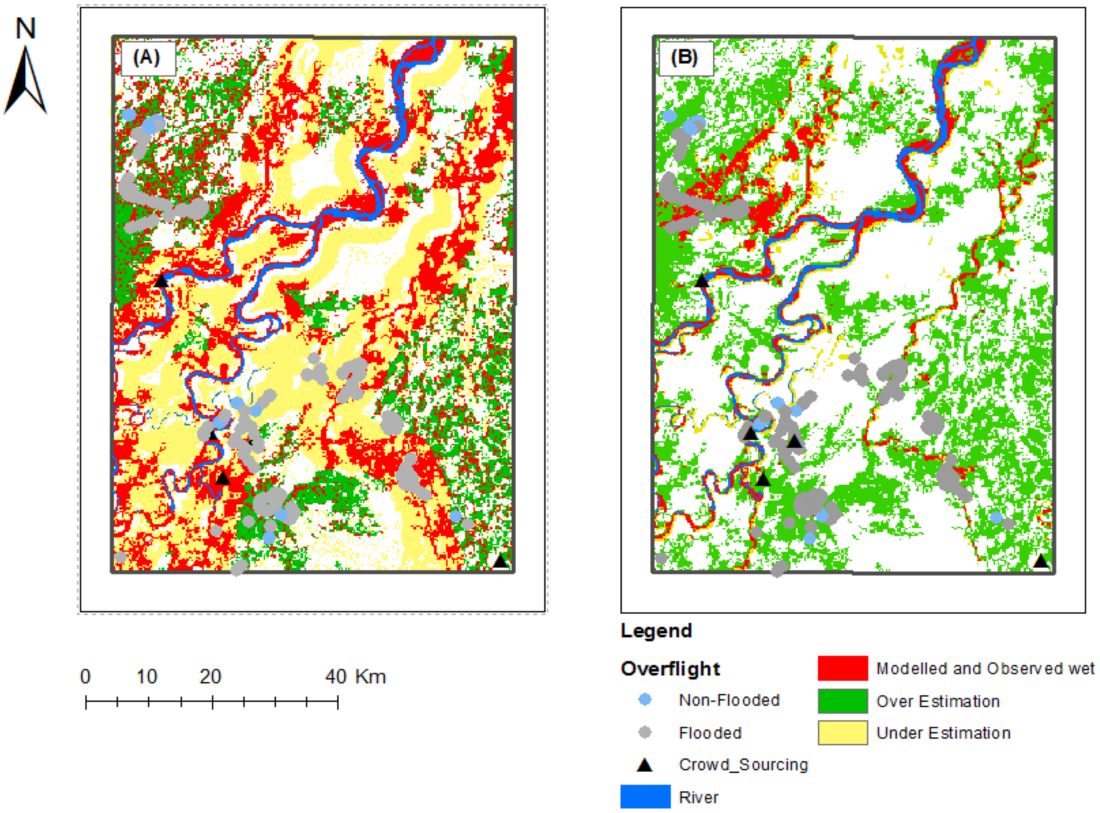


Figure 4 Decision Tree, Histogram Thresholding and CAESAR-LISFLOOD model visualisation

4. Conclusion

This study was focused on improving Synthetic Aperture Radar flood delineation in the mangrove dominated Niger Delta region of Nigeria to enhance hydrodynamic model validation. Multiple open-access data sets were combined and trained using the C4.5 decision tree algorithm to capture flooded and non-flood locations identified from overflight geotagged photos. The decision tree algorithm was initialized using 12 flood conditioning parameters including DEM and its derivatives (Slope, Curvature, Stream

Power Index, Topographic Wetness Index and Topographic Position Index), Soil type, geology, rivers, land use/cover and historical flood extent. The Decision Tree (DT) prioritised distance from the river, DEM, historical flood extent, land use/cover, slope and SPI as the most influential components for flood delineation in the decision-making process.

The accuracy of the DT flood extent was assessed using overflight and crowd-sourcing data and was found to be higher than derived by histogram thresholding. The DT flood extends also resulted in the improved assessment of the 2-dimensional CAESAR-LISFLOOD hydrodynamic model and reduced overall bias. However, the results of this study show the DT approach overestimates flood extent owing to the fact that locations susceptible to flooding were captured as flooded even though they were not necessarily flooded during the 2012 flood season.

Going forward, improved data collection is suggested in the region, especially river bathymetry, up-to-date high-resolution terrain and land use/cover dataset that captures the true complexities of the Niger Delta landscape, as well as training datasets with adequate spatial spreaf, for the improvement of the hydrodynamic model and flood mapping outcomes, to recude residual uncertainties that resulted in overestimation of flood exteent by both approaches. Also, we recommend the re-established of discontinued hydrological gauging stations along the Niger river discharging into the Niger Delta region (Abam, 2001b, Olayinka, 2012), to provide reliable hydrological data to improve for modelling with reduced uncertainty.

CHAPTER 8: CONCLUSION, CONTRIBUTIONS, LIMITATIONS AND RECOMMENDATIONS

Flood occurrences are often unexpected or with little warning, thereby making it difficult to manage. However, past flood experiences provide a baseline for planning and decision making for managing subsequent/expected flood events. In developing regions, such historical data is seldom available due to administrative, logistical, financial and technical drawbacks.

This study was aimed at overcoming data and resources limitations in flood modelling and mapping, thereby reducing the associated uncertainties. I applied open-access remote sensing and 3rd party data collected by individual (crowd-sourced) and organisations living/operating in the area of interest to fill the data void. Also, I used freely available tools complemented by student licensed and generally available commercial software to ensure study replicability in developing regions where invests in sophisticated systems are limited due to lack of funds (Appendix 2). This will thereby enable the establishment of an integrated flood management system that involves planning, response and recovery for several developing countries. The main findings of this study are summarised as follows:

1. Logistical, administrative, financial and technical factors are identified as the core causes of data sparsity at local and transboundary river basins in developing countries.
2. Alternative open-access remote sensing and third-party data acquired by individuals and organisations residing and operating in remote locations can be leveraged for flood modelling and mapping activities including flood frequency estimation, hydrodynamic modelling and risk mapping in data sparse regions.
3. Other than open-access geospatial data, organisations operating in developing regions and satellite consortiums such as the Disaster Charter occasionally collate high-resolution satellite and bathymetry data that can be requested and applied in flood modelling and mapping processes as demonstrated in this study.
4. Gaps in historic hydrological time series, sparsely distributed gauging stations and short records at newly established gauging stations are some of the challenges that hinder optimal flood frequency estimation in developing regions required to inform flood management decisions. This study curbs these challenges by (i) applying

radar altimetry and multiple imputations to reconstruct missing data, and (ii) regional flood frequency analysis to tackle gauging station paucity and hydrological record shortage.

5. In-filling missing data in hydrological times series using radar altimetry and multiple imputation is dependent on the consistency of the gaps within the dataset. Radar altimetry approach is recommended for widely gapped datasets greater than 3 years, while multiple imputation can be applied for gaps of not more than 3 years, to reduce the uncertainties associated with estimates derived from incomplete data sets.
6. Flood estimates based on the assumption of homogeneity is no longer valid, considering the growing influence of climate change and variability on the hydrological cycle. Using an open-access ICI-RAFT tool, the influence of Madden-Julian Oscillation multi-decadal climate variability indices on regional flood estimates in sparsely gauged Ogun-Osun basin was demonstrated, reiterating the need for the revision of flood management measures based on the assumption of stationarity.
7. Monitoring flooding as it occurs requires real or near-real-time data and processing that is seldom available, and in other instances, floods inundated roads, thereby causing logistical and accessibility challenges that hamper *in situ* data collection in remote areas. The results from this study suggest that crowd-sourcing and remote sensing when combined can capture micro and macro scale flooding in near-real-time, useful for evacuation planning and specific need assessment during flooding. Also, the discrepancy between government and citizen perception of flood risk is revealed, thus raising a question about the uncertainties in the GeoSFM and SWAT models, and the need for citizen knowledge integration into flood management and decision-making.
8. Open-access CAESAR-LISFLOOD hydrodynamic and remote sensing data were sufficient in modelling flooding in the Niger-South catchment area of Nigeria. However, the accuracy of the model outcome depended largely on the morphology of the area modelled and data availability. The location with constrained river channels and up-to-date river bathymetry data (Lokoja), resulted in more accurate flood extent and water level estimates to accuracies greater than 80% and RMSE of 0.564 respectively, despite using SRTM DEM as the topographical dataset.

Therefore, improved bathymetric survey is suggested, especially in the low-lying Niger Delta region for enhanced flood modelling and mapping.

9. At Lokoja sub-domain where improved model accuracy was achieved, the 2012 flood event inundation extent that resulted in damage to infrastructure, disruption of socio-economic activities and loss of lives, was simulated to an 85% accuracy, with impacts on population, settlements, built-up areas and road infrastructure estimated at similar accuracies. Also, the 2012 flood was within the 90% confidence level bounds of 1-in50 and1-in-100-year flood return period events.
10. The deficiency of Synthetic Aperture Radar (SAR) in delineating flood extent in the vegetation dominated region of the Niger Delta was revealed in this study, using overflight geotagged photos that captured the true state of flooding in the region, especially within mangrove canopies where SAR images were deficient. This overflight data for model validation resulted in better model to reality match, especially in low-density building, vegetation and bare earth locations.
11. SAR flood delineation capacity was improved in the mangrove-dominated delta region using a multi-criteria decision tree approach that combines various open-access geospatial data sets. This approach improved SAR inundation capture capacity by 100% from the previously applied histogram thresholding method when compared to crowd-sourced flood information. However, flood extent was over-estimated at locations that were not necessarily flooded, but susceptible to flooding.
12. Causes of flood modelling uncertainty identified in this study were (ii) poorly defined river bathymetry in the low-lying Niger Delta of Nigeria and (ii) unavailability of hydrological gauging station within the regions river segment, thus causing propagation of upstream uncertainties. Other factors that contribute to the complexity of modelling the region. These include the wetland nature of the delta, natural/artificial ponds, ongoing dredging and sand mining.

7.1. Contribution to Literature/Method

Open-access remote sensing has been widely applied in developing regions where data unavailability is pronounced. However, the application has been fragmented, focused on individual challenges that hamper flood modelling and mapping processes at specific points in time (Sanyal et al., 2013, Yan et al., 2015b, Degrossi et al., 2014, Corcoran et al., 2012, Tehrany et al., 2013). Chapter 2 of this Thesis presents a review of data sparsity challenges at a local, regional (transboundary) and global scales, also revealing the broad range of open-access data available to overcome data limitation at various scales.

This study presents an integrated approach that systematically solves the problem of data insufficiency at every stage of flood modelling and mapping from preparedness, response to recovery, using limited resources as often the case in developing regions. First, hydrological data with varying gap patterns (i.e. consecutive (1-3 years) and inconsecutive (> 3 years) were filled using radar altimetry and multiple imputation approaches in Chapter 3, and short duration hydrological time series data are agglomerated within regions of hydrologic similarity while accounting for climate variability effect using freely available ICI-RAFT tool in Chapter 4, thereby enhancing flood quantile estimation in sparsely gauged river basins. Annual Exceedance Probabilities (AEP) derived from both methods are essential to flood defence and hydraulic structures designs, and planning required for effective flood management.

Flood hazard mapping is critical to understanding the exposure of citizens and infrastructures to risk, to ensure efficient flood management plans are initiated and measures implemented to manage flood upon occurrence (Surendran et al., 2008, Ramirez et al., 2016, NIHSA AFO, 2014). Chapter 5 detailed an integrated RS and crowd-sourcing approach that can improve flood risk management if integrated into national flood management frameworks, given the discrepancy between government and citizen risk perception attributed to data and model uncertainties inherent in the flood model government decisions are currently based on. This model is incapable of capturing micro scale flooding caused by local factors such as poor urban drainage and waste management practices, and the model's bias in favour of fluvial flooding. Also, this study identifies a peculiar challenge of reluctant to divulge socio-economic data, an active crowdsourcing deficiency never disclosed in any previous literature - due to widespread internet fraud rampant in some developing regions.

Hydrodynamic models are strongly reliant on hydrographic, terrain and calibration data sets (Aerts et al., 2009, Els, 2013), and the accuracy of the flood model depends on the input data accuracy (Jung and Merwade, 2015, Sanyal et al., 2013, Domeneghetti et al., 2013). CAESAR-LISFLOOD model was applied in retrospect to recreate the 2012 flood event within the Niger-South basin, Nigeria (Chapter 6). Multiple open-access RS and data collected by organisations operating within the area of interest were applied. River channel bathymetry was super-imposed on Bare-earth SRTM, and ICE Sat altimetry applied in the elevation data accuracy assessment. Model calibrated/validated were executed using a combination of optical, radar satellite images, overflight geotagged photos and hydrologic data sets. This approach reveals how multiple data sets can be employed to reduced modelling uncertainties, and by sectioning the whole study area into sub-domains, the effect of data variability and river section geomorphology was captured, revealing how data combination can improve model performance and differ from when the entire domain was assessed as a single unit. Deficiencies in SAR imagery flood delineation within the vegetation dominated delta region was revealed using overflight geotagged photo that has the ability to capture underlying flooding with mangrove canopies where radar pulse cannot penetrate.

In a previous study in the Niger-South region of Nigeria, Olayinka (2012) recommended an approach that incorporates environmental, climatic and sociological factors for further research, envisioning that such approach will ensure effective flood risk planning and monitoring. Evidence from this research confirms this hypothesis, revealing improved flood monitoring and management using multiple open-access data, and, the need for citizen inclusion in flood management decision making.

7.2. Contribution to policy and practices in Nigeria

Flood management policies exist in Nigeria, with clearly defined objectives and plan of action detailed in the (i) Action Plan for Erosion and Flood Control (FME, 2005b), (ii) Technical Guidelines on Soil Erosion, Flood and Coastal Zone Management (FME, 2005ba) and (iii) Water Resources Master Plan (FMWR, 2013). Nevertheless, these policies have become obsolete, less the latter, and lacks clear definition responsibilities and effective implementation, judging by the recurring floods and increasing impacts in recent years. Also, the effect of climate change and climate variability on hydrological regime and data limitation challenges though mentioned in FMWR, (2013), are seldom accounted for during implementation, or a simple bias regression interpolation approach is applied to fill missing data (Dike and Nwachukwu, 2003), which results in predictable biases and corrected data variables (van der Heijden et al., 2006).

The Nigeria Erosion and Watershed Management Project (NEWMAP) initiated in 2012 through a collaborative effort of the Nigerian government and the World Bank is aimed at improving watershed management through effective monitoring and climate change effect inclusivity (The World Bank, 2012, Hogan, 2016), however, its implementation is still in progress, with advanced hydrological monitoring equipment yet to be distributed to river basin authorities (Hogan, 2016). This study disclosed contemporary issues surrounding flood management globally and locally (Nigeria), with results revealing missing and limited data effect on flood frequency and magnitude estimates, and how alternative altimetry data, statistical techniques and data amalgamation can be applied to improve long-term flood management at newly established gauge station locations. The results of this thesis, if taken into account, can help inform gauging station distribution to optimize flood management in Nigeria, reduce uncertainties associated with missing data in flood modelling processes, and also reconstruct historical data sets at locations where gauging stations are newly established.

The flood experience of 2012 in Nigeria was an eye opener, triggering the need to re-evaluate the Nigerian flood management strategy and improve the understating of the contributing factors (ACMAD, 2012, Agada and Nirupama, 2015, Ojigi et al., 2013, Ojinnaka et al., 2015). The retrospective approach undertaken in this study recreated the flood scenario in the Niger-South basin to an 85% accuracy where optimal data was available, suggesting that the flood would have been managed considerably if plans were in place for a 1-in-100-year. Also, this study disclosed that majority of the 2012 flood emanated from the Benue river, suggesting that Kiri and Lagdo Dam in Nigeria and Cameroon respectively were the likely causes of the flooding as indicated in previous literature (Tami and Moses, 2015, Ojigi et al., 2013). Furthermore, improved hydrological and bathymetric data collection is required especially in the Niger Delta region, to achieve improved modelling accuracies. Results from (Chapter 6) also suggests that flood management maps need to be developed for the eight hydrological areas in Nigeria using improved data, identifying flooded locations and safe points for relocation during flooding. Such flood maps can also help inform infrastructure and housing development planning, especially in locations where flood-prone lands are sold during the dry season to the uninformed populace (Ajibola et al., 2012).

The data sparsity challenges tackled in two hydrological areas V and VI in this study are common in the other six hydrological areas and the larger Niger Basin (Garba et al., 2013a, Adeogun et al., 2014), and the methods proposed here can be adapted to curtail similar data deficiencies. Stakeholder inclusion using crowd-sourcing approach (Chapter 5) disclosed discrepancy between government flood risk perception based on SWAT and Geospatial Stream Flow Model (GeoSFM) models and people's perception, owing to the uncertainty within the data and model. Recent studies (Liu et al., 2016), revealed how SWAT can be incorporated with LISFLOOD-FP for high-resolution large-scale modelling and can be applied by the Nigerian Hydrological Service Agency (NIHSA) to enhance the flood modelling predictions in Nigeria. This study also presented an integrated remote sensing and crowd-sourcing approach for flood monitoring that enable small and large-scale flood detection. This methodology if coordinated by a disaster management agency such as the National Emergency Management Agency (NEMA) for Nigeria, working in collaboration with the National Space Research and Development Agency (NASRDA) and the Federal Ministry of Information and Culture and leverage on such an approach to improve flood monitoring, communication, response and recovery. Although the head of NEMA Geographic Information System department argued in an interview (Uwazuruonye, 2016) about the possibility of citizens providing erroneous information data just to get relief as often the case from his disaster recovery experience, it is expected that time-stamped images captured as part of the crowd-sourcing data collection process, combined with remote sensing flood extracts will curb such discrepancies.

7.3. Contribution to data archive for Nigeria

This study revealed that other than genuine data scarcity caused by organisational, logistical, financial and technical drawbacks, artificial data scarcity also exists, caused by (i) the fragmented and unstructured nature of data collection and management, and (ii) inaccessibility to data due to bureaucratic bottlenecks and the absence of open database infrastructure. Ngene, (2009, 2015) also lamented the effect of poor data management practices on water resource management caused by factors including erroneous data imputation when transferring from paper-based to digital systems. Nwilo and Osanwuta, (2004) also suggested same and recommended a National Spatial Data Infrastructure (NSDI) to improve inter-organization data and knowledge sharing to improve access to data and reduce duplication of data scouring efforts. Although this study did not develop a national database, analogue (paper-based) hydrological data collected from Ogun-Oshun River Basin Development Authority, Benin-Owena River Basin Development Authority, National Inland Water Ways Authority, Niger Delta River Basin Authority and Nigerian Hydrological Service Agency were digitized, and are now readily available for use. Going forward, these datasets can be integrated into the NSDI.

Data format inconsistency has also been argued to be one of the challenges facing water resource management in the Niger Basin (Olomoda, 2002, Olomoda, 2012). In this research, topographic, bathymetric, and digital elevation data are converted to a single GeoTIFF format, and the vertical datum and Coordinate reference system corrected to Mean Sea Level (MSL) and UTM Zone 32N to ease manipulation, integration and application. The terrain, altimetry and river bathymetry datasets were originally available in a range of formats including paper-based topographic maps, AutoCAD (.DWG), ASCII, CSV, XLS, DSS and TIFF. The vertical datum of the raw datasets included EGM96, EGM2008, Lagos 1955 and MSL, while the spatial geographic coordinates systems varied from WGS 1984, UTM Zone 32N, Nigeria West Belt to Clarke 1880. Both reference systems if not correctly adjusted would result in topological errors that flaw model outcomes, consequentially resulting poor flood management decisions (Youngman et al., 2011, Aman Hj Sulaiman et al., 2012, Pe'eri and Armstrong, 2014). Hence, a standardized referencing system is recommended in Nigeria for flood management designs and analysis. This can be facilitated by the Federal Ministry of Water Resources and the National Space Research and Development Agency (NASRDA)

Furthermore, this study identified locations of past, present and future radar altimetry virtual stations in relation to *in situ* gauging stations (Chapter 2), that can be leveraged on to reconstruct the hydrological time-series of discontinued and/or newly established gauging stations for long-term flood management in data sparse regions of the country.

7.4. Limitations

The types of flooding predominant in the Niger South river basin include river, coastal, surface water and urban flooding. Coastal flooding emanates from sea level rise caused by climate change (Musa et al., 2016). Surface water flooding is triggered by non-river components such as pounds overtopping, wetland saturation or anthropogenic activities such as dredging that alter local hydrology (Okonkwo, 2012, Abam, 1999a). Urban flooding, on the other hand, is caused by increased impervious surfaces and aggravated runoff, as well as, and poor drainage and waste management (Ogundele and Jegede, 2011, Atedhor et al., 2011).

This study focused solely on river (fluvial) flooding owing to the recent flood events triggered by upstream dam water releases as a result of intense rainfall (Ojigi et al., 2013, Olojo et al., 2013). However, flood scenarios are more complicated in reality, and an inclusion of other flood causation factors is likely to improve the model outcomes as reported in other studies (Breinl et al., 2015, Chen et al., 2010, Ashton et al., 2012). Although executing complex models requires additional data such as precipitation, tidal water level, evapotranspiration and geomorphology which are sparse in this area of study, remote sensing technology provides alternative that fills such voids, i.e. Tropical Rainfall Measurement Mission (TRMM) (Adeyewa and Nakamura, 2003, Abiola et al., 2013), evaporation, soil moisture (Miralles et al., 2011, Martens et al., 2016) and tidal water levels (Din et al., 2015, Davis et al., 2010). A Recent review on “The Future of earth observation in hydrology” by McCabe et al., (2017) also detailed hydrological modelling data needs and alternative sources for improved outcomes in the future.

Other than climate variability effect on hydrological regimes, land cover/use changes (Zhang et al., 2016, Dwarakish and Ganasri, 2015) and hydraulic factors such as dams impoundments and releases (Olayinka, 2012, Abam, 1999b, Abam, 2001b) also influence hydrological regimes. Although post-dam creation hydrological data was used for this study to lessen the effects of Kanji, Jebba, Kiri and Lagdo dam constructions on the Niger and Benue rivers hydrological regime (Toro, 1997, Ojigi et al., 2013). Approximately 69 dams exist within the Niger Basin (Lehner et al., 2011), with majority hydraulically linked to the Niger-south river basin through Niger and Benue rivers tributaries. Therefore, the influence of hydraulic structures needs to be accounted for going forward. Typically, Reservoir Index (RI) is implemented to account for reservoir effect (Machado et al., 2015, López and Francés, 2013). Nevertheless, the number of dams within the Niger Basin complicates this process and was beyond the scope of this study.

Though this study presented an integrated approach on how open-access remote sensing, crowd-sourcing and third party acquired data sets can be combined to improve flood modelling and mapping in data-sparse regions, data deficiency was evident at the Onitsha and Niger Delta regions, where river bathymetry data was obsolete and non-existent respectively (Chapter 6). Also, dredging, illegal sand mining and wetlands ponds (Trigg et al., 2016, Abam, 2001a, Tamuno et al., 2009) were identified as factors that contributed to the complexity of modelling the Niger-South basin. High-resolution up-to-date terrain and river bathymetry data are required for improved modelling of these regions.

In recent years, crowdsourcing has been a useful tool/approach in disaster management studies and practices, especially for monitoring as evident in this study, and rehabilitation/reconstruction activities such as (i) identification of impacted populace, (ii) needs assessment and (iii) critical infrastructure damage (Schnebele et al., 2014, Schnebele and Cervone, 2013, Goodchild and Glennon, 2010, Degrossi et al., 2014). Internet scam has been rampant in recent years in some developing economies (Jegede, 2014, Wang and Huang, 2011), resulted in the reluctance of respondents to divulge socio-economic data, thereby limiting the number of responses received and consequently the results in Chapter 5 (Choi and Pak, 2004).

Decision tree classification provides the unique advantage of discriminating/classifying flooded and non-flooded landscape based on a combination of categorical or continuous data sets (Malinowski et al., 2015, Friedl and Brodley, 1997). The training data spatial distribution, quantity, ratio of class division and spatial resolution of satellite images from which conditions factors are extracted impacts on the accuracy of final classification outcome (Kavzoglu and Colkesen, 2012, Peter et al., 2013, Lamovec et al., 2013, Malinowski et al., 2015). Typically, high-resolution data, increased and optimally distributed training data would reduce such bias in the classification outcome. Applying third-party acquired and open-access data limited our control over the afore listed factors, thereby affecting the accuracy of the inundated area estimates as previously presented.

7.5. Hydrology, Hydrodynamics and Flood Mapping Uncertainties

The value of open-access remote sensing and third-party data collected in developing regions was clearly demonstrated in this study, despite the difficulty associated with acquiring data for flood modelling and mapping in these regions. The outcome of this thesis suggests that data is always available, though fragmented, and in other cases incomplete and not frequently available. The level of accuracy derived from the integrated application of such datasets, however, depends on their accuracy and inherent uncertainties, which are epistemic and aleatory in nature (Merz and Thieken, 2005).

The approaches presented in this thesis is useful in (i) curtailing gaps in hydrological data caused by distorted data collection; (ii) transfer of data from gauged to ungauged regions; and (iii) simulation of flooding in flood-prone areas that suffer from hydrological data insufficiency. Nevertheless, it is important to note that the hydrological, topography, as well as calibration and validation datasets applied in this study, contain inherent uncertainties that propagated the flood modelling and mapping process, thus making difficult to ascertain the levels of uncertainty in the final outcome.

These uncertainties were not addressed in this study, due to the high computational cost of combined hydrological and hydrodynamic simulations. However, the calibration process is undertaken in this study to reduce the uncertainty in the model prediction, through the variation of static manning's roughness parameters of the hydrodynamic model, while comparing the model outcome to observed data. Furthermore, details of specific uncertainties are elaborated below.

7.5.1. Uncertainty in Frequency Analysis:

Input flow data uncertainty: River discharge data is one of the most fundamental input (initial and boundary condition) required for flood modelling. River water levels within the study area are typically measured using staff gauge, then converted to discharge using established rating curves that relate water levels and discharge (Herschy, 2008, Di Baldassarre et al., 2012). This results in measurement and extrapolation uncertainties (Baldassarre and Montanari, 2009, Haque et al., 2014). Although this study attempts to understand the degree of rating curve extrapolation influence on the annual maximum time series using ratings ratio (Haddad et al., 2010), the approach applied here is not exhaustive, given that the actual uncertainty associated with observation and discharge estimation using rating curves are not quantified and accounted for in the flow estimation process.

Limited duration of flow records: Flood frequency analysis (FFA) is essential to estimating the likelihood of a flood event of specific magnitude occurring or be exceeded. Other than the apparent possibility of measurement and rating curve extrapolation uncertainties propagating unto the outcomes of the flood frequency estimates as previously discussed, the length of available historical hydrological records further contributes to flood estimation uncertainty (Reed, 1999). More data usually imply increased confidence in the flood estimate, especially for the standard 1-in-100year (1% chance of flood) flood estimate that can be significantly affected by the length of historical records (Feaster, 2010). This study adheres to the 5T rule stipulated in the Flood Estimation Handbook (Reed, 1999), which recommends that the available historical data should be applied to estimate a target return period that is at least five times its length (i.e. 20 years of data is required for a 100-year flood estimate). The gaps within the hydrological datasets used in this study make the original dataset less than 5T, revealing the typical degree of missing data evident in many developing regions. Nonetheless, the missing data infilling approaches proposed and applied in this study provides the unique advantage of filling these gaps, and can be applied to reconstruct historical data from when hydrological stations were yet to be established.

Probability Distribution Selection and Parameter Uncertainty: Other than the length of availability data, model selection is one of the relevant sources of epistemic uncertainty. In hydrological flood frequency estimation models, the choice of probability distribution and parameter estimation technique applied can affect the desired outcome significantly (Botto et al., 2014). As such, varying probability distribution functions including Generalized Extreme Value (GEV), Generalized Logistic (GLO), Extreme Value (type 1 – 3), Generalized Pareto (GPA), and Log-Pearson type 3 (LP3), can result in significantly different flood estimates for the same historical dataset, especially for large return periods, given the subjectivity associated with probability distribution selection (Di Baldassarre et al., 2012, Laio et al., 2009). Also, underlying parameter estimator bias and variance can contribute to flood estimate uncertainty (Tung and Yen, 2005). Typically a suitability analysis is undertaken to access the best probability distribution (Peel et al., 2001), as undertaken in chapter 4, but GEV is adopted in chapter 3 to estimate flood frequency and magnitude, due to its robustness, flexibility (Komi et al., 2016, Hailegeorgis and Alfredsen, 2017, Papalexiou and Koutsoyiannis, 2013) and wide applicability in the area of interest, for consistency (Izinyon and Ehiorobo, 2014, Garba et al., 2013b, Fasinmirin and Olufayo, 2006). The GEV probability distribution estimates are however affected by tropical cyclones and extratropical weather systems that results in extremely large shape parameters (Smith et al., 2011, Villarini and Smith, 2010), but these events do not manifest in Nigeria. Furthermore, the GEV like other probability distributions is affected by short hydrological time series and could result in uncertain flood estimates (Ragulina and Reitan, 2017, Botto et al., 2014).

7.5.2 Uncertainty in hydrodynamic Modelling:

Hydrodynamic model uncertainty: Hydrodynamic models are typically applied is predicting the route of water flow longitudinally along the river channel and laterally across floodplains with varying degrees of complexity, depending on the question of interest, and are usually governed by continuity and momentum equations (Casas et al., 2006). CAESAR-LISFLOOD applied in this study provides as a simplistic approximated approach that models longitudinal and transverse across river channels and floodplains respectively (Coulthard et al., 2013, Coulthard et al., 2007). Nevertheless, the simulation in this study assumes limited erosion and geomorphological changes, as well as infiltration, despite evidence of geomorphological dynamics within the catchment area (Musa et al., 2014b), due to the absence of field data, thus I adapted sedimentation and infiltration rate parameters from a previous study in the same catchment area (Olayinka, 2012). Also, the model is run at 270 m resolution for computational efficiency, and this further reduces the hydraulic complexity of the Niger-South river basin, and could potentially contribute uncertainty to the hydrodynamic model outcomes.

Digital Elevation Model (DEM) uncertainty in flood modelling: Digital elevation models are essential input parameters required for hydrodynamic modelling. DEMs are usually acquired through various approaches and at varying spatial scales, thus the accuracies of DEMs can varying considerably, depending on the method of acquisition and spatial resolution (Md Ali et al., 2015). When applied as input in flood modelling, DEM accuracy can affect model performance, thus resulting in uncertain outcomes.

Furthermore, GIS Processing procedures such as resampling often undertaken to improve model computation cost can further deteriorate DEM accuracies by averaging elevation pixels values in the resampled DEM (Casas et al., 2006). Low resolution and coarse DEM such as SRTM used in this study are known to result in less accurate flood modelling outcomes. This however varies with the scale of model (from small to large), given that open-access DEMs such as SRTM and ASTER DEMs have been recognised to be particularly useful and considered effective for large-scale modelling (Yan et al., 2015b, Patro et al., 2009, Komi et al., 2017). Also, elevation bias (forest canopy and urban areas sensor reflectance) corrected DEMs, as well as the integration of high-resolution DEM (such as dGPS survey and LiDAR) and bathymetry survey data with coarse DEM, have been found to improve hydrodynamic model outcomes (Ireneusz et al., 2017, Yamazaki et al., 2012, Baugh et al., 2013). DEM modification and integration are applied in this study, depending on data available within the specified sub-domains in chapter 6. The effect these variable DEM compositions were revealed in the varied calibration parameter values and final model outcomes for individual sub-domains, thereby demonstrating the impact of DEM and up-to-date bathymetry on flood estimates under different geomorphological conditions.

Flood delineation uncertainty: The performance of flood inundation models is often assessed using satellite (SAR and optical) observed data on water level or flood extent, especially where *in-situ* observations are unavailable. However, these data have inherent uncertainty that can impair its usage. The value of SAR in delineating accurate flood extent has been widely demonstrated, owing to the low radar backscatter from the surface of the water, which differs from the higher returns from the relatively rough landscapes (Smith, 1998). Nevertheless, this delineation is complicated by landscape properties such as vegetation and buildings which can cause multiple reflections, and meteorological conditions such as wind or rain that roughen water surfaces, resulting in increased backscatter and consequently misdelineation of flooded areas as no-flooded (Mason et al., 2016). Optical images are also useful in flood delineation, derived mostly from the discriminating between the spectral signatures of water surface and surrounding landscape in multi-temporal images, using image classification or spectral indices (Zhang et al., 2014, Stephen et al., 2015). Similarly, optical images are affected by atmospheric conditions such as cloud cover, and landscape properties such as vegetation and rugged terrain. These process uncertainties that are likely to reduce the usability of satellite information for the evaluation of model performance can be improved by better image processing techniques that reduce errors associated with flood extent delineation processes (Long et al., 2014, Veljanovski et al., 2011b, Zhang et al., 2014).

Limited number of crowdsourced data and responses: This study presents the first effort to adopt crowd-sourcing for flood management in Nigeria, and revealed the prospects, challenges and opportunity for improvement. The results presented reveal the prospect and potential benefits of integrated crowd-sourcing and remote sensing for flood detection and reporting in data spare regions; especially to capture micro-climatic conditions in urban areas, where both radar and optical imaging systems could be deficient (Musa et al., 2015). Nevertheless, the responses obtained in this study are limited to 50 respondents, and as such did not capture the general population's perspective on flooding, and therefore the results presented in chapter 4 cannot be interpreted definitively. Also, quality assessment of crowd-sourced and volunteer GIS has been a major debate in such studies (Wang et al., 2017, Foody et al., 2014, Goodchild and Glennon, 2010), and although cross-validation using media and remote sensing is adopted in this study, the validation datasets also contain inherent uncertainties, given that remote sensing can under-estimate flood extents and media outlets cannot reach all flood areas to report disaster incidents.

7.6. Recommendations and future research direction

1. The scarcity of gauging station networks and the need for the establishment of new ones have been largely established in the various literature, including this research. Efforts are currently ongoing, through a collaborative initiative between the World Bank and the Nigerian government through the Nigeria Erosion and Watershed Management Project (NEWMAP). The NEWMAP is working closely with various river basin authorities to establish hydro-met stations where needed and improve data collection, management and dissemination to improve flood management. It is expected that newly established gauging station data will be short, hence this study advises that radar altimetry tracks and virtual station locations be considered when establishing new gauging stations to enable reconstruction of historic hydrologic time-series for long-term flood management purposes.

2. The causes of data sparsity at local and transboundary scales are well documented in this thesis, with clear evidence of the prospect of remote sensing in managing such challenges. Though local data deficiencies can be managed considerably by (i) enhance inter-government agencies cooperation, and restructuring; (ii) capacity building; and (iii) infrastructure financing, the challenges of transboundary flood management agencies are more complex, as jurisdiction and independent government policies hinder effective cooperation. Open-access optical (Landsat, MODIS and Sentinel 2), radar (Sentinel-1) and altimetry satellite data provides huge prospect to improve integrated transboundary flood monitoring and management in riparian countries.

   The Database for Hydrological Time Series of Inland Waters (DAHITI) and Global Reservoirs/Lakes (G-REALM) database, for instance, provides water levels measurements at Lagdo, Kanji and Shiroro reservoirs/dams, that were identified as the water release points that resulted in the 2012 and 2105 floods in Nigeria (Agada and Nirupama, 2015, Ojigi et al., 2013). Likewise, the Geodesy, Oceanography et Hydrologie from Space and The Theia land data services (HYDROWEB) databases provide water level measurements along the Niger and Benue rivers. Such data sets can be applied in monitoring the impact of reservoir hydrological variations on downstream flooding while accounting for land cover/use change influences using multi-temporal satellite imageries.
3. Given the promising prospect of crowdsourcing and remote sensing application for near-real-time flood monitoring revealed in this study, a full-on implementation of a web-based disaster and response Requisition platform is recommended to the National Emergency Management Agency (NEMA). Existing platforms such as Flood Crowd or Ushahidi can be adopted, or a new system developed to improved disaster recovery and rehabilitation. The growing mobile internet subscription Nigeria (CIA, 2016) and household population tend (Demography and Health Survey, 2003) suggest the likelihood of increased flood exposure, and also an opportunity to leverage such trends to enhance mitigation and recovery using information provided by flood-impacted persons with access to mobile telecommunication technology.
4. With climate variability driving weather patterns and resulting in more frequent and intense floods, the assumption of stationarity of hydrological regimes is no longer

valid. In this study, it was proven that multi-decadal Maiden Julian Oscillation (MJO) influences flooding in Nigeria as previously established (ACMAD, 2012, Mohino et al., 2012, Mouhamed et al., 2013, New et al., 2006). Hence, there is need to review flood management policies and plans based on the obsolete assumption of stationarity.

5. The population of Nigeria like most developing countries is on a continuous rise and is expected to become the 3rd most populous country by 2050, according to the United Nations. Such population surge will result in an increased likelihood of exposure due to the vulnerable populace settling within high-risk regions of floodplains (Shabu and Tyonum, 2013, Tamuno et al., 2003). Going forward, it is essential that various upstream dam water release scenario's and downstream flood impact is simulated (Ramirez et al., 2016), applying reservoir hydrography, bathymetry, radar altimetry, optical and SAR imagery data, to improve floodplain planning and management.
6. Future radar satellite missions such as the L band NASA-ISRO Synthetic Aperture Radar (NISAR) and S-band Surface Water Ocean Topography (SWOT) proposed for launch by 2020 are expected to improve SAR water penetration and measurement parameters. These missions will provide unprecedented open-access remote sensing data sets to improve hydrological, hydrodynamic modelling and flood mapping, particularly in urban and vegetated regions of developing countries.

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APPENDICES

Appendix 1: Current Work: Informing Policy and Practice with Research in Nigeria, West Africa

I am currently consulting for the World Bank as an Environment and Natural Resources Consultant, working on projects that directly align with the objectives and outcomes of my research, thus allowing me to apply the skills and knowledge I developed over the period of this research to inform environmental management practices and policies in the real-world. These projects include:

1. **West African Coastal Area (WACA) Management Program**: The Project Development Objective (PDO) of WACA is to "strengthen the capacity of a select number of West African countries (including Nigeria) to reduce the vulnerability of their coastal areas and promote climate resilient integrated coastal management.".
2. **Nigerian Erosion and Watershed Management Program (NEWMAP)**: The Project development objective of NEWMAP is to "reduce vulnerability to soil erosion in targeted sub-watersheds".
3. **Ibadan Urban Flood Management Project (IUFMP)**: The Project development objective of the IUFMP is to "Improve the capacity of Oyo state to effectively manage flood risk in the city of Ibadan".
4. **Multi-Pollutant Management and Environmental Health (PMEH)**: is focused on Improving air quality monitoring in the city of Lagos and strengthen the capacity of Lagos State Government with regards to environmental quality management. The Research component this project will include air pollution monitoring optimization using remote sensing in developing countries, where ground observatory is limited.

Appendix 2: Data types, tools, sources and use

S/N	Type	Source	Usage
1	Landsat OLI	USGS	Land use and land cover mapping
2	Shuttle Radar Topography Mission (SRTM) and Bare-Earth Components	USGS, University of Bristol, http://www.earthenv.org/DEM[6]	Hydrodynamic modelling and flood mapping
3	Radarsat-2	Shell Petroleum Development Company	Flood extent mapping
4	CosmoSkyMed	Shell Petroleum Development Company	Flood extent mapping
5	Hydrography	NISHA, NIWA, OORBDA, BORBDA, GRDC	Flood frequency analysis
6	Aerial Photography	Shell Petroleum Development Company	Flood delineation in mangrove areas
7	Climate Indices	NOAA	Develop climate indices for climate variable flood frequency estimation
8	Bathymetry	HaskoningDHV, Digital Horizon Nig. Ltd.	Hydrodynamic modelling

[6] http://www.earthenv.org/DEM

9	Sentinel-1/2	European Space Agency	Flood extent mapping
10	Geological	NGSA	Criteria for decision tree flood mapping
11	MODIS NRT Flood Map	NASA	Large scale flood extent mapping
12	Socio-Economic	Socioeconomic Data and Applications Centre (SEDAC)	Assessment of social-economic impact of flooding
13	Spatial Data	DIVA-GIS	Derive administration maps
14	Global Active Archive of Large Flood Events	Dartmouth Flood Observatory, University of Colorado	Quantify historical floods in Nigeria and Globally
15	Radar Altimetry (Topex/Poseidon, Envisat, Jason1 and 2).	Centre for Topological studies of the Ocean and Hydrosphere (CTOH)	Extract radar altimetry water levels
16	TerraSAR-x	Disaster Charter	Flood extent mapping
17	Soil Grids	International Soil Reference and Information Centre (ISRIC)	Criteria for decision tree flood mapping
18	Dams data sets	Global reservoir and dam (grand) database	Identify dam locations upstream of area of interest

19	River Basin and networks	Hydro SHEDS	Delineate river locations and river width for flood modelling and mapping

	Name	Source	Usage
1	ArcMap	ESRI	GIS, Geospatial analysis, Hydrological analysis and Hydrodynamic model data preparation
2	ERDAS Imagine	Hexagon Geospatial	Optical Satellite Image classification and Radar flood extent mapping (Histogram thresholding).
3	ENVI	Harris Geospatial	Radar flood extent mapping (Decision Tree)
4	CAESAR-LISFLOOD, Raster edit and DEM edit tools	http://coulthard.org.uk/[7]	Two-dimensional grid based hydrodynamic modelling
5	ICI-RAFT	USACE Institute for Water Resources	Direct and Regional Flood Frequency Estimation
6	FLIKE	BMT WBM	Direct Flood Frequency Estimation
7	Weka	University of Waikato, New Zealand	Decision Tree Parameter characterization

[7] http://coulthard.org.uk/

8	SPSS	IBM	Quantitative Analysis and assessment of infilling approach statistical difference
9	GeoForm	ESRI	Crowd-sourcing flood data collection
10	R	www.r-project.org[8]	Statistical Analysis: Preliminary test, and quantitative assessment
11	Web Plot digitizer	http://arohatgi.info	Secondary data extraction from published journals.
12	XLSTAT	AddinSoft	Preliminary analysis for flood frequency analysis
13	Sentinel-1 Toolbox	European Space Agency	Sentinel 1 Image processing
14	SNAP	European Space Agency	Sentinel 1 and 2 Image processing
15	Broadview Radar Altimetry Toolbox (BRAT)	European Space Agency	Radar Altimetry Water level extraction

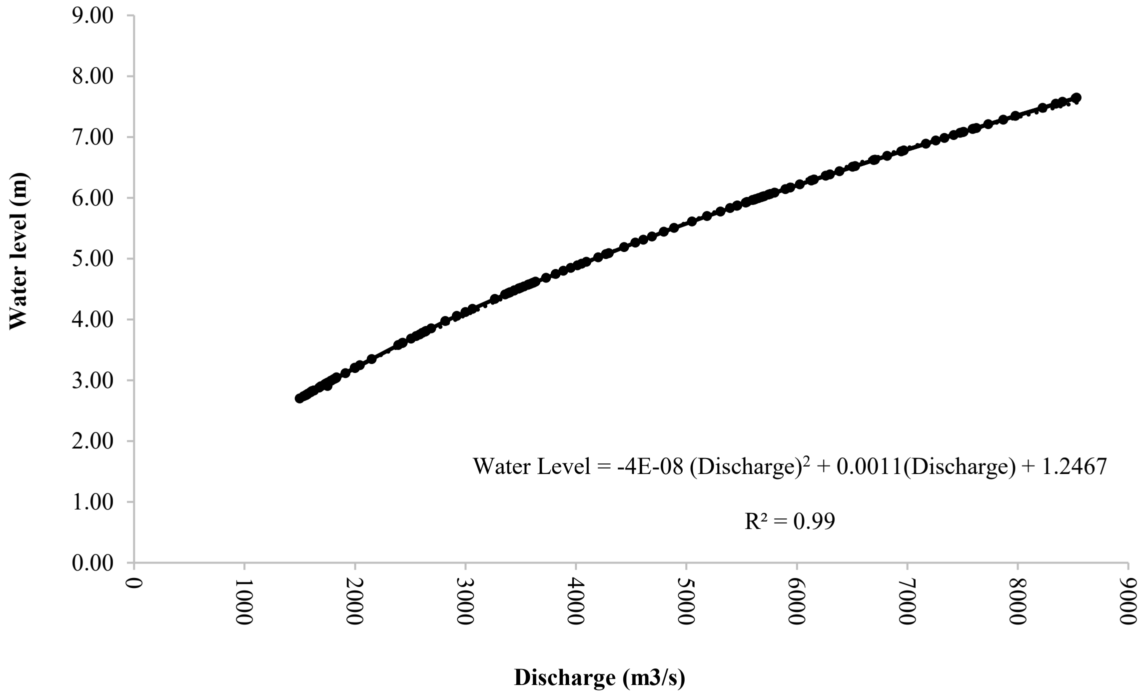
[8] www.r-project.org

16	ET Geo Wizard	http://www.ian-ko.com/[9]	Geospatial data analysis and pre-processing
17	Online Geoid Calculator	http://geographiclib.sourceforge.net/	Vertical Datum conversion
18	HEC-DSS	Hydrologic Engineering Centre USACE	River Bathymetry data extraction and conversion to ascii
19	Landsat 8 Bulk Processing (Arc toolbox)	Burnes, A. (2013) Landsat 8 Bulk Processing, NRCS Arizona.	Batch pre-processing for multiple Landsat Imageries
20	Topography Tools 10_2_1	Dilts, T.E. (2015) Topography Toolbox for ArcGIS 10.1 and Earlier, University of Nevada Reno.	Extraction of elevation data from DEM for hydrodynamic modelling
21	Polygon to Centreline Tool	Dilts, T.E. (2015) Polygon to Centreline Tool for ArcGIS, University of Nevada Reno	Geospatial data preparation for hydrodynamic modelling

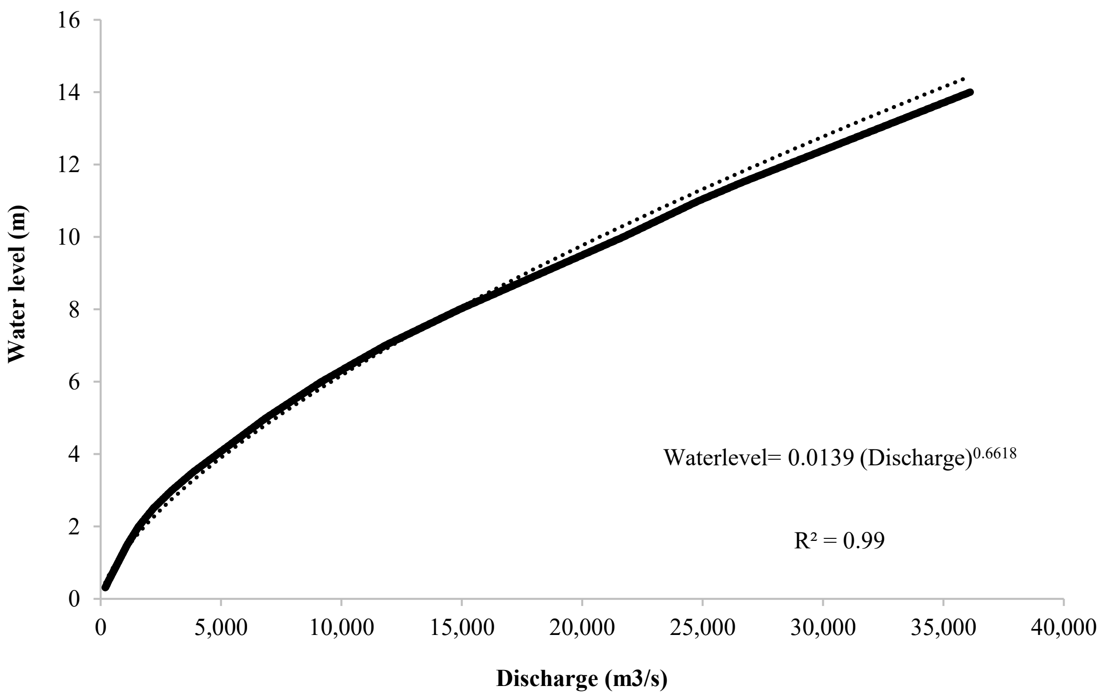
[9] http://www.ian-ko.com/

Appendix 3: Ratings Curve and Equation

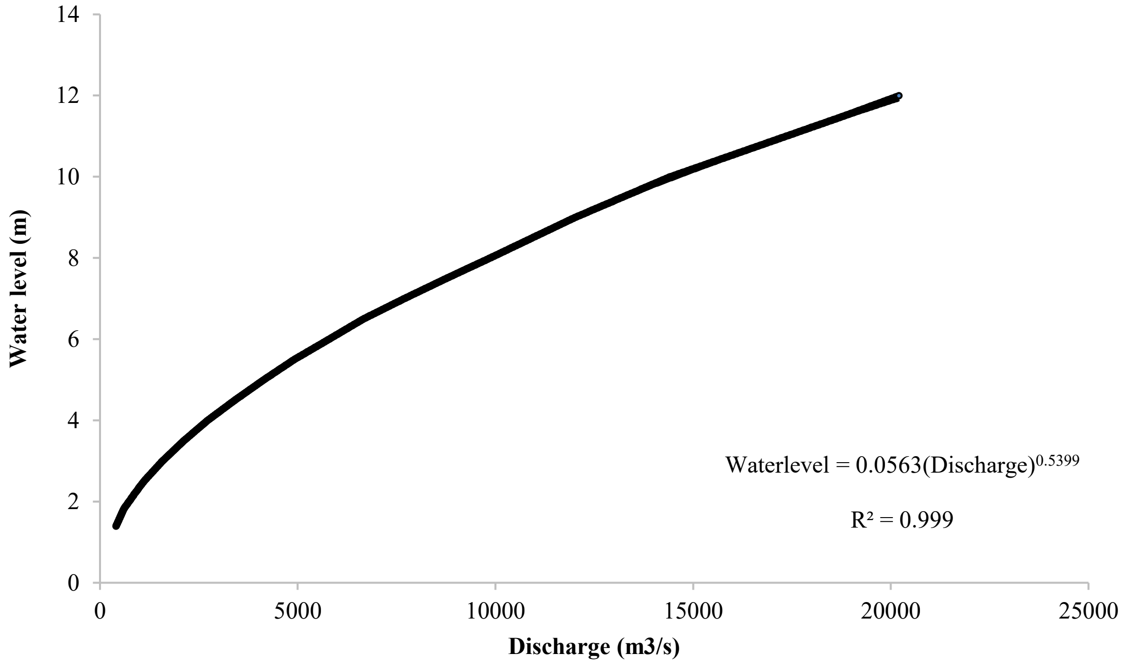
Baro



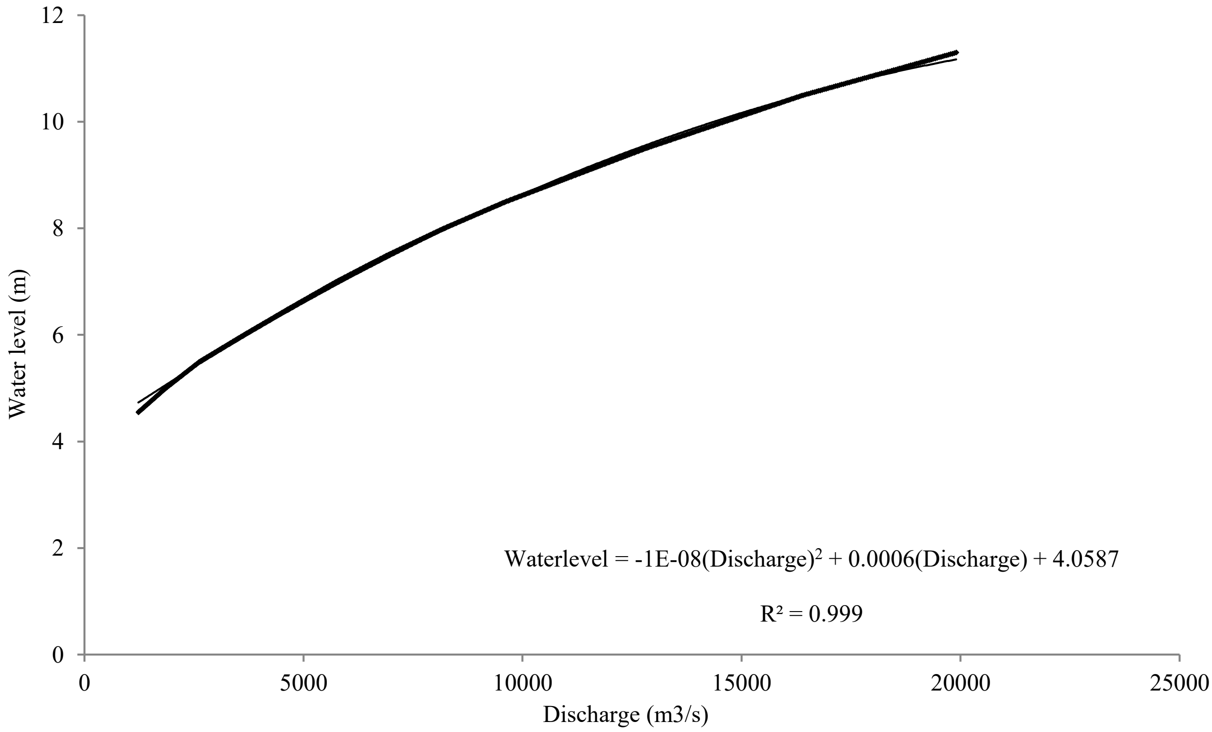
Lokoja



Onitsha



Umaisha



Appendix 4: GeoForm, crowdsourcing for flood monitoring in Nigeria

Lancaster University

Crowd Sourcing Flood data collection, Nigeria

The Purpose of this Geo-Form is to collect first-hand information on flood events by individuals residing within flood hazards locations for monitoring and Management.

1. Enter Information

State

Local Government Area

Village

Area

Employment Status
Employed, Unemployed or Student

Age
15 - 20, 20 - 30, 30 - 55, 55 Above

Number of persons in Residence
1, 2 - 4, 5 and above

Flood Map Awareness
Yes, or No

Cause of flood in Nigeria
Rainfall, Dam water release, Poor waste and drainage management

Affected by flood in 2012
Yes, or No

Affected by flood in 2015
Yes, or No

Level of flood risk exposure

Low, Medium, high

Previous flood experience

Yes, No

Property Insured

Yes, or No

River close to surrounding

Yes, or No

Aware of Displacement camp

Yes, or No

Flood Management Responsibility

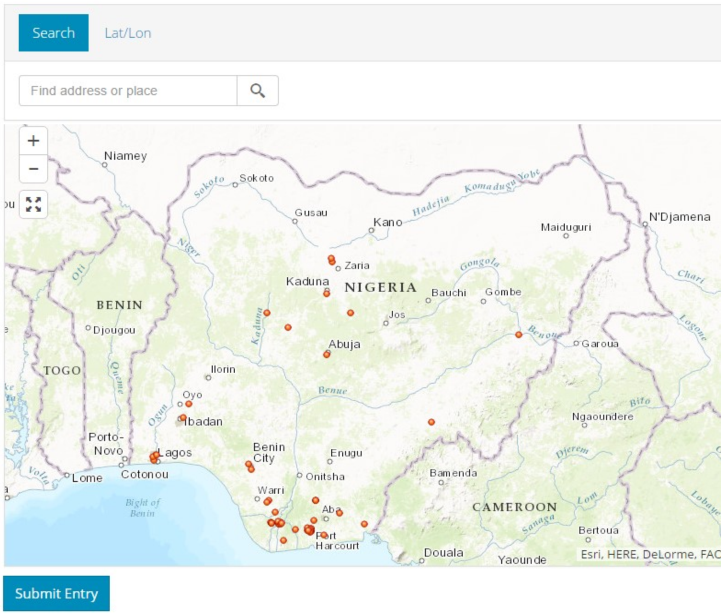
Local Govt., State Govt., federal Govt.

Flood Photo

Select File

2. Select Location

Specify the location for this entry by clicking/tapping the map or by using one of the following options.



3. Complete Form

Appendix 5: Sample Agreements/Correspondence for data usage from 3rd party data collection companies

CONFIDENTIALITY AGREEMENT

This **Agreement** is made this ...day of ....20xx ("Effective Date") between:

The Shell Petroleum Development Company of Nigeria Limited, a company incorporated under the laws of the Federal Republic of Nigeria and having its registered office at Shell Industrial Area, Rumuobiakani, Port Harcourt, Rivers State, Nigeria, in its capacity as a partner in and operator of the SPDC JV ("Disclosing Party")

And

EKEU-WEI IGUNIWARI THOMAS of [...Department of GEOGRAPHY, University of LANCASTER.....] and whose permanent address is . ("Receiving Party") LANCASTER ENVIRONMENTAL CENTRE (LEC), UNIVERSITY OF LANCASTER, LANCASTER, LA1 4YW; UNITED KINGDOM.

WHEREAS

a. The Disclosing Party is the operator of the SPDC JV, by virtue of which it operates the concessions and contract area of the SPDC JV, while the Receiving Party is a [Student of the University of ....].

b. The Receiving Party has approached the Disclosing Party for certain information to enable him complete his project work titled............................... at the University of LANCASTER, UK.

"APPLICATION OF GEOINFORMATICS FOR FLOOD MANAGEMENT AND URBAN PLANNING IN YENAGOA CITY, NIGERIA"

c. The Disclosing party is willing to avail the Receiving party with the required information and/or grant access to such information

d. In consideration of the disclosure of such information by the Disclosing Party to the Receiving Party, the Receiving Party undertakes to keep the disclosed information strictly confidential in accordance with the terms set out in this Agreement.

IT IS HEREBY AGREED AS FOLLOWS;

1. DEFINITIONS, INTERPRETATION

1.1 **Definitions** - As used in this Agreement, these words or expressions have the following meanings:

"Affiliate" means a company which, directly or indirectly through one or more intermediaries, controls or is controlled by, or is under common control with either of the Parties. For this purpose, control means the

(a) Disclosing Party
Shell Industrial Area, Rumuobiakani,
Port Harcourt, Rivers State, Nigeria

Facsimile No:
Attention:

(b) Receiving Party
EKEU-WEI IGUNIWARI THOMAS. LANCASTER ENVIRONMENTAL CENTRE. UNIVERSITY OF LANCASTER.

Facsimile No: LA1 4YW, LANCASTER, UNITED KINGDOM.
Attention: RESEARCH DATA REQUEST
1. Flow and Stage Readings (Abarani Gauge Station)
2. RadarSat-2 Satellite Imagery (See Appendix for Co-ordinates)

11 ASSIGNMENT

The Receiving Party shall not assign this Agreement. The Disclosing party may assign this Agreement to any of its Affiliates at any time and Notice of such assignment shall be provided to the Receiving Party. Without prejudice to the foregoing, this Agreement shall bind and inure to the benefit of the Parties and their respective successors and permitted assigns

12. GENERAL PROVISIONS

No Waiver

No waiver by any Party of any one or more breaches of this Agreement by the other Parties shall operate or be construed as a waiver of any future default or defaults by the same Party. No Party shall be deemed to have waived, released, or modified any of its rights under this Agreement unless such Party has expressly stated, in writing, that it does waive, release or modify such rights.

Modification

No amendments, changes or modifications to this Agreement shall be valid except if the same are in writing and signed by a duly authorized representative of each of the Parties.

Signed for and on behalf of
The Shell Petroleum Development Company of Nigeria Limited

Signature:____________________

Name:____________________

Designation:____________________

In the presence of

Signature:____________________

Name:____________________

Designation:____________________

Signed, sealed and delivered by the within named Receiving Party

Signature: [signature]

Name: EREY-WEI IGUNIWARI THOMAS

Designation: PHD RESEARCH STUDENT, LANCASTER ENVIRONMENTAL CENTRE (LEC), UNIVERSITY OF LANCASTER, UK.

Date 7/2/2014

In the presence of

Signature: Andy Harrod

Name: Andy Harrod

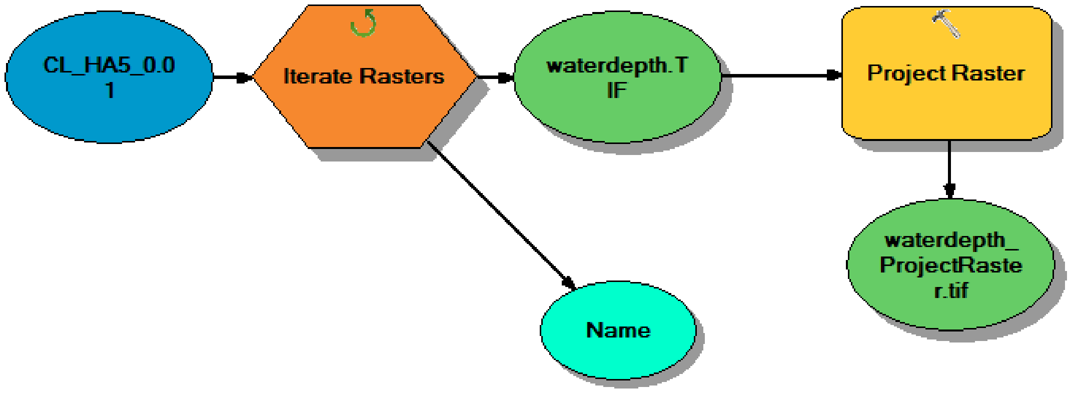
Designation: PGR Co-ordinator (LEC)

Date 7/2/14

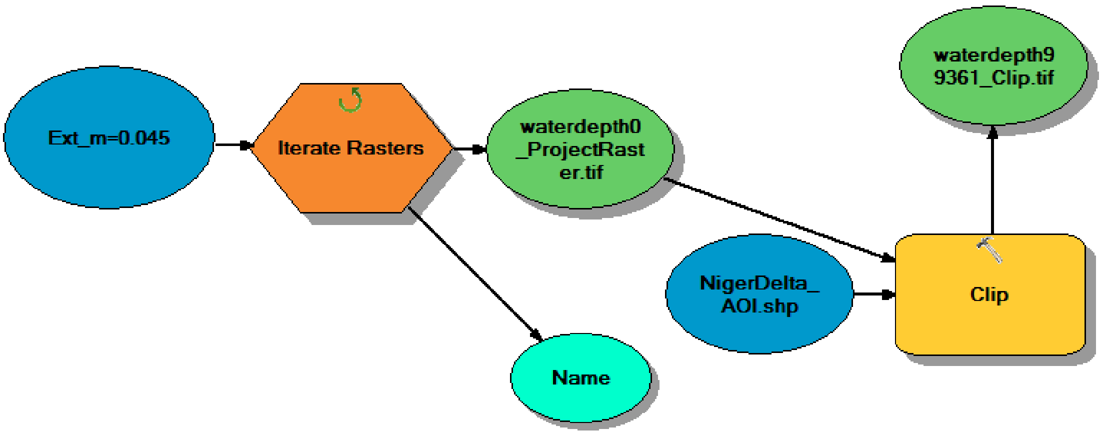
LANCASTER UNIVERSITY ENVIRONMENT CENTRE

Appendix 6: Model Built for CAESAR-LISFLOOD Output post-processing

Batch Projection



Batch Clip



Appendix 7: Weka Decision Tree

```
J48 tree

Distance from river <= 17897.6
|  DEM <= 13.507
|  |  Distance from river <= 3760.66: Flooded (317.0/8.0)
|  |  |  Distance from SAR flood > 3760.66
|  |  |  |  Distance from SAR flood <= 4130.21: Non-Flooded (3.0)
|  |  |  |  Distance from SAR flood > 4130.21: Flooded (22.0/2.0)
|  DEM > 13.507
|  |  Distance from river <= 1350: Non-Flooded (8.0/1.0)
|  |  Distance from river > 1350: Flooded (11.0/1.0)
Distance from river > 17897.6
|  DEM <= 11.665
|  |  Land Use/cover = Built-up: Non-Flooded (4.0/1.0)
|  |  Land Use/cover = Tampered Vegetation
|  |  |  SPI <= 0.009
|  |  |  |  TWI <= 219.091
|  |  |  |  |  TWI <= 0
|  |  |  |  |  |  SPI <= -0.072: Non-Flooded (2.0)
|  |  |  |  |  |  SPI > -0.072: Flooded (6.0/1.0)
|  |  |  |  |  TWI > 0: Flooded (2.0)
|  |  |  |  TWI > 219.091: Non-Flooded (3.0)
|  |  |  SPI > 0.009: Flooded (9.0)
|  |  Land Use/cover = Swamp: Flooded (5.0/1.0)
|  |  Land Use/cover = Matured Vegetation
|  |  |  DEM <= 10.018: Non-Flooded (8.0/2.0)
|  |  |  DEM > 10.018: Flooded (3.0)
|  |  Land Use/cover = Bare land
|  |  |  Slope <= 0.588: Flooded (8.0/1.0)
|  |  |  Slope > 0.588: Non-Flooded (2.0)
|  |  Land Use/cover = Waterbodies: Flooded (7.0)
|  |  Land Use/cover = Cultivated land: Flooded (1.0)
|  DEM > 11.665: Non-Flooded (23.0/3.0)

Number of Leaves:   19
Size of the tree:   32
```

Appendix 8 CAESAR LISFLOOD parameters. Adapted from Olayinka (2012) and sediment input.

Parameter	Value	Unit
Lateral erosion rate	0	
Number of passes for edge smoothing filter	100	
Number of cells to shift lateral erosion downstream	5	
Max difference allowed in cross channel smoothing	0.0001	
Max erode limit	0.03	
Water depth above which erosion can happen	0.02	
Min discharge for depth calculation	2.7	
Static Manning's n	0.035	
Erosion equation	Wilcock and Crowe	
Slope failure threshold	45	degree
Input output difference allowed	4485	m^3
Slope for edge cells	0.01	
Evaporation rate	0.03	m/day
Courant number	0.7	
Froude limit	0.6	

Sediment input grain sizes and distribution (Olayinka, 2012)

Grain Size (m)	Proportion (%)
0.000053	0.144
0.000074	0.022

0.00021	0.019
0.00042	0.029
0.000841	0.068
0.00168	0.146
0.00336	0.220
0.00635	0.231
0.0127	0.121

Appendix 9 Sample Flike Flood Frequency outcome (Umaisha, Radar Altimetry) and plot code in R

```
--------------------------------------------------------------------------------
FLIKE program version 5.0.251.0
FLIKE file version 3.10

Data file: C:\Users\iguni\Desktop\Flike2017\UmaishaRA.fld
Title: UmaishaRA


Flood model: GEV


Summary of Posterior Moments from Importance Sampling
Parameter Name                          Mean        Std dev       Correlation
--------------------------------------------------------------------------------
       1 Location u               11719.68731     402.28284  1.000
       2 loge (Scale a)               7.54851       0.15658  0.235  1.000
       3 Shape k                      0.04206       0.12775  0.282  0.213  1.000
-----------------------------------------------------------------------
Note: Posterior expected parameters are the most accurate in the mean-squared-error sense.
      They should be used in preference to the most probable parameters


Upper bound =   56847.1


 AEP 1 in Y     Exp parameter     Monte Carlo 90% quantile Mean(log10(q)) Stdev(log10(q))
                quantile             probability limits
-------------------------------------------------------------------------------------
     1.010        8721.75         7435.93         9488.8          3.9358          0.0356
     1.100       10028.88         9230.03        10636.8          3.9996          0.0194
     1.250       10807.40        10129.24        11407.3          4.0329          0.0159
     1.500       11540.84        10889.56        12182.1          4.0619          0.0149
     1.750       12033.08        11367.90        12720.3          4.0803          0.0150
     2.000       12409.97        11723.89        13140.8          4.0938          0.0152
     3.000       13400.86        12635.59        14306.2          4.1275          0.0166
     5.000       14478.52        13573.65        15642.9          4.1616          0.0193
    10.000       15794.82        14654.11        17589.3          4.2003          0.0253
    20.000       17019.00        15580.51        19756.0          4.2340          0.0338
    50.000       18549.53        16615.67        23108.6          4.2737          0.0482
   100.000       19657.77        17269.59        25951.1          4.3010          0.0607
   200.000       20730.07        17835.64        29330.9          4.3266          0.0745
   500.000       22097.61        18446.03        34289.5          4.3582          0.0941
  1000.000       23096.70        18816.55        38845.4          4.3807          0.1098
  2000.000       24066.72        19144.97        43543.6          4.4022          0.1261
  5000.000       25306.13        19490.54        51331.7          4.4292          0.1484
 10000.000       26212.39        19711.36        58081.0          4.4487          0.1657
 20000.000       27092.58        19893.24        65227.4          4.4676          0.1834
 50000.000       28217.42        20106.67        77158.7          4.4916          0.2071
100000.000       29039.98        20240.94        87384.7          4.5091          0.2254
```

Flood magnitude	Expected probability	<------------AEP------------> 1 in Y	90% limits	
8721.75	0.01559	1.02	1.00	1.1
10028.88	0.09697	1.11	1.04	1.2
10807.40	0.20525	1.26	1.13	1.5
11540.84	0.33698	1.51	1.28	1.9
12033.08	0.43065	1.76	1.44	2.3
12409.97	0.50077	2.00	1.60	2.7
13400.86	0.66450	2.98	2.18	4.5
14478.52	0.79629	4.91	3.20	8.9
15794.82	0.89592	9.61	5.27	24.
17019.00	0.94580	18.45	8.25	76.
18549.53	0.97549	40.80	13.77	0.59E+03
19657.77	0.98544	68.67	19.42	0.84E+04
20730.07	0.99070	107.54	26.42	0.84E+07
22097.61	0.99436	177.36	38.95	0.10E+11
23096.70	0.99592	244.93	49.82	0.10E+11
24066.72	0.99693	325.59	63.55	0.10E+11
25306.13	0.99779	452.51	86.53	0.10E+11
26212.39	0.99823	563.72	106.08	0.10E+11
27092.58	0.99855	687.66	127.12	0.10E+11
28217.42	0.99885	870.26	159.71	0.10E+11
29039.98	0.99902	1021.84	188.11	0.10E+11

```
##########################################################
#
# Plotting Flike output
# see https://tonyladson.wordpress.com/2015/10/20/better-frequency-plots-from-web-based-flike/
#
############################################################
library(stringr)
library(R.utils)

plot.new()
frame()

setwd ("C:/Users/iguni/Desktop/Flike2017")

my.path <- c('C:/Users/iguni/Desktop/Flike2017')
# my.path <- c('As required')
# see example file at https://goo.gl/mDeHJp
my.file <- c('UmaishaMIresult.csv')
fname <- str_c(my.path, my.file, sep = '/')
# find the line numbers of those lines that contain the word 'Number'
lineNum.number <- grep('Number', readLines(fname)) # line numbers of heading
lineNum.eof <- as.vector(countLines(fname) ) # end of file
# Read in the gauged data and deviates
flike.data <- read.csv(fname, header = TRUE, nrows = lineNum.number[2] - 2 )
# # It looks like flike sets any zero flow values to 0.001
# # we can delete those if necessary.
#
# flike.data <- flike.data[-which(flike.data$Gauged_value == -3), ]
my.ari <- c(1.5, 2, 5, 10, 20, 50, 100, 200)
my.aep <- 1/my.ari
my.z <- qnorm(1 - my.aep)
par(oma = c(5,3,0,0))
plot(Gauged_value ~ Deviate,
     data = flike.data,
     xaxt = 'n',
     yaxt = 'n',
     log = 'y',
     ylab = '',
     xlab = '',
     pch = 21,
     bg = 'grey'
)
axis(side = 1, at = my.z, my.ari)
mtext(text = 'ARI (years)', side = 1, line = 2)
my.label = str_c(round(100*my.aep), '%')
axis(side = 1, at = my.z, my.label, outer = TRUE)
mtext(text = 'AEP', side = 1, line = 7)
my.labels <- prettyNum(axTicks(2),
                       scientific = FALSE,
                       big.mark = ',')
axis(side=2, at=axTicks(2),
     labels=my.labels,
     las = 2)


mtext(side = 2, line = 4.5, text =' Discharge (cumecs)')
abline(h = seq(0.1,1,0.1), lty = 3, col = 'grey' )
abline(h = seq(1,10,1), lty = 3, col = 'grey' )
abline(h = seq(10,100,10), lty = 3, col = 'grey' )
abline(h = seq(100,1000,10), lty = 3, col = 'grey' )
abline(h = seq(1000,10000,1000), lty = 3, col = 'grey' )
abline(h = seq(10000,100000,10000), lty = 3, col = 'grey' )
abline(v =my.z, lty = 3, col = 'grey' )
# Read in the confidence limites and expected parameter quantile
# plot on graph
flike.cl <- read.csv(fname, header = TRUE, skip = lineNum.number[2] - 1, nrows = lineNum.number[3] - lineNum.number[2] - 1)
lines(Expected_par_quantile ~ Deviate, data = flike.cl) # Expected parameter quantile
lines(Lower_90._probabilty_limit ~ Deviate, data = flike.cl, lty = 2) #
lines(Upper_90._probability_limit ~ Deviate, data = flike.cl, lty = 2) #
# Readin and plot the expected probability quantile
flike.exp.prob <- read.csv(fname, header = TRUE, skip = lineNum.number[3] - 1, nrows = lineNum.eof - lineNum.number[3])
flike.exp.prob
# remove all rows where the Expected probably quantile value is zero
flike.exp.prob <- flike.exp.prob[flike.exp.prob$Expected_probability_quantitle > 0, ]
lines(Expected_probability_quantitle ~ Deviate, data = flike.exp.prob, col = 'red') # Expected parameter quantile
legend('bottomright',
       legend = c('90% CL', 'Gauged', 'Expected param', 'Expected prob'),
       lty = c(2, -1, 1, 1),
       pch = c(-1, 21, -1, -1),
       pt.bg = 'grey',
       bty = 'n',
       col = c(1, 1, 1, 2),
       inset = 0.01,
       cex=0.9)
```