Nnamdi Azikiwe University Journal of Civil Engineering (NAUJCVE)

Volume-4, Issue-1, pp-24-30

www.naujcve.com

Research Paper Open Access

Leveraging Artificial Intelligence To Predict And Reduce Flood Impacts On Construction Sites: A Case Study of Onitsha North, Anambra State

[1]Arinze Emmanuel E.,[2]Nnabugwu Chimezie P., [3]Nnozirim Ifeanyi V, [4]Ulu FearGod E. and [5]Ikpendu Kenneth C.

[1,2,3,4,5]*Department of Civil Engineering, Michael Okpara University of Agriculture, Umudike, Abia State, Nigeria*

***Corresponding Author**:nnabugwuchimezie7@gmail.com*

Abstract: *Flooding poses a persistent threat to urban centers in Nigeria, with Onitsha North in Anambra State experiencing recurrent inundation that severely impacts infrastructure, commerce, and livelihoods. This study applied artificial intelligence (AI) to predict and mitigate flood risks on construction sites using the FastFlood simulation platform. Input data included a 20-meter resolution Digital Elevation Model (SRTM), CHIRPS rainfall intensity of 10 mm/hour over six hours, infiltration rates, and urban land cover parameters. The October 7, 2022 flood event was modeled, revealing that 65% of Onitsha North (32.5 km²) was inundated, with depths ranging from 0.5 to 1.2 meters and a mean depth of 1.0 meter. Vulnerability analysis identified high-risk zones such as Okpoko, Main Market, and key residential areas, with model outputs validated against National Emergency Management Agency (NEMA) and Civil Justice Initiative (CJI) 2022 reports. The findings highlight the disproportionate impact on commercial and transport corridors and underscore the importance of AI-driven flood prediction for evidence-based mitigation planning. Recommended measures include elevated foundations, drainage optimization, flood barriers, and AI-based early warning systems. Overall, the study demonstratedthe potential of AI modeling to enhance disaster preparedness, strengthen construction resilience, and inform sustainable urban planning in flood-prone Nigerian cities.*

Keywords: *Flood modeling; Artificial Intelligence, FastFlood, Construction sites, Flood vulnerability, Urban resilience, Onitsha North Nigeria*

Date of Submission: 03-09-2025 Date of acceptance:23-09-2025

1. INTRODUCTION

Flooding is a recurring environmental hazard in Nigeria, causing widespread displacement, infrastructure damage, and economic losses. The 2012 flood disaster, one of the country's worst, displaced over 2.1 million people, while more recent events highlight the growing influence of climate change on rainfall intensity and flood frequency (Adekola & Lamond, 2012; Olanrewaju & Chit, 2022; Aderogba & Etuonovbe, 2014).Onitsha North, located along the River Niger in Anambra State, is highly vulnerable due to its flat terrain, poor drainage systems, and rapid urbanization (Efobi, 2013; Iro & Ezedike, 2020). The October 2022 flood displaced about 41,000 people in Anambra State and severely disrupted commerce and livelihoods in Onitsha's major markets (CJI, 2022; Oloruntade et al., 2024). Existing mitigation efforts remain inadequate, underscoring the need for innovative approaches to flood risk management. Artificial intelligence (AI) offers promising tools for predicting and managing floods. Machine learning and hydrological models can integrate geospatial, meteorological, and infrastructural data to generate accurate predictions of flood extents and vulnerabilities (Le et al., 2019; Mosavi et al., 2021). These capabilities can support disaster preparedness and inform resilient urban planning.

This study applied AI-based flood modeling to simulate the October 7, 2022 flood in Onitsha North. Using the FastFlood platform, it integrates elevation, rainfall, infiltration, and land cover data to predict inundation, assess vulnerabilities of construction sites, and recommend mitigation strategies. The findings provide insights for improving construction resilience and guiding sustainable flood management in Nigerian cities.

II. MATERIALS AND METHODS

A. STUDY AREA DESCRIPTION

This research was conducted in Onitsha North Local Government Area (LGA), Anambra State, Nigeria, located between latitude 6.15°N and longitude 6.78°E. Onitsha North is a densely urbanized district situated along the eastern bank of the River Niger. The terrain is relatively flat and low-lying, a feature that contributes significantly to its high flood susceptibility. The area experiences a tropical wet season between May and September, with heavy rainfall events that frequently overwhelm the city's drainage infrastructure. Major construction activities and economic hubs such as the Onitsha Main Market, Okpoko settlement, and several residential zones are located in areas prone to flooding. Historical flood disasters in 2012 and 2022 severely disrupted socio-economic activities, displaced thousands of people, and caused substantial infrastructural damage (Efobi, 2013; Iro & Ezedike, 2020; Oloruntade et al., 2024).

A. DATA SOURCES

To achieve a robust simulation of the October 7, 2022 flood event, multiple datasets were utilized:

Digital Elevation Model (DEM): A Shuttle Radar Topography Mission (SRTM) DEM with a spatial resolution of 20 m was automatically retrieved from the FastFlood platform in GeoTIFF format. The DEM provided the topographical foundation for simulating surface runoff and flow direction.

Rainfall Data: Daily rainfall data for October 2022 was obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). The peak event on October 7 was characterized by 10 mm/hour rainfall sustained for six hours. This was converted into an intensity-duration input suitable for hydrological modeling.

Soil and Infiltration Data: Soil characteristics for the study area were derived from the FAO global soil database. An infiltration rate of 5 mm/hour was adopted, consistent with sandy loam/clay soils typical of southeastern Nigeria.

Land Cover Parameters: Urban surface roughness was characterized using Manning's roughness coefficient (n = 0.035) based on established hydrological literature (Chow, 1959). This parameter accounted for the resistance to flow caused by buildings, roads, and vegetation.

Historical Flood Records: Reports from the National Emergency Management Agency (NEMA, 2022) and Civil Justice Initiative (CJI, 2022) were used as ground-truth references for validating simulated flood extents and depths.

B. SIMULATION SETUP

Flood simulations were carried out using the FastFlood platform, an AI-driven hydrological modeling tool designed to integrate geospatial and meteorological datasets for rapid flood prediction. The simulation workflow involved boundary delineation, parameter input, and execution of AI-based algorithms to generate flood inundation maps. The Onitsha North LGA boundary was defined within FastFlood using geographic coordinates (6.1°–6.2°N, 6.7°–6.9°E). The platform automatically retrieved and clipped the Shuttle Radar Topography Mission (SRTM) DEM (20 m resolution), ensuring topographical consistency across the study area. Rainfall data from CHIRPS for October 7, 2022, was processed into an event input of 10 mm/hour sustained for 6 hours. Soil infiltration capacity was fixed at 5 mm/hour, representing sandy loam/clay soils, while surface roughness was parameterized using Manning's coefficient (n = 0.035) to reflect the built-up urban environment (Chow, 1959).

FastFlood's AI algorithms then combined rainfall, infiltration, and terrain datasets to compute runoff generation, surface accumulation, and flow routing. The Niger River channel was automatically detected under the platform's "Channels" module to ensure accurate flow representation. Simulation outputs included spatial layers of flood extent, depth distribution, velocity fields, and arrival times. These results provided a hydrodynamic representation of the October 2022 flood event in Onitsha North.

C. VULNERABILITY ANALYSIS

To assess the exposure of construction sites to flood hazards, outputs from FastFlood were integrated with spatial information on urban land use. Construction zones such as markets, residential estates, and road projects were identified using GIS-based mapping and prior studies (Efobi, 2013).

Four key indicators were extracted from the model:

Flood Depth (m): maximum inundation depth at each site.

Percentage Inundation (%): proportion of site area submerged relative to its footprint.

Arrival Time (h): time between rainfall onset and initial site flooding, indicating flood onset speed.

Flow Velocity (m/s): intensity of moving water across site surfaces.

Based on these indicators, sites were classified into high, medium, or low vulnerability categories. For instance, Okpoko and Waterfront Apartments exhibited depths >1.0 m and velocities >1.2 m/s, resulting in a high vulnerability classification, while higher-elevation areas such as Inland Town exhibited lower inundation and were classified as medium vulnerability.

III. RESULTS AND DISCUSSION

D. SIMULATION RESULT OVERVIEW AND FLOOD DEPTH STATISTICS

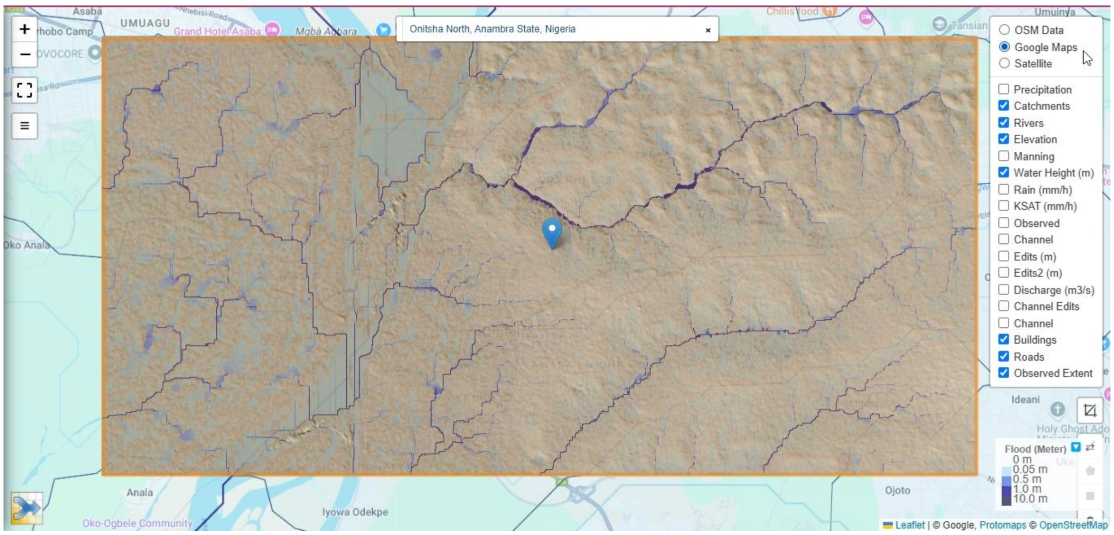

Fig. 1. Flood Simulation Map for Onitsha North (October 2022, FastFlood Model)

Fig.1 presents the results and analysis of flood simulations conducted using the FastFlood platform to model the October 7, 2022, flood event in Onitsha North, Nigeria. The primary objective was to simulate and analyze flood hazards using artificial intelligence-driven tools to quantify inundation extents, assess flood depths, and identify vulnerable locations across the study area

Table. 1. Flood Extent in Onitsha North

Parameter	Value
Total Area (km²)	50.0
Inundated Area (km²)	32.5
Inundation Percentage	65%

The FastFlood simulation revealed that 65% of Onitsha North's land area was inundated during the October 2022 flood event as shown in Table 1. This highlights the high level of exposure to flood hazards, particularly in areas near the Niger River, and indicates the need for targeted flood mitigation strategies

Table 2: Summary of Flood Depth Statistics

Parameter	Value
Minimum Depth (m)	0.5
Maximum Depth (m)	1.2
Mean Depth (m)	1.0
Median Depth (m)	1.0
Standard Deviation (m)	0.21

From Table 2, the average flood depth across the study area was 1.0 m, with depths ranging from 0.5 to 1.2 m. The relatively low standard deviation (0.21 m) shows that flood depth was fairly consistent across inundated locations, suggesting widespread moderate flooding rather than isolated extreme depths.

Table 3: Site-Specific Flood Impact Data

S/N	Site	Elevation (m)	Inundation (%)	Depth (m)	Velocity (m/s)	Arrival Time (h)	Vulnerability
1	Main Market	44	80	1.0	1.2	1.5	High
2	Okpoko	39	90	1.2	1.4	1.2	High
3	Fegge	46	70	0.9	1.1	1.8	Medium
4	Inland Town	60	40	0.5	0.9	2.2	Medium
5	Eke Market Expansion	43	75	1.1	1.3	1.6	High
6	LGA Secretariat Annex	47	65	1.0	1.0	1.9	High
7	Okpoko Bridge Approach	40	85	1.2	1.4	1.3	High
8	Fegge Residential Estate	48	60	1.0	1.1	2.0	High
9	New Layout Commercial Complex	45	70	0.9	1.2	1.7	Medium
10	Akpakpava Road Project	46	65	1.0	1.0	1.9	High
11	Waterfront Riverside Apartments	41	80	1.2	1.5	1.4	High

Most sites experienced flood depths between 0.9 and 1.2 m, with early flood arrival times indicating rapid inundation as shown in Table 3. Sites with lower elevation, such as Okpoko and Waterfront Apartments, experienced higher velocities and were classified as highly vulnerable. Inland Town, due to higher elevation, showed lower depths and slower flood onset.

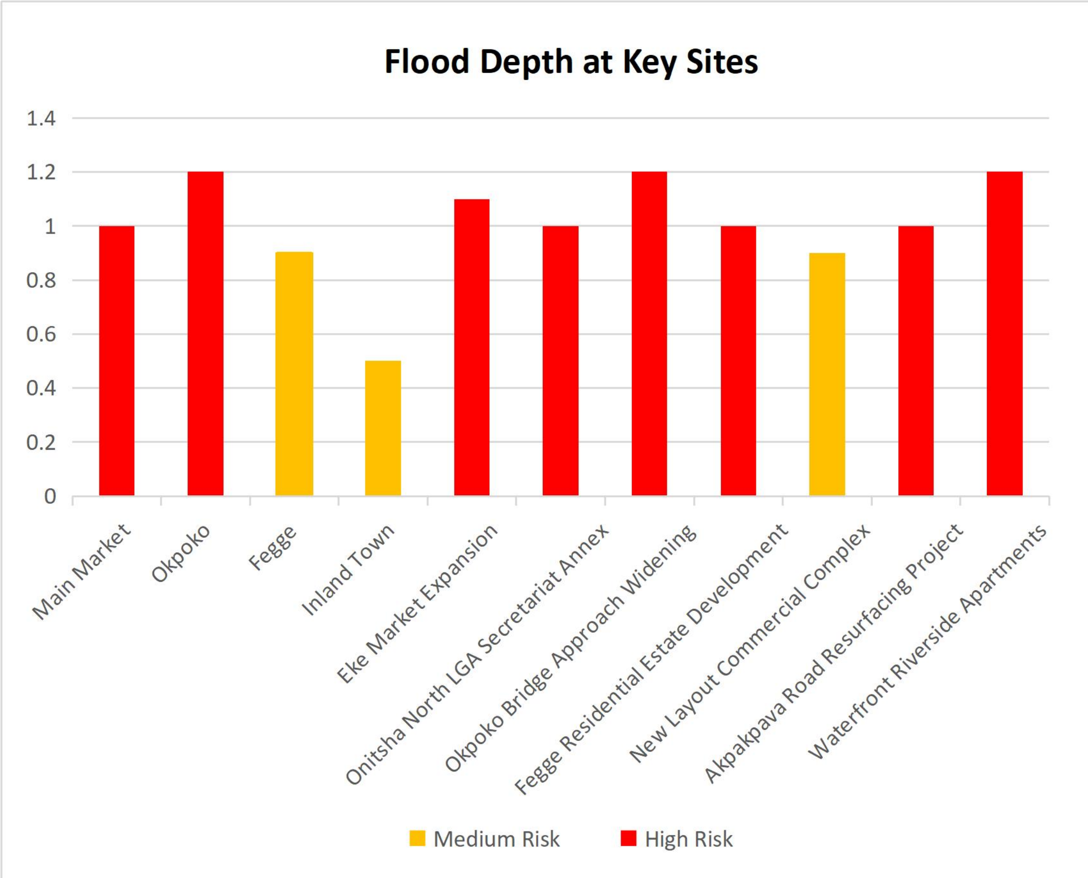

Fig. 2: Bar chart comparing average flood depths at affected sites.

Fig.2 illustrates the average depth comparison of the affected sites, where red bars indicate high-risk zones, and yellow bars indicate medium risk zones.

Depth by Land Use Classification:

Table 4: Flood Depth by Land Cover

Land Cover Class	Average Depth (m)	No. of Sites
Residential	0.96	5
Commercial	1.00	3
Transport/Urban	1.10	2
Institutional	1.00	1

As shown in Table 4, the transport and commercial zones recorded the highest average depths, which may impact mobility and commerce. Residential areas were also heavily affected, underlining the human impact of the flooding.

Mitigation Measures: The proposed measures target the most vulnerable locations, aiming to either reduce flood exposure or mitigate its effects through infrastructure and planning solutions as presented in

Table 5 Implementation would improve community resilience.

Table 5: Recommended Mitigation Measures

S/N	Measure	Target Area	Expected Outcome
1	Flood Barriers	Okpoko, Main Market	Reduce inundation
2	Elevated Foundations	High-risk zones	Protect structures
3	Green Infrastructure	Urban areas	Reduce runoff
4	Early Warning System	All areas	Timely evacuation alerts

IV. CONCLUSION

This study employed FastFlood, an artificial intelligence–driven simulation platform, to model and analyze the October 7, 2022 flood event in Onitsha North, Nigeria. The aim was to predict flood extents and depths, assess site-specific vulnerability, and propose data-driven mitigation strategies using AI-based tools. The simulation revealed that approximately 65% of Onitsha North (32.5 km²) was inundated, with flood depths ranging from 0.5 m to 1.2 m, and a mean depth of 1.0 m. Areas with the lowest elevations, especially near the Niger River, such as Okpoko, Main Market, and Waterfront Apartments, were the most severely affected. Flood arrival times in these areas were as short as 1.2 hours, with velocities up to 1.5 m/s, indicating both rapid onset and high destructive potential.

The spatial analysis also highlighted the influence of land cover on flood vulnerability, with transport corridors and commercial zones experiencing the highest average flood depths. Residential and institutional areas also exhibited significant exposure. The findings aligned well with the 2022 NEMA report, which recorded the displacement of over 41,000 persons in Anambra State, validating the accuracy of the simulation outputs. Overall, the study demonstrated that AI-based flood modeling tools such as FastFlood can provide accurate, timely, and spatially detailed flood risk predictions that are useful for urban planning, emergency preparedness, and infrastructure design. The integration of elevation, infiltration, rainfall, and land cover parameters enabled a comprehensive understanding of flood dynamics across Onitsha North.

REFERENCES

Adefisoye, T. (2015). Disaster risks and management policies and practices in Nigeria: A critical appraisal of the National Emergency Management Agency Act. ScienceDirect.

Adekola, O., & Lamond, J. (2012). Flooding, Food Security and the Sustainable Development Goals in Nigeria: An Assemblage and Systems Thinking Approach. MDPI.

Adelekan, I. O. (2016). Flood risk management in the coastal city of Lagos, Nigeria. Journal of Flood Risk Management.

Aderogba, K. A., & Etuonovbe, A. K. (2014). Causes and consequences of flooding in Nigeria: A review. ResearchGate.

Ahmadlou, M., Karimi, M., Alizadeh, S., Shirzadi, A., Parvinnejhad, D., Shahabi, H., & Panahi, M. (2019). Flood susceptibility assessment using integration of adaptive network-based fuzzy inference system (ANFIS) and biogeography-based optimization (BBO) and BAT algorithms (BA). Geomatics, Natural Hazards and Risk, 10(1), 1013-1032.

Amanambu, A. C., Obayelu, O. A., & Mashi, S. A. (2015). Flood management in cities of developing countries: the example of Ibadan, Nigeria. Academia.edu.

Benghanem, M., Maafi, A. (2018). "Data Acquisition System for Photovoltaic Systems Performance Monitoring". IEEE Transactions on Instrumentation and Measurement 47, 30–33 (2018).

Cirri, G. (2023). AI for flood adaptation plans and disaster relief. Oxford Insights.

Efobi, U. (2013). Urban flooding and vulnerability of Nigerian cities: A case study of Awka and Onitsha in Anambra State, Nigeria. Journal of Law, Policy and Globalization, 24, 1-10. https://iiste.org/Journals/index.php/JLPG/article/view/8928

Enegbuma, W. I., Aliagha, G. U., & Ali, K. N. (2015). Effects of perceptions on BIM adoption in Malaysian construction industry. Jt.

Etuonovbe, A. K. (2011). The devastating effect of flooding in Nigeria. ResearchGate.

Forero, N., Hernández, J., and Gordillo, G. (2006). "Development of a monitoring system for a PV solar plant. Energy Conversion and Management ". 47(15-16), 2329–2336 (2006).

Ganjirad, M., & Delavar, M. R. (2023). Flood risk mapping using random forest and support vector machine. ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences, X-4-W1-2022, 201-208.

Gevaert, C. M., Carman, M., Rosman, B., Georgiadou, Y., & Soden, R. (2021). Fairness and accountability of AI in disaster risk management: opportunities and challenges. Patterns, 2(8), 100363.

Granata, F., Gargano, R., & De Marinis, G. (2016). Support vector regression for rainfall-runoff modeling in urban drainage: A comparison with the EPA's storm water management model. Water, 8(3), 69.

Ikuabe, M., Aghimien, D., Aigbavboa, C., & Oke, A. (2020). Exploring the adoption of digital technology at the different phases of construction projects in South Africa. Proceedings of the International Conference on Industrial Engineering and Operations Management.

Iro, S., & Ezedike, C. E. (2020). Modelling flooding sites around River Niger area of Onitsha town, Nigeria, using remote sensing and GIS application. International Journal of Scientific & Engineering Research, 11(2), 1029-1038. https://www.ijser.org/researchpaper/Modelling-Flooding-sites-around-River-Niger-area-of-Onitsha-town-Nigeria-using-Remote-Sensing-and-GIS-Application.pdf

Jorge, A., Guerreiro, J., Pereira, P., Martins, J., and Gomes, L. (2020). "Energy Consumption Monitoring System for Large Complexes". In: Camarinha-Matos, L.M., Pereira, P., Ribeiro, L. (eds.) DoCEIS 2010. IFIP AICT, vol. 314, pp. 22–24. Springer, Heidelberg (2020).

Kazaure, M. A., & Inkani, A. I. (2012). Disaster management in Nigeria: A critical review. ResearchGate.

Kotecha, M. J., Bakori, D., Agarwal, S., Meraj, G., Kanga, S., Singh, S. K., & Farooq, M. (2024). Geoinformation for integrated urban water resource management. In Earth Observation in Urban Monitoring (pp. 93-111). Elsevier.

Le, X. H., Ho, V. H., & Lee, G. (2019). Application of long short-term memory (LSTM) neural network for flood forecasting. Water, 11(7), 1387.

Mosavi, A., Ozturk, P., & Chau, K. W. (2021). Flood prediction using machine learning models: A literature review. Water, 10(11), 1536.

Moshood, T. D., Nawanir, G., Sorooshian, S., Mahmud, F., & Adeleke, A. Q. (2020). Barriers and benefits of ICT adoption in the Nigerian construction industry: A comprehensive literature review. Asi.

Nadhim, E., Hon, C., Xia, B., Stewart, I., & Fang, D. (2016). Falls from height in the construction industry: A critical review of the scientific literature. Ijerph.

Nemni, E., Bullock, J., Belabbes, S., & Bromley, L. (2020). Fully convolutional neural network for rapid flood segmentation in synthetic aperture radar imagery. Remote Sensing, 12(15), 2532.

Ogbu, C. P., & Olatunde, N. A. (2019). Factors affecting the adoption of Building Information Modelling in the Nigerian construction industry. International Journal of Civil Engineering and Technology.

Oladokun, V. O., & Proverbs, D. G. (2016). Flood risk management in Nigeria: A review of its effectiveness. Hydrology Earth System Sciences.

Olanipekun, A. O., & Sutrisna, M. (2021). Digital technologies in construction: An overview of current practices and future trends. Sustainability.

Olanrewaju, C. C., & Chit, M. (2022). Impacts of flood disasters in Nigeria: A critical evaluation of health implications and management. Gale Academic OneFile.

Olatunde, N. A., Gento, A. M., Okorie, V. N., Oyewo, O. W., Mewomo, M. C., & Awodele, I. A. (2022). Construction 4.0 technologies in a developing economy: Awareness, adoption readiness and challenges. Emerald Insight.

Oloruntade, A., Bello, A., & Nkiruka, C. (2024). Integrated assessment of flood susceptibility and exposure rate in the lower Niger Basin, Onitsha, Southeastern Nigeria. Frontiers in Earth Science. https://www.frontiersin.org/articles/10.3389/feart.2024.1394256/full

Sharma, B. (2021). Google's AI-based flood forecasting system is saving lives in India: Here's how. TechCrunch.

Yahaya, S., & Mohammed, K. (2014). Causes and consequences of flooding in Nigeria: A review. ResearchGate.

Yusuf, S., Adindu, C., Badmus, A., & Muhammed, H. (2021). Pandemic in the Nigeria Construction Industry through Digitalization of Operations and Processes. ResearchGate.