IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 8.102 ⁜ Vol. 12, Issue 3, March 2023

DOI: 10.17148/IJARCCE.2023.12342

Unet-Based Flood Prediction And Warning System With Bulk SMS Using Sentinel-1A SAR Satellite Imagery

U. I. Nduanya[1], K. Akpado[2], F. A. Okoye[3]

Nnamdi Azikiwe University, Awka, Anambra, Nigeria[1,2]

Enugu State University of Science and Technology, Enugu, Nigeria[3]

Abstract: Floods are one of the world's natural disasters. The dramatic increase in the damages they have caused in the recent past has become a cause of national and international concern. Hence, there is a need for flood prediction and warning system that will directly inform the residents of the flood-prone area, with SMS, in order for them to make adequate preparations and brace themselves for the impact. As floods can cover a very large area, remote sensing is needed to detect the affected area and also to determine the direction so as to inform those in the area. Sentinel-1A SAR satellite images were utilized in the model development as a result of its cloud penetrating capability.The UNet model (modified architecture of that of Katiyar et al., 2020) was chosen for the research and it was trained on the dataset that was developed from scratch with the extracted images. The model was compared to the model developed by Katiyar et al. (2020). The performance evaluation was carried out with Jaccard Index or Intesection over Union (IoU) and Accuracy metrics. The IoU metric measures the number of pixels common between the target and prediction masks divided by the total number of pixels present across both masks while the Accuracy metric reports the percent of pixels in the image which were correctly classified. The results recorded in the evaluation had IoU as 0.42 and an Accuracy of 95%.

Keywords: Synthetic Aperture Radar, UNet, Semantic Segmentation, Sentinel-1A, Copernicus Satellite, Flood prediction.

I. INTRODUCTION

Floods are common natural disaster and one of the most harmful. It can be caused by excessive rainwater that the ground cannot absorb. It can also be caused by overflowing of waterbodies: rivers or lakes. The increasing effect of urbanization and climate change in recent times have made it more frequent and hazardous (Hirabayashi et al., 2013, Duan et al., 2016). They have a high frequency of occurrence, wide coverage and strong destructiveness (Li et al., 2022). Floods lead to tremendous losses of property, infrastructure, business and increased risk of diseases. Among natural disasters, floods have been reported to be responsible for almost half of casualties (Olanrewaju et al., 2019). Increasing climate variability in Nigeria is causing more intense and untimely rainfall.

Additionally, land degradation, flash floods, landslides, and gully erosion have worsened across the country as a result of climate change. By 2009, an estimated 6,000 gullies destroyed roads, highways, pipelines, and houses across rural and urban Nigeria. Many Nigerians lived in fear and despair due to these extreme weather conditions (The World bank, 2022). The worst flood recorded was the flood of 2012 which began in early July, 2012; it killed 363 people and displaced over 2.1 million people as of 5th November, 2012 (Wikipedia, Nigeria Floods 2012. January 8, 2013). Kogi State was the worst hit, with 623,900 people displaced and 152,575 hectares of farmlands destroyed. A NEMA coordinator, Jonathan, described the flooding as a "national disaster." (Al Jazeera, October 12, 2012). The flood of 2022, which is recent and seeming to be worse than the 2012 floods, also struck, affecting many parts of the country. It caused the displacement of over 1.4 million people; killed over 603 people and injured more than 2,400 persons. About 82,035 houses had been damaged, and 332,327 hectares of land had also been affected (Wikipedia, Nigeria Floods 2022. February 15, 2023).

As floods can cover a very large area, remote sensing is needed to detect the affected area and also to determine the direction so as to inform those in the area. Remote sensing is the gathering information about the Earth's surface without actually coming into contact with it. This is accomplished by sensing and recording reflected or emitted energy and then processing, interpreting, and applying the information (CCRS, 2009). Remote sensing technology has become an important means for flood prediction. This is as a result of its ability to sense the electromagnetic waves reflected or radiated by the target from a long distance (Pekel et al., 2016). Remote sensing technologies use various recording tools to collect data on objects and infrastructure on the Earth's surface without making direct contact. (Shah et al., 2019).

DOI: 10.17148/IJARCCE.2023.12342

Therefore, it is helpful in areas where no physical or close contact is possible (Widiasari et al., 2017). The Synthetic Aperture Radar (SAR) remote sensing technology has the ability to penetrate clouds, fog, overcome bad sunlight conditions throughout the flood period, and can achieve entire day and all-weather observations of the disaster-affected areas (He et al., 2022). A high-resolution synthetic aperture radar (SAR) has frequently been employed in the detection of flood-affected areas (Government of Canada, 2019). The system allows for real-time assessment of flooded and devastated areas. The ability of this technology to penetrate clouds, rain, and haze is its prime quality (Vicente and Filho, 2011). As radar employs microwaves, flooding surfaces can be easily detected by its sensors. The signals are reflected away from the sensor by the water's flat surface. This reduces the intensity of returning radiation in comparison to incident radiation, resulting in a darker pixel in the image (Kalantar et al., 2021). As a result, locations with water have darker pixels as compared with deflection through land areas.

II. LITERATURE REVIEW

Recently, researchers have taken advantage of the easily accessible satellite remote sensing data to monitor natural disasters. The free access to the satellite products enabled further research in different fields with the large amount of data. In recent times, satellite data are recorded as effective tools to estimate damages caused by disasters as a result of their sensors' modalities and massive volume with varying location, time, and spectral resolutions. As a result of the large volume of the data, appropriate models were sought to handle such amount of data. Hence, the start of the research with Deep Neural Networks. In recent years, a variety of methods have been proposed to predict and detect floods from remote sensing images. These methods on flood detection (Kang et al., 2018), extraction (Pappas et al., 2020), segmentation (Nemni et al., 2020), mapping (Long et al. 2014, Li et al. 2018, Kalantar et al 2021) and forecasting (Borovykh et al., 2018, Kimura et al., 2019, Kabir et al., 2020) applied the regular Artificial Neural Network, which has the disadvantage of lack of convergence and of being computationally expensive the deeper it becomes; or Convolutional Neural Network, which requires a large dataset for training. However, most of the available dataset is usually not adequate and the inability of CNN to properly localize and segment image features are usually disadvantageous to the model's performance. Thresholding methods were also used (Long et al. 2014 but a threshold selection is always complex and accompanied by algorithm innovation, which calls for solid mathematical skills. To make up for these shortcomings, the Fully Convolutional Network, which was capable of localizing was introduced. Kang et al. (2018) developed a Flood Detection model for SAR Images via Fully Convolutional Networks. The disadvantage of the FCN was its inability to recover the full features of the downsampled images. In a bid to discover a way of recovering the features of the original image, the UNet application in the area of SAR satellite image segmentation was introduced.

The UNet is built on the fully convolutional network architecture. Its ability to both localize and recover downsample features using upsampling and concatenation proved it a suitable method for the segmentation of SAR satellite images.

Feng et al. (2018) presented a Deep UNet model for water body extraction in remote sensing imagery; Nemni et al. (2020) designed a Fully Convolutional Neural Network for Rapid Flood Segmentation in Synthetic Aperture Radar Imagery; Katiyar et al (2020) developed a UNet in flood area detection using SAR images; Tuyen et al. (2020) proposed a model that combined Particle Swarm Optimization (PSO) UNet in the detection of flash floods. The UNet has the advantage of being trained with a small dataset but as a result of the unavailability of SAR satellite datasets of the area, very small sized datasets are often used, which question the efficiency of the model.

The aforementioned models achieved great success in the area of flood application using SAR satellite images but some of the models are complex are inefficient, difficult to train or take a very long time. Some can only achieve good results on a particular dataset or of a particular size. Most of these studies focused only on detection but not on prediction and others, not on warning. Therefore, this paper proposes model, a Flood Prediction and Warning System (FPWS-UNet). This model is trained on Sentiel-1A SAR satellite images of the chosen study area of Lokoja, Nigeria. The dataset, of images of 128x128 pixels, was built from scratch with the SAR images downloaded from the Copernicus data hub.

III. METHODOLOGY

1. Dataset

To train and evaluate artificial intelligence algorithms for earth observation datasets, a large amount of datasets are required. Unfortunately, there is a present scarcity of specific area datasets in the remote sensing sector. To acquire any dataset of remotely sensed images of any area, the images will have to be downloaded from the satellite's data site. Copernicus, which the European Union in its Earth Observation (EO) programme developed, is a programme that draws data and information from satellite EO and in-situ (non-space) data.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

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The Sentinel-1 mission is a polar-orbiting satellite constellation for the continuation of Synthetic Aperture Radar (SAR) operational applications. Sentinel-1 is a C-band imaging radar mission that provides an all-weather day-and-night supply of imagery for Copernicus user services. The data used to build the dataset were downloaded from the Copernicus open access hub. The images acquired and processed in this study are S1A data corresponding to Lokoja close to the lower basin of the Niger River;

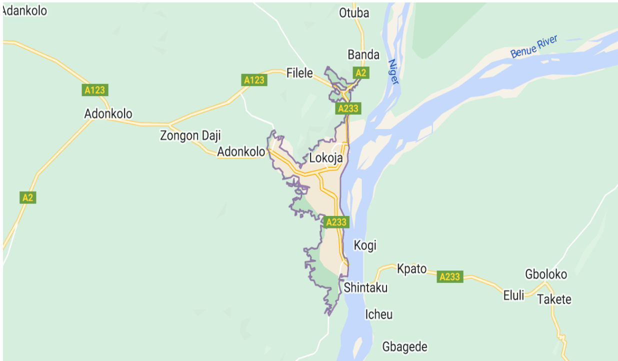

Fig. 1: Map showing Lokoja (Google Maps)

data from the upper part of the Niger up to Tungan papa, Kebbi and data from Benue river up to Jalingo, Taraba.

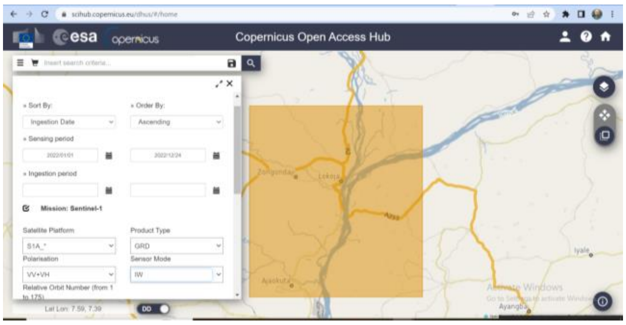

Fig. 2: Selecting and Filtering the search for the images

In this study, Level-1 ground range detected (GRD) data acquired in IW mode and in dual polarization (VV + VH) were employed in this study. The S1-GRD products (images) only retain amplitudes and not phase information. The generated images have pixels that are roughly square in size (10m x 10m). The products (images) were downloaded ranging from January to December, 2022. The products are 1.48GB in size. They were pre-processed in the SNAP software.

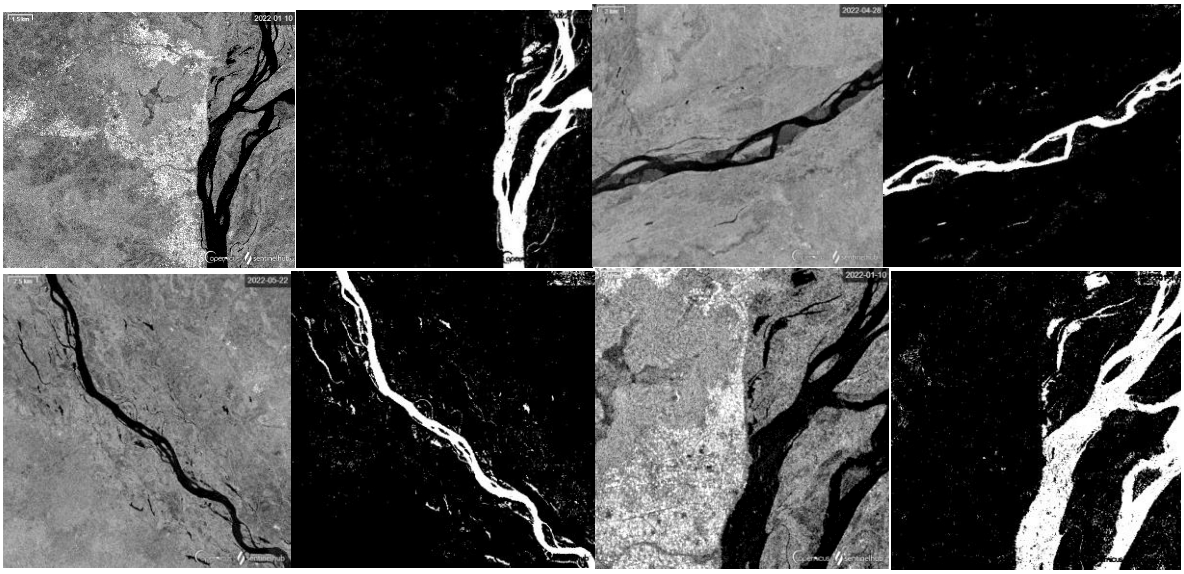

Fig. 3: Some of the images and masks that form the dataset.

International Journal of Advanced Research in Computer and Communication Engineering
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The pre-processed images were further processed in the program in order to apply the proper image size and dimensions of the images to the model.

During the image processing in the program, augmentations were applied to the images. This increased the number of the images to 17,036.

2. Model Architecture

In this research work, a flood prediction and warning system based on the UNet architecture is proposed (FPWS-UNet). The prediction phase is the UNet while the warning will be achieved through connection to a Bulk SMS API. The developed model is a forty-two layer network with Convolutional layers, ReLU, Batch normalization, Max pool and Up-sampling layers. This architecture enables very precise semantic segmentation results. UNet is a U-shaped encoder-decoder network architecture, which consists of four encoder blocks and four decoder blocks that are connected via a bridge. U-Net consists of Convolution Operation, Max Pooling, ReLU Activation, Concatenation and Up Sampling Layers with three sections: contraction, bridge/bottleneck, and expansion section. The UNET architecture has an encoder and a decoder (a contracting path and an expansive path). The contracting path is made up of a normal Convolutional network, which consists of multiple convolutions. Each of the convolution is followed by a rectified linear unit (ReLU), a Batch normalization to prevent overfitting and a max pooling operation for downsampling and spatial dimension reduction. The expansive part is made up of convolutions, ReLU, batch normalization and transpose convolutions or upsampling for spatial dimension increment. The final layer uses a Softmax activation function for multi-class output.

The size of the input data is 128 x 128 x 3. Each purple bar corresponds to a multi-channel feature map. The number of channels is denoted at the top of the bar. The size of feature maps for each layer is denoted on the left of the bar. The gray bars concatenated with purple bars are the copies of the feature maps from the encoder.

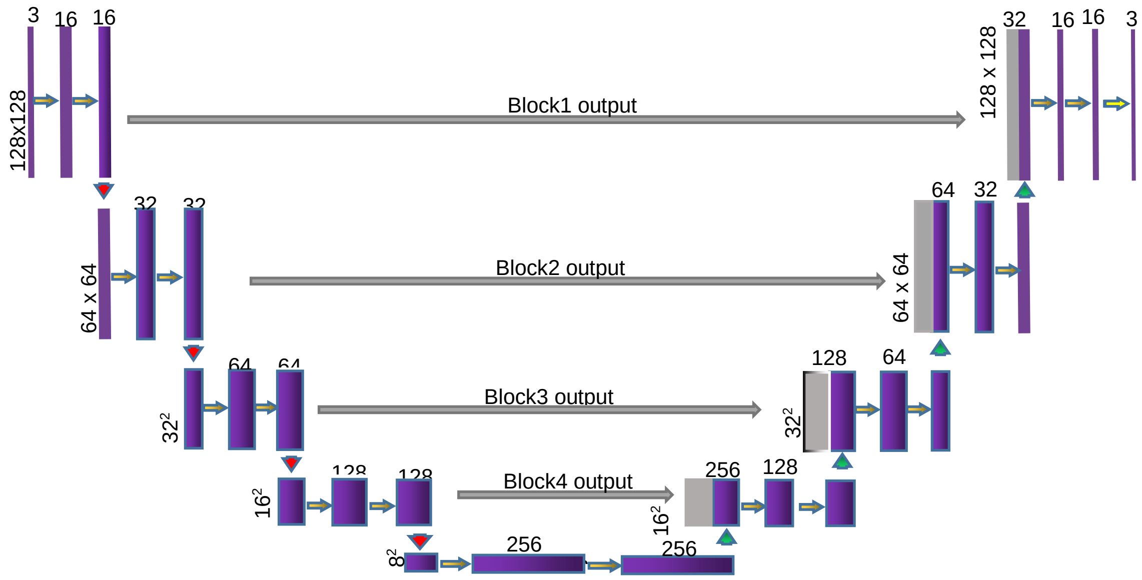

Fig. 4: Network Architecture of the UNet model.

3. Model Training

The model was trained using the generated dataset. It was trained on a satellite image dataset of 17,036 images of before, during and after flood. The input data images have a common size of 128 x 128 x 3. The dataset was randomly split into training, validation and test sets of percentages 55%, 20%, 25% respectively. The model was trained on 75% of the dataset and tested on 25%. The development and training were done on Intel Core i5 CPU @ 2.40GHz - 2.50 GHz with 8.00 GB RAM. The model was trained on the dataset for 100 training epochs with the Adam Optimizer with default parameters $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ $\epsilon = 10^{-8}$.

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IV. MODEL EVALUATION

The results on test data are presented with the evaluation metrics. The evaluation metrics, Jaccard Index or Intersection over Union (IoU) and Accuracy, were used in the assessment of flood prediction performance of the developed model. These are the common metrics used in the evaluation of semantic segmentation models.

1. Intersection over Union

The Intersection over Union (IoU) metric, also referred to as the Jaccard index, is essentially a method to quantify the percent overlap between the target mask and the prediction output. This method calculates the performance of the model by calculating the intersection and union between the Ground Truth and the Prediction. It measures the number of pixels common between the target and prediction masks divided by the total number of pixels present across both masks.

$$IoU = \frac{target \cap prediction}{target \cup prediction} \tag{4.1}$$

The intersection (A∩B) comprises of pixels from both the prediction mask and the ground truth mask, while the union (A∪B) is made up of all pixels from either the prediction or target mask.

2. Accuracy

Accuracy is a semantic segmentation metric that denotes the percent of pixels that are accurately classified in the image. This metric calculates the ratio between the amount of adequately classified pixels and the total number of pixels in the image. It is an alternative metric to evaluate a semantic segmentation, which is to simply report the percent of pixels in the image which were correctly classified. The pixel accuracy is commonly reported for each class separately as well as globally across all classes.

When assessing per-class pixel accuracy, we are essentially evaluating a binary mask; a true positive represents a pixel that is correctly predicted to belong to the given class (based on the target mask), whereas a true negative represents a pixel that is correctly identified as not belonging to the given class.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.2}$$

where True Positive (TP): Water pixels correctly classified as Flood.
True Negative (TN): Water pixels correctly classified as Not-flood.
False Positive (FP): Water pixels incorrectly classified as Flood.
False Negative (FN): Water pixels incorrectly classified as Not-flood.

Pixel accuracy reports the percentage of pixels in the tiles that are correctly classified irrespective of their class. It reports how well the class with the highest representation is predicted. When the class representation is small within the image, this metric can often produce deceptive results because the measure is skewed in reporting how effectively negative cases are identified, that is, where the class is not present.

N is the number of images in the dataset.

V. RESULTS

1. Training results

As mentioned above, the model was trained and validated on a SAR satellite image dataset of 17,036 images of before, during and after flood. The dataset was randomly split into training, validation and test sets of percentages 55%, 25%, 20% respectively. The model was trained on 80% of the dataset and tested on 20%. The progression of training and validation loss and training and validation IoU is depicted in figures 5 and 6.

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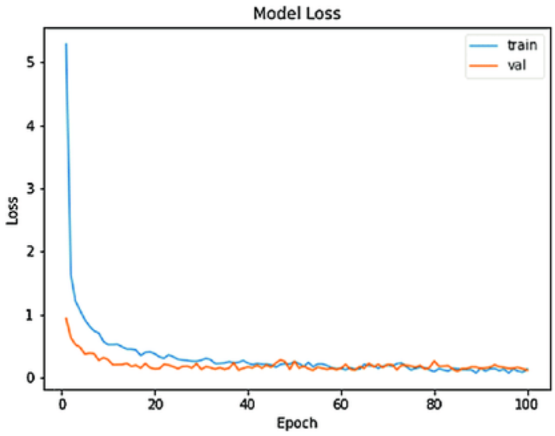

Fig. 5: The progression of Training and Validation loss

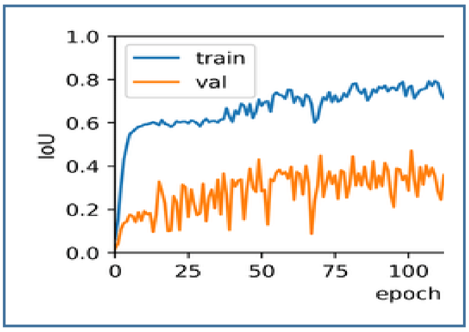

Fig. 6: Training and Validation IoU result

2. Results on Test data

The model was tested on 3,408 tiles of the dataset. Data augmentation was performed during testing. Each tile was rotated and the trained model was applied on them. The model then did some predictions depicted in figure 7.

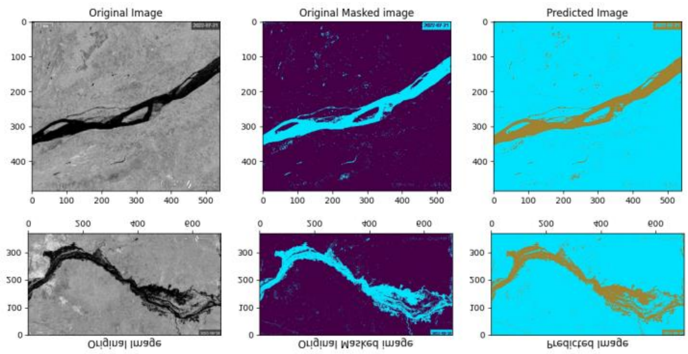

Fig. 7: Predicted images

VI. CONCLUSION

In this study, a UNet model was designed for flood prediction and warning (FPWS-UNet), using Lokoja as a study area. The proposed flood prediction and warning system used the Sentinel-1 A SAR satellite images to predict flood. The FPWS-UNet model is trained and evaluated on a Satellite image generated dataset of: before, during and after flood images. In the research, the performance of the model was evaluated with accuracy and IoU evaluation metrics. Its results were an accuracy of 95% and IoU of 0.42. The model's performance was compared to the recorded performance values of the Flood detection UNet model designed by Katiyar et al. (2020). The accuracy of FPWS-UNet was higher (95%) than that for Flood detection (89.57%) but the IoU of the FPWS-UNet was lower (0.42) than that for Flood detection

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(0.43). This shows that the FPWS-UNet model requires improvement. The hyperparameters can be adjusted to obtain better results.

At the start of the research, there were no readily available large SAR satellite datasets of the Niger and Benue rivers, therefore, the dataset had to be generated. The SAR data themselves are rather expensive to acquire, which also is an important factor impeding any SAR dataset compilation. The large sizes and the numerous images were of a high cost.

REFERENCES

[1] *Nigeria flooding called 'natural disaster'.* Al Jazeera. October 12, 2012. Retrieved from https://en.wikipedia.org/wiki/2012_Nigeria_floods.
[2] Borovykh, A., Bohte, S. and Oosterlee, C. W. (2018) Conditional time series forecasting with convolutional neural networks. *arXiv:1703.04691*. Retrieved from: http://arxiv.org/abs/1703.04691
[3] CCRS, "Fundamentals of Remote Sensing," Canada Centre for Remote Sensing, 2009.
[4] Duan, W.; He, B.; Nover, D.; Fan, J.; Yang, G.; Chen, W.; Meng, H.; Liu, C. (2016). Floods and associated socioeconomic damages in China over the last century. *Natural Hazards*, 82, 401–413
[5] Feng, W.; Sui, H.; Huang, W.; Xu, C. and An, K. (2019) Water Body Extraction From Very High-Resolution Remote Sensing Imagery Using Deep U-Net and a Superpixel-Based Conditional Random Field Model. *IEEE Geosci. Remote Sensing Letter*, 16, 618–622. https://doi.org/10.1109/LGRS.2018.2879492.
[6] Government of Canada Fundamentals of Remote Sensing—Introduction. [(accessed on 18 November 2021)];2019 Available online: https://www.nrcan.gc.ca/
[7] He, Q., Sun, X., Yan, Z., Li, B., & Fu, K. (2022). Multi-Object Tracking in Satellite Videos With Graph-Based Multitask Modeling. *IEEE Transactions on Geoscience and Remote Sensing*, *60*, 1–13. https://doi.org/10.1109/tgrs.2022.3152250
[8] Hirabayashi, Y.; Mahendran, R.; Koirala, S.; Konoshima, L.; Yamazaki, D.; Watanabe, S.; Kim, H. and Kanae, S. (2013). Global Flood Risk under Climate Change. Nature Climate Change 3, 816–821.https://doi.org/10.1038/nclimate1911
[9] Kabir, S, Patidar, S, Xia, X, Liang, Q, Neal, J & Pender, G. (2020). 'A deep convolutional neural network model for rapid prediction of fluvial flood inundation', *Journal of Hydrology*, vol. 590, 125481. https://doi.org/10.1016/j.jhydrol.2020.125481
[10] Kalantar B., Ueda N., Saeidi V., Janizadeh S., Shabani F., Ahmadi K., Shabani F. (2021). Deep Neural Network Utilizing Remote Sensing Datasets for Flood Hazard Susceptibility Mapping in Brisbane, Australia. *Remote Sens.* 2021;**13**:2638. doi: 10.3390/rs13132638.
[11] Kang, W., Xiang, Y., Wang, F., Wan, L., & You, H. (2018). Flood Detection in Gaofen-3 SAR Images via Fully Convolutional Networks. *Sensors*, *18*(9), 2915. MDPI AG. Retrieved from http://dx.doi.org/10.3390/s18092915
[12] Katiyar, V.; Tamkuan, N. and Nagai, M. (2020) Flood area detection using SAR images with deep neural. In Proceedings of the 41st Asian Conference of Remote Sensing—Asian Association of Remote Sensing, Deqing China, 9–11 November 2020.
[13] Kimura, N., Yoshinaga, I., Sekijima, K., Azechi, I., & Baba, D. (2019). Convolutional Neural Network Coupled with a Transfer-Learning Approach for Time-Series Flood Predictions. *Water*, *12*(1), 96. https://doi.org/10.3390/w12010096
[14] Li, Y.; Martinis, S.; Plank, S. and Ludwig, R. (2018). An automatic change detection approach for rapid flood mappingin Sentinel-1 SAR data. *International Journal of Applied Earth Observation and Geoinformatics*, 73, 123–135
[15] Li, W., Wu, J., Chen, H., Wang, Y., Jia, Y. and Gui, G.(2022) UNET combined with Attention Mechanism Method for extracting flood submerged range. *IEEE: Applied Earth Observations and Remote Sensing.* Vol 15.
[16] Long, S., Fatoyinbo, T. E. and Policelli, F. (2014). Flood extent mapping for Namibia using change detection and thresholding with SAR. *Environment Reserve Letters*, 9, 035002.
[17] 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*(16), 2532. MDPI AG. Retrieved from http://dx.doi.org/10.3390/rs12162532
[18] Olanrewaju, C. C., Chitakira, M., Olanrewaju, O. A., & Louw, E. (2019). Impacts of flood disasters in Nigeria: A critical evaluation of health implications and management. *Jàmbá: Journal of Disaster Risk Studies*, *11*(1). https://doi.org/10.4102/jamba.v11i1.557
[19] Pappas, O.A.; Anantrasirichai, N.; Achim, A.M. and Adams, B.A. (2020). River Planform Extraction From High-Resolution SAR Images viaGeneralized Gamma Distribution Superpixel Classification. IEEE Trans. Geoscience Remote Sensing, 59, 3942–3955

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁒ Impact Factor 8.102 ⁒ Vol. 12, Issue 3, March 2023
DOI: 10.17148/IJARCCE.2023.12342

[20] Shah S.A., Seker D.Z., Hameed S., and Draheim D. (2019). The Rising Role of Big Data Analytics and IoT in Disaster Management: Recent Advances, Taxonomy and Prospects. *IEEE Access.* 2019;**7**:54595–54614. doi: 10.1109/ACCESS.2019.2913340.
[21] Pekel, J., Cottam, A., Gorelick, N., & Belward, A. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, *540*(7633), 418–422. https://doi.org/10.1038/nature20584
[22] The World bank, Oct 19, 2022: Land, soil and climate change: How Nigeria is enhancing climate resilience to save the future of its people"
[23] Tuyen, D. N., Tuan, T. M., Son, L. H., Ngan, T. T., Giang, N. L., Thong, P. H., Hieu, V. V., et al. (2020). A Novel Approach Combining Particle Swarm Optimization and Deep Learning for Flash Flood Detection from Satellite Images. *Mathematics*, *9*(22), 2846. MDPI AG. Retrieved from http://dx.doi.org/10.3390/math9222846
[24] Vicente L.E. and Filho C.R.D.S. (2011). Identification of mineral components in tropical soils using reflectance spectroscopy and advanced spaceborne thermal emission and reflection radiometer (ASTER) data. *Remote Sens. Environ.* 2011;**115**:1824–1836. doi: 10.1016/j.rse.2011.02.023.
[25] Widiasari I.R., Nugroho L.E., and Widyawan. (2017). Deep learning multilayer perceptron (MLP) for flood prediction model using wireless sensor network based hydrology time series data mining; Proceedings of the 2017 International Conference on Innovative and Creative Information Technology (ICITech); Salatiga, Indonesia. 2–4 November 2017.
[26] Wikipedia contributors. (2013, January 10). *2012 Nigeria floods.* Wikipedia. https://en.wikipedia.org/wiki/2012_Nigeria_floods
[27] Wikipedia contributors. (2023, March 1). *2022 Nigeria floods*. Wikipedia. https://en.wikipedia.org/wiki/2022_Nigeria_floods