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**HYBRID APPROACH ON MULTI- SPATIOTEMPORAL DATA
FRAMEWORK TOWARDS ANALYSIS OF LONG-LEAD
UPSTREAM FLOOD: A CASE OF NIGER STATE, NIGERIA**



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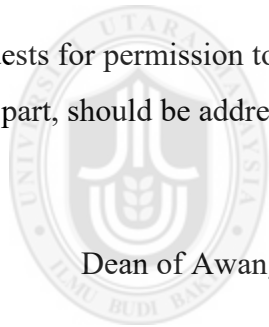
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Abstrak

Banjir telah menjadi kebimbangan yang serius di seluruh dunia kerana menyebabkan malapetaka kepada ekonomi dan ekologi. Oleh itu, strategi pengurangan risiko banjir digunakan untuk mengurangkan kesan yang berkaitan dengan banjir dengan mengenalpasti kejadiannya secara jangka panjang. Pelbagai faktor penyebab termasuk penggunaan kerangka data hibrid pelbagai ruang-masa dipertimbangkan dalam melaksanakan strategi tersebut. Selain faktor struktur atau bukan struktur homogen, penggunaan pelbagai alat berasaskan Sistem Maklumat juga diperlukan untuk menganalisis faktor penyebab semula jadi dengan tepat. Pada asasnya, strategi ini diperlukan untuk mengatasi pengelasan kerentanan banjir yang tidak tepat dan meramal kejadian banjir dalam jangka masa pendek. Oleh itu, kajian ini mencadangkan satu rangka kerja yang dinamakan: Rangka Kerja Data Hibrid Pelbagai Ruang-Masa Analisis Banjir Huluhan Jangka Panjang (HyM-SLUFA) untuk menyediakan dimensi baru mengenai kajian kerentanan banjir dengan mendedahkan pengaruh beberapa faktor yang diperolehi dari topografi, hidrologi, tumbuh-tumbuhan dan pemendakan terhadap pengelasan kelemahan banjir serantau dan analisis banjir jangka panjang. Dalam membangunkan cadangan rangka kerja, imej ruang diperbetulkan secara geometri dan radiometrik berbantuan Sistem Maklumat Geografi Kuantum (QGIS). Data temporal dibersihkan melalui kaedah *winsorization* dengan menggunakan perisian statistik STATA. Segmen rangka kerja hibrid mengklasifikasi kelemahan banjir dan membuat analisis jangka panjang. Pengelasan dan analisis dijalankan dengan menggunakan imej ruang yang diperbetulkan untuk memperolehi pemahaman yang lebih baik mengenai hubungan antara hujan dengan ciri yang diekstrak terhadap peningkatan kejadian banjir serta menghasilkan pelbagai kerentanan banjir serantau di kawasan kajian. Di samping itu, dengan bantuan teknik regresi, pemendakan dan paras air digunakan untuk membuat analisis banjir jangka panjang bagi mengenalpasti potensi kejadian banjir supaya langkah penyelesaian proaktif dapat diambil. Untuk memastikan kebolehpercayaan dan kesahan rangka kerja yang dicadangkan, satu penilaian ketepatan telah dijalankan ke atas hasil data. Kajian ini mendapati pengaruh Faktor Penyebab Banjir (FCFs) yang digunakan dalam rangka kerja HyM-SLUFA, dengan mendedahkan ketaksamaan jurang ruang menunjukkan bahawa cerun rantau mempengaruhi tahap kerentanan banjir adalah lebih tepat berbanding dengan FCF yang lain, yang secara umumnya menyebabkan banjir huluhan yang teruk apabila terdapat jumlah mendakan rendah di kawasan yang mempunyai tahap cerun yang rendah. Secara teorinya, HyM-SLUFA akan berfungsi sebagai panduan yang boleh digunakan atau disesuaikan untuk kajian yang serupa. Terutama, dengan mempertimbangkan gaya pemendakan dan klasifikasi kerentanan banjir yang ditentukan oleh pelbagai FCFs. Klasifikasi ini akan menentukan jenis polisi yang akan dilaksanakan dalam perancangan bandar, dan jumlah pengurangan kerentanan banjir dapat memberikan pandangan pada masa depan mengenai sebarang kejadian banjir agar tindakan penyelesaian proaktif yang praktikal dapat diambil oleh pihak berkuasa tempatan.

Kata kunci: Analitik data raya, Analisis alam sekitar, Kerentanan banjir, Sistem Maklumat Geografi (GIS), Sistem Maklumat.

Abstract

Floods have become a global concern because of the vast economic and ecological havoc that ensue. Thus, a flood risk mitigation strategy is used to reduce flood-related consequences by a long-lead identification of its occurrence. A wide range of causative factors, including the adoption of hybrid multi-spatiotemporal data framework is considered in implementing the strategy. Besides the structural or homogenous non-structural factors, the adoption of various Information Systems-based tools are also required to accurately analyse the multiple natural causative factors. Essentially, this was needed to address the inaccurate flood vulnerability classifications and short time of flood prediction. Thus, this study proposes a framework named: Hybrid Multi-spatiotemporal data Framework for Long-lead Upstream Flood Analysis (HyM-SLUFA) to provide a new dimension on flood vulnerability studies by uncovering the influence of multiple factors derived from topography, hydrology, vegetal and precipitation features towards regional flood vulnerability classification and long-lead analysis. In developing the proposed framework, the spatial images were geometrically and radiometrically corrected with the aid of Quantum Geographic Information System (QGIS). The temporal data were cleaned by means of winsorization methods using STATA statistical tool. The hybrid segment of the framework classifies flood vulnerability and performs long-lead analysis. The classification and analysis were conducted using the corrected spatial images to acquire better understanding on the interaction between the extracted features and rainfall in inducing flood as well as producing various regional flood vulnerabilities within the study area. Additionally, with the aid of regression technique, precipitation and water level data were used to perform long-lead flood analysis to provide a foresight of any potential flooding event in order to take proactive measures. As to confirm the reliability and validity of the proposed framework, an accuracy assessment was conducted on the outputs of the data. This study found the influence of various Flood Causative Factors (FCFs) used in the developed HyM-SLUFA framework, by revealing the spatial disparity indicating that the slope of a region shows a more accurate level of flood vulnerability compared to other FCFs, which generally causes severe upstream floods when there is low volume of precipitation within regions of low slope degree. Theoretically, the HyM-SLUFA will serve as a guide that can be adopted or adapted for similar studies. Especially, by considering the trend of precipitation and the pattern of flood vulnerability classifications depicted by various FCFs. These classifications will determine the kind(s) of policies that will be implemented in town planning, and the Flood Inducible Precipitation Volumes can provide a foresight of any potential flooding event in order to take practical proactive measures by the local authority.

Keywords: Big data analytics, Environmental analysis, Flood vulnerability, GIS, Information systems.

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List of Abbreviations

Acronyms	Abbreviations
AHP	Analytical Hierarchy Process
CAR	Centre for Atmospheric Research
CRED	Centre for Research on the Epidemiology of Disasters
CSTD	Centre For Satellite Technology Development
DEM	Digital Elevation Model
DMC.	Disaster Monitoring Constellation
DMSG	Disaster Management Support Group
DN	Digital Number
EKF	Extended Kalman Filter
EM-DAT	Emergency Events Database
EO	Earth Observation
EOSDIS	Earth Observing System Data and Information System
ESRI	Environmental Systems Research Institute
FCFs	Flood Causative Factors
FIPV	Flood Inducible Precipitation Volume
GIS	Geographical Information Systems
HyM- SLUFA	Hybrid Multi-spatiotemporal data framework for Long-lead Upstream Flood Analysis

ICT	Information and Communication Technology
LiDAR	Laser Detection and Range
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NASRDA	National Space Research and Development Agency
NDVI	Normalized Difference Vegetation Index
NEMA	National Emergency Management Agency
NIHSA	Nigeria Hydrological Services Agency
NNARX	Neural Network Autoregressive Model with Exogenous
NSEMA	Niger State Emergency Management Agency
OGC	Open Geospatial Consortium
P.R.O	Public Relation Officer
QGIS	Quantum Geographic Information System
RS	Remote Sensing
SSTL	Surrey Satellite Technology Limited
SVMs	Support Vector Machine
TM	Thematic Mapper
TOA	Top of the Atmosphere
TRMM	Tropical Rainfall Measuring Mission
TWI	Topographic Wetness Index
UNISDR	United Nations International Strategy for Disaster Reduction (

CHAPTER ONE

INTRODUCTION

1.1 Introduction

This chapter presents an overview and synopsis of this research, starting with the background information and the motivation for conducting the research in section 1.2. Section 1.3 focuses on the problem statement which captures the challenges regarding flood mitigation strategies. Also, the chapter outlines the research questions and the corresponding objectives in sections 1.4 and 1.5 respectively. The scope of the research is highlighted in section 1.6, while section 1.7 concisely presents the significance of the research. The structure of the thesis is provided in section 1.8. This chapter concludes by presenting a chapter summary in section 1.9, while the frequently used terms are contextually defined in section 1.10.

1.2 Background and Motivation of the Study

Flooding has become a serious issue in several parts of the world and will relentlessly affect the way in which cities grow [1]. Adversely, the current climate change has triggered major changes in rainfall pattern which in turn, has increased flood vulnerability in several regions[2],[3]. As a result, flood-related disasters will correspondingly continue to occur in the future – one can never achieve complete safety [4]. Yet, flood vulnerability can be seriously alleviated if an appropriate means of mitigation or preparedness is developed [4].

Broadly, there exists three strategies of flood mitigation [4]:

- I. Modification of vulnerability to flooding: this involves legislation, land-use planning and management to allow mapping and prohibition of development within certain areas identified to be vulnerable to floods;
- II. Modification of flood waters: this consists of employing structural measures by erecting flood defence such as dams, reservoirs, drainages and diversions, vegetation and avoiding bare soil during precipitation;
- III. Modification of flood-induced impacts: this ultimately consists of identifying the likelihood of flood occurrence, prediction of water or flow condition, warning to the appropriate authority, evacuation, construction of defences, and essentially, review of flood mitigation approaches to enhance the process and planning for potential event by combining strategies 1 and 2.

Currently, there is an adoption of structural measures (strategy II) to provide preventive measures, such as drainage, dikes, dams, embankments, flood control reservoirs and transhumance mechanisms in Malaysia, Netherlands, Bangladesh, China, and Nigeria as well as other parts of the world. This effort to cope with the extreme and varied climate change may no longer be able to mitigate flooding events due to changing of rainfall pattern [1], [4],[5],[6]. Also, this structural measures obstructs water from flowing which potentially leads to devastating impacts in downstream settlement and within agricultural lands [7],[8]. Therefore, non-structural measures involving flood prediction and identification of flood vulnerability, which can be obtained by pre-processing spatiotemporal data and performing long-lead flood prediction has been identified by experts to be very crucial in mitigating potential flooding events [9],[10]. Similarly,

disaster management coordinating agencies have equally placed a great emphasis on the non-structural means of flood mitigation, as stated in the studies conducted in [9],[10]. This emphasis on non-structural measures is because several or multiple factors that contributed to increasing the flood damage in the past were related to non-structural aspects of flood management[6],[9], which can be identified by pre-processing multiple spatiotemporal factors.

Pre-processing of multiple factors generally involves series of sequential operations on spatiotemporal data sets, including atmospheric correction, geometric correction, image enhancement and transformation that are required prior to the analysis of flood causative factors or spatial imageries[11],[12],[13], which will be beneficial in generating relevant Flood Causative Factors (FCFs), as in the case of this research. At present, the benefits of these imageries upon scientists as well as decision-makers around the globe are yielding great opportunities by providing enhanced imageries [14]. Nonetheless, despite these immense benefits, various studies which were conducted based on these vital sets of data still remain below considerable expectation [15]. This can be attributed to lack of theoretical and technological understanding of spatiotemporal data [15].

It is also noteworthy that employing spatiotemporal data for studies focusing on non-structural flood mitigation is normally based on complex flood models that are data intensive; a requirement which can only be addressed by research-level organizations [1]. Adoption of such approach by stakeholders or local communities may be difficult due to its complexity, poor understanding of underlying assumptions, lack of skill in utilizing spatiotemporal data sets, besides high maintenance costs of the system [1]. Hence, the

primary motivation behind this research, which is to provide solutions to these aforementioned issues.

Also, flood inundation maps generated from spatial data sets are at the base of flood risk management; informing the public and city planners about flood-prone areas in a region [16]. Nonetheless, despite recent advancements in computational techniques and availability of spatial data sets, flood hazard maps are still lacking in many countries [16]. The main difficulty in using a specific approach is primarily associated with the significant amount of data and parameters required by these approaches [16]. Hence, the need to pre-process these spatial data which classify and depict regions that are prone to floods within the study area.

Furthermore, the spatial description of vulnerability is of paramount importance in any flood analysis [17], which only satellite imageries of high resolution with a wide spatial coverage in conjunction with in-situ data sets can be used to obtain the required information for this purpose [17]. To this regard, previous studies on flood vulnerability and long-lead prediction in Niger state and other parts of the world are still constrained by their inability to sufficiently consider several relevant factors that induce floods which in turn, would have accurately classified various regions that are vulnerable to floods prior to performing the long-lead predictions. This, on the other hand, had impeded on the adequacy of the lead-time prediction and overly affects the decision-making aimed at flood mitigation. Therefore, a holistic approach is required to bridge the existing gaps; correct identification of regional flood vulnerability and long-lead analysis.

Similarly, due to the fact that flood disaster is one of the heaviest disasters in the world, it is therefore necessary for it to be monitored and analyzed in order to mitigate its related havocs. Obtaining the flood extent is a basis for monitoring and analyzing the flood-induced disasters. Currently, satellite imageries without the limitation of weather and time, can provide important information for obtaining the flood extent [18]. Even more, Earth Observation (EO) satellites offer a unique capability on geomorphology by providing temporally repetitive views at the desired spatial scale (e.g., global, regional, or local) [19]. This wealth of remote sensing data conveys a huge potential for preventing, monitoring, and mitigating natural or anthropogenic (Man-made) disasters [19].

Essentially, focusing on flood risk, a successful exploitation of this vital data requires not only an accurate and reliable image-analysis approach to pre-process the desired imageries, but also, the ability to relate these information with multiple physical factors, such as topography, hydrology and vegetation of the observed processes [19]. Therefore, a multidisciplinary approach combining remote sensing with Geographical Information System (GIS) is a fundamental requirement in this regard. In essence, relating this expertise permits, in particular, satellite data to be exploited within the various phases of flood risk mitigation: risk assessment, prevention, mitigation, monitoring, and management [17],[19]. However, to date, the adoption of satellite imageries in flood analysis remains underutilized, as it is mostly restricted to binary segmentation into flooded and non-flooded representations, which is associated with the limitation of the satellite capabilities [17], [20].

Even though it is an achievement to possess the capability of space and environmental assets, such as satellites and terrestrial remote sensors [19],[21], the deficiency of

scientific approaches to pre-process multiple data sets obtained from these facilities needed for earth observation and environmental analysis is greatly undermining the ability to efficiently utilize these costly and vast acquired data [22],[23]. The need for multiple factors is of an immense importance because the surface of the earth has multiple geomorphological features, such as water bodies, non-vegetal surface, topography, geomorphology, each considered as a factor having different characteristics in inducing floods when influenced by rainfall [24],[25]. The level of influence of rainfall on these factors can only be identified when imageries are pre-processed [11], [25],[26],[27].

In a practical context, there is an ardent need by decision-makers to know which region(s) should mitigation efforts be focused on during floods or which regions are more vulnerable to floods [28]. The accurate knowledge of regions that are vulnerable to flood can only be obtained by the use of a multi-factorial approach. Therefore, this research is essential, especially for the study area (Niger state), which has always been affected by annual flooding event since the creation of the State in 1976 [29]. The exposure of this State to floods could be attributed to the geographical location of vast parts of the state within a lower terrain, presumed to be valleys and plains [29], which can only be identified by an accurate analysis of spatiotemporal data. However, the presence of these features has been causing devastating flooding impacts on annual basis, leading to death and destruction of properties. Consequently, the need to conduct this research becomes pertinent since the extant already conducted with the aim of addressing flood-related issues, which neither considered the use of multiple factors to delineate floodplains nor performed long-lead flood prediction simultaneously, as further detailed in ensuing section of the research problem.

1.3 Problem Statement

The exploitation of remotely sensed data, also referred to as spatiotemporal data is very crucial for knowledge discovery in environmental analysis [30]. This knowledge discovery as well as the understanding of environmental phenomenon can be enhanced when analysis is performed based on multiple heterogeneous data sets[31]. At present, numerous attempts have been made to overcome the inherent limitations of spatiotemporal data, often by the integration of multiple spatial data sets to provide a more accurate and comprehensive flood assessment[32]. Even more, in a time-critical disaster situation, utilization of multiple data sources is particularly, desirable to aid in the estimation of flood inundation extent [33]. Contrary to the approaches employed by various existing studies presented in the literature review section, which were based on one or a very scanty set of factors.

For instance, regional flood vulnerability were identified by non-spatial(survey-based) study conducted in the State of Kelantan, Malaysia [34] and Abeokuta, Nigeria [35]. Despite the successes recorded in identifying regions vulnerable to floods, the studies recommend the need for long-lead prediction and also the need to identify the changes in water body to prevent flood-induced impacts. These recommendations involve the use of additional relevant factors that can reveal the pattern of vegetation and water content within the regions for better decision-making as adopted in [36]. This is because, accurate information obtained from multiple factors to depict the extent of water content is crucial in flood management [37].

Often, this information is difficult to obtain using the aforementioned survey techniques as a result of the fast movement of water contents in floods, tides, and storm, or may be inaccessible using the survey means [38]. The synoptic, repetitive nature of spatiotemporal data set enables monitoring of water bodies over large regions of land [38]. The use of these data sets to generate multiple relevant factors that influence floods was equally recommended in the study conducted by [39]. To this effect, in assessing the level of havoc caused by flooding event, satellite imageries were equally pre-processed in the study conducted by [40]. Although, the pre-processing approach employed generated the desired results by identifying vegetal and anthropogenic causative factors. Nonetheless, inclusion of other relevant factors (i.e. multiple factors) based on the hydrological, and topographical components to reveal the direction or accumulation of flow would have considerably enhanced the result beyond damage assessment to vulnerability identification which would have been employed for flood management in the future.

In the same vein, while classifying regional flood vulnerability in Niger state, i.e. the study area considered in this research, in the study conducted by [29], a single set of spatial data was pre-processed to identify the variability of regional flood vulnerability [29]. Evidently, the result obtained from this study presented a relative level of accuracy. Nevertheless, the regions of Suleja, in Niger State, Nigeria was incorrectly classified to be non-vulnerable. Unfortunately, these regions have continued to experience severe floods in the past two years. This erroneous analytical result can be attributed to the use of a single factor to determine regional flood vulnerability within the aforementioned study [29]. Therefore, this research addresses this limitation by employing multiple factors aimed at generating better analytical results.

Comparing today's availability of satellite imagery to the situation about ten years ago, the availability of satellite imagery covering a certain disaster event has improved substantially [41]. Nonetheless, as demonstrated by these aforementioned studies, the analysis was based mainly on a single or paucity of flood causative factors to identify flood vulnerability instead of multiple factors. Thus, in order to achieve a reliable and accurate results, multiple relevant factors, such as topographical, hydrological factors, etc. are required to be identified to accurately classify vulnerable regions prior to performing long-lead upstream flood prediction [42].

Additionally, it is noteworthy that the identification of these multiple spatial factors leads to the collection of a heterogeneous and voluminous amount of data [43]. Evidently, satellite imageries exude an intensive nature; the increase in volume of data, increases the complexity of the pre-processing [1],[44]. While some studies have claimed that, the ideal means of averting the complexity in a voluminous sets of data is by avoiding the use of such data sets due to the presence of noise[45], which can adversely lead to erroneous analysis[46]. And even though pre-processing spatial data is by no means an easy task [47], nonetheless, since the basis for this research is formulated around an intensive spatiotemporal data pre-processing scope, an approach was proposed to ensure accurate pre-processing of the identified multi-factors. This essentially is due to the fact that the scientific study of extreme hydrological events, such as flood still has not yet been fully explored, in addition to the constraint faced by bodies responsible for flood risk assessment and flood warnings in providing efficient procedures [48]. Unfavorably, accurate estimation of flood vulnerability is not a simple issue as multiple factors must be

considered[49].Hence, this research proposes a holistic procedural means to pre-process the identified multi-factors.

On the other hand, the political pressure on the scientific bodies to proffer long-lead flood prediction has increased in light of the recent flooding events in some parts of the world [50]. While flood predictions have been a widely known area of research [51],[52], only a few works have been reported on spatiotemporal and GIS-based approaches [51],[52], as in the case of this research. This is attributed to the inefficiency and unreliability of the existing works [51],[52], An effective flood predictive approach can aid to mitigate the worst impacts of flood-induced events resulting from heavy precipitation lasting for days [53]. quintessentially, a sufficient lead time (long-lead) is required for proactive measures[54].

Generally, long-lead prediction of extreme precipitation, i.e., prediction of 6-15 days ahead of time is important for understanding the prognostic predictive potentials of many natural disasters, such as floods [55]. This enables an adequate implementation of rescue and evacuation operations as well as mitigating measures [56],[57]. More essentially, the need for an improved lead-time allows time to prepare and disseminate more information and also to mobilize towards the vulnerable regions[58]. Hence, the need to have an adequate long-lead prediction of any flooding events became crucial. Conversely, various adopted techniques and approaches reviewed are constrained due to the lead-time obtained which ranges between 1 hour to 24 hours. Also, due to the paucity of data sets used and the scope considered [51],[59],[60],[61],[62]. Interestingly, the study conducted for the State of Kelantan, Malaysia in[63], which attained the lead-time of seven days presented

a considerable lead-time towards flood mitigation. Nonetheless, this study is equally constrained due to its inability to identify those other flood influencing factors in addition to the influence of precipitation. And as a result, the recommendation for further studies to identify other flood influencing factors prior to performing the prediction was made therein.

Thus far, this research has identified the challenges posed by the insufficient use of flood causative factors, the complexity of adopting such data intensive approach and above all, the inadequacy of predictive lead-time. Therefore, to address the theoretical perspectives of this research, and to attain its underpinning practical objectives, this research proposes a hybrid technique that is capable of classifying regional flood vulnerability and performing long-lead upstream flood prediction for those regions identified to be vulnerable as adapted from [63] and [64]. Essentially, a hybrid approach was needed to combine both pre-processing of multi-spatiotemporal data and prediction of upstream flood occurrence in order to have a better understanding of influence of rainfall on other relevant other flood causative factors which essentially has practical implications in determining the accuracy in the classification of flood vulnerability. This is because flood occurrence depends on the complex interactions between rainfall and the spatial factors[65], considered to be FCFs.

Finally, while various studies which were reviewed provided useful insights on the exploration of multi-spatiotemporal factor for regional flood classification and also long-lead upstream flood analysis, nonetheless, they equally presented some analytical errors ranging from the inaccurate identification of vulnerable regions to inadequate predictive

lead-time. Therefore, to ensure the reliability of the obtained analytical results from this research, the accuracy of the developed hybrid multi-factorial framework needed to be ensured. Although, the development of robust accuracy assessment methods for the validation of spatial data represents a difficult challenge for the geospatial science community[66]. However, the need for assessing the accuracy of a map generated from any spatiotemporal data has become universally recognized as an integral component of any research in order to ensure the reliability in decision-making [66]. Consequently, an accuracy assessment approach was proposed.

Sequel to the aforementioned challenges associated with multiple spatiotemporal data pre-processing for long-lead prediction, this research outlines the following issues:

1. Insufficiency of relevant flood causative factors considered, resulting in poor identification of regional flood vulnerability and long-lead analysis;
2. Complexity in pre-processing multiple spatiotemporal sets of data considered for regional flood vulnerability classification;
3. Inaccuracy in identifying regional flood vulnerability, and inadequacy in performing long-lead prediction;
4. Absence of a reliable accuracy assessment approach for the obtained results.

In order to fill these aforementioned research gaps, an approach based on multi-spatiotemporal data sets, which requires the identification and collection of multiple relevant flooding causative factors to be pre-processed in order to accurately classify

regional flood vulnerability and perform an adequate long-lead upstream prediction was proposed.

1.4 Research Questions

This research addresses the following research questions:

- I. What are the relevant spatiotemporal causative factors in flood vulnerability?
- II. How can multi-spatiotemporal flood causative factors be pre-processed for regional flood vulnerability classification?
- III. How can a hybrid framework be developed to classify flood vulnerability based on multi-factors and perform long-lead upstream flood analysis?
- IV. How can the accuracy of the developed hybrid framework for both vulnerability classification and long-lead analysis be assessed?

1.5 Research Objectives

The novelty of this research lies at the intersection of the broadly-defined multiple spatial and temporal data to perform a long-lead upstream flood prediction within vulnerable regions. Therefore, the overarching objectives of this research are as follows:

- I. To identify multiple relevant spatiotemporal causative factors in flood vulnerability;
- II. To define a multi-spatiotemporal FCF pre-processing approach needed for regional flood vulnerability classification;
- III. To develop a hybrid framework capable of classifying regional flood vulnerability and performing long-lead upstream flood analysis;
- IV. To assess the accuracy of the developed hybrid framework for both vulnerability classification and long-lead analysis.

1.6 Scope of the Study

In line with the scope of this research, which is uniquely to focus on the upstream cause of flood, this section discusses various forms of data as well as the components of the proposed hybrid framework adopted in order to attain the defined objectives of the research.

1.6.1 Data

As earlier identified in the problem statement, various reviewed studies are inherently defective due to the paucity data employed. In order to address this limitation, multiple sets of data considered suitable for the purpose of this research were identified from the use or recommendation of such data sets by the extant studies. The generality of these sets of data include:

- I. NigeriaSat-x Satellite Image: Needed for Topographical and hydrological features of the study area;
- II. Daily Water Level: Needed to estimate the volume of water discharged by river towards the neighboring surroundings;
- III. Precipitation (Rainfall) Data: Data from continuous measurement of natural rainfall to identify the amount of rainfall covering from 1979-2016;
- IV. Temperature data: To determine the correlation between the rainfall and temperature and the influence on upstream flooding;
- V. Flood Inventory in the study area: To recognize the records of flooding events as well its regional the frequency that occurred at a place;

- VI. Satellite LandSat8 Image: Needed to identify water bodies and vegetal stratification;
- VII. Shape file: Shapefiles contain all the geographical attributes of a map such as boundaries, states and the regions;
- VIII. LandSat Path and Row Map: Needed to download LandSat8 scenes for the study area;
- IX. Global Inventory on natural disasters.

1.6.2 Framework Hybridization

Broadly, hybridization denotes the merging or combination of two elements to form a single enhanced element. Recently, there is an effort being made towards overcoming some methodological limitations of a single technique by combining other research techniques simultaneously [67]. This is because, the complexity of systems and their multi-faceted relationships requires combination of technical approaches in order to provide a greater insights to problem solving [67]. Ultimately, within the scope of this research, the combination of techniques to form the hybrid framework was ensured by considering the underlying methodological strengths of pre-processing multi-spatiotemporal features and the functionality of long-lead analysis.

Essentially, the developed hybrid framework is the fusion of two distinct facets; combining the multi-spatiotemporal data to identify and classify regional flood vulnerability, while the other facet performs the long-lead upstream flood prediction, which were adapted from several arrays of studies in flood mitigation, the novelty of this framework resides in its exhaustive approaches in ensuring the use of multiple flood

causative factors to identify and classify regional flood vulnerability and also to perform a long-lead flood prediction at a considerable amount of lead-time over a wide area. The result of the hybrid framework is intuitive and comprehensible enough to enable end-users leverage the full potentials of the acquired output for decision-making especially, in proactive flood mitigation.

Additionally, the hybrid framework describes the approaches of multi-spatiotemporal data cleaning and feature extraction which are needed to enhance the interpretive accuracy in analyzing upstream floods over a complex and vast terrain. Accordingly, each phase of the framework performs distinct tasks. With an initial phase being the identification and collection of multi-spatiotemporal data, the second consists of the pre-processing tasks of these collected data sets. While the third, is the vulnerability classification, and long-lead flood analysis, and the accuracy of outputs was assessed in the course accuracy assessment in phase four prior to the validation of the developed Hybrid Multi-spatiotemporal data framework for Long-lead Upstream Analysis (Hym-SLUFA), as detailed in Chapters Three and Four.

As mentioned thus far, spatiotemporal data sets remain the fundamental components for performing the flood vulnerability classification and long-lead analysis in this research. However, to avoid a redundant presentation of literature, and to also adhere to a logical and structural presentation of thesis writing, a detailed discussion on the data sets and tasks involved in various segments of the proposed framework is made in Chapter Three.

1.7 Significance of the Study

This research contributes to the body of knowledge within the domains of big spatial data and big data analytics. This is particularly dominant in the facets of multi-spatiotemporal data pre-processing and its analysis for flood vulnerability classifications, and long-lead analysis of potential flooding events. As earlier mentioned, to mitigate the impacts of floods, it is essential to identify those areas that are vulnerable to floods with their corresponding levels of vulnerability and the recognition of any potential flooding events in a long-lead timeframe. Concisely, the contributory aspects of this research to the body of knowledge are summarized as follows.

1.7.1 Theoretical Contribution

This research has proposed a hybrid framework to pre-process multiple spatiotemporal data sets and perform a long-lead upstream flood analysis based on geographic information system GIS theory. The developed HyM-SLUFA framework was adapted from the concepts of other existing frameworks and recommendations provided by other studies in the areas of flood disaster management within the study area and other parts of the world as detailed in Chapter Two. As highlighted in section 1.2 (problem statement), the existing studies for flood analysis are constrained by the lead-time and the absence of other several relevant causative factors to correctly identify vulnerable areas. Therefore, this research has addressed these aforementioned limitations by utilizing multi-factorial approach to accurately classify regional flood vulnerability prior to performing long-lead analysis within the study area.

1.7.2 Methodological Contribution

Broadly, various procedural approaches employed in the phases of the proposed hybrid framework have an important contributory significance to the body of knowledge. Particularly, since the data sets used in this research were initially acquired covering the entire surface of Nigeria. These sets of data did not only present the information in an unclean and raw format, but the coverage of the satellite imageries transcends the study area. Therefore, demonstrating the methods used in acquiring, cleaning and extracting scenes and coordinates representing the study area using the framework is considered a useful methodological contribution which can be adopted or adapted in similar data intensive studies. This is in addition to various means of classifying regional flood vulnerabilities. The results obtained from both theoretical and methodological facets were used to make various practical recommendations for decision-making in order to take proactive measures aimed at mitigating the impacts of any potential events within the study area.

1.7.3 Practical Contributions

This research has a practical contribution resulting from the proposed frameworks which aid in the classification of regions based on their corresponding levels of vulnerability. Also, the identification of any potential flooding events within the study area. These were required in order to proffer suggestions and recommendation for the local authorities in the study area for flood mitigation decision-making. Hence, these aspects of this research fundamentally demonstrate the importance of the developed hybrid framework in recognizing regional flood vulnerability and a potential floodable situation. More essentially, in identifying the minimum volume of rainfall that instigate a flooding event,

referred to as Flood Inducible Precipitation Volume (FIPV), policies as well as proactive measures can be implemented to mitigate or entirely avert flood induced disasters, which has been the underpinning motivation of the research. Beyond the regional scale, the proposed frameworks can be adopted or adapted in Malaysia, or other parts of the world facing similar flood-related issues.

1.8 Organization of the Thesis

The overall structure of the thesis detailing the research takes the form of six chapters, which includes:

Chapter I— Introduction

This Chapter introduces the study and provides background details on the need to employ multiple factors in flood vulnerability classification and also highlights the importance of long-lead prediction. It discusses the context of the research and the motivation behind it. The chapter also outlined the research questions, and objectives. It further provides an overview of the research contributions and the data sets employed for the proposed framework in the research in addition to definition of some key terms used in the course of writing the thesis.

Chapter II— Literature Review

This chapter reviews the academic literature on floods and its related environmental as well as economic impacts. Various approaches adopted for flood mitigation and the associated limitations have been presented in this chapter. This chapter equally presents a review on lead-time flood predictions, and also discusses the supporting and the underpinning research theory.

Chapter III— Research Methodology

This chapter discusses the research design and the methodological approaches employed in conducting this research. It further explains the rationale for pre-processing multiple factors for flood analysis, which provides insights on the process of performing the hybridization towards classifying regional flood vulnerability and performing long-lead upstream flood prediction. The chapter also presents various means of accuracy assessment prior to the validation of the developed framework.

Chapter IV— Framework Development

This chapter demonstrates the developmental strategies employed in the development of the framework using multi-spatiotemporal-based approach. Ultimately, this chapter implemented a hybrid technique to perform regional vulnerability classification and long-lead flood predictive analysis using the pre-processed multiple factors. It also generated the major findings of this research which are elaborated in Chapter Five.

Chapter V— Research Findings and Discussion

This chapter presents a comprehensive discussion on the findings, drawing on both experimental and inferential observations in the course of conducting this research.

Chapter VI— Conclusion and Recommendations

This chapter provides answers to the research questions, and also explains how findings have fulfilled the research objectives and how the identified problems were addressed. In

addition, it summarizes the key findings and makes policy recommendations for the local authority towards flood mitigation. Finally, it presents the limitations of the research and outlined the aspects that can be considered in future studies.

The aforementioned chapters are intrinsically linked in order to produce a logical and well-structured thesis as illustrated in Figure 1.1.

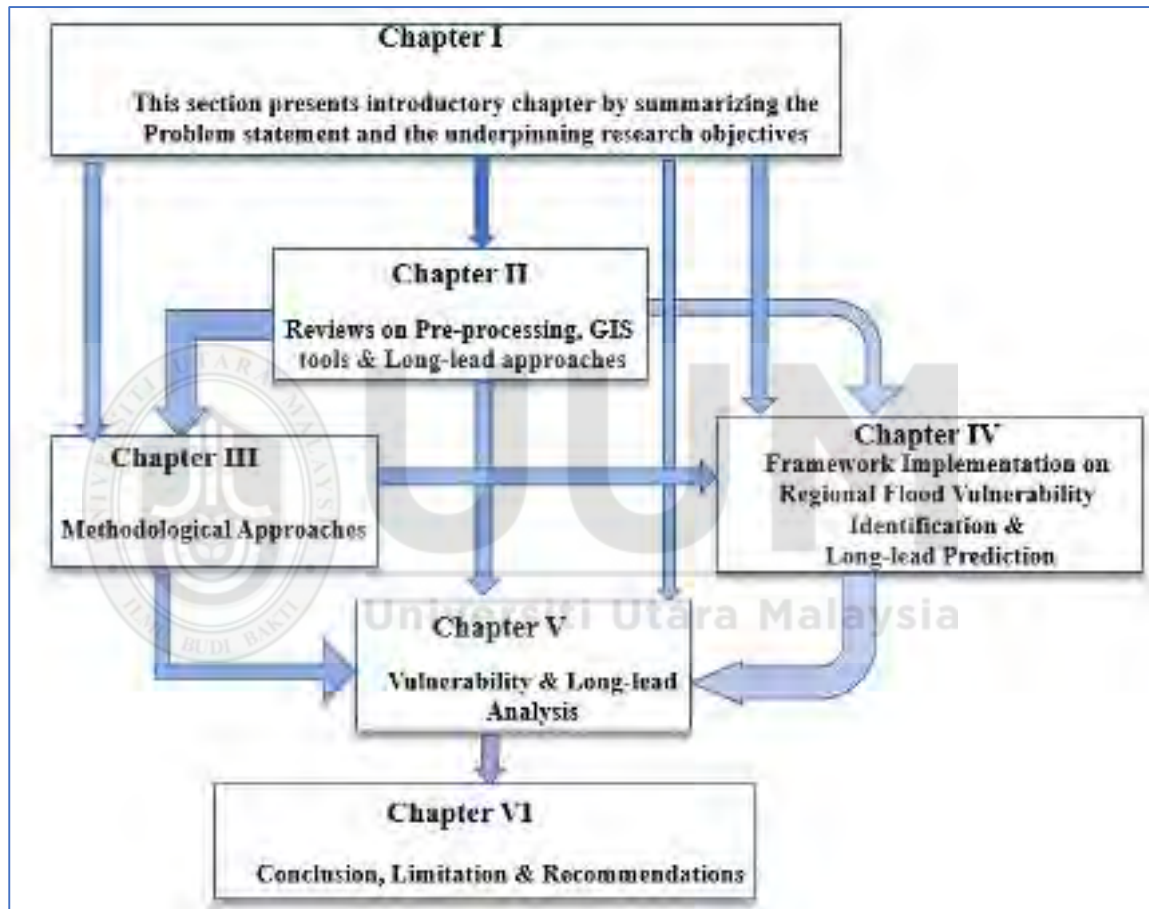


Figure 1.1. A Schematic Illustration of Sectional Links

Although, this thesis is structured from Chapter One. However, the systematic review of the literature in Chapter Two was initially done prior to the formation of chapter one as well as other chapters. Broadly, the entire foundation (problem statement) of this study as presented in Chapter One was identified from the reviewed studies in Chapter Two. In the

same vein, Chapter Two generated the research methodologies in Chapter Three based on various methods used in the reviewed studies, as well as the recommendations made in those studies. The methods served as a guide in the implementation of the framework in Chapter Four, which was needed to extract various flood causative factors. The extracted factors were employed in Chapter Five to identify regional flood vulnerability and long-lead analysis. Finally, the thesis was concluded with a presentation of the obtained results, which served as the basis for the assessment and the eventual validation of HyM-SLUFA framework.

1.9 Definition of Terms

For the aim of clarification and simplified comprehension of this thesis, these frequently used terms were gathered from Environmental Systems Research Institute (ESRI) based on contextual definition as appeared within the literature:

- I. **Delineation:** Defining the physical boundaries of a stream, floodplain, jurisdictional wash, etc.
- II. **Error Term:** An error term is a variable in a statistical or mathematical model, which is created when the model does not fully represent the actual relationship between the independent variables and the dependent variables. As a result of this incomplete relationship, the error term is the amount at which the equation may differ during empirical analysis. The error term is also known as the residual, disturbance or remainder term.
- III. **Exposure/Vulnerability:** The presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social, or cultural assets in places that could be adversely affected by flooding events.

- IV. **Feature Extraction:** The process to represent raw image in a reduced form to facilitate decision making such as pattern detection, classification or recognition.
- V. **Framework:** a basic conceptual structure of interlinked ideas represented by processes which supports a particular approach required to attain a desired objective(s).
- VI. **Geomorphology:** The study of the physical features of the surface of the earth and their relation to its geological structures.
- VII. **Hydrology:** The scientific analysis of rainfall and runoff, its properties, phenomena and distribution; as well as water dynamics below the ground and in the atmosphere.
- VIII. **Isohyet:** A line on a map connecting points having the same amount of rainfall in a given period.
- IX. **Lithology:** The lithology of a rock unit is a description of its physical characteristics visible at outcrop, in hand or core samples or with low magnification microscopy, such as contour, texture, grain size, or composition.
- X. **Long-lead:** The ability to recognize any potential upstream flooding occurrence to at least 6-15 days in advance.
- XI. **Nonlinearity:** A process is called nonlinear when there is no simple proportional relation between cause and effect. The climate system contains many such nonlinear processes, resulting in a system with a potentially very complex behavior. Such complexity may lead to abrupt climate change. See also Predictability.
- XII. **Normal Distribution:** The normal distribution, also known as the Gaussian or standard normal distribution, is the probability distribution that plots all of its

values in a symmetrical fashion, and most of the results are situated around the probability's mean. Values are equally likely to plot either above or below the mean. Grouping takes place at values close to the mean and then tails off symmetrically away from the mean.

- XIII. **Pattern:** In image processing, the computer-based identification, analysis, and classification of objects, features, or other meaningful regularities within an image.
- XIV. **Peak Flow:** The maximum rate of flow through a watercourse for a given storm
- XV. **Runoff:** Surface water resulting from rainfall or snowmelt that flows overland to streams, usually measured in acre-feet (the amount of water which would cover an acre one-foot deep). Volume of runoff is frequently given in terms of inches of depth over the drainage area. One inch of runoff from one square mile equals 53.33 acre-feet.
- XVI. **Situation:** An interpretive representation recognizing the severity or mildness of an upstream flood.
- XVII. **Stratification:** The process of dividing an area to be monitored up into units to increase the efficiency of monitoring.
- XVIII. **Spatiotemporal data:** Spatiotemporal datasets normally comprise of condition of an entity, an event or a position in space over a period of time.
- XIX. **Topography:** The term topography represents the study of the shape and features of land surfaces.
- XX. **Trend:** A spatially nonrandom variation in the value of a variable that can be described by a mathematical function.
- XXI. **Transient response** also referred to as natural response represents the response of a system to a change from an equilibrium or a steady state.

- XXII. **Upstream:** Related to event induced by heavy rainfall or natural factors inducing downstream havoc.
- XXIII. **Vulnerability:** The characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard.

1.10 Chapter Summary

This chapter provides the background for the research as well as the statement of the problems, which formed the underpinning motivation for this research. The identified limitations in the extant studies prompted the need for the research questions and its corresponding objectives as itemized in this chapter. The main aim of this research is to devise a mechanism for accurately measuring long-lead flood prediction. Broadly, flooding events are intrinsically dynamic due to the involvement of multiple flood causative factors which require multifaceted means of pre-processing multi-spatiotemporal data for reliable analysis. Therefore, the ensuing chapter discusses the review made on floods and its related impacts, mitigating measures proposed by various studies, the corresponding challenges as well as the limitations within these studies.

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

This section provides a broad discussion on floods in comparison with other weather-related hazards in section 2.2. The impacts of floods is presented in section 2.3. Section 2.4 describes the study area and its associated flood vulnerability. Essentially, the foremost step in developing a body of knowledge commences by considering previous studies in order to gain insights on the extent to which the extant studies have attained, and identify the procedures employed in addressing the focus of these studies [68]. Therefore, a critical review of relevant literature was ensured to proffer insights on the major challenges associated with flood management strategies, the approaches that have been employed to pre-process spatiotemporal data for regional flood classification, and the need for long-lead upstream flood analysis were explained in sections 2.5 and 2.6 respectively. The concepts of flood causative factors and GIS theory are also introduced in section 2.7, and the chapter concludes with a summary in section 2.8.

2.2. Background on Flooding

Floods are among the most devastating natural disasters known globally, inflicting monumental harm to lives and causing severe damages to properties, thereby presenting direct impacts to the socio-economy as well as the environment of the affected area(s) [69],[70],[71]. Contextually, flood represents a momentary state of incomplete or total inundation of a normally dry portion of land as a result of excess of waters from an uncommon increase from natural or artificial sources [72]. However, it is generally

believed that poor countries will suffer excessively from flooding disasters not only because of the global warming, but also as a result of population, poverty and their poor adaptive capacity [73], [74].

At present, weather-related disasters are becoming progressively recurrent, due mostly to a constant upsurge in the numbers of floods and storms. And regarding the rate of fatalities caused by these natural disasters, data collected from a disaster research organization based in Belgium, Centre for Research on the Epidemiology of Disasters (CRED) [75], as illustrated in Figure 2.1, indicates that 605,000 lives were lost in weather-related disasters between 1995 and 2015 with 242,000, 164,000, 157,000, 22,000 and 20,000 for storm, extreme temperature, flood, drought and landslide respectively.



Figure 2.1. Number of People Killed by Weather-related Disasters(1995-2015)[75].

From this illustrative data, between 1995-2015, 157,000 lives have been lost due to flooding events representing 26%. While it has also been reported that, floods has caused the number of impacts amongst natural disasters globally as illustrated in Figure 2.2.

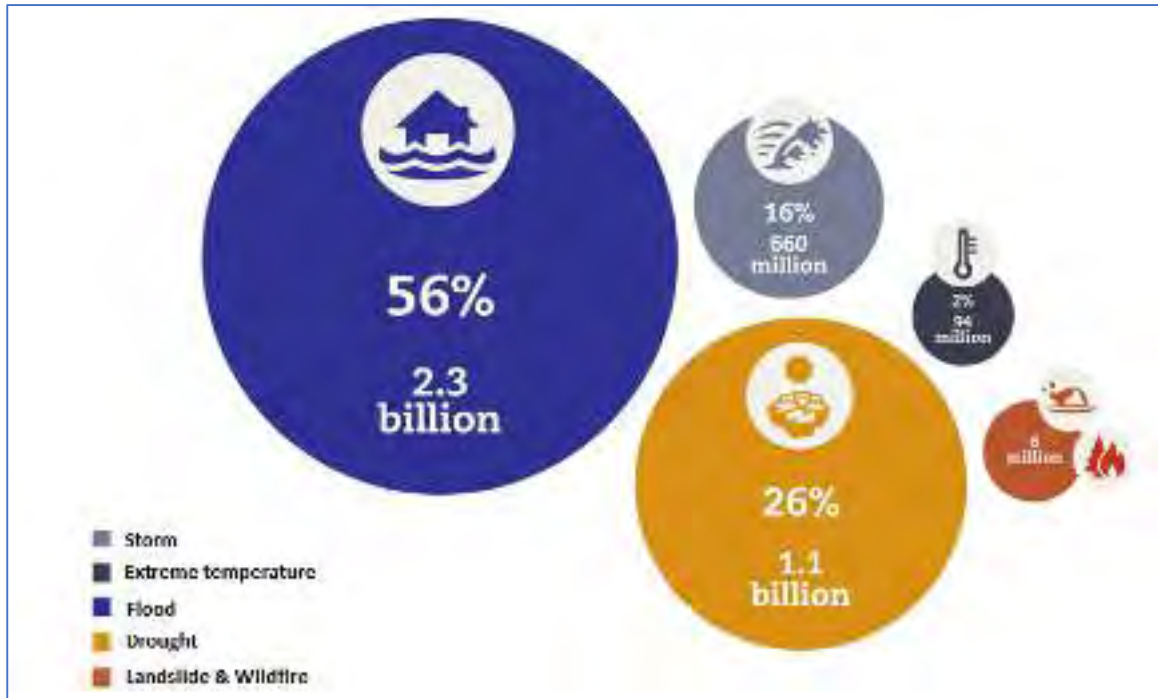


Figure 2.2. Number of People Affected by Weather-related Disasters (1995-2015)[75].

As illustrated by Figures 2.1 and 2.2, in the last twenty years, the overwhelming majority (90%) of disasters were caused by floods, storms, extreme temperature and other weather-related events. In total, 6,457 weather-related disasters were recorded globally by Emergency Event Database (EM-DAT). Over this period, weather-related disasters claimed 605,000 lives, an average of around 30,000 per annum, with an additional 4.1 billion people who were either injured, left homeless or in need of emergency assistance.

At present, there is a consensus that hazards which occur due to hydrological extremes such as flooding, are on the rise amongst other natural disasters such as storms and extreme temperature. The nature of disastrous floods has also changed in recent years, with flash floods, acute riverine and coastal flooding increasingly frequent. In addition, urbanization has significantly increased flood run-offs, while recurrent flooding of

agricultural land, particularly in Asia, has taken a heavy toll in terms of lost production, food shortages, consequently leading to economic losses as shown in graph represented by Figure 2.3.



Figure 2.3. Annual Reported Economic Losses and Time Trend from Disasters: 1980 - 2015 [75].

Figure 2.3 (Graph) is a copyrighted data with a given permission to use in Appendix A shows the annual reported economic losses and time trend from disasters between 1980 and 2015 comparing present to the past (EM-DAT, 2016).

A critical examination of the aforementioned global disaster databases from EM-DAT for over four decades (1980-2015), revealed that climatic events (flood, storms, extreme temperature and drought) had led to the total estimated economic loss each year from disasters ranging between the US \$ 250 billion and the US \$ 300 billion. Evidently, flooding events have demonstrated an increasing trend in various parts of the world. The root causes are attributed to the increased extreme rainfall as a result of climate change which is also aided by both natural and anthropogenic factors. For instance, the level of flood vulnerability and the magnitude of its impacts are largely attributed to many causative

factors such as the topography, hydrology and the vegetal nature of the study area considered. These causative factors influence flooding in various modes and at various degree in exposing the environment to devastating flooding events as further elaborated in the ensuing section.

2.2.1 Flood Causative Factors

Generally, floods occur primarily as a result of heavy downpour, unexpected or substantial melting of ice as well as failure of river protective walls [74]. The moment there is a rainfall, there occur an evaporation of a certain quantity into the atmosphere, and a certain quantity penetrates the soil descending into the system of groundwater. In this process, some volumes are captured by vegetation while the remaining quantity eventually moves into rivers, which is referred to as runoff. This generally gives [74]:

$$\text{Runoff} = \text{Precipitation} - \text{Infiltration} - \text{Interception} - \text{Evaporation}$$

Evaporation carries a small value of this representation, mostly within a short window of time, and as such, infiltration, precipitation as well as interception carry larger values which define runoff and the subsequent release toward the river [74]. Generally, floods are mostly caused either by natural factors or anthropogenic factors as illustrated in the Figure 2.4.



Figure 2.4: Flood Causative Factors

Primarily, precipitation or rainfall is the most influential factor in instigating a flood. Nonetheless, there are several other contributing factors. For instance, when rain falls on a catchment, the volume of precipitation that gets to the water ways reaches the streams depends on the nature of the catchment, mostly topography, and vegetation [76]. Specifically, with the occurrence of a heavy rainfall than usual within a specific region, runoff is likely to increase, consequently, presenting a high tendency for flood to occur [74]. Substantial downpour could be represented with the aid of Figure 2.5, illustrating curves (isohyets), while the Figure is referred to as isohyetal maps[74]:

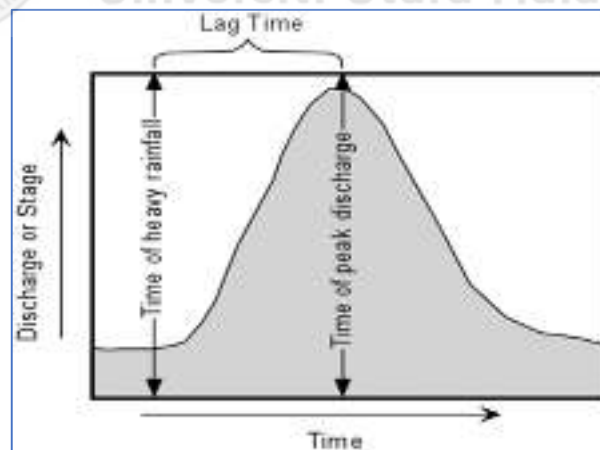


Figure 2. 5. Distribution of Rainfall

1. When the quantity of downpour is much within a little time, the corresponding lag time will be short.

2. When the quantity of the downpour is prolonged, the corresponding lag time will be extended, and the lag time is reduced in the absence of infiltration and interception.

2.2.1.1 Natural Causative Factors

In addition to precipitation, there are other natural flood causative factors which can be considered to reveal regions that vulnerable to floods and the corresponding levels of vulnerability within the study area as discussed in the ensuing sub-subsection.

2.2.1.1.1 Topography Factors

Topography plays a crucial role in spatial variability of hydrological situations, such as soil moisture and flow of groundwater. For some regions, vulnerability is often intensified by regional topographic conditions [77]. This generally involves the elevation and the slope angle of the area. Elevation and slope equally play vital roles in determining the stability of a surface. The slope affects the direction and volume of surface runoff/subsurface drainage reaching a site. Slopes have a more influential influence in contributing rainfall to stream flows [78], since it determines the extent of overland flows, infiltration as well as subsurface flow.

The combination of the slope angles fundamentally outlines the form of the slope and its relationship with the lithology, structure and the soil type. By implication, steeper slopes are more susceptible to surface runoff, while flat terrains are susceptible to water logging. Relatively, low gradient slopes are highly vulnerable to flood occurrences. While in most of the regions, the entire flood vulnerable area situated within a straight or flat elevated surface [78].

2.2.1.1.2 Hydrological Factors

Generally, the hydrology of a surface is associated with the identification of water flow on the surface within hydrological cycle, and the conveyance of elements, such as sediments and pollutants along with flowing water [79]. In order to reveal the hydrological characteristics and the level of influence in flooding, the flow direction, flow accumulation and topographical wetness index are indispensable. This is because, a spatial hydrological process triggers the flow of water and transport over specific regions of the study area which can consequently cause severe flooding.

2.2.1.1.3 Land Cover Factors

Land cover variation is known to affect both surface water and soil hydrological contents by changing the hydrological substances of the surface and modifying the forms and rates of water flow [80]. More precisely, land cover changes influence evapotranspiration and surface runoff routing by altering the physical structure of vegetation and surface roughness[80]. These causative factors are considered within the scope of this research in order to determine the level of regional vegetation or greenness determined by Normalized Difference Vegetation Index (NDVI). The NDVI is the greenness index associated with the proportion of radiation that are photosynthetically absorbed which reflects the chlorophyll activity in plants within the surface.

Precisely, when there is a rainfall over a barren slope, it flows on the surface faster than in forest area [81]. Based on various levels of vegetal density, the land cover was classified into “Bare soil”, “low vegetation”, “dense vegetation” and “water bodies” these

classifications equally have their distinct levels of flood vulnerability as discussed in the framework development analytical section as discussed in Chapter Four of the thesis. More importantly, understanding the distribution and dynamics of land cover is crucial to enhance the comprehension of the earth's relevant features, including productivity of the land, the diversity of plant and animal species, and the biogeochemical as well as the hydrological cycles [82]. Assessing and monitoring the distribution of this factor remains an utmost priority in studies on global environmental changes as well as in daily planning and management [82].

2.2.1.2 Anthropogenic Causative Factors

Anthropogenic or man-made factors such as crops, buildings, and infrastructure directly replace portions of natural systems. In addition, anthropogenic influence can also obstruct species' movements across landscapes or contribute to environmental degradation through waste[83]. While the vegetal or greenness of a surface prevents a free flow of water that can lead to flood, in the case of these anthropogenic factors, the vegetation is removed thereby causing floods[84].

2.2.1.2.1 Impervious Surfaces

The impervious surfaces mostly correspond to regions where runoff is rapidly active during a storm event as a result of lack of infiltration of water into the soil. Employing the means of identifying the land use in GIS, the assessment of the impervious regions are performed by identifying imagery cells that correspond to roads, building as well as gullies[85]. Within the scope of this research, vegetal stratification was considered since the activities of land use generally determines the vegetal level of a region.

2.2.1.2.2 Buildings

Erecting structures on river floodplains, indiscriminate waste dumping are common in both rural and urban regions. In some instances, building approvals are given without clearly considering the nature of the surface and the impacts of the construction on the quality of the environment and location. Such buildings hinder the free flow of water, and can lead to floods at the downstream. Ironically, some of the motives for building around these floodplain regions are due to violation of government building regulations, ignorance, inheritance and scarcity of land suitable for development [86]. Aside the losses of lives and other devastating impacts to environments as a result of flooding events, the ensuing sections also highlight some of the impacts to the ecosystems as well as the economic impacts.

2.3 Impacts of Flooding

Globally, approximately 122,000 lives have been lost due to flood related issues in the last decade. It has also been estimated by the United Nations University that two (2) billion individuals could be affected by floods by 2050, out of which a greater portion will be Asians [99]. Despite huge monetary budgets committed into flood-control protective structures, such as levees and dams, the damages caused by flood still persist on a very high level over the years[87], resulting to some chemical and economic impacts.

For impacts of flood on soil contents, flood removes gas openings which can restrict soil and gaseous interchange towards the molecular distribution in soil water [87]. Consequently, the strength of the soil is reduced by the loss of cohesion, making it impossible to use heavy equipment on the affected area as a result of the chemical impacts.

In the aspects of the economy, flood leads to a possible primary and secondary monetary losses within a region as a result of havoc inflicted on properties and both in agricultural and industrial sectors, leading to reduction in efficiency and earnings [88], [87],[89]. The impacts of flooding do not primarily concern lives, but most severely properties and social activities. This can be attributed to the uncertainty created by the increasing trend of climate change which on the other hand, has continuously increased the level of havoc as a result of the floods experienced. After an elaborate discussion of flooding, impacts and causes on a global point of view, the ensuing section describes the study area and its associated vulnerability to flood.

2.4 Study Area and Associated Flood Vulnerability

Further to the previous discussion, Nigeria like some other parts of the world, experiences annual rainfall-induced flooding events that cause severe havoc[90],[91],[92]. Early 2012, Nigeria was hit by a severe flood, claiming lives of about 430 persons, rendering 566,466 homeless, and affecting a land area of around 4,701 km² [92]. The raining seasons of May and October in Nigeria are usually marked by flash floods. Recently, the country witnessed one of its worst devastating impacts in 40 years in 2012 [116]. The post disaster estimation indicated that about 70% of the population is vulnerable to this disaster, which is detrimental to lives and properties [93].

Specifically, the study area, which is Niger State, has a history of flood due to its location at the discharge point of the River Niger, measured at 4160 km long, considered the 12th longest river in the world and the third longest in Africa[94], after rivers Nile (Egypt) and

Zaire(Congo) with 6,650km and 4,700km length respectively. The general scope of this research is to identify a reliable and accurate means of explaining the regional variation in flood vulnerability and its occurrence in Niger State of Nigeria by pre-processing multiple spatiotemporal data sets related to the State and also performing long-lead upstream flood prediction accordingly. Here, in order to predict any potential flooding event for the regions identified to be susceptible to upstream floods, this research considers Niger State which is geographically indicated in Figure 2.6 as the study area because of the vast complex land mass that is prone to annual flooding events.

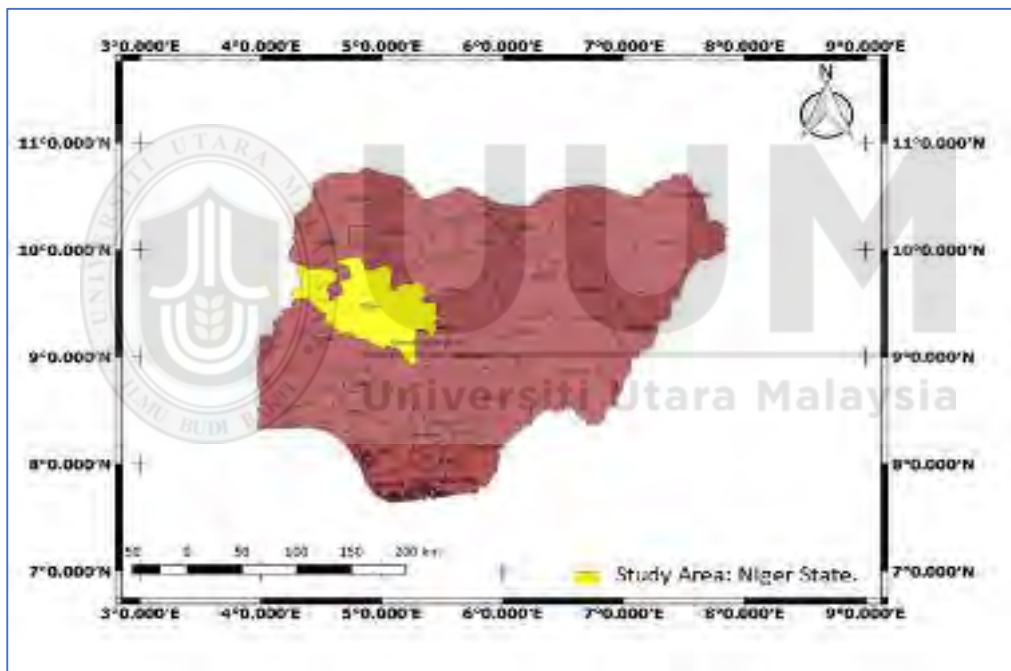


Figure 2. 6. Geographical Location of Niger State, Nigeria

Furthermore, Niger state which is located between latitudes 8.02°N and 10.20°N and longitudes 4.38°E and 5.73°E. Based on the census conducted in 2006 has an estimated population to be 3,954,772[30]. The State covers a landmass of 72,200.14km² with 18,007.38km², 24,181.04km², 20616.09km² and 9,593.3km² for valley, plains, upland and

highlands respectively [29],[95]. Additionally, the state is situated in the central part of the country with Minna as the capital [96], [95], as shown in Figure 2.6. Also, Niger state is the home for main hydro-electric plants, which are the Kainji[97], Tagwai and Shiroro dams[98], contributing greatly in the generation of electricity to the country. Unfortunately, these same hydro-electric plants serving as sources for social amenities are also the sources of some destructive events affecting lives and properties as a result of flooding [98].

Additionally, Niger State experiences variation in the volume of rainfall between the average of 1200mm to 1800mm at its peak level in the southern region of the state to an average of between 800mm and 1500mm at the northern region. Rainfall is prevalent during the wet season, with the months of June to October which are usually identified as the months witnessing the highest volume of rainfall instigating to flooding havoc occurring around these months. The latitudinal situation of the state has rendered the state to high flood vulnerability with large regions of the states situated within the lower terrain along the largest river in Nigeria, River Niger inducing the hazards of annual flooding towards the communities adjacent to this river as well as those within the valleys [29].

Evidently, floods present the most profound events worldwide[99],[100]. Inhabitants in various parts of the world have experienced devastating events resulting from flood in the past, spawning severe impacts to both lives and properties within the affected environment. Essentially, these global impacts of flooding events and devastating havoc highlight the increasing importance of flood hazard studies [101]. Thus far, this chapter has discussed the concepts of flood, the causes and the impacts at both global and regional

levels. With various identifiable havoc created by this natural disaster, it has become pertinent to also identify the strategies that can be employed in managing some of the related impacts.

2.5 Global Flood Management Strategies

Flood management is a major concern for countries that are vulnerable to floods. In the last centuries, in various regions, a variety of strategies and technologies utilized for flood management have evolved [102]. Flood risk management approaches broadly involve the use of structural and non-structural interventions to mitigate flood risks [102],[103] as illustrated by Figure 2.7.

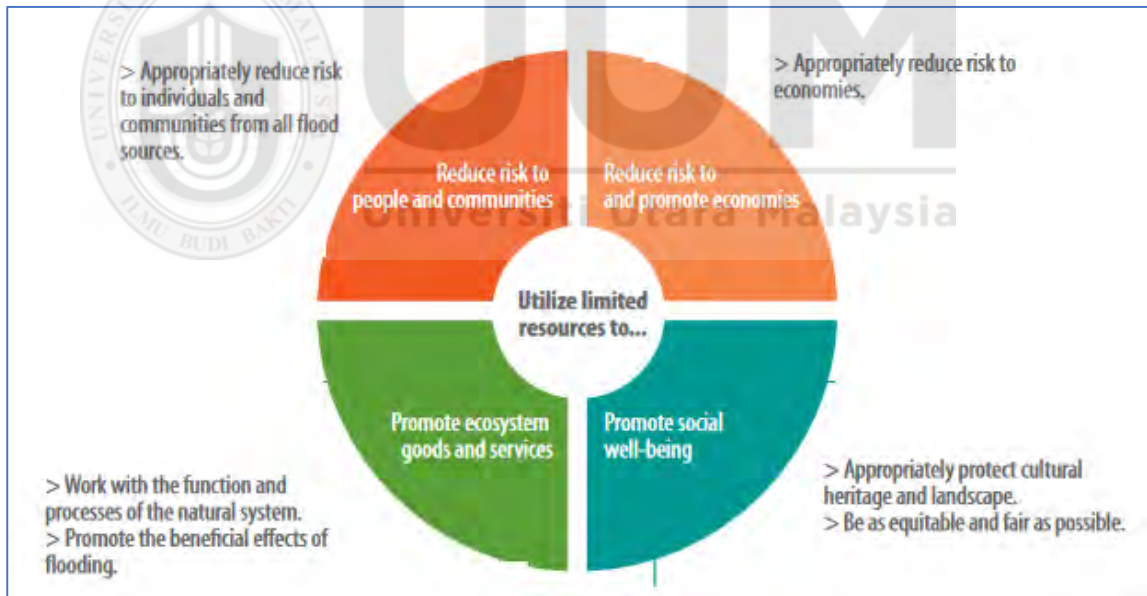


Figure 2.7. Characteristics of an Ideal Flood Vulnerability Management: [103]

These characteristics form the building blocks of a good flood vulnerability management (Figure 2.7) and represent an approach that concurrently seeks to make space for water while supporting appropriate economic use of the floodplain.

Notably, flood vulnerability management possesses multiple aims associated with multiple time and space scales. Achieving these aims depends on the development and implementation of appropriate strategically measures [103]. Flood management consequently embeds a continuous process of adaptation that is classified under structural and non-structural means of flood mitigation[71],[104].

In flood management strategies, the structural measures are hard-engineered structures such as dams, dikes, flood defences, embankments, breakwaters, levees and drainage channels as commonly deployed in Netherlands, Bangladesh, India and Nigeria [8],[105],[106],[107]. However, according to Haque and Burton [108], these structural measures only address the physical vulnerability of people, property, and assets, as such, are considered inadequate to cover the full spectrum of disaster management. Similarly, as a result of the current climate change, the uncertainty of atmospheric condition is changing and a result, the structural measures have been considered ineffective to efficiently manage flooding events by the studies conducted by [1],[5],[4],[6]. As a result, the need to consider non-structural measures becomes important.

2.5.1 Flood Management Strategies in other Countries

Globally, various strategies have been implemented in mitigating flooding events. For instance, in Malaysia, where floods are the most prevalent natural disasters affecting 4.9 million people and inflict havoc worth of several millions of ringgits every year[109], some structural measures such as Flood Control Dams, Canalization, Ring Bund, Tunnels and Storage Ponds have been adopted to mitigate flood disasters. In another joint efforts between Hong Kong and Singapore aimed at mitigating the impacts of floods, a structural-based means was deployed. Drainage systems were constructed with 190 million SGD annually from 2010 to 2014[105]. Nonetheless, it has been identified that flood management can be enhanced through non-structural measures with emphasis being placed on land use policies, vulnerability zoning and flood monitoring as implemented in this research.

Also in China, a study conducted in[104], shows that an effort is currently being made by the government towards an urban flooding disasters by constructing a ‘Sponge City’ which is believed to help in regulating and also to serve as a storage capacity for urban regions. At present, thirty (30) cities have been selected as the pilot sites for the project with a corresponding cost of around US\$1 billion for each city. However, despite this huge investment, nineteen (19) out of the thirty (30) pilot cities were affected by devastating water disasters due to the failure of the Sponge City project. Consequently, the reliability and efficiency of this structural measures (Sponge City) became doubtful. The failure and inappropriateness of the Sponge City is generally attributed to the spatiotemporal variability of China which has also led to variability in flooding occurrences in various regions.

Table 2.1.

Structural Measures of Flood Mitigation

Ref	Structural Measures	Country
[109]	Flood Control Dams, Canalization, Ring Bund, Tunnels and Storage Ponds	Malaysia
[104]	Sponge City for water absorption	China
[105]	Marina Barrage Embankments/sea walls	Singapore
[8]	Dikes	Netherlands
[106]	Dikes	Bangladesh
[107]	Dams	Nigeria

Summarily, even though the concept of structural flood mitigative measures have been known since the World War II between 1950s to 1960s [105], nonetheless, the lessons learnt from large flooding events presented a paradigm shift towards the mitigation of the impacts based on multi-factorial mitigation approach, i.e. non-structural measures [105]. Essentially, flood analysts and decision-makers understand flood vulnerability with the aid of a model-based assessment to identify sources of vulnerability, floodplains and the potential victims (lives, properties and ecosystem) as encompassed in non-structural approaches [105]. With regards to effective and efficient flood mitigative measures, flood hazard and regional vulnerability that affect individuals and communities, there is the need to integrate non-structural measures which involves flood prediction, monitoring and warning systems, resettlement of population, and identification of floodplains for policy implementation for land use [109]. For instance, in other parts of Nigeria, and specifically, within the study area, there have been several conventional measures implemented at the national and regional levels based either on the structural or non-structural means towards flood mitigations, as elaborated in the ensuing sub-subsection.

2.5.2 Flood Management Strategies in Niger State and other parts of Nigeria

Fundamentally, the interaction between natural and anthropogenic activities are unavoidable. As a result, the likelihood of increasing scale and frequency devastating flooding events. The extant policies or regulations, as well as other structural measures for flood mitigation of the environment in Nigeria are poorly coordinated and counterproductive. Due to poor implementation and inadequate enforcement of these laws, regulations standards and guidelines, as well as climate change[110]. Some of the national and state policies/regulatory means of flood mitigation are reviewed as follows:

- I. Identification and Mapping of Disaster Prone Areas:** The first intervention by the Nigerian government towards flood management in year 1962 as part of National Development Plans of 1962-68, 1970-74 and 1975-80, the Federal and States Ministry of Works was established in order to identify and map areas that are prone to floods as well as other natural hazards[111]. This management practices was employed to sensitize the citizenry about flood risk, and development of flood mitigation and preparedness.
- II. Structural Measures:** In the use of structural measures, the impoundment of dams within the flood prone areas in Nigeria in addition to a reservoir with a capacity of 36 million m³ have immensely impacted on mitigating the associated impacts resulting from floods in various parts of the country. Essentially, the construction of the dams, such as Kaji and Shiroro dams in Niger State (The study area), which results in an unexpected drop of water level which allows recovery operations in case of any flooding events. Even

though the use of these measures seems helpful, the usefulness is only immediate and does not support a longer window time for proper proactive measures to be implemented [112].

III. Policies and Institutional Frameworks: As one of the units in Federal Ministry of Works and Housing, Federal Environment Protection Agency (FEPA was established to develop policies and institutional frameworks that can mitigate the impacts of ecological disaster in Nigeria. Its entire responsibility is to oversee environmental management and protection but without an appropriate enabling law on enforcement issues.

Currently, flood risk management seeks to lessen the magnitudes of flooding as well as its likelihood to occur by considering a mix of management options which extend beyond traditional engineering measures such as flood defences (structural measures) and incorporate a wide range of mechanisms which are referred to as being non-structural [113]. More pertinently, the growing likelihood that climate change will increase flood occurrence in many parts of the world enhances the need to examine how to improve flood mitigation [105]. Therefore, in order to propose the most reliable means of flood mitigative measures, which involves identifying floodplains, and also providing warnings for any potential flooding events, this research seeks to adopt a hybrid approach based on non-structural means by pre-processing multiple factors based on spatiotemporal data and also performing long-lead prediction that can reduce economical and human risks. In addition to promotion of goods and services within the study area as represented in the preceding illustration in Figure 2.7. Generally, floodplain classification or mapping is a

requirement, and non-structural measures remains a pre-requisite for prioritizing land use practices and planning better flood mitigative measures which can be achieved by pre-processing spatiotemporal data[114].

2.6 Spatiotemporal Data Pre-processing

Spatiotemporal data pre-processing involves the identification of appropriate satellite data (spectral resolution, radiometric correction, geometric correction and the extraction of useful information for decision-making)[115]. There is no substitute for optimal data identification, however, after optimal data identification and collection, data pre-processing remains the most important step[116]. Essentially, pre-processing of spatiotemporal data is a vital and crucial stage of data analysis in which at the initial stage, raw data sets are transformed to “cleaned” data, from which unwanted contents have been removed, so that this cleaned data is better suited for flood mitigative measures[117], [101].

Also, the ability to observe a vast region has greatly enhanced the quality as well as the quantity of spatiotemporal data which is continuously gaining more relevancy in various domains. However, these sets of data are exposed to noise during the acquisition from the orbit and as such, need to be pre-processed in order to retain only useful features required for analysis[118]. Additionally, in the phase of pre-processing multiple spatiotemporal factors, an excellent geographical reference enhances the accuracy in environmental analysis by bringing an image into a standard projection as well as locating the study area [119] prior to the extraction and classification of cleaned features in the analytical phase [119], [120].

As earlier mentioned, the demand for spatiotemporal data is growing, and remotely sensed imagery is the primary source of these sets of data[121]. These data sets are also becoming more enhanced as a result of the increasing number of EO satellites in the orbit[121]. Even though there is an improvement in quality of these images, and at an affordable cost, there exists an identified obstacle in the pre-processing of these data for environmental analysis in general [121],and specifically, in flood mitigation as in the case of this research. Therefore, it is vital and urgent to identify suitable pre-processing techniques to be used [121]. This is mainly because, in many decades, several studies have adopted varied approaches in pre-processing satellite imageries for flood analysis. With certain levels of accuracies, limitations and most importantly, the recommendations.

Broadly, flood analysis remains a complex process which has led to several studies addressing its different facets in order to contribute towards mitigating approaches[1]. Nonetheless, these studies exude some strengths as well as limitations. Therefore, in order to identify a more suitable and illustrative means of analyzing regional flood vulnerability, the ensuing subsection has reviewed some related literature based on spatial and non-spatial means.

2.6.1 Spatiotemporal Data and Vulnerability Paradigm

The use of multiple factors in flood vulnerability classification is pre-requisite in this research. Therefore, in order to identify various relevant factors, this subsection reviews recent literature related to spatiotemporal data approaches for flood mitigative measures which is based on non-structural approach; its aims, methods and the constraints

surrounding their implementation, and further examine how applicable they may be in attaining the underpinning objectives of this research.

Generally, flood vulnerability assessments are done using various approaches of varying complexity, depending on the volume of data sets, resources available and the time required[122]. In the context of this research, the following studies have been reviewed. A study conducted to identify the level of vulnerability in urban areas was conducted by Adelekan for the regions of Abeokuta in Nigeria[35]. This was attained by administering questionnaires to 248 respondents over fourteen affected regions. The responses gathered from the respondents indicated that approximately, 50% had witnessed flooding events in the past. The respondents also indicated the absence of warning as flood mitigating measures were not implemented. Most of the respondents (85%), admitted to the absence of a warning system, while a smaller number of respondents (8%) admitted of having experienced flooding warning related to increased volume of precipitation as well as river overflow. As a result of high level of flood vulnerability observed by the study[35], several mitigating measures ranging from effective watershed management, control on removal of vegetation cover were recommended[35].

In a less technical approach, a potentially floodable map representing river basin of Kelantan, Malaysia was drawn. A geological map was used to identify the lithological attributes of Kota Bharu, Kelantan. In order to recognize the pattern of flooding events, questionnaires were administered to some respondents in the state of Kelantan based on various, secondary and tertiary stages of flood impacts. A hundred and sixty (160) questionnaires were administered with 85.63% admitted to experiencing flooding events

on annual basis, while 76.25% admitted having experienced floods over the depth of one meter. Kota Bharu capital city of Kelantan 53.13% admitted being rarely affected by flooding events while 46.88% are frequently affected by floods. This study recommended the identification of changes in surface and how to prevent it from flooding impacts. The recommendation made in this study can involve the use of elevation data and other features showing the direction and accumulation of flow which will greatly enhance the reliability of this study in mitigating the impacts of flood within the area of interest[34].

Also, in order to generate a map depicting flood inundation, a study conducted based on the application of remote sensing and GIS for flood hazard management for the region of Sindh in Pakistan [123], employed MODIS imageries. The imageries were pre-processed using Object-based classification approach to classify elevation, land cover, settlement and road to delineate vulnerable regions from the non-vulnerable ones. In another closely related study, flow accumulation, land use, rainfall, slope and soil were pre-processed as FCFs for flood vulnerability delineation in alappuzha district, India, which were further assessed using AHP[124]. In another study conducted for Bashar River downstream of Yasooj city in Iran, land use, elevation and land slope as well as distance to the discharge channels were pre-processed to identify regions that are prone to a potential flooding events [125] . While Topography Wetness Index (TWI) was applied to identify flood vulnerability towards proper land use planning in state of Victoria, Australia. This was done with the aid of Laser Detection and Range (LiDAR). Disadvantageously, the TWI approach did not simulate the hydrological contents of the study area [126]. And even though this study in [123] stated the need to derive information from diverse imageries

for flood-related studies, similar to other related studies, it is found to be constrained in the sets of FCFs considered.

Elsewhere in Nigeria, flood prone areas were efficiently classified using GIS for Makurdi, Nigeria [39]. The results obtained attributed the vulnerability of the area to either a continuous or intense downpour, causing flash floods and also increasing the volume of River Benue beyond its bank. The generated results were used also by town planners in modernizing the plan of the town, considered to be a mitigating measure. Despite these impactful results obtained, this study recommended the use of satellite imageries for a more advanced and enhanced results needed to mitigate the havoc of upstream floods.

Similarly, in the mapping of flood dynamics and spatial distribution of vegetation in the Amazon floodplain using multi-temporal SAR data [36], sets of imagery data acquired from JERS-1 were used in this regard within a vast amazon floodplain. The approach used in the mapping was based on decision rule to classify the entire time series in mapping the minimum and the maximum flood situation level by determining three flood situations based on the occurrence of flooding events to its non-occurrence. The flooding events were classified into Never Flooded (NF), Occasional flooded (OF) and the Permanently Flooded (PF). The correctness of the map was assessed using the intermediary flood level, illustrating a correctness of 90%. However, to attain this exactitude, the study recommended the use of additional images on the classifier. This study was particularly defective because the map obtained identified the occasionally flooded regions but does not identify flood dynamics, e.g. when or for which water level each pixel representing the occasionally flooded was submerged during the rising water period.

In another study based on spatial factor conducted by [127], land cover was classified into the classes of water, sand, agriculture, cropland, island and settlement for flood inundation mapping. Inundation map was also created using maximum discharge data. The mapping was primarily aimed at the protection of wetland and management of land-resources. Even though, this study seems to have adopted a holistic approach, the use of other hydrological factors, such as flow accumulation and flood direction would have ensured the accuracy of inundation mapping. The study recommended the use of high resolution imageries and multiple time series data. Also, based on topographic factors, spatial imageries were pre-processed to assess flood vulnerability in the study conducted by [128]. The pre-processed factors were further weighted using Multiple-criteria Decision Analysis (MCDA). Even though, the result generated could be employed to classify flood vulnerability, integrating other factors as in the case of this research provides more insights on accuracy of the vulnerability.

In another breakthrough using imageries captured aially [129], an Unmanned Ariel Vehicle (UAV) was used to acquire topographic imageries of 6cm resolution for flood assessment. Seemingly, the idea behind the use of imageries captured by UAV seems fast and relatively less time consuming to identify topographical features as in the case of an extensive pre-processing task. However, the coverage which is 0.25 sq Km. makes the services of such data sets and approach questionable. More so, during the hot summer season autopilot used to heat up quickly to 65°C or above which causes the sensor malfunction. Hence, the reliability on such means for flood assessment is farfetched.

In assessing flood vulnerability in Niger state, which is the study area of this research, satellite imagery was also employed in [29], to identify various levels of regional flood vulnerability in the state. This study classified the regions with a relative level of success. However, some of the regions around Suleja identified to be non-vulnerable have being affected with recurrent annual flooding events because the analysis was only based on the elevation feature. The primary limitation of this study dwells in the use of a single feature to classify the vulnerability of the entire region. Even though areas identified to be highly vulnerable have a corresponding traits of high flood vulnerability, the use of slope feature as well as other topographic or hydrological features as in this case of this research would have yielded more accurate and reliable results. Therefore, this research proposes a pre-processing framework that employed multiple features in order to enhance the identification of flood vulnerability within the study area.

In the same vein, supervised classification was used to learn of the pattern land cover[130]. This was done by pre-processing multi-spectral from Landsat Thematic Mapper(TM) data

scenes in assessing the impact of Land Use (LU) changes to water turbidity in multiple watersheds. However, this study focused more on vegetal features such as palm oil, urban, forest, water bodies and bare features in the absence of flow direction as well as the flow accumulation of the terrestrial surfaces and subsequently recommended additional studies to identify the influence of LU and rainfall runoff as well as flood prediction. Another satellite image pre-processing was performed in applying Support Vector Machine (SVM) algorithm, both pre-disaster and post-disaster TerraSAR-X satellite images, data analytics for a rapid mapping events damage evaluation caused by the flood that occurred in 2013 and the 2011 tsunami in Japan. Some factors were extracted by the use of SVM algorithm in order to identify the damaged and non-damaged features of the area. The adopted approach produced a relevant visual analytical representation of the data needed by end-users for post disaster event assessment, which indicated about 30% of the area being affected by flood[40].

Correspondingly, a fuzzy based algorithm was adopted to distinguish between lands from water regions using spatiotemporal data[131]. The approach combines homogeneous features with averaged data that signifies a clear means of facing textural features. However, according to [132], currently, TWI is being employed in land cover studies, therefore, for an accurate identification of land cover features, this research employs both the TM land and Topographic Wetness Index (TWI) alongside other factors to correctly identify various spatial representations. This reviewed study successfully performed the pre-processing of the imagery for land cover. Auspiciously, the study further recommended the use of varied resolutions of imageries for other domain application as in this case of this research.

In the study conducted by [133], spatial imageries were pre-processed for the extraction of coastlines. Due to some inherent constraint observed by the study, the need to use imageries of higher resolution to monitor coastline was suggested. While in estimating the volume of flood in near real-time, a surface water detection using Moderate Resolution Imaging Spectroradiometer (MODIS) with DEM was performed by [134], in order to produce flood maps. Similarly, as also demonstrated by the study in [135], spatial imageries were pre-processed to extract areas affected by flood in order to monitor flood situations. Even though, the results showed a certain level of reliability, it could not detect flooded urban regions easily as a result of the limitation of their spatial resolutions. To this effect, this research still identifies the need to collect spatial data of high resolution in order to avoid similar issues.

While in another flood mapping study conducted by [136], DEM was pre-processed to identify flood vulnerability. Also, the wet surfaces were delineated from the dry areas before the inundated regions were eventually delineated from water bodies. In the same vein, spatial data was again pre-processed by [137], specifically, regions were classified into flooded, rain, and non-identified regions. This study demonstrated useful insight in using DEM for various classifications beyond topographic factor i.e. the inclusion of rainfall. Nonetheless, the reliability of the result was further marred by the exclusion of elevation and slope factors in addition to several other factors which can readily be obtained using the same set of data employed within the study. Hence, this research adopts an approach based on multi-factors in order to ensure the reliability and also the accuracy of the results. This is because, as earlier stated, the surface of the Earth exudes various

morphological features such as water bodies, vegetal features, and topographical features. Hence, the need for multiple sets of data to derive a holistic and accurate representation of these features.

Also, in the assessment of vegetal ecology on regional forestry, the study conducted by [132] pre-processed DEM where GPS plots were chosen. From each plot, list of plant species was identified, and the related vegetal stratification was identified in order to determine the soil moisture and differences of species composition. Even though, the study was conducted to identify the performance of various algorithmic applications, nonetheless, the result obtained from this study indicates the importance of TWI in vegetal stratification. Hence, this research identifies TWI as a relevant factor in causative upstream flooding events.

Finally, in another study, threshold segmentation algorithm was applied in order to extract flood extent with the aid RADARSAT-1 images in addition to digital topographic information [18]. The initial approach was to filter the images using filter of Enhanced Frost followed by geo-registration topographic data. Afterwards, the extent of the flood was mainly extracted from these images with the aid of threshold segmentation before the generation of Digital Elevation Model from the topographic data. Thus far, this research has reviewed some related studies on flood mitigation based on spatiotemporal data sets as further summarized in Table 2.1.

Table 2.2

Summary of the Pre-processing Approaches and Flood Mitigation Paradigm

Ref	Approach	Strength	Weakness	Opportunity for this research/Resolution(s)
[29]	Topographic-based approach	Identified flood vulnerability to a certain level.	Use of only elevation factor to identify and classify flood vulnerability.	RESOLUTION: The pertinent issue was resolved by using multi-factor to accurately identify and classify regional flood vulnerability.
[35]	Survey-based approach	Was able to identify the population residing within flood prone areas as well as those at non-vulnerable areas	Survey methods are unable to determine the hydrological characteristics of water bodies [38].	Identified the need for long-lead prediction to allow pro-active measures instead of reactive measures currently implemented. RESOLUTION: This issue has been resolved by successfully obtaining long-lead to allow proactive measures in section 4.2
[18]	DEM-based approach	Extraction of flood extent	Use of single factor to classify flood extent.	RESOLUTION: The limitation was addressed in this research by adopting Multi-factors pre-processing approach to identify flood vulnerability.
[34]	Survey-based approach with geological map.	Was able to identify the depth of the flood. In addition, the	Survey methods are unable to determine the hydrological characteristics of water bodies [38].	Recommended the need to consider water body and identify its changes. RESOLUTION:

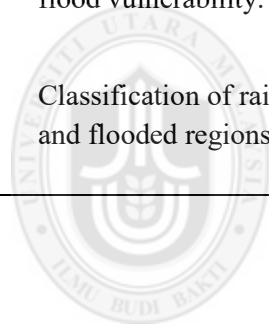
		study also observed that properties are more vulnerable to flooding events		The weakness as well as the recommendation were addressed in this research by classifying the vulnerability using NDVI and also learning the trend of water level alongside other temporal factors in subsections 4.1.2 and section5.2
[39]	GIS-based approach with physical elevation map.	The study was able to identify areas vulnerable to floods.	Floods are generally caused by multiple factors such as topography, geomorphology and climate[34]. As a result, the use of multiple factors to identify vulnerable regions would have generated more accurate result in place of the approached based on a paucity of data as adopted by[39]	The study recommends the use of satellite imageries. RESOLUTION: The recommendation was implemented in the research by using spatiotemporal sets of data in identifying and classifying regional flood vulnerability in section 4.1
[40]	Pre-processing EO imageries.	Identified pre- and post-disaster manages.	Pre- or post-disaster assessment only allows reactive measures to be implemented [35].	RESOLUTION: As the basis of this research, the pre-processed imageries were used to identify vulnerable regions for flood prediction in order to take proactive

[36]	Vegetal-based approach.	Ability to classify areas that are always, occasionally or never flooded.	Accuracy assessment for the permanently flooded forest theme could not be attained.	measures to enhance the adequacy of flood mitigation. RESOLUTION: The limitation of this study was tamed in this research, by using the vegetal stratification to classify flood vulnerability to region based on the density of vegetation (Sub-section 5.2)
[123], [124], [125] [126].	Elevation, Slope, TWI and Downstream-based approach.	Recommended the use of Multiple FCFs.	Absence of other factors that can influence inundation such as hydrological factors.	Recommended the use of high resolution imageries and multiple time series data. RESOLUTION: This research employed multi-factor approach in classifying and mapping flood vulnerability in addition to the use of several points of times series data as described in sub-sections 4.1 and 4.2 respectively.
[127]	Vegetal/Land cover classification approach.	Was able to classify water, sand, agriculture, cropland, island and settlement for flood inundation.	Absence of other factors that can influence inundation such as hydrological factors.	Recommended the use of high resolution imageries and multiple time series data. RESOLUTION: This research employed multi-factor approach in classifying and mapping flood vulnerability in addition to the use of several points of times series data as described in sub-sections 4.1 and 4.2 respectively.

[128].	Topographic-based approach.	Successfully, assessed flood vulnerability.	Absence of other relevant factors such as hydrological and vegetal factors	RESOLUTION: The limitation was addressed by employing multi-factors to assess flood vulnerability in section 4.1
[129]	Topographic-based approach.	Simplified means of identifying topographic factors.	Only topographical factor Limited coverage.	RESOLUTION: Emphasis placed more on the need to use EO imageries to ensure wider coverage in addition to finding other relevant factors.
[130]	Land cover-based approach.	Successfully classified vegetal factors such as palm oil, urban, forest, water bodies and bare features.	Required more factors to be considered.	Recommended the need to identify the relationship between vegetal factor, precipitation runoff and flood prediction RESOLUTION: Multi-factors utilized including vegetal factors, precipitation was equally used to predict any potential flooding events.
[131],[132]	Land Cover/TWI based approach.	Delineation of lands from water regions.	Absence of Topographic Wetness index as employed in [132].	Recommends the need to use other imageries beside Landsat TM. RESOLUTION: Nigeria-Sat-X was used in addition to LandSat-8

[133]	Pre-processing based on textural enhancement.	Coastline extraction	Scanty set of data Low image resolution utilized.	Recommended the need for high-resolution spatial data RESOLUTION: This limitation was addressed by using a relatively imageries of higher resolution in this research. In addition, multiple factors were considered.
[134]	Pre-processing based on MODIS and DEM	Combination of both MODIS and DEM	Only few factors considered. Very low Image resolution (500 m). Near real-time flood identification does not allow adequate time for proactive measures to be implemented.	Recommended the need for high-resolution spatial data. RESOLUTION: The recommendation as well as the limitations were addressed by using imageries of higher resolution (28 m). Multi-factors considered as well.

[135]	Pre-processing based on spatial data and DEM	Flood vulnerability extraction	Low resolution imageries and few factors considered	<p>RESOLUTION:</p> <p>The limitations were addressed by using imageries of higher resolution (28 m) described in section 3.2. In addition to the use of Multi-factors demonstrated in section 4.1.</p>
[136]	Pre-processing based on DEM	Identification of flood vulnerability.	Scanty sets of data considered.	<p>RESOLUTION:</p> <p>The limitation was resolved by employing multiple factors to identify flood vulnerability (section 4.1)</p>
[137]	Pre-processing using DEM	Classification of rain and flooded regions	Unspecified regions were classified. Scanty set of data	<p>RESOLUTION:</p> <p>The limitation was addressed by assigning various spatial features to their classes in section 4.2</p>



As identified from these various studies, the use of spatial data has been of a considerable contribution leading to flood disaster mitigation in various parts of the world. However, these studies are constrained by the use of limited factors in deriving insights for flood inducing factors which has undermined the level of accuracy in identifying regions that are prone to floods. Therefore, this segment of this research addresses the first component of the framework, i.e. the definition of flood hazard regions. The aim is to identify flood hazard zones, where mitigative measures should be taken. Thus, multiple spatiotemporal factors were introduced to delineate such regions.

Furthermore, it is noteworthy that, the basis of this research is to adopt a hybrid approach which pre-processing multiple flood causative factors to accurately identify and classify regional flood vulnerability within the study area. The second segment of the hybridized approach is to perform long-lead prediction for regions identified to susceptible to upstream floods, whose related studies have been reviewed in the ensuing subsection.

2.6.2 Lead-time Flood Analysis

In the last decade, several flooding events with relative devastating impacts in some parts of the world have caused loss of lives and economic havoc [138]. Identified factors such as streams have been equipped with warning features [138]. Nonetheless, more frequent severe precipitation has correspondingly led to an increase in flooding events. As a result, there is a need to propose a comprehensive predictive means for flooding events in order to implement a timely warning within the vulnerable regions [138]. Currently, a key research issue faced in the 21st century is to proffer early warning for any flooding events

with potentially devastating consequences[139]. A considerable long lead-time for flood prediction that allows timely issuance of flood warnings and proactive measures is a necessity due to the numerous logistical intricacies in securing vulnerable regions[140].

There exists several studies related to flood prediction and lead-time trend identifications in the past, with significant contributions in mitigation flood impacts either in the pre-flooding events or post-flooding events. Despite the immense contributions of these studies, there also exists some inherent limitations in the lead-time identification of any potential flooding events or the associated date of occurrence.

To this regard, this section meticulously reviews the state-of-the-art of various systems and techniques adopted in long-lead flood analysis which are highly needed by metrological department and most specifically, disaster monitoring/reporting agencies with the aim of mitigating the impacts of floods.

In an attempt to identify a potential flooding event in Pahang basin in Malaysia, structure based Neural Network Autoregressive Model with Exogenous Input (NNARX) for flood prediction within a lead-time of 10 hours with the aid of Gradient Descent as training algorithm was conducted. In the study, a model was obtained by segmenting data sets into Training data, Validation and testing data [51]. The water level data was cleaned by normalization approach between ± 1 prior to running the model. This was performed to remove the outliers in the data set[51]. The model was first obtained using training samples and then validated using validation samples. A historical data acquired for the period of ten days totaling 1463 were used for training sample.

Meanwhile, for model validation, 2000 data records acquired for a period of 13 days were used while 4000 data sets which were acquired for a period of 28 days were utilized as testing sample. The model was able to perform a 10-hour prediction of water level. Even though this approach seemed efficient, the lead-time of 10-hours is below the required 6-16 days lead-time to efficiently implement flood mitigating measures in alleviating any potential flooding havoc. More so that the model underestimated the water level and as such the prediction of the level of flood water does not correspond with the exact water level[51].

Similarly, a 7-hour prediction was made by utilizing the technique of Artificial Neural within the region of Terengganu [60], using the water level at the upstream and the water level and the site of the flood as parameters where a four-day samples of 542 data sets were acquired for modeling. While another four days data sets of 542 were collected for validation. For testing, a three-day data sets of 428 were used. The results indicated a successful 7-hour prediction of flood using NNARX technique. In another study, using an enhanced NNARX structure with the aid of Back Propagation Algorithm was successfully adopted to predict a water level flooding event in Kuala Lumpur with the lead-time of 5 hours[59]. The study utilized a real-time data for both input as well as the output data collected from the Department of Irrigation and Drainage, Malaysia [59].

The prediction of flash flood over small rivers based on time series conceptual rainfall-runoff technique has been in use since 1980 to predict the water level of Werra River in Germany using Least squares approach [138]. The period of calibration was between 1/11/2006 and 31/10/2008. While the data acquired between 31/3/2010 and 8/11/2010

were used for validation. The result yielded a slightly reduced level of accuracy due to some radar errors encapsulated in the precipitation data in addition to the low rate of rainfall within this period [138]. The overall performance of this technique was marred by the erroneous precipitation data that was recorded by a radar when it was not the period for a considerable rainfall.

In the same way, a survey-based study was also conducted in within the vicinity of Kainji in Niger State, Nigeria [141], where 100 respondents were administered 51% of which admitted receiving flood warning from Local radio station, 21% from market square, while small number received from religious centres and TV station. The study also made use of supervised form of classification to preprocess satellite imagery Landsat7 MSS on scene representing 191/053 spectral to identify the changes within Kainji in and its effect in Borgu community. The deteriorating effects of the environment was attributed to the agricultural activities of the inhabitants of the region which increases the vulnerability of the region to flooding events. As a result, the study recommends the development of an effective long-lead warning which will used against the impacts of potential flooding events.

Additionally, in [142], a study was conducted using NARX Neural Networks as well as Extended Kalman Filter (EKF) techniques to predict a flooding event with the aid of an algorithm based on back propagation which is commonly used. This however, was conducted without yielding any dependable results [142]. The study shows that NARX predicted relatively better, and despite the success it recorded in the predictions, the nonlinearity-related problems of data as well as the absence of input parameters requires an urgent solution. Consequently, the study proposed the integration of EKF alongside NARX technique to address this issue because EKF was developed to address nonlinearity issues [142].

In [143], a study on a two-three hour lead-time flood identification was equally conducted. Hourly precipitation records from 1988-2000 consisting of 30 incidents was used based on ANNs. Even though ANN-based serial-propagation generated a satisfactory output, the study identified the limitations of using ANN in decreased rate of learning as well as its performance in validation and testing phases. As a result, the approach was declared unsuitable especially within complex sets of data, and a recommendation for a more suitable and reliable approach was made.

In the study area of this research, a major milestone was attained by adopting a predictive technique based on Best Fit Probability Distribution to evaluate the volume of rainfall and runoff using one of the three Dams in the state as the case study. However, factors that induce a flooding event are not limited only to the volume of rainfall or runoff [144]. The use of time series data indicating water volume and discharge volume from other rivers as well as the satellite images to identify the attributes of the terrain and the hydrological

nature as recommended by previous studies [39], which if utilized, can accurately identify any potential flooding events as well as its severity within the study area and beyond [39].

In the same vein, a combined model based on Adaptive Neuro fuzzy Inference System, was employed to perform an hourly prediction in Yaojiang watershed[145]. Even though, the result indicated a four-hour prediction based on two-hourly inputs, further study was equally recommended for an issuance of a more enhanced early warnings. Similarly, a study conducted by Noor et al in [57], developed an NARX-based model to perform a twenty-four hour lead-time prediction. This was successfully done using ten months precipitation and river flow data[57].

In a flood predicting project embarked by EU, a cascading methodological approach for a 10-day lead-time flood prediction of river discharge and flooding within the European measure river bodies were performed using mesoscale precipitation prediction. The study [50] was guided by uncertainty cascade model involving atmospheric, rainfall and inundation approaches. Even though the approach seemed effective, the analytical result was affected by the under prediction of rainfall. Thus, was considered defective for a long-lead flood prediction. Therefore, the study suggested the enhancement in predicting rainfall as well as better comprehension of uncertainties in the precipitation and inundation mechanisms to reduce the prediction quantile in future studies.

Finally, using both spatiotemporal and big data analytical approaches, studies on long-lead were conducted in the State of Kelantan, using both precipitation and water level values to predict a seven day-lead time, and also for the State of Iowa, United States to

perform the prediction for a location using the heavy precipitation volume and the historical volume of precipitable water [63],[64]

Summarily, various approaches employed within a predictive domain are summarized in the Table 2.3.



Table 2.3

Summary of the Predictive Approaches

Ref	Approach	Strength	Weakness	Prospects to the present research/Resolutions
1	[51] Water level based prediction	10 hours	Lead-time Data sets	Provided longer lead-time using sufficient sets of data
2	[57] Prediction based on precipitation and water flow	24-hours lead-time and prediction	Scanty sets of data (10 Months); Insufficient lead-time	The pertinent issue was resolved by employing precipitation and water level data sets of 37 years to perform a thirteen day lead-time prediction
3	[59] Water level	5 hours	Real-time data	Historical sets of data was used within this research
4	[60] Water level Prediction	7-hours	Lead-time Data sets (four days)	Employed larger volume of data sets to perform a long-lead prediction of 13 days
5	[63][64]	Long-lead	Absence of FCFs	Adoption of the proposed hybrid approach.
6				

7	[143- [146]	Precipitation-based Prediction	3 hours	Lead-time	Longer lead time provided
8	[145]	Precipitation-based prediction	4 hours	Lead time	Provided longer lead-time using sufficient sets of data
9	[146]	Prediction based on water level	5-hours 5 years data	Lead-time Relative adequate data	Provided longer lead-time using sufficient sets of data



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Concisely, it is also worthy of note that, each of the reviewed studies tend to manage flood vulnerability in a slightly different manner which is broadly encompassed in flood management techniques as illustrated in Figure 2.8 from [147].

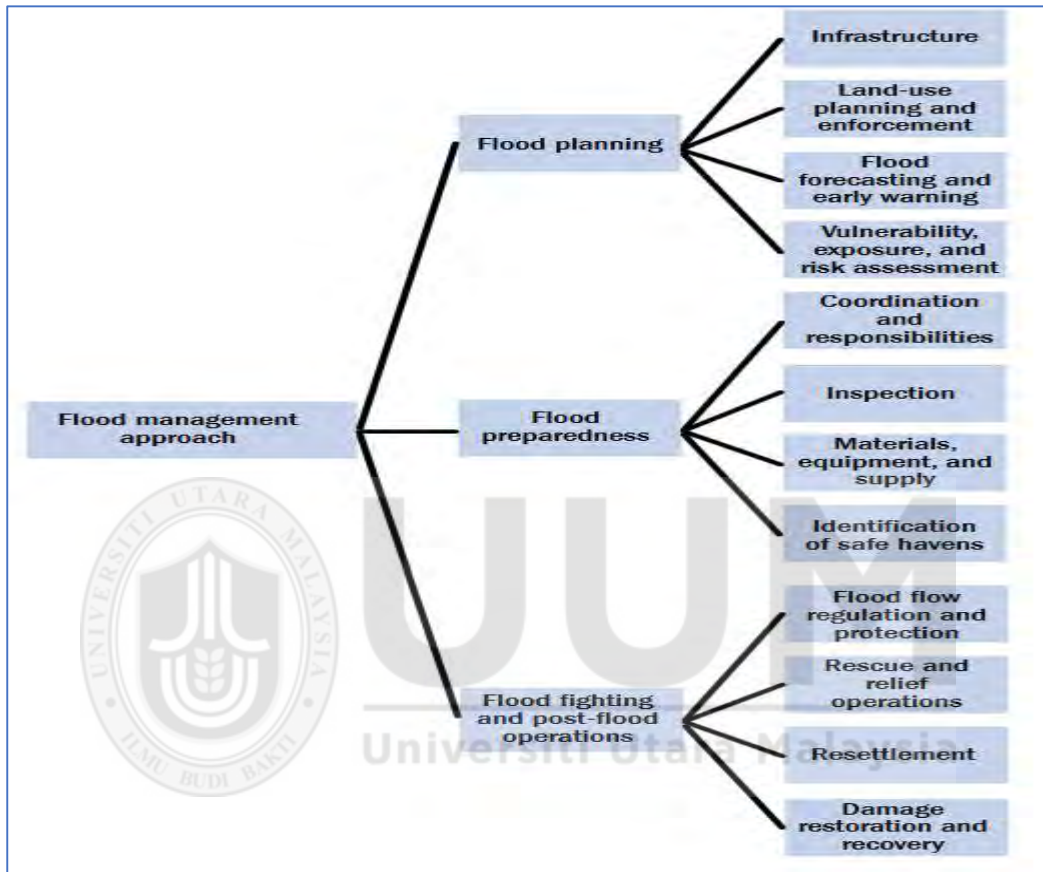


Figure 2.8. Flood Management Techniques

Concisely, the use of satellite imageries, survey means, and precipitation data as utilized by various studies for the purpose of flood mitigation, has immensely contributed towards a holistic understanding of spatiotemporal data pre-processing, flood prediction and ultimately, flood mitigation practices. The contributions also highlighted the primal need for more satellite features, and also the requirement for a longer lead-time in flood prediction. Aside the contributions and opportunities of these studies, there equally exists

some associated limitations as discussed in the ensuing subsection, which elaborates more on the critical aspects of the reviewed studies.

2.6.3 Limitations of the Extant Studies

As stated in the aforementioned subsections, the limitation, strengths and the prospects of the reviewed studies dwell on the effort made in identifying flood vulnerability associated with various parts of the world, with the aid of numerous approaches ranging from survey means to spatial data pre-processing using GIS-based environments. Despite the successes recorded in the various instances of vulnerability assessment and potential flood mitigation efforts, these approaches also present number of drawbacks. For instance, upstream floods can be instigated by either, topographic, hydrological, vegetal or anthropogenic factors[148]. However, in the reviewed studies, these causative factors were employed distinctively to identify and classify flood vulnerability. This practice evidently led to a reduced level of accuracy in flood identification within the areas of interest. In addition to the absence of the Flood Inventory or means of accuracy assessment. Therefore, to address these inherent issues, this research employs a multi-factorial approach that combines multiple factors to identify various regions that are potentially prone to flooding events in order to enhance the level of accuracy in identifying various regions that are susceptible to upstream flood within the study area.

In terms of lead-time flood prediction or analysis, the related studies in this regard were found to be challenged in providing accurate means of protecting and accommodating flood-related disasters. This is because, the lead-time which would have served to avert flood disasters considerably, was found to be short (1-24 hours), which is inadequate to

efficiently implement proactive measures in situation of flooding events, which are itemized as follows[149],[10]:

- I. to protect (avert and alter disasters);
- II. to accommodate (alter some structures used by humans to suit disasters);
- III. to evacuate (resettlement, prohibit development in disaster prone areas); and
- IV. to do nothing.

By implication, the first and the second strategies are proactive measures which are prioritized considerations for an effective disaster mitigation. While strategies based on three and four are usually considered passive efforts in the case of any disaster beyond human control. From the reviewed studies, most attention was focused on the passive option (To evacuate). While little attention was given to the first and second options as observed from the extant studies.

Essentially, a sufficient lead-time is required for proactive measures as in the case of Strategy One [54]. For instance, lead-time of 6-15 days of precipitation can aid to this effect[55],[56],[58].For instance, given a week's lead time, the sequence of information actions might be [58]:

- I. 3-5 days lead-time: to provide advisory or period of heightened risk; participate in awareness raising activities through media, mobilize support organizations for the vulnerable regions; initiate participatory information dissemination by local authorities;
- II. Hourly lead-time: to provide flood warning; activation of emergency response; evacuation of most vulnerable groups; provide prescriptive advice to individuals.

While the above sequence of events may seem to be ideal for a flood event mitigation, it will not be possible to provide much advanced information for all types of proactive measures to be implemented within a short period of time [58]. Hence, the need to have an adequate long-lead prediction of any flooding events as proposed within this research. This will ultimately enhance measures for Strategies One, Two and Three, in order to avert, accommodate and evacuate against any potential flooding events.

On the other hand, the study conducted by P. Taylor on Statistics of extremes and estimation of extreme rainfall, it has been identified therein that, the Gumbel distribution theory, which has predominantly been used for quantifying risk related to extreme precipitation is constrained by underestimating the high volume of precipitation [150]. Therefore, this research adopts approaches based on GIS theory as elaborated in the ensuing section.

2.7 Research Theory

Over the past decades, the structure of data used for GIS as well as the geographical representation has witnessed an exponential growth [151]. Faced with this inherent complexity created as a result of this growth, every potential GIS user is equally faced with the following issues:

- I. The need to identify the means of simplifying the complexity exuded by these sets of data;
- II. The need to identify a multidimensional theory to address and simplify the design and development of GIS research about the surface of the Earth, which consists of the descriptive, representative and the analytical features [151].

Therefore, to meet these needs, a theory that provides a simplified approach for spatial representation has been identified to be quintessential. Especially, in aspect of any scientific research and management of the surface and near-surface of the Earth, involving its description, representation, analysis and visualization [151]. Within the scope of this research, the proposed GIS-based theory in [151], was used to identify the approach needed in response to several desiderata of a spatiotemporal analysis which is aimed at:

- I. Providing appropriate patterns of spatial representation to identify the interrelationship between domains and features of the environment;
- II. Extending the domain and feature representations, and the pattern of representation developed to handle them, into the temporal domain;
- III. Providing a means of developing spatiotemporal visualization extent and develop their essential properties.

Another significant aspect of the GIS theory is that, analysis utilizes continuous comparisons of the events. This implies that as events are identified, they are associated to other events for comparisons or dissimilarities. The subsequent concepts will then be characterized, and within time, they are equally compared and classified. These comparisons can aid to attain an enhanced level accuracy. Correspondingly, this research compares flooding events and the regions targeted with other regions in order to identify the levels of vulnerability and the most influencing factors of the flooding events and eventually with Flood Inventory.

As discussed thus far, the principles of the adopted theory encompass the general approach on data collection, spatiotemporal data pattern representation, visualization and analysis of regional flood vulnerability.

2.8 Chapter Summary

The literature review in this chapter provides related background details on the impacts of flood, flood mitigating paradigms, and essentially, various approaches employed in spatiotemporal data pre-processing and flood prediction. The review serves as an ideal lens of identifying relevant flood causative factors as well as the processes utilized in flood vulnerability classification. Ultimately, in order to develop the desired hybrid framework, several works from the reviewed studies were adapted based on multi-factorial approach to accurately classify regional flood vulnerability, and also to perform long-lead prediction which are the basis of this research. The next section explains in detail, the research methodology adopted at attaining all the research objectives.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the research design which discusses the approaches adopted in the conduct of the research with the corresponding flow of applied research processes to answer the research questions in Section 3.2. Section 3.3 discusses the means of identifying multiple flood causative factors which eventually aided in identifying the forms of data needed to be collected. Methods employed in pre-processing the collected multi-spatiotemporal data is described in Section 3.4. The hybridization processes involving regional flood vulnerability classification and long-lead prediction is presented in Section 3.5. Section 3.6 discusses the justification for using spatiotemporal data sets. Means of accuracy assessment is explained in section 3.7, and eventually, the chapter concludes with a summarized segment in section 3.8.

3.2 Research Design

A research design plays a crucial role in any meaningful research. It represents the general guiding precepts utilized by a researcher to combine several components of a research in a rational and structured manner, in order to successfully attain research objectives. Similarly, a research design ensures the adequacy of the procedures employed in obtaining valid and accurate answers to research questions[152]. It serves as a focal point for a well-conducted research and provides comprehensive processes for the collection, analysis and interpretation of data. Consequently, Figure 3.1 illustrates the components of the adopted design in the course conducting the research.

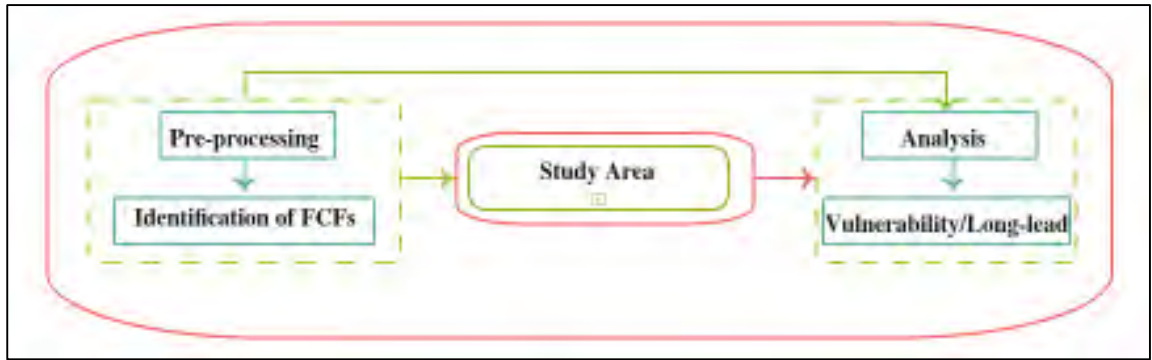


Figure 3.1. Research Design: Adapted from [152].

By context, this research is based on experimental approach. By definition, scientific experiment represents a systematic approach to conducting a research in which the researcher employs one or more variables, and measures any change in other variables and to reliably establish a cause-effect relationship between the variables [152], [153].

Within the scope of this present research, it can be concluded that the utilization of spatial data to measure and classify the regional flood vulnerability as well as the temporal and seasonal observation of the precipitation leading to upstream floods, reflect effectively on the experimental mode of research. This is essentially so, because the phenomenon which is the upstream flood and the attempt to observe what caused it (causative factors), has led to the revelation and equally the identification of the various factorial influence to establish the effects leading to a potential upstream floods in various regions.

Therefore, by implementing this research design as shown in Figure 3.1, various tasks from the identification of multiple flood causative factors to vulnerability classification, as well as long-lead prediction were accomplished in phases in order to meet the objectives of the research. The phases with the corresponding tasks are detailed in Figure 3.2.

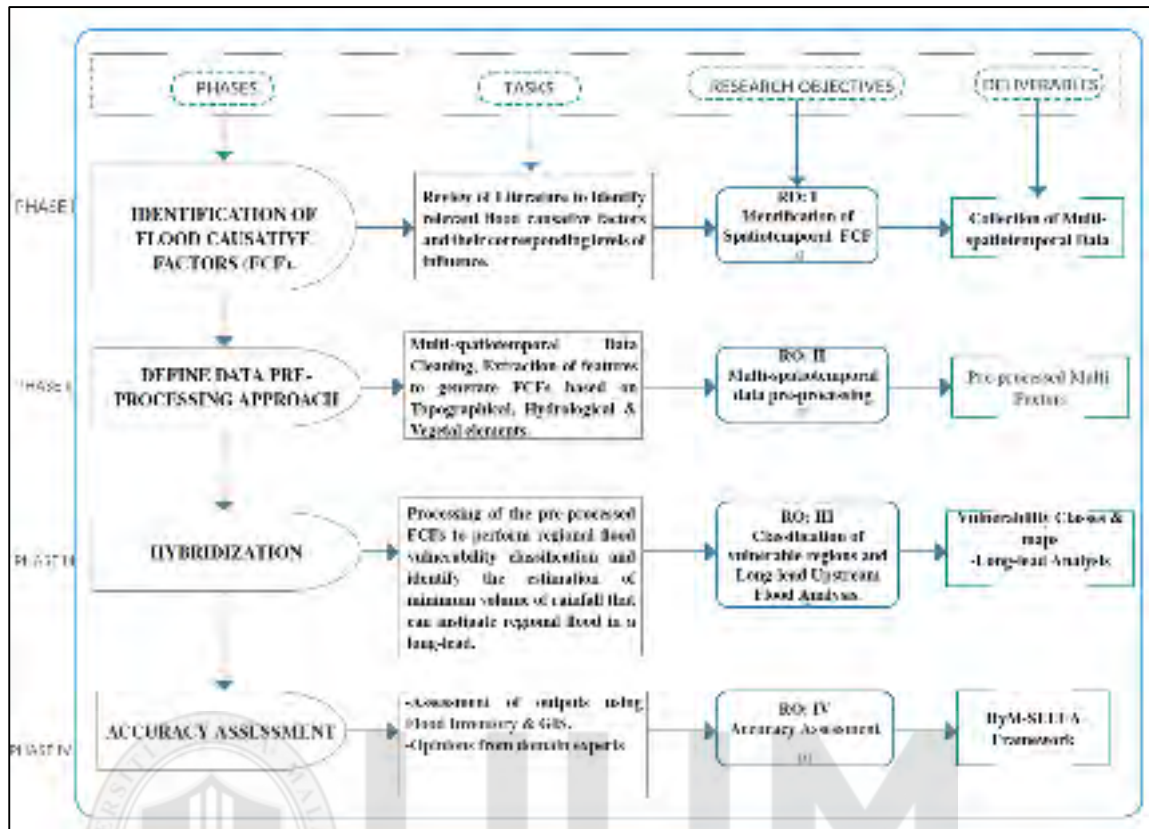


Figure 3.2. Applied Research Processes

Essentially, Figure 3.2 describes various tasks in phases and the corresponding deliverable that led to the realization of the hybrid framework.

Overall, there are four phases involved in the applied research processes, which are: 1) Identification of multiple flood causative factors, 2) Definition of data pre-processing approach, 3) Develop hybridization approach and 4) Framework accuracy assessment, which correspond to research objectives one, two, three and four respectively. Furthermore, these processes are further detailed in the ensuing section distinctly.

3.3 Phase I: Identification of Flood Causative Factors

As earlier stated in the problem statement (section 1.2), the main issue that led to the reduced level of accuracy in flood vulnerability classification, was associated to the

inadequacy of factors considered in classifying regional flood vulnerability. Therefore, in order to fill this gap, this section elaborates the approaches used in identifying multiple factors, which can enhance the level of analytical accuracy of the research. Fundamentally, this research identified other relevant flood causative factors from the insight gained when such factors were either adopted or recommended in the reviewed studies in subsections 2.1.1 and 2.1.2 for both spatial and temporal factors respectively, or as further revealed by the experimental assessment conducted subsection 4.2.1

Also, the identification of these factors within the reviewed studies essentially determines the type and the sources of spatiotemporal data collected in order to adopt a multi-factorial approach when classifying regional flood vulnerability. The use of several spatial features is primarily required to generate relevant flood causative factors (multi-factors) aimed at addressing this inherent research gap posed as objective one in section 1.4. Ultimately, the need to address this issue has further been supported by other studies. For instance, according to [154], in order to provide the most accurate spatial and temporal resolutions of data and framework, it is crucial to consider heterogeneous data sources. It stems from the fact that natural disasters are typical examples of complex conditions in which multiple factors have to be considered to proffer accurate and robust assessments.

Specifically, in flood identification, the presence of several land features (factors), each with a specific traits requires classification into floodable or non-floodable vulnerability conditions, which will ultimately aid in identifying the locations and the extent to which the region are exposed to floods is the most basic information needed for flood mitigation strategies[154]. Regrettably, a comprehensive identification of these regions is still

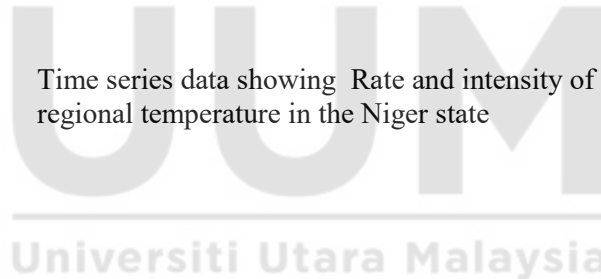
lacking in many parts of the world[154]. Concisely, the identification of the aforementioned relevant flood causative factors has led to the collection of multi-spatiotemporal data collection. Therefore, the subsection that ensues discusses the concept of spatiotemporal data collection.

3.3.1 Data Collection

Generally, studies based on GIS are more focused on the collection, visualization and analysis of spatial data sets. However, the most valuable aspect therein, is the data collection facet[155].Therefore, in order to collect various data sets required for this research, both terrestrial (Remote sensors) and space assets (Satellites) were considered as the main sources of the utilized data sets. It is pertinent to highlight that these devices have been deployed by the space research bodies such as the National Aeronautics and Space Administration (NASA), European Space Agency (ESA), the National Space Agency (Malay: Agensi Angkasa Negara), abbreviated ANGKASA and the Nigerian National Space Research and Development Agency (NASRDA) in order to capture weather-related information and features associated with geographical locations at both national levels and beyond as summarized in Table 3.1.

Table 3. 1.
List of Collected Spatiotemporal Data Sets

S/N	Collected Data	Purpose	Source
1	NigeriaSat-X (22m Resolution)	To extract the following factors: -Topographical -Hydrological.	Satellite, NASRDA, Nigeria
2	Water Level (1979-2016)	Time series data showing the volume and rate fluctuation of water body in Niger state.	Remote Sensors, NIHSA, Nigeria
3	Precipitation/Rainfall(1979-2016)	Time series data showing Rate and volume of regional rainfall in Niger state	Remote Sensors CAR, Nigeria
4	Temperature (1979-2016)	Time series data showing Rate and intensity of regional temperature in the Niger state	Remote Sensors CAR, Nigeria
5	Flood Inventory (2006-2017)	Records of the past flooding events in the state. This consists of the date, and the regions affected	In-situ NEMA &NSEMA Nigeria
6	LandSat-8 Data (30m resolution)	Land Cover	Satellite, NASA, USA
7	Shape file (Administrative)	Indicating the attributes of a map (states, cities and the boundaries)	Satellite, NASRDA, Nigeria



8	Shape files (Water bodies)	Used to identify water bodies in Nigeria and extract water bodies in the study area	Satellite, NASRDA, Nigeria)
9	Global Disaster Inventory(1980-2015)	To identify the trend of global flooding events	In-situ CRED, Belgium
10	TRMM Data	Regional Precipitation Average	Satellite, NASA, USA

Here, even though Tropical Rainfall Measuring Mission (TRMM) data was collected to depict the seasonal and regional precipitation volume, this research only made use of the time series temporal data (Appendix B) for long-lead analysis. This is because, in the study conducted using TRMM for performance assessment over Pehand River [156], it has been identified that TRMM tends to overestimate the rainfall measurement by 26.95% on average. Therefore, terrestrial remotely sensed data was collected since it has more precision and its daily format covering many periods allows long-lead analysis to be performed reliably, while the TRMM was used for regional precipitation mapping.

Similarly, LandSat Map representing Nigeria was needed to be employed for the identifications of scenes depicting Niger state as illustrated in Figure 3.3

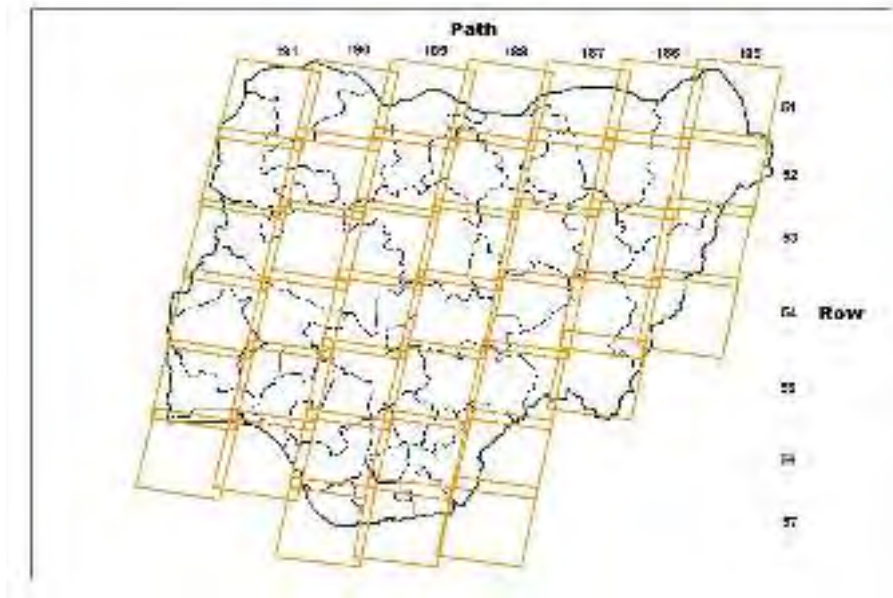


Figure 3.3. Land-Sat Map of Nigeria

Adapted from [157].

Illustratively, LandSat 8 was acquired from the United States Geological Survey website using both paths and rows corresponding to the boundaries of Niger State identified on the Landsat Scene map.

The points corresponding to Paths and Rows of the study area were outlined to be 189/053, 189/054, 190/052, 190/053, 190/054, 191/052, 191/053 which were used to identify the scenes on United States Geological Survey's website to obtain seven corresponding scenes as illustrated in ensuing illustration in Figure 3.4.

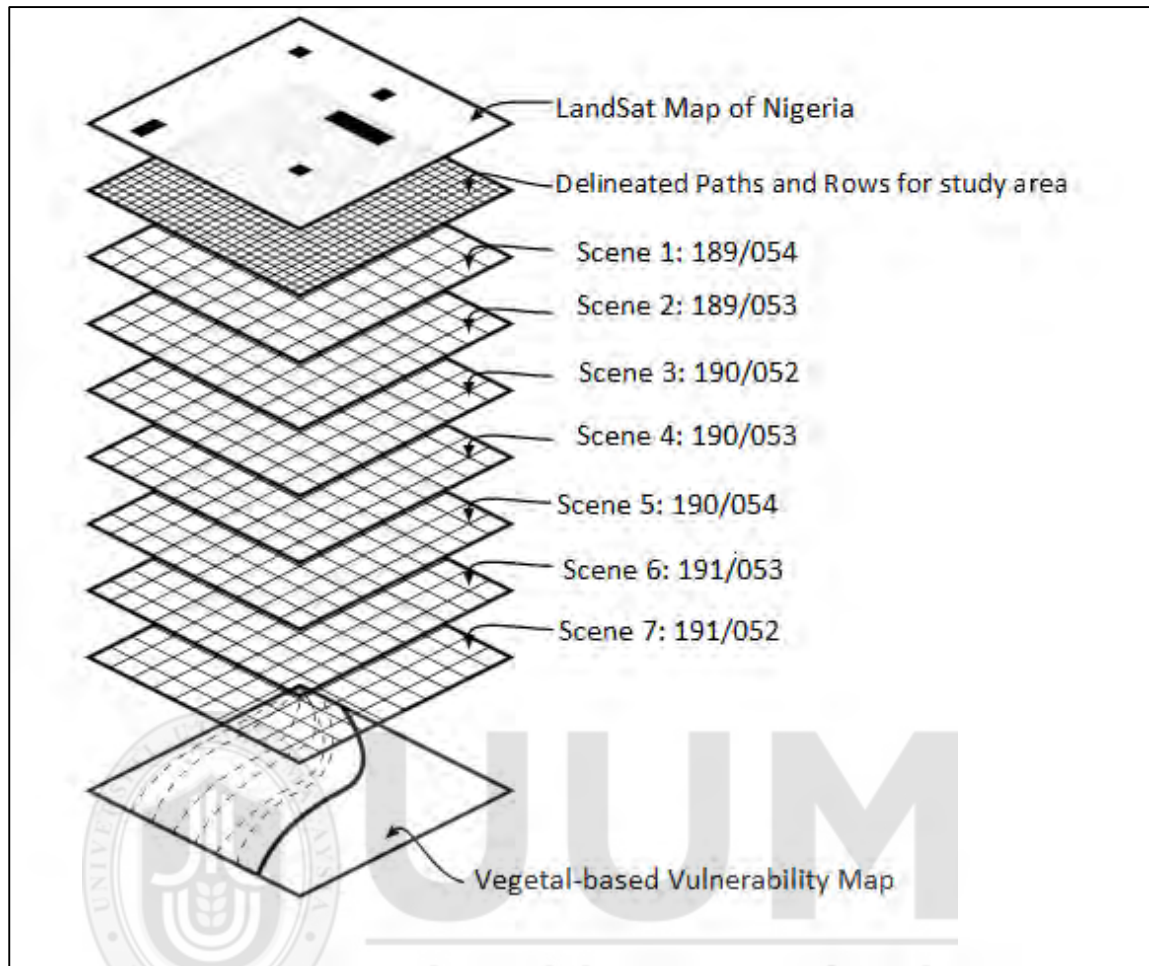


Figure 3.4. Landsat8 Collected using Scene Method

In collecting satellite imageries using scene method for the study area, the Landsat map of Nigeria as shown in Figure 3.3, was used in identifying the values of both Paths and rows to get the nearest scene center latitude and longitude coordinates of the study area to produce the vegetal-based vulnerability map in Figure 4.5 in Chapter Four.

Here, the values corresponding to paths and rows generated seven scenes for the study area as shown in Appendix K. This is because the study area is associated with a vast and complex geographic pattern. Hence, the need to have these scenes to have a complete spatial coverage of the state, which eventually reveals the vegetal features of the state.

3.3.2 Source of Data

As illustrated in Table 3.1, most of the data were collected from the Nigerian Space agency known as National Space Research and Development Agency (NASRDA). The agency uses NigeriaSat-2 and NigeriaSat-x which are controlled from the ground receiving segment stationed in Abuja, Nigeria [158],[159]. Operations, such as task schedules, data capturing, and classification of satellite data are carried out from this terrestrial segment [159].

3.3.3 Data Policy

Data acquired from this satellite are free for Nigerian-based researches, while the imageries are marketed within Africa by GeoApps Plus Ltd; a marketing department under NASRDA. The marketing of data beyond Africa is done by Disaster Monitoring Constellation (DMC). NASRDA owns a conventional support department situated within its premises to proffer support for UN-SPIDER in the field of disaster management and Technical Advisory Mission [160],[161]. Thus far, the sets of the data collected, the methods and their use have been further summarized in Figure 3.5.

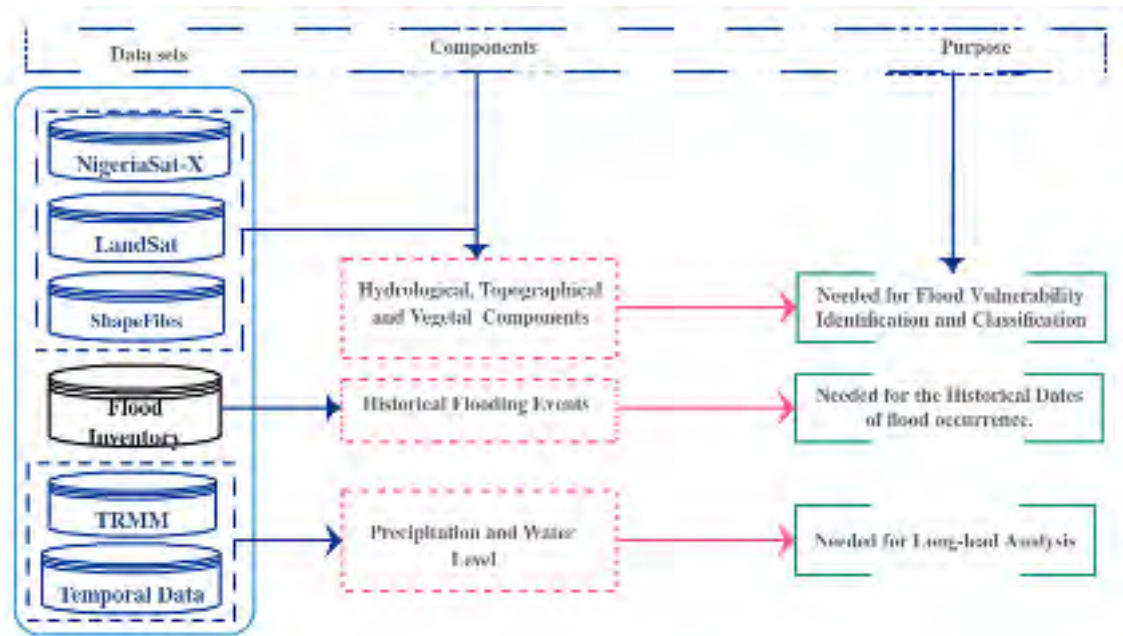


Figure 3.5. Summary of Collected Spatiotemporal Data

Briefly, one of the contributions of this research in addressing the first objective is that, the final output is not constrained by the limitations of using insufficient sets of data since the entirety of the research is based on multi-factorial approach of spatiotemporal data pre-processing. Thus, minimizing the impacts of analytical inaccuracy in the overall quality of the proposed hybrid framework. Ultimately, this approach is sought to enhance the accuracy of classification of regional flood vulnerability and also long-lead upstream flood prediction for better decision-making.

As earlier discussed in section 3.3, spatiotemporal data were collected from multi-sources. Pre-processing these Big Data necessitates an effective methods to be implemented to exploit their information [154]. Even though it has been identified that, a seamless integration of techniques to pre-process these sets of data is challenging [162],nonetheless, the ensuing section details an adapted architectural processes employed to address the

fundamental challenges involved in pre-processing these vast and complex data sets required to reveal the encapsulated factors capable of inducing upstream floods.

3.4 Phase II: Definition of Multi-spatiotemporal Data Pre-processing Approach

Here, the collected spatiotemporal data were pre-processed to obtain the required multiple flood causative factors, which further processed for vulnerability classification. Generally, pre-processing involves data cleaning as well as various tasks involved in transforming a set of data to an enhanced formats prior to the analytical tasks[12],[163]. In this research, the collection of data sets was done from a data-intensive sources and as such, the uncertainty of these data is intrinsic [162]. Additionally, the collected sets of spatiotemporal data involve varied forms of data from multiple sources; a typical characteristics of “Big Data” which are known with various forms of complexity[164],[165],[166],[167]. Therefore, making an accurate decision in strategic spatial domain is heavily reliant on the extraction of knowledge from vast volume of data sets[168].

As a result of the large volume of spatiotemporal data collected for this research, and due to the uncertainty of spatial factors, pre-processing this sets of data remains a very complex practice[168]. Hence, this section addresses the inherent complexity in pre-processing these vast volume of data that are crucial in this research which in turn, fills the gap of research objective two by defining a pre-processing technique to determine multiple spatial factors needed for regional flood vulnerability classification.

To this effect, the ensuing procedural architecture in Figure 3.6 was adapted to ensure the pre-process and processing of these multiple sets of data.



Figure 3.6. Information systems framework and Spatiotemporal Data Management Architecture

Adapted from [162],[169],[170], [171].

As shown in Figure 3.6, the spatiotemporal data management architecture exudes a suitable illustration on how to properly pre-process and process these complex sets of data. This essentially was conducted by the guiding principles of Information System, which states that any methodological framework must ensure a span through the whole range of developmental phases, i.e., from project identification to the successful completion of any project[171]. Within various phases of this present research, the pre-processing segment of the architecture encompasses phases– from data cleaning through feature extraction. While the processing segment involves pattern classification, regional flood classification and evaluating the levels of influence posed by the factors in inducing upstream floods using AHP. After which, the accuracy of the approaches was assessed prior to framework validation.

Specifically, within the context of this research, cleaning of these sets of data as discussed in the following section, is considered an effective means of ensuring the accuracy and analytical reliability [172],[173]. This practice was equally needed to ascertain the veracity (i.e., Big Data characteristics) traits in the pre-processed data prior to its extraction for subsequent flood vulnerability classification.

Similar with other domain, environmental analysis, the utilization of tools for problem solving is one thing; to proffer these tools is another. Not all every tool is suitable for a specific environmental application. Broadly, managing spatiotemporal data sets involves approaches ranging from data acquisition, data analysis as well as the generation or presentation of the eventual output. In the past, these approaches have been based on analogue means of data acquisition and manual methods of processing [174]. The recent advent of modern technologies has prompted an increase utilization of Information Systems required for the creation, manipulation, and storage as well as an enhanced use of spatiotemporal data compared to conventional applications in every facets of spatiotemporal data management; Geographic Information Systems. Essentially, an Information System, which is a collection of tools for data management— through data acquisition, data retrieval, data pre-processing as well as data processing, contains both analogue and digital forms of data sets describing the real world phenomena.

Explicitly, with the aid of Information Systems tools, the data sets were selected, classified and synthesized to generate details representing these phenomena, such as the use the topographical, hydrological and vegetal data sets to reveal and classify the real representation of flood vulnerability within the study area. Also, while spatiotemporal data is always associated with geographical locations, i.e., large-scale location consisting of topography, hydrology and land cover land use climatic factors beyond human, Information Systems is employed as the main tools needed to derive knowledge or insights from these spatial elements for decision-making. A comprehensible representation of geographic location for decision-making, is the factor that determines the tools required for spatiotemporal data processing, and placing more emphasis on the observable and

describable spatio-temporal effects with the information systems. To this effect, the ensuing subsection describes the approaches employed on data cleaning.

3.4.1 Data Cleaning

Broadly, data cleaning which is also referred to as data cleansing, focuses on the detection and elimination of errors and inconsistencies from data which is aimed at improving the quality of the data sets to suit a desired objective[175],[176]. Essentially, proper utilization of high-quality sets of data aids in making better predictions, analysis and decisions[177]. Inversely, low-quality sets of data are unsuitable for the intended purpose. For all intents and purposes, data cleaning is the process of normalizing or eliminating inaccurate sets of data[177]. This process is indispensable and particularly vital for Big Data Analytics, because erroneous data can lead to poor inference and analyses[177]. This becomes a concern mostly, when large-scale heterogeneous data from varied sources are integrated for a purpose of data analytics [177], as in the case of this research.

In satellite imageries, the cleaning processes involve using radiometric, geometric and data enhancement techniques, which aids in correcting, transforming and revealing the encapsulated information within the spatial imageries. While the temporal data sets were subjected to winsorization in order to identify and remove the outliers and missing values as illustrated in Figure 3.7.

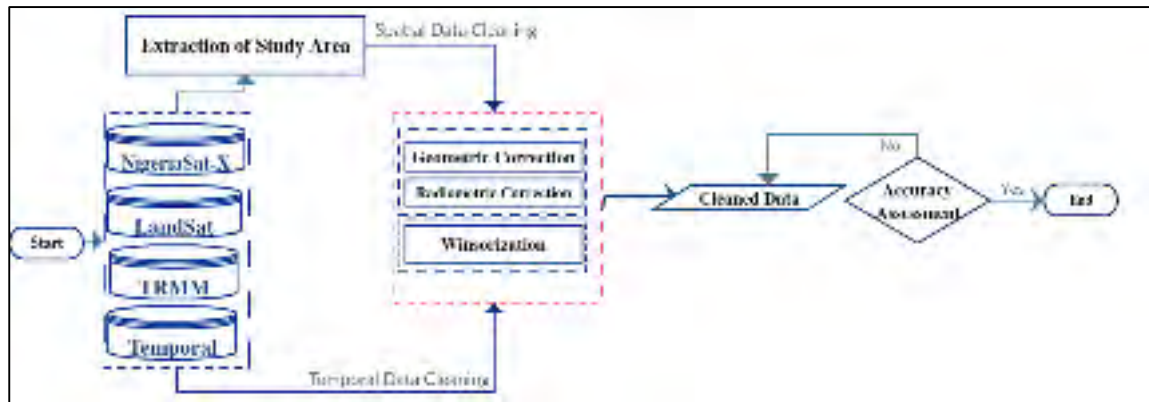


Figure 3.7. Flowchart of Spatiotemporal data Cleaning

Adapted From:[130],[164],[178],[179],[180],[181]

As earlier discussed, satellite or spatial images like every other raw data are prone to errors. Therefore, the following processes were performed in order to obtain data sets with a relatively reduced error.

3.4.1.1 Spatial Data Cleaning

Mostly, spatial data cleaning is a fundamental first step of multi-sourced spatial data pre-processing and knowledge discovery [182]. Conventionally, spatial data cleaning is the process of enhancing the quality of spatial data. This primarily involves examining and affirming the completeness and consistency of the collected sets of data[182]. Furthermore, it also encompasses the elimination of erroneous data, filling of missing details, denoising, performing both radiometrical and geometrical corrections, and enhancing the whole usability of the data. Beyond this, spatial data cleaning also analyzes the spatial data[182].

Specifically, an accurate interpretation of remotely sensed data requires that digital imageries be corrected radiometrically and geometrically prior to analysis[183]. This pre-

processing step is one of the basic elements of image analysis [183]. To this effect, the study area was extracted from other regions of Nigeria prior to the aforementioned corrective processes of the imageries as demonstrated in the following sub-subsection.

3.4.1.1.1 Extraction of Study Area

The extraction of the satellite image representing the study area was performed with the aid of the EO satellite NigeriaSat-x digital imageries at 22m resolution as shown in Figure 3.8. Primarily, the satellite image collected covered the whole of Nigeria. Hence, the need to extract only the area of interest (i.e., Niger state). Using the shapefile shown in Appendix D. Even though, the imagery does not have any regional attributes, but broadly, it depicts both hydrological and topographical causative factors of Nigeria in addition to the identification of major water bodies (Appendix E). While Landsat8 was used to determine the vegetal factors.

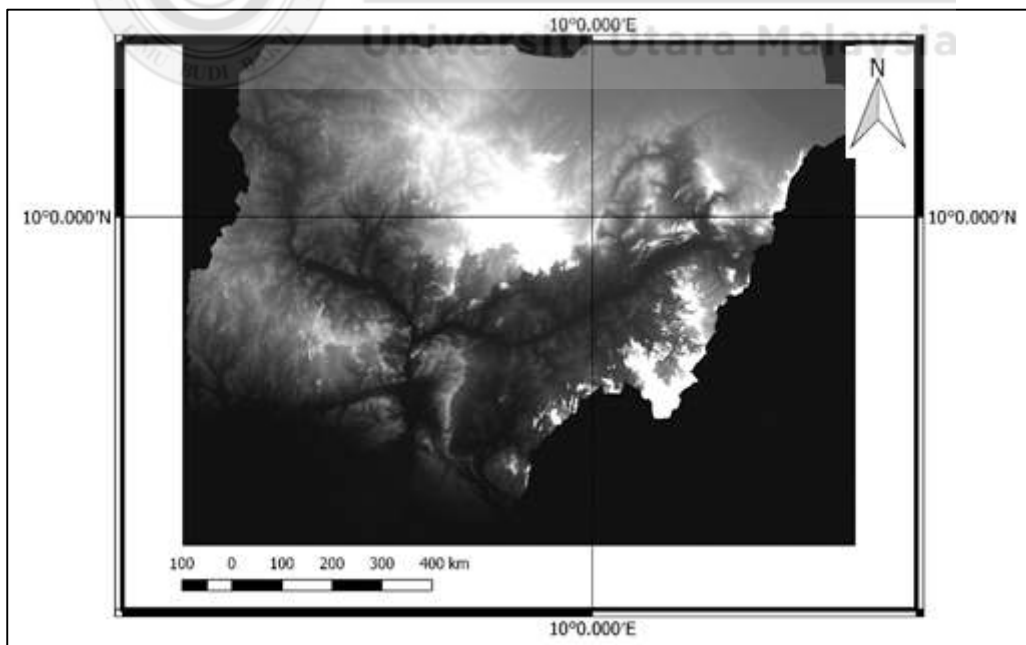


Figure 3.8. Raw NigeriaSat-x

Raw satellite images with the coverage of Nigeria; the lighter and darker regions represent higher and lower elevated regions respectively. From the satellite imagery in Figure 3.8, the study area as illustrated in Figure 3.9, was extracted using the administrative shapefile, which contains the thirty-six states of Nigeria in addition to the Federal Capital, and these states have a total number of 775 Local governments out of which, 25 are under the administrative boundaries of the study area (Appendix D).

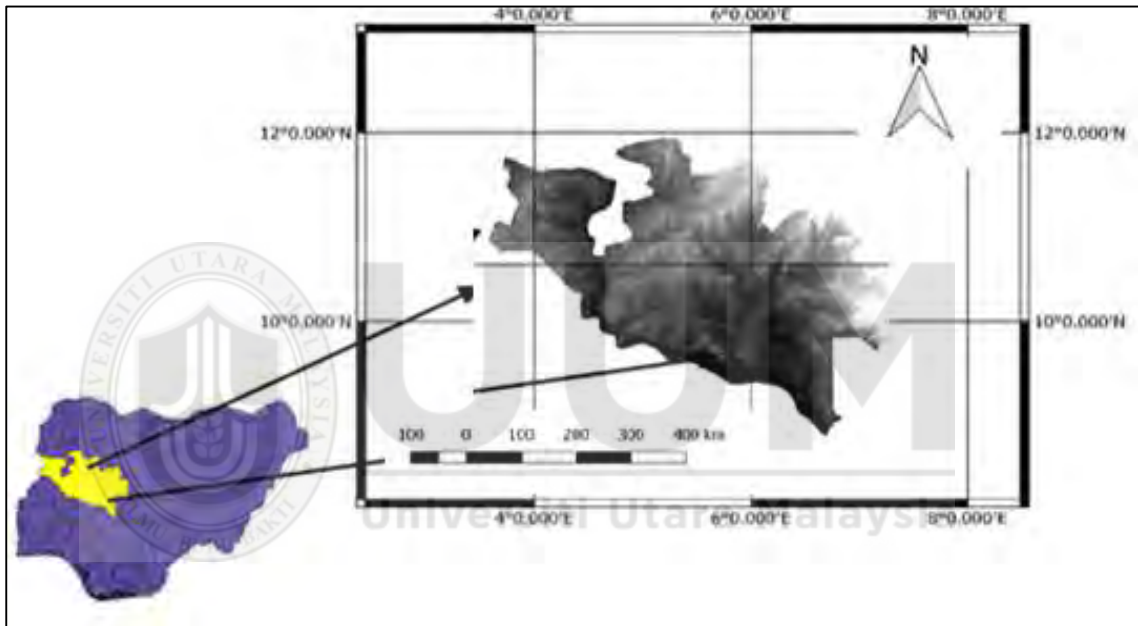


Figure 3.9. Extraction of Study Area

The above figure shows the extracted study area clipped from the rest of the Nigerian spatial map with the aid of NigeriaSat-X and Administrative Shapefile.

Generally, this method of extraction approach in Geographical Information System (GIS) was performed by clipping the imageries, which refers to the overlaying of a polygon on a target and extracting a raster data (satellite image) that are within the indicated study

area of the polygon. In applying the clipping method, the study area was therefore extracted while the features outside of the boundary are delineated.

Similarly, in identifying the vegetal causative factors, the images acquired based on paths and rows (LandSat8) were used. These images had a swath, a coverage beyond the study area. Therefore, the TM imageries comprising of seven scenes were equally delineated. As earlier highlighted in the previous chapters, satellite imageries exude numerous errors, which range from random to human errors within the acquisition of these images as a result of the equipment used in the calibration. In addition, these errors could equally be as a result of either atmospheric distortion or cloud cover. These errors can directly impede the accuracy of the input data and indirectly affect the accuracy of the output data. As a result, the foremost task within this section was the cleaning of the extracted imagery as explained in the ensuing section.

3.4.1.1.2 Radiometric Correction

As a result of vast scale of spatial coverage of satellite imageries, acquisition of imageries over a curved terrain in two dimensional representations leads to geometric distortions[184]. Additionally, with recurrent acquisition, radiometric reliability is hard to preserve between different scenes of imageries due to different atmospheric conditions, variations in the solar illumination angles, and sensor calibration trends[184],[185]. Consequently, among the various aspects of image pre-processing, there are two outstanding requirements: geometric and radiometric corrections[186]. Fundamentally, as identified in [187], radiometrically correcting a raw data is vital in order to remove missing

lines of data, and also for the elimination of the existing intensive variations in bands which are induced by the conflicting sensitive nature of satellites calibration.

The adoption radiometric correction approach, which is matched with the study's purpose yields accurate results after correction on the TM imageries as methodologically illustrated in Figure 3.10.

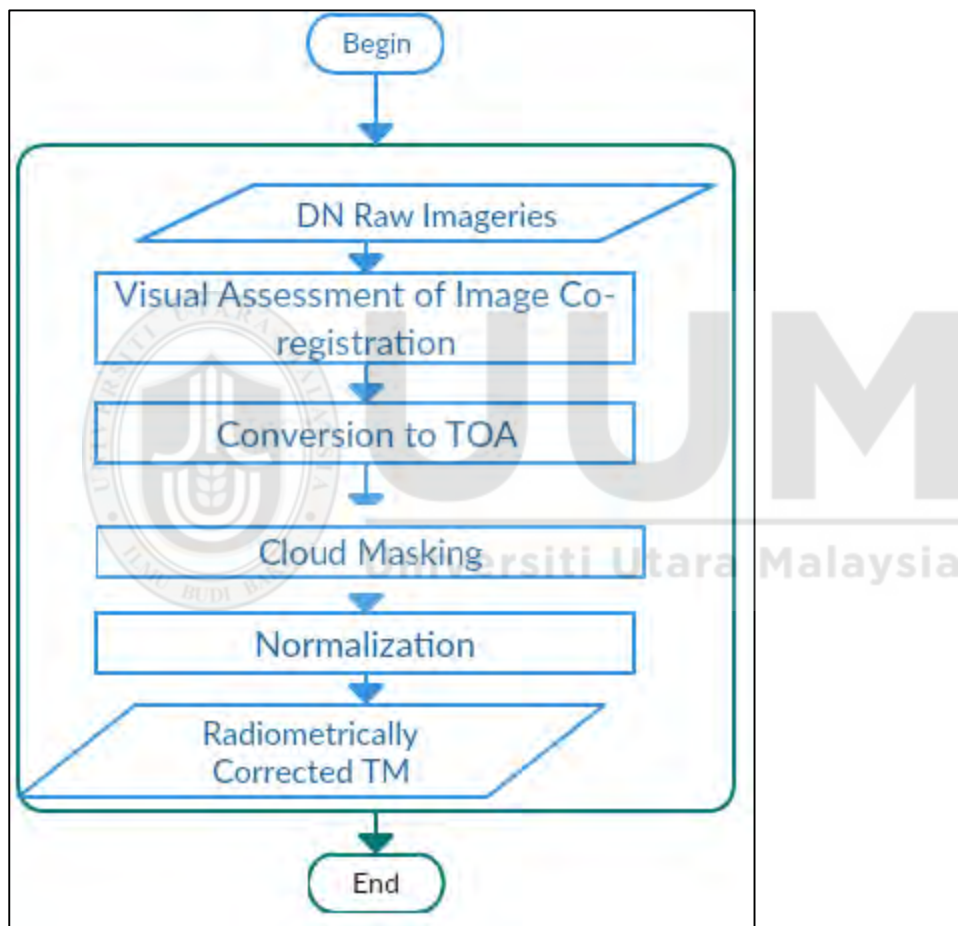


Figure 3.10. Radiometric Correction of TM Imageries

Specifically, this process involves the use of GIS tools to convert DN values to spectral radiance, then converting the resultant spectral radiance to apparent reflectance as recommended in the study conducted in [188].

After these initial processes, the atmospheric effect as removed before the reflectance of pixel of the Earth's surface was derived for the subsequent processes of the study. Additionally, since there was no cloud-free Landsat-8 TM images that were available for the study area at the point of data collection at the United States Geological Survey repository, the collected images were acquired under the cloud cover of 10 percent. Therefore, in order to meet the basic criteria defined in [189], which is to ensure less than 10 percent of cloud cover, the scenes of the spatial imageries were further corrected to remove the atmospheric distortions.

This practice involved the co-registration of the scenes in the same coordinate system because the study area was captured using seven scenes at different paths and rows. Also, the study area is within the equatorial region. Therefore, the cloud in the images were masked to decrease the problem encapsulated in satellite images which can potentially affect the output of the images in conformity with [13]. The output of this correction generated vegetal index and water bodies in the study area which were used to identify areas with low, moderate, dense or non-vegetal surfaces. The identification of the vegetal feature was crucial in the classification of regional flood vulnerability as presented in Chapter Four.

In the same vein, an accurate approach that can geometrically correct these images as presented in the ensuing sub-subsection is equally very crucial for environmental analysis. This geometrical correction is mostly pertinent to Digital Elevation Models (DEMs) as well as flows which can severely induce floods in the study area[190].

3.4.1.1.3 Geometric Correction

In general, the vast utilization of satellite imageries in various domains presents the need to geometrically correct the inherent distortions of the images to a desired projection[191]. Therefore, in furtherance to ensure the accuracy of the framework, this study after the radiometric correction, also performed the geometric correction which has the primary aim of eliminating the geometrical alterations displaying in the raw satellite images. Remotely acquired images are directly assigned coordinates referred to as projection. The challenges that are frequently experienced during the acquisition process is distortion, which can lead to serious discrepancy between the exact point on the ground and these coordinates in the acquired imageries, as a result of the satellites in the orbit. In applying geometric correction, reference map was used to assign the projection needed to determine the spacing as well as the grid points as illustrated in Figure 3.11.

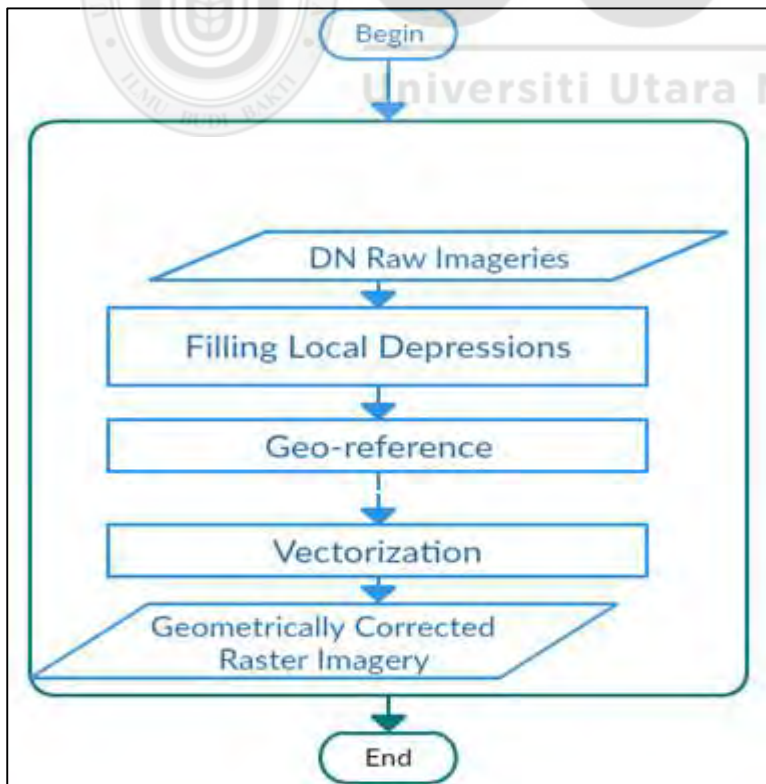


Figure 3.10. Geometric Correction

The standardization of the imageries into various formats from the originally collected formats enables the integration of the various data sets into the GIS tools for pre-processing processes. The satellite imageries were first pre-processed (filling local depressions), the sinks and imperfections of DEMs were identified and filled because if not done, they will cause the surface flow to disappear and invalidate the water balance [192],[128]. After this preliminary correction, the images were geo-referenced to Universal Transverse Mercator (WGS84- Zone 32N) and a common window covering the same geographical coordinates was then extracted from each of the images in conformity with [192],[193],[194].

In search of comprehensible and relevant factors needed to describe imageries, it is required to render the imageries interpretable by humans [195], in form of image enhancement as discussed in the resulting sub-subsection. Spectral, textural, and contextual characteristics are the basic components utilized in human interpretation of imageries. Spectral characteristics define the tonal disparity in bands, while textural characteristics encompasses details on spatial distribution of tonal disparity in the band. Contextual characteristics comprises of details resulting from imagery of the study area.

3.4.1.1.4 Image Enhancement

Over the years, satellite images are used in many applications such as geographical information system, astronomy, and geoscience studies. Image enhancement is a decisive and fundamental step for remote sensing information retrieval and

classification[196]. It is typically used to locate objects and boundaries in images[196]. Image enhancement is currently regarded as one of the most important issues in image pre-processing. Image enhancement is the technique, which is most widely required in the field of image pre-processing to improve visualization features presented in the image[196]. In the case of satellite imageries, precisely finding efficient enhanced result in the existence of inherent uncertainty and ambiguity is a challenging task. Such suitable and accurate multispectral remote sensing image enhancement can appreciably support the applications in numerous fields ranging among agriculture, defense, geology, environmental science, etc. [196].

Similarly, the gray value assigned to a pixel is also the typical reflectance of many kinds of land covers. Consequently, assigning proper enhanced features with firmness is an inherent problem for satellite images[196]. In general, raw satellite images have a relatively narrow range of brightness values. Therefore, contrast enhancement is frequently employed to enhance the multiband satellite images for better interpretation and visualization. The images representing a change of surface features' gray value are within a narrow range and these images look unclear. The process of image enhancement performed in this research was to enhance the valuable attributes of images to facilitate the visual identifications of features for flood analysis as recommended by [197].

And finally, color enhancement was used in order to have a clear visualization of features that are potentially causing flooding events within the study area as elaborated in the next chapter (Chapter four). As earlier stated, the cleaning process was performed on both

spatial and temporal data sets. Therefore, the ensuing sub-subsection demonstrates how the winzORIZATION on temporal data sets was performed.

3.4.1.2 Temporal Data Cleaning

Generally, floods are natural events associated with increase in the intensity of precipitation [198]. Every potentially floodable event is characterized by the periodic determination of the total, average intensity as well as the maximum precipitation volume that can induce it [199]. For clarity, in this research, these precipitation values are referred to as Flood Inducible Precipitation Values (FIPV). Therefore, in order to determine the FIPV, a large daily time series data records representing precipitation, water level and temperature from 1979-2016 were collected.

The use of large sets of time series data was needed to learn the historical pattern of rainfall and its associated disastrous events in the past, which in turn reveals the trend for any potential flooding event. Inherently, these large data were recorded within a format that is lacking normality distribution, thereby leading to some difficulties in analysis. While some studies presume that, the ultimate means of avoiding the difficulty in a large volume of data is by avoiding the use of such data [45], this can be associated with the presence of noise or outliers [45], which can adversely lead to erroneous analysis [46]. Nonetheless, as the basis of this research was formulated around a framework known to be suitable in handling very large and complex forms of data, the resolution of this limitation had to be taken into account.

Therefore, cleaning this data by means of winsorizing became pertinent as recommended in [200], as demonstrated by Figure 3.12.

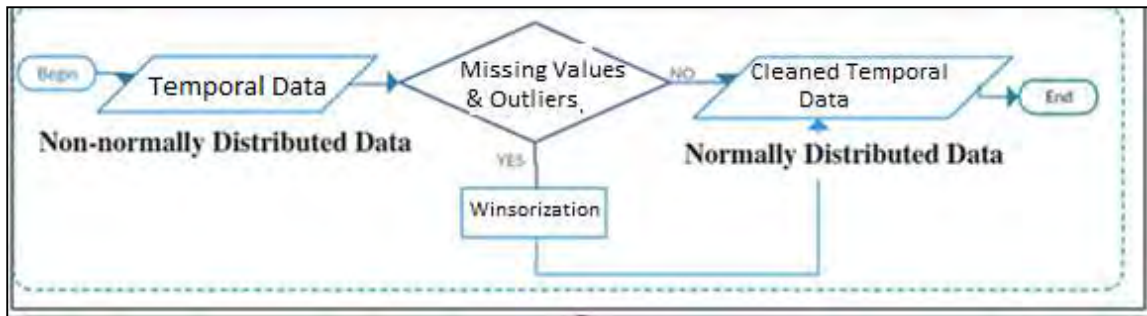


Figure 3.1. Temporal Data Cleaning

As illustrated in Figure 3.12, both the presence of outliers and missing values were corrected by employing Winsorization in order to have a cleaned set of temporal data for long-lead prediction and pattern learning.

3.4.1.2.1 Winsorization

Essentially, winsorization has a pivotal role in removing any potential outliers since it consists of substituting a record in both tails of a set with the subsequent having a reduced extreme value[46]. Similarly, winsorization decreases the extreme sensitivity in the mean values while enhancing the efficiency of the median at light tailed distributions during the statistical analysis[46]. As illustrated in Figure 3.12, the temporal data sets used for the long-lead analysis, with the aid of visual data exploratory approach, was assessed to identify the presence of missing values as suggested in [46]. Although, the temporal data set did not exude any traits of missing values. However, after the identification of outliers using graphical-based visual data exploratory approach as elaborated in subsection 4.2.2 and also with Figure 4.10, the identified outliers were winsorized based on 5% in

conformity with [200],[201],[202],[203], in order to normalize the data before running multiple regression for assumptions on descriptive analysis and eventual predictive inferential statement.

Thus far, these preceding processes generated cleaned and normalized sets of spatiotemporal data required for the multiple feature extraction to identify upstream flood causative factors and also for long-lead upstream flood analysis. The cleaning of spatiotemporal sets of data performed in the preceding subsection was not only to enhance the appearance of the features but as well to facilitate the tasks involved in feature extraction processes[204], as demonstrated in the following subsection.

3.4.2 Multi-factorial Feature Extraction

As earlier mentioned, floods are one of the most destructive of natural hazards, and cause extensive loss of life, as well as havoc to both land and property. As a result, it is imperative that an efficient flood assessment framework be developed to collect details on the occurrence and damage caused by floods[205], which will eventually aid in mitigating any potential flooding events within the study area. The need to mitigate the impacts of flood hazards or disaster becomes very imperative because it is difficult to control basic atmospheric processes which produce floods. The first step attempt by man in the process of flood disaster reduction is therefore, to identify relevant factors influencing the occurrence of flood within a region [43].

As already identified within the scope of the reviewed studies, the fundamental limitation therein dwells on the paucity of factors considered to represent flood causative factors.

Therefore, this research adopts an approach based on the extraction of multiple factors, which is also considered to be very crucial in environmental analysis[154], [206]. This consideration of multiple factors invariably ensures accuracy in flood vulnerability classification. Effectively, this helps in identifying regions that require long-lead flood prediction due to their vulnerability to floods; the underpinning objective of this research. To this effect, topographical, hydrological and vegetal factors were pre-processed as illustrated in Figure 3.13.

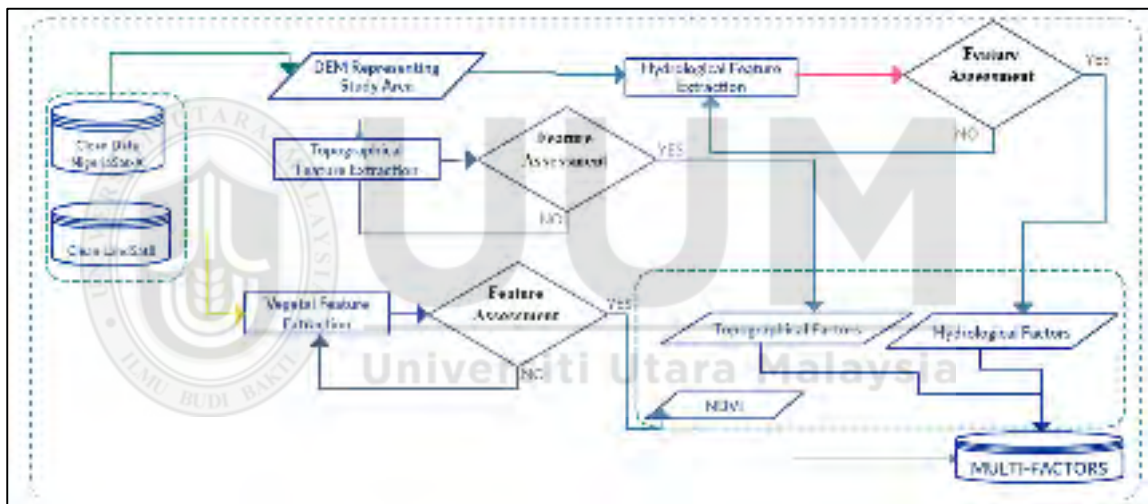


Figure 3.13 Flowchart for Extraction of Flood Causative Factors

Adapted from[207].

As illustrated in Figure 3.13, the pre-processed spatial data generated multiple flood causative factors. Essentially, it is very important to note that, understanding as well as addressing each factor of vulnerability, and their interactions, is crucial for effective flood disaster mitigation [23]. To this regard, pre-processing multiple spatiotemporal elements, involving topographical, hydrological and vegetal features were pre-processed in order to

generate multiple flood causative factors which were earlier addressed to fulfil the research objective one in Phase I of the proposed hybrid framework.

Additionally, the relative severity of hydrological processes (flood) affecting the landscapes are sensitive to the nature of the topography within the region [208]. Therefore, indicator of these process can be designed as functions of distributed soil, vegetal, and particularly topographical features since it provides the opportunity for realistic representation of these factors[208]. Consequently, this subsection has been segmented into three sub-subsections. The first sub-subsection discusses characteristics as well as the procedures employed in generating topographic features for the identification of some relevant factors such as elevation and angular slope. The second sub-subsection presents modes of extracting hydrological features aimed at identifying factors such as flow direction, flow accumulation and Topographic Wetness Index. While the third sub-subsection aids in describing the approach used in extracting vegetal stratification by the use of Normalized Difference Vegetation Index (NDVI).

3.4.2.1 Extraction of Topographic Factors

The topography of an area plays a very important role in determining the exposure of the area to a potential flooding event. More so, topographic factors determine the severity, the volume of flow as well as the velocity of runoff [209],[210]. In the topographical factor extraction, the cleaned raster imageries were used to extract the following components.

3.4.2.1.1 Elevation Factors

The creation of elevation was considered foremost in topographical factor extraction because other factors are dependent on it. In the predefined values, the vertical exaggeration value (Z value) used in the generation of the elevation was set to 1. This was required in the representation of regions with flat topographic features. It is advantageous for this exaggeration value in order to clearly identify those existing regions with relatively gentle or low elevation features. While the scale of ratio between vertical and horizontal units was set to 1. This ration of Vertical exaggeration represents the comparison of both horizontal and vertical scales on the profile of Digital Elevation Model.

Procedurally, the value was obtained by taking an inch which denotes the scale of the horizontal axis and dividing it by the scalar value of the vertical axis. In the standard format, the values for both axis are $100^{\text{inch}}/100^{\text{inch}}= 1$, signifying the absence of vertical exaggeration. And eventually, the output of the aforementioned processes generated the elevation factor with an altitude ranges between 45m and 511m above mean sea level, indicating the lowest and the highest elevation values respectively. The identification of regions within the Elevation classification was done by using regional latitude and longitude coordinates. By implication, the likelihood of flooding increases when slope angle is below a critical value and then decreases logarithmically low gradient elevation are highly related to flood vulnerability compared to high elevation, as supported by [210] and [211]. Contrary to some studies that have only considered the elevation as the only topographic causative factor, according to [125], the angular slope must be regarded as a causative factor, since it plays a vital role in identifying the velocity as well as vertical

percolation in inducing flooding events. Therefore, the ensuing sub-subsection demonstrates the method of extracting the angular slope.

3.4.2.1.2 Angular Slope

Angular slope generally reveals surfaces with low or high values of slope in degree or percentage. The obtained slope elaborated in Chapter Four, equally has a surface indicator to identify regions that are susceptible to floods as it plays a vital role in recognizing the vertical percolation as well as the velocity of the surface runoff and, consequently, leads to flooding. Therefore, the angular slope was further extracted from the cleaned spatial data to have an exhaustive information on the influence of topography to flood vulnerability within the study area. This was done by defining the cleaned spatial data as the input in QGIS from the raster environment. The values for Z-factor earlier used in the creation of elevation were maintained throughout the creation of the other topographic factors, by implication, the Z-factor for slope as inherited from the previous process is 1, while the unit of measurement was selected in degree ($^{\circ}$) and the output was vectorized.

The lesser slope value signifies a flat surface, while the slope with higher values signifies, the steeper the slope of the surface, the higher the runoff leading to the increased probability of flood in regions at Depression or lower steep level. Noticeably, the pre-processing of both elevation and slope fills the topographical-based issues found in some of the reviewed studies which only used elevation factor or survey means to classify regional flood vulnerability. Thus far, this sub-section has presented the methodological approaches in extracting topographical factors. The ensuing sub-subsection presents the

methods of extracting hydrological factors which play a major role is determining the flow of water as well as its concentration on the topographic surface.

3.4.2.2 Extraction of Hydrological Factors

The extraction of hydrological factor as well as other relevant factors as recommended in the study conducted by [212], is equally critical in flood vulnerability classification. This is because many of the flood causative factors are interrelated, and part of the approaches required to be considered in identifying regions susceptible to floods consists of identifying the most relevant factors in each of the closely related factors [213]. Essentially, the hydrological factors were considered to determine the level of susceptibility of various regions within the study area since both vertical and horizontal water flow can occur at the study area. More so, the hydrology of a surface is associated with the movement of water on the surface within hydrological cycle, saturation and the conveyance of elements such as sediments and pollutant along with flowing water [214]. As a result, the following hydrological factors were extracted to aid in the classifying regional flood vulnerability.

3.4.2.2.1 Flow Direction

In the facet of feature extraction within the pre-processing phase, it is very essential to obtain the directions of flow in order to implement some physical or structural measures needed to mitigate any potential flooding events within the regions where flow of water is directed at. This is because the flow direction shows the possible direction of water run-off on the elevation factor [215]. Procedurally, the directions within which water flows were extracted by the determination of direction which is taken by flows in every cell

within the eight cells of the neighbor. This direction was defined by recognizing the direction of the steepest descent of the cells. It has been identified that flow is directed towards a cell when a cell is less than eight neighbors and then, it is assigned the lowest value. Illustratively, the extraction of flow direction is demonstrated by Figure 3.14.

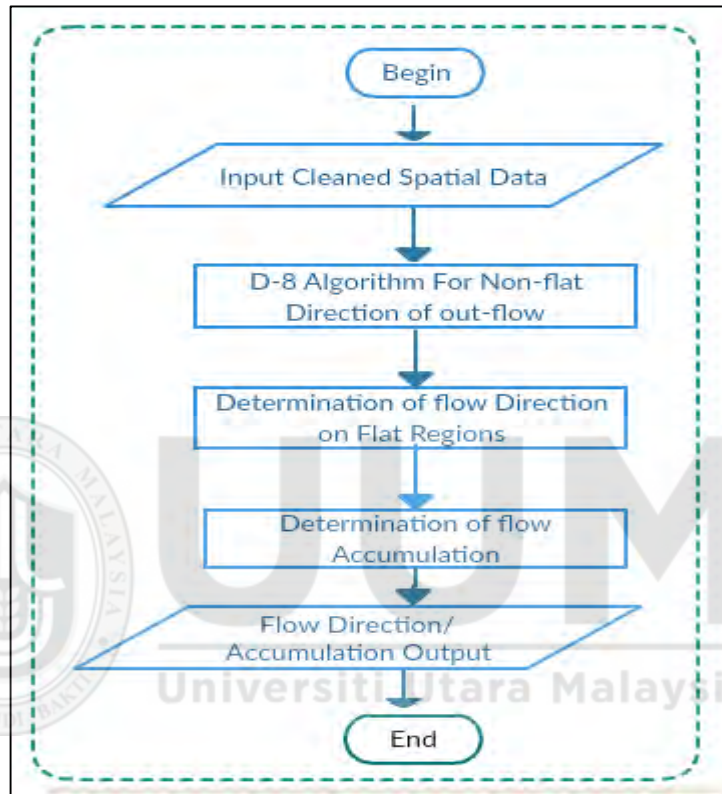


Figure 3.14. Hydrological Factor Creation Flowchart

In creating the flow direction, the cleaned spatial raster was also declared as the input data, while the D8 algorithm was used to extract pattern for non-flat regions. Generally, a cleaned spatial data is needed to run the D8 algorithm[216]. The D8 algorithm which is integrated in the QGIS application is usually used to obtain the flow direction using the directional coding: 1 - East, 2 - Northeast, 3 - North, 4 - Northwest, 5 - West, 6 - Southwest, 7 - South, 8 – Southeast, and subsequently generated the flow accumulation output. In addition to the flow direction, flooding events can be influenced by the

accumulation of water, which can be assessed using the flow accumulation factor as elaborated in the following subsection.

3.4.2.2.2 Flow Accumulation

Sequel to the preceding process in creating the flow direction, the flow accumulation was concurrently computed by means of the accumulated number of pixels in upstream. Factors representing the flow accumulation were further obtained by the generation of a grid for accumulated flow to every cell. The output cells having a high volume of accumulation representing regions having flow concentration, and consequently, was utilized to recognize stream channels. While output cells having a low flow accumulation (zero value) were considered the local topographic heights and was employed to recognize ridges.

Generally, regions with indicative traits of flow accumulation have the tendency of flood vulnerability, especially, when further influenced by heavy downpour. This factor is crucial especially, for large river basins[217]. It is evident that the distribution of plant species is not random, and is associated with the distribution of hydrological and topographical factors[214]. Therefore, after the extraction of both topographical and hydrological factors, the extraction of land cover features to obtain the vegetal factor was performed in order to identify regions with bare soil, dense vegetation and water bodies.

3.4.2.3 Extraction of Land Cover

Land cover plays a key role in global-scale patterns of the climate and biogeochemistry of the earth system[218]. More recently, remote sensing has been utilized as a basis for mapping global land cover. Conventionally, similar to the approaches adopted in this

research, spatial data sets provide maps of potential vegetation inferred from climate variability, such as precipitation. Therefore, to identify the level of influence posed by land cover factor, this research extracts the vegetal feature of the study area and the TWI as discussed in the following subsection.

3.4.2.3.1 Vegetal Stratification

The NDVI can be considered as an indirect indicator of the amount of biomass added to the soil, which may be related to the soil content[219]. Changes in NDVI also correspond to changes in the vegetation health, thus intimating at the availability of water to the plant and in turn to the bulk density, pore size/structure evolution and the soil hydraulic properties[219]. The generation of this factor was required in order to identify the vegetal contents of the study area. Essentially, satellite imageries provide the opportunities for vegetal analysis over a large area as in the case of this research. Vegetation Indices, such as the NDVI, is commonly used for vegetal trend analysis to identify the regional greenness of the area of interest.

In extracting the vegetal stratification, the cleaned Landsat-8 images were classified based on Bands 02 (Blue),03 (Green) 04(Red) 05(Near Infrared (NIR)). While the NDVI was used to quantify the vegetation at the individual pixel. Using supervised classification, the color composite was defined at 3-2-1 to depict the natural color of the terrestrial features to classify the water bodies, bare soil and the vegetation density.

3.4.2.3.2 Topographic Wetness Index

The Topographic Wetness Index (TWI) is commonly employed to quantitatively depict the conditions of soil moisture within a watershed, and it is the most frequently utilized indicator for static soil moisture content[220],[221]. So, it plays a vital role in flood-based researches[220]. The extraction of TWI was done by declaring the cleaned DEM as an input raster data. The output presented the regions with low and high levels of wetness. The output data was then classified to reveal various levels of regional flood vulnerability.

Thus far, the preceding subsections have demonstrated the approaches employed in extracting various flood causative factors. The identification of these factors yielded the extractions of the needed multiple factors, attaining the research objectives One and Two respectively. As already established, this research entails the development of a hybrid framework. Therefore, the extraction of multiple factors was required to accurately perform regional flood vulnerability classification prior to performing the long-lead upstream flood prediction as discussed in the next section.

3.5 Phase III: Hybridization of Vulnerability Classification and Long-lead

Upstream Flood Analysis

Disasters, such as floods, are determined by the vulnerability index and capacity index amongst other factors [222]. The vulnerability index comprises of losses and the exposure of the population indicator. While the capacity index comprises of early warning, preparedness indicators and mitigating indicators [222]. These indicators form the basis of the hybrid approach proposed within the context of this research to perform vulnerability classification and long-lead analysis in order to provide useful insights and

recommendations for appropriate mitigating measures against upstream flood disasters in Niger State. In order to identify the indicators of vulnerability, the extracted factors were classified. While the temporal factor was used to perform a long-lead prediction to enable adequate level of mitigative measures to be implemented using the generated results obtained from the proposed hybrid framework in Figure 3.15.

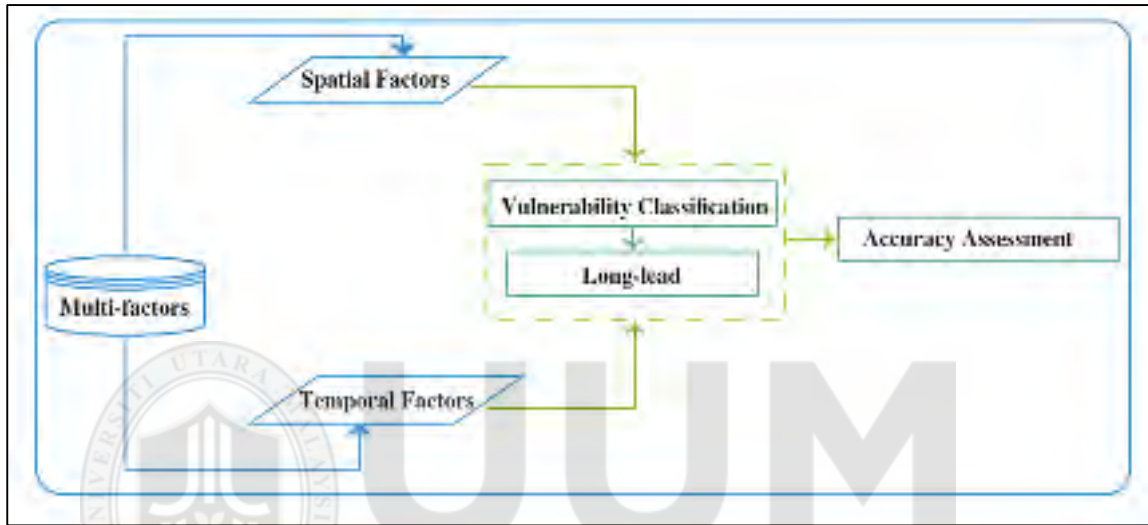


Figure 3.15. Hybridization of Vulnerability Classification and Long-lead Flood Analysis

As illustrated in Figure 3.15, the extracted multi-spatial and temporal factors were employed to classify regional flood vulnerability and perform long-lead flood prediction respectively. As concisely described in the ensuing subsections.

3.5.1 Classification of Regional Flood Vulnerability

As earlier established in the previous chapters, flooding event is one of the natural hazards which occur globally, and it is critical to be controlled through proper management. Thus, employing approaches to recognize vulnerable regions with the aid of RS and GIS is vital for decision-making [223]. It has also been corroborated that the detection of flood

susceptible regions is a basic component in flood mitigation[224]. Therefore, in order to identify and classify regional flood vulnerability, the extracted factors were classified by the means of symbology, which in the context of Cartographic design, is the use of graphical techniques to represent geographic information on a map, such as size, color and shape. The approach was performed using single band color to classify the factors into four distinct classes of Highly Vulnerable, Vulnerable, Marginally Vulnerable and Non-Vulnerable. By this means, regions were correspondingly classified based on their levels of vulnerability.

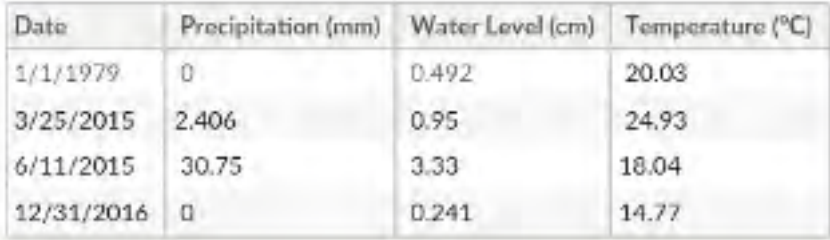
Essentially, the outputs of the classification were transformed into maps depicting the locations as well as the interpretive legends to show regions and their related levels of vulnerability to flood. This is because the creation of maps is indispensable for regional prioritization in the decision-making and as such, are needed by disaster management agencies [225].

On the other hand, in flood mitigation, time is one of the most important factors [223]. In view of addressing various limitations related to lead-time in the reviewed studies, this research adopts the second segment of the hybrid framework, which is to perform the long-lead upstream flood prediction for the regions mapped within the flood-prone areas. This was done by learning the trend of the temporal factors, consisting of daily precipitation, water level and temperature data acquired over the period of 37 years, which formed the basis for seasonality identification in the historical rainfall. This consequently helped in knowing the floodable periods and non-floodable periods over a long time span. The procedural approaches are further discussed in the following subsection.

3.5.2 Long-lead Upstream Flood Analysis

It is noteworthy that, floods triggered by upstream factors, such as precipitation are among the most devastating natural disasters and one of the most rampant hydro-meteorological disasters globally[226]. Adversely, the current global warming is altering the pattern of precipitation, leading to an increase in the intensity and frequency of precipitation thereby increasing the potential for floods [227]. Generally, within the study area, upstream flooding events have been associated with heavy precipitation lasting for days or weeks. To ensure preventative and mitigating measures, accurate prediction of the regional flood inundation and dissemination of information on the inundation areas to emergency managers, city planners, and the general public is necessary[228].

Accordingly, this subsection demonstrates the approaches employed in performing long-lead analysis using the temporal time series data comprising of precipitation, water level and temperature with daily records of 13850 days i.e. from 1979-2016 as illustrated in Figure 3.16 and also Appendix B. with the authorization in Appendix L.



Date	Precipitation (mm)	Water Level (cm)	Temperature (°C)
1/1/1979	0	0.492	20.03
3/25/2015	2.406	0.95	24.93
6/11/2015	30.75	3.33	18.04
12/31/2016	0	0.241	14.77

Figure 3.16. Illustrative Sample of Temporal Data

Here, the long-lead upstream flood analysis, i.e., prediction of potential flooding by estimating the volume of precipitation that can potentially lead to a flood over a period of several days was obtained following the ensuing approaches as illustrated by the flowchart in Figure 3.17.

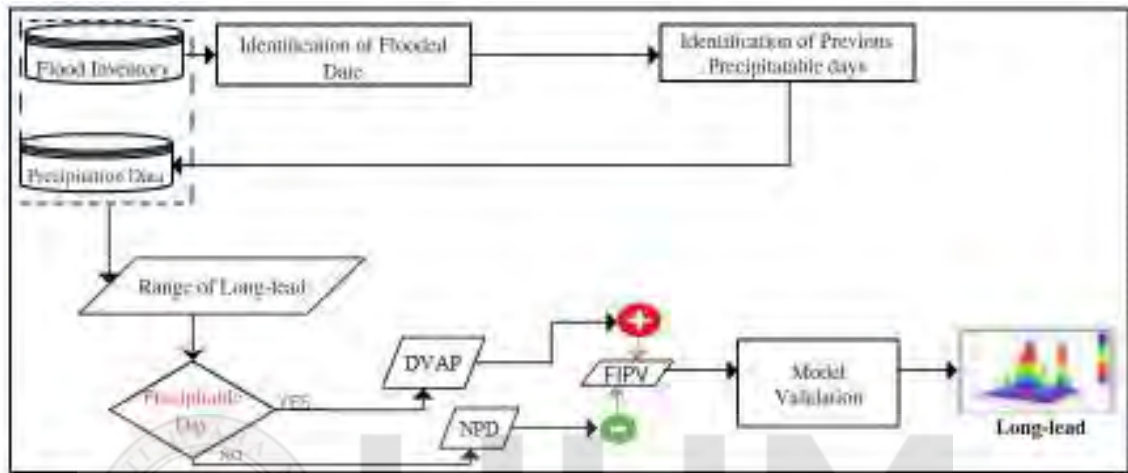


Figure 3.17. Long-lead Upstream Analysis

As illustrated in the flowchart in Figure 3.17, the determination of the long-lead prediction was performed with the aid of Flood Inventory and cleaned Temporal Data using clustering algorithm obtained with the aid of python programming language as elaborated in the ensuing sub-subsection.

3.5.3 Long-lead Clustering Algorithm

From the above flowchart, the algorithm is developed to determine the Flood Inducible Precipitation Volume (FIPV) as the corresponding lead-time towards a long-lead prediction. Ultimately, the clustering algorithm is based on logic reading from the precipitation data within the range long-lead i.e. 5-16 days. The primary aim of the algorithm is to return the various regional FIPV and the corresponding number of lead-

time in days. This advertently, enables the local authority to gain an insight on the daily accumulation volume of precipitation that can lead to upstream flood.

Algorithm	
<i>Input: Set of Temporal Data, = P, Precipitation, W, Water level</i>	
<i>Output: Flood Inducible Precipitation Values</i>	
<i>Begin: read file("For_Python.csv")</i>	
<i>Displaying Dataframe</i>	
<i>Columns = .Precipitation</i>	
<i>Precipitation records = .values</i>	
<i>Dataframe=Precipitation</i>	
<i>Range=df3.loc Date ['Date1':'Date2']</i>	<i>Date1 represents the date of the flood occurrence as identified from the Flood Inventory data set, while Date2 is the preceding historical rainfall dates prior to the flooding event.</i>
<i>Display(Range)</i>	
<i>DVAP=Range.values.sum()</i>	<i>Summation of Daily values of accumulated Precipitation</i>
<i>Display("DVAP")</i>	
<i>Display(df1)</i>	<i>Summing all days with 0s in precipitation</i>
<i>NPD=df1[df1.Precipitation == [0].shape[0]]</i>	
<i>Display (df1[df1.Precipitation !=0].shape[0])</i>	
<i>Display(DVAP-NPD)</i>	
<i>Display("FIPV")</i>	<i>Shows the FIPV</i>
<i>End</i>	

Figure 3.18. Long-lead Clustering Algorithm

As illustrated in the preceding clustering algorithm in Figure 3.18, the initial step in determining the FIPV consists of identifying the date when flood had occurred in the past, which is contained in the Flood Inventory data. Once this is identified, with the aid of python programming language, the precipitation (rainfall) of the identified date is clustered alongside previous Precipitable and Non-Precipitable Days (NPD). The number of Daily Volume Accumulated Precipitation (DVAP) minus NPD is computed to have the accumulated volume as well as the number of days recorded. This process is repeated for a study area with different dates of flooding event consisting of a decadal record. Finally, the minimum accumulated volume over the number of days is termed FIPV.

Practically, the FIPV for long-lead analysis, the dates for a flooding events were referred to in the Flood Inventory data. Using the records of the historical flooding events, the preceding days of precipitation were marked. The clustering algorithm identifies all the precipitable days and aggregates the volume of the precipitation with the corresponding number of days. While days within the threshold of FIPV that did not experience rainfall were ignored to have the exact number of days where rain fell leading to the accumulation of FIPV. Using the daily precipitation and the historical flooding events in the flood inventory, the experiment was repeated for other regions to obtain their corresponding lead-time. As a result, each location within the study area has its FIPV. Nonetheless, the variation of the FIPVs can be associated with other spatial flood causative as explained in Chapter Four.

For instance, the 2012 flood which was the most devastating flooding event in Nigeria [229], as well as the study area also affected Katcha region on 28/08/2012, when a

considerable amount of rain was recorded from 19/08/2012 to 28/08/2012 with an accumulated value of 213.24mm precipitation over a period of 9 days. These results provide important insights into the region of Katcha which continuously experiences flooding events as a result of voluminous rainfall recorded. Therefore, it was inferred that, when a rainfall occurs and accumulates to a minimum volume of the 213.24mm or above, without an intermittent stoppage of not more than a day, then there is a likeliest tendency of experiencing flooding in the coming days.

This procedure was repeated for all the regions to identify their corresponding FIPV and the threshold for the long-lead. The identified volumes were regressed to identify the correlation between other temporal variables i.e. water level and temperature, while a proposed algorithm for a long-lead forecast is given Figure 3.18, and eventually, the model specification test was performed to validate the predictive model employed in performing the long-lead. From the preceding algorithm, vast volume of temporal data sets was utilized to determine the FIPV. Remarkably, this methodological discussions demonstrate the means by which the long-lead analysis was attained based on the historical records. Expressly, from the identified historical FIPVs, a long-lead prediction can be performed using a range of forecast daily precipitation data which was as demonstrated using the ensuing pseudocode in Figure 3.19.

```

Input Regions FIPV
//Case of formation of FIPV
Input precipitation value 1
Input precipitate date 1
If precipitation value1 < Regions FIPV
Then
Print("Accumulation of FIPV in Progress": on)+ precipitate date 1
End if

//Case of Flood Prediction
Input precipitation value 2
Input precipitate date 2
Else if
Input precipitation value 2
If precipitation value1+ precipitation value2 ≥ Regions FIPV
Then
Print ("Expected date of flood") +precipitate date 2
End If

//Case of Recession of FIPV
Input precipitation value 3
Input precipitate date 3
If precipitation value3 = 0
Then
Print("Recession of FIPV on:")+ precipitate date 3
End if

//Case of Re-accumulation of FIPV
Input precipitation value n
Input precipitate date n
If precipitation value n ≥ 0
Print('Re-accumulation of FIPV)+ precipitate date n
End if

```

Figure 3.19. Long-lead Clustering Algorithm

From the preceding pseudo codes, the values of the forecast generated four distinct indications. The first is the period of gradual formation of volume of rainfall that can instigate upstream flood, the second is the prediction of long-lead after several observations must have been inputted. The third is the period when the rainfall will decline or halt, which indicates a recession in FIPV. And lastly, the re-accumulation of precipitation for yet an extension of flooding period or yet another flooding event. Instances of these distinct values are further presented in subsection 4.3.2 of Chapter Four.

Furthermore, in order to ensure a reliable and accurate output from the developed hybrid framework, the present study further adopts an accuracy assessment of the developed for the framework. By this means, decision-makers or the local authority are clearly and unambiguously shown the correctness and the reliability of the generated results. Therefore, the ensuing subsection demonstrates the approaches employed in assessing the accuracy of the hybrid framework.

3.6 Phase IV: Accuracy Assessment

With the emergence of more enhanced techniques on spatiotemporal data sets, the need to perform accuracy assessment has received a renewed interest [230]. This is not to portray the accuracy assessment in traditional approaches (for instance, studies based on survey) as unimportant. Nonetheless, due to the complexity of digital classification, there is more of requirement to assess the accuracy of the results generated from digital imageries [230]. Making it crucial to consider a means of assessing the accuracy of the obtained pre-processed outputs as well as the predicted results prior to the implementation of the

inferential statement on the long-lead predictions. Building on the aforementioned arguments, this research has proposed the following flowchart in Figure 3.20.

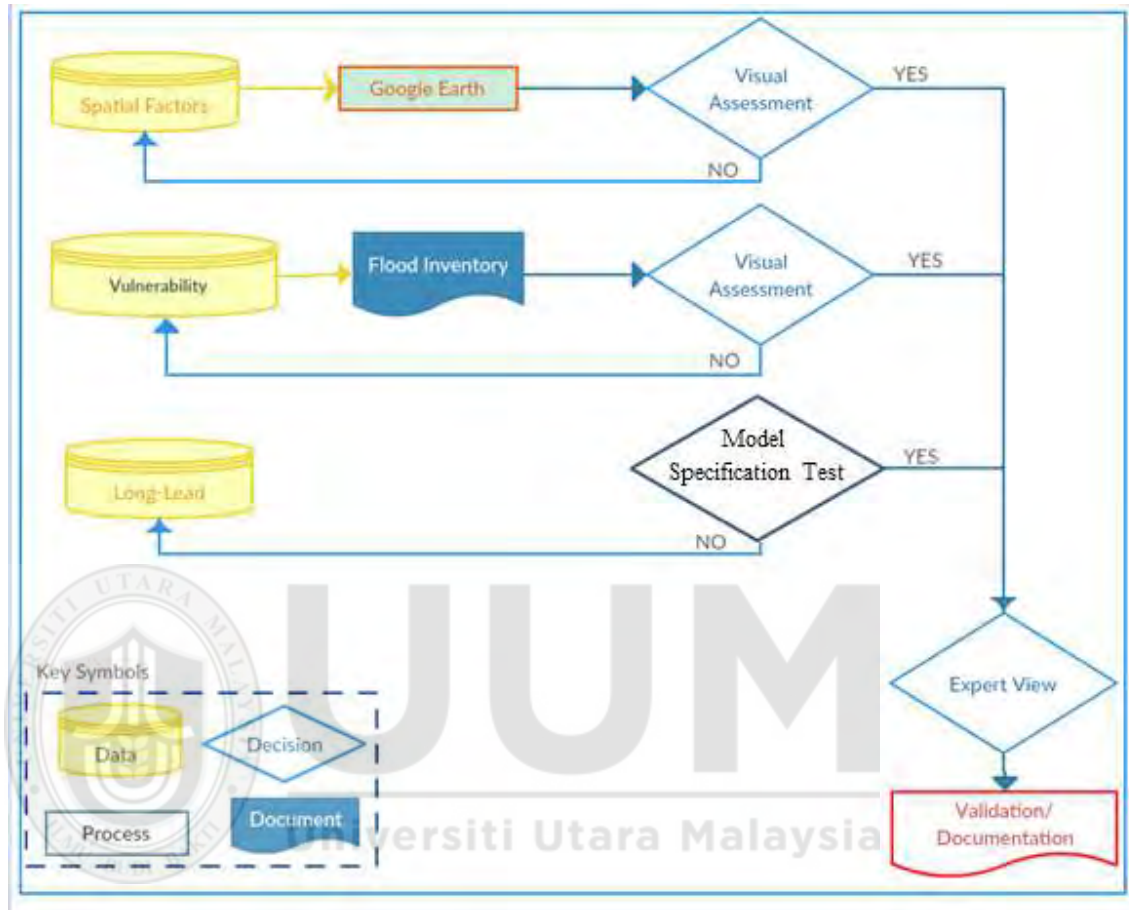


Figure 3.20. Validation Flowchart for Framework Assessment

In accessing the accuracy of the spatial factors, the correctness of the extracted multiple spatial factors was assessed using Google Earth and physical maps. This approach allows the identification of the extracted features to be associated with the terrestrial features using Keyhole Markup Language (KML) file for visual inspection based on Good Earth. Once the attributes were accurately identified geographically, the features were further assessed by experts in GIS as equally adopted the study conducted on GIS-based landslide susceptibility for Northeast Algeria in [231]. Correspondingly, in assessing the

correctness of the classified regional flood vulnerability, various regions were associated with their corresponding frequency of flooding events contained in the Flood Inventory data set covering the period from 2006 to 2017 (Appendix C).

Ultimately, this was validated when regions identified to be highly vulnerable have a high frequency of flooding events. Inversely, regions identified to be least vulnerable have the least frequency of flooding events. Finally, experts in the domain of GIS were engaged to consolidate the preceding accuracy assessment of the outputs by providing insight into the underlying causes of flood vulnerability through the lens of multiple causative factors. The assessment was equally opined by experts in disaster management agency within the study area. The accuracy of both multi-factorial and vulnerability classification was assessed using the methods adopted in the study conducted a on flood risk assessment in China[232]using the following iterative flows:

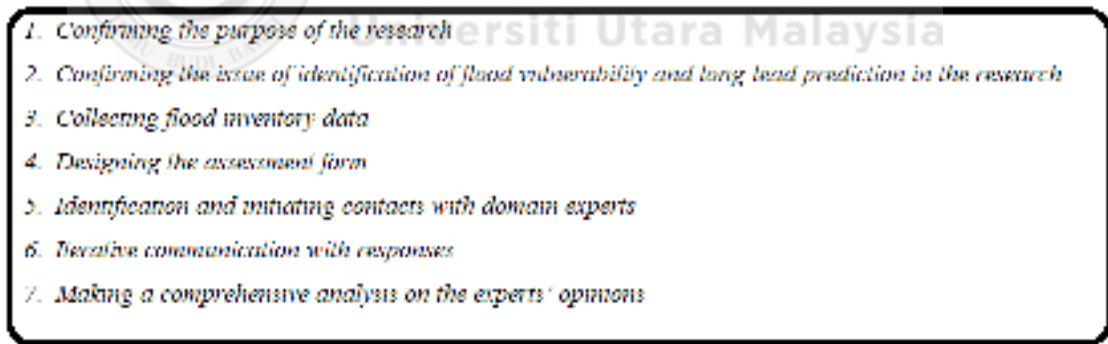
- 
- 1. Confirming the purpose of the research*
 - 2. Confirming the issue of identification of flood vulnerability and long lead prediction in the research*
 - 3. Collecting flood inventory data*
 - 4. Designing the assessment form*
 - 5. Identification and initiating contacts with domain experts*
 - 6. Iterative communication with responses*
 - 7. Making a comprehensive analysis on the experts' opinions*

Figure 3.21. GIS-based Expert Iteration

Using the above iterations, the accuracy of the output as well as the significance of the framework was assessed by the experts as analyzed in subsection 4.5.3.

The final assessment was done on the long-lead prediction made using a statistical approach. Essentially, this was performed with the aid of model specification link test

using Stata tool. This approach consists of selecting an appropriate functional form for the predictive model. As demonstrated thus far, the entirety of the research was based on spatiotemporal sets of data. Therefore, for clarity, the modes of acquisition as well the justification for the use of spatiotemporal data are discussed in the following sub-section.

3.7 Spatiotemporal Data Acquisition

Broadly, the Earth's surface is observed using EO satellites from the space and terrestrial remote sensors in order to provide essential data needed for natural disaster monitoring and mitigation such as upstream flooding and Katrina [233],[234]. Additionally, the past, present as well as the future trends of flood risks require accurate spatial and temporal information on potential flood vulnerabilities [235]. Satellite imageries as further explained in subsection 3.7.1, are generally more reliable in identifying the vulnerability of a surface to any disaster compared to the survey or questionnaire-based method used in some of the reviewed studies [35],[34], [141] in the previous chapter.

3.7.1 Justification for using Spatiotemporal Data Sets

The primary need for data acquired from EO satellite and RS (spatiotemporal data) which were majorly provided by Nigerian authority are as follow [236], [235],[237],[238]:

- I. Data from EO satellite serve as supporting means to remote sensors in analytical facet needed for prediction of natural disasters and other environmental analysis. Nevertheless, in some countries, EO satellite is adopted as the only source of environmental data, either as a result of the nonexistence of terrestrial remote sensors, or due to the ability of the EO satellite to capture environmental data efficiently without being affected by climate factors, such as cloud and heavy

downpour which attenuate the signal of the satellite which consequently, will reduce the quality of the data.

- II. Satellite images are useful for the estimation of water coverage, landscape and the dynamics within the study area. While data sets from remote sensors are useful in measuring temporal climatic data such as precipitation, temperature and water level.
- III. Topographical station without any atmospheric interference to attenuate the signals.
- IV. EO satellites provide near-real time data capable of enhancing analytical results in addition to the provision of continuity of data downlink for analytical task.

As previously reviewed in the preceding chapter, numerous spatiotemporal data pre-processing frameworks have been developed to classify regional vulnerability to flood disasters. Despite the emergence of these frameworks, [239] affirms that studies are yet to address the issue correctly. This is attributed to the absence of an exhaustive regional vulnerability analytical means [240]. Traditionally, early studies only focused on analyzing uniquely physical or structural features of vulnerability, as well as the researches published that are related to the natural and anthropogenic situations [241]. These limitations have therefore presented the need to employ a more robust and suitable framework to analyze upstream flood vulnerability aimed at obtaining an effective flood risk mitigation, especially, within the continent of Africa, which has been recognized by researchers to be a hotspot for floods. Thus, presenting the need for a reliable flood mitigation [35],[242],[243],[244].

Conclusively, with these results, this research has addressed all the pertinent scientific issues highlighted in the problem statement by attaining all the objectives outlined in Chapter One (section 1.4). And as such, the proposed hybrid framework is considered valid as further elaborated in section 4.5 in Chapter Four.

3.8 Chapter Summary

This chapter has demonstrated the methodological approaches employed in conducting the research by examining the novel concepts based on hybrid approach for multi-spatiotemporal data pre-processing and long-lead upstream flood prediction. It also outlines a comprehensive description of the procedural phases adopted with a detailed illustrative representations to demonstrate how the tasks were performed to attain the defined research objectives. The chapter captured the classifications of regional flood vulnerability using multiple pre-processed spatial data, while the long-lead was attained by employing the temporal data, prior to the validation of the proposed framework. Having described the research methodological approach for this research, the ensuing chapter presents the development of the proposed hybrid framework.

CHAPTER FOUR

HYBRID FRAMEWORK DEVELOPMENT

4.1 Introduction

Previously, the research methodology was described. The sequential approaches adopted herein gives an illustrative idea of the expected outputs from various phases of the proposed framework. In developing the proposed hybrid framework, this chapter is structured into two main segments. The first segment is the hybridization, which comprises of flood vulnerability classification in subsection 4.2.1, and the second segment discusses the long-lead analysis in subsection 4.2.2. A detailed discussion on long-lead trend representation is presented in section 4.3. Since the entire research is based on multi-factorial approach, which presents various FCFs with diverse levels of influence towards flood vulnerability, the AHP-based evaluation of each factors to determine the level of influence posed in inducing flood is detailed in section 4.4. Section 4.5 presents the accuracy assessment within the framework. And the chapter ends with a summary in section 4.6.

4.2 Formulation of Hybrid Elements

To understand the concepts of floods, two central approaches must be considered. The first is to identify geographic nature of flood and the level of vulnerability in various regions. The second relates to the general nature of flood and the ability for a practical implementation of policies in flood mitigation[245]. Nonetheless, the absence of a unifying framework for flood vulnerability based on multi-factors to accurately identify

and classify geographic nature of flood and its level makes it problematic to select one single approach from among the various available approaches. Hence, the need to employ a hybrid approach based on multi-factors for both flood vulnerability classification and long-lead prediction. Therefore, in this section, multiple flood causative factors that were extracted have been considered in identifying and classifying regions that are susceptible to floods. The identification of flood-prone regions is vital, since flood risk is less likely to decrease anytime soon because of its association with climate change [215]. What can be done however, is to be able to identify regions that are at high risk of flooding, which will be the basis for prioritizing mitigative measures and to create awareness for prevention and proactive measures [215]. Additionally, a high level of information, i.e. a suitable scale of flood maps is a fundamental precondition for a reliable flood risk mitigation.

A detailed spatial information on flood vulnerability is required for the development of regional flood management concepts, planning and cost-effective analysis of flood mitigative measures and, extremely vital, for the preparedness and prevention strategies of individual stakeholders (e.g., communities, companies, house owners etc.)[122]. As a result, in order to perform a long-lead upstream flood prediction, a hybrid approach was adopted to initially classify and map out regions that are prone to upstream floods prior to performing regional long-lead prediction using the pre-processed spatiotemporal data as illustrated in Figure 4.1.

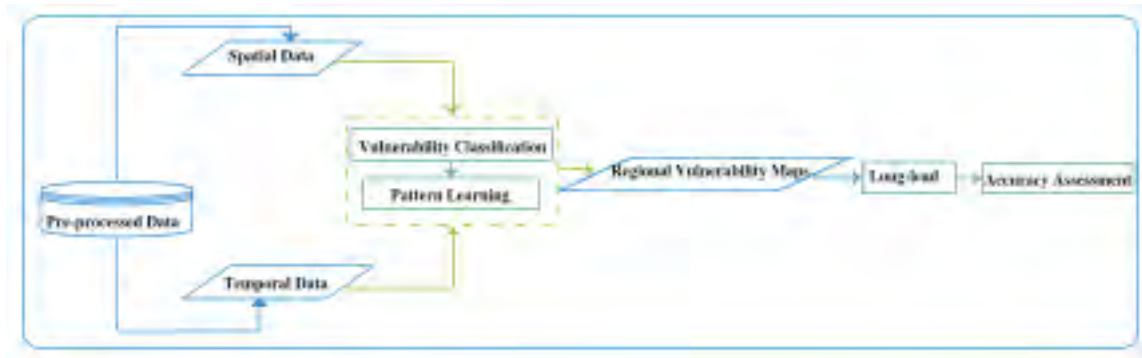


Figure 4.1. Proposed Hybrid Approach for Vulnerability Classification and Long-lead Analysis
Adapted from: [246].

The approaches adapted in Figure 4.1 represents the procedures based on hybrid approach, which provides a better understanding of the impact on the physiographical and morphological characteristics of the study area on the occurrence and magnitude of floods.

As earlier mentioned, EO satellites provide a distinct capability for monitoring the surface of the earth by providing periodically repetitive global or regional images at a desired spatial scale. This rich remotely sensed data offers a vital means for prevention, monitoring, as well as management of disasters that are naturally or anthropogenically (man-made) induced [20]. In analyzing upstream flood vulnerability, an effective use of these means does not only necessitate accurate and reliable analytical approaches to extract the desired details, but also, the methods of combining the obtained details with physical attributes of the floods are crucial[247]. Therefore, this research considers the extracted features as the underlying factors responsible for the increase flood vulnerability within the study area. To this effect, various regions were classified based on the extracted factors in the ensuing subsection.

4.2.1 Vulnerability Classification from Spatial Data

Currently, there are several methods adopted for vulnerability classifications. The study conducted by [248], however identifies the need for an effort to be made towards providing a broad, yet usable means of understanding vulnerability that can be used by communities to assess their own risk, and to decide which mode of measures to take in mitigating associated risks by planners and other relevant agencies. Generally, when classifying regions vulnerable to floods, the initial indication can be obtained by estimating the frequency of flooding events using the historical data (Flood inventory). Expediently, with the advent of satellite images, this can easily and accurately be classified [246], as in the case of this research.

One of the most important roles of regional flood vulnerability classification within the concept of this research, is to identify a clear relationship amid the theoretical conception within flood vulnerability and regular administrative process aimed at mitigating the impacts of floods. Considering the contextual representation of vulnerability, the following causative factors were utilized using the Flowchart in Figure 4.2.

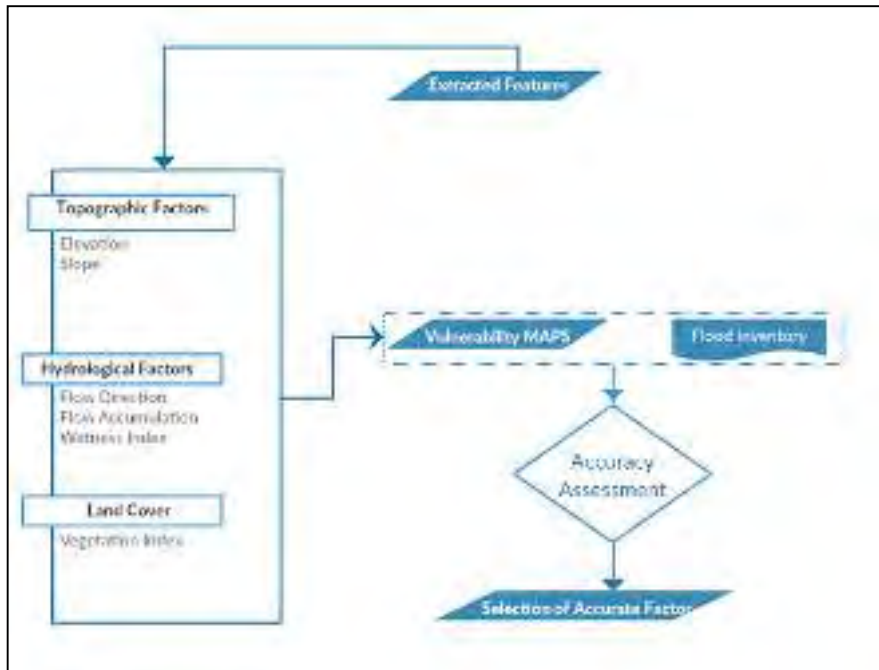


Figure 4.2. Regional Flood Vulnerability Mapping Flowchart.

The use of limited FCFs to identify flood vulnerability within extant studies has been identified by this research to be the factors undermining the analytical accuracy in flood-related studies. Therefore, the novelty of this research as illustrated in Figure 4.2, is the use of multi-spatiotemporal FCFs based on Topographical, hydrological and vegetal factors to classify regional flood vulnerability prior to long-lead analysis.

Alarming, flooding events are likely to increase given the current prediction on the global warming, particularly in terms of monetary losses [249]. Whilst much more people live within low-elevated regions, these regions become more susceptible to floods [249]. Therefore strategies to cope with flooding, for instance, structural means such as reservoir and levee project, as well as non-structural means such as regulations, emergency preparedness etc. are implemented [249].

Essentially, these proactive measures depend on flood predictive efficiencies, and particularly, the ability to map out flood inundation areas is one of the most important requirements [249]. Consequently, various factors were employed to map out regions that are vulnerable to floods prior to performing long-lead upstream flood prediction as discussed in the succeeding sub-subsections.

4.2.1.1 Topographical-based Vulnerability Classification

Generally, topographical factors or features are the graphical representations of the regional landscape which provides interpretive presentation of the land surface, and the level of regional flood vulnerability[250]of the study area to potential flooding event(s).

The various topographic based features identified to be flood causative features include Elevation and Slope.

4.2.1.1.1 Elevation-Based Vulnerability Classification

Primarily, in assessing the regional flood risk, elevation factor was classified into high, low, very low and very high elevations, which contributes to the exposure to floods. The classification of the elevation representing the study area was required to have a general knowledge on the regional topographic (terrain) for understanding and identification of the regions vulnerable to floods as well as their corresponding levels of vulnerability as illustrated in Figure 4.3.

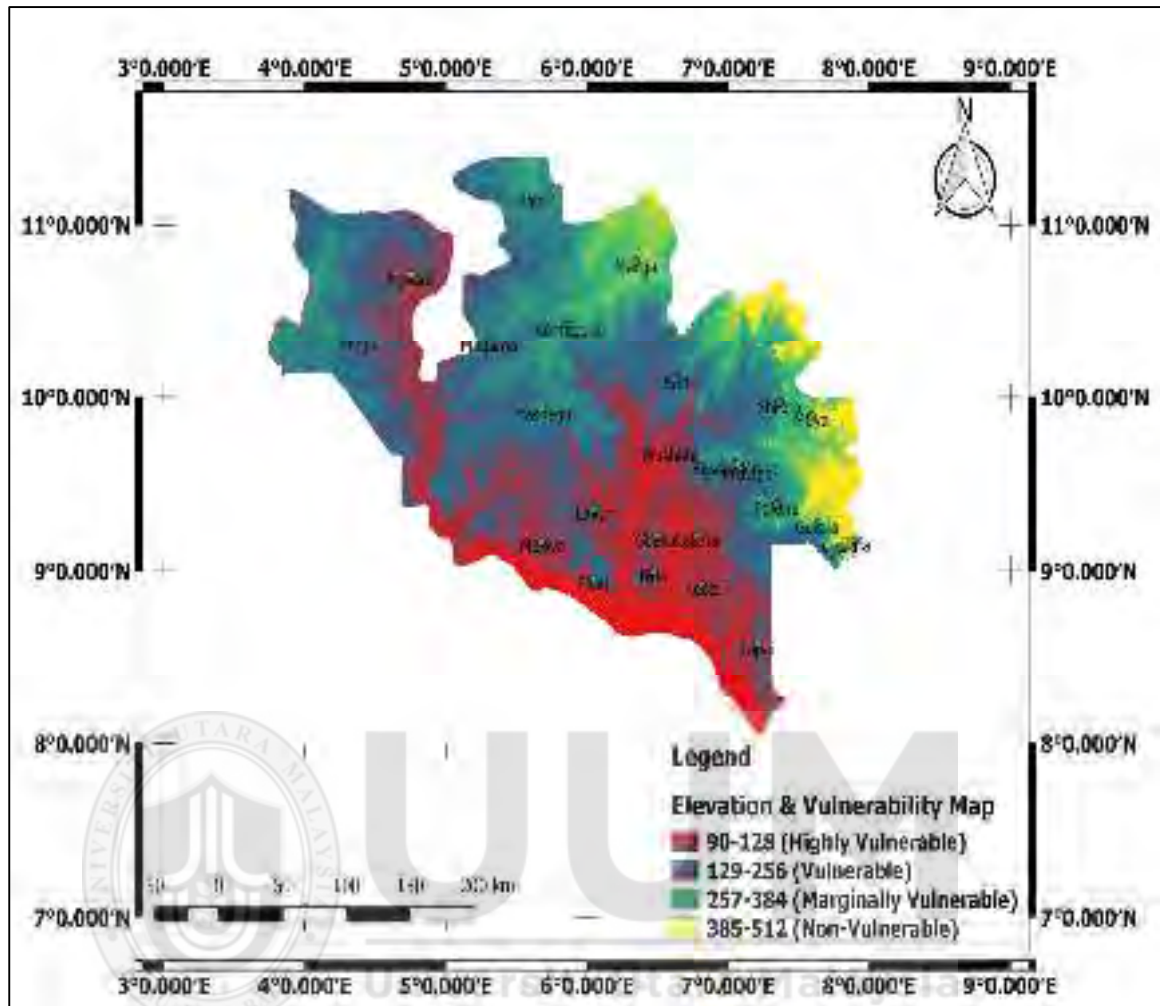


Figure 4.3. Elevation-based Vulnerability Map

The value of elevation obtained for various regions represent the gradient of the surface within the region in metres(m). Within the region of Katcha, which was marked by the lowest level of elevation (90.2457m), while Tafa possesses the highest elevation value at 511m as shown in Table 4.1

Table 4. 1.

Regional Elevation Values

Regions	Elevation (m)
Aga	117.6239
Agw	161.5762
Bid	123.0762
Bor	262.6028
Bos	270.5563
Cha	252.5918
Eda	159.9411
Gur	127.6221
Gba	406.2143
Kat	90.2457
Kon	330.9187
Lap	183.7931
Lav	161.9863
Mag	295.8828
Mar	430.8329
Mas	268.456
Mok	169.6565
Mun	415.7286
Pai	307.8022
Raf	288.6829
Rij	365.2663
Shi	280.1323
Sul	451.6622
Taf	511.152
Wus	145.1833

These elevation values were further classified into four classes of regional vulnerability as illustrated in Table 4.2

Table 4. 2.

Classification of Elevation-Based Vulnerability

S/N	Regions	Elevation	Class
1	Bida, Gbako, Katcha	90-128	Highly Vulnerable
2	Agaie, Agwara, Edati, Lapai, Lavun, Mokwa Wushishi	129-256	Vulnerable
3	Borgu, Bosso-Minna, Chanchaga, Kontagora, Magama, Mashegu, Paikoro, Rijau, Shiroro, Gurara, Mariga, Munya, Rafi	257-384	Marginally Vulnerable
4	Suleja, Tafa	385-512	Non-Vulnerable

From the elevation factor, the four classes of vulnerability as adopted in the study conducted within the same study area, which was done by Ikusemoran et al in[29], have influence in various regions of the study area. With Suleja and Tafa considered non-vulnerable. However, due to the unreliability of the results obtained using elevation features as earlier stated in the previous section, the angular slope must be regarded as a causative factor. Most importantly, since it plays a vital role in identifying the velocity as well as vertical percolation in inducing flooding events. Therefore, this research identifies the regional vulnerability based on the slope as described as follows.

4.2.1.1.2 Slope-Based Vulnerability Classification

The slope of a surface plays a significant influence topographically due to its ability to determine the direction as well as the volume of runoff on the surface, in addition to its contribution to stream flow. Therefore, angular slope causative feature aided to determine the form of a slop and how it influences structure, soil type as well as the drainage in

regional upstream flood vulnerability. Notably, as classified within the extracted feature, the slope at depression level ($0-22.5^\circ$) causes a quick flow of water which greatly initiates floods within the study area. Inversely, extreme slope ($67.5-90^\circ$) reduces the flow of water. However, steep and extreme slopes cause flood in regions with lower slopes while depression slope causes water logging.

Broadly, low gradient or depression slopes ($0-22.5^\circ$) are more vulnerable to flooding events compared to slopes with steep and extreme forms. This is because, water from rain or from rivers always accumulates within regions marked by low gradient (depression) pattern. As shown in Figure 4.4.

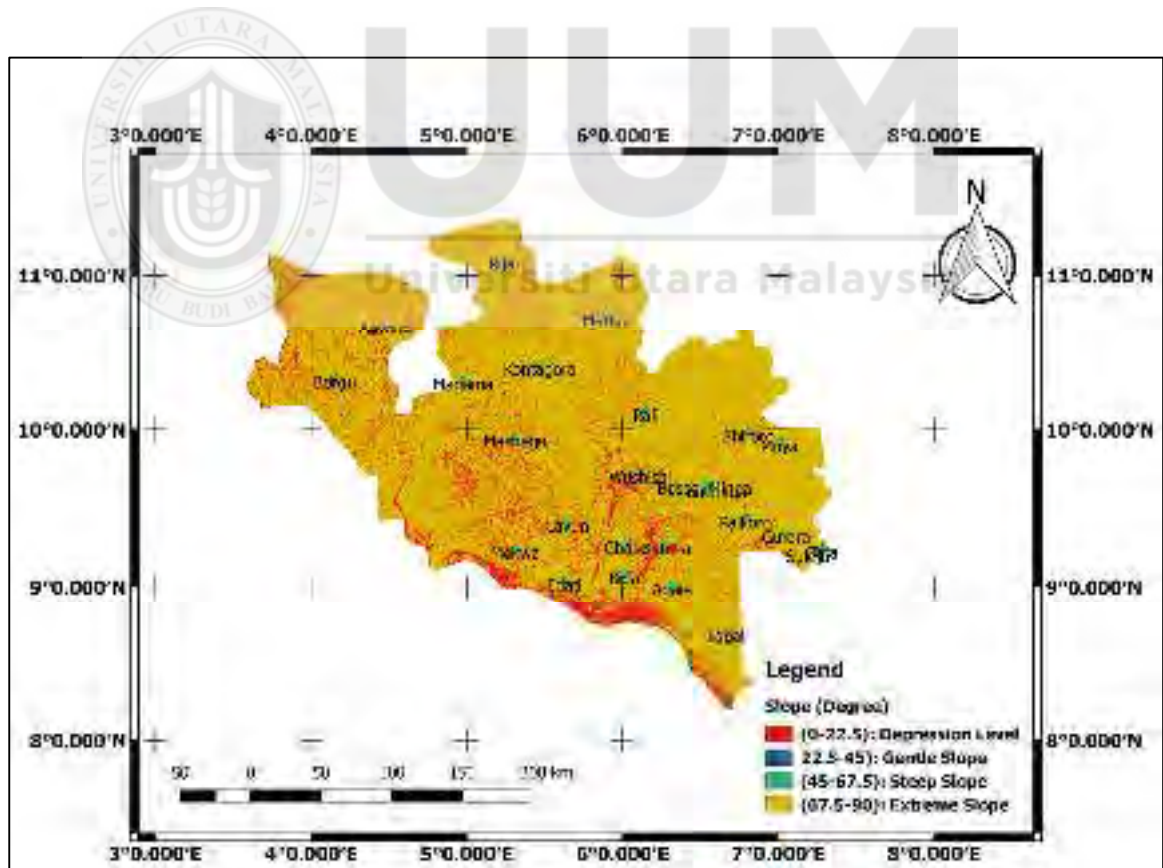


Figure 4.4. Vulnerability Map based on Slope Angles

As illustrated in Figure 4.4, the surface slope is discretized into depression level, gentle slopping, steeply slopping and extremely slopping classes which will be used to analyse various degree of regional flood vulnerability in the next chapter.

As represented by the map in Figure 4.4 above, a vulnerability map based on the slope factor representing the study area was further generated from regional slope. The classification of the vulnerability-based slope as represented in Table 4.3, has been classified into the ranks of Depression (Highly vulnerable), Gentle slope (Vulnerable), steep slope (Marginally Vulnerable) Extreme slope (Non-Vulnerable). For the study area, the vulnerability map based on the slop shows that Niger state lies largely between depression slope and steep slope. By implication, virtually all the regions have their peculiar traits of flood vulnerability. However, regions, situated within the depression slope are more exposed to flood vulnerability as a result of the flow emanating from the regions of extreme slope with a high velocity. The levels of vulnerability based on regional slope is classified in Table 4.3.

Table 4.3.

Classification of Vulnerable Areas Based on Slope Angles adapted from [208] and [215]

S/N	Regions	Slope (°)	Class
1	Mokwa, Mashegu, Borgu, Lavun, Agawara, Wushishi, Katcha, Gbako, Edati, Gurara	0-22.5	Highly Vulnerable
2	Agaie, Bida, Rijau, Bosso, Chanchaga	22.6-45	Vulnerable
3	Shiroro, Munya, Suleja, Lapai, Paikoro, Kontagora, Magama, Rafi, Tafa, Mariga	46-67.5	Marginally Vulnerable
4	N/A	67.6-90	Non-Vulnerable

As tabulated in Table 4.3, the slope values were obtained in the phase of processing the topographic element of the framework. Remarkably, the regional vulnerability identified using slope angles classified all the regions into four classes of highly vulnerable, vulnerable, marginally vulnerable and non-vulnerable. Contrary to the classifications made using the elevation values. The outputs obtained were further assessed with the data sets containing the records of regional Flood Inventory in order to ascertain the factors that provide the most reliable regional vulnerability classification output.

Although, there is a dissimilarity in the generated vulnerability classification by both elevation and slope, a high gradient value of both slope and elevation features do not permit water to accumulate that could result into flooding. However, in the case of floods induced by water bodies, the elevation difference of various elevation cells from the water body could be considered. Whereas, for pluvial flood, local depressions, *i.e.*, elevation cells with lower elevation than the surrounding ones would be more important. This implies that, the way in which the elevation could be associated with risk is important, even though it is also influenced by the density of vegetation attributed to the surface of the region(s) because infiltration of water in the soil is determined by the level of vegetal cover of the region as described in the subsequent subsection.

4.2.1.2 Vegetal-based Vulnerability Classification

Land cover equally influences hydrologic flow. For instance, by decreasing rain splash and increasing soil organic contents and soil porosity, vegetation could increase the rate at which water flows into the subsurface by means of infiltration. While in the subsurface, water can be transpired, flow laterally into surface water body, or move to deeper

groundwater channels. Water stored in the near subsurface is available to deep-rooted vegetation and can be transpired. So, enhancing infiltration may entail a reduction in the total volume of water available downstream [251], which can eventually reduce the vulnerability of floods.

Correspondingly, enhanced soil water retention capacity enhances the protective effect of the soil on precipitation and delays the runoff processes, hours or days after a rainfall event. At present, one of the vast domains of utilizing EO satellite images has been to learn the pattern in the vegetal greenness, which is determined by climatic condition as well anthropogenic activities within the region [252]. Mostly in urbanized areas, these anthropogenic activities can either enhance or reduce the vegetal greenness of a region by adopting agricultural areas into a habitable area [252]. This can subsequently reduce the level of the vegetation of the affected area thereby increasing the vulnerability to upstream floods. As earlier identified in the previous chapter, NDVI generated various degree of vegetation as well as the water bodies present within the study area. As elaborated in ensuing sub-section.

4.2.1.2.1 Normalized Difference Vegetation Index-based Vulnerability

Classification

Generally, vegetation plays an important role in controlling soil erosion. It has been identified that an insignificant number of roots found on the soil can reduce the erodibility of the area when compared with regions without vegetation. Slopes having the features of a dense vegetation exude the ability to resist floods. The classes of vegetation shown in Figure 4.5 were determined by vegetation indices, which has the role of estimating the

greenness of vegetation of the study area and consequently reveals the regional vulnerability accordingly as contained in Table 4.4.

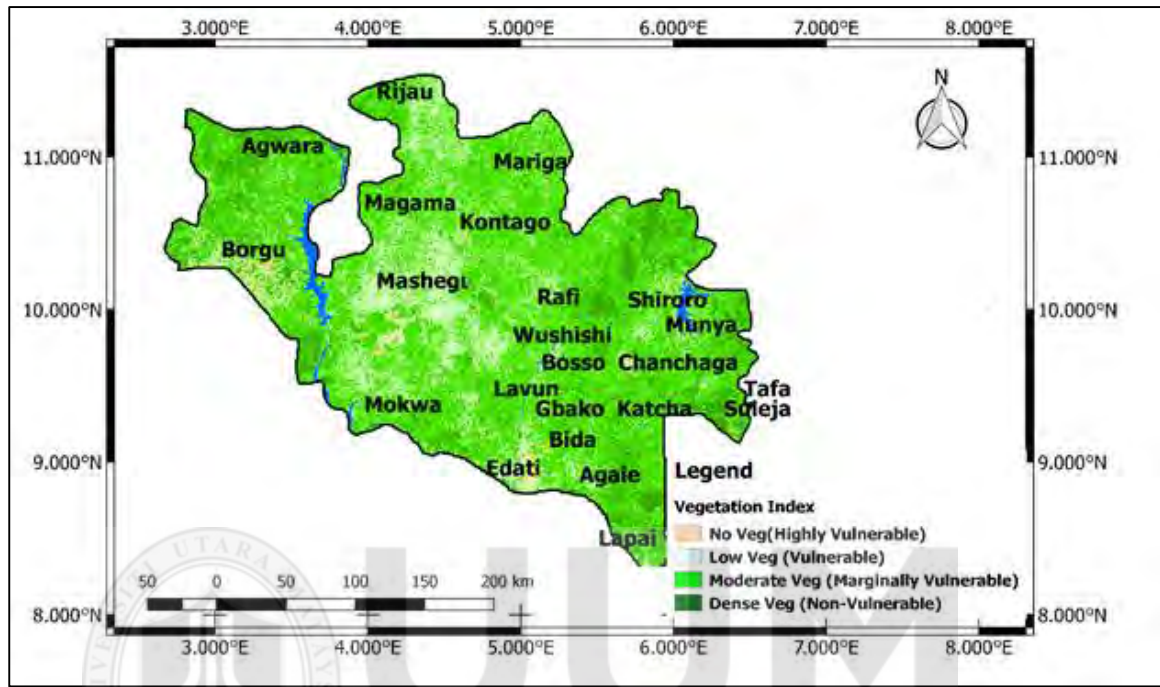


Figure 4. 5. Vulnerability Map based on NDVI

Normalized Difference Vegetation Index (NDVI) of Niger state showing various degree of vegetal density in addition to water bodies. The NDVI presents a stratified form of vegetal classes consisting of water bodies, no vegetation (bare soil), low vegetation, moderate vegetation and dense vegetation which correspond to various levels of flood vulnerability within the study area as shown in Table 4.4.

Table 4.4.

Regional Classification of Vulnerable Areas Based on Vegetation Index

S/N	Regions	Vegetation	Class
1	Borgu, Edati	No Vegetation (Bare soil)	Highly Vulnerable
2	Mashegu, Rafi	Low Vegetation	Vulnerable
3	Mokwa, Mariga, Lavun, Wushishi, Gbako, Bida, Rijau, Bosso, Chanchaga, Shiroro, Munya, Kontagora	Moderate Vegetation	Marginally Vulnerable
4	Agawara, Lapai, Agaie, Suleja, Tafa, Katcha, Magama	Dense Vegetation	Non-Vulnerable

As shown in Table 4.4, Niger state is largely covered with moderate vegetation and partly dense vegetation. As provided by the vegetal feature, supposed, the vast portion of the state experiences upstream floods marginally since land cover characteristic plays a role in flooding event as most of the regions within the State are identified to be marginally prone to upstream floods. Inferentially, this could be due to the impact of majorly regional greenness of the surface within the state. As earlier presented, both topographic and vegetal factors are directly influenced by the hydrological factors which determines the accumulation as well as the direction of flows as presented in the next subsection.

4.2.1.3 Hydrological-based Vulnerability Classification

Hydrological features are essential elements to identify the geographical proximity or interaction of an area with water [249]. These features help in recognizing the source as well as the routes taken by water. Although, the delineation of watershed can enhance the knowledge of areas that are potentially vulnerable to floods [249]. Nonetheless, the identification of flow on the surface needs a detailed physical illustration of the region at

the drainage structure in order to accurately describe the pattern of the flow during a flooding event [249]. Even though data sets or features obtained from various EO satellites, such as terrain features aid in the identification and assessment at various levels, the utilization of combined heterogeneous sets of data to reveal in-depth details of all the flood causative factors can enhance the flood analytical results.

4.2.1.3.1 Flow Direction-Induced Vulnerability Classification

The features representing the flow direction was required to identify the pattern at which the runoff on a surface causes flood using the slope from the adjacent cells within the study area. Especially, since the hydrological representation of flow direction is usually used to reveal the paths taken by water. Additionally, flow direction within a cell identifies the possibility of water flowing to either one or more of the adjacent regions which is also influenced by the slope of the study area. As such, Figure 4.6 illustrates various paths that water takes to potentially cause upstream flooding within the study area.

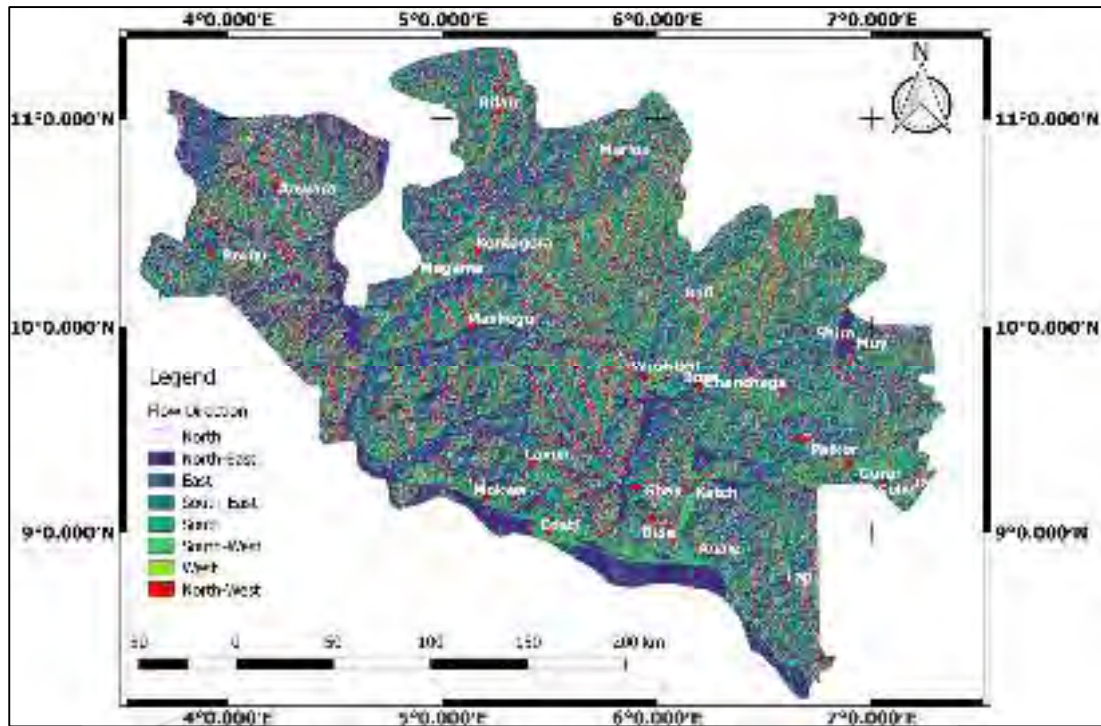


Figure 4.6. Flow Direction Induced Vulnerability

In the generated flow direction factor (Figure 4.6), it shows that the flow direction/Pattern across the state is majorly around the Southern axis of Katcha, Agaie and Edati. Thus exposing these regions to a high level of flood vulnerability, while it is slightly and uniformly distributed in other regions, with some regions like Shiroro and Munya are naturally drained into the adjacent water body, and other natural drain channels in neighboring surfaces.

Furthermore, even though the direction of flow remains one of the factors that influences flooding events, regions which receives high volume of accumulation need to be identified as well. The identification of this flow accumulation is presented in the resulting sub-subsection.

4.2.1.3.2 Flow Accumulation-Induced Vulnerability Classification

The generated feature representing the flow accumulation as shown in Figure 4.7 estimates the volume of the accumulated or accrued flow of water within the study area, which is also used to identify the stream channels present within the study area. This output as illustrated in Figure 4.7 equally reveals the volume of rain that falls on the surface which could flow towards each direction.

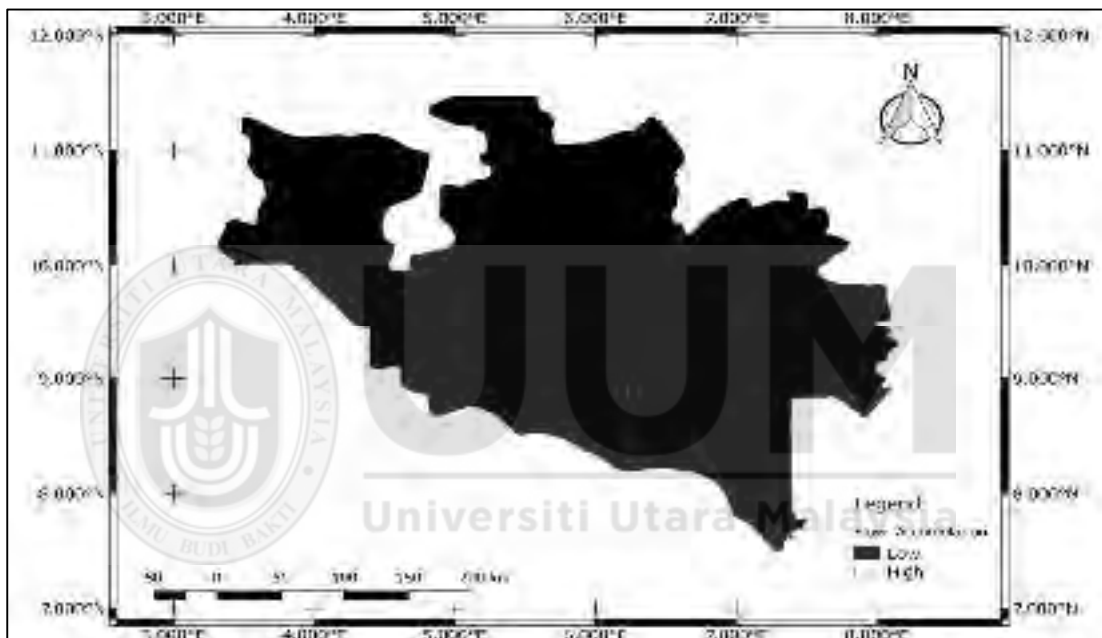


Figure 4.7. Flow Accumulation

The grids with the highest volume of accumulation are uniformly distributed mostly at the bottom of the pits within the South-Eastern regions of Gbako, Wushishi, Katcha and Rafi.

With the identification of the direction and accumulation of flow and the regions associated with the vulnerability therein, the ensuing sub-subsection determines the level of wetness of the terrain known as Topographic Wetness Index (TWI).

4.2.1.3.3 Topographic Wetness Index-Induced Vulnerability Classification

The Topographic Wetness Index (TWI) reveals the dispersal of regional topography which fundamentally determines the influencing region at the moment of rainfall in function of different slopes within the study area. The first assumption consists of approximating the transient response of the regions as a sequence throughout a stable condition and the supposed rate of discharge to be uniformly spatial which is given by equation 4.1:

$$q_i^t = a_i P^t \quad (4.1)$$

Where a_i represents upstream region flowing via cell I/m, draining factor (rainfall), P^t represents the rain within a given period t(m/hr); While q_i^t represents the discharge of the surface due to region being saturated, measured in m²/hr.

The use of TWI in regional flood vulnerability classification is reliable, because it is derived from DEM based on the principle that a topographical profile controlling the dispersal of water and regions that contain the accumulation of water can also foretell the observed trend of saturated region. Therefore, in this research, the TWI was used to identify higher water content around the regions of Bida, Agaie, Borgo and Agwara of the state, while other regions have been attributed to a low water content. These low and high level of water contents represent lower and higher flood vulnerability respectively in the study area. Implicitly, the TWI of the surface within the study area was determined by the evaluation of slope, flow direction and accumulation. The output generated a terrestrial representation of regions having drainage depression with a potential water accumulation. The regional value of TWI is determined as follows:

$$I = \ln(a/\tan\beta) \quad (4.2)$$

Where I represents the value of index;
 with a representing the high contributing surfaces;
 while β represents the topographical slope.

Another significant aspect of TWI dwells in its ability to observe the spatial influence on hydrology as well as its ability to identify the flow direction within the surface of the study area. The vulnerability classification obtained from TWI showing various regions and their corresponding soil saturation is illustrated by Figure 4.8.

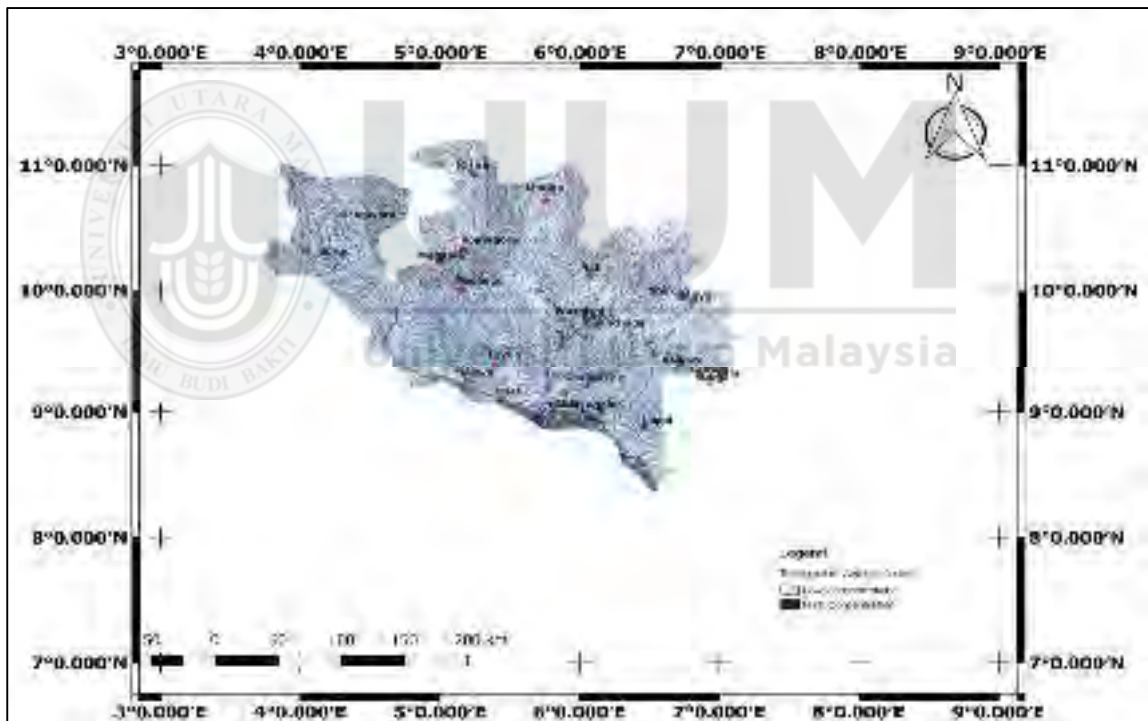


Figure 4.8. Topographic Wetness Index

In the TWI map, regions with low values of TWI represent the less vulnerable for forming ponding; while larger values of TWI are formed when the high surfaces are drained over a gentle slope.

Table 4.5

TWI-based Classification

S/N	Regions	Concentration Level	Class
1	Mokwa, Edati, Katcha	High Concentration	Highly Vulnerable
2	Borgu, Agwara, Bosso, Gbako, Chanchaga, Paikoro, Rafi, Kontagor, Magama, Mashegu, Mariga	Moderate Concentration	Vulnerable
3	Munya, Shiroro, Lavun, Rijau	Low Concentration	Marginally Vulnerable
4	Bida, Lapai, Agaie, Wushishi, Gurara, Tafa, Suleja	Least Concentration	Least Vulnerable

Here, surface ponding denotes the stagnant water on depressional surface where the surface soils gets to a point of saturation or flooded concrete depressions when precipitation is unable to infiltrate the surface. The TWI has identified lower water content around the North-East region of the state, while the regions which are situated around the central and the western regions. It has also been identified by [253], that, TWI can effectively be utilized to reveal regions that are associated with flood vulnerability. The values and the level of vulnerability in relation to the classified factors are summarized in Table 4.6.

Table 4.6.

Interpretation of Flood Causative Factor Classification

Flood Causative Factors	Values/ Classification	Classification	Interpretation
Elevation (metres)	90 - 128	1	Highly Vulnerable
	129 - 256	2	Vulnerable

	257 - 384	3	Marginally Vulnerable
	385 - 512	4	Non-Vulnerable
Slope(Degree)	0 - 22.5	1	Highly Vulnerable
	22.5 - 45	2	Vulnerable
	45 - 76.5	3	Marginally Vulnerable
	67.5 - 90	4	Non-Vulnerable
Flow Direction	Directed Flows	1	Highly Vulnerable
		2	Vulnerable
	Non-Directed Flows	3	Marginally Vulnerable
		4	Non-Vulnerable
Flow Accumulation	High Accumulation	1	Highly Vulnerable
		2	Vulnerable
	Low Accumulation	3	Marginally Vulnerable
		4	Non-Vulnerable
Topographic Wetness Index	High Accumulation	1	Highly Vulnerable
		2	Vulnerable
	Low Accumulation	3	Marginally Vulnerable
		4	Non-Vulnerable
Vegetal Factor	No Vegetation	1	Highly Vulnerable
	Low Vegetation	2	Vulnerable
	Moderate Vegetation	3	Marginally Vulnerable
	Dense Vegetation	4	Non-Vulnerable

Thus far, the extracted features have been used to identify various regions and their associated levels of vulnerability within the study area. In the identification of regional upstream flood vulnerability, various causative factors were independently used to classify regions based on their respective levels of vulnerability. In summary, the output

of the generated regional flood vulnerability is contained in Table 4.7 with classification of HV,MV,V,NV representing Highly Vulnerable, Marginally Vulnerable, Vulnerable and Non-vulnerable respectively.

Table 4.7
Regional Flood Classification

Causative Factors	Number of Classifications out of 4
Elevation	HV,MV,V,NV
Slope	HV,MV,V,LV
Vegetation	HV,MV,V,NV
Flow Dir	HV& NV
Flow Acc	HV& NV
TWI	HV,MV,V,NV

The classified outputs were further compared with the Flood Inventory data collected over ten years as graphically represented in Figure 4.9.

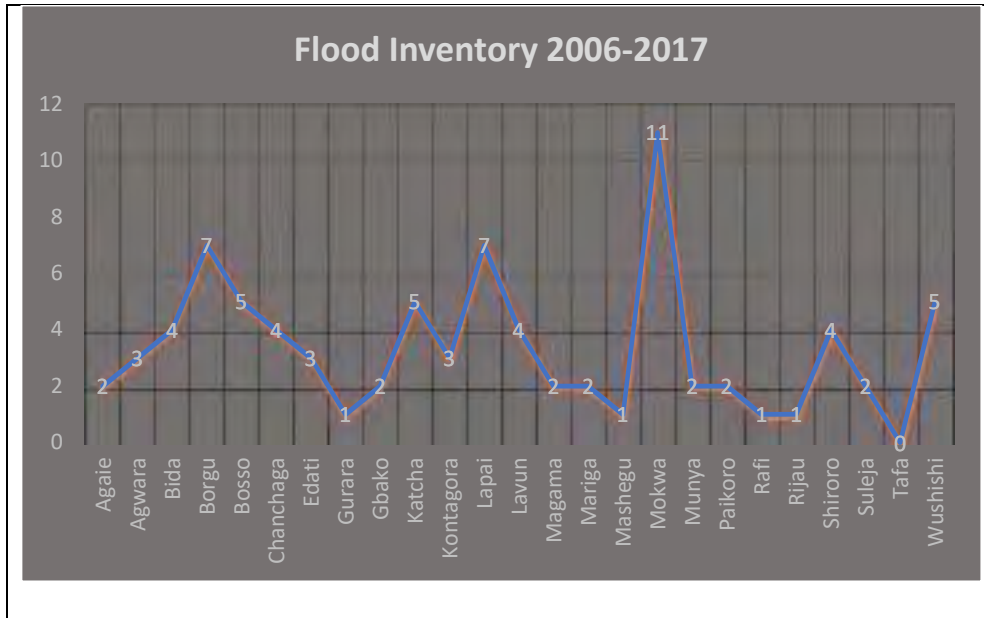


Figure 4.9. Flood Inventory

From the record contained in the flood inventory, it is evident that twenty-four out of twenty-five regions have experienced flooding events within the period of 2006-2016. This indicated that virtually, all the regions are vulnerable to floods except one as contained in the record. Therefore, the accuracy of the hydrological and vegetal factors is deemed defective. This is primarily because both hydrological and vegetal factors failed to reveal other regions that are vulnerable to floods.

However, in comparison with topographical factor, it is noteworthy that, topographic factor generated a more reliable result when compared with the flood inventory. This is because, all other factors made a partial identification of regions vulnerable to flood. However, topographical factors generated a result that classified all the regions within various levels of flood susceptibility. Hence, it can be inferred that the topographical factor, most especially the angular slope is more accurate in identifying flood vulnerability. This was further elaborated in the Findings Section i.e. Chapter Five of the

thesis. Meanwhile, in conformity with the proposed hybrid approach, which is to identify regional flood susceptibility prior to performing long-lead upstream flood prediction for the vulnerable regions, next sub-subsection describes the approaches employed in identifying the minimum value of precipitation that can potentially instigate flood in these regions.

Generally, precipitation data remains a vital variable required to learn the pattern of rainfall required for hydrological cycle[254]. The intensity of precipitation immensely influences the severity of flood, as the hydraulic conductivity; which is the property of soil or plants that describes the ease with which water can move through pore spaces tends to be exceeded by the volume of the precipitation[255]. In addition, the increase of rainfall induces more rate of runoff and the depth of inundation path [255]. Similarly, it has been identified that the present climate change immensely contributes to the increase in flooding globally [256],[257].

Therefore, learning pattern of varied climatic conditions such as rainfall aids in understanding the potential environmental impacts which in turn, will be very crucial in decision-making[258]. This is because, early prediction systems can aid in enhancing the efficiency of any flood mitigating measures, which decreases losses, such as evacuation, flow diversion, alerting the populace and preparedness of the flood managers[258]. In view of this, descriptive analysis based on statistical approach was adopted on the data in order to correct the data set and also have a global insight on the data prior to the long-lead prediction.

4.2.2 Long-lead Statistical Assumptions from Temporal Data

This research employed a statistical approach to correct and describe the influence of precipitation on regional upstream flooding in the study area. Within the scope of this research, the descriptive analysis of temporal variables are as represented in Table 4.6. The Table indicates the Minimum (min), mean, Standard Deviation (SD) obtained from daily temporal records containing the precipitation, temperature and water level data over the period of 37 years.

More specifically, this sub-subsection presents the descriptive analysis for temporal data consisting of Precipitation, Temperature and Water level adopted for long-lead flood analysis. The descriptive analytics were presented based on the analytical output using regression. Besides, the daily descriptive statistics for regional precipitation, Temperature and Water Level is presented in Table 4.7.

Table 4.7

Values of Descriptive Analytics.

Variable	Min	Mean	Sd
Precipitation (mm)	0	20.924	4.905544
Temperature (°C)	10.212	46.2384	6.877063
Water Level (mm)	1.03	95.59	95.59

Descriptively, the temporal components contained in the Table 4.7 above shows varied minimum, mean and Sd values for precipitation, temperature and water level. The summary of the results as shown in the above table describes the variables being considered for the long-lead analysis. Also, the correlation between the variables which

determines the relationship among variables is further elaborated in the ensuing sub-subsection.

4.2.2.1 Correlation Analysis

Correlation analysis amongst the temporal variables was also considered within the scope of this research. Correlation analysis is performed fundamentally to describe the strength and direction of the relationship between variables [259]. The interpretation of the influence or strength within the variables based on of the relationship between variables was done based on criteria regarded in [259], which states that a correlation value of ($r=0.9$ and higher) is unsuitable and indicates multicollinearity within the approach. Therefore, as contained in Table 4.8, the correlation between variables of regional precipitation, water level and temperature are within the values of a suitable threshold (<0.9). Accordingly, the highest value between the variables is 0.099526.

Table 4.8

Variable Correlation

Precipitation	Coef.	Std. Err.	T	P> t 	[95% Conf	Interval]
Temperature	-0.1385825	.0053255	-26.02	0.000	-.1490213	-.1281438
Water Level	.0995206	.0017436	57.08	0.000	.0961028	.1029384
Cons	3.771378	.1725279	21.86	0.000	3.4332	4.109556

As contained in Table 4.8, the coefficients indicating a very weak correlation to precipitation, which is the upstream factor. However, the results show a significant correlation with both negative and positive correlation for Precipitation-Temperature and

Precipitation-Water level respectively. Analytically, when a unit of precipitation increases, it will cause decrease of 14%, while water level will increase with 10%.

Ultimately, the positive relation between precipitation and water level is indicative of influence of precipitation to increasing level of water within the water body which capable of instigating flooding events within Borgu regions, which is adjacent to the main water body in the study area. A conservative rule of thumb, then, seems to be that absolute values of Kittler-Illingworth (KI) > 10.0 suggest a problem, and absolute values of KI > 20.0 indicates a more serious one implementing the obtained FIPV. From this insight, there is no identifiable record of multicollinearity between the temporal data used in this research. To this effect, diagnostic tests were performed within the statistical analysis to further reveal any violation of statistical inference.

4.2.2.2 Diagnostics Test

Conducting diagnostics test is an important approach within the concept of the descriptive analysis. Its usefulness is due to the role it plays in identifying any potential defilement of fundamental assumptions related to multivariate data analysis [260]. As such, this research conducted tests to address any issues associated with missing values, outlier evaluation and normality check in order to ascertain the validity assumptions prior to performing inference for the long-lead prediction.

4.2.2.3 Missing Values

Missing values represents the unavailability of suitable value of one or more variables for data analysis. Similarly, missing values can lead to a biased estimate and consequently, a distorted and erroneous decision-making [261]. Given the need for analytical accuracy

needed for decision-making, this research, performed an initial descriptive analytics to identify the volume of missing values within the large temporal data sets. Subsequently, the output of the descriptive statistics showed a total of 13850 records in the dataset (Appendix B), out of which no value was missing. Therefore, the assessment of possible outliers was done as presented in the resulting sub-subsection.

4.2.2.4 Assessment of Outliers

Outliers are observations in a dataset that are substantially different from the bulk of the data [262],[263]. In a regression-based analysis, the existence of outliers in a dataset can substantially distort the estimates of regression coefficients and consequently lead to unreliable results. However, to check for possible existing of outliers, several methods are often employed including standardized residual, cook's distance and Mahalanobis distance statistic. For this research, graphical-based and standardized residual method were used to detect any possible observation which is outside the expected range, as illustrated in Figures 4.10 and 4.11.

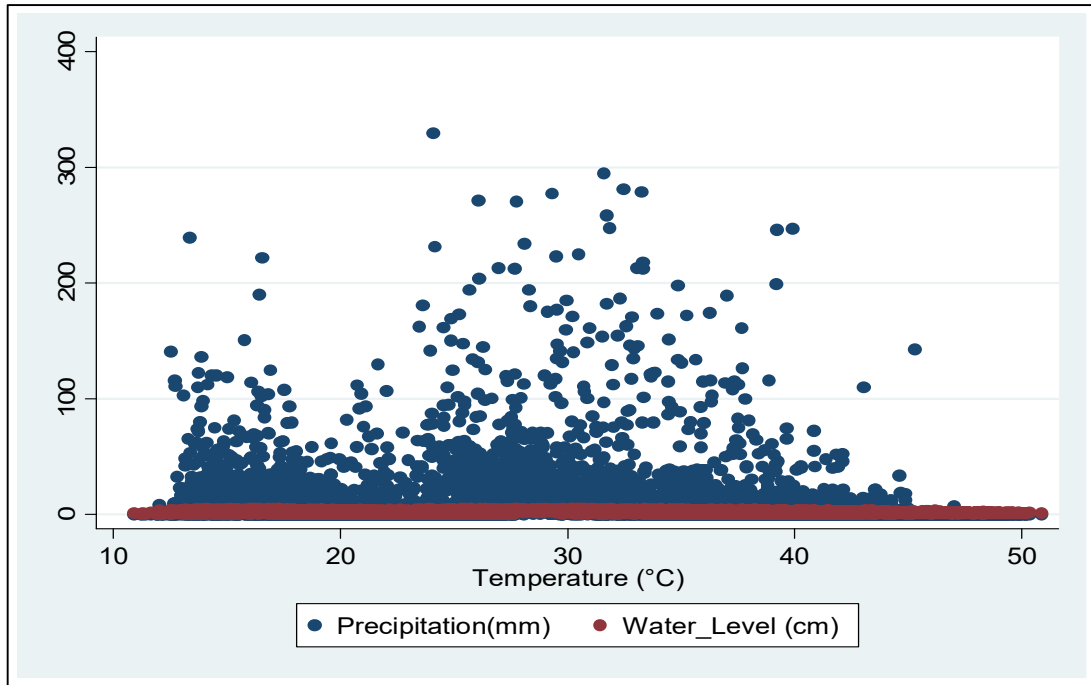


Figure 4.10. Graphic-Based Outlier Representation for 1979-2016 Daily Record

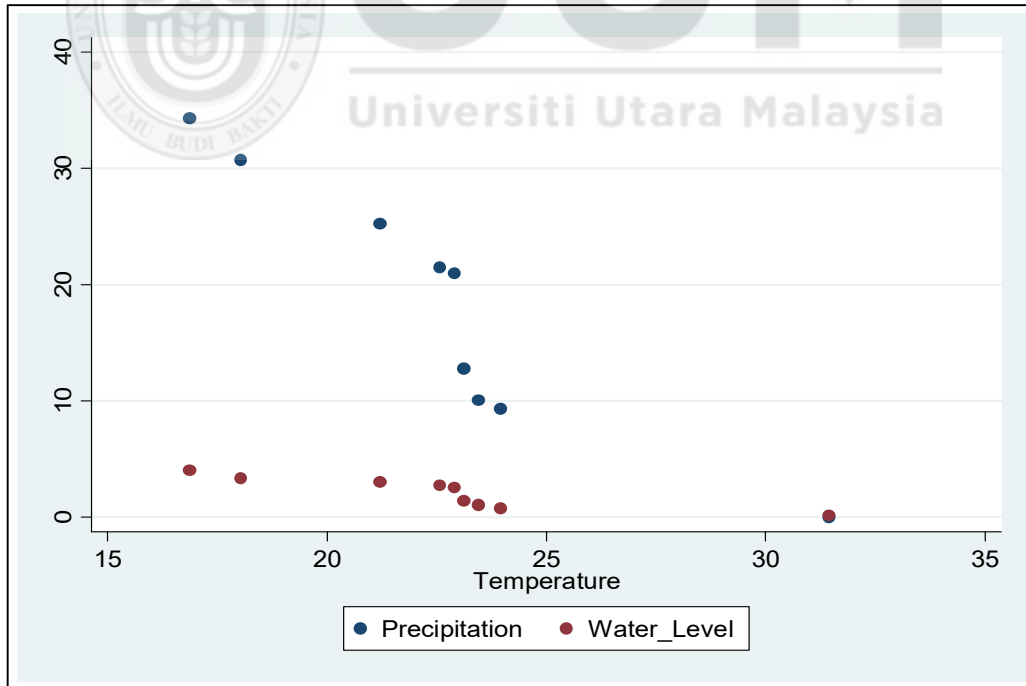


Figure 4.11. Graphic-Based Outlier Representation for Long-lead Record Over 8 Days

From the above graphical representation, the records representing the 1979-2016 daily temporal data sets is highly overwhelmed by the presence of outliers. Contrarily, within Long-lead record of 8 days, there is no any sign of this effects. To further ascertain this claim, standardized residual method was assessed.

Generally, standardized residual method is the most widely used measure for detecting outliers. According to the rule of thumb, observations with standardized residual above +3 or -3 are considered as outliers[264],[265]. From the obtained results using all the temporal records, the residual results showed high presence of outliers depicted by the outputs of the residual results.

Table 4. 9.

Summary of Residual 1979-2016 Records

Source	Sum of Sq.	Degree of Freedom	Mean Sum of Sq	Number of Obs = 13850
Model	473914.725	2	236957.363	F(2, 13847) = 738.65 Prob > F = 0.0000
Residual	4442097.3	13847	320.798534	R-squared = 0.0964
Total	4916012.03	13849	354.972347	Adj R-squared = 0.0963 Root MSE = 17.911

As contained in Table 4.9, the record of the variable i.e. precipitation, temperature and water level contains 13859 number of observations comprising of records from 1979-2016.

Table 4.10

Summary of Residual for Non-floodable Observations

Source	Sum of Sq.	Degree of Freedom	Mean Sum of Sq.	Number of obs = 9 F(2, 6) = 4.54 Prob > F = 0.0630 R-squared = 0.6021 Adj R-squared = 0.4694 Root MSE = 0.58193
Model	3.07418162	2	1.53709081	
Residual	2.031856	6	0.338642667	
Total	5.10603762	8	0.638254703	

As contained in Table 4.10, the record of the variables i.e. precipitation, temperature and water level contains 9 number of observations comprising of records of 9 days of non-floodable period, while the statistical values for floodable period contained in Table 4.11.

Table 4.11

Summary of Residual Long-lead Records

Source	Sum of Sq.	Degree of Freedom	Mean Sum of Sq.	Number of Obs = 9 F(2, 13847) = 2142.67 Prob > F = 0.0000 R-squared = 0.9958 Adj R-squared = 0.9943 Root MSE = 0.83697
Model	986.8801	2	493.44004	
Residual	4.203071	6	.700511853	
Total	991.0832	8	123.885394	

As contained in Table 4.10, the record of the variable i.e. precipitation, temperature and water level contains 9 number of observations comprising of records of 9 days of long-lead floodable period.

As contained in Tables 4.8, 4.9 and 4.10, the value of R^2 for the entire records of temporal data from 1079-2016 contained in Table 4.8 indicates an unfitness of the predictive model due to the presence of outliers. While the values of R^2 for the non-floodable and long-lead floodable records in Tables 4.9 and 4.10 show the fitness of the predictive model. This in general, shows the correctness of the model since the higher the R-squared, the better the model fits the data set. Summarily, the values of the residual indicate that the maximum and minimum standard residual values are within the limit of +3 or -3 as suggested by [264],[265],[266]. Based on this indication, none of the observations showed a high standard residual that has the potential to be an influential outlier. Accordingly, there is no case in the data set that is found to be an outlier for Non-floodable and Long-lead observations in Tables 4.9 and 4.10 respectively.

4.2.2.5 Normality Test

Normality represents the assumption indicating a normal distribution of the temporal variables as well as the linear combination within a model [266]. Several statistical analysis consisting of correlation and regression depend on the assumption that the sets of data conform to normality distribution. As a result, the normality of data sets has to be verified to ensure the correct use of statistical tests prior to an acceptance of a suitable hypothesis [267]. Additionally, normality test is vital in several approaches, linear

operations inclusive. Broadly, several assumptions for any potential occurrence of events are obtained from statistical inferences using normality [268].

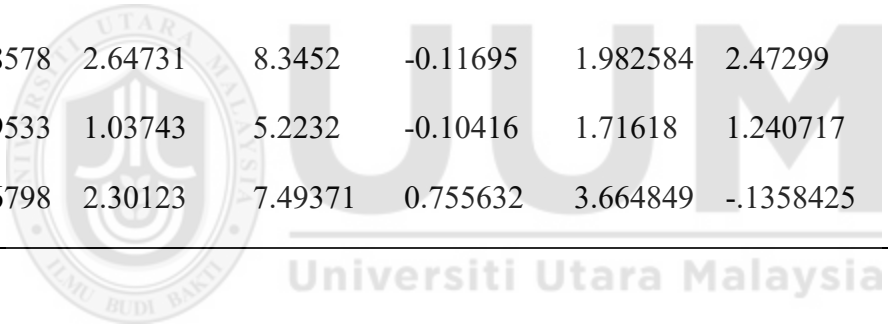
Also, normality-based test is required in data estimation since one of the assumptions of multiple regression requires the need for residual to be normally distributed. The generally adopted means of normality assessment was conducted with the aid of skewness and kurtosis values[269]. Therefore, to conduct a normality assessment on data using skewness and kurtosis, various acceptable values for both skewness and kurtosis were employed were required. Accordingly, [265] suggests a value of ± 3 for skewness and ± 10 for kurtosis. In this research, a skewness and kurtosis test was performed for all variables.



Table 4.12

Skewness and Kurtosis for All records, Long-lead and Non-flooded Observation

Variable	Panel A		Panel A'		Panel B		Panel C	
	All Records Before Winsorization		All Records After Winsorization		Long-lead Observation		Records for Non-Flooded Observation	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Precipitation	7.301158	74.28578	2.64731	8.3452	-0.11695	1.982584	2.47299	7.119635
Water Level	0.8443582	2.809533	1.03743	5.2232	-0.10416	1.71618	1.240717	2.880278
Temperature	0.1527965	1.596798	2.30123	7.49371	0.755632	3.664849	-1.1358425	1.91514



Considering the records Before Winsorization (Panel A) of Table 4.12, contrary to records after Winsorization (Panel A'), the results indicate that the skewness and kurtosis value for precipitation and water level were beyond the acceptable defined limit. Even though, with a large volume of data set, this assumption are not considered,(i.e. sample size greater than 30 are exempted from normality distribution tests) nonetheless, in order to uphold the established assumption of normality in respect of data distribution, the affected variables were further Winsorized at 5% in conformity with [270]. After performing the Winsorization as demonstrated in sub-section 3.4.1.2, a descriptive statistics values (Table 4.11), were generated to derive the values for skewness and kurtosis. At this point, the value of skewness and kurtosis for all the variables as presented in Table 4.11, were within the acceptable threshold of ± 3 and ± 10 for skewness and Kurtosis respectively as recommended by [265].

As contained in Panel B and C of Table 4.11, skewness values for precipitation, water level and temperature were within the acceptable value of ± 3 and kurtosis value lower than 10. Explicitly, this approach was able to efficiently address issues related to normality within various variables used in this research. Aside, adopting this numerical approach for normality assessment within the variables, graphical means is equally used to further ensure the normality of the variables, which is in addition, was adopted in this research in order to have an elaborate and reliable assessment prior to the implementation of model specification test for long-lead upstream prediction. Consequently, a normality P-P plot and histogram were used to assess the fulfilment of the normality assumptions.

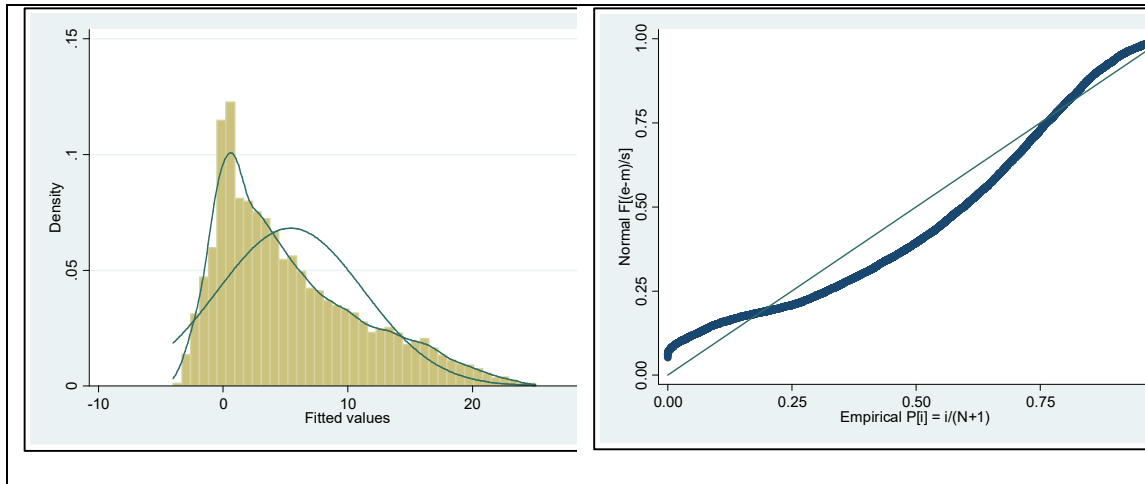


Figure 4.12. Probability Plot and Histogram: All records (1979-2016)

Evidently, the pictorial results of both P-plot and Histogram in Figure 4.12 above, which was obtained from the 1979-2016 daily records showed a skewed pattern, denoting a non-normally distributed data. Contrary to the results obtained for the long-lead observations as illustrated in Figure 4.13.

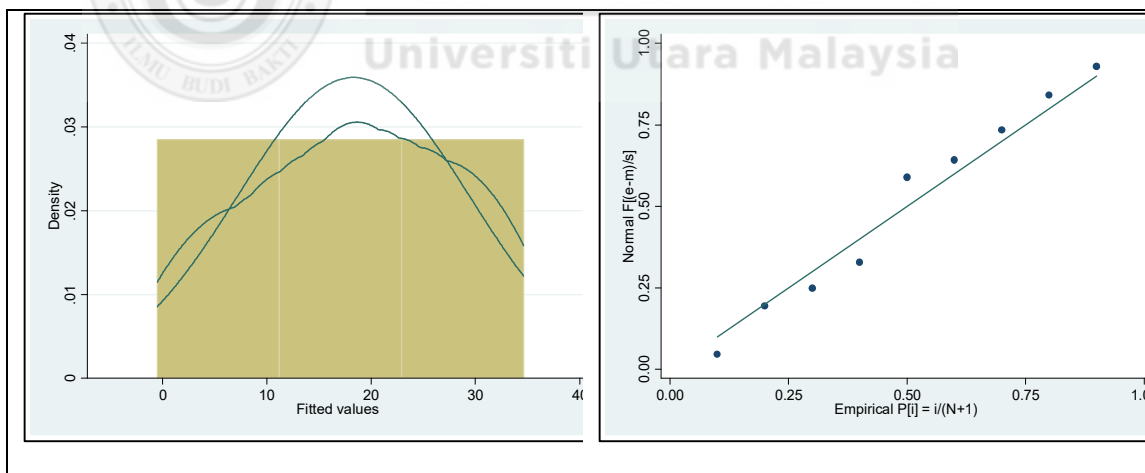


Figure 4.13. Probability Plot and Histogram: Long-Lead

Figures 4.10 and 4.11 depict the probability plot and histogram for both long-lead records and the complete data sets.

As illustrated in Figures 4.10 and 4.11, both the normality P-P plot and histogram confirmed that the temporal data used for all the records and long-lead upstream flood records fulfilled the normality trend. The normality P-P plot illustrates that the data points form an approximate straight line that is close to the fitted line. An indication that the variables are in a normal distribution trend. Likewise, the trend of all the bars on the histogram. As such, from these results, normality assumptions are assumed not to be violated in this research. Illustratively, the results for long-lead (Figure 4.11), showed a normal distribution pattern, while the representation for all records showed a skewed pattern, indicating a non-normal distribution.

Essentially, conducting the correlations test for various regions independently showed both negative and positive relationships. Correlation coefficient between 0.0995206 to -0.1385825 were found with statistically significance at 86-99% based on t-test, this suggests certain connection between precipitation, water level and the temperature. It is worth noting that, this research is entirely based on big data, which allows the exemption of normality threshold test on the output. However, due to importance attached to the accuracy of the seasonal trends towards long-lead, validity of the normality was ensured because if the assumptions derived from the normality are not substantiated, it is impossible to draw accurate and reliable conclusions about practical events. More so, in statistical data analysis, many data sets are prone to outliers which increases the value of the kurtosis. Hence, the need to ensure the absence of outliers which could affect the accuracy of the lead-time [267],[268]. With these obtained values below the threshold, it can be concluded that assumptions based on the normality are valid.

4.2.2.6 Regression Results

Thus far, the aforementioned approaches conducted various diagnostic tests on the temporal data sets using multiple linear regression. Specifically, the regression was performed using precipitation data as the dependent variable, while water level and temperature were also considered. Consequently, the normality test needed for the hypothetical inference was conducted between the variables using normality distribution assessment based on the adapted study on flood information [63], which was personally recommended by the principal author of the paper. The obtained results correspond to the defined values of coefficient (β), t-statistics and p-values. Hence, the following section determines the trend of the data sets prior to the determination of FIPV in order to identify the lead-time for the long-lead analysis.

4.3 Long-Lead Trend Representation

In recent times, interest has increased in learning about precipitation variability and trend in order to improve the periodic predictability for climate studies[271]. Identification of trends using time series related to environmental sciences can be obtained through a set of familiar classical procedures [272]. This is especially significant due to the explosion of spatiotemporal data sets that provide a common basis for data utilization aimed at attaining meaningful and applicable output for better decision-making. Particularly, depiction of historical trends and variations are significant for comprehension of the fundamental processes of flood, and then to predict for the motive of monitoring and mitigating any adverse impacts from floods [272].

Broadly, precipitation is extreme spatiotemporally since it is the result of complex interactions between a variety of dynamic processes with characteristic of spatial and temporal measures [271]. As earlier established in this research, the need to learn the pattern variability of precipitation (rainfall) allows the long-lead upstream prediction to be focused towards periods where there is an extreme precipitation volume. While the prediction ignores months with an insignificant or no rainfall. Therefore, in order to identify the magnitude of the trend in hydro-meteorological time series, Normality Distribution test based on adapted study for long-lead prediction [55][63] and[273] was employed. Fundamentally, the trend of the temporal data depicting the temporal variability was obtained within the framework as shown in Figure 4.14.

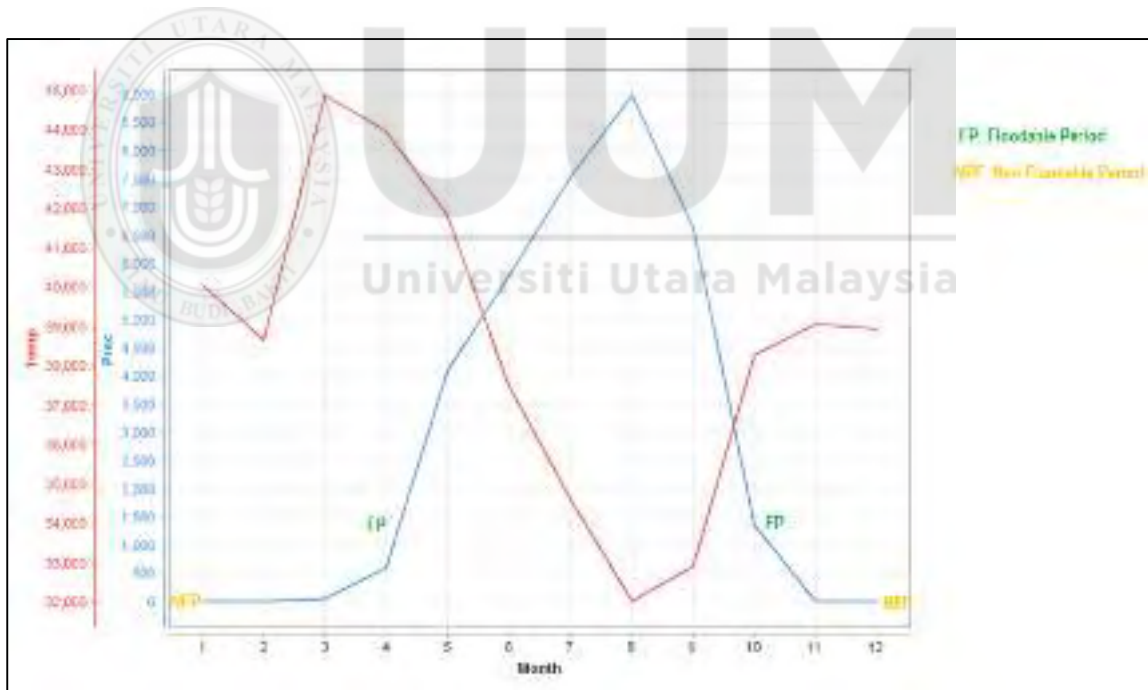


Figure 4.14. Temporal Trend Variation

From the generated results of the learned trends above, the overall observation identified, the months of November, December, January, February and March are normally

associated with no rainfall. While April to October are the months with rainfall records, with August having the peak rainfall round the year.

Accordingly, the period from 2006–2016 experienced a relative increase in precipitation, and water level, leading to an associated increase in flooding events. This increase in the hydro-meteorological trend is directly associated to the current climate change experienced globally. With respect to upstream floods, this research identifies the general definition of flood as the large accumulation of precipitation capable of submerging the surface of the land [274]. Therefore, the following subsection presents the approaches used in identifying accumulated volume of precipitation that can lead to a flooding events in various regions of the study area referred to as Flood Inducible Precipitation Volume (FIPV).

4.3.1 Determination of Flood Inducible Precipitation Volumes

The preceding section drew an understanding on the trend of rainy and non-rainy seasons within the study area. Broadly, understanding the trend of rainy seasons can be crucial in managing the floods affecting millions of individuals as well as damaging properties [274]. Extreme precipitation generally impedes several economic activities as a result of the detrimental events caused by these floods[275]. Therefore, considerable lead-time identification of such extreme precipitations is required for decision-making, as well as strategic adaptations. Consequently, in order to determine the FIPV, the volume of a daily precipitation was determined by examining the quantity of the daily rainfall value in a succession of daily rainfall using the following equations.

$$\text{With } \bar{x} = \frac{\sum^N x}{N} \quad (4.3)$$

Where \bar{x} represents a trend observation \sum is the sum while N represents the total number of observed trends. While the standard deviation (SD) utilized is represented as:

$$SD = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{n-1}} \quad (4.4)$$

Where SD Standard Deviation

\bar{x} = The value of the observed trend while

$$CV = CV = \frac{SD}{\bar{x}} \times 100 \quad (4.5)$$

Where:

X = Daily records for a defined time

N = Number of records considered

\sum = Sum of all the values

Consequently, the FIPV = \sum

Thus, generating the accumulation of precipitation both non-floodable and floodable values that can potentially induce upstream flooding events over a long-lead time frame in the region of Borgu is contained in Table 4.13.

Table 4.13

NIPV and FIPV of BorguRegions

Panel A: Non-Floodable Observation Over 9-Days				Panel B: Floodable Observation with 8-Days Lead Time			
Date	Precipitation (mm)	Water Levl (cm)	Temperature(°C)	Date	Precipitation (mm)	Wat Level (cm)	Temperature (°C)
24/03/2015	2.4075	0.946	24.93	03/06/2015	9.31	0.769	23.96
25/03/2015	0.045	0.145	26.18	04/06/2015	12.75	1.390	23.12
26/03/2015	0.0225	0.401	29.8	05/06/2015	34.3	4.014	16.87
27/03/2015	0	0.096	33.63	06/06/2015	0	0.101	31.45
28/03/2015	0	0.044	32.25	07/06/2015	10.02	1.026	23.45
29/03/2015	0	0.057	34.73	08/06/2015	21.5	2.710	22.57
30/03/2015	0	0.046	37.28	09/06/2015	20.95	2.504	22.9
31/03/2015	0.0225	0.115	30.34	10/06/2015	25.21	3.012	21.21
1/04/2015	0	1.230	38.46	11/06/2015	30.75	3.333	18.04
Total	2.4975	3.081394762	287.6	Total	164.79	18.85901	203.57

Table 4.13 containing both floodable and non-floodable volumes. The records contained in Panel A contains the total accumulation of precipitation of 2.4975mm collected over 9 days, with no associated flooding events. While the values under Panel B, the accumulated volume of precipitation from 03/06/2015 to 11/06/2015 led to flooding event. This was obtained after the identification of the flooded date from the flood inventory. And the previous rainy days were identified with their corresponding volumes of precipitation, which gave the accumulated volume of 164.79mm over 8-days lead-time. Here, the number of days from the aforementioned dates is nine. Nonetheless, on 06/06/2015, no rainfall was experienced as depicted by the value corresponding to zero (0). Hence, the total number of the cluster is number of rainy days minus(-) the number of dry days to measure the lead-time/days. From these values, the formation towards FIPV commenced from 03/06/2015, while 06/06/2015 witnessed recession of volumes because there was no rainfall experienced. The re-accumulation of the FIPV recommenced on 07/06/2015 with precipitation volume at 10.02 mm.

Correspondingly, the regional values of the FIPVs for other regions were identified as summarized in Appendix J. This research has identified an uneven distribution of FIPV to the influence of other spatial factors, such as elevation, vegetation, slope, flow direction and flow accumulation of the surface in various regions of the study area tabulated in Appendix J.

Inferentially, when the FIPV for various regional elevation is at the verge of accumulation, the estimated value can be used to determine the lead-time of a potential flooding events. Hence, proactive measures can be implemented within the vulnerable region(s) to mitigate

the havoc that can be inflicted by floods. Furthermore, the observations of the trends made indicated that flood frequencies in various regions vary substantially depending on elevation, flow direction, slope and vegetal nature of the associated area.

Noticeably, the mean annual precipitation varies regionally in Niger state showing a distinct variation at various regions. Additionally, precipitation has a more adverse effect on flood vulnerability within some regions compared to others. Such as Mokwa, Katcha and Lapai. While areas adjacent to water bodies in the case of Borgu and Shiroro are also greatly affected when induced by an expected FIPV. This impact around Borgu and Shiroro is due to precipitation experienced around the water bodies which contributes to high level of discharge during the rainy season between the months of July and August, thereby increasing the severity of upstream floods in addition to the downstream factor.

Thus far, this research has adopted heterogeneous features to identify the vulnerabilities as well as the levels of regional vulnerabilities within the study area in addition to the utilization of temporal data to identify a long-lead trend of upstream flood and the corresponding FIPV for any potential flooding events. This effectively, has implemented the two technical entities of the research, which are the big data for the voluminous, heterogeneous and initially unstructured data for detailed information gathering for the analysis. While the second was the analytics, which is the gathering of various tools required for the description and inference approaches as adopted in the adapted studies[64],[63].

Sequel to the previous analytical results generated from the long-lead predictive model specification, the level of influence of temporal factors was $p=40.8\%$, indicating that other factors are also influential to the dependent variable, which is the upstream flood. Also, seeing that the research was based on multi-factorial approach to classify regional flood vulnerability, and each factor having a distinct level of influence in inducing flood, this research further examined the associated influence of these relevant factors for proper decision-making by the local authorities within the study area. Essentially, analysis of relevant factors is crucial in view to implementing suitable of flood mitigative measures[276].

In this regard, it has been identified that, both Analytical Hierarchical Process (AHP) and Analytical Network Process (ANP) are very effective for flood vulnerability assessment [277], nonetheless, ANP is difficult to provide correct network structure among factors even for experts, and different structures lead to different results[278]. Hence, this research considers the utilization of Multi-criteria evaluation of the factors considered based on AHP as elaborated in the ensuing section.

4.4 Multi-criteria Evaluation of Causative Factors

The use of Multi-criteria evaluation provides an enhanced accuracy in decision-making when evaluating the influence of causative factors in flood vulnerability [279]. Therefore, this section assesses the level of influence of the considered causative factors in inducing upstream floods as considered within the scope of this research. In this research, the two primary GIS-based approaches; pairwise comparison approach i.e. AHP, as well as Ranking approaches in the calculation of weights of the causative factors were employed

to determine the level of influence within the factors. With the aid of AHP flowchart illustrated in Figure 4.15, the individual weightage for the causative factors was derived based on their influence in inducing floods in the study area.

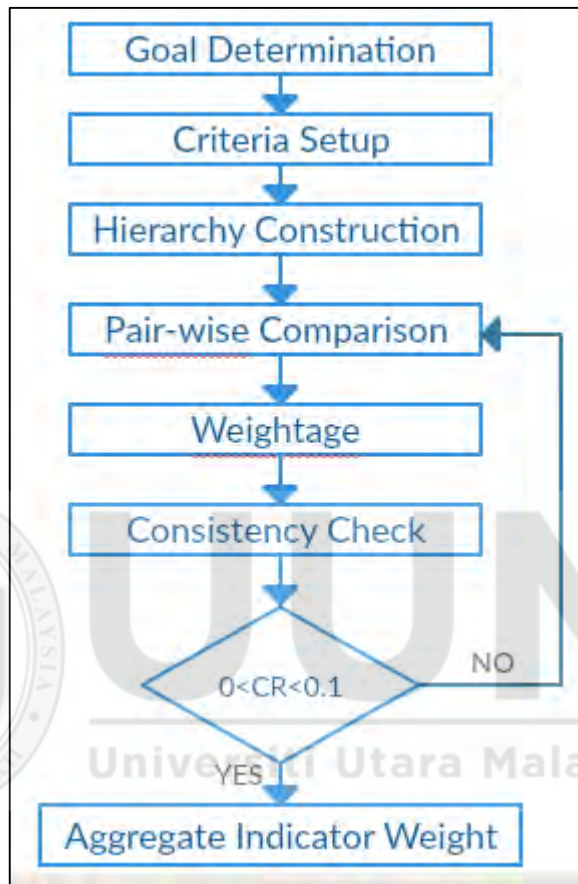


Figure 4.15. Analytic Hierarchy Process Flowchart: Source[280].

As illustrated in the Figure 4.1, the AHP of the flood causative factors considered within the scope of this research were further analyzed. AHP is known to be an organized approach used in the analysis of complex issues in both voluminous interrelated ideas and factors. This analysis consists of criteria setup and hierarchical construction prior to pair-wise comparison.

Pairwise Comparison approach was utilized in defining the weights for the factors. Broadly, this approach consists of comparing factors and permits the comparisons of only two factors simultaneously. The pairwise-based matrix uses the pairwise comparisons as an input and provides the associated weights as output, while AHP uses a mathematical approach for interpreting this matrix into vectors for the various factors. The evaluations made on the flood causative factors associated with the study area were specifically identified experimentally and also based on the reviewed literature. These factors were also itemized in order of their influences towards flood vulnerability within the study area, as contained in Table 4.14.

Table 4.14.
Ranking of Causative Factors

S/N	Causative Factor	Ranking	Weightage
1	Precipitation	1	40.8%
2	Slope	2	18%
3	Elevation	3	12%
4	Vegetation	4	9%
5	Flow Direction	5	8.2%
6	Flow Accumulation	7	7%
7	Topographic Wetness	9	5%

The values of the weightage were initially obtained for precipitation from the model specification values. While the weightage of other factors is determined by a subjective means of using the Analytical Hierarchical Process (AHP).

Specifically, the weight of the factors is determined after the ranking of the corresponding factors based on their influence or importance in causing floods. After sorting the factors

in a hierarchical order, a comparison based on pairwise matrix for each matrix was formed to enable the comparison with other selected factors that also contribute to the flooding events within the study area. Generally, values from 1-9 are used to rank the factors. However, in this research, the relative significance between the factors were formed using 1, 2,3,4,5,7 and 9 representing the importance of the factors. The pairwise approach adopted used a matrix of 7 by 7, where the elements at the diagonal equaled 1. Table 4.15 shows the values of every row representing the existing importance between two factors.

Table 4.15.

Comparison of Factors

Causative Factors	Precip	Slope	Elev.	Veg.	Flow Dir	Flow Acc	TWI
Precipitation	1	2	3	4	5	7	9
Slope	1/2	1	2	3	4	5	7
Elevation	1/3	1/2	1	2	3	4	5
Vegetation	1/4	1/3	1/2	1	2	3	4
Flow Direction	1/5	1/4	1/3	1/2	1	2	3
Flow Accumulation	1/7	1/5	1/4	1/3	1/2	1	2
Topographic Wetness Index	1/9	1/7	1/5	1/4	1/3	1/2	1

The first row represents the importance of precipitation when compared with the remaining factors. Precipitation has been regarded as the most important or influential factors in this research in alignment with the events of rainfall that has always instigated flooding within the study area.

This was made evident from the trend learned using the precipitation data from 1979-2016 (Collected from Centre for Atmospheric Research, with authorization in Appendix L), which showed that, flooding events only occurred as a result of high precipitation volume during the rainy season. This is in addition to records of Flood Inventory which equally showed the dates various flooding events had occurred in the past, which is also corroborated by the study conducted on Flood Disaster in Central Parts of Nigeria[281]. While slope and elevation were considered second and third most important respectively. This is because vulnerable surfaces are often situated in a region with a low value of slope/elevation. Vegetation and flow direction are of a perilous influence in instigating flood. Particularly in Borgu and Edati associated with a very low vegetal cover.

Flow accumulation and Topographic Wetness Index were considered sixth and seventh respectively. While flow accumulation was considered the most important factor by some studies, however, since this research has considered the factors influencing flood on a wider surface by implementing the natural factors in the perception of upstream causes, the importance is placed more on the rainfall. Essentially, even though precipitation as in the case of upstream flood, is the most influential factor, it is also pertinent to compare the level of influence posed by precipitation to other factors and vice versa. This practice is referred to as Pairwise Comparison, with the comparative results in Table 4.16.

Table 4.16

Pairwise Comparison

Causative Factors	Precip	Slope	Elev	Veg.	Flow Dir	Flow Acc	TWI	Weightage (%)	Priority Vector
Precipitation	1	2	3	4	5	7	9	40.8	0.408
Slope	0.5	1	2	3	4	5	7	18	0.18
Elevation	0.33	0.5	1	2	0.33	4	5	12	0.12
Vegetation	0.25	0.33	0.5	1	2	3	4	8.2	0.9
Flow Direction	0.2	0.25	0.33	0.5	1	2	0.333	9	0.82
Flow Accumulation	0.14	0.2	0.25	0.33	0.5	1	2	7	0.07
Topographic Wetness Index	0.11	0.14	0.2	0.25	0.33	0.5	1	5	0.05
Total	2.53	4.42	7.28	11.08	13.16	22.5	28.333	100	1

Furthermore, since each factor is measured in different units, for instance, millimeter for precipitation, degrees for slope and metres for elevation, therefore, the need to be normalized in order to obtain dimensionless classifications, i.e. a common numeric range/scale, to enable the aggregation into a final score. Normalization is an essential part of any decision making process because it transforms the input data into numerical and comparable data, allowing methods to rate and rank alternatives [282],[283]. The normalized values are therefore contained in Table 4.17.

Table 4.17

Normalized Matrix

Causative Factors	Precip.	Slope.	Elevatio	Veg.	Flow Dir	Flow Acc	TWI	Total Row (Priority)
Precipitation	0.40	0.45	0.41	0.36	0.32	0.31	0.29	0.36
Slope	0.20	0.23	0.27	0.27	0.25	0.22	0.23	0.24
Elevation	0.13	0.11	0.14	0.18	0.19	0.18	0.16	0.16
Vegetation	0.10	0.07	0.07	0.09	0.13	0.13	0.13	0.10
Flow Direction	0.08	0.06	0.05	0.05	0.06	0.09	0.10	0.07
Flow Accumulation	0.06	0.05	0.03	0.03	0.03	0.04	0.06	0.04
Topographic Wetness Index	0.04	0.03	0.03	0.02	0.02	0.02	0.03	0.03
Total	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

4.4.1 Consistency Check

Prior to the verification or consistency check, AHP-based eigenvector matrix was formed, which required the need for the level of its consistency to be assessed. The needed consistency level is obtained by the ensuing index:

$$CR = \frac{CI}{RI} \tag{4.10}$$

Where:

CR: Ratio of consistency

CI: Index of the consistency

RI: Random Index

The given values of RI are in Table 4.17. The results depend on the dimension of factors used with the corresponding values of RI. In the case of this research, seven (7) factors have been considered.

Table 4. 18

n/RI Values: Source:[284]

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

From the values presented in Table 4.17, the value of RI = 1.32.

While AHP suggests that the consistency ratio (CR) must be <0.1 .

CI is calculated using Eq (4.11)

With λ_{max} being the maximum eigenvalue of the comparison matrix which were calculated in the Table 4.19

Eigenvalue (λ_{max})

Table 4.19

<i>Eigen vector</i>	
eigenvalue	Value
1	0.3971
2	0.2306
3	0.1389
4	0.0912
5	0.67
7	0.0469
9	0.0315
Total	1.6062

1.6062; and n is the number of criteria. RI values are given in specific tables.

CI =

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (4.11)$$

For values in Table 4.17, CI was determined:

for $\lambda_{\max} = 1.6062$, $n=7$ while $RI = 1.32$. Consequently, $CR = -0.8989$. This validates the consistency of the weight since the value of CR is less than 0.1.

4.4.2 Significance of the Obtained AHP Results

The significance of the AHP-based Multi-criteria evaluation results obtained substantiates that precipitation is the most influential causative factor in causing floods within the study area. Particularly, as learned within the precipitation trend, accumulated volume of precipitation experienced over a period influences other causative factors in inducing floods within the study area. High volume of precipitation accumulates to attain the FIPV and consequently, instigate floods in an already vulnerable region as earlier inferred. The FIPV vary based on the features of the region. Eventually, various recommendations were made for both theoretical and practical implementation of the findings provided by this research in the concluding section for proper mitigating strategies.

As earlier mentioned, the need for assessing the accuracy of spatiotemporal outputs is considered to be an essential element of any study in order to ensure the reliability in decision-making [66]. Therefore, the ensuing section elaborates on the accuracy of the developed hybrid framework.

4.5 Accuracy Assessment and Framework Validation

In recent years, accuracy assessment or validation has become a fundamental element in spatiotemporal data analysis. The motive for accuracy assessment is mainly to reliably utilize the extracted spatiotemporal data for decision-making [285]. As such, it is absolutely imperative for some steps to be taken in assessing the accuracy of the output instead of simply assuming the correctness of the generated outputs. Within the scope of this research, the accuracy was assessed by visual inspection and difference image creation as adopted in a study conducted on accuracy assessment and validation of remotely sensed and other spatial information by Congalton [285]. In addition, expert review was sought for from both domain experts in GIS as well as disaster monitoring agency in the study area in lieu of error budgeting, and on-site techniques which are defective in accuracy assessment as they only compare the total area or land without taking into account the location [286]. The assessment of the extracted outputs and the analytical results was performed with the following techniques [66],[285].

4.5.1 Visual Inspection and Aerial Photographic Interpretation

In assessing the extracted output from spatiotemporal data visual inspection was the first step used to assess the accuracy of the features. This practice was essentially needed in order to ascertain the visual correctness of the features pre-processed. The visual accuracy assessment was done by identifying and comparing the features on the imageries to the truth-ground features and their various locations using physical maps and Keyhole Markup Language (KML) based on Google Earth (GE) services. Google Earth has of a recent been identified for its excellent potentials in visualization of spatiotemporal sets of

data[287], which can equally be employed to distinguish between types of land cover as well as other relevant factors within a spatial image[288].

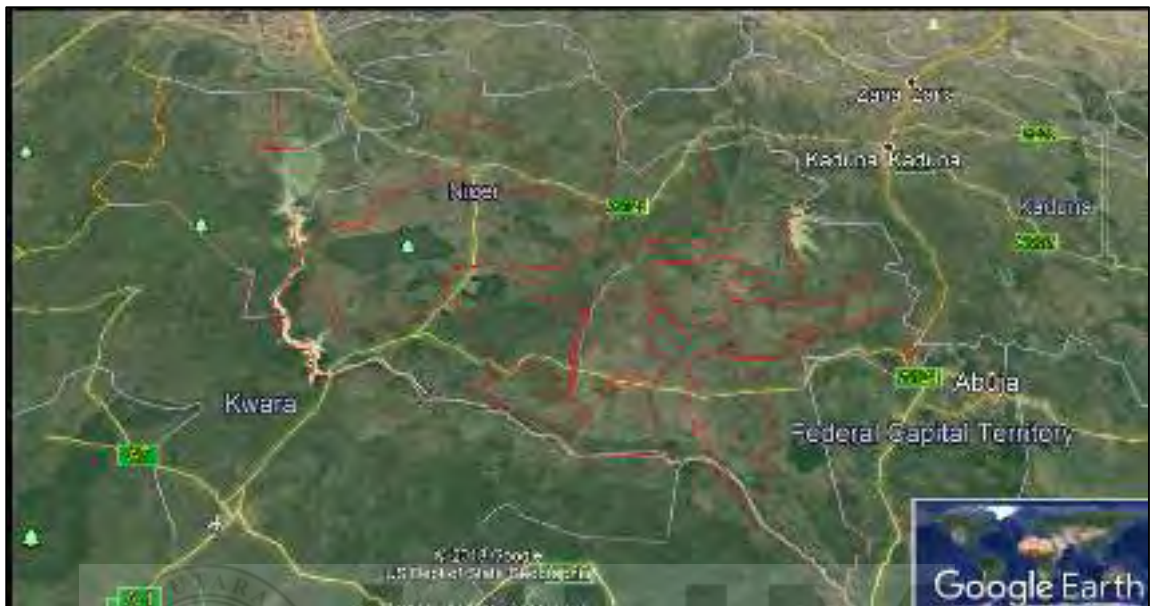


Figure 4.16: Generated Map of the Study from the Pre-processed Spatial data with KML

The results generated using the created KML file of the study area depict the visual representations for various features such, as boundaries and land cover within the study area. Essentially, the identification of the boundaries also validates the result to be free from locational errors. Also, reference data, such as aerial photography are considered to be accurate, which are commonly utilized to assess the output of spatial mapping [66]. Therefore, the correspondence of the visualized outputs to the ground-truth feature as depicted in Figure 4.16, further confirmed the accuracy of the outputs.

4.5.2 Difference Image Creation

Secondly, in order to assess the accuracy of the imageries, a direct comparison of imageries generated after pre-processing was compared with similar output generated by another research as adopted in the study conducted by[285]. Broadly, the spatial patterns

on the generated outputs conformed to those of the compared imagery. Especially, considering a similar study conducted by Ikusemoran et al in [29], which also applied spatial data on flood vulnerability within the same study area as in this research. Consequently, the accuracy was assumed to be valid as well. In continuation to ascertaining the accuracy of the proposed framework, reviews from experts in domains of GIS and flood mitigation were also considered as discussed in the ensuing section.

4.5.3 Expert Review and Validation

The array of experts contacted were engaged considering their expertise and their levels of education, knowledge on the study area as well as their years of working experience in GIS and disaster management. In this research, four practitioners from the GIS domain in addition to Disaster Management Agency in the study area were engaged in verifying the output obtained from the developed framework prior to validation. The demographic data of experts is contained in Table 4.20.

Table 4.20
Demographic Data of Experts

Expert (E)	Expertise	Current Position	Years
E1	GIS	Professor, Department of Geomatics, Faculty of Environmental Design, Ahmadu Bello University, Zaria, Nigeria	24
E2	GIS	Assistant Director, Research NASRDA	12
E3	GIS	Head of Satellite Ground Station Software, CSTD	10
E4	GIS	Lecturer	5
E5	Disaster Management	P.R.O, NSEMA	11

The expertise of the practitioners is majorly in the domain of GIS, who are currently working in the domain of satellite imageries and GIS, while one is the Niger State Emergency Management Agency (NSEMA), which oversees both natural and anthropogenic forms of disaster within the study area. NSEMA was also engaged to verify regions classified to vulnerable to floods as well as their related levels of severity and exposure to floods. The use of this agency was pertinent because, they are the only custodians of the Flood Inventory. Three experts have 24 to 10 years of working experience, while one has 5 years of working experience. The disaster management agency been responsible for various forms of disasters within the study area for over 11 years, since the establishment of the agency breaking from the National Emergency Management Agency (NEMA).

Assessment of Dimensions

As earlier stated within the scope of this research, the expert assessment process was performed based on three dimensions namely, factorial/vulnerability classification, accuracy and the overall assessment on HyM-SLUFA framework as described in Table 4.21 presents the description of these dimensions used to further verify the accuracy of HyM-SLUFA, which were selected based on the preference and recommendations by researchers, such as [289] , for framework as well as model verification.

Table 4.21

Description of the Assessment Dimensions for HyM-SLUFA

Dimension	Description
Factorial/Vulnerability classification	Classify and ensures various regions are assigned to their respective classes of flood vulnerability based on the considered factors.
Accuracy	The correctness of the produced results.
Overall assessment on HyM-SLUFA Framework	This dimension evaluates the ability of users or decision-makers to gain useful insight from the information representation, pattern classification and the outputs within the framework. Additionally, the interpretability, presentation, practicability, organization of the flow of the framework was assessed using this dimension.

Expressly, the dimensions on the factorial/vulnerability classification were outlined to determine the output of the pre-processed and processed multi-spatiotemporal. This was confirmed by providing an option for the experts to either Agree, Disagree or make a comment when required. The second accuracy dimension was considered to seek for the accuracy of information representation, formats and the outputs. With option to rate the corresponding accuracy based on the level of satisfaction by selecting Not-satisfactory (NS), Fairly satisfactory (FS), Satisfactory (S) and Very satisfactory (VS). Essentially, these options provides four Linkert scale in order to avoid misunderstanding within opinions that are likely neutral which may not show any evidence of purposeful assessment from the opinion of an expert[290]. The third dimension represents the Overall assessment on HyM-SLUFA Framework factor with either an implicit Agree/Disagree option. Finally, at the end of the assessment form, experts can provide additional suggestions required to enhance the framework.

4.5.3.1 Analysis of Experts' Opinions

The output of the pre-processed and processed multi-spatiotemporal data sets along with assessment forms were sent to the experts for the assessment of the methodology, the outputs as well as the vulnerability classifications prior to the validation of the framework. While some experts required some clarifications via emails, some sought for a voice conversation for further clarification in the process of the assessment. The feedbacks were analyzed by employing descriptive and content analysis. Essentially, the feedbacks from the experts were analyzed in order to describe their individual opinions on the outputs, the accuracy of the output as well as the overall correctness of the framework and its usefulness as elaborated in ensuing sub-sections.

In determining the opinion of the experts, various classifications of the factors into patterns and the classes of regional flood vulnerability was assessed by using the Agree/Disagree option with four experts out of four confirming positively as contained in Table 4.22.

Table 4.22

Expert Assessment on Multi-factorial/Vulnerability Classification Dimension

Multi-factorial/Vulnerability Classification	Frequency (n=4)	
	Agree	Disagree
Do DEM patterns correspond to the various high and low lands of the surface in Niger state?	4	0
Does the unit of measurement used correspond to the DEM unit of measurement?	4	0
Is the classification method used in conformity with the various elevation patterns?	4	0
Are the patterns of the Slope in correspondence with the various high and low lands of the surface in Niger state.	4	0
Does the classification method used distinguish clearly between the various patterns of the slope?	4	0
Do the identified features represent flow accumulation?	4	0
Is there any tendency of flow accumulation as identified in the feature?	4	0
Is there any tendency of flow direction as identified in the feature?	4	0
Do the identified features represent flow direction?	4	0
Are the regions identified with low or dense vegetation have the traits of such vegetation on the true-terrestrial features?	4	0
Are the water bodies identified in the output exist in the study area?	4	0
Are the regions correctly positioned on the maps?	4	0

From the responses provided in Table 4.22 above, Figure 4.17 further depicts the results of multi-factorial and vulnerability classification dimension, showing all the experts agreed to the correctness of the dimension the framework.

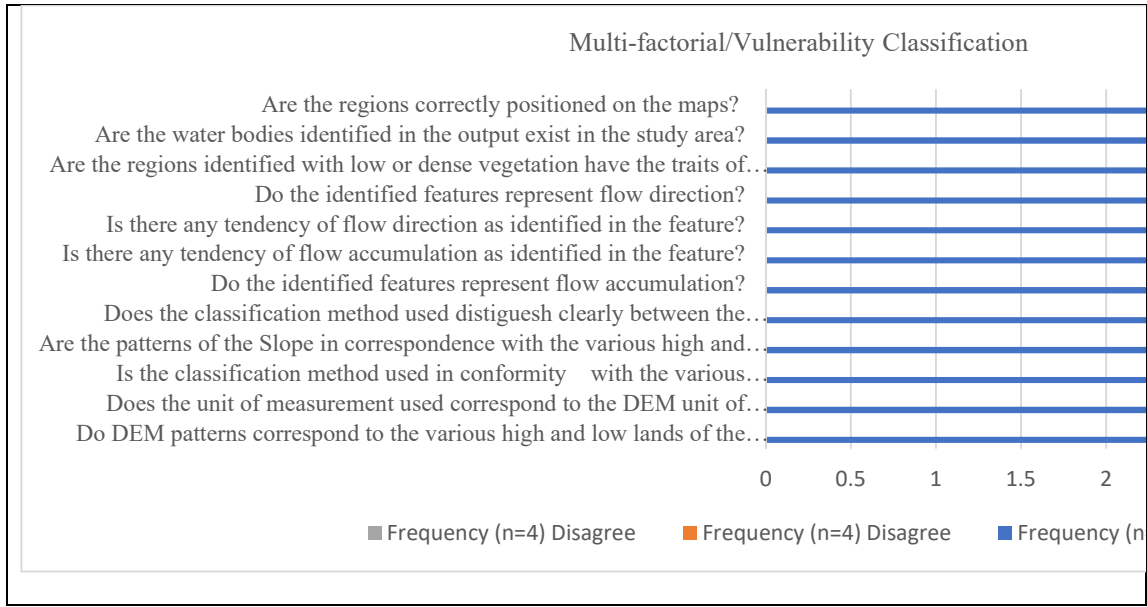


Figure 4.17. Experts’ Assessment: Multi-factorial/Vulnerability Classification

From the above analyzed experts’ opinions, the classifications of factors and regional vulnerability were opined to be correctly done according to the experts engaged. The results showed an overall agreement to the correctness by the experts. Similarly, in Accuracy dimension, the opinions of the experts were assessed using the level of satisfaction as tabulated in Table 4.23.

Table 4.23.

Expert Assessment on Accuracy Dimension

Accuracy	Frequency n=(5)			
	VS	FS	S	NS
Satisfaction with graphical presentation.	2	3	0	0
Precision of the output formats	1	3	1	0
Satisfaction with outcome of the MCE using AHP	5	0	0	0
Satisfaction with information representation	5	0	0	0
Satisfaction with legends representation	0	2	0	0
Satisfaction with classification	5	0	0	0
Satisfaction with coordinate representation	3	2	0	0

Key To Abbreviation:

VS: Very Satisfactory

FS: Fairly Satisfactory

S: Satisfactory

NS: Non-satisfactory

From Expert Assessment on Accuracy Dimension, the level of acceptance opined on the results by the experts is mainly between Very Satisfactory (VS) and Fairly Satisfactory (FS).

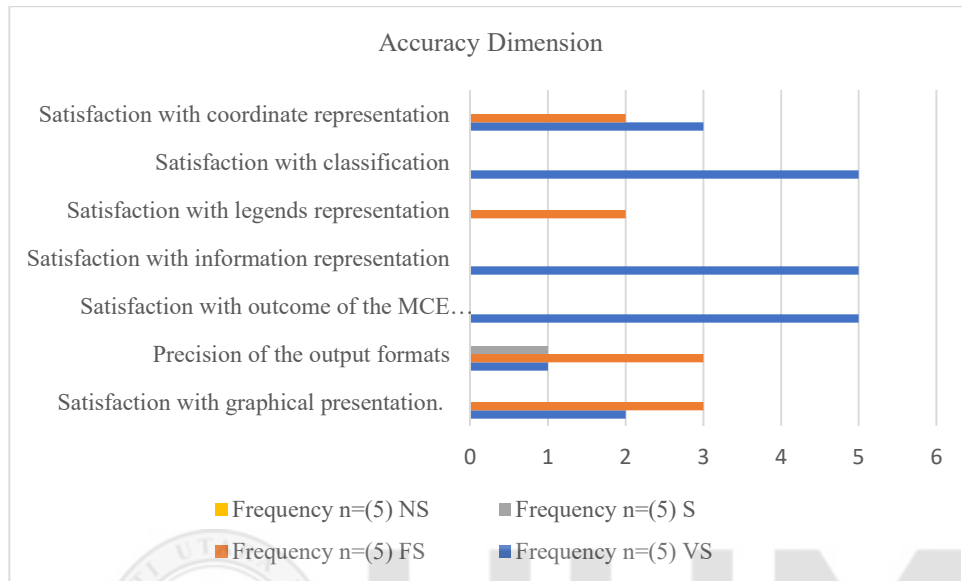


Figure 4.18. Experts' Assessment: Accuracy Dimension

The accuracy dimension provided by the Experts generated a generally satisfactory results in terms of the accuracies of the framework and various obtained outputs as represented by Figure 4.18 above.

Table 4.24

Expert Assessment on Overall Accuracy of HyM-SLUFA

Overall Assessment of HyM-SLUFA Framework	Frequency n=(5)	
	Agree	Disagree
Relevancy to the intended application	5	0
Decision Support Satisfaction	5	0
Comparison with existing usability evaluation method	5	0
Clarity	5	0
Tasks appropriateness	5	0
Ease of use	5	0
Internally consistent	5	0
Well-organized (organization)	5	0
Presentation (readable and useful format)	5	0
Ability to produce expected results	5	0
Ability to produce relevant and useful results	5	0
Practicality (Ease of implementation)	5	0

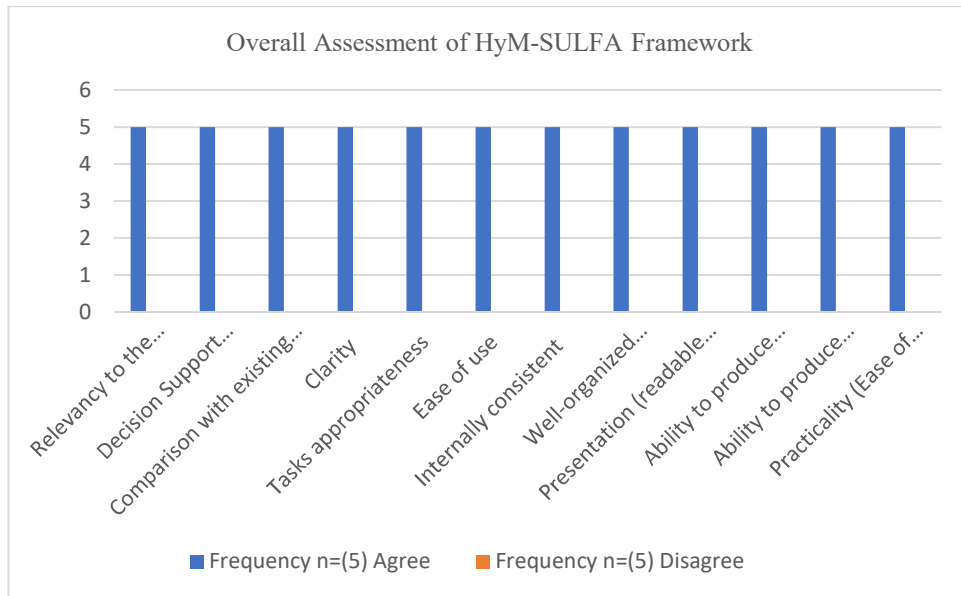


Figure 4.19: Experts' Overall Assessment of the Framework

As illustrated in Figure 4.19 above, all the experts engaged provided a positive and unbiased opinions towards the dimensions related with each component of the framework. Additional assessment questions were provided in order to cajole experts to provide additional opinion or suggestion aimed at enhancing the framework. The opinion provided for this dimension showed that all the experts agreed with the overall performance and contribution of HyM-SLUFA framework. Additionally, this segment of the thesis discusses the approaches of framework validation which also serves for benchmarking the analytical results obtained in comparison with other studies, which is explained in the flowing subsection.

4.5.4 Benchmarking and Accuracy Assessment

As earlier mentioned, additional accuracy assessment of the pre-processed data was performed by GIS experts in order to validate the proposed framework. This was mainly performed by assessing the accuracy of the spatial representations of the generated outputs

in relation to the objectives and scope of the research. Furthermore, the usefulness and efficiency of the framework was equally determined by the domain experts in addition to various supported literature already cited in the research as indicated in the assessment request letter and assessment forms sent to the experts (Appendix F, G, and H). Essentially, this subsection further assesses the accuracy of the obtained results in the classification of flood vulnerability and the long-lead predictive model.

Table 4.25

Benchmarking of Vulnerability using a study conducted by and the obtained result.

Class of Vulnerability	Extant Study	Current Research	Affected Regions from Flood Inventory out of 25
Number of Highly Vulnerable Regions	12	10	42
Number of Vulnerable	9	6	13
Number of Marginally Vulnerable	1	9	30
Number of Non-Vulnerable	3	0	2
Total Number of Vulnerable Regions.	22	25	24

From the above benchmarked results in Table 4.20, the extant study in [29], claimed that regions of Munya, Suleja and Tafa are the Non-vulnerable. However, with the results obtained from this present research using slope factor, these regions have been classified under marginal form of vulnerability. And when compared with the Flood Inventory data, the results obtained by the present research presented a more accurate classification, since these regions presumably non-vulnerably in the extant study have continuously being faced with flooding events for the past three years. Thus, presenting the stringent

limitation of the existing study, while revealing the accuracy of this framework on the other hand. A more concise assessment is discussed in the ensuing sub-subsection.

4.5.4.1 Assessment of Vulnerability Classification

Generally, flood inventory is a vital means of quantifying spatial and temporal distribution of flooding events which are also used to assess the accuracy of flood predictive frameworks[101]. As it also shows the historical occurrence and frequency of flood hazards[246]. Thus, providing a reliable process of allowing the accuracy of the vulnerability classification to be assessed. By this means, the accuracy of the classification made was assessed primarily, by comparing various regions and their corresponding frequency of historical flooding events with the associated vulnerability classification from all the factors employed.

In performing the accuracy of the developed framework, various classification revealing the regional flood vulnerability, as depicted by FCFs was assessed to identify any vulnerability traits, which was equally supported by the record of Flood Inventory with the events of floods that occurred – through the regions of high vulnerability to regions of marginal vulnerable from 2006-2017. In total, 85 events had occurred between 2006-2017, with 24 regions out of 25 with associated flood records while the total number of identified vulnerable regions are 25 as contained in Table 4.26.

Table 4.26

Classes of Flood Vulnerability and Corresponding Flooding Events

No. of flooding Events	Number of Affected Regions	Number of Un-affected Region(s)	Number of Identified Vulnerable Regions
85	24	1	25

As contained in Table 4.25, even though 24 out of 25 regions had experienced floods in the past, this assessment can be inferred that the region of Tafa, which does not have any record of flooding event can be affected by an impending flood as a result of the current global warming. Thus, the validation using the flood inventory was assessed to further ascertain the accuracy of the obtained outputs of the developed framework.

In another phase of accuracy assessment, disaster management agency (Niger State Emergency Management Agency) was engaged. In the present study, regions within the study area were classified based on their levels of vulnerability to upstream floods. Even though the frequency of floods in a region determines the level of vulnerability as represented in the flood inventory data, disaster managers further validated this claim in order to ensure an accurate and reliable framework devoid of uncertainty. Therefore, an assessment form (AppendixF,G,H) was sent to Niger State Emergency Management Agency, which is the body responsible for disaster management within the study area considered in this research. Interestingly, the assessment obtained from the agency corroborates with the results generated by this research. As a result, a holistic approach has been utilized in ensuring the accuracy of the regional flood vulnerability.

4.5.4.2 Assessment of Long-lead Predictive Analysis

On the other hand, to assess the accuracy of the predictive analysis, this research employed model specification approach to determine if adequacy of the predictive analysis and also assesses the possibility to identify any strongly influential outliers in the model using the link test. Fundamentally, the link test is based on the idea that when a regression is properly specified, no additional significant independent variables are found. By implication, if the p-value of hat squared ($_hatsq$) is significant at 40.8%, the model is deemed not to be properly specified. In this model, the hat-squared was not significant therefore, the results indicate that the long-lead predictive model was adequately specified and had a reliable good fit (P -value=0.408) as contained in Table 4.26 from the test conducted on the model specification.

Table 4.26

Model Specification Test

Precipitation	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
$_hat$	0.928153	0.084591	10.97	0	0.721166	1.13514
$_hatsq$	0.002075	0.002333	0.89	0.408	-0.00363	0.007783
$_cons$	0.392557	0.688425	0.57	0.589	-1.29196	2.077071

By including an error term, the long-lead predictive model and factors inducing upstream floods are derived as in equation 4.12, in case of multiple linear regression:

$$Uf_j = \beta_0 + \beta_1 PRECIP_j + \beta_2 TOPF_j + \beta_3 HYDF_j + \beta_4 NDVIF_j + \varepsilon_j \quad (4.12)$$

Where:

U_f represents upstream flood as the dependent variable, β_0 is a constant and β is the coefficient of each respective variable. The flood causative factors considered as independent variables are PRECIP which represents the precipitation, TOPF denotes topographical factors, HYDF depicting the hydrological factors while NDVIF representing the vegetal factors, and ε_j is the error term.

Eventually, with the value obtained from the predictive model specification as well as the assessment using MCE-AHP, the proposed framework was ultimately validated in addition to the remarks and suggestions made by the selected experts. Considering these aforementioned results, Figure 4.20 shows the developed hybrid framework that was employed to pre-process spatiotemporal data and also perform long-lead upstream flood analysis.

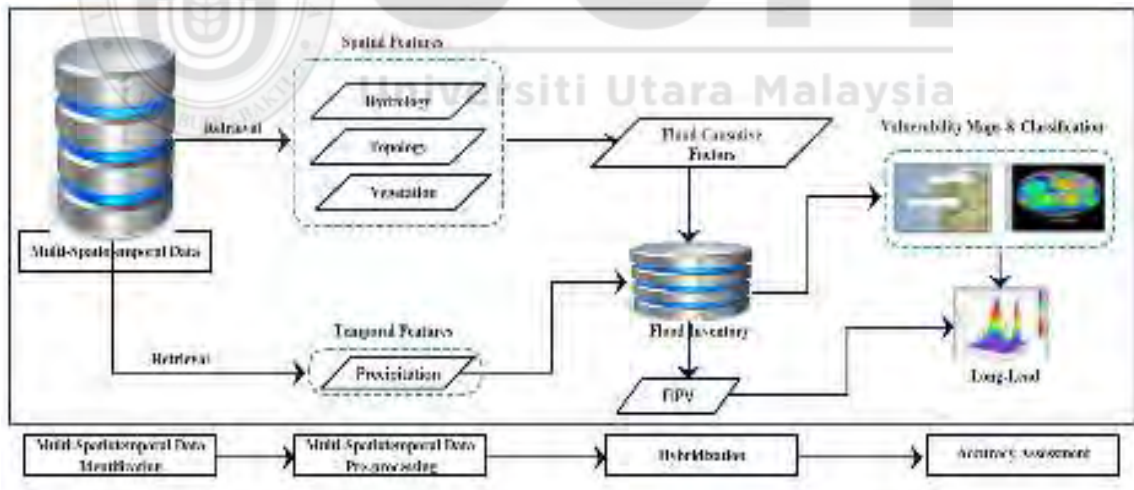


Figure 4.20: Hybrid Multi-spatiotemporal Long-lead Upstream Flood Analysis Framework (HyM-SLUFA)

With studies conducted by [162], [169], [170], which were used to formulate the basic architecture, as well as the sequence of the basic tasks involved within the phases of the

framework. This is based on knowledge discovery process using big data technique focusing on data cleaning, presentation, Data analysis, visualization and interpretation and decision-making. While studies conducted on flood mitigation in [29],[208] and [215], were used as a means of flood classifications and their associated interpretation of severity. Within the framework, studies based on BDA focusing on flood prediction conducted by[55],[63],[64], were adapted to perform the long-lead prediction. In conclusion, the benchmarking and the validation of the developed framework was validated by adapting the results and the recommendations of studies conducted by [29],[101], [246].

Figure 4.20 illustrates the hybridization of multi-spatiotemporal factors to classification of flood vulnerability and long-lead prediction. To this end, the developed framework serves as a contributory output of this research since, it was able to accurately pre-process multiple spatiotemporal data for flood vulnerability classification and long-lead prediction. This developed framework includes the phases of data identification/collection, data pre-processing, the hybridization of vulnerability classification and long-lead prediction, and the phase for accuracy assessment corresponding to the research objectives of the research.

Essentially, the ability to identify the level of vulnerability of natural disasters and influence of global warming has been acknowledged as a vital research field, which has been attracting the interest of researchers from various domains [291],[292],[293],[294]. Furthermore, of note it is that the developed framework is entirely based on Multi-factors and BDA with a seamless pre-processing approach. According to [295], an impediment

to efficient flood risk mitigation is the absence of a structured spatial framework with hydrodynamic results. More importantly, in order to address the aforementioned issues in proper developing a hybrid framework for pre-processing multiple spatiotemporal data and performing long-lead upstream flood prediction is required, Figure 4.20 depicts the developed hybrid framework to pre-process multi-spatiotemporal data sets and also perform long-lead upstream flood prediction over Niger state.

4.6 Chapter Summary

In this chapter, the formulation of the various components for the proposed hybrid framework is explained. The theoretical background that supports the need for various factors leading to the use of multi-spatiotemporal factors was detailed. Furthermore, the hybridization between multi-spatial and temporal factors for flood vulnerability classification and long-lead was equally elaborated. The levels of influence posed by each factor in inducing floods were equally estimated. The accuracy of the vulnerability classification and the long-lead predictive model was assessed using GIS approach and also opinions from experts related to the field of GIS and Disaster Management. The outputs from the GIS approaches employed and the inputs from the experts eventually enabled the validation of the proposed framework. In the course of performing various tasks in developing the framework, various findings were made, which are discussed in the ensuing chapter.

CHAPTER FIVE

RESEARCH FINDINGS AND DISCUSSIONS

5.1 Introduction

Sequel to the tasks performed in developing the framework in the preceding chapter, this chapter discusses the key findings observed in the four distinctive stages of the hybrid framework, which correspond to the defined research objectives. Although, in general, the hybrid framework was able produce a more reliable flood vulnerability classification and long-lead predictions using multi-spatiotemporal data over a large and complex terrain, there are other specific findings observed in the course of its development. To this effect, section 5.2 discusses the findings at the initial phase of multi spatio-temporal data identification and collection. Sections 5.3 and 5.4 discuss the findings in the aspects of multi-spatiotemporal data pre-processing and hybridization respectively, and the chapter concludes with a summary in section 5.5.

5.2 Findings on Multi-spatiotemporal Data Identification

Within the scope of this research, contrary to the current approaches used by some extant studies, which was based on one or very scanty flood causative factors. However, in the process of developing the hybrid framework, some additional spatiotemporal FCFs which are influential in inducing flood vulnerability were identified. This identification of factors was initially done with the aid of the reviewed literature, while this research has further revealed the influence of these factors by the means of experimental assessment. These

causative factors range from the hydrological, topographical to vegetal elements with varied levels of influence on flood vulnerability. As concisely discussed in Table 5.1.

Table 5.1.

Associated Influence of FCFs

S/N	Flood Causative Factors	Level of Influence (%)	Geomorphology
1	Precipitation	40.08	Upstream
2	Slope	18%	Hydrology
3	Elevation	12%	Hydrology
4	Flow Direction	9%	Topography
5	Flow Accumulation	8.2%	Topography
6	NDVI	7%	Land Cover
7	TWI	5%	Hydrology

From the above listed relevant FCFs within the framework, various factors have been identified to be directly involved in instigating floods either due to the topographical, hydrological or vegetal geomorphological content of the study area as elaborated in the ensuing subsection.

5.2.1 Precipitation

The focus of this research dwells on the influence of upstream factor by considering the effect of precipitation upon other causative factors in inducing regional flooding events. This is because, the generation of an upstream flood depends on the ways in which precipitation is converted into hydrological discharge [296]. Therefore, this segment of the framework identifies the relationship of trends in precipitation trend most closely

related to historical regional flooding event within the study area. Essentially, the identified thresholds between dry and wet seasons were based on annual precipital records which correspondingly revealed flooding events occurring only during the wet seasons. Inversely, the treshold covering the dry season has no relationship with floods. An understanding of this threshold and the relationship between the seasonality and the occurrence of floods revealed the influence of precipitation in inducing regional upstream floods when acted on other factors to generate regional flood vulnerability, as further illustrated by the regional precipitation map of Figure 5.1.

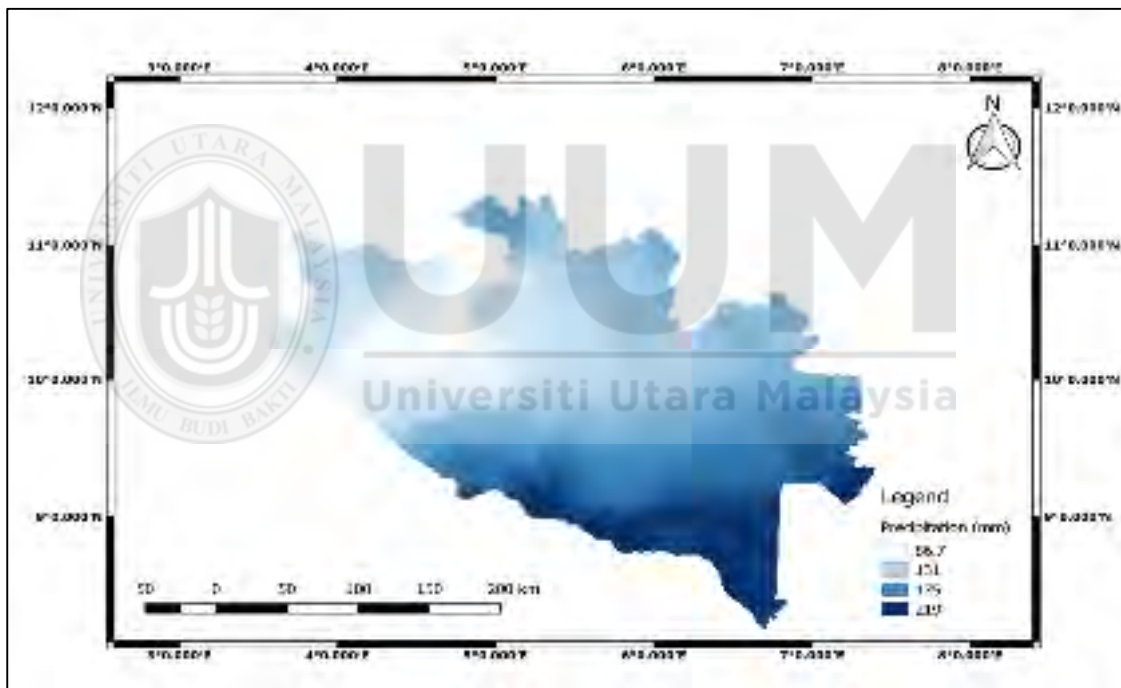


Figure 5.1. Regional Precipitation Map

As illustrated in Figure 5.1, regions of Tafa and Suleja within the study area are situated around the regions of high precipitation volumes, yet with reduced levels of flood vulnerability. Correspondingly, these regions have the most resilience topographical and vegetal features. This therefore, explains the reduced level of flood vulnerability despite

the high volume of precipitation received. Evidently, it has been observed that regions with high volume of precipitation are not associated with high flood vulnerability. Consequently, the justification for the need of considering several factors that can potentially lead to flood vulnerability as employed in this research, instead of the assumption of generally relating floods to high precipitation.

Specifically, within an empirical assessment conducted, the level of influence of the precipitation as revealed by the Model Specification statistical approach was identified to be 40.08%, (Table 4.26 of Chapter Four), which was also validated by some domain experts. Thus, indicating a high influence of precipitation when compared with other FCFs. Similarly, the developed framework further identifies that even though there is a strong relationship between precipitation and regional floods since floods are only experienced during the peak precipitation. As anticipated, there is a considerable amount of variations in the levels of vulnerability within various regions, left unexplained. Some of the unexplained variations are as the results of unevenness of floods in some regions experiencing more precipitation, yet, with a reduced cases of flooding being recorded. This underscores the need to further identify the level of influence presented by other causative factors towards regional flood vulnerability, particularly given the apparent vast and complex nature of the terrain within the study area which can also be regarded to be an underlying conditioning causes of these variations. Therefore, this framework has sought to correlate the influence of slope with the prevailing regional upstream flood vulnerability within the study area.

5.2.2 Slope

Currently, the notion of regional flood vulnerability is rarely considered by geomorphologists using slope factor, perhaps due to a reluctance to transcend beyond their perceived area of expertise or as a result of the absence of an approach which would have assessed the accuracy or inaccuracy of their adopted method, which would have in turn popularized the need for the consideration of slope. Therefore, within the slope-based classification made in this research, it has been observed that regions with low or depressionless slope patterns have an associated history of flooding events when compared with regions with relatively high or steep pattern. Thus, signifying the influence of slope in inducing flood vulnerability. This classification also shows the influence of slope in inducing floods within the study area is enormous and widespread.

The consideration given in implementing a slope-based vulnerability classification has furnished an additional identification of regions that are potentially vulnerable to upstream floods within the study area which is manifestly impossible to reveal using other FCFs. In comparing with the historical flooding events, and also the assessment by domain experts, which has been weighted at 18% influence rate in Table 4.13 of the previous chapter, this assumption equally corroborates with various records of floods experienced in the State. Also, it can be seen in the slope map that almost in all low or depressionless regions have higher frequencies of floods; as a consequence, low slope regions are at the peak of exposure and severity.

5.2.3 Elevation

Elevation factor, on the basis of the vulnerability classifications made in the preceding chapter has shown that the terrain of the study area is topographically diverse, ranging from high to low elevation patterns. In this case, upstream floods were not only experienced at a concentrated region(s) or uniquely to some particular elevation class, but as revealed, the flood vulnerability is associated virtually with all the classes, except for the extreme classes. Here, when the vulnerability representations of the elevation were compared with the Flood Inventory, the influence of elevation as causative factor may not be significant for the entire study area. Nonetheless, it is significantly influential to those regions having very low, low and marginally low elevation patterns with a corresponding history of floods. Therefore, it implies that elevation is a significant causative factor and thus, was given a weightage value of 12%.

In the same vein, the sole adoption of elevation factor as employed in some studies is not reliable. This is because elevation alone is insufficient to reveal an accurate level of regional flood vulnerability. For instance, the regions of Katcha has the least elevation value at 90.2457m, expectantly, it should have the highest frequency of flooding events. Nonetheless, this region has moderately been experiencing floods compared to other regions with relatively higher elevation values like Mokwa 169.6565m with 5 and 11 cases of floods respectively. Thus, the need to consider more FCFs in flood vulnerability classification as adopted in this research.

5.2.4 Flow Direction

Generally, even though hydrologists employ flow direction factor to identify how surface runoff contributes to flooding, this processed output has revealed that the channels of the flow as observed, are mainly targeted towards the diagonals of Katcha, Agaie Mokwa and Edati; implying the influence of flow direction factor to regional flood vulnerability within the surfaces as well as sub-surfaces of the study area, which has also been weighted at 8.2%. This geomorphologic characteristics also presents regions that have a history of floods, when compared with Flood Inventory, and when processed, it showed the vulnerability to floods.

5.2.5 Flow Accumulation

As revealed by this hydrological factor, the traces of cells flowing into other cells in the pre-processed raster data shows the accumulated volume of water. This revelation ultimately was able to depict the amount of rain that would flow spatially, especially when it tends to cause any flooding event. Thus, demarcating non-saturated regions from saturated ones, which can lead to a potential flooding events. Remarkably, this factor has a corresponding influence to regional flood vulnerability to be at 7%, consisting of relatively low effects when compared with other relevant FCFs.

5.2.6 Normalized Difference Vegetation Index

Vegetation presents a foremost restraint to flooding; vegetation decreases runoff and aid in percolation. The influence of vegetation to our environment is well-known globally. While some surfaces are naturally less vegetal, some are rendered bare surfaces by anthropogenic activities, such as deforestation and urban development. Specifically, the

lack of vegetation of an area can influence the occurrence of flood as well as its severity. Therefore, as identified in the preceding chapter, regions with low vegetation have an associated high frequency of floods when compared with regions with high or dense vegetation. This has experimentally corroborated the aforementioned inference considering vegetation as equally a relevant FCF, which has furthered associated the level of its influence to floods to 9%.

5.2.7 Topographic Wetness Index

The consideration of this factor in the developed framework in this research has revealed its relevance in identifying regional flood vulnerability by delineating flood-prone regions. This finding also tallies with the claim made by the study conducted on Topography Wetness Index Application in Flood-Risk-Based Land Use Planning by Pourali et al, in [126], which says TWI is usable in identifying regions that are potentially vulnerable to upstream floods as well as regions that are highly vulnerable to floods. The influence of this factor is measured at 5%.

Thus far, various relevant flood causative factors have been identified, and their levels of influence in inducing regional flood vulnerability has been stressed experimentally. That is, in addition to their identification in the literature review in Chapter Two. Thus, meeting research objective one. The subsequent section elaborates the findings made in the course of pre-processing these relevant factors, which in turn, meets the research objective two of this research.

5.3 Findings on Multi-spatiotemporal Data Pre-processing

Among the voluminous sets of multi-spatiotemporal data used in developing the hybrid framework, there is an implicit, nontrivial and previously unknown knowledge unable to be captured by GIS operations in other studies. Under this premise, the interactive and iterative processes in multi-spatiotemporal data pre-processing have revealed some vital details on the levels of influence posed by each flood causative factors considered. The findings observed in the course of performing data pre-processing are spatially and temporally related. For instance, during the spatial data pre-processing phase within the framework, the results from this investigation have provided information on the relative effects of radiometric and geometric artifacts on NigeriaSat-X and Landsat-8 image products.

Although, NigeriaSat-X and LandSat-8 are known for their high resolutions of 22m and 30m respectively, nonetheless, it is clear from the sets of data collected, which involves several scenes at different temporal period that there will normally be significant (and generally increased) levels of noise in the data. Therefore, the need for both geometric and atmospheric corrections. In the context of radiometric and geometric corrections, it has also been observed within the developed framework that most of the options required for LandSat imageries for noise removal is the atmospheric correction in order to reduce the atmospheric distortion below 10%[189].

More importantly, the underpinning findings of this section indicate that there is high potential of applying both radiometric and geometric corrections in spatial imageries. On the other hand, in pre-processing the temporal data sets, the main operation performed

was the cleaning of the data aimed at addressing the outliers-related issues. By this practice, in the absence of missing values, the outliers were trimmed using Winsorization to detect and remove outliers. Importantly, within the large sets of data covering 1979-2016 daily records, these data sets were heavily identified with outliers, even with the adoption of Winsorization at 5% as elaborated subsection 3.4.1. This has evidently revealed the importance and applicability of Winsorization on data sets as a reliable means of data pre-processing. This is because, the level of outliers were not only suppressed, but the normality of the data was enhanced, as earlier illustrated in Figure 4.10 in Chapter Four. Concisely, the implementation of these pre-processing approaches have evidently enhanced the analytical accuracy and the interpretability of the output generated for vulnerability classification and long-lead prediction which are the primary basis for the formation of the hybrid framework.

Ultimately, the findings have further strengthen the proposed pre-processing approaches in pre-processing multi-spatiotemporal data sets thereby accomplishing the tasks involved in phase II of the developed framework and consequently fulfilling the research objective II concurrently.

5.4 Finding on Vulnerability Classification and Long-lead Hybridization

The findings of this section provide the scientific insight on the vulnerability classification and long-lead analysis needed by both decision-makers and scientific body of knowledge in the domains of GIS and flood mitigation, as elaborated in the ensuing subsections.

5.4.1 Findings on Vulnerability Classification

In this subsection, the findings on the potential vulnerability of various regions within the study area as classified by multiple FCFs were revealed for appropriate mitigating measures to be implemented by the local decision-makers. Even though the FCFs used within the framework depicted various classes of flood vulnerability, the most important finding identified by the developed framework is the contrasting vulnerability classifications between various FCFs. Especially, within the same elements. For instance, between Elevation and Slope, which belong to the same topographic element or between Flow direction and Flow accumulation. As revealed for regions of Borgu being characterized by dense vegetation, which expectantly have the ability to suppress any adverse impact of precipitation resulting to upstream floods. However, it has been observed that these regions tend to be more vulnerable to major flood impacts due to their proximity to water bodies and moderate elevation within the environment, as equally corroborated by the engaged experts in Disaster management within the study area as discussed in 4.5.3 of the preceding chapter.

Also, regions of Mokwa covered by moderate vegetation, with relatively moderate elevation have witnessed the most frequent record of flood. This can be attributed to the associated direction of flow directed towards this regions. Overall, flood vulnerability is principally low at Mashegu, Paikoro, Suleja, Lavun, Mariga, Agaie, Rafi, Rijau regions. Although, it has been found that these regions have reduced values of elevation and slope features, nonetheless, they have very high levels of resilience from other factors, such as vegetation and geographical distance from hydrological factors. This as a result, can translate the low record of flooding events in these regions. While Tafa has the highest

volume of precipitation with the least occurrence of flooding events even though it is classified with a relative vulnerability level. This can equally be attributed to its ideal topographical vegetal nature serving as a means of suppression and resistance to flood vulnerability. Other regions collectively have from marginal to higher vulnerability levels compared to the rest. Eventually, these findings from component-level implementation can be utilized to recommend practical approaches towards flood mitigation. These include the implementation of proactive and reactive measures within vulnerable regions.

Furthermore, it is noteworthy that, even though regions of Tafa in Niger State of Nigeria which has not had a record of flooding event was spatially found to be vulnerable, however, this can aid in taking some proactive measures before any flooding event occurs. This is because the impacts of the climate change have no sign of subsiding. Remarkably, the accuracy of the spatial results obtained dwells on the use of multiple relevant factors. Disregarding the use of these multifactorial approach contrary to what has been adopted within the proposed framework would have misrepresented regional flood vulnerability which would have in turn, led to an erroneous inference of flood vulnerability classification. Especially, in finding the regions of Suleja and Tafa amongst the vulnerable regions. This finding has further indicated the accuracy in using angular slope for regional flood vulnerability classification.

Essentially, the reliance on angular slope factor to identify flood susceptibility has been identified to be more accurate compared to other factors. Therefore, this finding demonstrates that regional flood vulnerability mapping is inadequate using a few flood causative factors. Nonetheless, the spatial classification of regional vulnerabilities

obtained from various causative factors exudes the patterns for various levels of vulnerability. While there are differences in regional vulnerability levels, there is a general pattern of homogeneity in the levels of vulnerability across regions indicating slight variances between regions. The pattern from the topographical features showed more details on the regional vulnerability classification compared to those obtained from hydrological and vegetal stratification. It is more apparent and reliable using the flow direction and slope factors due to their abilities to have provided more accurate results on regional flood vulnerability classification. Similarly, flow accumulation and flow direction yielded a relatively reduced level of regional flood vulnerability identification; it presents the most spatially differentiated identification of regional vulnerability by identifying regions that are marginally vulnerable to flooding events. The findings from various factors are summarized in Table 5.2 with HV signifying Highly Vulnerable, while MV, V, and NV signifying Marginally Vulnerable, Vulnerable and Non-Vulnerable respectively.

Table 5.2

Comparative Results of Regional Vulnerability Classification

Causative Factors	Regional Vulnerability Identified Classes	No. of identified classes out of 4
Elevation	HV,MV,V,NV	3/4
Slope	HV,MV,V,LV	4/4
Vegetation	HV,MV,V,NV	3/4
Flow Dir	HV& NV	2/4
Flow Acc	HV& NV	2/4

Despite the relatively uniform level of regional vulnerability classifications to a certain extent using these aforementioned factors, there is a clear pattern of high vulnerability within the regions of Katcha, Lapai, Edati and Borgu. This can be attributed to the low level of elevation, depressional degree of angular slope and proximity to the water body. Similarly, regions identified to be non-vulnerable as identified using elevation values, were identified to be vulnerable with the aid of slope. A possible explanation is that the spatial distribution of regional vulnerability could be associated to its Slope, which plays a significant role in identifying the velocity as well as filtration capable of causing flooding event as stated in [125]. This is a further evidence that slope-based vulnerability classification generates more accurate results as against the elevation-based study conducted within the study area in [29].

Explicitly, variations in pattern classification was not unlikely. Hence, the justification for regional vulnerability classification using multiple causative factors in order to have a holistic assessment of the vulnerability for appropriate decision-making needed in disaster mitigation for any potential flooding event within any study area. This is essentially crucial since every vulnerability classification was able to identify the peculiarity and the factor inducing regional floods. Additionally, the findings related to spatial data pre-processing informs prospective researchers on the spatial merits and the demerits of each Flood Causative factors ranging from hydrological, topographical or vegetal elements in their adopting flood vulnerability classification and mapping. This is vital information

when deciding which of the spatial data sets to use for similar studies at local, regional or national scale in order to accurately mitigate flood disaster since it enables the concerned authorities to reliably derive insight on regions that are potentially vulnerable to floods.

5.4.2 Findings on Long-Lead Analysis

The world has witnessed a drastic climate change within the last hundred years. One of the issues posed by the climate change is the accurate identification and quantification of trends in precipitation, as well as the hydrological implications related to the precipitation [297]. Therefore, in order to formulate suitable measures in hydrological management, information on spatiotemporal variability of precipitation, time series is essential [297]. In the process of learning the trends, it has been observed that the main identifiable characteristics of trends presented by the precipitation data sets was the strong seasonality; irregular trend between wet and dry seasons which is also reflected in the runoff pattern over the regions. However, the period of peak precipitation is between June-September of the raining season which coincides with a relative low period of low temperature.

Evidently, the decline in rainfall during the dry seasons reflects easily in the general decline in flooding events within the study area as shown by the illustrated graph in Figure 5.2 and the monthly precipitation values. This further substantiated by the Flood Inventory.

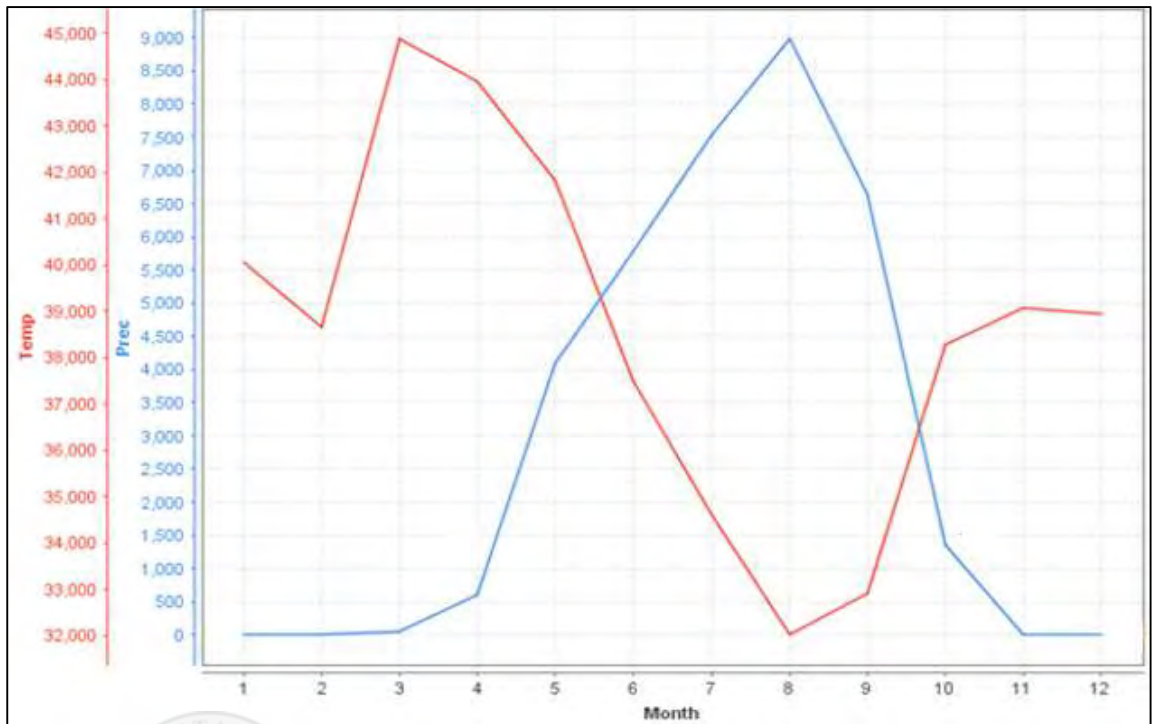


Figure 5.2: Monthly Pattern of Precipitation and Temperature

As illustrated in Figure 5.2, the winter season, also referred to as the dry season (November, December, January, February and March), with a corresponding high temperature experienced during this period, thereby making the entire region to be devoid of any flooding events in the study area during this period of insignificant amount of rainfall. This is evidently contained in the Flood Inventory.

While the raining season was found to be at its peak between the months of June, July, August and September, with related high frequency of floods recorded as a result. Whereas, May, September, October present flood inducible rainfall, early November only experience scarce amount of rainfall with a relative reduced frequency of flooding events. The peak volume of rainfall usually experienced during the month of August which can be translated into the regular flooding events recorded within this period. Remarkably,

various regions show varied levels of FIPV, conforming the inference that other than precipitation, there are other factors (such as the topography, hydrology and vegetation of an area) that induce floods in different regions to different levels of severity. This ultimately reveals that the FIPV are region dependent and are determined by the influencing FCFs within the regions.

As further indicated by the descriptive analysis, which revealed that even though there is a positive correlation between precipitation and water level, there is no significant correlative influence between these factors. Considering the spatial nature of the study area, regions with reduced vegetation and low slope are associated with relatively low FIPV. This finding further confirms the aforementioned finding on the influence of FCFs in determining flood vulnerability at varied scales in various regions. For instance, even though the days for long-lead equally vary based on the intensity of rainfall, flash floods are readily experienced around regions of Borgu. This short lead-time can be attributed to the proximity of the regions to water bodies which also a contributing factor.

In another observed evidence, using the Flood Inventory to define the lead time for the upstream prediction, any potential flooding events within the regions of Tafa could not be performed since the region has not yet experienced any events of flood. Therefore, it will be correct to assume that no flood prediction can be performed without the use of historical data sets as contained in the Flood Inventory, since the scope of the long-lead prediction are spatially focused on regions with historical event of floods. Another finding within the framework is the variability of rainfall in both seasons and regions. With an upward trend in the regions. This finding also corroborates the current climate change as the main

inducing factor of floods. These current increased variations are, nevertheless, higher than the respective regional annual precipitation previously learned in the preceding years. This is equally evident in the increasing FIPVs between previous and the succeeding years. Consequently, it is assumed that alterations in the pattern of current precipitation, would inadvertently lead to more frequent and more severe regional flood.

5.5 Accuracy Assessment

Overall, the findings indicate how various regions are confronted with different class of flood vulnerability which were only identified by the implementation of an array of flood causative factors. Here, the use of Flood Inventory has proven to be a reliable means of accuracy assessment if regional flood vulnerability classification provided in the Benchmarking and Accuracy Assessment at 4.5.4 of Chapter Four, while the statistical method of identifying the fitness of the model has also confirmed to be a reliable and acceptable means of accepting long-lead predictive inference.

5.6 Chapter Summary

Multi-spatiotemporal data pre-processing for long-lead upstream flood analysis is an example of a complex and data intensive research where the various factors influencing flooding events at various degree have been identified. A comparative assessment made using the outputs generated from the use of the developed framework has provided a very useful insight to identify the most suitable factors that can accurately reveal the level of regional flood vulnerability. Also, the interactive impacts of both spatial and temporal factors were identified in this framework. Concisely, it is evident from findings that flood causative factors have varied levels of inducing regional vulnerability when induced with

an upstream factor. An array of strategies ranging from effective urban developmental control, climate change adaptation and flood risk management that recognize equity and environmental policies can make a difference in suppressing any potential impacts as further detailed in the ensuing concluding chapter of the thesis.



CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1 Introduction

Before concluding this thesis, it is essential to first have a review of the aim and objectives in order to assess the extent to which they have been accomplished. Therefore, this chapter reviews the objectives in section 6.2, contributions are presented in section 6.3. Section 6.4 summarizes the research findings made by this research based on the defined research objectives. Evidently, in the course of conducting this research, some challenges were met. Some were addressed, while for those yet to be addressed, they are presented as the limitations of the research in section 6.5. Additionally, due to the complex and dynamic nature of flood disaster, there are still some aspects that can be covered in future research. Therefore, this section recommends and highlights the need for further studies in section 6.6. And finally, the concluding remark of the research is presented in section 6.7.

6.2 Examination of Research Objectives

Primarily, the central focus of this research has been to develop a hybrid framework capable of classifying regional flood vulnerability and to perform long-lead upstream flood analysis based on multiple spatiotemporal data for Niger State, Nigeria. Due to the fact that the success or failure of a project or research is difficult to be determined if the anticipated results are not clearly enunciated[298], therefore, this section enunciates the accomplishments recorded at various stages of the developed framework which will in turn, confirm the fulfilment of the research objectives posed in Chapter One (1.4).

The approaches through which the four research objectives in Section 1.4 have been achieved is summarized as thus:

6.2.1 Research Objective I

To identify multiple relevant spatiotemporal causative factors in flood vulnerability.

The preliminary issue identified by this research was the insufficiency of relevant flood causative factors considered in the extant studies. This resulted in poor identification of regional flood vulnerability and long-lead prediction. Therefore, the purpose of research objective I was to identify relevant factors that induce upstream flood by assessing the spatial contributory effects of these factors to regional flooding susceptibility within various regions of the study area. This was attained with the aid of relevant literature reviewed in subsection 2.6.1 on flood vulnerability in the global context with specific focus given to the study area, and the experimental observations made in the course of vulnerability classifications performed and revealing levels of influence at 18%, 12%, 9%, 8.2%, 7%, 5% for slope, elevation, flow direction, flow accumulation, NDVI and TWI respectively illustrated in subsection 4.2.1.

Interestingly, this percentage depicting the influence assigned to these factors have revealed their corresponding influence in inducing regional floods. Thus, confirming the relevance of the identified factors. Additionally, while the identification was made, the relevance and the corresponding levels of influence of the identified factors was corroborated by domain experts as explained in subsection 4.5.3 and further stressed in the Findings of the research elaborated in section 5.2.

6.2.2 Research Objective II

To define a multi-spatiotemporal FCF pre-processing approach needed for regional flood vulnerability classification.

Here, the associated issue to this research objective is the complexity in pre-processing multiple spatiotemporal factors considered for regional flood vulnerability classification. Even though, this research has identified these factors, pre-processing these vital factors presents a challenging task that also required a methodological approach to accurately obtain the needed features. Therefore, the main focus of objective II was to adopt radiometric, geometric and winsorization corrective approaches to pre-process the identified multiple factors depicting the geomorphology of the study area. This was attained by proposing a spatiotemporal data pre-processing approach to clean the spatial data by removing the atmospheric noise, correcting the geometric distortion prior to the extraction of multiple factors from the spatial imageries needed for flood vulnerability classification of the study area. While the temporal data sets was subjected to cleaning approach in order to eliminate the outliers with the aid of Winsorization approach explained in subsection 3.4.1, with the results shown in Table 4.11. The obtained outputs of the pre-processing approach in this research, which generated three elements of flood causative factors; with topographical, hydrological, vegetation and precipitation being the indicators considered for vulnerability has consequently fulfilled the corresponding research objective.

6.2.3 Research Objective III

To develop a hybrid framework capable of classifying regional flood vulnerability and performing long-lead upstream flood analysis.

In attaining this research objective, a hybrid framework was developed upon both spatial and temporal data sets representing the FCFs to perform regional flood vulnerability classification and also to perform long-lead analysis, detailed as thus:

Vulnerability Classifications

Within this segment of the research objective, the use of the pre-processed multi-factors is primarily, to classify regional flood vulnerability as well as their corresponding levels of vulnerability. Consequently, this segment of the research objective III focused on developing the first segment of the hybrid framework to delineate regions that are potentially prone to floods using various FCFs as detailed in sub-sections 4.2.1. This approach ultimately provided relevant knowledge on the regional flood vulnerability, the corresponding levels of vulnerability and the main inducing factors in all the regions within the study area. On the other hand, the second segment of the framework performs the long-lead analysis, as elaborated in the following subsection.

Long-lead Analysis

In attaining the main objective of this research, which is to perform the long-lead upstream flood analysis, the winsorized temporal data sets were used to perform long-lead flood prediction for those regions identified to be vulnerable to flooding events. This was attained with the aid of historical flooding events (Flood Inventory) and the volume of

rainfall that can potentially lead to upstream floods over a number of days was determined for various regions. With the intersection of these two approaches, Hybrid Multi-spatiotemporal data Framework for Long-lead Upstream Flood Analysis (HyM-SLUFA) illustrated by Figure 4.20 in Chapter Four, was successfully developed as the deliverable of this research.

6.2.4 Research Objective IV

To assess the accuracy of the developed hybrid framework for both vulnerability classification and long-lead analysis.

GIS and flood related studies have various means of accuracy assessment. However, the extant studies did not demonstrate this crucial aspect. The limitations of some of the extant studies was largely due to the absence of any means of assessing the accuracy within these studies as explained in subsections 2.6.1, 2.6.2, and 2.6.3. This has further prompted this research to implement an accuracy assessment approach at the two segments of the hybridization. Ultimately, the accuracy of the proposed hybrid framework was assessed based on the spatial and temporal results obtained:

I. Vulnerability Classification

In accessing the accuracy of the generated spatial results, the regional classifications made using various FCFs accurately revealed regional flood vulnerability at various classes from highly vulnerable to non-vulnerable. When these results were compared with the record of Flood Inventory, the classifications corroborate with the regional flood frequencies contained in the Flood Inventory as detailed in the benchmarking of the result in subsection

4.5.4 in Chapter Four. Additionally, the positive remarks from the domain experts analyzed in subsection 4.5.3 of Chapter Four, which assessed the pre-processed FCFs, vulnerability classifications and the overall accuracy of the developed framework further confirmed the accuracy of the classifications as well as the inferences made for various regions in relations to factors instigation floods.

II. Long-lead Predictive Accuracy Assessment

In assessing the accuracy of the long-lead analysis, and prior to the acceptance of the inferential statement on long-lead analysis, various tests were conducted on the precipitation data sets. This includes the normality, the identification of outliers and the Fitness of the predictive model. Ultimately, the data set depicting the FIPV for the long-lead prediction showed normality in its distribution with 0.11695 and 1.982584 for skewness and kurtosis respectively. While no evidence of outlier was observed as illustrated in Figure 4.10 in Chapter Four. And finally, the values obtained from the long-lead predictive model (Table 4.26) indicated a well-specified model showing a reliable goodness of fit with $p\text{-value}=0.408$. Accordingly, the accuracy of the long-lead has been attained. Thus, confirming the accuracy and the successful development of the hybrid framework. Nonetheless, in addition to the framework development, the research also made some vital contributions as discussed in the ensuing sections.

6.3 Research Contributions

The findings of this research suggest significant contributions to the existing body of knowledge; regarding flood disaster risk mitigation and multi-spatiotemporal data pre-

processing. The study illustrated an innovative approach in understanding varied causes of upstream flood vulnerability as well as the insight into the disparity of regional flood vulnerability in the study area. Also, the findings of this research have contributed to the theoretical, methodological and practical facets towards the general aim of disaster management as detailed in the ensuing sub-sections.

6.3.1 Theoretical Contribution

The theoretical aspect of this research uncovers the disparity as well as the depiction of various satellite features to reveal various influence of FCFs towards upstream floods in Niger State. It equally provides insights to understand the impacts of these multiple causative factors in other parts of the world. Additionally, the long-lead trend identified also serves to reveal the pattern of rainfall that can cause floods in various parts of the study area. An effective framework that presents all the possible causes of flood remains crucial for an enhanced adaptation and mitigation efforts, since only with a comprehensive identification of vulnerability and trend of rainfall can the causes and characteristics of the increasing flood hazard be mitigated appropriately. This framework has proven to be an auspicious step for understanding of regions and their corresponding levels of vulnerability. Thus, this research has contributed to the growing body of knowledge by providing novel approaches in addressing unequal regional flood vulnerability over wider scale, in addition to the identification of any potential flooding events in long-lead timeframe.

Ultimately, recalling the underpinning research theory in section 2.7, which requires the provision of appropriate patterns of spatial representation to identify the interrelationship between domains and features of the environment, in addition to providing a means of

developing spatiotemporal visualization extent and developing their essential properties, this research has reliably strengthened the adopted GIS theory. This has been strengthened by identifying and relating the flood vulnerability to the GIS and environmental domains, particularly by using the geomorphological properties to represent and analyze regional flood vulnerability within the study area.

6.3.2 Methodological Contributions

Generally, a framework has the ability to guide researchers towards applicable methodological and design considerations [299]. Therefore, in addition to the theoretical contributions, various techniques employed as illustrated by the developed framework in both pre-processing and long-lead analysis are other significant contributions. For instance, illustrative approaches in cleaning, correcting and extracting features from the big spatial data sets as well as the approaches employed in identifying the FIPV can serve as a methodological guide to adapt or adopt the framework to address similar issues at regional or national level. This has been corroborated in the study conducted on a Review of Flood Risk Analysis in Nigeria in [300], that Nigeria has not been able to evolve a model to a level which can be used to estimate flood damages and predict future occurrences and losses. Therefore, the developed framework can fill this gap when implemented.

Decisively, the approaches employed to identify the FIPV based on the Flood Inventory and historical temporal data sets will serve as immense methodological contribution. In addition to this, the approaches used to perform a long-lead prediction which identifies the commencement of FIPV, the period of recession of FIPV and the period of re-

accumulation of FIPV as elaborated in subsection 3.5.2 of Chapter Three, can equally be adopted in various similar studies.

Additionally, the study[300], equally identified the need for an open-source environment to improve the flood risk analysis in Nigeria. Hence, the utilization of Quantum GIS, which a python-based open source tool to successfully conduct this research can entice other researches to be conducted using the same GIS tool.

6.3.3 Practical Contribution

In order to contribute to reducing the impacts of upstream floods in the study area, this research provides practical suggestions to the local authorities in the disaster management sector. Especially, since the results provided by this research proffers a practical insight for local disaster management agency as a means of enhancing regional flood control adaptation technique by prudently locating those regions identified to be highly vulnerable to promptly implement some structural measures to advertently mitigate any potential havoc that can severely affect the regions. While focusing on the non-structural means, such as the predictive analysis provided by this research in section 4.3, a routine flood monitoring using the amount of daily rainfall or the forecasted precipitation volume by the National Meteorological agency in Nigeria (NiMet) for long-lead prediction is recommended. In addition, some approaches ranging from public awareness and stringent technical policies as presented in the ensuing sub-subsections can equally be implemented.

6.3.3.1 Development Control

In view of the current realities in Niger State in terms of increase in population and structural development, there is a pressing need to assess and reappraise the structural development as well as planning guidelines to pave the way for a suitable master plan. An efficient flood mitigative measures will serve as a main contributor to a sustainable town planning, as flooding events have become an event that are more severe within habitable environments.

6.3.3.2 Political Will

Organizations are influential in managing and mitigating the risks of disasters within various social groups [301],[302]. There is a need for every level of government, especially, the local authority, to employ political will in developing long-term measures to mitigate flood risk by working together with private organizations as well as residents at vulnerable regions. These collaborations should contribute towards the disaster mitigation [303]. Redefining and empowering local authorities will enhance a more equitable access to materials, and social welfare will go a long way in developing community resilience to potential flooding events.

6.3.3.3 Poverty and Vulnerability Reduction

Any effort in mitigating disaster, vulnerability as well as poverty are intertwined. According to [304], it is projected that, in the next year alone, if every natural disaster is averted in 89 countries, around 26 million individuals will move out of extreme poverty. By implication, the more the disaster, the poorer the individuals become. Consequently, sustainable actions (such as the implementation of a poverty alleviation program that

considers disaster risk mitigation plans) can make individual less vulnerable to flooding events.

6.3.3.4 Technical and Institutional Adaptation

Technical or structural mitigating measures need to be implemented in the vast major regions of the study area identified with a high level of vulnerability. Drainage systems and dams have widely been identified to be very useful against floods. These are advantageously used for irrigation and electrification in addition to serving as preventive measures against flooding events within the vulnerable regions.

6.4 Summary of the Main Findings

Broadly, the causative factors employed generated results illustrating regional flood vulnerability is unevenly distributed. With some regions showing less vulnerability than others. This result was further confirmed using the flood acquired from 2006-2017 (Appendix C). The study further demonstrated that angular slope is more reliable in the classification of regional flood vulnerability. Evidently, since some regions identified to be non-vulnerable by other causative factors as well as in the study conducted by [29]. This claim was further verified by the record of flooding events which showed the accuracy of the results generated using angular slope.

The use of large amount of data sets has been discourage by [46] over the complexity and its susceptibility to errors. Nonetheless, performing winzORIZATION which was explained under temporal data cleaning in subsection 3.4.1, enhances the accuracy of a result regardless of the size of the data sets. This was demonstrated in employing the daily

records of time series data from 1979-2016 representing precipitation, water level and temperature readings. Similarly, the identified trend shows a negative correlation between temperature and rainfall of [-0.1385825], and a positive correlation between precipitation and water level at [0.0995206]. By implication, when there is an increase in the amount of rainfall, there is a decrease in temperature. While the water body experiences an increase in water content when the amount of rainfall increases. This positive relationship between these two variables results in an increase in the level of flood severity within the regions adjacent to the water body.

6.5 Limitations of the Research

The research is explicitly centered on the natural flood causative factors. Hence, the research only covers the relevant factors necessary to determine the levels of influence posed by topography, hydrology and vegetation of the study area in relation to precipitation, which is the upstream factor used in performing long-lead prediction. Therefore, regarding the limitations within this research, a number of caveats needs to be noted especially, in relation to the anthropogenic factors, such as settlement and dams which should be considered alongside upstream factors for continuous future research as elaborated in the ensuing section.

6.6 Recommendation for Future Studies

At this stage, the developed hybrid framework can further be explored to assess a broader set of case studies in other regions of Nigeria, or other parts of the world, concentrating on urban vulnerability to flood hazards and anthropogenic factors that influence the unequal occurrence of flood vulnerability. This is because, while this research provided a

hybrid approach for identification of both regional upstream flood vulnerability classification and long-lead analysis, it encompassed only to natural factors. Therefore, as an extension for this research, future studies should include, but not limited to the exploration of other forms of vulnerabilities in relations to anthropogenic factors, such as the regional settlements and the sectorial vulnerability classifications. Although, the prospect of having such data for both settlements and the sectorial vulnerability classifications to meet this recommendation remains unlikely due to the paucity of the required data sets on regional settlements and population density, especially in Nigeria as elaborated in the ensuing subsection.

6.6.1 Settlement Classification of Vulnerability

The limitation faced by the current institutional policies for environmental management especially, in land use policies have led to several detrimental events within some regions[86]. Therefore, accessing an accurate settlement estimation data for future research will aid in revealing the number of populations that are potentially vulnerable to flooding events which will in turn, help in sectorial classification of flood vulnerability as discussed in the following subsection in order to take additional proactive measures in mitigation flooding events.

6.6.2 Sectorial Classification of Vulnerability

The identified regional vulnerabilities within this research were classified based on the levels of its potential susceptibility to floods. Future studies can in addition, adopt a relatively simplified form of sectorial vulnerability such as the sector that are more vulnerable either agricultural, health or educational sector in other to complement the

measures suggested to by this research. A sectorial classification will relate vulnerability directly to the targeted institution thereby, providing a platform for institutional policy-making, since even with the disaster management agencies, they are constrained by insufficient budget to implement some preventive measures.

6.7 Concluding Remarks

Upstream floods have become a regular and virtually ubiquitous threat in Niger state during the last decade. The annual flooding from heavy downpour is increasing; not only the mean volume, but also the extremes have increased. Therefore, this research has adopted a hybrid approach employing multi-spatiotemporal data for upstream flood vulnerability classification and long-lead analysis as a contribution towards the mitigation of potential flooding events within the study area. More essentially, during the analysis, the developed hybrid framework has illustrated its efficiency in identifying various flood vulnerability when using flood causative factors represented by satellite features. These features have provided relevant results for many facets that could serve as a guide for the improvement of such GIS applications and disaster management. Furthermore, the findings obtained, and also the remarks from the experts in subsection 4.5.3, showed that the proposed hybrid framework is significantly applicable in a practical aspect. However, the framework may not be adoptable within a flood analysis that focuses on anthropogenic (man-made) factors that could come in the future because the generality of this research dwelled on the consideration of natural causative factors. It is therefore hoped that this research will not only exemplify to the everyday flood mitigating practices within flood-prone areas, but will as well show the applicability of Big Data Analytics in performing long-lead upstream flood prediction. Finally, from the results and the recommendations

provided by this research, when compared with the practical guiding principles of the United Nations International Strategy for Disaster Reduction (UNISDR), as elaborated in [305], which requires that every framework aimed at disaster management must ensure the identification of vulnerability and enhance early warning, and above all, strengthen the disaster preparedness for effective response at all levels. Thus, from the outputs of the vulnerability classifications and long-lead analysis, the developed HyM-SLUFA framework has successfully fulfilled these conditions.



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APPENDICES

Appendix A: Copyright Permission

Dear Sir,

No problem to use some of our products based on EM-DAT until you put the full citation : "EM-DAT: The Emergency Events Database – Université catholique de Louvain (UCL) – CRED, D. Guha-Sapir – www.emdat.be, Brussels, Belgium” and the complete reference for the graph taken from ‘2015-Disasters in Numbers’ report.

Best regards,

Pascaline Wallemacq
Geographer at CRED – EMDAT
30, Clos Chapelle-aux-Champs - B.1.30.15
1200 Brussels - Belgium
Tel : +32-2-764-33-66

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From: Ahmed Ndanusa <elahmedn@gmail.com>

Sent: mercredi 11 avril 2018 09:11

To: contact@emdat.be

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Your consideration shall greatly be appreciated and acknowledged.

Best regards

Ahmed Ndanusa

Appendix B: Sample of Temporal Data

Date	Temperature	Precipitation	Water Level
1/1/2015	19.29	0	0.226
1/2/2015	18.91	0	0.280
1/3/2015	18.14	0	0.176
1/4/2015	17.67	0	0.144
1/5/2015	17.33	0	0.136
1/6/2015	17.83	0	0.175
1/7/2015	17.84	0	0.208
1/8/2015	18.47	0	0.196
1/9/2015	17.98	0	0.146
1/10/2015	17.4	0	0.180
1/11/2015	17.18	0	0.149
1/12/2015	16.91	0	0.129
1/13/2015	17.5	0	0.150
1/14/2015	18.77	0	0.148
1/15/2015	19.31	0	0.143
1/16/2015	19.95	0	0.139
1/17/2015	21.03	0	0.142
1/18/2015	21.1	0	0.157
1/19/2015	22.02	0	0.146
1/20/2015	21.07	0	0.275
1/21/2015	20.8	0	0.313
1/22/2015	21.08	0	0.258
1/23/2015	21.55	0	0.176
1/24/2015	21.49	0	0.160
1/25/2015	21.55	0	0.236
1/26/2015	21	0	0.327
1/27/2015	21.25	0	0.372
1/28/2015	21.1	0	0.250
1/29/2015	20.52	0	0.261
1/30/2015	20.93	0	0.421
1/31/2015	21.07	0	0.455
2/1/2015	21.57	0	0.337
2/2/2015	21.57	0	0.267
2/3/2015	21.57	0	0.264
2/4/2015	22.52	0	0.390
2/5/2015	23.09	0	0.327
2/6/2015	22.48	0	0.309

2/7/2015	23.21	0	0.321
2/8/2015	22.11	0	0.322
2/9/2015	22.71	0	0.271
2/10/2015	23.07	0	0.356
2/11/2015	21.69	0	0.463
2/12/2015	21.24	0	0.222
2/13/2015	21.3	0	0.318
2/14/2015	21.45	0	0.285
2/15/2015	22.7	0	0.315
2/16/2015	22.78	0	0.367
2/17/2015	22.86	0	0.351
2/18/2015	24.21	0	0.472
2/19/2015	21.31	0	0.448
2/20/2015	23.54	0	0.413
2/21/2015	23.04	0	0.367
2/22/2015	20.81	0.405	0.356
2/23/2015	20.59	0	0.202
2/24/2015	21.86	0	0.235
2/25/2015	22.26	0	0.314
2/26/2015	21.19	0	0.257
2/27/2015	20.59	0	0.226
2/28/2015	20.95	0	0.348
3/1/2015	21.47	0	0.477
3/2/2015	21.48	0	0.250
3/3/2015	20.95	0	0.226
3/4/2015	20.82	0	0.394
3/5/2015	21.33	0	0.236
3/6/2015	22.26	0	0.195
3/7/2015	22.17	0	0.249
3/8/2015	23.33	0	0.289
3/9/2015	22.78	0	0.350
3/10/2015	22.42	0	0.308
3/11/2015	23.65	0	0.347
3/12/2015	21.66	0	0.355
3/13/2015	21.86	0	0.317
3/14/2015	21.84	0	0.293
3/15/2015	22.39	0	0.328
3/16/2015	24.28	0	0.284
3/17/2015	21.74	0	0.283
3/18/2015	23.54	0	0.367
3/19/2015	24.78	0	0.353

3/20/2015	24.56	0	0.395
3/21/2015	23.57	0	0.402
3/22/2015	23.46	0	0.431
3/23/2015	26.19	0	0.388
3/24/2015	24.93	2.4075	0.946
3/25/2015	26.18	0.045	0.145
3/26/2015	29.8	0.0225	0.401
3/27/2015	33.63	0	0.096
3/28/2015	32.25	0	0.044
3/29/2015	34.73	0	0.057
3/30/2015	37.28	0	0.046
3/31/2015	30.34	0.0225	0.115
4/1/2015	38.46	0	1.230
4/2/2015	38.46	0	1.230
4/3/2015	22.39	0	0.555
4/4/2015	25.03	0	0.216
4/5/2015	23.43	0	0.400
4/6/2015	22.09	0	0.468
4/7/2015	23.17	0	0.404
4/8/2015	21.46	0	0.425
4/9/2015	25.13	0	0.450
4/10/2015	25.04	0	0.481
4/11/2015	22.28	0	0.475
4/12/2015	21.72	0	0.518
4/13/2015	22.03	0	0.592
4/14/2015	22.06	0	0.230
4/15/2015	21.5	0	0.179
4/16/2015	21.7	0	0.228
4/17/2015	21.45	0	0.320
4/18/2015	22.08	0	0.167
4/19/2015	22.1	0	0.260
4/20/2015	22.12	0	0.219
4/21/2015	22.65	0	0.293
4/22/2015	24.79	0	0.339
4/23/2015	24.31	0	0.518
4/24/2015	24.3	0	0.366
4/25/2015	22.89	0	0.393
4/26/2015	22.12	0	0.516
4/27/2015	24.21	0	0.460
4/28/2015	23.26	0	0.363
4/29/2015	23.62	0	0.340

4/30/2015	22.44	0	0.399
5/1/2015	23.32	0	0.393
5/2/2015	24.5	0	0.449
5/3/2015	23.74	0	0.439
5/4/2015	22.05	0	0.440
5/5/2015	23.66	0.765	0.658
5/6/2015	19.92	0.0675	0.707
5/7/2015	23.15	0	0.398
5/8/2015	22.78	0	0.457
5/9/2015	22.32	1.1925	0.510
5/10/2015	23.74	0.3825	0.521
5/11/2015	21.89	0.0225	0.556
5/12/2015	22.27	0	0.468
5/13/2015	23.2	0	0.522
5/14/2015	21.82	0	0.466
5/15/2015	17.63	2.475	0.656
5/16/2015	21.04	0.1575	0.594
5/17/2015	19.69	0	0.510
5/18/2015	21.98	0	0.715
5/19/2015	21.77	0	0.488
5/20/2015	22.71	0	0.523
5/21/2015	21.3	0	0.547
5/22/2015	21.97	0	0.474
5/23/2015	22.7	0	0.462
5/24/2015	21.85	0	0.554
5/25/2015	24.04	0	0.579
5/26/2015	22.59	0	0.661
5/27/2015	22.38	0	0.610
5/28/2015	22.13	0	0.623
5/29/2015	22.33	0	0.667
5/30/2015	21.9	0	0.583
5/31/2015	21.58	0	0.604
6/1/2015	22.33	0	1.081
6/2/2015	21.28	0	1.016
6/3/2015	23.96	9.31	0.769
6/4/2015	23.12	12.75	1.390
6/5/2015	16.87	34.3	4.014
6/6/2015	31.45	0	0.101
6/7/2015	23.45	10.02	1.026
6/8/2015	22.57	21.5	2.710
6/9/2015	22.9	20.95	2.504

6/10/2015	21.21	25.21	3.012
6/11/2015	18.04	30.75	3.333
6/12/2015	22.58	0	0.861
6/13/2015	21.03	0	0.823
6/14/2015	20.91	0	0.739
6/15/2015	21.01	0	0.814
6/16/2015	22.26	0.6075	0.749
6/17/2015	22.31	0.1125	0.751
6/18/2015	21.87	0.27	0.699
6/19/2015	21.11	0.6075	0.850
6/20/2015	23.01	0.0675	1.019
6/21/2015	20.81	1.665	1.226
6/22/2015	20.32	0	1.020
6/23/2015	20.83	0	0.931
6/24/2015	20.91	0	0.847
6/25/2015	20.57	0	0.795
6/26/2015	19.94	1.17	0.842
6/27/2015	20.68	0.225	0.883
6/28/2015	20.89	0	0.843
6/29/2015	20.49	0.09	0.781
6/30/2015	22.18	0	0.877
7/1/2015	23.28	0.945	0.762
7/2/2015	21.37	3.9375	0.928
7/3/2015	19.44	16.7625	0.859
7/4/2015	20.02	11.0925	0.876
7/5/2015	19.22	2.6325	0.887
7/6/2015	19.14	0	0.818
7/7/2015	20.2	0.0225	0.704
7/8/2015	20.59	0.1125	0.798
7/9/2015	19.96	18.81	0.686
7/10/2015	21.1	3.06	0.694
7/11/2015	18.9	6.4575	0.725
7/12/2015	20.95	6.4125	0.856
7/13/2015	19.86	0.6075	0.841
7/14/2015	20.58	0	0.708
7/15/2015	16.8	0.4725	0.728
7/16/2015	18.49	2.0925	0.791
7/17/2015	21.67	0.18	0.689
7/18/2015	22.3	0.09	0.758
7/19/2015	20.97	11.565	0.886
7/20/2015	14.33	119.7675	1.361

7/21/2015	17.09	0.7875	1.597
7/22/2015	18.32	0.0225	1.314
7/23/2015	20.25	1.8225	0.792
7/24/2015	18.22	0.99	0.682
7/25/2015	18.97	0.36	0.985
7/26/2015	17.21	33.57	1.097
7/27/2015	14.63	30.8925	0.961
7/28/2015	14.33	5.895	1.331
7/29/2015	17.31	0.6975	1.661
7/30/2015	16.42	2.61	1.134
7/31/2015	18.26	0.0225	1.345
8/1/2015	17.4	0.09	0.964
8/2/2015	14.98	12.375	1.427
8/3/2015	16.94	0.3375	1.304
8/4/2015	15.08	8.3025	1.700
8/5/2015	16.13	2.07	1.363
8/6/2015	17.22	3.2625	1.064
8/7/2015	15.19	2.115	1.457
8/8/2015	14.71	4.0725	1.303
8/9/2015	16.37	5.2425	1.740
8/10/2015	15.19	32.1525	1.678
8/11/2015	16.86	6.9525	1.343
8/12/2015	15.63	19.8	1.040
8/13/2015	17.19	0.675	1.704
8/14/2015	17.61	0.0225	1.176
8/15/2015	17.53	0	1.106
8/16/2015	19.09	0.135	1.071
8/17/2015	16.67	83.6325	0.981
8/18/2015	16.85	0.6525	1.555
8/19/2015	18.36	0.045	1.095
8/20/2015	18.12	11.4075	1.089
8/21/2015	15.57	19.2375	1.158
8/22/2015	17.36	0.045	1.512
8/23/2015	18.84	3.69	1.160
8/24/2015	17.59	4.005	1.348
8/25/2015	15.78	12.5775	1.194
8/26/2015	14.67	14.4675	1.354
8/27/2015	17.6	1.395	1.280
8/28/2015	16.84	5.6025	1.257
8/29/2015	13.56	43.11	1.595
8/30/2015	15.65	12.105	1.286

8/31/2015	16.95	9.495	1.220
9/1/2015	14.9	53.46	1.217
9/2/2015	17.28	4.8375	1.495
9/3/2015	13.97	32.13	1.535
9/4/2015	17.58	0.3375	1.555
9/5/2015	17.68	0	1.067
9/6/2015	16.93	7.5825	1.657
9/7/2015	17.57	0.09	1.319
9/8/2015	15.99	10.305	1.167
9/9/2015	16.91	2.52	1.754
9/10/2015	18.06	0	1.107
9/11/2015	18.66	0.1575	1.196
9/12/2015	17.41	0	1.412
9/13/2015	18.26	0.09	1.168
9/14/2015	18.62	0.675	1.049
9/15/2015	18.24	4.8825	1.122
9/16/2015	18.01	5.265	1.414
9/17/2015	13.75	121.8375	1.440
9/18/2015	15.6	4.1625	1.848
9/19/2015	17	0.5625	1.353
9/20/2015	17.77	4.9725	1.068
9/21/2015	17.55	0.045	1.329
9/22/2015	18.4	0	1.137
9/23/2015	18.85	0	1.028
9/24/2015	19.05	0	1.084
9/25/2015	17.69	0.45	1.136
9/26/2015	18.09	0	1.684
9/27/2015	18.78	0.18	1.110
9/28/2015	18.88	0.765	0.943
9/29/2015	17.9	0	1.076
9/30/2015	18.14	0	1.244
10/1/2015	18.58	0.09	1.000
10/2/2015	18.72	0	1.000
10/3/2015	18.25	0	1.038
10/4/2015	19.05	1.26	1.004
10/5/2015	18.12	5.7825	1.846
10/6/2015	19.1	0.945	1.035
10/7/2015	18.57	0	1.110
10/8/2015	18.32	0	0.985
10/9/2015	17.31	0.9225	1.217
10/10/2015	18.94	0.0225	1.142

10/11/2015	19.28	0.6525	0.835
10/12/2015	19.96	0.2925	0.955
10/13/2015	19.94	0	1.000
10/14/2015	19.28	0	0.926
10/15/2015	19.62	0	0.996
10/16/2015	20.51	0	0.915
10/17/2015	19.45	0	0.921
10/18/2015	19.46	0.0225	0.880
10/19/2015	19.54	0	1.000
10/20/2015	20.72	7.8525	0.824
10/21/2015	18.86	8.3475	0.860
10/22/2015	18.97	0	0.942
10/23/2015	19.8	0	0.904
10/24/2015	19.48	0	0.880
10/25/2015	20.7	0.3825	0.920
10/26/2015	20.8	0.2025	0.890
10/27/2015	19.41	0	0.901
10/28/2015	20.2	0	0.981
10/29/2015	20.09	0	1.080
10/30/2015	19.35	0	0.917
10/31/2015	19.5	0	0.819
11/1/2015	19.33	0	0.719
11/2/2015	19.12	0	0.681
11/3/2015	19.42	0	0.916
11/4/2015	19.49	0	0.630
11/5/2015	19.59	0	0.579
11/6/2015	19.1	0	0.674
11/7/2015	19.3	0	0.608
11/8/2015	19.2	0	0.560
11/9/2015	19.37	0	0.506
11/10/2015	18.68	0	0.501
11/11/2015	19.21	0	0.495
11/12/2015	19.51	0	0.441
11/13/2015	19.65	0	0.359
11/14/2015	19.62	0	0.355
11/15/2015	19.25	0	0.335
11/16/2015	19.17	0	0.470
11/17/2015	19.1	0	0.517
11/18/2015	19.64	0	0.473
11/19/2015	19.5	0	0.305
11/20/2015	19.42	0	0.349

11/21/2015	19.38	0	0.366
11/22/2015	20.17	0	0.378
11/23/2015	20.14	0	0.369
11/24/2015	20.19	0	0.335
11/25/2015	20.16	0	0.321
11/26/2015	20.78	0	0.304
11/27/2015	21.52	0	0.400
11/28/2015	20.65	0	0.488
11/29/2015	20.43	0	0.467
11/30/2015	19.91	0	0.413
12/1/2015	13.32	0	0.327



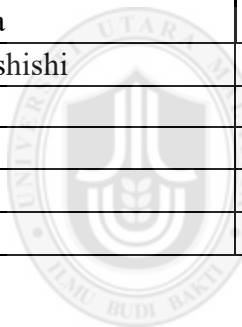
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Appendix C: Flood Inventory 2006-2017

Regions	Date of Flood
Agaie	27-Jul-12
	15-Aug-12
	9-Aug-14
	29-Sep-16
Agwara	9-Jul-12
	29-Jun-15
	11-Jun-16
Bida	17-May-06
	13-Aug-10
	20-Jul-12
	16-Jul-16
Borgu	17-May-06
	2-Jun-09
	23-Jul-12
	11-Jun-15
	26-Jul-16
	1-Oct-16
	29-Aug-16
Bosso	24-Aug-12
	11-Jun-12
	14-Aug-15
	27-Sep-15
	25-Aug-16
Chanchaga	28-Aug-17
	3-Jul-12
	1/9/2012
	28-Jul-16
Edati	1-Jul-12
	27-Jul-15

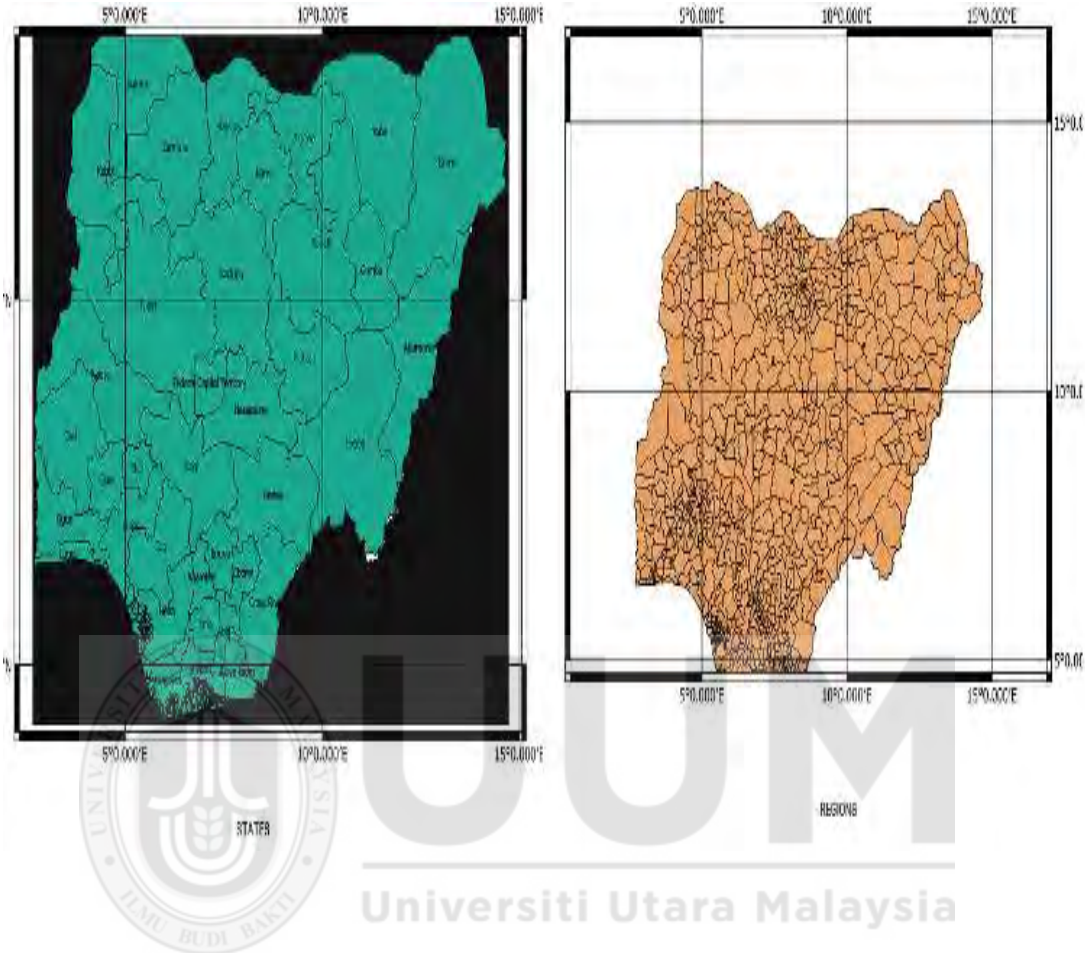
	16/08/2015
Gurara	10-Jul-12
Gbako	22-Aug-12
	9-Jul-15
Katcha	28-Aug-10
	4-Jul-12
	28-Aug-12
	13-Jul-15
	25-Jul-16
Kontagora	5-Jul-12
	13-Aug-16
	17-May-06
Lapai	24-Sep-15
	21-Jul-15
	8-Jul-09
	24/8/2016
	24-Aug-10
	3-Jul-12
	30-Jul-16
Lavun	25-Jul-09
	17-Jul-15
	29-Jul-16
	24-Sep-15
Magama	4-Oct-16
	15-Aug-12
Mariga	19-Jul-14
	22-Aug-12
Mashegu	8-Sep-16
Mokwa	23-Jun-09
	15-Aug-10
	2-Jul-10
	24-Aug-12
	24-Aug-12
	27-Jun-14
	28-Jun-14

	16-Aug-15
	7-Jul-15
	19-Sep-15
	29-Jul-16
Munya	15-Jun-12
	21-Jul-16
Paikoro	9-Aug-12
	27-Sep-15
Rafi	9-Jul-14
Rijau	17-Aug-12
Shiroro	24-Jul-09
	29-Jul-12
	15-Jul-12
	11-Aug-15
Suleja	26-Jul-16
Tafa	0
Wushishi	31-May-09
	17-Aug-10
	6-Jul-13
	21-Jul-15
	20-Jul-12

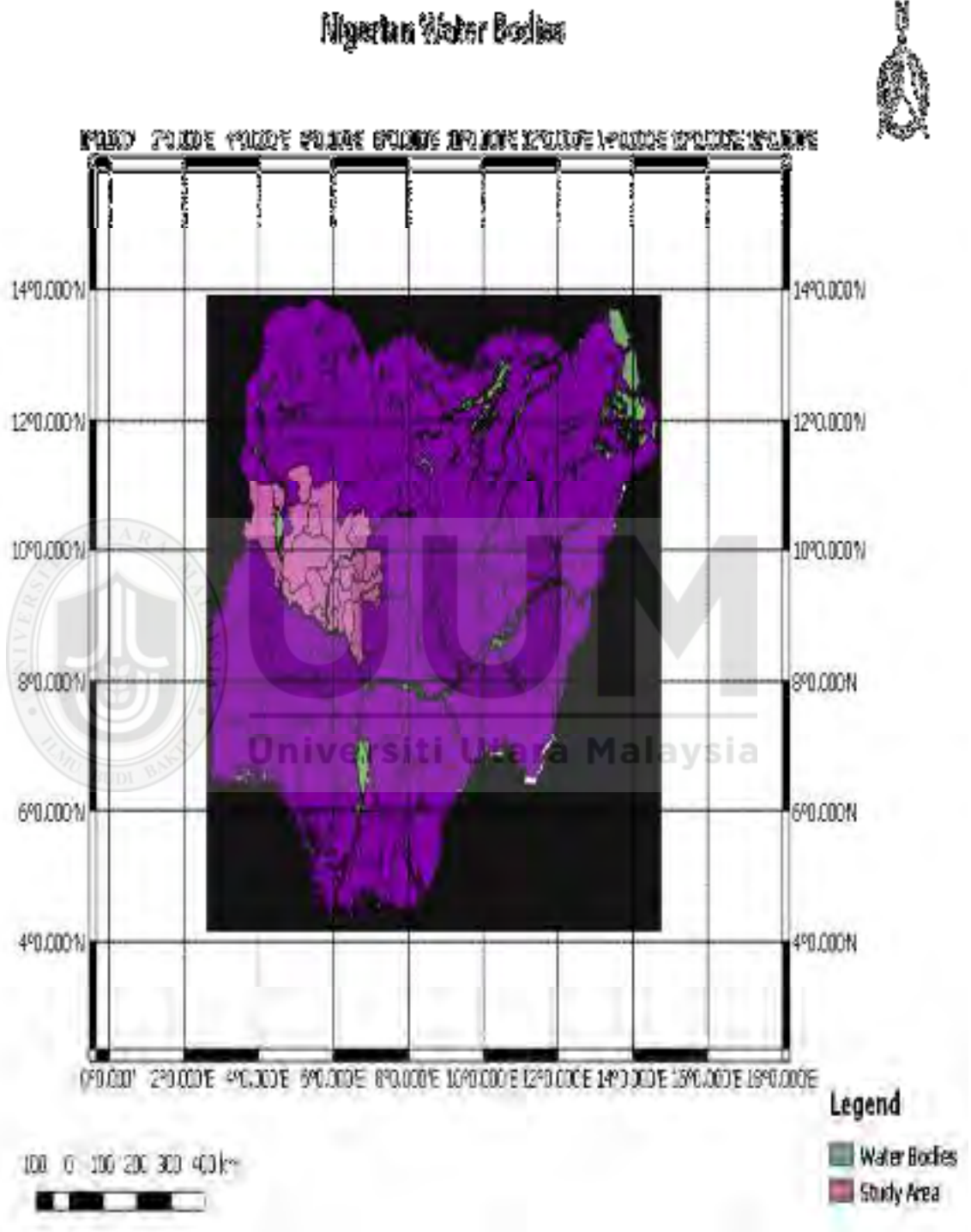


UUM
Universiti Utara Malaysia

Appendix D: Administrative Shapefile



Appendix E: Water bodies from Shapefile



Appendix F: Invitation to Participate in Framework Assessment



Dear Prof. / Dr. / Sir / Ma,

I am Ndanusa B. Ahmed who is currently pursuing his PhD study in Information Technology at Universiti Utara Malaysia. I am delighted to respectfully request for your ample time to participate in the review as well as validation of my proposed framework. You have been selected to participate for this research based on your expertise/experience in GIS and remote sensing data analysis.

The main aim of this review and validation is to examine the accuracy and applicability of the proposed framework within the domain of spatiotemporal data and flood analysis. Moreover, the validation is one of the objective of my PhD research. Therefore, upon agree to participate, the proposed framework and sets of generated outputs shall be sent to you for your perusal. Furthermore, once this is done, please you will provide feedback using a validation form that is attached with the documents of the proposed framework.

I assured you, the information given will be treated as confidential and will be used exclusively for the research purposes, which will be reported anonymously in academic publications.

Please feel free to contact me or my supervisors by email:

Thank you

Ndanusa B. Ahmed
elahmedn@gmail.com

Supervisors

Prof. Dr. Zulhairi Md. Dahalin
zul@uum.edu.my myazman@uum.edu.my

Dr. Azman Ta'a

Appendix G: Expert Review & Validation Form

Please validate and give comments on the below mentioned outputs on the proposed Multi-spatiotemporal approach for flood vulnerability classification and Long-Lead Upstream Flood Analysis for a Case of Niger state, Nigeria: Respondent: GIS Expert

Relevancy to the intended application	The proposed framework is useful to the long-lead flood analysis.	Agree Disagree Comments/ Suggestions: ----- ----- -----
Decision Support Satisfaction	The proposed framework provides appropriate results for valid decision-making.	Agree Disagree Comments/ Suggestions: ----- ----- -----
Comparison with existing usability evaluation method	The proposed framework is straight forward and easy to use compared to existing usability evaluation method	Agree Disagree Comments/ Suggestions: ----- ----- -----
Clarity	The flow of assessment process (items) is defined clearly	Agree Disagree Comments/ Suggestions: ----- ----- -----
Tasks appropriateness	The tasks in the proposed framework are appropriate and efficient	Agree Disagree Comments/ Suggestions: ----- ----- -----
Ease of use	The proposed framework can be implemented easily	Agree Disagree Comments/ Suggestions: ----- ----- -----

Internally consistent	The proposed framework is consistent, dependable and easy to apply	Agree Disagree Comments/ Suggestions: ----- -----
Well organised (organisation)	The proposed framework is organized and well-structured.	Agree Disagree Comments/ Suggestions: ----- -----
Presentation (readable and useful format)	The proposed framework is readable and can produce results in a useful format.	Agree Disagree Comments/ Suggestions: ----- -----
Ability to produce expected results	The proposed framework can produce usability problems for the intended flood analysis.	Agree Disagree Comments/ Suggestions: ----- -----
Ability to produce relevant and useful results	The proposed framework produces results that can be used for future improvement	Agree Disagree Comments/ Suggestions: ----- -----
Practicality (Ease of implementation)	The proposed framework is practical to be implemented in the real-world environment	Agree Disagree Comments/ Suggestions: ----- -----

Appendix H: Disaster Monitoring/Management Agency

Expert Review & Validation Form

Respondent: Disaster
Monitoring/Management Agency Experts

Institution:

.....

.....

Phone:

Email:

Address of the Institution:

.....

.....

Please choose where appropriate:

YES

NO

Does the classification of the vulnerability for various regions match the levels of flood frequency within these regions?

Accuracy on Vulnerability

Borgu region has been identified to be adjacent to a water body, does the discharge from the water body during a heavy rainfall contribute to flooding events?

Niger state is highly vulnerable to floods due to rainfall.

Are Tafa and Suleja regions the least vulnerable areas in Niger state as identified regions to flooding events?

		Are the regions identified with low or dense vegetation have the traits of such vegetations on the true-terrestrial features?				
	Land Cover Features	Are the water bodies identified in the output exist in the study area?				
		Identification of features images to the ground truth features				
		Are the regions correctly positioned on the maps?				
			NS:Not Satisfactory	NS	FS	S VS
			FS:Fairly Satisfactory			
			S:Satisfactory			
			VS: Very Satisfactory			
Visual Assessment	Vulnerability	Satisfaction with graphical presentation				
		Precision of the output formats				
		Satisfaction with information representation				
Interpretability	Layouts/Presentation	Satisfaction with legends representation				
		Satisfaction with classification				
		Satisfaction with coordinate representation				
		Satisfaction with scale and distance illustration				

Satisfaction with output display and format

Please validate and give assessment comments on the below mentioned vulnerability and geographical outputs on the proposed multi-spatiotemporal Data framework and flood vulnerability classification for Long-Lead Upstream Flood Analysis for a Case of Niger state, Nigeria.

Additional comments (if any):

.....
.....
.....
.....

.....Date.....

(Signature & Official Stamp)

Signed by(Name):

Thank you for your time and effort.



APPENDIX I: GIS Expert Review

Expert Review for Validation of Multi-spatiotemporal Data Framework Representing Niger State.

Respondent: **GIS (Satellite Imageries) & Geographical Experts**

Name: Prof./Dr./Mr./Mrs. (Other.....)

Years of Experience:

Place of work:

.....

.....

Position:.....

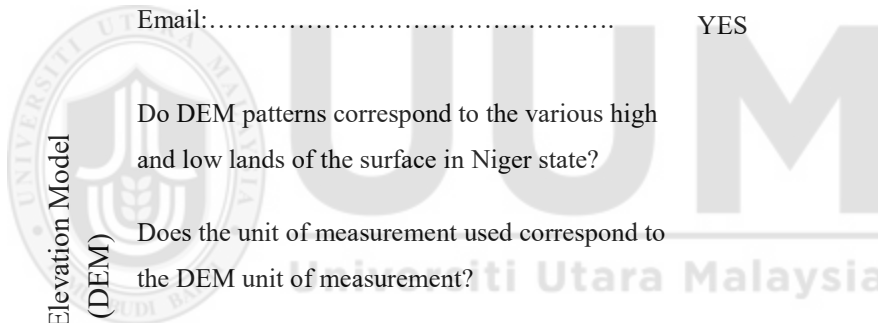
Phone:

Email:.....

YES

NO

Expert's Profile



Digital Elevation Model (DEM)

Do DEM patterns correspond to the various high and low lands of the surface in Niger state?

Does the unit of measurement used correspond to the DEM unit of measurement?

Does the classification method used in conformity with the various elevation patterns?

Terrain Feature

Are the patterns of the Slope in correspondence with the various high and low lands of the surface in Niger state.

Slope

Does the classification method used distinguish clearly between the various patterns of the slope?

Hydrological Features	Flow Accumulation	Do the identified features represent flow accumulation?				
		Is there any tendency of flow accumulation as identified in the feature?				
Land Cover Features	Flow Direction	Do the identified features represent flow direction?				
	(Vegetation)	Are the regions identified with low or dense vegetation have the traits of such vegetations on the true-terrestrial features?				
Accuracy	Water bodies	Are the water bodies identified in the output exist in the study area?				
		Identification of features images to the ground truth features				
		Are the regions correctly positioned on the maps?				
		<u>NS:Not Satisfactory</u>	NS	FS	S	VS
		<u>FS:Fairly Satisfactory</u>				
		<u>S:Satisfactory</u>				
		<u>VS: Very Satisfactory</u>				
		Satisfaction with graphical presentation				
		Precision of the output formats				

Satisfaction with outcome of the MCE using AHP

Satisfaction with information representation

Satisfaction with legends of representation

Satisfaction with classification of the patterns

Satisfaction with coordinate representation

Satisfaction with scale and distance illustration

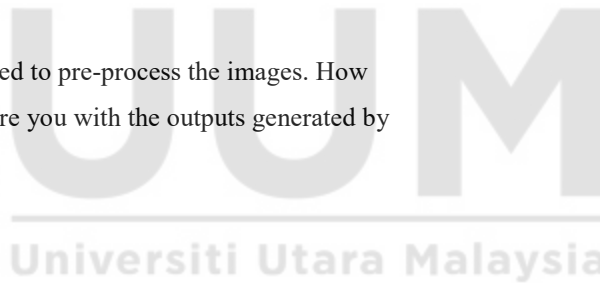
Satisfaction with output display and format

Interpretability
Layouts/Presentation



Tools

QGIS was used to pre-process the images. How satisfactory are you with the outputs generated by this tool?



Additional comments (if any):

.....
.....
.....
.....
.....

Thank you

.....

Date.....

(Signature & Official Stamp)

Appendix J: Regional FIPV

Locations	FIPV (mm)
Aga	190.32
Agw	301.08
Bid	208.540
Bor	164.79
Bos	213.44
Cha	181.44
Eda	361.64
Gur	247.52
Gba	295.8
Kat	215.89
Kon	317.81
Lap	287.05
Lav	170.27
Mag	199.23
Mar	281.60
Mas	485.90
Mok	386.41
Mun	218.88
Pai	203.66
Raf	235.74
Rij	243.85
Shi	292.11
Sul	579.92
Taf	N/A
Wus	351.81

Appendix K: A Sample of LandSand Imagery



Appendix L: Authorization for Data Usage

******* CAR Data Request Form *******

FOR THE ATTENTION OF:
Project Manager,
TRODAN, Centre for Atmospheric Research (CAR), NASRDA

Please print very clearly:

Your Name: Nolusa B. Alimic

Your Position: Senior Engineer /Ph.D. Research Student

Your Institute: National Space Research and Dev. Agency/University of Ilorin, Nigeria

Telephone/fax number: (include country code) +2348035329994

Email address: nibgat@yahoo.com

Purpose of Request of Data: Research in Total Aerosols

Please specify your request in this way:
station code (3 characters), and time period (yyyymmdd).

Eg. AYB, 20120101-20120331

Note: _____

Conditions of Use of TRODAN Data

The data made available by CAR are provided for research use and are not for commercial use or sale or distribution to third parties without the written permission of the Centre. Publications including those making use of the data should include an acknowledgment statement of the form given below. A citation reference should be sent to the TRODAN Project Manager (trodan@car.nasrda.com) for inclusion in a publications list on the TRODAN website.

Acknowledgement of data from TRODAN

The results presented in this paper rely on TRODAN data collected and managed by the Centre for Atmospheric Research, National Space Research and Development Agency, Federal Ministry of Science and Technology, Anyigba, Nigeria. We thank the Centre for Atmospheric Research and their partners for promoting high standards of atmospheric observatory practice as well as the Federal Government of Nigeria for continuous funding of the Nigerian Space programme (www.nasrda.com).

I agree to conform to all data usage rules of CAR.

Signature, Name and Date: Nolusa B. Alimic

CENTRE FOR ATMOSPHERIC RESEARCH
P.O. BOX 1000
WOGH STATE UNIVERSITY, ANYIGBA
DIRECTOR'S OFFICE
Request for Data
for the project
for the research

24/July/2014

Email completed form to: trodan@car.nasrda.com ; nalibat@yahoo.com