A conceptual framework for phase-dependent, composite flood risk index (FRI) curves based on the relationship between temporal probability of flood occurring (PH) and flood vulnerability index (FVI) along with maps of FVI within the Amite River Basin based on the August 2016 Flood.

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A CONCEPTUAL FRAMEWORK FOR PHASE-DEPENDENT, COMPOSITE FLOOD RISK INDEX (FRI) CURVES BASED ON THE RELATIONSHIP BETWEEN TEMPORAL PROBABILITY OF FLOOD OCCURRING ($P_H$) AND FLOOD VULNERABILITY INDEX (FVI)

A Thesis

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Master of Science

in

The Department of Civil and Environmental Engineering

by
Austin Scott Guerin
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ABSTRACT

Efforts directed at determining community vulnerability to flooding are limited and only include economic (dollar damages) and public safety impacts and do not consider the phase dependency of the system, i.e., pre-, during- and post-storm, both critical shortcomings for more broadly assessing community risk and developing comprehensive plans and mitigation strategies. This thesis first develops a framework based on a Flood-Vulnerability Index (FVI) approach and then demonstrates its usefulness, at the census tract level of detail, for three parishes in the Greater Baton Rouge, LA area, based on the August 2016 flood. FVI’s indicators are multidimensional and phase dependent: “Pre-Flood” Susceptibility Indicator (FSI\textsubscript{PF}); “During-Flood” Exposure Indicator (FEI\textsubscript{DI}); and “Post-Flood” Adaptive Capacity Indicator (FACI\textsubscript{PF}). The social and economic component of FSI, and FACI, were both computed using well-being variables developed as part of the Inland from the Coast (IFC) project (Moles, A., Birch, T., Chan, et al., 2020). FSI\textsubscript{ep} was created using the Flood Hazard Index (FHI) methodology developed by Kazakis et al., (2015); which serves to identify flood prone zones based on the community’s hydrological, morphological and land-use, land-cover (LULC) characteristics. FEI was developed utilizing a structure inventory, included in Dewberry’s Amite River Basin Numerical model, and direct economic loss shapefiles, produced for HEC-FIA (Flood Impact Analysis) model. These two shapefiles were spatially joined using only matching attributes between the two shapefiles, which plans to represent the exposed elements of risk.

Results from this work showed two primary trends. First, the shift from high pre-storm FVI values, indicating greater levels of susceptibility, in the East Baton Rouge Parish census tracts to high during-storm FVI values, indicating larger levels of exposure, in Livingston and Ascension Parishes that were inundated by floodwaters from the Amite and Comite Rivers. Furthermore,
going from during-flood to during-recovery phase FVI, the number of highly vulnerable census tract areas increased within Ascension Parish and Livingston Parish along the southern end of the Amite River Basin. Given the severity and extent of the August 2016 event, this is not unexpected, but does highlight the ability of this approach to capture the spatial and temporal aspects of community vulnerability. In addition, while this demonstration used only a single event, future work could utilize this framework with probabilistic storm events to develop Flood Risk Indices. Finally, the framework allows for a very comprehensive and wide-ranging set of data types and sources, scaling and weighting techniques, and data aggregation methods. While the methodology and results in this work are limited by the availability of datasets and certain assumptions for scaling and weighting, the framework provides opportunities to identify data gaps and incorporation of more rigorous and meaningful statistic.
1. INTRODUCTION

Communities, people, and their assets have always been vulnerable to hazards. Over time, communities are suffering greater and greater consequences, which are due to the following problems: increases in both magnitude and frequency of extreme flood events, urbanization, migration to high-flood risk areas, increases in wealth gap, poor flood-risk management strategies, and population growth (Greiving, 2006; Kotzee & Reyers, 2015). Such problems increase a community’s risk to flood hazards, and subsequently, increases the probability of succumbing to disastrous levels of life loss, infrastructural loss, economic loss, impacts to physical and mental health, and other place-specific units of interest. To mitigate these negative impacts, improving upon current flood-risk management strategies are vital for adequately reducing community vulnerability for future events.

This thesis is aimed at helping mitigate community risk by improving upon current flood-risk management plans by addressing several implementational gaps surrounding current flood-risk management methodologies. The first step is by creating a conceptual framework for creating a multi-dimensional, time-dependent composite flood-risk index (FRI) curve. The second step is to produce and interpret results for the Flood Vulnerability Indicator (FVI) for the following phases of the disaster risk cycle: the preparedness phase, the impact phase, and the recovery phase. The second step is to demonstrate the process of producing the Flood Vulnerability Indicator (FVI) for the preparedness, impact, and recovery phases of the disaster risk cycle. This demonstration will evaluate the flood vulnerability of three parishes within the Amite River Basin, East Baton Rouge Parish, Ascension Parish, and Livingston Parish, relative to the August 2016 flood.
2. LITERATURE REVIEW

2.1. Flood-Risk Management (FRM) Approaches: DRR vs. CCA

After a review of academic literature, it is apparent that different flood-risk management methodologies have unique approaches, definitions, and quantitative methods. The two main approaches, applied in most flood-risk management, are Disaster Risk Reduction (DRR) and Climate Change Adaptation (CCA); (Birkmann, 2006). Engineers and natural scientist apply DRR while social scientist apply CCA (Hadipour, Vafaie & Deilami, 2020). It is important to understand which approach is being used because it influences the selection, definition, and quantification style for risk and each of the risk’s subcomponents. DRR is the concept and practice of reducing disaster risks through systematic efforts to analyze and manage the causal factors of disasters, including through reduced exposure to hazards, lessened vulnerability of people and property, wise management of land and the environment, and the improved preparedness for adverse events (UNISDR, 2009). DRR considers the social, physical, environmental, and economic components in which a hazard is situated and can influence (Alexander, 2000; Weichselgartner & Obersteiner, 2002). Strategies for DRR include hazard, vulnerability, and capacity assessments. On the other hand, CCA is explained as the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities (UNFCCC, 2006). This research will apply both the DRR and CCA approaches.

2.2. Flood-Risk and Flood Vulnerability Assessment Terminology

Risk can be simply put as the combination of the probability of an event and its negative consequences. For this paper, risk will be defined as “the potential disaster losses pertaining to lives, health status, livelihoods, assets, and services; which could occur to a particular community or a society over some specified future period of time” (UNISDR, 2009). The two major
components of flood risk consist of the flood hazard and community vulnerability. For the general framework, the flood hazard will be defined as the condition that expresses the probability of occurrence, within a specific period of time, and in a determinate area, of a potentially damaging/dangerous natural phenomenon (UNISDR, 2009). Even though the parameter will not be computed in this thesis, it is assumed to be a function of the storm and project area (i.e., August 2016 and East Baton Rouge Parish, Ascension Parish, and Livingston Parish). Vulnerability will be defined as the extent of harm, which can be expected under certain conditions of exposure, susceptibility, and adaptive capacity (IPCC, 2001a). The quantification of community vulnerability is difficult because of the system’s phase-specific components, intrinsic, extrinsic, multidimensional, and multi-scalar characteristics. Therefore, most vulnerability assessments are conducted using a composite index approach, which is the only vulnerability assessment type that successfully addresses the aforementioned characteristics (Kotzee & Reyers, 2016). By applying CCA’s approach of vulnerability, vulnerability is further broken down into susceptibility, exposure, and adaptive capacity (Lei et al., 2013; Tingsanchal et al., 2010; Yamin et al., 2005).

Depending on the approach and qualitative method for calculating/estimating flood risk and/or flood vulnerability, the indicators of vulnerability have different definitions, which are governed by the flood vulnerability approach and quantitative method applied. The definitions of each indicator are vital in composing vulnerability. Think of indicator definitions as puzzle pieces: If the subcomponent definition changes, then the shape of the puzzle piece changes as well. This results in tweaking of other subcomponents to properly construct the vulnerability puzzle. In the following paragraph, the definitions of vulnerability’s components, along with their relationship to flood hazards, will be defined to provide clarity.
To begin, once a potential hazard is identified; risk emerges due to the presence of exposed elements: exposure, susceptibility, and adaptive capacity. Exposure is defined as the potential (maximum) level of harm that communities, containing social, physical, and economic dimensions, are affected by a potential hazard (Birkmann et al., 2013). However, different elements exposed are subjected to different degrees of vulnerability which can be explained through susceptibility. Susceptibility can be defined as the predisposition of elements at risk to suffer harm resulting from the levels of fragility of settlements, disadvantageous conditions, and relative weaknesses (Cutter et al., 2000). The last component to disaster risk is adaptive capacity; which can be defined as the community’s ability to adapt and recover from adverse disasters (UNISDR, 2009). Essentially, adaptive capacity, governs the rate of recovery, of a community, to return to pre-flood conditions.

2.3. Methods for Quantifying Flood-Risk and Flood Vulnerability

There are both quantitative and qualitative methods for quantifying flood-risk, and its subcomponents, include the following: quantitative risk assessment, event tree analysis, risk matrix, and indicator-based approach (Caribbean Handbook on Risk Management, 2010). There are two quantitative approaches: quantitative risk assessment and event tree analysis. The quantitative risk assessment method evaluates exposure for one single storm by overlaying inundation and inventory maps using Graphical Information System (GIS) operations, which are used to analyze the exposure. The second quantitative approach—event tree analysis—is a system which is applied to analyze all the combinations and the associated probability of occurrence for series of hazards that affect the system under analysis.

The two qualitative methods are risk-matrix and indicator-based approach. These methods are useful for situations where risk assessments are too complex and do not allow for a full numerical
The risk matrix is composed of classes of frequency of the hazardous events on one axis, and the consequences on the other axis. The other qualitative method, the indicator-based approach, is used when semi-quantitative methods for risk mapping are not viable. The indicator-based approach of disaster risk assessment is divided into several components, such as hazard, exposure, vulnerability, and capacity through a so-called criteria tree, which list the subdivision into composite indices, indices, and indicators.

Data for each of these indicators are collected at a particular spatial level, for instance by administrative units. These indicators are then standardized, weighted internally within a sub-objective, and then the various sub-objectives are also weighted amongst themselves. Normally the individual indicators consist of quantitative data and the resulting vulnerability, hazard, and risk results are scaled between 0 and 1. In this research, the indicator approach will be applied to create the Social and Economic Flood Susceptibility Indicator (FSI_{s,e}), the Physical and Environmental Flood Susceptibility Indicator (FSI_{en,p}), and the Flood Vulnerability Index (FVI).

In addition, the quantitative risk assessment approach will be used to develop the flood exposure indicator (FEI) by using a flood-impact assessment model (HEC-FIA) to compute social (i.e., population exposure), economic, and physical losses.

### 2.4. Limitations in FRM Approaches, Terminology, and Quantifications

After performing an extensive literature review on flood-risk assessment methodologies, several knowledge gaps were identified. Knowledge gaps with similar characteristics were grouped into broad knowledge gap sections. The first broad section of knowledge gaps pertains to risk’s subcomponent vulnerability. Vulnerability, relative to flood risk and hazard, has received far less attention when assessing flood risk. The first knowledge gap, within this section, pertains to quantitative vulnerability assessments that only focus on reducing the external component of
Reducing the external component of vulnerability entails reducing the impacts of hazards from outside the community system; thus, decreasing the maximum exposure within the community (UNISDR, 2009). In this perception, vulnerability is often confined to a physical-component assessment that relates to the vulnerability of buildings, cars, assets for a given flood depth (depth-damage curve.) Nevertheless, vulnerability has a broader meaning in flooding, and capturing the vulnerability of residents remains limited in such studies (Hadipour, Vafaie & Deilami, 2020). From the social scientists’ perspective (CCA), the vulnerability can be identified as an inherent characteristic of the system (people or community) before encountering the external hazard event (Birkmann et al., 2013; Hadipour, Vafaie & Deilami, 2020). Reducing internal vulnerability is completed by doing either or both of the following: decreasing a community’s susceptibility to flood hazards and/or increasing a community’s adaptive capacity. To address this limitation in quantitative vulnerability assessments, one can integrate a qualitative vulnerability assessment produced using indicator-based approach (Gain et al., 2015; Rana & Routray, 2016). Integrating the two methods will result in both multidimensional and time-dependent vulnerability assessments. The other knowledge gap of this group pertains to the temporal characteristics of vulnerability. The phases of the disaster cycle include the following: preparedness, response, recovery, and mitigation (Tascón-González et al., 2020). Each phase corresponds to one of the subcomponents of vulnerability.

The second broad section of knowledge gaps relate to details regarding model-produced exposure indicators that are developed by qualitative methods producing a composite vulnerability index. When considering indicator-based vulnerability assessments, almost all model-based exposure assessments involve some sort of hydrologic and hydraulic modeling software, mainly the Hydrologic Engineering Center River Analysis Center (HEC-RAS) to find the percent inundation
of building, cars, and assets within the impact area (Yang, Zhang, Dai, et al., 2020). There are zero composite-vulnerability methodologies that apply HEC-FIA (Flood Impact Analysis), which helps compute multidimensional exposures and consequences (FIA 3.1 Documentation, 2019). When reviewing literature applying HEC-RAS, one only considers the physical dimension of vulnerability (Chen, 2019; Mazzorana, Simoni, Scherer, et al., et al., 2014). However, such approaches should consider the multidimensionality of vulnerability. HEC-FIA can be useful for applying a model-based approach that considers the full multidimensionality of vulnerability during the exposure assessment.

2.5. Concluding Remarks and Summaries of Tasks

A majority of vulnerability assessments fail to address (at least one of) limitations mentioned in the literature review section. This is not desirable because such limitations prevent proper analysis and thus truly prevents capturing a community’s flood vulnerability. Therefore, the motivation for this thesis is improving upon current composite flood-vulnerability index methods. This will be accomplished by making flood vulnerability assessments multidimensional and phase dependent.

1. Create a framework for developing a composite flood vulnerability indicator that accounts for all phases of the disaster risk cycle.
   - 3 FVI conceptual frameworks - one for each phase: pre-flood, during-flood, during-recovery phases of disaster risk cycle.

2. Apply the FVI methodology to compute and map parish-level FVI, within the Amite River Basin, based on the August 2016 Flood, during the preparedness and response phases of the disaster risk cycle.
   - Conduct a “Pre-Flood” vulnerability assessment (to compute FVIPF), using a susceptibility-based vulnerability assessment (creating FSIse and FSi_en,p), to evaluate a community’s pre-flood susceptibility.
- Conduct a “During-Flood” vulnerability assessment (to compute $\text{FVI}_{\text{Di}}$) by averaging the exposure-based vulnerability assessment (creating $\text{FEI}_{\text{Di}}$) with $\text{FVI}_{\text{PF}}$.
- Conduct a “During-Recovery” vulnerability assessment (to compute $\text{FVI}_{\text{DR}}$) by averaging the recovery-based vulnerability assessment ($\text{FACI}_{\text{DR}}$) with $\text{FVI}_{\text{Di}}$.
- For each parish, map FVI to observe how vulnerability is influenced at different disaster-risk cycle phases during the August 2016 flood.
3. STUDY SITE AND METHODOLOGY

3.1. Study Site

The study area encompasses the portion of the Amite River Basin, which consist of the following Louisiana parishes: Ascension, Livingston, and East Baton Rouge. The primary channels are the Amite and Comite Rivers, which drain into Lake Maurepas and ultimately through to the Gulf of Mexico via Lake Pontchartrain (Figure 1). To observe the project area relative to the Amite River Basin, refer to Figure 2. The census tract level delineation of the Amite watershed has an area of approximately 1,880 square miles (U.S. Geological Survey, 2017). This study, however, will use the 2,220-square mile version of the Amite Basin used in Dewberry Engineers’ (2019) Amite River Basin Numerical Model.

Figure 1. Amite River Basin showing main channels of the Comite (left) and Amite (right) Rivers and their outlet channels, including the Amite River Diversion Canal (bottom) (Cowles, 2021). Note: The actual project area extent was designated with a red polygon.
The project area is relatively flat and low-lying; elevation peaks under 500 ft. above mean sea level (MSL) in the Plio-Pleistocene Terrace of southern Mississippi, but most of the southern third of the Basin consists of bottomland hardwood swamps at 1-5 ft. MSL (Gulf Engineers and Consultants Inc., 2015). Away from the river channels, soils are silty and loess-like, while deposits along the rivers are more heterogeneous mixtures of sands, silts, and clays (U.S. Army Corps of Engineers, 2012). Hydrologically, most of the Basin’s soils are classified as Hydrologic Soil Group C or D soils, which are characterized by slow or very slow infiltration rates, respectively (Soil Survey Staff, 2020). Precipitation levels are also quite high, regularly exceeding 60 in. per year in the Baton Rouge region (Gulf Engineers and Consultants Inc., 2015). In addition to these intrinsic characteristics, the Amite River system is also hydrologically connected to coastal processes; the lowland areas between Lake Maurepas and Baton Rouge are at additional risk of flooding from major storm surge events pushing through Lake Maurepas (Bilskie & Hagen, 2018). The flat
topography, low elevation, high precipitation, poorly drained soils, and proximity to coastal processes lend themselves to a naturally high flood hazard in the Basin.

Within the project area, about 688,066 people reside in these three parishes. Of those people, 286,584 (42 percent) belong to a minority group (Lotfata & Ambinakudige, 2019). Major rivers delineate the parishes, making them flood prone. Approximately 46 percent of East Baton Rouge has a flooding potential by a 1 percent annual chance (Flood Zone A). Most of the remaining land in East Baton Rouge Parish is in an area that has a 0.2 percent chance of annual flooding, which is known as an X zone (FEMA 2016). Many locations in the Ascension and Livingston parishes are in areas with a 1 percent annual chance of flooding (FEMA 2016). Livingston Parish and the eastern part of Ascension Parish has a history of extensive Flooding. The low topographic relief of these parishes is the major cause of flooding. The City of Gonzales, in Ascension Parish, has seen major flooding in 1926, 1961, 1966, 1977, 1983, 1989, 1991, 1995, 2001, and 2016 (Ascension Parish, Louisiana 2017).

In August 2016, a heavy rainfall in the Mississippi River Basin caused flooding in the Louisiana parishes of East Baton Rouge, Ascension, and Livingston (FEMA 2016). Together, historical rainfall, rising river levels in the Comite and Amite rivers, and low topographic relief caused the flooding (FEMA 2016). On August 14, 2016, the Comite River reached almost 34 feet at Comite (flood stage is 20 feet), while the Amite River reached 45 feet Louisiana Flooding and People’s Vulnerability 135 near Denham Springs (flood stage is 29 feet) and nearly 9 feet above flood stage near the French Settlement (flood stage is 4 feet). The flooding event caused an estimated $8.7 billion dollars of damage for the three parishes to project area infrastructure.
3.2. Methodology

The relationship between flood-risk and hazard are directly related while the relationship between flood-risk and adaptive capacity is inversely related (UNISDR, 2004; Wang et al., 2018; Wisner, Blaikie, Cannon, & Davis, 2004). In the field of DDR, the most applied disaster-risk formula can be seen below in equation 1.

\[
\text{Flood-Risk} = f(\text{Hazard, Vulnerability})
\]

Equation 1

Additionally, the CCA approach defines vulnerability as a function of both positively related susceptibility, exposure, and negatively related adaptive capacity. Those two approaches can be combined to provide a more comprehensive measure of flood-risk (Wisner et al., 2004; UNISDR, 2009; Wang et al., 2020). Furthermore, components of vulnerability will be sequentially computed throughout phases of the disaster risk cycle: event and recovery, similar to work done by Chen (2019), who developed a time-varying Flood Resilience Index, which was used to quantify resilience levels of households in Maxvorstadt. This can be seen in Error! Reference source not found..
The key takeaway was that the flood resilience consists of two sequential phases, the event phase and the recovery phase. The event phase uses physical indicators from flood modeling. Once the flooding has completely resided ($t = t^*$, where $t^*$ is the time flooding has completely resided), then it is assumed that the recovery phase has begun. Aside from the physical indicators, social and economic indicators are considered to evaluate the recovery capacity.

Several studies have stated that vulnerability and resilience are inversely related. This option of resilience as the opposite of vulnerability is found both in the disaster risk reduction and climate change scientific literature (León, 2006; Cannon, 2008). Therefore, the graph, from Chen (2019), will be inverted; but will not start at 0, rather the initial starting point will be the value of FSI. It should be noted that this will result in flood vulnerability having three phases, which corresponds to the following literature source: Sharma & Ravindranath, 2019. Additionally, the components of vulnerability will correspond to one of the first three phases of the disaster cycle, which are
preparedness, response, and recovery phases, respectively. A modified version of Chen (2019)’s graph is shown in Figure 4.

The components of vulnerability being computed during each phase of the disaster risk cycle are susceptibility assessment during the preparedness phase \( (FVI_{PF}; \text{equation 2a}) \); exposure assessment during the response phase \( (FVI_{DI}; \text{equation 2b}) \); and adaptive capacity assessment during the recovery phase \( (FVI_{DR}; \text{equation 2c}) \).

Pre-Flood (Preparedness) Phase Flood Vulnerability Index Formula:

\[
FVI_{PF} = FSI_{PF}(0-1) \quad \text{(Equation 2a)}
\]

During-Impact (Response) Phase Flood Vulnerability Index Formula:

\[
FVI_{DI} = \frac{FSI_{PF}(0-1) + FEI_{DI}(0-1)}{2} \quad \text{(Equation 2b)}
\]

During-Recovery (Recovery) Phase Flood Vulnerability Index Formula:

\[
FVI_{DR} = \frac{FSI_{PF}(0-1) + FEI_{DI}(0-1) - FACI_{DR}(0-1)}{3} \quad \text{(Equation 2c)}
\]

Where:
3.3. Pre-Flood: FVI_{PF}

This section will cover the methodology taken to produce the pre-flood vulnerability index (FVI_{PF}) along with its respective indicators (FSI_{se} and FSI_{en,p}) and components. The indicators will have social, economic, physical, and environmental dimensions and will be computed during this “Pre-Flood” phase of the disaster risk cycle, which will consist of the following: Flood Susceptibility Indicator for social and economic components (FSI_{se}) and the Flood Susceptibility Indicator for the environmental and physical components (FSI_{en,p}). The method applied for computing and mapping FSI_{se} are based on the Inland from the Coast (IFC)’s method for producing their Human wellbeing sub-indicator data, the Community and Economic Stress indicator (Cutter et., 2003). On the other hand, the method proposed for computing FSI_{en,p} is based on the “FIGUSED” methodology, which applies an extensive series of GIS processing steps for incorporating quantitative and qualitative data (Kazakis, et al., 2015). It should be noted that this study focuses on flood hazard assessment that can support decision-makers to apply appropriate mitigation measures. The reason why this assessment was also integrated into the flood susceptibility indicator (FSI_{PF}) and not the flood exposure indicator (FEI_{DI}) was because the methodology did not include a flood inundation thematic map.
In this thesis work, FSI_{PF}, i.e., the pre-flood FVI_{PF}, was computed using a simple arithmetic average of FSI_{se} and FSI_{en,p}. An example of this was performed in the research conducted by Rana & Routray, 2018. The overall framework for developing FVI_{PF} and FSI_{PF} can be seen in Figure 5.
Figure 5. Conceptual diagram for developing the Pre-flood Vulnerability Index (FVI PF)
3.3.1 Physical and Environmental Flood Susceptibility Indicator (FSI\textsubscript{en,p}): 

Kazakis, et al., 2015 developed an index model, built within a GIS environment, aimed at defining flood hazard areas with a regional focus. The model utilized a multi-criteria analysis to develop what they referred to as a Flood Hazard Index (FHI). In this research, FHI is denoted as FSI\textsubscript{en,p} and aims to assist the identification of flood-hazard hotspots related to flood risk and allow a comparative analysis between different basins.

FSI\textsubscript{en,p} adopts a methodology called “FIGUSED” that is comprised of seven criteria parameters: flow accumulation (F), rainfall intensity (I), geology (G), land use (U), slope (S), elevation (E) and distance from the drainage network (D) (Figure 6).

The proposed method for computing FSI\textsubscript{en,p} was a weighted linear equation.

\[
FSI_{en,p} = \sum_{i=1}^{n} r_i \ast w_i
\]

\[
FSI_{en,p} = F \ast w_F + I \ast w_I + G \ast w_G + U \ast w_U + S \ast w_S + E \ast w_E + D \ast w_D
\]  
(Equation 3)

Figure 6. F.I.G.U.S.E.D Methodology (Kazakis, et., 2015)
The variables within Equation 3 consist of the following: \( r_i \) = rating for parameter “i”; \( w_i \) = weighting for parameter “i”; \( F \) = flow accumulation; \( I \) = rainfall intensity; \( G \) = geology; \( U \) = land use; \( S \) = slope; \( E \) = elevation; and \( D \) = distance from the drainage network. The next two sections will discuss the rating and weighting scheme, respectively. The next two sections pertain to the weighting and rating of the thematic variables mentioned above.

Variable Weighting:

Over the past years, many pieces of the literature have utilized extensive amounts of statistical and machine learning (Hadipour, Vafaie & Deilami, 2020) for compiling and weighting variables into indicators/indices. The most used methods are frequency ratio (Rahmati, Pourghasemi & Zeinivand, 2015), analytical hierarchy process (AHP) (Kazakis, et., 2015), weight of evidence (Tehrany, Pradhan & Jebur, 2014), logistic regression (Youssef, Pradhan & Sefry, 2015), multiple criteria decision (Wang, Hong, Chen, et al., 2018), fuzzy weight of evidence (Hong, Tsangaratos, Ilia, et al., 2018), support vector machine (Tehrany, Pradhan, Mansor & Ahmad, 2015), decision tree (Khosravi, Pham, Chapi, et al., 2018), random forest (Chen, Li, Xue, Shahabi, et al., 2020) and ensemble models (Costache, Hong, Pham, 2020).

Unlike quantitative methods, semiquantitative methods combine indicators in a simplified way to build a flood hazard index (Kazakis, et., 2015). To implement semiquantitative methods, spatial multi-criteria decision analysis (SMCDA), generally based on the AHP can be employed (Kazakis, et., 2015). It can be easily linked to Geographic Information System (GIS) for further geospatial analysis. Therefore, AHP was utilized in this thesis.

The weight of each parameter is defined following the Analytical Hierarchy Process (AHP) (Saaty, 1990a, Saaty, 1990b). AHP is a structured technique used for analyzing complex problems,
where many interrelated objectives or criteria are involved. Thematic variable weights are a function of their resulting rank, which was a measure of their relative importance to flooding. Accordingly, once all criteria are sorted in a hierarchical manner, a pairwise-comparison matrix for each criterion is created to enable a significance comparison. The relative significance between the criteria is evaluated from 1 to 9 indicating less important to much more important criteria, respectively. The selected procedure suggests a pairwise comparison, using a $6 \times 6$ matrix, where diagonal elements are equal to 1 – this can be seen in Table 1. B below. The values of each row characterize the importance between two parameters. The “rank” column in Table 1b illustrates the importance of flow accumulation regarding the other parameters which are placed in the columns. For example, flow accumulation is significantly more important from geology and therefore assigned the value 6. Row describes the importance of geology. Therefore, the row has the inverse values of the pairwise comparison (e.g., 1/6 for flow accumulation). Once the pairwise comparison was completed, these pairwise-values were then normalized by dividing each pairwise value by their “column” sum. Then, these normalized values were row-averaged, which results for each thematic variable weight. These criteria which can be seen in Table 1a.

Table 1a-1b. Analytical Hierarchy Process (AHP): a.) Selected ranking and weights of thematic variables and b.) piecewise comparison matrix of relative importance of thematic variables (Goepel, 2018)
Flow accumulation has been considered the most important parameter in alignment with relevant studies. Distance from drainage network and elevation are assigned an equal importance since flooded areas are often located in low elevation and near the drainage network. Land use and rainfall intensity were considered as the third more important parameters, although in other studies these parameters have been prioritized (Liu et al., 2003, Kourgialas & Karatzas, 2011). Since this research also examines smaller basins containing urban areas, land cover has a higher influence in flood occurrence compared to large forest or agricultural areas. The terrain slope is somehow considered in the elevation parameter, explaining its lower importance. Geology and permeability can be of critical importance for the runoff and the occurrence of flood, especially in smaller basins with sparse vegetation (e.g. due to deforestation). Since this is not the case of the studied area, geology has been assigned a lower weight.

Variable Ratings:

To obtain each parameter’s rating, a spatial analysis of studied areas evaluates each grid-cell on every parameter raster dataset. Each raster possesses unique numbers of columns and rows, which are spatially analyzed. Then, according to the local conditions, each grid-cell is assigned values in a scale between 2 and 10 (rating score). All the thematic variables mentioned above were reclassified into defined data-break intervals using the grading method of natural breaks which has been used in similar studies (Kazakis, et al., 2015). The natural breaks method is a classification method designed to optimize the arrangement of a set of values into “natural” classes. This classification method seeks to minimize the average deviation from the class mean while maximizing the deviation from the means of the other groups. The method reduces the variance within classes and maximizes the variance between classes (Jenks, 1967). It should be noted that the slope and distance from the drainage network classifications should have been defined by
processing records of historical floods in the study area; however, this paper classified them using the Natural Breaks (Jenks) scheme as well. The qualitative parameters of land use and geological formation were classified similarly to previous studies with modifications accordingly the characteristics of the study site. The acquired values are processed to calculate the relative significance of each criterion and the corresponding weighting factor (w).

I. Process for the Elevation Thematic Variable Map:

A project’s topography plays an important role in a region’s susceptibility to a flood hazard. Areas in low elevations and in flat areas (Tehrany et al., 2017) are particularly prone to flooding hazards. Detailed flash flood hazard mapping production requires low resolution (i.e., 10 ft) DEM that provides detailed description of elevation changes (UNSPIDER, 2020). In general, it can be said that Elevation is inversely proportional to flooding (Kwak & Kondoh, 2008.)

The elevation map requires data from Dewberry, L.L.C., which would be topographic data consisting of the project area, in this case the Amite River Basin. The next step is inserting the 10 feet Amite River Basin DEM (raster) into Arc-GIS. The next step is applying the spatial analyst tool called “Fill”, from the ArcGIS toolbox, on the imported file. The tool essentially locates, and fills sinks and peaks in an elevation surface raster to remove small imperfections in the data. The function will fill in an iterative process until all sinks are filled within the specified Z Limit (https://www.un-spider.org/advisory-support/recommended-practices/recommended-practice-flood-hazard-mapping/step-by-step). Since the true project area is smaller than the Amite River Basin, the spatial analyst tool, “Clip (data-management),” was used to make the Elevation map the same extent as the available data extent of the FSIse map. To properly display the within the symbology tab, select “Quantities” and make the value field “Elevation.” Additionally, the
variables should be classified into 5 classes with the re-classification method being “Natural Breaks (Jenks).” The results of this can be seen in Figure 7. This elevation map has units of feet.

Once this map has been exported into a working folder, the map’s data ranges will then be reclassified into rating values ranging from 2 to 10 in intervals of 2. Here are the descriptions for each of the ratings: 2 relates to very low susceptibility—highest-elevation range; 4 relates to low susceptibility; 6 relates to medium susceptibility; 6; 8 relates to high susceptibility; and 10 relates to very high susceptibility—lowest-elevation range. Finally, using ArcGIS’s raster calculator tool, multiply the “Fill” elevation by its corresponding weight.
II. Process for the Slope Thematic Variable Map

Slope was produced using the “Slope (Analyst) Tool” provided by ArcGIS. The only required input is the (filled) elevation raster dataset. Slope is another factor that serves as a strong benchmark to indicate flood susceptibility within flat areas along with areas with low elevation. The danger of flooding increases as the surface slope decreases. This is because smaller sloped areas produce smaller flow velocities, resulting in ponding of water in areas of low elevation. On the other hand, higher sloped areas can push water downwards which will prevent ponding from occurring. Therefore, the relationship between slope and flood susceptibility are inversely related.

The next thematic variable map to be created is the slope thematic variable map. This map is developed by using ArcGIS’ “slope (spatial analyst)” tool. The tool had the following settings, which needed to be selected: The input raster was the elevation map produced after the “clip” and “fill” ArcGIS tools; the output measurement was “Percent RISE”; and the method for computing “relative to a datum” was the “PLANAR.” After the slope thematic map has been produced, go within the symbology tab and then select “Quantities” for value type and “Slope (%)” for value field. As mentioned before, the classification method was “Natural Breaks (Jenks)” and there are 5 classes. The figure of this can be seen in Figure 8. It should be noted that the slope map has units of percent. Once this map has been exported into a working folder, the map’s data ranges will then be reclassified into rating values ranging from 2 to 10, in intervals of 2 rating points. Here are the descriptions for each of the ratings: 2 relates to very low susceptibility—highest-slope range; 4 relates to low susceptibility; 6 relates to medium susceptibility; 8 relates to high susceptibility; and 10 relates to very high susceptibility—lowest-slope range. Finally, using ArcGIS’s raster calculator tool, multiply the “Fill” elevation by its corresponding weight.
III. Process for the Geology Thematic Variable Map

The geology thematic map will serve basically as an extension to the LULC thematic variable map, which represents surface runoff (or infiltration), by serving as the sub-surface permeability rates ($K_{sat}$), which was produced from USGS’s web-soil survey guided user interface. $K_{sat}$ refers to the ease with which pores in a saturated soil transmit water and indicate the soil’s infiltration capacity. $K_{sat}$ will have units of micrometers per second. It should be noted that higher $K_{sat}$ values will correspond to lower levels of susceptibility while lower $K_{sat}$ values will correspond to higher levels of susceptibility.
The geology thematic variable will require subsurface soil permeability data, which can be found on the United States Geologic Survey (USGS) website in the web soil survey section (https://websoilsurvey.nrcs.usda.gov/app/). This geologic-data collection process will be completed for the following parishes: East Baton Rouge, Ascension, and Livingston. The first step is to obtain shapefile data, which will serve as a shell for the geologic data of interest. This shapefile data can be downloaded from “Download Soils Data” tab. The next thing that is required is generating soil-property tables pertaining to sub-surface saturated permeability rates (Ksat), which are then copied and pasted into an excel file (3 excel files were created). This can be done by clicking on the “Soil Properties and Qualities” tab and then the “Soil Physical Properties” sub-tab. Before generating the Ksat tables, it is important to refer to Ksat’s description, which states the following: “For each soil layer, Ksat is recorded as three separate values in the database: a low and high value of Ksat and a representative value.” The value of interest is the representative value; therefore, certain advanced settings were applied. Due to the geologic requirements pertaining to this thesis, the following advanced settings needed to be adjusted: Aggregation Method, Tie-Break Rule, Interpret Nulls and zero, and Layer Options. Since soil layers are not homogeneous and consist of multiple soil types, aggregation methods help simplify the soil properties of that layer into one representative value. The aggregation method chosen was the weighted average method, which determine how much weights to apply to each soil type based on each soil types of volumetric contribution to the soil layer. The next setting is the Tie-Break Rule—it indicates which values should be selected from a set of multiple candidate values, or which value should be selected in the event of a percent composition tie. The selected option was slowest, to produce “conservative” results. The Interpret Nulls as zero setting was set to yes (to prevent holes within the data map). Regarding the Layer Options (Horizontal Aggregation Method), all the sub-surface
layers were considered since sub-surface permeability is of interest—the values for all these layers were combined using a weighted averaging scheme. Then, a table is generated, which was copied and pasted into an excel sheet.

After collecting all the necessary data (i.e., shapefiles and excel sheets for each of the parishes), the next thing is to insert the shapefiles and excel files into ArcGIS. For each parish, right click on its respective shapefile and select the “join” function. Within the join function, select the “tabular join” setting and add the respective parish excel file containing sub-surface permeabilities and surface hydrologic soil codes. The join was completed using identical columns within the shapefile and excel file. After that process is completed for each parish, then all these joined parish shapefiles were merged into one joined shapefile using the “Merge” tool within ArcGIS. The Merge Tool combines data from multiple sources, then adds them into a new data set. This tool is not only merging the shapefile geometries, but it also merging each shapefiles attributes with the option to match fields from input datasets. When you use the Merge Tool, features must be the same geometry type (points, lines, or polygons). Once the consolidated, joined shapefile has been created, it must be clipped into using FSI_{se} extent boundary (note: use clip (analysis) and not clip (data management) since the shapefile to be clipped is a polygon and not a raster). Within the symbology tab, select “Quantities” and make the value field “Saturated Permeability (Ksat).” This can be seen in Figure 9 below. The classification scheme is “Natural Breaks” and will consist of five classes. The units of the geology parameter (Ksat) are micrometers per second. Polygon to Raster. Regarding the tool’s settings, select Ksat for the value field. Then, reclassify the ranges of values using rating values ranging from 2 to 10 on 2-interger intervals. Here are the descriptions for each of the ratings: 2 relates to very low susceptibility—highest-slope range; 4 relates to low susceptibility; 6 relates to medium susceptibility; 8 relates to high
susceptibility; and 10 relates to very high susceptibility—lowest-slope range. Finally, using ArcGIS’s raster calculator tool, multiply the classified geology map by its corresponding weight.

IV. **Process for the LULC Thematic Variable Map**

Land use affects the level of surface infiltration and alternatively, the amount of runoff. Forests and dense vegetation support infiltration and interception by canopy, while urban and grassland settlements support surface runoff. The original classifications came from the National Land Cover Database (NLCD) website (Homer, Dewitz, Jin, Suming, Xian, George, Costello, Danielson, Patrick, Funk, Wickham, Stehman, Auch, Roger, Riitters, 2016), which were then reclassified based on the United Nations Office for Outer Space Affairs (UN-SPIDER, 2020). The reclassified
land covers consisted of the following: bodies of water, high-medium development, low-medium development, agriculture (shrubs, prairies, farmland, etc.), and forest/woodlands. These new classifications were then linked to a hydrologic soil code (A, B, C, D, A/D, B/D, or C/D), which were then used to produce curve numbers (CN) based of the Department of Transportation and Development (DOTD)’s Hydraulic Manual (Table 5). The larger the CN value, the larger the runoff and potential for the area to flood (and vice-a-versa). In general, bodies of water received highest CN values and forest/woodlands received the smallest CN values.

The data/tables required for LULC Data consisted of NLCD’s LULC descriptions and USGS web-soil survey’s “hydrologic soil code” parameter. The NLCD data can be collected from the Multi-Resolution Land Characteristics Consortium website (Homer et. al., 2016). After clicking the URL, download the 2016 CONUS LULC Data, which should download a folder called: NLCD_2016_Land_Cover_L48_20190424.zip. Unzip the folder and obtain the following file: NLCD_2016_Land_Cover_L48_20190424.img this is a raster file. Regarding the hydrologic soil code parameters, this was obtained in a similar fashion to Geology’s Ksat parameter above. The aggregation method was the “dominant condition,” which basically provides the hydrologic soil code relevant to the most significant soil type within a layer. The layer options were set to surface layer only since the surface infiltration is desired. Then, a table is generated, and this is copied and pasted into the same excel spreadsheet created for the “Ksat” parameter mentioned within the Geology section (IV. Geology Thematic Variable Map).

The LULC thematic variable map will utilize the data collected in Step II, which consisted of the NLCD Continental United States (CONUS) 2016 Land Cover data and the USGS’s Hydrologic Soil Code data (joined to the geologic thematic variable map in the previous step). The NLCD data will be imported into the pre-existing ArcGIS file containing the geology map data. After the
NLCD data has been imported, it is worth observing the files properties. After looking at Figure 10, the file is an IMAGINE Image raster set.

![Figure 10. Dialog box for clip (data-management) tool.](image)

Therefore, the only clipping tool that will work on this file type is the clip (data management) tool. Due to the importance of clipping this data correctly, a screenshot of the tool settings, seen in Figure 11, was included.

![Figure 11. NLCD Image Raster File](image)
It is very important that “Use Input Features for Clipping Geometry” and “Maintain Clipping Extent” are checked on. The first setting makes the extent of LULC match the extent of the geology thematic map. And the other setting, Maintain Clipping Extent, makes the number of rows and columns and cell size of LULC equivalent to the geology map. This is a crucial setting because the cells size and distribution of each set need to be the same to properly unionize LULC’s revised classifications with Geology’s Hydrologic soil codes. Lastly, it’s important to understand that the clipping procedure was done prior to the reclassification process because certain LULC labels pertain to CONUS and thus, a lot of the labels will not be found within the extent of the project area.

Within the symbology tab, select “unique” values and make the value field “NLCD_Land.” After that step is completed, the legend for this LULC image raster should look identical to the legend seen in Figure 12 located on the top of the next page.

![Figure 12. National Land Cover Database (NLCD) LULC Classifications](image)
To properly re-classify this dataset, it is important to understand how each of the initial land cover types were classified and defined. The definitions of each of the NLCD land cover labels can be seen in Table 2 below.

Table 2. National Land Cover Database (NLCD) Classification Class/Value and Definitions

<table>
<thead>
<tr>
<th>Class\Value</th>
<th>Classification Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td></td>
</tr>
<tr>
<td>11<strong>Open Water</strong></td>
<td>areas of open water, generally with less than 25% cover of vegetation or soil.</td>
</tr>
<tr>
<td>12<strong>Perennial Ice/Snow</strong></td>
<td>areas characterized by a perennial cover of ice and/or snow, generally greater than 25% of total cover.</td>
</tr>
<tr>
<td>Developed</td>
<td></td>
</tr>
<tr>
<td>21<strong>Developed, Open Space</strong></td>
<td>areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.</td>
</tr>
<tr>
<td>22<strong>Developed, Low Intensity</strong></td>
<td>areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.</td>
</tr>
<tr>
<td>23<strong>Developed, Medium Intensity</strong></td>
<td>areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.</td>
</tr>
<tr>
<td>24<strong>Developed High Intensity</strong></td>
<td>highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.</td>
</tr>
</tbody>
</table>

(table cont’d.)
Barren

| 31 Barren Land (Rock/Sand/Clay) | areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover. |

Forest

| 41 Deciduous Forest | areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change. |
| 42 Evergreen Forest | areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage. |
| 43 Mixed Forest | areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover. |

Shrubland

| 51 Dwarf Scrub | Alaska only areas dominated by shrubs less than 20 centimeters tall with shrub canopy typically greater than 20% of total vegetation. This type is often co-associated with grasses, sedges, herbs, and non-vascular vegetation. |
| 52 Shrub/Scrub | areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions. |

Herbaceous

| 71 Grassland/Herbaceous | areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling but can be utilized for grazing. |

(table cont’d.)
Table 4. National Land Cover Database (NLCD) Classification Class/Value and Definitions

<table>
<thead>
<tr>
<th>Class/Value</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>72 Sedge/Herbaceous</td>
<td>Alaska only areas dominated by sedges and forbs, generally greater than 80% of total vegetation. This type can occur with significant other grasses or other grass like plants, and includes sedge tundra, and sedge tussock tundra.</td>
</tr>
<tr>
<td>73 Lichens</td>
<td>Alaska only areas dominated by fruticose or foliose lichens generally greater than 80% of total vegetation.</td>
</tr>
<tr>
<td>74 Moss</td>
<td>Alaska only areas dominated by mosses, generally greater than 80% of total vegetation.</td>
</tr>
<tr>
<td>81 Pasture/Hay</td>
<td>Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation.</td>
</tr>
<tr>
<td>82 Cultivated Crops</td>
<td>Areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled.</td>
</tr>
<tr>
<td>90 Woody Wetlands</td>
<td>Areas where forest or shrubland vegetation accounts for greater than 20% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.</td>
</tr>
<tr>
<td>95 Emergent Herbaceous Wetlands</td>
<td>Areas where perennial herbaceous vegetation accounts for greater than 80% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.</td>
</tr>
</tbody>
</table>

Once the definitions for each label are understood, use ArcGIS’ “reclassify” tool to group NLCD terms based on runoff potential. The results from the reclassification can be seen below in Table 3 below.
Table 5. The Reclassification of NLCD’s Original Classifications.

<table>
<thead>
<tr>
<th>Original NLCD Classification</th>
<th>Revised Classification</th>
<th>Grid Code</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>11 Open Water</td>
<td></td>
<td></td>
<td>5 Water</td>
</tr>
<tr>
<td>90 Woody Wetlands</td>
<td></td>
<td></td>
<td>5 Water</td>
</tr>
<tr>
<td>95 Emergent herbaceous wetlands</td>
<td></td>
<td></td>
<td>5 Water</td>
</tr>
<tr>
<td>21 Developed, open space</td>
<td></td>
<td></td>
<td>4 Low-Medium Residential</td>
</tr>
<tr>
<td>22 Developed, low intensity</td>
<td></td>
<td></td>
<td>4 Low-Medium Residential</td>
</tr>
<tr>
<td>23 Developed, medium intensity</td>
<td></td>
<td></td>
<td>3 Medium to High Residential</td>
</tr>
<tr>
<td>24 Developed, high intensity</td>
<td></td>
<td></td>
<td>3 Medium to High Residential</td>
</tr>
<tr>
<td>41 Deciduous forest</td>
<td></td>
<td></td>
<td>1 Forest</td>
</tr>
<tr>
<td>42 Evergreen forest</td>
<td></td>
<td></td>
<td>1 Forest</td>
</tr>
<tr>
<td>43 Mixed forest</td>
<td></td>
<td></td>
<td>1 Forest</td>
</tr>
<tr>
<td>31 Barren land</td>
<td></td>
<td></td>
<td>2 Agriculture</td>
</tr>
<tr>
<td>52 Shrub/scub</td>
<td></td>
<td></td>
<td>2 Agriculture</td>
</tr>
<tr>
<td>71 Grassland/herbaceous</td>
<td></td>
<td></td>
<td>2 Agriculture</td>
</tr>
<tr>
<td>81 Paster/hay</td>
<td></td>
<td></td>
<td>2 Agriculture</td>
</tr>
<tr>
<td>82 Cultivated Crops</td>
<td></td>
<td></td>
<td>2 Agriculture</td>
</tr>
</tbody>
</table>

Each Revised Classification description, denoted as grid code(s), will be ranked in the following manner: Forest land corresponds to a grid code value of 1; agriculture land covers have a grid code value of 2; low-medium development has a grid code value of 3; medium-high development covers have a grid code value of 4; and water has a grid code value of 5.
To apply the union tool, the two files being unionized need to be polygon shapefiles. The next step pertains is converting the LULC raster into a polygon shapefile using the “raster to polygon” spatial analyst tool. Regarding this tool’s settings, the following need to be used: select “grid code” (not NLCD reclassified labels) as the desired attribute and then select “yes” for the simplify polygons setting. Now, the user can connect the NLCD LULC class “gridcodes” (1, 2, 3, 4, or 5) with the Hydrologic Soil Code (A, B, C, D, A/D, B/D, or C/D) located within the Soil Map Polygon Shapefile. Table 4 below represents definitions for each of the Hydrologic Soil Code values.

<table>
<thead>
<tr>
<th>Hydrologic Soil Group</th>
<th>Soil Group Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Soils having high infiltration rates, even when thoroughly wetted and consisting chiefly of deep, well to excessively-drained sands or gravels. These soils have a high rate of water transmission.</td>
</tr>
<tr>
<td>B</td>
<td>Soils having moderate infiltration rates when thoroughly wetted and consisting chiefly of moderately deep to deep, moderately fine to moderately coarse textures. These soils have a moderate rate of water transmission.</td>
</tr>
<tr>
<td>C</td>
<td>Soils having slow infiltration rates when thoroughly wetted and consisting chiefly of soils with a layer that impedes downward movement of water, or soils with moderately fine to fine texture. These soils have a slow rate of water transmission.</td>
</tr>
<tr>
<td>D</td>
<td>Soils having very slow infiltration rates when thoroughly wetted and consisting chiefly of clay soils with a high swelling potential, soils with a permanent high-water table, soils with a claypan or clay layer at or near the surface, and shallow soils over nearly impervious material. These soils have a very slow rate of water transmission.</td>
</tr>
</tbody>
</table>

This connecting process is performed using ArcGIS tool called “Union.” The Union tool combines input data layers into a single composite layer, preserving the boundaries and attributes from all input features. When features overlap, it creates separate features for them. Essentially, this tool creates a new shapefile that links information from both the LULC (the “gridcode” values) data
and the Geology (Hydrologic Soil Codes) data into one composite shapefile. The last thing required to complete the LULC thematic variable map is figuring out a methodology for producing curve number (CN) values based on combinations of land cover and hydrologic soil codes criteria. The LULC grid code values (2 to 10) and Geology rating values (A to A/D) were the two attribute columns selected and exported as a comma separated values (CSV) file. The csv file was then converted into an excel file. Next thing is obtaining a table that produces CNs as a function of land cover type and hydrologic soil codes. Therefore, Table 5 was obtained from the Louisiana Department of Transportation and Development (DOTD) Hydraulics Manual.

Table 7 Department of Transportation and Development (DOTD)'s Curve Number Table
Within the Excel file, embedded if-loops were constructed to produce hydrologic soil code-based curve numbers, which included the following: CN(A), CN(B), CN(C), CN(D), CN(A/D), CN(B/D), and CN(C/D). The table produced can be seen below in Table 6.
The excel formulas used to compute the CNs seen in Table 6 can be seen in Appendix A. Once the excel sheet is tabulated with composite CN results for each polygon (row), the next step is to join this data back with the composite LULC shapefile, which contains both land cover grid codes and hydrologic soil code attribute columns. This was completed by right-clicking on the composite shapefile and selecting the join function. The type of join will be a tabular join, and the common attribute, used to combine the excel data and composite shapefile, was the grid code attribute. This produces a LULC composite shapefile with the CN attribute, which will be the parameter of interest for this thematic variable map. Within the symbology tab, select “Quantities” and make the value field “CN.” This can be seen in Figure 13. This thematic variable map shapefile consists of five classes, which were separated using a “Natural Breaks (Jenks)” classification scheme. The parameter of interest is CN – its units are “unitless.”

This map was exported within the working folder and then converted to a raster file using the “polygon to raster” tool. Then, the LULC raster was reclassified using the “Reclassify” spatial analyst tool, which converted the ranges of values, into assigned “rating value.” The rating values
range from 2-10 on 2-integer intervals. The ratings were defined as the following: Forest land covers have a rating of 2 (lowest susceptibility, lowest runoff potential); agriculture land covers have a rating of 4 (low susceptibility); low-medium development covers have a rating of 6 (medium susceptibility); medium-high development covers have a rating of 8 (high susceptibility); and water covers have a rating of 10 (highest susceptibility, highest runoff potential). This reclassified map will then be exported as a PDF. The final step pertains to using the raster calculator to multiply the LULC thematic variable map by its respective weight.
V. Flow Accumulation

Flow accumulation is the total accumulated water which is flowing from higher elevated areas to a lower elevated area. The flow accumulation thematic map is produced by using the flow accumulation tool, located within the spatial analyst section of ArcGIS, which produces a raster of accumulated flow to each cell, as determined by accumulating the weight for all cells that flow into each downslope cell. The tool supports three flow-modeling algorithms while computing accumulated flow: D8, Multiple Flow Direction (MFD), and D-Infinity (DINF) flow methods (ArcGIS, 2021). High values for accumulated flow indicate areas where water flows concentrate and have consequences as flood areas.

Producing the flow accumulation thematic variable map requires a series of ArcGIS tools located within the ArcHydro toolbox. The first thing that is required is the “fill, clipped” elevation map created for the elevation thematic variable map. Next, apply the “flow direction” tool, which is an essential tool for deriving the hydrologic characteristics of an elevation surface. This tool takes a surface (i.e., elevation map) as the input and outputs a raster showing the direction of flow out of each cell. The next step is to use the flow accumulation tool, which requires the following inputs: elevation raster and flow-direction raster. The result of Flow Accumulation is a raster of accumulated flow to each cell, as determined by accumulating the weight for all cells that flow into each downslope cell. There was clipping required for this raster because the input raster files were already clipped to the project extent.

Within the symbology tab, select “unique” values and make the value field “Value.” Next, make sure there are nine classes, instead of five, and make the classification scheme “Natural Breaks (Jenks).” The resulting map can be seen in seen in Figure 14.
The parameter of interest is Flow Accumulation, which has units of “flow-cells.” Lastly, it should be noted that nine classes were used because this was the only way to see the color gradient within the Amite and Comite rivers. Whenever there were only five classes, the color of those rivers was
all red and thus failing to show the increase in flow accumulation as you go downstream. This map will be exported into a working folder.

The Flow Accumulation map was reclassified using the “Reclassify” spatial analyst tool, which converted the ranges of values into assigned “rating value”. The rating values range from 2-10 on 1-integer intervals. The ratings were defined as the following: dark green denotes a rating of 2 (very low susceptibility, lowest flow accumulation); lighter shade of dark green denotes a rating of 3 (very low to low susceptibility); an even lighter shade of green denotes a rating of 4 (low susceptibility); the lightest shade of green denotes a rating of 5 (low to medium susceptibility); yellow denotes a rating of 6 (medium susceptibility); lightest shade of orange denotes a rating of 7 (medium to high susceptibility); a slight darker shade of orange denotes a rating of 8 (high susceptibility); the darkest shade of orange denotes a rating of 9 (high to very high susceptibility); and finally, red denotes a rating of 10 (very high susceptibility). This reclassified map will then be exported as a PDF. The final step pertains to using the raster calculator to multiply the LULC thematic variable map by its respective weight.

**VI. Process for the Flow Distance Thematic Variable Map**

Separate from the concentrated area of surface water (quantified by the flow accumulation thematic map), river overflow (i.e, distance from river network) is crucial for accessing a community’s flood susceptibility. In most fluvial flooding scenarios, the origin of flooding occurs near the river and spreads in the transverse directions. The impact of the river for flooding decreases with increasing distance from the river. This thematic variable was derived using the Euclidean distance tool within ArcGIS analyst toolbox. This toolbox requires a stream network raster and study-based class divisions, also known as, buffer zones. The stream network raster was produced using the stream definition tool, from ArcGIS toolbox, with the input raster being flow
accumulation. The buffer zones criteria were all a function of the default GIS settings besides the maximum buffer zone criteria being limited to the project extent. Class divisions (minimal and maximum buffer zones) for this criterion should be based on previous literature findings pertaining to the study area. Based on Kazakis, et al., 2015, the author proposed areas less than 200 m from the river are high flood areas and the effect will decrease with increasing distance more than 2000 m. For this project, the respective buffer zones were the following: 335 m (1,100 feet) and 1650 m (5,500 ft). These buffers were chosen due to the following constraints: 1.) The buffer zones were developed with respect to the Natural Break (Jenks) classification and 2.) The outer buffer zone was governed by the extent of the project area; basically, any value over 1650 m would extend pass the project extent.

The Flow Distance thematic variable map was derived through extending the series of ArcGIS tools used to compute the flow accumulation thematic variable map. The first step is opening the ArcGIS file containing the final flow accumulation raster. Then, the next step is applying the “Stream Definition” tool, which essentially extracts the river stream from the flow accumulation map. This can be seen in Figure 15.

![Stream Definition](image)

Figure 15. Dialog box for stream definition.
Objective methods for the selection of the stream delineation threshold to derive the highest resolution network consistent with geomorphological river network properties have been developed and implemented in the TauDEM software (http://www.engineering.usu.edu/dtarb/taudem). For this research, the default parameters for number of cells and area were applied. Upon successful completion of the process, the stream grid Str is added to the map. This Str grid contains a value of "1" for all the cells in the input flow accumulation grid (Fac) that have a value greater than the given threshold. All other cells in the Stream Grid contain no data.

The next step is applying the “Euclidean distance” tool, which is typically used for susceptibility map representing the distance from a certain object is needed. A tool that creates sequential buffer zones radiating out from the river stream network. The settings applied for this tool can be seen in Figure 16.

![Euclidean Distance](image)

**Figure 16.** Dialog box for Euclidean Distance tool.

It should be noted that the input barrier, representing the most dangerous zone located right around
the river stream raster, was not filled out due to uncertainties regarding the Amite’s fluvial flood zone characteristics. The maximum distance was selected to be 5500 feet—the reason being that a value any larger would go beyond the extent of the project area. The resulting image can be seen in Figure 17.

This thematic map’s parameter of interest is zonal length, which is measured in feet. Also, the resulting file is an IMAGINE image raster. Due to the file type, the data needs to be reclassified before it can be clipped. The flow distance raster was then reclassified using the “Reclassify” spatial analyst tool, which converted the ranges of values, into assigned “rating value.” The rating values range from 2 to 10 on 2-integer intervals and their respective ranges were computed using the “Natural Break (Jenks)” classification scheme. Here are the descriptions for each of the ratings:
2 relates to very low susceptibility—buffer zone closest to the river; 4 relates to low susceptibility; 6 relates to medium susceptibility: 8 relates to high susceptibility; and 10 relates to very high susceptibility—buffer zone farthest from the river and closest to the project area boundary. It should be noted that the process of reclassifying the image raster resulted in the file changing to a normal, generic raster type. Therefore, the reclassified river distance raster map was clipped using the clip (data management) tool. This map was then exported as an PDF to the working folder. Then, using the raster calculator, multiply the Flow Distance thematic variable map by its respective weight. Finally, produce a map and export it as a PDF.

VII. Process for creating FSI\textsubscript{en,p}

Once the equation three has been applied, the resultant FSI\textsubscript{en,p} map can be seen in Figure 18 below. The final step that needs to be performed is rescaling the FSI\textsubscript{en,p} map from 0-1 using the “positive” max-min approach. This can be seen in the results section.

Figure 18. FSI\textsubscript{en,p} computed using weighted linear combination equation.
3.3.2 The Social and Economic Flood Susceptibility Index (FSI\textsubscript{s,e}):  

The Flood Susceptibility Indicator (FSI) will be a “pre-flood” characteristic of vulnerability; additionally, FSI is assumed to stay constant with time. FSI will have social and economic dimensions. The source of the data used to create FSI (and FACI as well) will come from Well-being data developed by Dr. Traci Birch, and then adjusted by Dr. Aimee Moles from Inland from the Coast (IFC). Dr. Birch developed the Well-being indices by collecting variables, from the 2015 Census (hence why this data serves a perfect “pre-flood” indicator for vulnerability (Moles et al., 2020). However, after testing for multicollinearity among the variables, only a subset of the original variables were derived (Cutter et al., 2003). The variables derived consisted of the following: Kitchen; Vacancy; Plumbing; Medical; NFIP; Shelters; Miles; Violent; Non Violent Crimes; Death Rate; Emergency Medical Service (EMS) Employees; Forested Area; Wetland Area; Land Change (Normalized); Cultivated Area; Park Area; Tree; Flood Plain; Single Home; Cycling; Sidewalks; Occupants; Developed Area; Impervious Area; Employment; Per-Capita Income; Banks; Payday; NFIP; Professional; Less Than 30% Spending on Housing; Homeowner; Population without Disability; Population Not A Minority; Population With High school Diploma; People Under 65; Childcare; College To High school Ratio; Worship; Library; Advocacy; Vehicle; Occupants; Telephone; Minor; and English. After all the computations and normalization of data (to percentages, per capita, or density functions), a smaller subset of (independent) data were used in statistical analysis. The resulting variables and components can be seen in the Appendix B (Table B-1).

Dr. Aimee Moles then applied primary statistical measures (factor analysis and principal component analysis) to help decrease the data to a usable and reliable format. There were steps taken in refining the data. The first step was running the entire data set in Stata, or any other
statistical software programs, using factor analysis function for Kaiser-Meyer-Olkin (KMO) and Bartletts tests to determine whether the dataset was big enough related to the index categories and to look for redundancy of variables. The next step is to run an exploratory factor analysis to observe factor loadings to keep variables that add to the explanatory power and drop those which do not. After dropping variables that did not contribute, run principal component analysis to see what Stata would come up with for the best combinations of variables, within each indicator, to increase reliability—within the boundaries of theory. Variables that load as only moderately valuable statistically but are very important theoretically were retained. One should observe the new components and recombine categories using this as a suggestion of what to try. Then run Cronbach’s Alpha on these new combinations. After applying these steps, the new Well-being indicators became Public Health; Environment (combo of natural and built); and Community Stress (combination of economic and community stress). It should be noted that the component pertaining to FSI_{s,e} is the community and economic stress indicator. These categories, along with which variables were included or dropped, can be seen in Table 8 below.

Table 9. List of components and variables corresponding to FSI_{s,e}.

<table>
<thead>
<tr>
<th>Vulnerability Component</th>
<th>Component</th>
<th>Variable</th>
<th>Description</th>
<th>Correlation to Susceptibility</th>
<th>Justification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social and Economic Flood Susceptibility Indicator (FSI_{s,e})</td>
<td>Social Component (FSI_{s})</td>
<td>Pct Under 65</td>
<td>% Of Population Under 65</td>
<td>Negative</td>
<td>Cutter et al., 2010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not Minority</td>
<td>Population that is not a minority</td>
<td>Negative</td>
<td>Tobin, 1999</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Telephone</td>
<td>% Population with telephone access</td>
<td>Negative</td>
<td>Cutter et al., 2010</td>
</tr>
</tbody>
</table>
Social Variable Justifications: (Moles et al., 2020)

Percent Under 65: (Cutter et al., 2010)

There are higher concentrations of older populations located within hazardous coastal environments. This increase in older populations represents emerging public health and emergency management challenges for high-risk coastal locations. These emerging management challenges are because of the older population’s heightened physical and psychosocial vulnerabilities to natural hazards, disasters, and weather extremes. Additionally, the older population’s vulnerability increases from their limited mobility, need for better healthcare, and, most importantly, significantly higher mortality rates during disasters.

Not Minority: (Tobin & Chen, 1999)

Racial and ethnic minorities are also more susceptible to hazards because they are more likely to live in poverty (Peacock et al., 2008). For example, in the US, 21.8 percent of the minority African
American community are below the 100 percent poverty threshold. Only 11.2 percent of the majority White population are below the 100 percent poverty threshold (US Census Bureau 2017). Furthermore, racial minorities are often geographically segregated from the majority race (Lichter et al. 2010, Ambinakudige et al., 2017), making them more vulnerable during a hazardous event.

*Telephone:* (Cutter et al., 2010)

Access to telephones is vital in the face of flood disasters. Studies have shown that having access to a social network reduces community susceptibility by keeping them informed about potential disasters along with evacuation plans. Networks were widely found to be key information sources for warnings and evacuation and communication from mass media and official sources. Therefore, people who have access to telephones are less susceptible to flooding as opposed to people who don’t have access to telephones.

**Economic Variable Justifications:**

*Principal Arterial Miles:* (Cutter et al., 2010)

Principal arterials are an integral part of transportation systems worldwide due to their ability to carry large traffic volumes. As a result, community exposure to them is abundant, especially in urban areas. In addition, arterial roads govern commercial and cultural resources; therefore, arterial roads positively influence community health and reduce community susceptibility. Reducing community susceptibility is accomplished through supporting social cohesion, economic opportunities, and cultural opportunities.

*Vehicles:* (Cutter et al., 2010)

Rates of automobile ownership are generally lower in urban areas, especially among inner-city poor populations (Pucher & Renne, 2004). Thus, transportation out of an evacuation zone is problematic for people who do not have access to a vehicle (Morrow, 1997). In addition, fuel costs
may prevent vehicle use (Brodie et al., 2006). Paradoxically, lower urban auto-ownership rates do not necessarily translate into easy evacuation for people with vehicles because the high-population densities of cities can cause severe traffic congestion on interstate highways and other major roads.

*Spend Who Spend Less than 30% of Income on Housing:* (Cox et al., 2010)

People who spend less than 30% of their income on housing are less susceptible to a flood hazard as opposed to people who spend more than 30% of their income. This is because people who spend less of their income on housing will have more available income for preparing for the storm along with recovering from any damages suffered during the storm, which reduces that person’s economic stress before a storm and vice-a-versa for people who spend more of their income on housing.

*Homeowners:* (Cutter et al., 2010)

The Homeowners variable is an interesting topic—the reason being that it can fall under both the social and economic component of susceptibility. The theory of owning a home provides the following insights: owning a home will decrease your social susceptibility because it will protect from impacts of flooding and increase your economic susceptibility because of flood-induced monetary damages. In order to simplify the variable selection process, it is was assumed to fall under the economic susceptibility because people are more worried about their finances as oppose to their life (i.e., only 12 people died in the Amite River Basin while there was over 7 billion dollars’ worth of economic damages).

**Excel and ArcGIS Steps for FSI, and FSI_e:**

Now that the variables and components listed in Table 2 have been defined, it is time to look into the process of computing FSI,e. As mentioned above, the “raw” variable data was already collected by IFC on the census tract-level. The first important data file collected was the Composite Well-
being Indicator (and subcomponent) shapefile. This shapefile was populated with indicators and indices produced before cleaning had occurred. The indicators and indices included the following: composite Well-being Index values (census tract); Community Stress Indicator values (census tract); Economic Stress Indicator values (census tract); Public Health Indicator values (census tract); Built Environment Indicator Values (census tract); and Natural Environment Indicator Values (census tract). The second important datafile was an excel sheet which consisted of the cleaned Well-being data resulting from the “principal component” analysis. In particular, the excel sheet consisted of raw data, z-scores, indicators, indices pertaining to human Well-being for the years 2015 and 2017.

Now that the data is been collected, it is time to discuss the modifications that need to be applied to the human Well-being data. Looking at the excel data initially, it should be noted that the z-scores computed were performed using a positive max-min equation. The positive max-min equation can be seen below in equation 5.

\[ Z_{\text{pos}} = \frac{x - \min(x)}{\max(x) - \min(x)} \]  
\[ \text{(Equation 5)} \]

However, since human Well-being has an inverse relationship to vulnerability (as mentioned in Table 2), a negative max-min equation needs to be applied to the raw variable data located in the excel file, within the community and economic stress indicator tab. Assuming the raw variable data is the inputted data, then the negative max-min equation required can be seen below in equation 6.

\[ Z_{\text{neg}} = \frac{\max(x) - x}{\max(x) - \min(x)} \]  
\[ \text{(Equation 6)} \]

Assuming the positive z-value variable data is the inputted data, then the negative z-score variable can be determined using Equation 7.
\[ Z_{\text{neg}} = 1 - Z_{\text{pos}} \quad \text{(Equation 7)} \]

The two equations make sense because they produce variables that accurately depict community vulnerability. Lastly, these z-scores, either positive or negative, will have a range between 0 and 1. Once all the community and economic stress variable z-scores for each census tract have been computed, then the next step is to simply compute FSI_s and FSI_e. These to subcomponent maps can be accomplished using a simple averaging equation, which can be seen in Equation 8.

\[ FSI(\text{neg.})_{i,j} = \frac{\sum_{i=1}^{n_p} Z_{\text{neg},i,j}}{n_p} \quad \text{(Equation 8)} \]

Where:
- \( i = \) Subcomponent “i”
- \( j = \) census tract “j” corresponding to subcomponent “i” and FSI_se
- \( n_p = \) total number of community and economic stress variables corresponding to FSI_se
- \( Z_{\text{neg},i,j} = \) The disproportional “z-score” relative to community and economic stress variable “i” for census tract “j”
- \( FSI_{i,j} = \) Subcomponent “i” of FSI_s,e for census tract “j”.

The next step is rescaling both FSI_s and FSI_e using the positive maximum-minimum equation (Equation 5). Then, take an arithmetic average of the rescaled FSI_s and FSI_e subcomponent maps, which can be seen in Equation 9 below.

\[ FSI_{se} = \frac{FSI_s(0 \text{ to } 1) + FSI_e(0 \text{ to } 1)}{2} \quad \text{(Equation 9)} \]

An important note to take is that none of these variables were not weighted due to the concerns of prioritizing certain social or economic aspects over others. Once the excel sheet has been
updated with the new negative z-scores and indicator values, it is time to open the Well-being shapefile data, using ArcGIS 10.8, and then perform a series of steps. The first step consists of adding the wellbeing shapefile into ArcGIS guided user interface. Then right click the data and select the join and relate button, which will then allow the user to “tabularly” combine the excel sheet containing the FSI(neg)se to the shapefile the one containing FSI(pos.)se. Afterwards, it is recommended to delete the attribute field corresponding to FSI(pos.)se to prevent any future confusion. In conclusion, the modified shapefile with the correct variables, z-scores, indicators, and FSIse values are presented. The results of using equation 8 can be seen in Figure 19.

![Figure 19. Subcomponent for FSI_{s,e}: FSI_s and FSI_e](image)

The resultant map for FSI_{s,e}, produced from Equation 9, can be seen in Figure 20. This result for FSI_{s,e} will be rescaled from 0 to 1 using the “positive” max-min equation (Equation 5). The result for this can be seen in the results section.
3.3.3 The “Pre-Flood” Flood Susceptibility Index (FSIPF):

Using the indicator produced in the “during-impact” stage, FEI_DI, and the indicator produced during the “pre-flood” phase, FSI_PF, FVI_DI can be computed using an arithmetic average, which can be seen in Equation 10.

\[
FSI_{PF} = \frac{FSI_{en,p} + FSI_{se}}{2}
\]  
(Equation 10)

The resulting FSI_{PF} map will be exported as a PDF into a working folder and can also be seen in Figure 21. The resulting map will be rescaled from 0 to 1 using the “positive” max-min equation (equation 5). Once that is finished, this rescaled FSI is the value for FVI during the “pre-flood” phase of the disaster risk cycle.
3.4. During-Impact: FVI\textsubscript{DI}

The next phase of the disaster risk cycle is the “during-impact” phase where the phases corresponding Flood Vulnerability Index (FVI\textsubscript{DI}) will be computed along with its respective indicator and components. The indicator being computed is the “during-impact” indicator: the flood exposure index (FEI\textsubscript{DI}). Furthermore, the indicator’s corresponding components are the following: social component (FEI\textsubscript{s}), economic component (FEI\textsubscript{e}), and physical component (FEI\textsubscript{p}). This index, in theory, could vary with time, but is assumed to be stagnant with time in this thesis. Furthermore, the indicator’s value will be represented as the maximum value throughout flood duration. The FEI assessment will be completed using both inundation data, pertaining to the August 2016 flood’s magnitude and extent, produced from Dewberry’s HEC-RAS (River Analysis System) model and structure/inventory shapefile, which was also provided by Dewberry’s HEC-FIA model and datasets.
Variable, component, indicator, and indices maps were created within Arc-GIS and contribute to one of the following components of FEI: social (FEI_s), physical (FEI_p), or economic (FEI_e). These components will be computed on the census tract level. All the components of FEI will be calculated using an arithmetic average of the component’s respective variables. Then, each component of FEI will be re-scaled from 0 to 1. Finally, the three components will be averaged together, which will ultimately produce FEI. The final step will consist of rescaling FEI using the “positive” max-min standardization technique. The next paragraph will go into the method used for producing each components respective variables.

The joining of structure inventory with the buildings and cars respective direct consequences can be done using GIS techniques, the level of exposure was governed by the elements at risk (i.e., the factors that suffer adverse effects from urban flooding within the community, such as populations, buildings, and cars). In this research, the water depth and extent of flooding from the Amite River Basin Numerical Model for the August 2016 flood, were overlaid on other spatial data layers, such as populations, buildings, and cars, to determine the affected elements. Then, the exposure elements were identified and counted in each neighborhood using GIS tools and selected as exposure variates. The construction of FEI can be seen in the flow chart shown in Figure 22.
Figure 22. Conceptual framework for computing the During-impact Flood Vulnerability Index (FVI_{DI})
I. Creating the August 2016 Inundation map.

The first step for producing the FEI is formulating the inundation map representing the storm of interest, which is the August 2016 flood. It should be noted that the inundation data utilized in this section will be setup in the same format as inundation data being inputted into HEC-FIA; i.e., “max-inundation grids”. This can be completed by using the RAS Mapper export tool, which exports the max-inundation grid maps with a GeoTif.tif format. Appendix C will discuss the steps required to properly export the August 2016 inundation map from RAS Mapper using Dewberry’s couple 1D-2D model.

II. Data Collection

The second step necessary for producing FEI is data collection pertaining to the exposed elements at risk (point-counts, populations, building values, and car values) and census tract averaged flood inundation depths. The flood inundation depth data was obtained from the inundation map produced from RAS-Mapper and will be incorporated in the physical component of FEI. Regarding the exposed elements at risk, the data collection process will be separated into three sections – these sections will correspond to FEI’s three primary components: the physical component (FEI_p), the social component (FEI_s), and the economic component (FEI_e).

All these components require the population/inventory data produced by Dewberry’s LLC HEC-FIA model; in particular, the structure inventory shapefile. Additionally, the direct consequence, from HEC-FIA, is also required because these consequences show which elements at risk are being exposed along with a point-based flood depth. The data required for FEI_p is the number of exposed buildings/cars and the average census tract flood depth. The data required for FEI_s are the number of exposed people under 65 years old and the number of exposed people over 65 years old. The data required for FEI_e are the total economic value of exposed buildings and the
total economic value of exposed cars. The key word in all these variables is “exposed”. Exposed is simply referring to point structure inventories being exposed to the flood. A visual example of this can be seen by looking at the red points in Figure 23. After all necessary data was collected, ArcGIS pre-processing steps were taken, which can be seen in Appendix E. The steps applied in ArcGIS to produce each component of FEI will be discussed.
III. ArcGIS Steps for FEI<sub>p</sub>

The next series of steps will be related to production of the final census tract scale polygon-shapefile for FEI<sub>p</sub>. Within the symbology tab, select “unique” values and make the value field “Sum_Count”. The data should be classified using “Natural Breaks (Jenks)” and should be broken up into five classes. The resulting map will be exported as a PDF to a working folder. This same procedure will be performed for the average inundation depth map. The results can be seen in Figure 24.

![Figure 24](image)

**Figure 24.** (Left) Average Flood Inundation Depth per Census Tract and (Right) Total Exposed Building/Car Count Per Census Tract

The next step is creating a new field to the shapefile by rescaling the “normal” attribute fields, from Figure 24, using the positive max-min standardization technique (Equation 5). This new fields will be denoted as “Count_RS” and “AvgFlowDepth_RS”, respectively. The subsequent step consists of using the “Polygon to Raster” tool, where the value field should be “Count_RS”. Export this map as a PDF into a working folder.

Finally, FEI<sub>p</sub> is computed using an arithmetic average (Equation 11).

\[
FEI_p = \frac{\text{Count} \ (0 \text{ to } 1) + \text{AvgFlowDepth} \ (0 \text{ to } 1)}{2}
\]  

(Equation 11)
The resulting FEI_p can be seen below in Figure 25. FEI_p will be used in calculating FEI_D1 which will be used in calculating the “During-Impact” Flood Vulnerability Index (FVI_D1).

![Figure 25. The FEI_p map computed from the arithmetic average of the two physical variables: Count_RS and AverageDepth_RS.](image)

**Legend**

**FEI_p_6_18**

- **Value**
  - High: 0.793988
  - Low: 0.000207628

**IV. ArcGIS Steps for FEI_s**

The next series of steps will be related to production of the final census tract scale polygon-shapefile for FEI_s. The steps for this component are almost identical to the previous component. There are only three changes that need to be made: 1.) The social variables of interest are “Exposed Population Over 65 years old” and “Exposed Population Under 65-year-old”; 2.) The procedure performed for FEI_e will be performed twice (one for each variable); and 3.) The reclassification
will occur after the raster files are produced (not during the shapefile manipulation). Assuming that the symbology settings were set up correctly for both variables, these two variables can be seen in Figure 26.

Figure 26. (Left) Total Population Under 65 Per Census Tract and (Right) Total Population Over 65 Per Census Tract. These two maps will be exported as PDFs into a working folder. The next step is applying the “Polygon to Raster” tool twice to the polygon shapefile (one for each variable selection). Finally, these two raster files need to be reclassified using the “positive” max-min standardization technique. These reclass raster files will also be exported as PDFs into a working folder. Finally, FEI$_s$ will be computed using an arithmetic average (Equation 12).

\[
FEI_s = \frac{PopU65(0 \text{ to } 1)+PopO65(0 \text{ to } 1)}{2}
\] (Equation 12)

The resulting FEI$_s$ can be seen in Figure 27. FEI$_s$ will be used in calculating FEI$_{DI}$ which will be used in calculating the “During-Impact” Flood Vulnerability Index (FVI$_{DI}$).
V. ArcGIS Steps for FEIe

Most of the pre-processing ArcGIS steps for calculating FEIe were completed in the previous step. The next series of steps will be related to the final census tract polygon-shapefile previously produced and are almost identical to the social component of FEI. There was only one change that needs to be made: The economic component’s variable of interest are “Exposed Economic

Figure 27. The FEIs map computed from the arithmetic average of the following two social variables: TotPopU65_RC and TotPopO65_RC
Building Value” and “Exposed Economic Car Value” and maps of these two variables can be seen in Figure 28 (left: Building Value, right: Car Value).

Export these two maps as PDFs into a working folder. The next step is applying the “Polygon to Raster” tool twice to the polygon shapefile (one for each variable selection). Finally, these two raster files need to be reclassified using the “positive” max-min standardization technique. These reclassified raster files are then exported as PDFs into a FEI working folder. Finally, FEI\textsubscript{e} is computed using an arithmetic average (Equation 13).

\[
FEI_e = \frac{Building\ Value\ (0\ to\ 1)+Car\ Value\ (0\ to\ 1)}{2} \quad (\text{Equation 13})
\]

The results for FEI\textsubscript{e} can be seen in Figure 29. FEI\textsubscript{e} will be used in calculating FEI\textsubscript{DI} which will be used in calculating the “During-Impact” Flood Vulnerability Index (FVI\textsubscript{DI}).
VI. Computing FEI Using Raster Calculator

FEI will be computed by taking the arithmetic average of all the FEI components: FEI_s, FEI_p, and FEI_e. The equation for computing FEI_{DI} can be seen below in Equation 14.

\[
FEI_{DI} = \frac{FEI_p + FEI_e + FEI_e}{3}
\]

(Equation 14)

The resulting FEI_{DI} can be seen in Figure 30. FEI_{DI} will be used in calculating the “During-Impact” Flood Vulnerability Index (FVI_{DI}).

Figure 29. The FEI_e map produced from the arithmetic average of the following two economic variables maps: TotEconBuilding Reclass and TotEconCar Reclass.
VII. Computing FVI Using Raster Calculator

Using the indicator produced in the “during-impact” stage, FEI\(_{DI}\), and the indicator produced during the “pre-flood” phase, FSI\(_{PF}\), FVI\(_{DI}\) is computed using an arithmetic average (Equation 15).

\[
FVI_{DI} = \frac{FSI_{PF} + FEI_{DI}}{2}
\]

(Equation 15)

The resulting FVI\(_{DI}\) map is then exported as a PDF into a working folder (Figure 31). The final step uses the “reclassify” tool from ArcGIS to rescale FVI\(_{DI}\), using the “positive” max-min standardization technique, from 0 to 1.
3.5. During-Recovery (DR): FVIDr

This section will cover the methodology used to produce the during-recovery vulnerability index (FVIDr) along with its respective during-recovery indicators and components. The indicator being computed during this phase of the disaster risk cycle is the Flood Adaptive Capacity Indicator (FACI). Two components of FACI are computed in this work: social (FACIs); and economic (FACLs). The construction of FEI can be seen in the flow chart shown in Figure 32.
Figure 32. Conceptual framework for computing the During-impact Flood Vulnerability Index (FVI_{DR})
The Flood Adaptive Capacity Indicator (FACI) is the “during-recovery” indicator of vulnerability and, for this work, is assumed to stay constant with time. The source of the data used to create FACI will come from Wellbeing data developed by Moles et al., 2020 and then adjusted by Dr. Aimee Moles from Inland from the Coast (IFC) (Cherry et al., 2020). The process for developing the human wellbeing indicators was already discussed in the FSI indicator section; therefore, it will not be discussed again. A majority of the variables chosen for FACI pertain to the Public Health component of the human wellbeing data collected after the August 2016 flood. Additional components within the Community and Economic Stress component were also selected. These variables were grouped at the census tract level and can be seen in Table 8.

Table 10. List of components and variables corresponding to FACID1 (Moles et al., 2020)

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Component</th>
<th>Variable</th>
<th>Variable Definition</th>
<th>Relationship to Adaptive Capacity</th>
<th>Justification Source</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Kitchen</td>
<td>Presence of kitchen facilities</td>
<td>Positive</td>
<td>Economic Innovation Group (2017)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Disability</td>
<td>% Population without a disability</td>
<td>Negative</td>
<td>Cutter et al., 2010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>At least HS diploma</td>
<td>% Population with at least a high school diploma</td>
<td>Positive</td>
<td>U.S. Indian Ocean Tsunami Warning System Program, 2007)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ratio of college degree to HS diploma</td>
<td>Ratio college degree to high school diploma</td>
<td>Positive</td>
<td>Cutter et al., 2010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Non-Violent Crimes</td>
<td>Pre and Post Crime Non-Violent</td>
<td>Negative</td>
<td>Cutter et al., 2010</td>
</tr>
</tbody>
</table>
### Social Variable Justifications (FACL):

**Kitchen and Plumbing:** (Economic Innovations Group, 2017)

Communities impacted by flooding have a weaker ability to recovery when facing housing burdens, such as incomplete kitchen and plumbing facilities; thus, negatively effecting that community’s public health. After a disaster occurs, not having access to a complete kitchen facility will lower that household’s ability to recovery due to potential food insecurity. On the other hand, not having access to plumbing facility will lower that household’s ability to recovery due to water insecurity.

**Disability:** (Cutter et al., 2010)

People with disabilities experience inequalities which increase their exposure to the negative effects of a flood event. An understanding of people with disabilities vulnerability and adaptive capacity can be gained by studying and considering how disabled people fare during a flood event. The more people with disabilities within a community, the less ability that the community is able to recover from a flood which causes a negative adaptive capacity.
High School and Ratio of College Degree to High School Degree: (U.S. Indian Ocean Tsunami Warning System Program, 2007; Cutter et al., 2010)

People with a college degree tend to have a broader knowledge base, financial ability and are better at interpreting potential risk factors than high school graduates. College graduates may potentially have a better financial ability to purchase homes located in a more urban areas with better drainage systems which makes them less vulnerable to flood impacts. College degree graduates tend to have a more positive effect on the relationship to adaptive capacity than high school graduates.

Non-Violent Crimes: (Cutter et al., 2010)

The disastrous effects of a flood event can cause people to commit nonviolent crimes such as theft and violence to survive. This seriously effects a community’s ability to recover from a flood event and start the process of rebuilding. Non-Violent crimes or any crimes have a negative effect on the community’s adaptive capacity to recover from a disastrous flood event.

Economic Variable Justifications (FACI_e):

Employment: (Cutter et al., 2010)

People that have steady long-term employment tend to invest more heavily in their homes than unemployed people or parttime workers. Fulltime employed people tend to protect their plumbing and keep the area surrounding their home well maintained due to their financial stability and ability. This helps to decrease the impact of the flood event. Employment has a positive effect on the relationship to adaptive capacity following a flood event.

Professional Occupations: (Cumming et al., 2005)

Professional education can help to decrease the effects of a flood event dramatically. By having a Professional education, people have more access to better living areas, better insurance, better
assistance, and better social connectivity for physical, financial, and emotional support. A Professional Occupation has a positive effect on the relationship to adaptive capacity of a flood event.

*Per-Capita Income:* (Tobin, 1999)

Research findings demonstrate that people of low socioeconomic status are more vulnerable during a flood event and suffer more consequences during impact, ranging from homelessness to financial devastating impacts. Per capita income is used to determine the average amount of income per person in a community to determine the standard and quality of life of a community. The higher the per-capita income the more positive the effect on the relationship to adaptive capacity of a community following a flood event (Altınkamış & Özcan, 2017).

*Banks:* (Queste and Lauwe, 2006)

Banks are great resource for community members that have been negatively affected by a flood event. Banks provide people the ability to withdraw money for expenses and in many cases allows people to borrow money to begin to rebuild. Having access to a bank both during and following a flood event has a positive effect on community adaptive capacity to recover after a flood event.

*Worship:* (Cutter et al., 2010)

Worship centers are an extremely important aspect of community connectivity and rebuilding. Worship centers allow community members the ability to share their concerns and hardships and have supportive people available to listen and provide mental, physical, and financial assistance. Parishioners are very supportive and reach out to widowers, single moms or dads, and sickly members of their communities initially but are available to anyone in need. Worship centers have a positive effect on a community’s adaptive capacity to recover following a flood event.

*NFIP:* (Cutter et al., 2010)
NFIP is a flood insurance program that provides individuals and businesses with insurance during a flood event. Rates and coverage are usually based on property location and zone. This supplemental insurance can sometimes be the only thing that keeps a family or business from losing everything during a flood event. Flood insurance is a great way to lessen negative effects of a flood event and has a positive effect on the relationship to adaptive capacity after a flood event.

Excel and ArcGIS Steps.

**Excel and ArcGIS Steps for FACI_{s} and FACI_{e}:**

The first step in producing FACI is to collect the necessary census tract-level wellbeing data from Inland from the Coast (IFC); in particular, the variables belonging to the public health component. It should be noted that the pre-processing data steps taken in this section are identical to the ones taken when computing FSI_{s,e} in section 3.4.2. The only difference is that both the “positive” and “negative” z-score equation were both applied (Equation 5 and Equation 6, respectively). To determine whether to use the positive or negative equation is based on the variable’s relationship to adaptive capacity (refer to Table 9). Excel was then used to compute both FACI_{s} and FACI_{e}, on the census tract level (Equation 16).

\[
FACI_{i,j} = \frac{z_{i \in \text{np}} \cdot z_{\text{pos/neg},i,j}}{n_p}
\]  
(Equation 16)

Where:

- \( i \) = Component “i”
- \( j \) = census tract “j”
- \( n_p \) = total number of variables corresponding to subcomponent “i” FACI
- \( z_{\text{pos/neg},i,j} \) = The proportional/disproportional “z-score” relative to component “i” of FACI for census tract “j”
FACI_{ij} = \text{Component \textquotedblleft}i\textquotedblright\text{ of FACI for census tract \textquotedblleft}j\textquotedblright

The next step is rescaling both FACI_s and FACI_e using the positive maximum-minimum equation (Equation 5). Then, take an arithmetic average of the rescaled FSI_s and FSI_e subcomponent maps using Equation 17.

\[
FACI_{DR} = \frac{FACI_s(0 \text{ to } 1) + FACI_e(0 \text{ to } 1)}{2} \quad (\text{Equation 17})
\]

The production of FACI_{DR} was accomplished in ArcGIS. The first step is inserting the original shapefile into ArcGIS. Once the “Wellbeing.shp” has been updated with the new negative z-scores and indicator values, open the Well-being shapefile data, using ArcGIS 10.8, and then perform the following steps:

1. Adding the wellbeing shapefile into ArcGIS guided user interface.
2. Right click the data and select the join and relate button, which will then allow the user to “tabularly” combine the excel sheet (containing the FACI(neg)) to the shapefile (the one containing FACI(pos.)).
3. The modified shapefile consists of the correct variable z-scores, indicators, and FACI values.

The results from Equation 16 were computed and then rescaled using the positive maximum-minimum scheme (Equation 5). Both the rescaled component maps (FACI_s and FACI_e) and indicator map (FACI_{DR}) can be seen in Figure 33.
3.5.1 The “During-Recovery” Flood Vulnerability Index (FVI$_{PF}$):

Using the indicator produced in the “during-recovery” stage, FACI$_{DR}$, along with the previously computed indicators such as the “during-impact” stage, FEI$_{DI}$, and the “pre-flood” phase, FSI$_{PF}$; FVI$_{DI}$ can now be computed using the “during-recover” FACI, “during-impact” stage, FEI$_{DI}$, and “pre-flood” phase, FSI$_{PF}$, using an arithmetic average (Equation 18).

$$FVI_{DR} = \frac{FSI_{PF} + FEI_{DI} + (1 - FACI_{DR})}{3} \tag{Equation 18}$$

The resulting FVI$_{DR}$ map will be exported as a PDF into a working folder and can also be seen in Figure 34. The final step consists of using the “reclassify” tool from ArcGIS to rescale FVI$_{DI}$, using the “positive” max-min standardization technique, from 0 to 1 (Equation 5).
Figure 34. The FVI\textsubscript{DR} map produced from the arithmetic average of FSI\textsubscript{PF}, FEI\textsubscript{DI}, and FACI\textsubscript{DR}. 
4. RESULTS AND DISCUSSIONS

The results section will explain the rescaled-versions of the variable, component, indicator, and index maps produced for each of the three phases of the disaster risk cycle maps produced during the methodology section. The result section was divided into four sections. The first three sections pertain to the variables, component, and indicator maps produced during the pre-flood, during-impact, and the during recovery phases of the disaster risk cycle. The last section will display, compare, and discuss results for FVI during all three phases of the disaster risk cycle. The results for each map will be analyzed and interpreted with respect to their relevancy to flood vulnerability.

4.1. Pre-Flood Results:

Computation of the FVI\textsubscript{PF}, requires the pre-flood indicator, FSI\textsubscript{PF}, which consists of two sub-indicators: FSI\textsubscript{s,e} and FSI\textsubscript{en,p}. The FSI\textsubscript{s,e} sub-indicator can be broken down into the following components: FSI\textsubscript{s} and FSI\textsubscript{e}.

4.1.1 Variables for subcomponent FSI\textsubscript{s}

FSI\textsubscript{s}, which contains values on the census tract level for: people who are over 65 years old; people who are a minority; and people with access to communication (telephone and/or landline). Figure 35, Figure 36, and Figure 37 shows the rescaled (0 to 1) maps for over 65, minority, and communication, respectively. Each of these maps will be discussed using the following outline:

- The variables relationship to Flood Susceptibility
  - Positive \(\Rightarrow\) Normalized using “positive” maximum-minimum scheme (Equation 5)
  - Negative \(\Rightarrow\) Normalized using “negative” maximum-minimum scheme (Equation 6)
- For each Parish:
  - Identifying census tracts with high “variable” values
  - Identifying census tracts with low “variable” values
Identifying variability of “variable” census tract values

It is worth noting that variability was simply executed by visually comparing the spectrum of census tract colors found within each of the three parishes. For example, when looking at Figure 35, East Baton Rouge Parish has more variability than Ascension Parish because East Baton Rouge Parish has census tracts with almost every possible color within the legend while Ascension Parish only has census tracts with orange colors.

![Figure 35. Rescaled “Population Over 65” Map](image)

The first FSI variable corresponds to the percentage of people under 65 years old. In theory, the following can be said: the more people under 65, the less susceptible a community is to flood. Since these variables are inversely related, the inverse z-score formula was applied. This makes
the variable read as the following: “the number of people over 65”. Therefore, this map indicates that East Baton Rouge has the highest levels of people over 65 years old (35, 36, 68, and 70), the lowest levels of people over 65 years old (20, 27, 54, 78, and 94) and the highest variability in people over 65 years old. Ascension has the second highest levels of people over 65 years old along with the lowest variability in people over 65 years old. Lastly, Livingston has a relatively strong level of variability along with areas of high and low people over 65 years old, but all these parameters fall in the middle of the other two parishes.

Figure 36. Rescaled “Minority Population” Map

The second variable of interest corresponds to the percentage of people who are not a minority. In theory, the following can be said: the more people who are not a minority, the less susceptible a community is to flood. This is because non-minority groups tend to belong to higher economic
status, settle in flood-safe areas, and have better community connectivity (Lotfata & Ambinakudige, 2019). Since this term is inversely related to vulnerability, the inverse z-score formula was applied. This essentially makes the variable read as the following: “The number of people who are a minority”. Therefore, this map indicates that East Baton Rouge has the highest levels of minority populations (12, 13, 14, 15, and 19), the lowest levels of minority populations (26, 77, and 93) and the highest variability in minority populations. Ascension’s minority populations fall in between East Baton Rouge Parish and Livingston Parish. Lastly, Livingston has the lowest and most consistently lowest levels of minority populations and variability of minority populations.

Figure 37. Rescaled “Telephone” Map
The third variable of interest corresponds to the percentage of people with access to a telephone. In theory, the following is said: the more people with telephones, landlines or cellphones, the less susceptible a community is to flood. Since the population is inversely related to flood susceptibility, the inverse z-score formula was applied. This redefines the variable read as the following: “the number of people without a telephone”. Therefore, this map indicates that East Baton Rouge has the highest levels of telephone access (31, 59, and 94), the lowest levels of telephone access (21, 66, and 67), and the highest variability in telephone access. Ascension has the second highest value of telephone access (2). Lastly, Livingston has, consistently, the lowest telephone access levels (103, 104, 110, and 114).

**4.1.2 Subcomponent FSI**

After combining the previous three social variables using an arithmetic averaging scheme, the resulting component FSI, which is not rescaled, was seen in Figure 19 within the methodology section (Section 4.3.2). The map from Figure 19 was then rescaled using the positive maximum-minimum scheme (Equation 5), which can be seen in Figure 38.
This map indicates that East Baton Rouge has the highest levels of social susceptibility (31, 44, 47, 83), the lowest levels of social susceptibility (26, 27, 66 and 93), and the highest variability in social susceptibility. Lastly, Livingston and Ascension Parish both consistently the lowest levels of social susceptibility.

4.1.3 Variables for Sub-component FSI_e

The variables corresponding to FSI_e consist of the following per census tract: people who own a vehicle; people who spend less than 30 percentage on housing; people who are homeowners; and
principal arterial miles. These maps can be seen in Figure 39, Figure 40, Figure 40, and Figure 41, respectively. Each of these variable maps will be discussed using the following outline:

- The variables relationship to Flood Susceptibility
  - Positive ➔ Normalized using “positive” maximum-minimum scheme (Equation 5)
  - Negative ➔ Normalized using “negative” maximum-minimum scheme (Equation 6)

- For each Parish:
  - Identifying census tracts with high “variable” values
  - Identifying census tracts with low “variable” values
  - Identifying variability of “variable” census tract values
The first economic variable of interest corresponds to the percentage of people with access to a vehicle. The premise here is that the more people with access to cars, the less susceptible that a community is to flood. Since they are inversely related, the inverse z-score formula was applied. This means that the variable will read as the following: The percentage of people without a car (Figure 39). Therefore, this map indicates that East Baton Rouge has several census tracts consisting of the highest levels of vehicle access (10, 13, 22, 25, 95, and 97.) Also, the majority of East Baton Rouge census tracts has the lowest levels of vehicle access to flooding along with the highest variability of vehicle access levels amongst all the parishes. Ascension Parish, amongst all the census tracts, has the lowest levels of vehicle access along with the lowest variance of vehicle access. Livingston Parish falls in the middle in terms of both vehicle access levels and variability of vehicle access levels.
The second economic variable of interest corresponds to the percentage of people who spend less than 30 percent of their income on housing. It could be concluded that the more people who spend less than 30 percent on their house, the less susceptible a community is to flood. Since the variables are inversely related, the inverse z-score formula was applied. This extrapolates the variable will read as the following: “the number of people who spend more than 30 percent on housing” (Figure 40). Therefore, this map indicates that East Baton Rouge has the highest levels of people spending more than 30 percent of their income on housing (69 and 76), the lowest levels of people spending more than 30 percent of their income on housing (7, 71, and 80) and the highest variability in people spending more than 30 percent of their income on housing. Both Livingston and Ascension
have low to medium levels of people spending more than 30 percent of their income on housing along with medium variability of people spending more than 30 percent of their income on housing levels.

![Legend](image)

**Figure 41. The Rescaled “Homeowner” Map.**

The third economic variable of interest corresponds to the percentage of people who are homeowners. The premise here is that the more people who own homes, the less susceptible a community is to flooding. Since they are inversely related, the inverse z-score formula was applied. This essentially makes the variable read as the following: “the percentage of people who do not own homes”. Therefore, this map indicates that East Baton Rouge has the highest levels of homeowners (7, 44, and 54), close to half of the census tracts have the lowest possible levels of homeowners, and the highest variability in homeowners. Ascension has one census tract with the
highest possible level of homeowners (7). Lastly, Livingston has a strong level of variability along with areas of high and low homeowners, but all these observational metrics fall within the observations amongst the two other parishes.

Figure 42. The Rescaled “Miles” Map.

The last economic variable of interest corresponds to the number of principal arterial roads miles. In theory, the following is said: The more principal arterial road miles, the less susceptible that a community is to flooding. Since they are inversely related, the inverse z-score formula was applied. Therefore, this map indicates that East Baton Rouge and Livingston both have the highest levels of arterial miles; however, East Baton Rouge also has the lowest levels of arterial miles to flooding.
(19, 20, 21, and 22.) Ascension Parish falls in the middle in terms of their level of arterial miles but have the lowest variance of arterial miles.

4.1.4 Subcomponent FSI$_e$

After combining the previous four economic variable maps using an arithmetic averaging scheme, the resulting component FSI$_e$, not rescaled, can be seen in Figure 20. The FSI$_e$ map was then rescaled, from 0 to 1, using the positive maximum-minimum equation (Figure 43).

![Figure 43. The Rescaled FSI$_e$ Map.](image)

This map indicates that East Baton Rouge has the highest levels of economic susceptibility (31, 44, 47, and 83), the lowest levels of economic susceptibility (26, 27, 66 and 93), and the
highest variability in economic susceptibility. Lastly, Livingston and Ascension Parish both consistently have the lowest levels of economic susceptibility.

4.1.5 Component FSI$_{s,e}$

To produce FSI$_{s,e}$, the maps of FSI$_{s}$ and FSI$_{e}$ were combined using an arithmetic average. The resulting map can be seen in Figure 20 which is in the methodology section. Then the FSI$_{s,e}$ map was re-scaled, from 0 to 1, using the positive max-min equation. The resulting figure can be seen below in Figure 44.

![Image of FSI$_{s,e}$ map]

Figure 44. The Rescaled FSIs,e Map.

This map indicates that East Baton Rouge has the highest levels of social/economic susceptibility (31, 44, 47, and 83), the lowest levels of social/economic susceptibility (26, 27, 66 and 93), and
the highest variability in social/economic susceptibility. Lastly, Livingston and Ascension Parish both consistently possess the lowest levels of social/economic susceptibility.

### 4.1.6 Variables for Component FSI_{en,p}

The FSI_{en,p} sub-indicator can be broken down into the following thematic variables: Flow Accumulation, Distance to Drainage Network, Land Use Land Cover (LULC), Elevation, Slope, and Geology. The raw-value thematic variable maps were already produced within Section 4.3.1 of the methodology section. These new maps were reclassified using the natural break method scheme. The new ratings, from 2 to 10, for each of the thematic maps can be seen in Table 9.

#### Table 11. The Ranges of Thematic Variable Values Corresponding to New Ratings

<table>
<thead>
<tr>
<th>Rating</th>
<th>Distance to Drainage Network (Feet)</th>
<th>Land Use Land Cover (Runoff, CN)</th>
<th>Elevation (ft, NAVD88)</th>
<th>Slope (%)</th>
<th>Geology (Ksat, ( \text{micrometers per second} ))</th>
<th>Rating</th>
<th>Flow Accumulation (accumulated flow to each cell)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.96 - 19.39</td>
<td>92.1 - 100</td>
<td>0.96 - 19.39</td>
<td>0 - 1.88</td>
<td>0.00 - 1.30</td>
<td>10</td>
<td>94,392,956.5 - 146,193,969.2</td>
</tr>
<tr>
<td>8</td>
<td>19.4 - 41.02</td>
<td>86.1 - 92</td>
<td>19.4 - 41.02</td>
<td>1.89 - 7.52</td>
<td>1.31 - 5.04</td>
<td>9</td>
<td>67,341,316.53 - 94,392,956.49</td>
</tr>
<tr>
<td>6</td>
<td>41.03 - 64.25</td>
<td>74.1 - 86</td>
<td>41.03 - 64.25</td>
<td>7.53 - 17.55</td>
<td>5.05 - 9.23</td>
<td>8</td>
<td>30,505,040.83 - 67,341,316.52</td>
</tr>
<tr>
<td>4</td>
<td>19.4 - 41.02</td>
<td>60.1 - 74</td>
<td>19.4 - 41.02</td>
<td>17.56 - 33.22</td>
<td>9.24 - 18.02</td>
<td>7</td>
<td>26,476,073.17 - 30,505,040.82</td>
</tr>
<tr>
<td>2</td>
<td>0.96 - 19.39</td>
<td>60</td>
<td>0.96 - 19.39</td>
<td>33.23 - 159.82</td>
<td>18.03 - 91.74</td>
<td>6</td>
<td>21,295,971.9 - 26,476,073.16</td>
</tr>
</tbody>
</table>

**Rating Interpretation:**
2 = very low susceptibility; 3 = very low to low susceptibility; 4 = low susceptibility; 5 = low to medium susceptibility; 6 = medium susceptibility; 7 = medium to high susceptibility; 8 = high susceptibility; 9 = high to very high susceptibility; 10 = very high susceptibility

The reclassified results for each of these thematic variables corresponding to FSI_{en,p} can be seen below in Figure 45, Figure 46, Figure 47, Figure 48, Figure 49, and Figure 50, respectively.

Each of these variable maps will be discussed using the following outline:

- For each Parish:
- Identifying census tracts with high “variable” ratings
- Identifying census tracts with low “variable” ratings
- Identifying variability of “variable” census tract ratings
- Justify the previously 3 bullet points above using Table 10

The first thematic variable map, Flow Accumulation, can be seen in Figure 41a. It should be noted that majority of the map was assigned a rating value of 2, which occurred in census tracts located on non-river elements. All the ratings within the Amite and Comite River networks received a rating values greater than or equal to 3 and less than or equal to 10.
The next thematic variable map, Distance to Drainage, can be seen in Figure 42b. Similar to the flow accumulation map, the largest ratings (i.e., a rating of 10) is assigned within Amite and Comite River networks; however, there are also ratings equal to or greater than 4 and less than 10 located on land near the two river networks. Each buffer zone has a length of around 150 meters. The closer the buffer is to the river, relative to other buffer zones, the higher rating value that buffer zone is assigned. Therefore, environmental flood susceptibility is higher for people who reside closer to the Amite and Comite River network. On the other hand, environmental flood susceptibility decreases as people settle in areas farther away from the Amite and Comite River.
sections. For more information on Distance to Drainage classifications and descriptions, please refer to pages 40 through 42.

The third thematic variable map, LULC, can be seen in Figure 47. The value being assessed was CN. Areas of small CN have low susceptibility while areas with high CN have greater physical flood susceptibility. Physical flood susceptibility varies significantly throughout the census tracts of any parish within the project area. Physical flood susceptibility was measured based on the amount of percentage of impervious, surficial area. Higher susceptibility was assigned to areas with larger amounts of impervious area and lower susceptibility was assigned to areas with smaller...
amounts of impervious area. For more information about both LULC and CN’s descriptions and classifications, please refer to pages 28 through 38.

![Figure 48. The Reclassified “Elevation” Map](image)

The fourth thematic variable map, elevation, can be seen in Figure 48. It appears that that elevation decreases downstream and increases upstream. This is because the more susceptibility areas were assigned a rating value of 10, which were located in the southern portion of the project area. Going from south to north, the rating values assigned to conglomerates of census tracts and would consistently decrease by 2-rating points in the northern direction. For more information about the elevation descriptions and classifications, please refer to pages 24 and 25.
The fifth thematic variable map, Slope, can be in Figure 49. It appears that high susceptibility values corresponded to the average slope. The slope value is low (i.e., a rating value of 10) anywhere besides the river network, where it was assigned lower levels of 4 or 6, yellow and orange, respectively. A rating value of 6 can be seen in areas near the outer banks of the river and rating values of 4 can be seen closer to deepest and steepest portion of the riverbed. Therefore, the distribution of the highest susceptibility rating values for slope were consistent amongst all the census tracts within the project area because their slopes were very low and thus scored a consistent rating value 10. For more information about the slope descriptions and classifications, refer to pages 25 and 26.
The final thematic variable map, Geology, can be seen in Figure 43d. This variable map was interested in sub-surface permeability rates. Therefore, areas with higher amounts of silts would score a higher susceptibility rating as oppose to areas such as sand which would score lower susceptibility rating. For information regarding the actual soil, refer to pages 26 through 28.

To produce $\text{FSI}_{\text{en,p}}$, the thematic maps were combined using a weighted linear combination scheme. The resulting map can be seen in Figure 18 and is in the methodology section. Then the $\text{FSI}_{\text{en,p}}$ map was re-scaled, from 0 to 1, using the positive maximum-minimum equation. The resulting figure can be seen in Figure 51.
4.1.7 Component FSI\textsubscript{en,p}:

Looking at Figure 51, it is apparent that the highest value of susceptibility corresponds to the river network itself.

![Figure 51. The rescaled FSI\textsubscript{en,p} map.](image)

Also, the susceptibility values decrease as the raster cells radiate outwards from the river network. The main reason contributing to this was flow accumulation and distance to drainage network variables had the two highest weights. The weights for each of the variables can be seen in Table 1a. It was apparent that the larger the variables weight contributed, the more impact the variable had on the resulting FSI\textsubscript{en,p} map. Therefore, East Baton Rouge and Livingston Parish both experience high values of susceptibility near river networks, which general serve as the parish
borders, and low values of susceptibility farthest away from the river network/parish boarders. Ascension Parish only experienced a high level of susceptibility near its borders and lower levels of susceptibility in the heart of the project area’s portion of Ascension Parish.

4.1.8 Indicator $FSI_{PF}$

To produce the pre-flood indicator, $FSI_{PF}$, the maps of sub-indicators $FSI_{s,e}$ and $FSI_{en,p}$ were combined using an arithmetic average scheme. The resulting map can be seen in Figure 20, which is in the methodology section. $FSI_{PF}$ map was then rescaled, from 0 to 1, using the positive max-min equation. The resulting figure can be seen below in Figure 52.

Figure 52. The rescaled $FSI_{PF}$ map, which is equivalent to the $FVI_{PF}$ map.
It should be noted that FSI_{PF}, rescaled, is equivalent to FVI_{PF}. The contributing maps used for the map in Figure 43 were equally valued and thus the characteristics of both maps can be seen in the figure. The highest values of flood susceptibility occurred in East Baton Rouge, which were the census tract number 44 and 83. The lowest values of flood susceptibility corresponded to East Baton Rouge Parish and Livingston Parish, which were 26, 27, 66, 77, 78, 79, 101, 114. The parish with the highest variability in levels of flood susceptibility was East Baton Rouge Parish. It is interesting to note that the river network still scored a yellow color (or value around 0.5). This makes sense because the FSI_{en,p} had a maximum value of 1 within the river network, but since its contributing weight was 0.5 percent, then maximum resulting value is 0.5 assuming that rating value of FSI_{s,e} within the same piece of are little to known.

4.2. During-Impact Results:

To compute FVI_{DI}, the required during-impact indicator was FEI_{DI} along with the indicator computed during the pre-flood phase, FSI_{PF}. FEI_{DI} consists of the following components: FEI_{p}, FSI_{e}, and FEI_{s}. Furthermore, these three components will all have two corresponding variables.

4.2.1 Variables for Component FEI_{p}:

The FEI_{p} component can be broken down into the following variables: Total Building/Car Count Per census tracts and Average Flood Depth Per census tract. The results for each of these variables can be seen in Figure 52 and Figure 53, respectively. Each of these maps will be discussed using the following outline:

- The variables relationship to Flood Susceptibility (Positive or Negative?)
  - Positive ➔ Normalized using “positive” maximum-minimum scheme (Equation 5)
  - Negative ➔ Normalized using “negative” maximum-minimum scheme (Equation 6)
- For each Parish:
- Identifying census tracts with high “variable” values
- Identifying census tracts with low “variable” values
- Identifying variability of “variable” census tracts values

Figure 53. The rescaled “Total Exposure Building/Car Count Per Census Tracts” map.

The first physical variable map, seen in Figure 44a, is the total exposed count of buildings and cars per census tract. An interesting observation to make is that most exposed buildings and cars are generally located in the census tracts along the Amite and Comite River networks. The first example of this can be observed in East Baton Rouge Parish. Large amounts of exposed buildings
and cars can be seen in census tracts numbered 77, 81, 82, and 83. The second example can be seen in Livingston Parish, which can be seen by looking at the following census tracts: 107, 109, 110, and 113. Also, the count of exposed buildings tends to decrease as the census tracts are farther away from the Amite and Comite River network. This applies to all the parishes but is exceptionally noticed in East Baton Rouge and Livingston Parish.

Figure 54. The rescaled “Average Flood Depth Per CENSUS TRACT” map.

The other physical map, the Average Flood Depth Per Census Tract, shows a somewhat similar story to the total building and car map. The largest average flood depth value was in Livingston; in particular, census tract number 108. Also, there were some relatively high values of
average flood depth near the southern end of the project area closest to the Amite River (i.e., 110 and 115). The lowest average flood depth values occurred in East Baton Rouge Parish, which included, but was not limited to, the following census tract numbers: 16, 21, 22, and 25. Also, East Baton Parish experienced some higher values of average flood depth near the Amite and Comite River junction. Due to the similar characteristics found in the average flood depth map and total building and car count map, these two maps were grouped under the same component of FEI. The only issue with this map is that it is better represented in areas of high-count densities. For example, this variable is not ideal for large census tracts with limited number of samples, i.e., exposed buildings and cars.

4.2.2 Component FEI_p:

After combining the previous two physical variable maps using an arithmetic averaging scheme, the resulting component FEI_p, not scaled, can be seen in Figure 25 within the methodology section. Then the FEI_p map was rescaled, from 0 to 1, using the positive maximum-minimum equation. The resulting figure can be seen below in Figure 55. The resulting map shown in Figure 55 is FEI_p. This map, just like its physical variable maps, tend to display high values of exposure closer to the Amite and Comite River network and lower values as the census tracts are farther away from the river network. The larger values can be seen in East Baton Rouge and Livingston Parish, which include the following census tracts: 82, 83, 107, 109, 110, and 113. The lowest values can be seen in East Baton Rouge on the west to southwest quadrant of the project area.
4.2.3 Variables for Component FEI$_p$

The FEI$_p$ component can be broken down into the following variables: Total Population Under 65 Years Old Per Census Tract and Total Population Over 65 Years Old Per Census Tract. The results for each of these variables can be seen below in Figure 56 and Figure 57. Each of these maps will be discussed using the following outline:

- The variables relationship to Flood Exposure (Positive or Negative?)
  - Positive $\Rightarrow$ Normalized using “positive” maximum-minimum scheme (Equation 5)
o Negative ➔ Normalized using “negative” maximum-minimum scheme (Equation 6)

- For each Parish:
  - Identifying census tracts with high “variable” values
  - Identifying census tracts with low “variable” values
  - Identifying variability of “variable” census tract values

Figure 56. The rescaled “Total Exposed Population Under 65 Per Census Tract” map.

The first social variable map, seen in Figure 45a, is the total exposed population of people under 65 years old Per Census Tract. A notable observation to make is that the most exposed
populations under 65 are generally located in the center of the project area. The first example of this can be seen in East Baton Rouge Parish. Large amounts of exposed people under 65 can be seen in census tracts numbered 46, 48, and 82. The second example can be seen in Livingston Parish, which can be seen by looking at the following census tracts: 107, 108, and 109. Also, the count of exposed population under 65 tends to decrease as the census tracts are farther away from the center of the project area. This observation is apparent when looking at all the parishes within the project area.

Figure 57. The rescaled “Total Exposed Population Over 65 Per Census Tract” map.

The other social map, the total exposed population over 65 Per Census Tract, displays parallel data to the total exposed population under 65 Per Census Tract. The largest amounts of exposed
population over 65 was in East Baton Rouge Parish; in particular, census tract number 82. Also, there were some relatively high values of average flood depth near center of East Baton Rouge Parish (i.e., 46, 48, and 53). The lowest exposed population over 65 values occurred in all the parishes: in particular, around the edges of the project area. Due to the similar characteristics found in the two social maps, these two maps were grouped under the same component of FEI.

4.2.4 Component FEI,:

After combining the previous two social variable maps using an arithmetic averaging scheme, the resulting component FEIs (not scaled) can be seen in Figure 27 within the methodology section. Then the FEIs map was rescaled, from 0 to 1, using the positive maximum-minimum equation. The resulting figure can be seen in Figure 58. The resulting map shown in Figure 58 is FEIs. This map, similar to the social variable maps, tend to display high values of exposure closer to center of the project area and lower values as the census tracts are farther away from the center of the project area. This larger value can be seen in East Baton Rouge and Livingston Parish, which include the following census tracts: 46, 48, 82, and 108. The lowest values can be seen in East Baton Rouge on the west, south-west, and south-east quadrants of the project area.
4.2.5 Variables for Component FEI_e

The FEI_e component can be broken down into the following variables: Total Economic Building Value Per census tract and Total Economic Car Value Per Census Tract. The results for each of these variables can be seen below in Figure 58 and Figure 59, respectively. Each of these maps will be discussed using the following outline:

- The variables relationship to Flood Susceptibility (Positive or Negative?)
  - Positive ➔ Normalized using “positive” maximum-minimum scheme (Equation 5)
  - Negative ➔ Normalized using “negative” maximum-minimum scheme (Equation 6)

- For each Parish:
  - Identifying census tracts with high “variable” values
Identifying census tracts with low “variable” values

Identifying variability of “variable” census tract values

Figure 59. The rescaled “Total Exposed Economic Building Value Per Census Tract” map.

The first economic variable map, seen in Figure 45a, is the total exposed economic value of buildings per census tract. A noticeable observation to make is that only a few of the exposed buildings and cars census tracts are large and are generally spread out through the project area. The first example of this can be seen in East Baton Rouge Parish, where the largest amounts of exposed building value can be seen in the census tract numbered 68. The second example can be
seen in Livingston Parish by looking at the census tract numbered 107. Also, the count of exposed building value tends to decrease as the census tracts are farther away from the center of the project area, besides census tract 68. This observation is apparent when looking at all the parishes within the project area, besides Ascension which has consistently lower levels of exposure.

Figure 60. The rescaled “Total Exposed Economic Car Value Per Census Tract” map.

The other economic map, the Total Exposed Car Value Per Census Tract, shows a different tangent than total exposed building value per census tract. The largest amounts of exposed car value were in East Baton Rouge Parish; in particular, census tract number 46 and 82. Additionally,
in same portion of East Baton Rouge Parish, there were also some relatively high values of exposed car value found in census tracts 46, 48, and 53. The lowest exposed car value occurred in all the parishes: in particular, around the west to southwest edges of the project area. Due to both maps having same units of measurement, these two economic maps were grouped under the same component of FEI.

4.2.6 Component FEIe

After combining the previous two economic variable maps using an arithmetic averaging scheme, the resulting component FEIe (not scaled) can be seen in Figure 31 within the methodology section. Then the FEIe map was rescaled, from 0 to 1, using the positive maximum-minimum equation. The resulting figure can be seen in Figure 61.
The resulting map shown in Figure 61 is FEI_e. This map, just like its economic variable maps, tend to display high values of exposure closer to center of the project area and lower values as the census tracts are farther away from the center of the project area. The only exception can be found in the south-west quadrant of East Baton Rouge Parish is 68. The larger values can be seen in East Baton Rouge and Livingston Parish, which include the following census tracts: 46, 82, 83, and
107. The lowest values can be seen in both East Baton Rouge Parish in the west, south-west, and south-east quadrants and Livingston Parish in the east-south quadrant.

4.2.7 Indicator FEI_{DI}

To produce FEI_{DI}, the maps of FEI_{p}, FSI_{s}, and FSI_{e} were combined together using an arithmetic average scheme. The resulting map can be seen in Figure 30, which is located in the methodology section. FEI_{DI} map was then re-scaled, from 0 to 1, using the positive maximum-minimum equation. The resulting figure can be seen in Figure 62. The resulting map shown in Figure 62 is FEI_{DI}. This map is similar to the FEI component maps, tend to display high values of exposure along the Amite and Comite River networks and lower values as the census tracts are father away from the river networks. The larger values can be seen in East Baton Rouge and Livingston Parish, which include the following census tracts: 46, 82, and 107. The lowest values can be seen in East Baton Rouge Parish on the west to southwest quadrant of the project area.
4.3. During-Recovery Results:

To compute $FVI_{DR}$, the required during-recovery indicator was $FACI_{PF}$ along with the pre-flood indicator, $FSI_{PF}$, and during-impact indicator, $FEI_{DI}$. To further break this $FACI_{DR}$, the indicator can be broken down into the following components: $FACI_s$ and $FACI_e$. Lastly, these two components with both have two respective sets of variables.

4.3.1 Variables for Component $FACI_s$

The $FACI_s$ component can be broken down into the following variables: Kitchen, Plumbing, Disability, High School, Ratio of College to Highschool Degree, and Non-Violent Crimes. It
should be noted that due to adaptive capacity having an inverse relationship to vulnerability, these maps were derived using the positive maximum-minimum equation as oppose to FSI\(_{s,c}\) variables which used the negative max-min approach. The results for each of these variables can be seen below in Figure 62, Figure 63, Figure 64, Figure 65, Figure 66, and Figure 67, respectively. When looking at these figures, green areas indicate high adaptive capacity while areas in red show areas of low adaptive capacity. Each of these maps will be discussed using the following outline:

- The variables relationship to Flood Susceptibility (Positive or Negative?)
  - Positive ➔ Normalized using “positive” maximum-minimum scheme (Equation 5)
  - Negative ➔ Normalized using “negative” maximum-minimum scheme (Equation 6)

- For each Parish:
  - Identifying census tracts with high “variable” values
  - Identifying census tracts with low “variable” values
  - Identifying variability of “variable” census tract values
The first social variable of interest corresponds to the percentage of people with access to a working kitchen. In conclusion, the following can be said: The more people with access to kitchens, the more adaptive capacity that a community is to flooding. Since the two variables are positively related, the positive z-score formula was applied. Therefore, this map indicates that most of East Baton Rouge Parish’s census tracts achieve the lowest levels of adaptive capacity. Also, two of East Baton Rouge census tracts has the highest levels of adaptive capacity to flooding (40, 68, and 76) along with the highest variability of susceptibility levels amongst all the parishes. Ascension Parish, amongst all the census tracts, have medium to high levels of adaptive capacity.
along with the lowest variance of susceptibility. Livingston Parish falls in the middle in terms of both adaptive capacity levels and variability of susceptibility levels.

The second social variable of interest corresponds to the percentage of people with access to a plumbing. In theory, the following is said: The more people with access to plumbing, the more adaptive capacity that a community has to flooding. Since the variables are positively related, the positive z-score formula was applied. Therefore, this map indicates that most of East Baton Rouge Parish’s census tracts achieve the highest levels of adaptive capacity. Also, a couple of East Baton Rouge census tracts has the highest levels of adaptive capacity to flooding (40, 68, and 76) along with the highest variability of susceptibility levels amongst all the parishes. Ascension Parish,
amongst all the census tracts, have medium to high levels of adaptive capacity along with the lowest variance of adaptive capacity levels. Livingston Parish falls in the middle in terms of both susceptibility levels and variability of susceptibility levels.

The third social variable of interest corresponds to the percentage of people with disabilities. Regarding disasters, the following is said: The more people with disabilities, the less adaptive capacity that a community has to flooding. Since the variables are inversely related, the negative z-score formula was applied. Once the inverse z-score equation was applied, the term becomes the following: the number of people who do not have disabilities. Therefore, this map indicates that most of East Baton Rouge Parish’s census tracts achieve the highest levels of adaptive capacity.
(42 and 67). Also, several East Baton Rouge census tracts received the lowest levels of adaptive capacity to flooding along with the highest variability of adaptive capacity levels amongst all the parishes. Ascension Parish, amongst all the census tracts, have low to medium levels of adaptive capacity along with the lowest variance of adaptive capacity. Livingston Parish falls in the middle in terms of both adaptive capacity levels and variability of adaptive capacity levels.

The fourth social variable of interest corresponds to the number of people with high school degrees. The postulation here is that the more people with high school diplomas, the more adaptive capacity that a community has to flooding. Since the two variables are positively related, the
positive z-score formula was applied. Therefore, this map indicates that East Baton Rouge and Livingston Parish both have the highest and lowest levels of adaptive capacity. Ascension Parish falls in the middle in terms of their level of adaptive capacity but have the lowest variance of adaptive capacity levels.

Figure 67. The Rescaled “Ratio of College Degree to Highschool Degree” Map

The fifth social variable of interest corresponds to the ratio of people with college degrees to high school degrees. The conjecture here is that the more people with both a college degree and high school degree relative to just a high school degree, the more adaptive capacity that community has to flooding. Since they are positively related, the positive z-score formula was applied. Therefore, this map indicates that East Baton Rouge, Livingston, and Ascension parishes have the
lowest levels of adaptive capacity. However, Livingston Parish also has a couple of census tracts with the highest levels of adaptive capacity (99, 102, 104, and 112).

Figure 68. The Rescaled “Non-Violent Crimes” Map

The last social variable of interest corresponds to the percentage of non-violent crimes. In theory, the following is said: the more non-violent crimes there are, the less amount of adaptive capacity that a community has to flooding. Since they are inversely related, the inverse max-min formula was applied. Therefore, this map indicates that East Baton Rouge and Livingston both have the highest levels of adaptive capacity (for the most part); however, East Baton Rouge and Livingston Parish also has the lowest levels of adaptive capacity to flooding. Ascension Parish
falls in the middle in terms of their level of adaptive capacity but have the lowest variance of adaptive capacity levels.

### 4.3.2 Component FACIs

After combining the previous six social variable maps using an arithmetic averaging scheme, the resulting component FACIs, not scaled, can be seen in Figure 33 (top-left) within the methodology section. Then the FACIs map was rescaled, from 0 to 1, using the positive maximum-minimum equation. The resulting figure can be seen below in Figure 69.

![Figure 69. The Rescaled FACIs Map](image)

The resulting map shown in Figure 69 is FACIs. This map indicates that East Baton Rouge has the highest levels of adaptive capacity (68 and 69), the lowest levels of adaptive capacity (59), and the highest variability in adaptive capacity. Livingston also has the largest value level of
adaptive capacity (109) and the lowest level of adaptive capacity (104) but falls in the middle in terms of variability of susceptibility. Lastly, Ascension Parish both consistently the lowest levels of adaptive capacity along with variability of adaptive capacity levels.

4.3.3 Variables for Component FACI_e

The FACI_e component can be broken down into the following variables: Employment, Professional Occupation, Income, Banks, Worship, and NFIP. The results for each of these variables can be seen below in Figure 69, Figure 70, Figure 71, Figure 72, Figure 73, and Figure 74. Each of these maps will be discussed/analyzed using the following outline:

- The variables relationship to Flood Susceptibility (Positive or Negative?)
  - Positive ➔ Normalized using “positive” maximum-minimum scheme (Equation 5)
  - Negative ➔ Normalized using “negative” maximum-minimum scheme (Equation 6)
- For each Parish:
  - Identifying census tracts with high “variable” values
  - Identifying census tracts with low “variable” values
  - Identifying variability of “variable” census tract values
The first economic variable of interest corresponds to the percentage of employed people. The assumption here is the more people who are employed, the more adaptive capacity that a community has to flooding. Since they are positively related, the positive z-score formula was applied. Therefore, this map indicates that most of East Baton Rouge Parish’s census tracts achieve the highest levels of adaptive capacity. Also, some East Baton Rouge Parish census tracts have the lowest levels of adaptive capacity to flooding (40, 68, and 76) along with the highest variability of susceptibility levels amongst all the parishes. Ascension Parish, amongst all the census tracts, have medium to high levels of susceptibility along with the lowest variance of susceptibility. Livingston
Parish falls in the middle in terms of both susceptibility levels and variability of susceptibility levels.

The second economic variable of interest corresponds to the percentage of people who are professional occupants. The presumption here is the more people who are professional occupants, the more adaptive capacity that a community has to flooding. Since the variables are positively related, the positive z-score formula was applied. Therefore, this map indicates that most of East Baton Rouge Parish’s Census tracts achieve the highest levels of adaptive capacity. Additionally, some of the East Baton Rouge census tracts have the lowest levels of adaptive capacity to flooding (40, 68, and 76)
along with the highest variability of susceptibility levels amongst all the parishes. Ascension Parish, amongst all the census tracts, have medium to high levels of susceptibility along with the lowest variance of susceptibility. Livingston Parish falls in the middle in terms of both susceptibility levels and variability of susceptibility levels.

Figure 72. The Rescaled “Income” Map

The third economic variable of interest corresponds to per-capita income. The assertion here is the more per-capita income, the more adaptive capacity that a community has to flooding. Since the two variables are positively related, the positive z-score formula was applied. Therefore, this map indicates that most of East Baton Rouge Parish’s census tracts achieve the highest levels of
adaptive capacity. Also, a couple of East Baton Rouge census tracts have the lowest levels of adaptive capacity to flooding (40, 68, and 76) along with the highest variability of adaptive capacity levels amongst all the parishes. Ascension Parish, amongst all the census tracts, have medium to high levels of adaptive capacity along with the lowest variance of adaptive capacity. Livingston Parish falls in the middle in terms of both adaptive capacity levels and variability of adaptive capacity levels.

Figure 73. The Rescaled “Banks” Map

The fourth economic variable of interest corresponds to number of lending institutions. The postulation here is the more lending institutions, the more adaptive capacity that a community has to flooding. Since the variables are positively related, the positive z-score formula was applied.
Therefore, this map indicates that East Baton Rouge and Livingston parishes have the highest levels of adaptive capacity (for the most part); however, East Baton Rouge Parish also has the lowest levels of adaptive capacity to flooding. Ascension Parish falls in the middle in terms of their level of adaptive capacity but have the lowest variance of adaptive capacity levels.

The fifth economic variable of interest corresponds to the number of religious institutions. In theory, the following is said: The more religious institutions, the more adaptive capacity that a community has to flooding. Since the variables are positively related, the positive z-score formula was applied. Therefore, this map indicates that East Baton Rouge and Livingston parishes both have the highest levels of adaptive capacity; however, East Baton Rouge also has the lowest levels
of adaptive capacity to flooding. Ascension Parish falls in the middle in terms of their level of adaptive capacity but have the lowest variance of adaptive capacity levels.

Figure 75. The Rescaled “NFIP” Map

The last economic variable of interest corresponds to the percentage of non-violent crimes. In conclusion, the following is said: The more non-violent crimes there are, the less amount of adaptive capacity that a community has to flooding. Since these variables are inversely related, the inverse maximum-minimum formula was applied. Therefore, this map indicates that East Baton Rouge and Livingston parishes both have the highest levels of adaptive capacity; however, East Baton Rouge Parish also has the lowest levels of adaptive capacity to flooding. Ascension Parish
falls in the middle in terms of their level of adaptive capacity but have the lowest variance of adaptive capacity levels.

4.3.4 Component FACI_e

After combining the previous six economic variable maps using an arithmetic averaging scheme, the resulting component FACI_e (not scaled) can be seen in Figure 33 (bottom-left) within the methodology section. Then the FACI_e map was rescaled, from 0 to 1, using the positive maximum-minimum equation. The resulting figure can be seen below in Figure 76.

![Figure 76. The rescaled FACI_e map.](image)

The resulting map shown in Figure 76 is FACI_e. This map indicates that East Baton Rouge has the highest levels of adaptive capacity (11-19, 35, and 36), the lowest levels of adaptive
capacity (53, 65, and 88), and the highest variability in adaptive capacity. Livingston has medium levels of adaptive capacity (all census tracts) and lowest variability of adaptive capacity. Lastly, Ascension Parish both consistently the lowest levels of adaptive capacity (3) along with medium levels variability of adaptive capacity levels.

4.3.5 Indicator FACI_{DI}

To produce FACI_{DI}, the maps of FACI_{s} and FACI_{e} were combined using an arithmetic average scheme. The resulting map can be seen in Figure 34 which is located in the methodology section. FACI_{DR} map was then re-scaled, from 0 to 1, using the positive maximum-minimum equation. The resulting figure can be seen below in Figure 77.

Figure 77. The rescaled map of FACI_{DR}
The resulting map shown in Figure 77 is FACI\textsubscript{DR}. This map indicates that East Baton Rouge has the highest levels of adaptive capacity (17, 68, 69, and 17), the lowest levels of adaptive capacity (59, 66, and 94), and the highest variability in adaptive capacity. Majority of Livingston Parish census tract levels for adaptive capacity are low. Additionally, Livingston Parish has medium levels of variability of adaptive capacity. Lastly, Ascension Parish consistently has low levels of adaptive capacity and lowest levels of variability of adaptive capacity.

4.4. FVI Throughout the Disaster Risk Cycle:

The maps representing the resulting census tract values of FVI during the preparation (“Pre-Flood”; FVI\textsubscript{PF}) phase, response (“During-Impact”; FVI\textsubscript{DI}) phase, and recovery (“During-Recovery”; FVI\textsubscript{DR}) phase were computed using Equation 2a-2c, respectively. The subsequent step was rescaling all the formulated maps using the “positive” maximum-minimum equation (Equation 5). The rescaled results are displayed in Figure 78.

4.4.1 Pre-Flood FVI (FVI\textsubscript{PF})

Looking at the “Pre-Flood” phase FVI\textsubscript{PF} (Figure 78; left), these results represent the intrinsic vulnerability of the community; therefore, vulnerability is inherent to the community prior, during, and after the storm of interest (i.e., August 2016). East Baton Rouge Parish was one of the most inherently vulnerable parishes, relative to the August 2016 Flood, based off census tracts numbered 44, 68, and 83. This was due to FSI\textsubscript{e,p} expressing high values of social and economic susceptibility within East Baton Parish (Figure 38, 40, and 41). On the other hand, FSI\textsubscript{en,p} (Figure 51) displayed high values of physical and environmental susceptibility along the Amite and Comite river networks due to Flow Accumulation (Figure 45) and Distance to Drainage Network (Figure 46) thematic maps since the maps possessed the largest and second largest weightings, respectively (Table 1a). On the other hand, the parishes, Ascension and Livingston Parishes, scored average
levels of vulnerability during the “Pre-Flood” phase, which ranged from green to yellow. This was
due to both Livingston Parish and Ascension Parish having relatively low values of social and
economic susceptibility (Figure 38, Figure 43, and Figure 44). However, similarly to East Baton
Rouge Parish, both parishes have high values of physical and environmental susceptibility (Figure
51) due to the river networks as well. Since $FSI_{s,e}$ and $FSI_{en,p}$ were combined using a simple
arithmetic average (Equation 10), it makes sense that averaging a low and high value will result in
a medium value.

The reason for East Baton Rouge Parish being the most vulnerable parish is the level of
urbanization. The first side-effect from urbanization is increased levels of impervious areas (lowest
CN), which appears to be the most abundant in East Baton Rouge Parish. Another side-effect of
urbanization pertains to settlement patterns of communities. The two main settlement patterns
being densification and sprawling. Regarding central parts of urbanized cities, population
densification occurs. Within these census tract areas, they consist of populations with varying
social and economic levels of susceptibility. The most socially vulnerable census tracts consist of
the following: High counts of people over the age of 65 years old; high counts of people who are
a minority; and high counts of people without access to telephones. The most economically
vulnerable census tracts consist of the following: People without access to vehicles; people who
do not own a home; people who spend more than 30 percent of their income on housing; and
density of principal non-arterial miles. Last thing about people who live within the urbanized
census tracts are the larger amounts of impervious areas, resulting in higher levels of physical
susceptibility. On the other hand, they tend to live farther away from the FEMA flood zones so
they have smaller levels of environmental susceptibility. The second portion of settlement patterns
pertain to people of (typically) lower income status who choose to save money by sprawling to the
suburbs. This plan sufficiently minimizes social and economic vulnerability, which can be identified by looking at the “inverse” of variables mentioned during the first settlement pattern type: densification. However, these decreases in social and economic susceptibility were offset by increases in both physical and environmental susceptibility. Suburban homes are settling closer to the Amite Comite River networks, resulting in higher values flood susceptibility.

4.4.2 “During-Impact” FVI (FVI\textsubscript{DI})

Looking at the “During-Impact” phase, FVI\textsubscript{DI}, it is apparent that East Baton Rouge Parish is the most vulnerable parish by looking at the following census tracts: 44, 68, and 83. It is also apparent that the FVI value computed during this phase consist of the largest possible values throughout the disaster risk cycle. The reason being FVI\textsubscript{DI} (Figure 62) shows high values of exposure along the Amite & Comite River networks and was combined with FSI\textsubscript{PF} (Figure 52), which displays high values of susceptibility closer to Louisiana State University and downtown Baton Rouge. As previously discussed, in Figure 62, the higher exposure values mainly congregate near the center of the project area and quasi-along the river networks. This behavior is apparent when comparing the “Pre-Flood” (left) and “During-Impact” (middle) maps within Figure 78. The next parish of interest was Livingston, which also had high vulnerability levels near the center of the project area (106-108) and along the Amite River after the river junction (109 and 112).

4.4.3 “During-Response” FVI (FVI\textsubscript{DR})

Looking at the “During-Response” phase FVI, it is apparent that FVI\textsubscript{DR} spatially varies with respect to FVI\textsubscript{DI}. Additionally, it should be noted that the ranges of FVI found within this phase fall in between the values of FVI produced within the “Pre-Flood” and “During-Impact” phases. These observations were deducted based off the contribution of the FACI\textsubscript{DR} map, which reduced the community vulnerability within the project area during the recovery phase of the disaster risk.
cycle. As previously discussed in Figure 77, the higher adaptive capacity values were mainly in East Baton Rouge Parish near the western-southern portion. On the other hand, relative to EBR Parish, lower values of adaptive capacity for Livingston Parish were located near the western quadrant of the parish along the Amite River network. This behavior is apparent when comparing the “During-Impact” (middle) and “During-Recovery” (right) maps located in Figure 78.

The reason for East Baton Rouge Parish having the highest levels of adaptive capacity is due to urbanization. An interesting observation to make is that urbanization positively influences adaptive capacity. The general reason for this is because urbanized areas tend to have the following: greater connectivity; more money for hazard relief; more post-disaster shelters with adequate water and food supplies; more lending institutions; more houses covered by the National Flood Insurance Program (NFIP); and finally, places to worship and/or relate to other people in times of post-disaster where people need to cope from high social and economic stresses.
Figure 78. FVI mapped throughout the first three phases of Disaster Risk Cycle: Preparedness, Response, and Recovery
5. CONCLUSION

In the field of flood risk assessments, the increasingly popular topic of integrating phase-dependent social and economic dimensions of flood vulnerability to pre-existing flood risk assessments have significantly increased in popularity in recent years. Therefore, this study outlined an integrative method for assessing community vulnerability to urban flooding through use of multiple data types such as census data and flood modeling. The results were rescaled and combined using a map overlaying tools provided within ArcGIS. Integration of various data types computed during various phases of the disaster risk cycle were conducted to reveal the phase-specific, extrinsic/intrinsic, and multidimensional properties of vulnerability throughout the disaster risk cycle.

The pre-flood FVI identified the communities intrinsic, or inherent, vulnerability, which can be found prior to any hazard introduced. High levels of pre-flood FVI were mainly found in East Baton Rouge Parish. It was apparent that there were strong correlations between vulnerability and urbanization. Urbanization results in communities going through the following: population densification in urban areas and population sprawling in suburban areas; ethnic and financial segregation; increase in impervious area, etc. Such listed, and more unlisted, factors drive community vulnerability which was apparent in East Baton Rouge Parish. Going from pre-flood to during-flood FVI, the census tracts with high levels of vulnerability shifted from just East Baton Rouge to any census tracts along the Amite and Comite River network. This shift is logical because the during-flood FVI considers FEI\textsubscript{DI} on top of FSI\textsubscript{PF}, which represents the external vulnerability introduced to the community by the August 2016 flood. Lastly, going from during-impact to during-recovery FVI, it was apparent that East Baton Rouge has the largest adaptive capacity. East Baton Rouge Parish was the most “successful” parish in terms of reducing community
vulnerability, which can be seen by comparing the middle and right maps in Figure 78. On the other hand, Livingston and Ascension Parish hardly reduced their vulnerability from the during-impact to during recovery phases of the disaster risk cycle; thus, those two parishes have smaller levels of adaptive capacity relative to East Baton Rouge Parish.

In the present study, some major limitations appeared and are worth noting. These limitations were discovered during the execution of indicator-comparisons whose normalization were based on the maximum-minimum technique. The selection of these values has shown to be the most difficult step of the methodology due to the users lack confidence of determining whether the variables truly depict a community’s flood vulnerability. Additionally, the method used for producing and integrating these indicators could significantly influence the result and thus should be studied further. Lastly, due to uniqueness of this work along with the extensive amounts of indices, indicators, components, and variables used within this thesis, producing a validation procedure was very difficult. If validation procedures were identified (i.e., visually comparing FEI maps to direct consequence maps produced from HEC-FIA), the procedures still failed to provide a compelling justification for accuracy of indices, indicators, components, and variables maps produced.

The method for assessing community flood vulnerability, to the August 2016 flood, took place in portions of Ascension Parish, East Baton Rouge Parish, and Livingston Parish located within the Amite River Basin, Louisiana; however, it could be used in other flood-prone cities due to its strong replicability. Additionally, due to the composition of the exposure portion of this methodology, the methodology can potentially be applied to hazard scenarios consisting of at least one of the following: consecutive storms and/or combined fluvial and storm surge. The potential
paper for determining a community’s vulnerability and risk to compound-flooding can be seen in Bilskie & Hagan, 2018.

There are two interesting points within the paper: 1.) Three inundation cases, consisting of fluvial, storm surge, and combined inundation maps, were produced and 2.) The inundation data was time dependent. In theory, this could allow for the following things to happen: Make FEI$_{DI}$ time dependent; less confusion with integrating CCA into DDR, due to the contribution of sea-level rise to previously used rainfall, which are both related to climate change; and the ability to plot three FVI$s$ corresponding to each of the phases of the disaster risk cycle for the following exposure cases: Fluvial, storm surge, and combined inundation maps. The biggest issues with incorporating storm surge consist of the following: Determining the fluvial, storm surge, and composite “combined” probabilities that the hazard is occurring, $P_H$. Additionally, if considering impacts of climate change, should both fluvial and storm surge be adjusted? If so, what climate change projections would be used? And how would the “combined” value be determined? Hopefully these are questions that can be addressed in future flood risk assessment research.

The results of this study can guide urban managers and policymakers on community flood management. These results revisit the gaps in current flood measures and provide guidance to identify vulnerability. Further validation of the assessment results is required in future studies, including those on flood simulation and vulnerability.
### APPENDIX A. HUMAN WELLBEING DATA

Table A-1: Human Wellbeing Variables (Moles, Birch, Chan, Yang, Zhu & Cherry, 2020)

<table>
<thead>
<tr>
<th>Community stress</th>
<th>Variable</th>
<th>Sources</th>
<th>Justification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>% population that is not elderly</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>% population that doesn’t speak English as a second language</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>% population without a disability</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>% population that is not a minority</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>% population with at least a high school diploma</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>% of population that are &lt;18</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Child care programs per 1000 population</td>
<td>Louisiana Department of Education</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Ratio % college degree to % no high school diploma</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Religious organizations per 1000 population</td>
<td>Reference USA</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Social advocacy organizations per 1000 population</td>
<td>Reference USA</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>% population with vehicle access</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>% population with telephone access</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>Community services (Historic Sites, Libraries, Museums) per 1000 population</td>
<td>Reference USA</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Vacancy rate</td>
<td>2016 ACS</td>
<td></td>
</tr>
</tbody>
</table>

**Economic health**

<table>
<thead>
<tr>
<th>Economic health</th>
<th>Variable</th>
<th>Sources</th>
<th>Justification</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>% of households spending &lt;30% of income on housing</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>% homeownership</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>% working-age population that is employed</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>Per capita household income</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>Leasing institutions per 1000 population</td>
<td>Reference USA</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>Payday loans per 1000 population</td>
<td>Reference USA</td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>% workforce employed in professional occupations</td>
<td>2016 ACS</td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>Hazard-related financial stress – flood insurance</td>
<td>Louisiana Watershed Resilience Study (FEMA)</td>
<td></td>
</tr>
<tr>
<td>Environmental health</td>
<td>Built environment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>----------------------</td>
<td>-------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>23</td>
<td>% population living in high-intensity urban areas (ratio of road density/population density)</td>
<td>2016 ACS/DOT</td>
<td>Gels and Rutzmark (1995)</td>
</tr>
<tr>
<td>24</td>
<td>% of population with more than 1.5 occupants per room</td>
<td>2016 ACS</td>
<td>Economic Innovation Group (2017)</td>
</tr>
<tr>
<td>26</td>
<td>% land area that is developed open space</td>
<td>2011 NLCD</td>
<td>Gels and Rutzmark (1995)</td>
</tr>
<tr>
<td>27</td>
<td>Sidewalks</td>
<td>ADA compliant sidewalks from EBR Parish GIS</td>
<td>Corburn (2015)</td>
</tr>
<tr>
<td>28</td>
<td>Impervious surfaces</td>
<td>2011 NLCD</td>
<td>Lundgren and Jenson (2013)</td>
</tr>
<tr>
<td>29</td>
<td>Dedicated cycling trails</td>
<td>Bike BR</td>
<td>Cox et al. (2010)</td>
</tr>
<tr>
<td>Natural environment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>% land area that does not contain erodible soils</td>
<td>USDA NCRS</td>
<td>Bradley and Grainger (2004)</td>
</tr>
<tr>
<td>31</td>
<td>% land area not in an inundation zone (100-year flood plain)</td>
<td>2016 FEMA</td>
<td>Cutter et al. (2008a)</td>
</tr>
<tr>
<td>32</td>
<td>% land area that is nondeveloped forest</td>
<td>2011 NLCD</td>
<td>Cutter et al. (2008a)</td>
</tr>
<tr>
<td>33</td>
<td>% land area with no woodland decline</td>
<td>2011 NLCD</td>
<td>Cutter et al. (2008a)</td>
</tr>
<tr>
<td>35</td>
<td>% land area that is arable cultivated land</td>
<td>2011 NLCD</td>
<td>United Nations Department of Economic and Social Affairs (2007)</td>
</tr>
<tr>
<td>36</td>
<td>Access to parks (Access to areas of public open space, Appearance of public areas)</td>
<td>EBR Parish GIS, Ascension Parish GIS, and hand digitization</td>
<td>Cox et al. (2010)</td>
</tr>
<tr>
<td>37</td>
<td>Tree canopy</td>
<td>2011 NLCD</td>
<td>Corburn (2015)</td>
</tr>
<tr>
<td>Public Safety</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>Presence of complete kitchen facilities</td>
<td>2016 ACS</td>
<td>Economic Innovation Group (2017)</td>
</tr>
<tr>
<td>41</td>
<td>Doctors and medical professionals per 1000 population</td>
<td>2016 ACS</td>
<td>Cutter et al. (2010)</td>
</tr>
<tr>
<td>42</td>
<td>% households covered by National Flood Insurance Program policies</td>
<td>2017 FEMA</td>
<td>Cutter et al. (2010)</td>
</tr>
<tr>
<td>43</td>
<td>% workforce employed in emergency services (firefighting, law enforcement, protection)</td>
<td>2016 ACS</td>
<td>Cutter et al. (2008b)</td>
</tr>
</tbody>
</table>
APPENDIX B. LULC EXCEL EQUATIONS

The excel formulas used to derive each of these CN values can be seen in the series of equations below:

For CN(A):

\[
C2 = IF(AND(A2=5, B2="A"), 37, IF(AND(A2=4, B2="A"), 60, IF(AND(A2=3, (B2="A")), 54, IF(AND(A2=2,B2="A"), 77, IF(AND(A2=1, B2="A"),100,0)))),)
\]

For CN(B):

\[
D2 = IF(AND(A2=5, B2="B"), 61, IF(AND(A2=4, B2="B"), 73, IF(AND(A2=3, (B2="B")), 70, IF(AND(A2=2,B2="B"), 85, IF(AND(A2=1, B2="B"),100,0)))),)
\]

For CN(C):

\[
E2 = IF(AND(A2=5, B2="C"), 74, IF(AND(A2=4, B2="C"), 82, IF(AND(A2=3, (B2="C")), 80, IF(AND(A2=2,B2="C"), 90, IF(AND(A2=1, B2="C"),100,0)))),)
\]

For CN(D):

\[
F2 = IF(AND(A2=5, B2="D"), 80, IF(AND(A2=4, B2="D"), 85, IF(AND(A2=3, (B2="D")), 86, IF(AND(A2=2,B2="D"), 92, IF(AND(A2=1, B2="D"),100,0)))),)
\]
For CN(A/D):

\[ G2 = \text{IF(AND(A2=5, B2="A/D"), AVERAGE(37, 80), IF(AND(A2=4, B2="A/D"), AVERAGE(60, 85), IF(AND(A2=3, B2="A/D"), AVERAGE(56, 86), IF(AND(A2=2, B2="A/D"), AVERAGE(77, 92), IF(AND(A2=1, B2="A/D"), 100, 0))))}) \]

For CN(B/D):

\[ H2 = \text{IF(AND(A2=5, B2="B/D"), AVERAGE(61, 80), IF(AND(A2=4, B2="B/D"), AVERAGE(73, 85), IF(AND(A2=3, B2="B/D"), AVERAGE(70, 86), IF(AND(A2=2, B2="B/D"), AVERAGE(85, 92), IF(AND(A2=1, B2="B/D"), 100, 0))))}) \]

For CN(C/D):

\[ I2 = \text{IF(AND(A2=5, B2="C/D"), AVERAGE(74, 80), IF(AND(A2=4, B2="C/D"), AVERAGE(82, 85), IF(AND(A2=3, B2="C/D"), AVERAGE(80, 86), IF(AND(A2=2, B2="C/D"), AVERAGE(85, 92), IF(AND(A2=1, B2="C/D"), 100, 0))))}) \]

Once all the sub-CN\textsuperscript{s} have been computed, then you need to determine the composite CN, which was done using the following equation:

For CN:

\[ J2 = \text{SUM(C2:I2)}. \]
APPENDIX C. EXPORTING INUNDATION MAPS USING RAS MAPPER

The first step is to open Dewberry’s HEC-RAS model and open the RAS Mapper portion of the model. Then, within RAS Mapper, go to the tool menu and select “Manage Map Results”. This results in the “Manage Results Maps” dialog box to open. From the table, click “Add New Map”, which results in the dialog box to open up. The dialog box can be seen in the Figure below.

To create a maximum depth grid, from the “Map Type” list box, select depth. From the “Unsteady Profile” box, select “Maximum”. From the “Map Output Mode” box, select “ Stored Raster—using current terrain as layout”.

Figure C.1. Dialog box for exporting 1
APPENDIX D. STEPS FOR DURING-FLOOD INDEX (DETAILED)

Note: All computations for developing components, indicators, and indices will be done in ArcGIS (ArcMap). Also, the method for combining indicators is uncertain and should be looked at by a statistician.

Figure D.1. Detailed FVI_DJ methodology.
APPENDIX E. GENERAL ARCGIS STEPS FOR FEI’s COMPONENTS.

Once data collection is complete, the first step is to insert the following files into ArcGIS: Amite Inventory Shapefile (Amite_Structure_Inventory_NAVD88.shp), direct consequence, from the August 2016 flood, shapefile produced from HEC-FIA (EconResults.shp), and census tract boundary shapefile of the project area (Well-being.shp). Before any other steps are performed, the two shapefiles should be clipped to the project area’s extent by using the “clip analysis” tool. The next thing is joining the two tables together – note, this is very important because the resulting shapefile will only contain the structure inventory parameters that were exposed during the August 2016 flood. In order to properly join these two tables, right click on EconResults_Clip.shp and select join. A dialog box will open, which can be seen in Figure E.1.

Figure E.1. Dialog box for joining using.
The most important portion of this figure is the “Keep only matching records” setting. The resulting point-shapefile is called “FlowDepth_PlusFH_AVGandSUM.shp”. The reasoning for the naming convention was because after joining the two point-shapefiles, it was observed that the flow depths were measured relative to the foundation height. Therefore, a new field was created, which essentially combined the flow depth plus the foundation height for each point structure. This calculation made the reference datum for all flow depths relative to the ground surface.

For FEI in general, it is desired to have all variables computed on the census tract level by means of averaging or summation, depending on the variable of interest. The point-variables that need to be summed include the following: building/car count, economic value of buildings, economic value of cars, total population under 65, and total population over 65 years old. The point-variable that needs to be averaged are the flood depths originating from the economic results shapefile on the census tract level. Therefore, the next step pertains to another join, in particular, a spatial join. This was completed by right clicking on “Well-being.shp” and opening a dialog box, which can be seen in Figure E.2.

![Figure E.2. Dialog box for a spatial join](image-url)
REFERENCES


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VITA

Austin Scott Guerin was born and raised in Baton Rouge, Louisiana with his parents, Scott Guerin and Debra Guerin, and his younger sister Alden. Growing up in Baton Rouge, Austin became interested in science and especially in coastal activities associated with the Mississippi River. Austin attended Louisiana State University (LSU), where his younger sister, both of his parents, and extended family all attended. Austin received a B.S. degree in Civil Engineering May 2019. Austin worked part-time as a Graduate Research Assistant for Dr. Clinton Willson during his first two years of graduate school. Austin then proceeded to accept a job at W.F. Baird and Associates doing coastal restoration projects.

In August 2019, Austin started graduate school for Civil and Environmental Engineering at LSU. Austin met Dr. Clinton Willson in Spring of 2018, and began working for him in August 2020 as a graduate assistant; where he was able to conduct his thesis research in the Flood Risk Assessments. He plans to receive his Master’s degree in August 2021. After completion of his M.S. degree, Austin plans on starting his career as a Coastal Engineer, preserving wetlands all over the world.