2050 Puerto Rico
Plan de Transportación
Multimodal a Largo Plazo

Appendix:

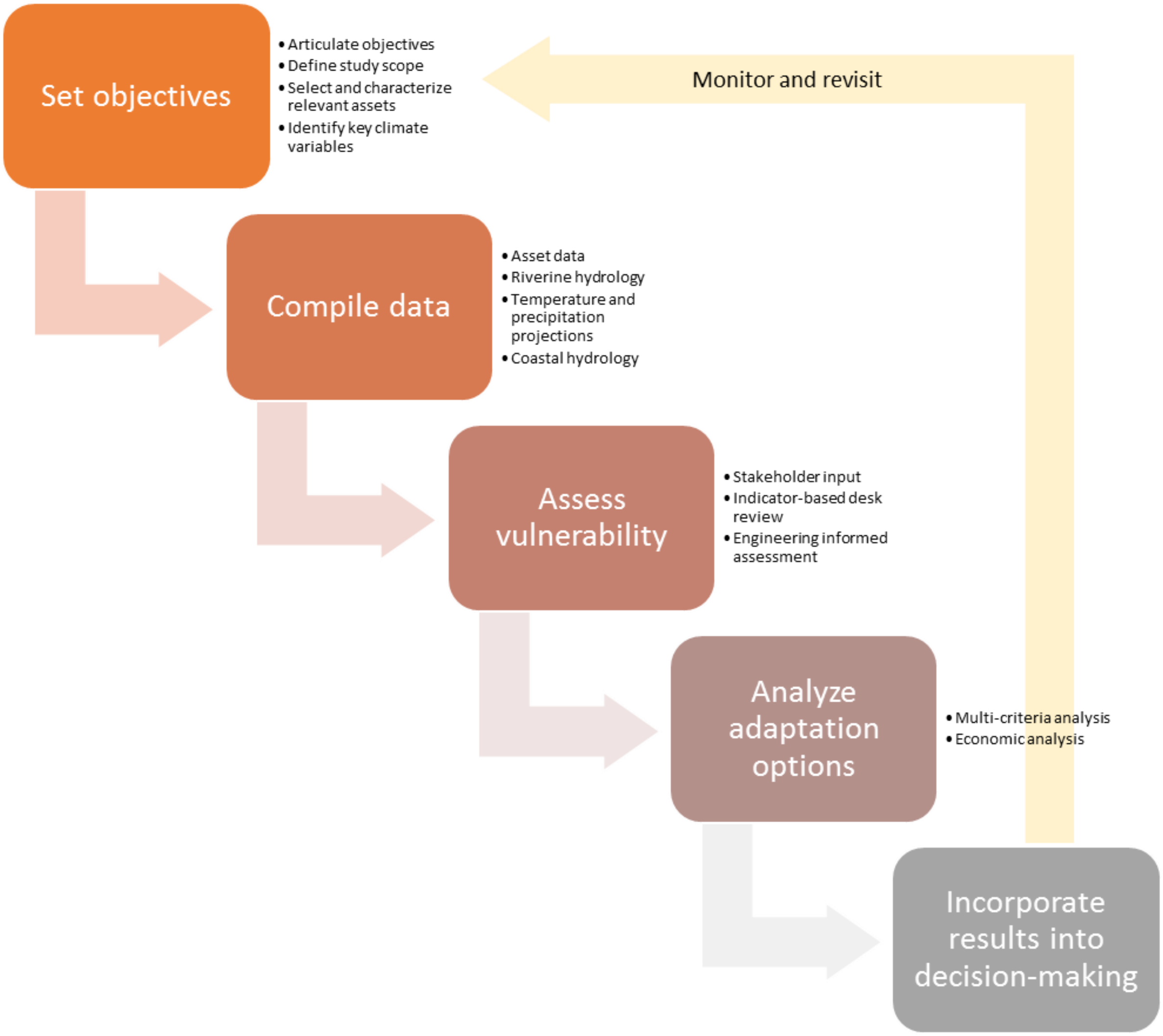
Chapter 6- Resilience Component for the Long Range Transportation Plan

I APPENDIX I - RESILIENCE COMPONENT FOR THE LONG-RANGE TRANSPORTATION PLAN

VULNERABILITY ASSESSMENT AND ADAPTATION FRAMEWORK

Federal Highway Administration developed a manual to conduct vulnerability analysis to transportation systems and incorporate actions into decision making. This section presents a brief description of each step of the framework and is summarized in Figure I.1. For a complete explanation and examples please refer to The Framework's document in (Federal Highway Administration, 2017).

Figure I.1: Steps of the Vulnerability Assessment and Adaptation Framework



Source: SDG based on (Federal Highway Administration, 2017)

Set Objectives

The first step of the framework is to define the objectives and scope of the vulnerability analysis. The analysis' scope may be defined in terms of (Federal Highway Administration, 2017):

- Level of detail required for decision-making: A vulnerability assessment is usually developed to support certain action over assets. This can be as general as to define annual budget for maintenance of the transportation system, or as granular as to define the best cost-benefit reinforcement alternative for a bridge. Depending on the level of granularity of the decision, is the level of detail required for the vulnerability analysis.
- Motivation for the study: If there is a particular reason why the vulnerability analysis is needed, or required by an authority, then this will set the parameters for the assessment. For example, in Puerto Rico, Hurricane María unveiled the need for greater vulnerability

examination. Therefore, hurricane hazard should define the scope of the study, in terms of climate variables included.

- Constraints: If there are any constraints in terms of time, resources, range of expertise, availability of data, or any other; these would directly impact the scope of the vulnerability assessment.

Including other considerations such as previous studies in the area or analysis conducted by other agencies, may also expand or limit the scope of the vulnerability assessment.

The output of this first step should at least include:

- Relevant assets and define which characteristics of such assets will be included in the assessment; and
- Key climate variables to study.

For this study 49 critical segments were identified by stakeholders and the climate variables focused on rainfall, landslides and floods. In the next chapter this is explained in detail.

Compile Data

Once the scope of the study is clear, the next step is to gather the required data of the assets and the key climate variables. The type of data collected should be consistent with the level of detail and scope defined in the previous step. This might be a challenging task since usually different pieces of information are hold by different agencies and therefore, they differ in scale, age, quality and extent (Federal Highway Administration, 2017).

To gather the appropriate amount of data, it is required to start collecting it from the beginning of the study. Common sources are:

- Local government;
- Agencies (including operations, maintenance, planning, etc.);
- Universities;
- Existing data; and
- If resources are available, collect regarding data on the field.

Finally, it is a good practice to use Geographic Information Systems (GIS) to collect, share and analyze data. This practice facilitates discussions with different experts, doing multi-layer analysis and reporting.

For this analysis data was collected regarding hazards (landslides and floods) and the infrastructure from different agencies (e.g., National Weather Service, Highway and Transportation Authority, FEMA, NOOA and Puerto Rico main stakeholders). In the next chapter the gathered information is presented, most of it in GIS format.

Assess Vulnerability

According to (Federal Highway Administration, 2017) vulnerability in transportation analysis depends on system's Exposure to climate events, Sensitivity to disruption due to climate and Adaptive Capacity of the system. Exposure is defined in terms of the intensity of the previously defined climate variables on the location of the asset (or system) being evaluated. On the other hand, Sensitivity is related to the magnitude of disruption (if any) when the asset (or system) is exposed to climate change events. Finally, Adaptive Capacity is a systems' level measure; it represents how the system as a unity is affected by a disruption.

The framework is flexible to the level of detail for the vulnerability assessment and the resources available, with three different approaches for assessing vulnerability:

- Stakeholder input approach: This is a qualitative analysis based on practitioners' knowledge. It is developed through workshops and surveys, where experts are asked to identify climate variables, Exposure, Sensitivity and Adaptive Capacity based on the knowledge they have regarding the asset (or system) in maintenance, operations, emergency management and/or engineering. This approach is recommended for analysis of assets that have not been previously assessed.
- Indicator-based desk review approach: This is a data-driven approach, where data is used to develop models and score each of the components of vulnerability. Therefore, data from climate variables are used to create climate projections and measure Exposure. Then, data regarding the asset is collected to measure Sensitivity; and data regarding system's behavior before and after a disruption is used to measure Adaptive Capacity. Finally, vulnerability is quantified as a combination of previous scores. Even though this is a data-driven analysis, stakeholders from different fields should be involved during the process, due to uncertainties within models and lack of data that might not represent the conditions for every asset. This approach is recommended as a scanning tool, to identify system-wide vulnerabilities and support system's level decision-making.
- Engineering informed assessments: This is a quantitative, asset-specific analysis. This type of analysis provides a better insight of specific assets' vulnerabilities than the indicator-based one. It can be used to measure effectiveness of different type of mitigation strategies, and can be incorporated into a cost-benefit analysis. This approach requires (Federal Highway Administration, 2017):
    - Understand site context and future climate;
    - Test the asset against future climate scenarios;
    - Develop, evaluate, and select adaptation measures;
    - Review additional considerations; and
    - Monitor and revisit as needed.

For this study, a combined approach was selected joining the "Stakeholder input approach" d with data-based analysis, since enough information regarding climate variables was available. A thorough explanation in exposed in the next chapter.

Analyze Adaptation Options

Once vulnerabilities are identified, the next step is to recognize, analyze, and prioritize adaptation options. The adaptation or mitigation activities can be natural, structural, or policy-based, depending on which type of approach was developed in the previous step (site-specific or system-wide). The Framework proposes two approaches:

- Multi-criteria analysis (MCA): Comparison of adaptation options across qualitative and quantitative criteria; and

- Economic analysis: Cost-benefit evaluation that allows to analyze long-term benefits of each adaptation option.

A stakeholder approach is used in this study, since a detailed financial analysis for vulnerability mitigation was outside of the scope of the Lon Range Transportation Plan.

Incorporate Results into Decision-Making

The framework considers this additional step, where the vulnerability analysis is incorporated into transportation programs. The data collected during this type of analysis and conclusions might enrich other processes that are part of transportation engineering. The framework identifies the following processes where vulnerability results might be considered:

- Transportation planning;
- Project development and environmental review;
- Project level design and engineering;
- Transportation systems management, operations, and emergency management; and
- Asset management

Finally, it is important to define policies for re-assessment and monitor relevant climate variables and assets identified during the vulnerability assessment.

This step was not included in this analysis because it is outside the scope of this analysis.

OBJECTIVES AND SCOPE OF THE ANALYSIS

Key Climate Variables

The incorporation of resilience and vulnerability analysis into transportation planning is a relatively new task, fostered by awareness of climate change and the consequences it might have to transportation infrastructure. Therefore, many municipalities are beginning to incorporate it into their studies. This is the case of Puerto Rico, where there is not a previous system-wide vulnerability assessment of transportation infrastructure for system planning. However, awareness of climate change has been part of planning in the island due to regular hurricanes impacting it. This is noticeable by the several weather stations installed throughout the island, storm surge NOAA analysis, landslide susceptibility map, flood susceptibility map, among other data related to climate change that is currently available.

The key climate variables identified for this analysis are:

- Landslides in Hurricane María;
- Flooding data;
- Weather stations;
- Rainfall historic data;
- Slope;
- River map;
- Land use;
- Susceptibility to landslides;

- Infrastructure damage due to Hurricane María; and
- Coastal floods.

Relevant Assets

Data availability of transportation assets' Sensitivity is not as structured as weather historical conditions; however, practitioners in operations and maintenance of transportation infrastructure hold valuable knowledge regarding these assets and their Sensitivity to the climate variables.

Additionally, the last event revealed vulnerabilities of the transportation system that current practitioners might have not seen before. Therefore, the relevant assets were identified throughout a series of workshops with stakeholders.

Stakeholders from different areas of expertise and regions were selected to be part of the identification task. The attendees included members of:

- Highway and Transportation Authority:
  - Environmental studies;
  - Soil engineering; and
  - Emergency planning.
- Multimodal Transportation Planning;
- Federal Highway Administration;
- Emergency interagency branch – South region;
- Transportation agency – East region;
- Transportation agency – Metropolitan;
- Transportation agency – Mayaguez region; and
- Transportation agency – North region.

The identification of relevant assets was developed in three stages:

Introduction to the Vulnerability Assessment and Adaptation Framework. This meeting was held on February 7th, 2018. The Framework was explained by the Federal Highway Administration focused on the indicator-based approach and the VAST tool. Later, the consultancy team explained the scope of the study and the survey sent to stakeholders.
Survey for identification of relevant assets. A survey regarding asset characteristics was sent to each participant agency, the objective was that each identified at least five relevant assets for each hazard (landslides and floods). For each asset included in the list, the stakeholders were asked the following questions:

- Name of the asset;
- Municipality;
- Location;
- Length;
- Is it a coastal road?;
- Type of facility:
  - State road;
  - Municipality road;
  - Bridge;
  - Tunnel;

  - Viaduct;
  - Recreative road; and
  - Other.
- Relevance of the asset:
  - Important connection;
  - High demand;
  - Evacuation route; and
  - Other.
- Land use near asset:
  - Residential;
  - Services;
  - Commercial;
  - Industrial;
  - Agriculture;
  - Cattle raising;
  - Protected area; and
  - Other.
- Type of disruptive climate events – landslide:
  - Erosion;
  - Scouring; and
  - Other.
- Type of disruptive climate events – flood:
  - Overflow of water body;
  - Surge;
  - Rainfall;
  - Urban flood; and
  - Other.
- Frequency of disruptive climate events:
  - Rarely;
  - Sometimes;
  - Often; and
  - Usually.
- Magnitude of disruption:
  - Total failure;
  - Temporary closure; and
  - Reduction of capacity (without closure).
- Asset age;
- Remnant lifespan;
- Elevation;
- Number of repairs per year;
- Type of regular repair:
  - Temporary repair;
  - Definite repair; and
  - Other.

- Approximate cost of repair;
- Year of last repair;
- What are the mitigation actions usually implemented for this type of climate event; and
- Additional comments.

Revision of identified segments: A total of 19 segments were identified by the stakeholders before the last workshop. The information and location of each asset were consolidated and the results shown in a third workshop. In this meeting there was a discussion of relevance and state of each segment. As a result, the location of some of the identified segment was rectified and new segments were included, for a total of 49 segments for the analysis.

DATA COMPILATION

Hazard

Flooding and landslide have rainfall as common trigger, therefore gathering information regarding historical records for precipitation levels becomes paramount for hazard analysis in the Long-Range Transportation Plan.

The National Weather Service gathers and maintain 135 weather stations in Puerto Rico and the data collected is available online in (National Weather Service, 2017). For this study, we gathered the historical annual and monthly mean precipitation data from 1981 to 2010 for all the weather stations. Also, the National Weather Service published online the estimated rainfall data during Hurricane María.

The data is available in text format. However, as the Framework recommends, it is better to manage data in GIS format. For this reason, each weather station was geo-referenced and then, the historical precipitation data was assign to each station location. After this adjustment, only 91 out of 135 stations have enough historical data and those were selected to represent rainfall behavior on the island (see Figure I.2 below).

Figure I.1: 91 Weather Stations of the National Weather Service

Source: SDG based on locations available

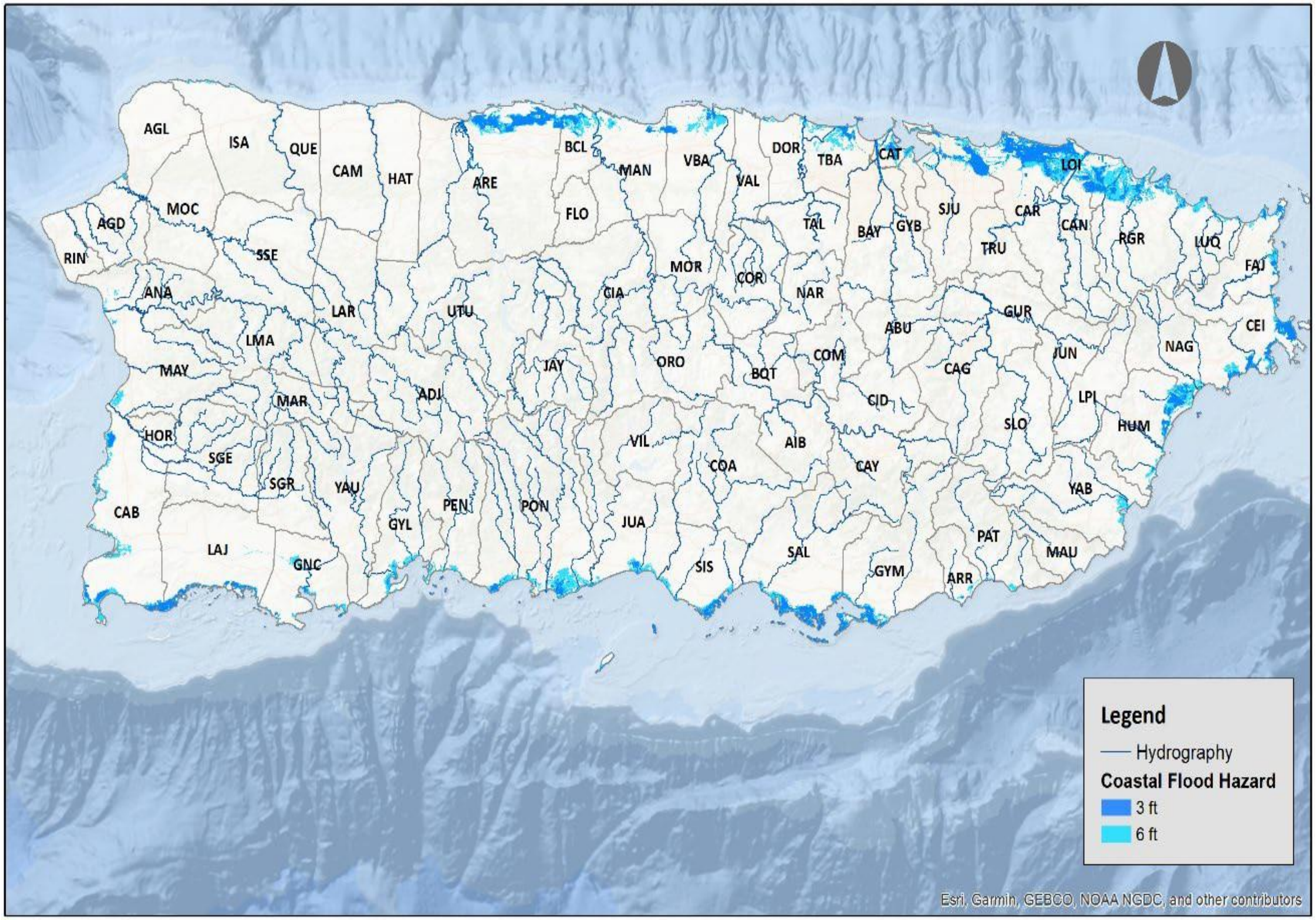
Floods

The Federal Emergency Management Agency (FEMA) has dedicated their efforts to map the flood hazard from statistical information, including data of river flow, storm tides, hydrologic/hydraulic analyses, rainfall and land surveys. Their results are the basis of the National Flood Insurance Program (NFIP) and flood insurance requirements, being the most accurate source to guide mitigation actions and hazard analysis studies (FEMA, 2018). For this reason, this information is known as Flood Insurance Rate Map (FIRM) and define the areas subject to inundation by the 1% annual chance flood (100-year flood or base flood), classified on these types of zones (FEMA, 2017):

- Zone A: No base flood elevation determined;
- Zone A99: Areas that will be protected by a Federal flood control system where construction has reached specified legal requirements;
- Zone AE: Base flood elevation determined;
- Zone AH: Flood depths with an average depth ranging from one to three feet (usually areas of ponding); Base flood elevation determined;
- Zone AO: River or stream flood hazard areas with an average depth ranging from one to three feet; and
- Zone VE: Coastal flood zone with velocity hazard (wave action); base flood elevation determined.

The FIRM map for Puerto Rico can be obtained from the Planning Board page (Junta de Planeación, 2017). Due to the level of detail for the construction of this map, and the level of detail needed in the vulnerability assessment, this data was selected to represent the flood hazard. Similarly, for coastal floods, the coastal flood frequency by the National Oceanic and Atmospheric Administration (NOAA, 2017) was used as shown in Figure I.3.

Figure I.3: Coastal Flood Hazard Map



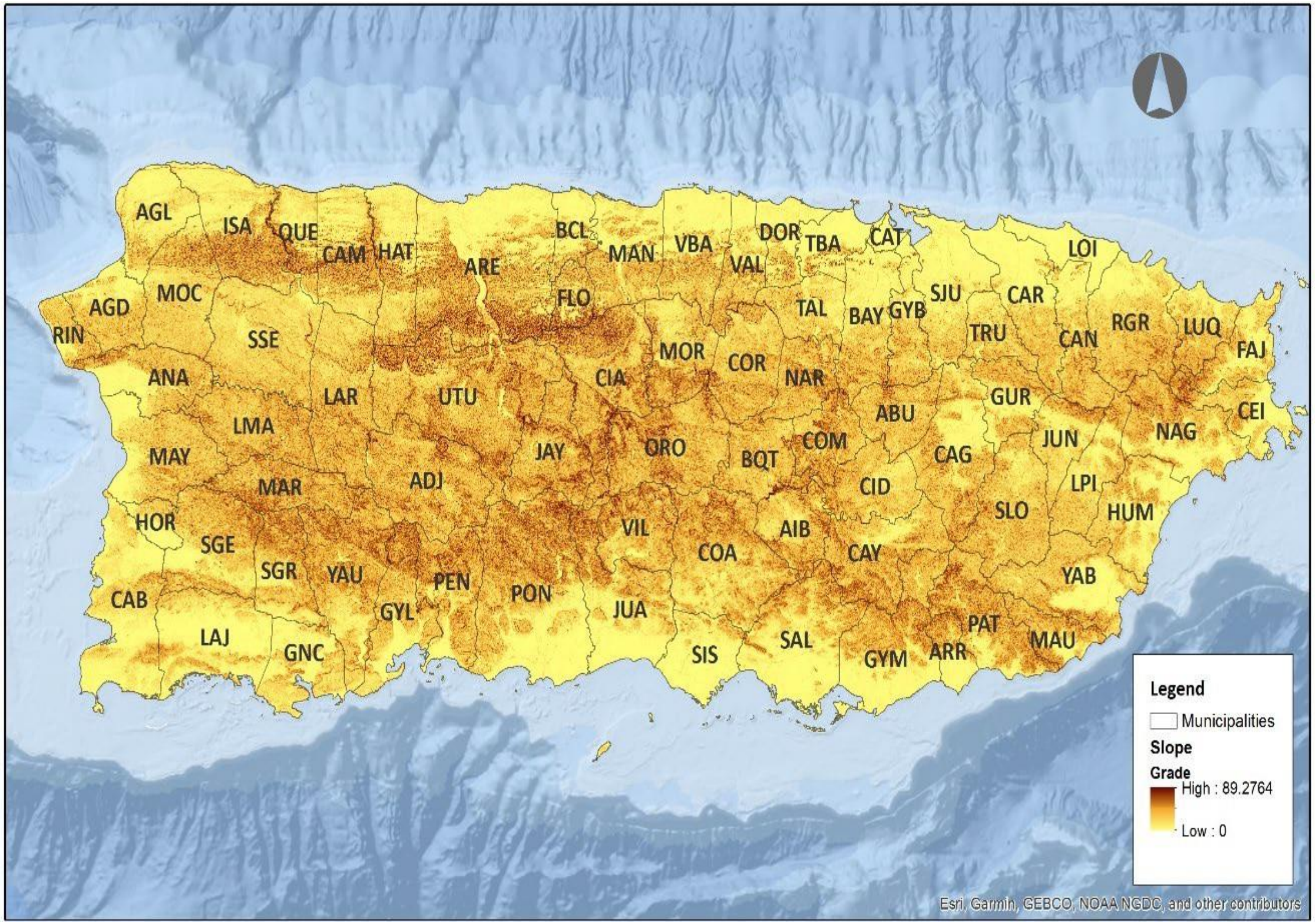
Source: SDG based on information from (NOAA, 2017).

Landslides

Analysis of landslides required further information due to the complexity of this hazard in which many triggers are involved. The data gathered for this analysis was:

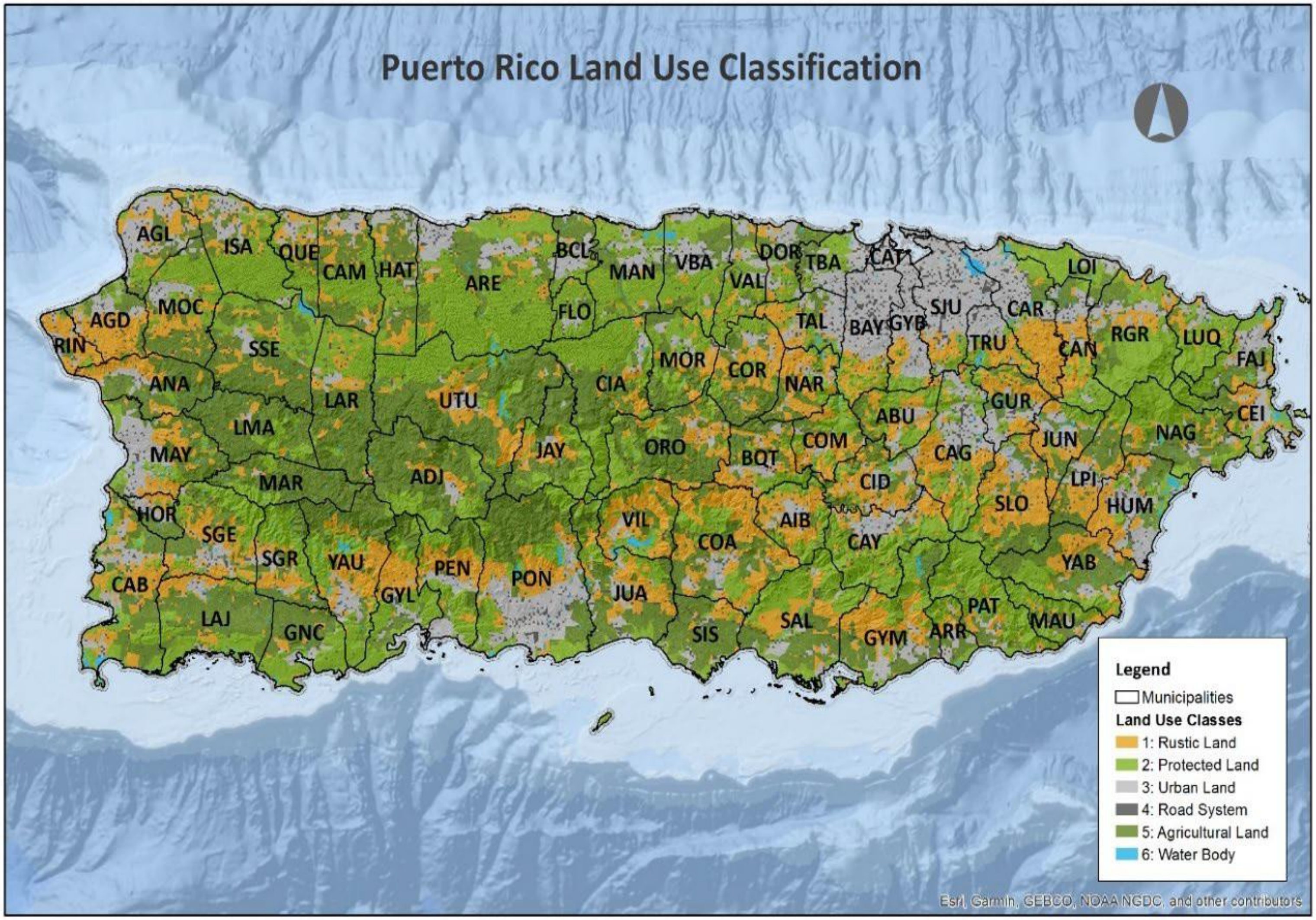
- Digital Elevation Model (DEM) of Puerto Rico obtained from Highway and Transportation Authority (raster with spatial resolution of 7m x 7m) (see Figure I.4);
- Land use data in shapefile format from the Highway and Transportation Authority (geographical layer) (see Figure I.5);
- The landslide susceptible zones from the Planning Board (geographical layer) (see Figure I.6);
- A shapefile with all the hydrologic system pathways information (geographical layer) (see Figure I.7); and
- A map of concentration of landslides caused by Hurricane María from the National Weather Service page: (National Weather Service, 2017) (PDF file) (see Figure I.8).

Figure I.4: Digital Elevation Model



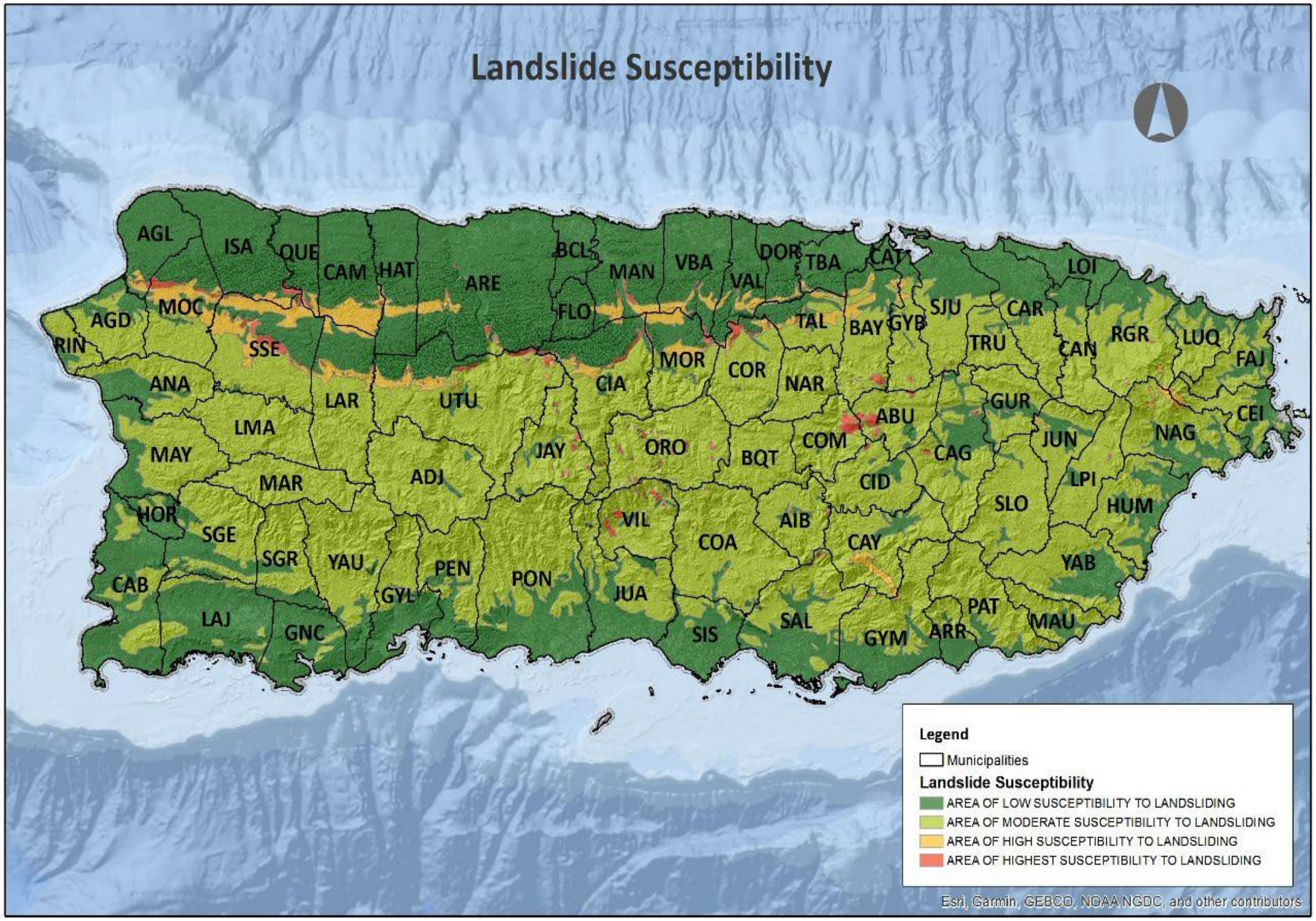
Source: SDG based on information given by Highway and Transportation Authority

Figure I.5: Land Use in Puerto Rico



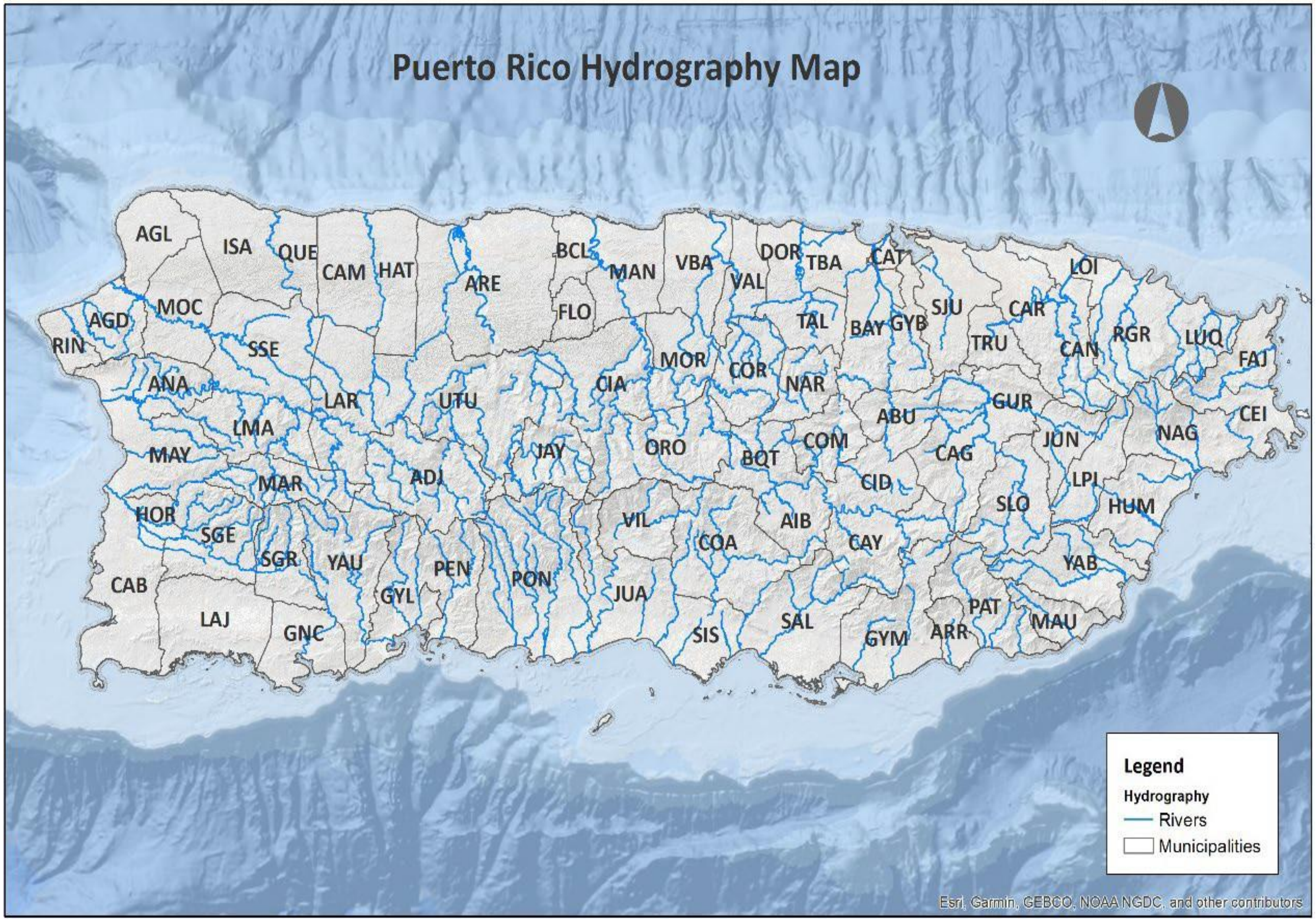
Source: SDG based on information given by Highway and Transportation Authority

Figure I.6: Landslide Susceptibility



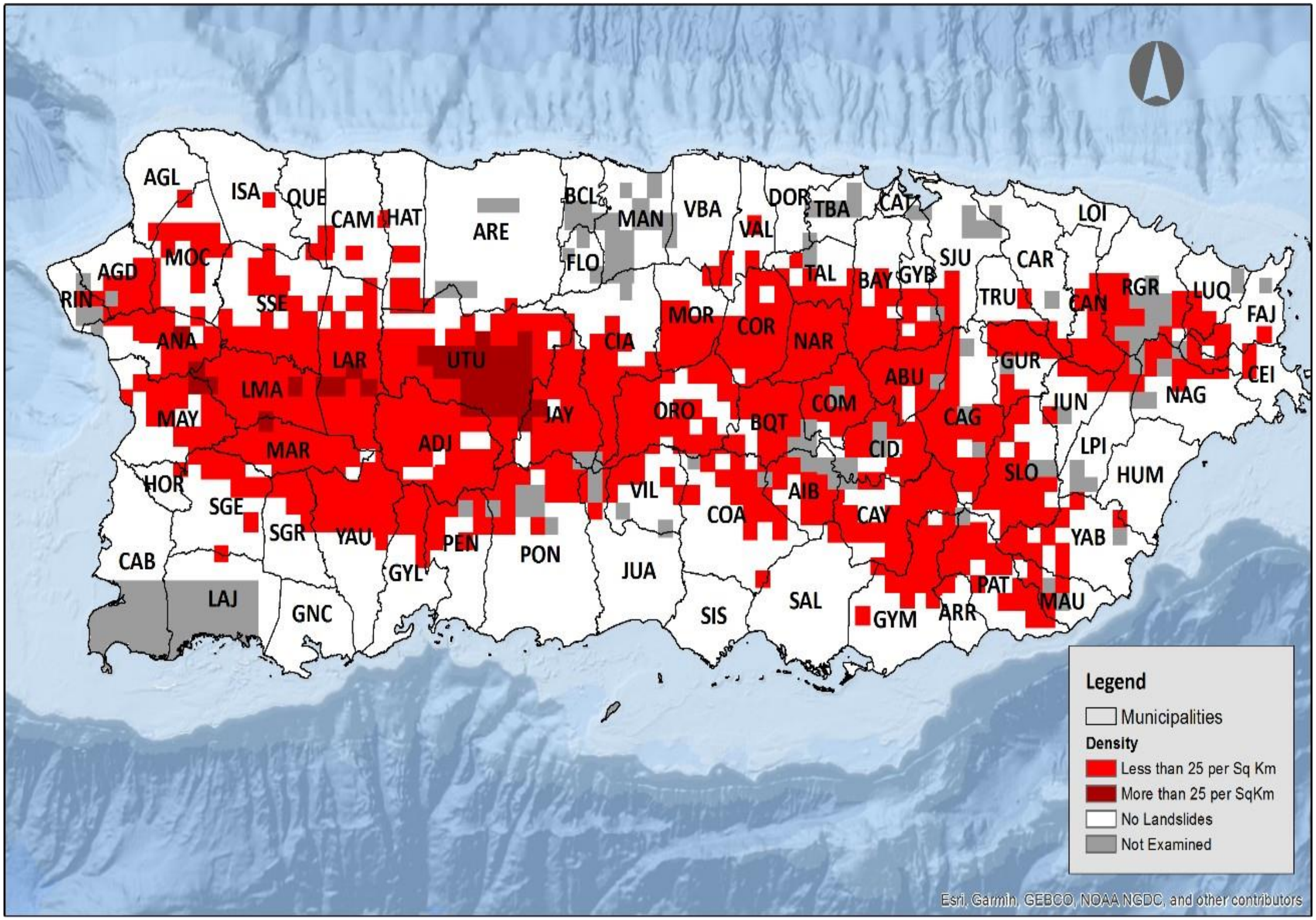
Source: SDG based on information given by the Planning Board

Figure I.7: Hydrology System Pathways



Source: SDG based on information given by Highway and Transportation Authority

Figure I.8: Concentration of Landslides During Hurricane María



Source: (National Weather Service, 2017)

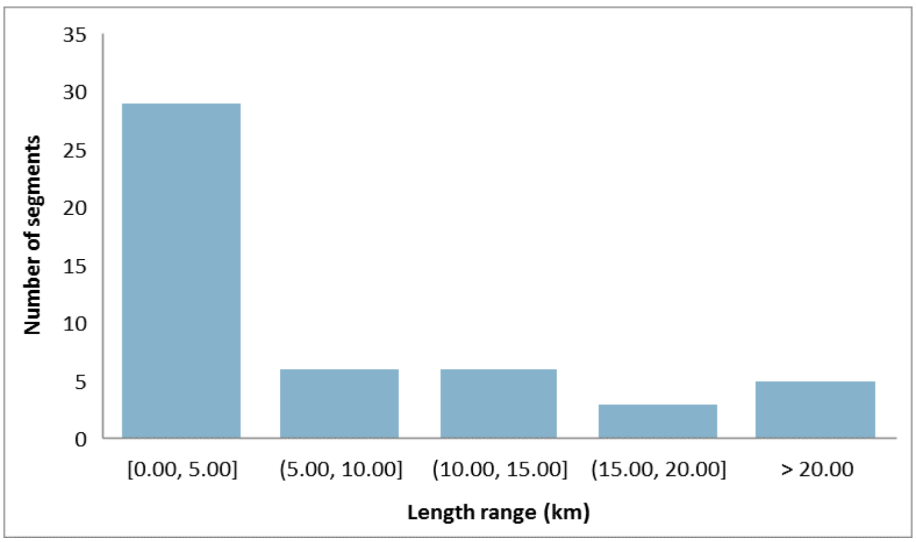
Infrastructure

Asset data was collected by two different means: first, through the Stakeholders survey, which included information regarding the specific asset (i.e., length, location, resistance, etc.) and information regarding how hazard interacts with the infrastructure such as, type of hazard, frequency of disruption, common repairs, etc. Second, data related to the functionality of such asset such as volumes, speed (free-flow and congested), capacity and number of lanes were obtained from the existing transportation model. The following sections show a summary of the data collected for the relevant assets identified.

Stakeholders Input

As it shown in Figure I.9 below, most of the segments were less than 5 km long. These segments correspond to specific problems that are presented when the reported hazard interacts with the conditions of the asset. For these types of problems an adaptation option should be defined. On the other hand, in segments whose length is greater than 5 km, the interaction between hazard and asset is less specific and it might reflect in any part of it. These segments might need additional data gathering to identify the problem and find the best mitigation strategies.

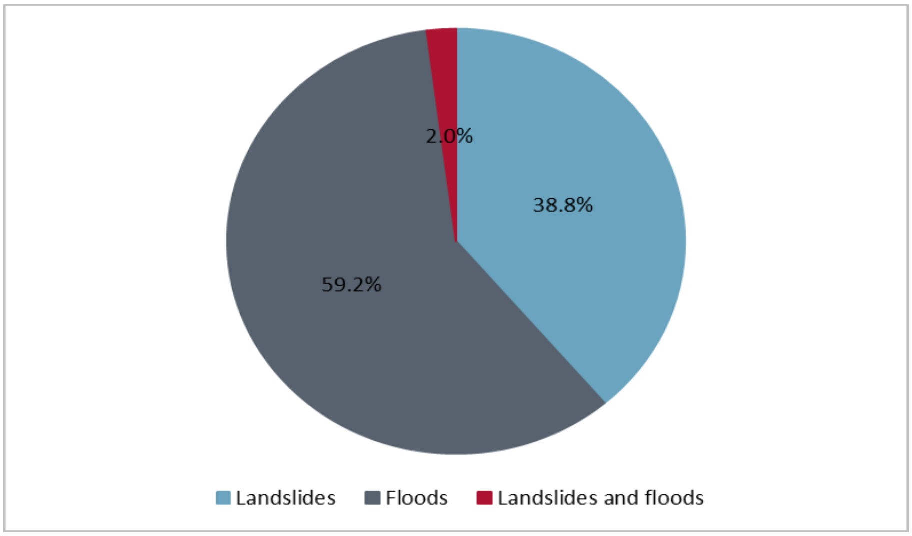
Figure I.9: Length of Segment



Source: SDG based on Stakeholders' survey

According to the reported segments, it can be concluded that transportation infrastructure in Puerto Rico is more exposed to floods than it is to landslides. Even though most segments are highly exposed to floods, landslides can have higher impact in the infrastructure; and therefore, have higher vulnerability, as it can be seen in Figure I.10**.**

Figure I.10: Type of Hazard Reported

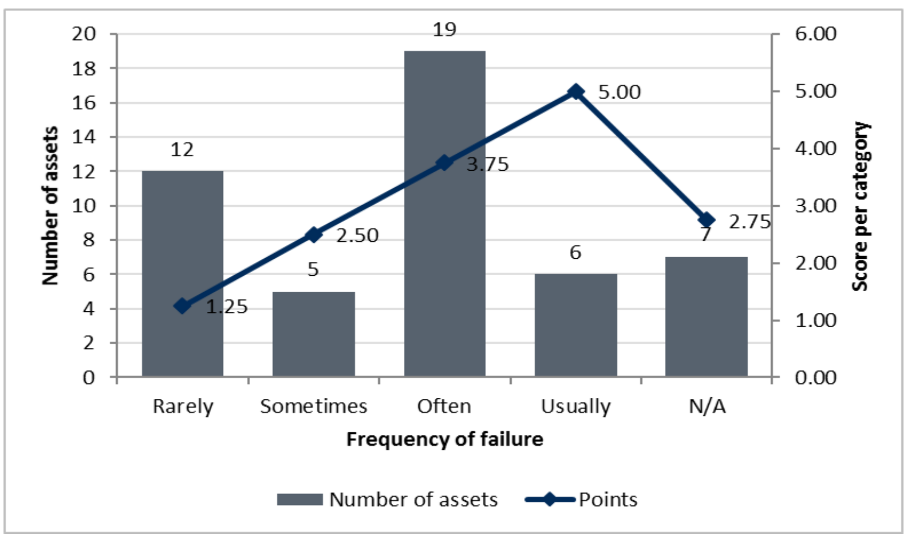


Source: SDG based on Stakeholders' survey

In terms of frequency of disruption by climate change, most of the relevant assets often present this event (2-4 times per year), i.e., often occurrence (see Figure I.11). This frequency might be related to heavy precipitations that occur during hurricane season and during rainy season; or it might be related with a particular condition of the asset which makes it more sensible to its main hazard.

Another interesting result is the 12 segments where disruption events are not frequent. However, since stakeholders selected them as relevant, these might be segments that are either important because of its connectivity and demand or for being connectors that were highly affected by Hurricane María but have not previously failed.

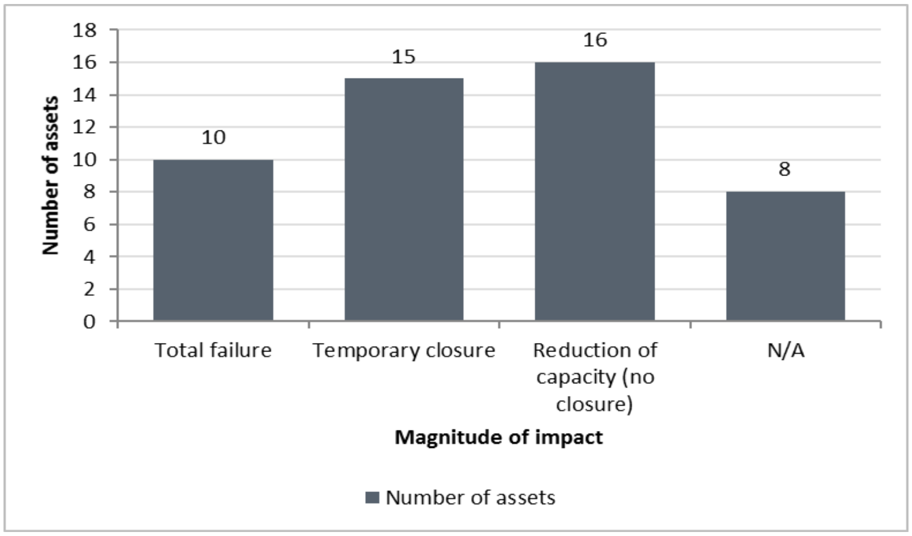
Figure I.11: Frequency of Failure



Source: SDG based on Stakeholders' survey

As it can be seen in Figure I.12, the distribution for magnitude of failure is almost uniform. This distribution reflects different conditions of assets (i.e., different level of Sensitivity). The fact that most of the assets do not present total failure is an indication that in general, the most relevant ones are quite resistant to the hazards under study.

Figure I.12: Magnitude of Failure



Source: SDG based on Stakeholders' survey

Transportation Model

The data extracted from the transportation model give us information regarding the normal condition of the transportation system, i.e., before Hurricane María. This information is important to measure Adaptive Capacity since it serves to understand how the system is affected by disruption of a segment and can be expressed in terms of how this segment manages the demand of vehicles. In the same way, an index for criticality[20] (a component of Sensitivity) can be defined in terms of volume and capacity in normal state.

The information extracted from the transportation model is:

- Distance;
- Facility Type;
- Number of Lanes;
- National Functional Class Code (NFC);
- Traffic Assignment Zone (TAZ);
- Terrain;
- Capacity;
- Free-Flow speed;
- Congested speed; and

[20] A critical element can be defined as such whose removal would result in significant losses to the area of study and it is measured in terms of the objectives of the study. (ICF International, 2014).

- Total assignment volume;

The period of highest demand (i.e., AM) is selected for this analysis, since it represents the most critical state of the transportation system in terms of demand.

VULNERATIVE ASSESSMENT

In the following sections the detailed analysis for each of the components of vulnerability is presented.

Exposure

Rainfall

The precipitation data for each weather station was collected in an Excel file, in which a filter was made to work only with stations that had valid values in the study period (other than zero). Having this information, each station and their corresponding precipitation information was georeferenced in ArcGIS, obtained a point shapefile.

As this information was obtained from point based data, corresponding to the weather stations records, it was necessary to interpolate this information to the entire island using an inverse distance weighted (IDW) process, in ArcGIS software tool. This process was developed for all three seasons, however, to have comparable results for the different precipitation levels, it was necessary to estimate the daily precipitation level for each category.

This process was done using these mathematical equations:

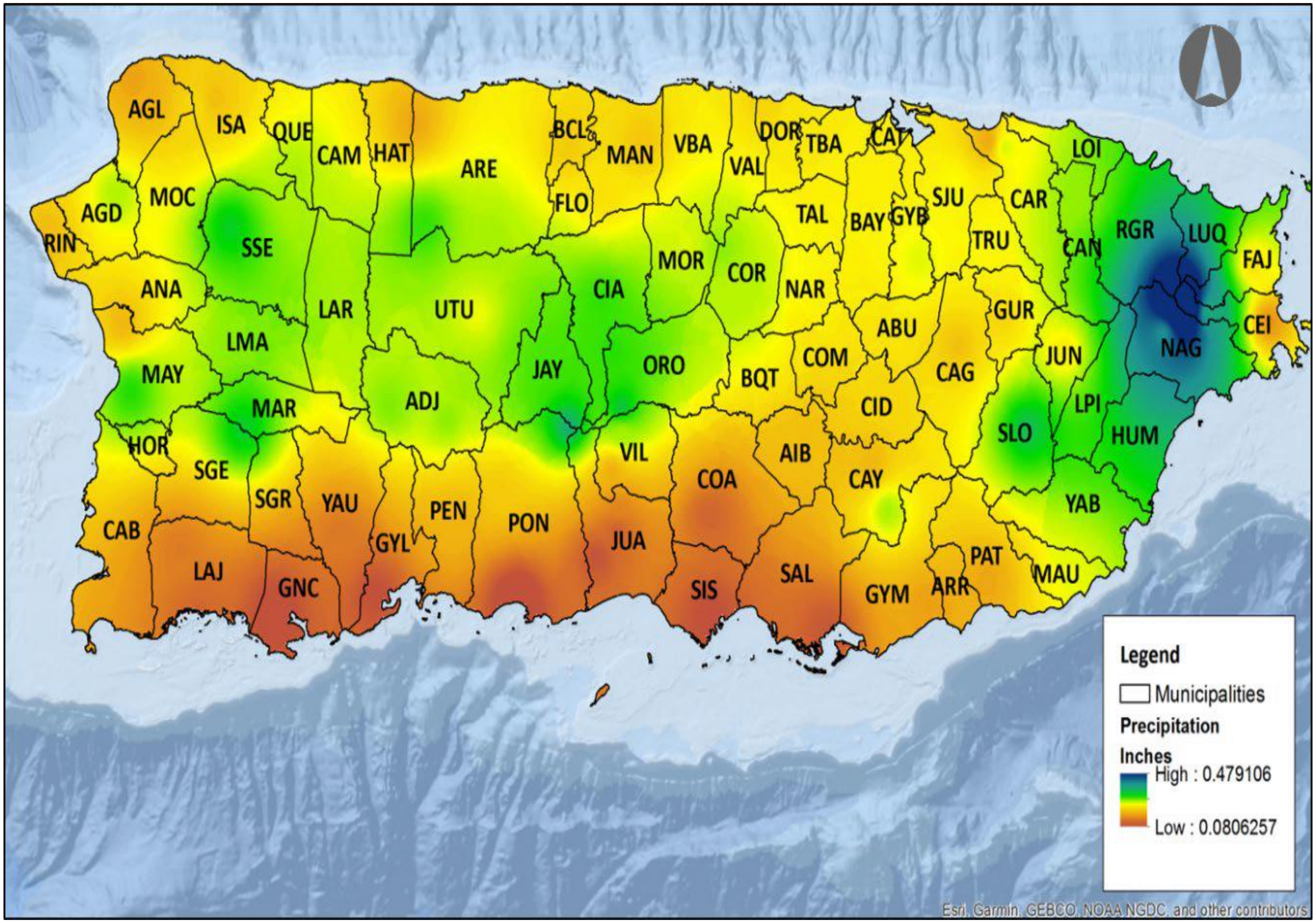
$$AAAAJJJJDDWWJJ\ DDDDTTTTJJ\ PPJJJJDDTTPPTTDDDDDDDTTJJJJ = \frac{\frac{IDW_{AADDPPPPWWAAP\ P\ PPPPWWPPPPPP}}{12}}{30} \quad \frac{IIJJDDhJJDD}{aaDDJJ}$$

$$GGJJJJJJTTDDDDJJJJ\ DDJJDDDDJJJJ\ aaDDTTTTJJ\ PPJJJJDDTTPPTTDDDDDDTTJJJJ = \frac{\frac{IIDDWW_{HHAAPPPPttTTWWPPP\ P\ PPPPWWPPPPPP}}{3}}{30} \quad \frac{IIJJDDhJJDD}{aaDDJJ}$$

$$GGJJJJJJTTDDDDJJJJ\ MMDDJJTTDD\ DDDDTTTTJJ\ PPJJJJDDTTPPTTDDDDDDTTJJJJ = \frac{(IIDDWW_{HHAAPPPPttTTWWPPPP\ MMWWPPttWW})}{2} \quad \frac{IIJJDDhJJDD}{aaDDJJ}$$

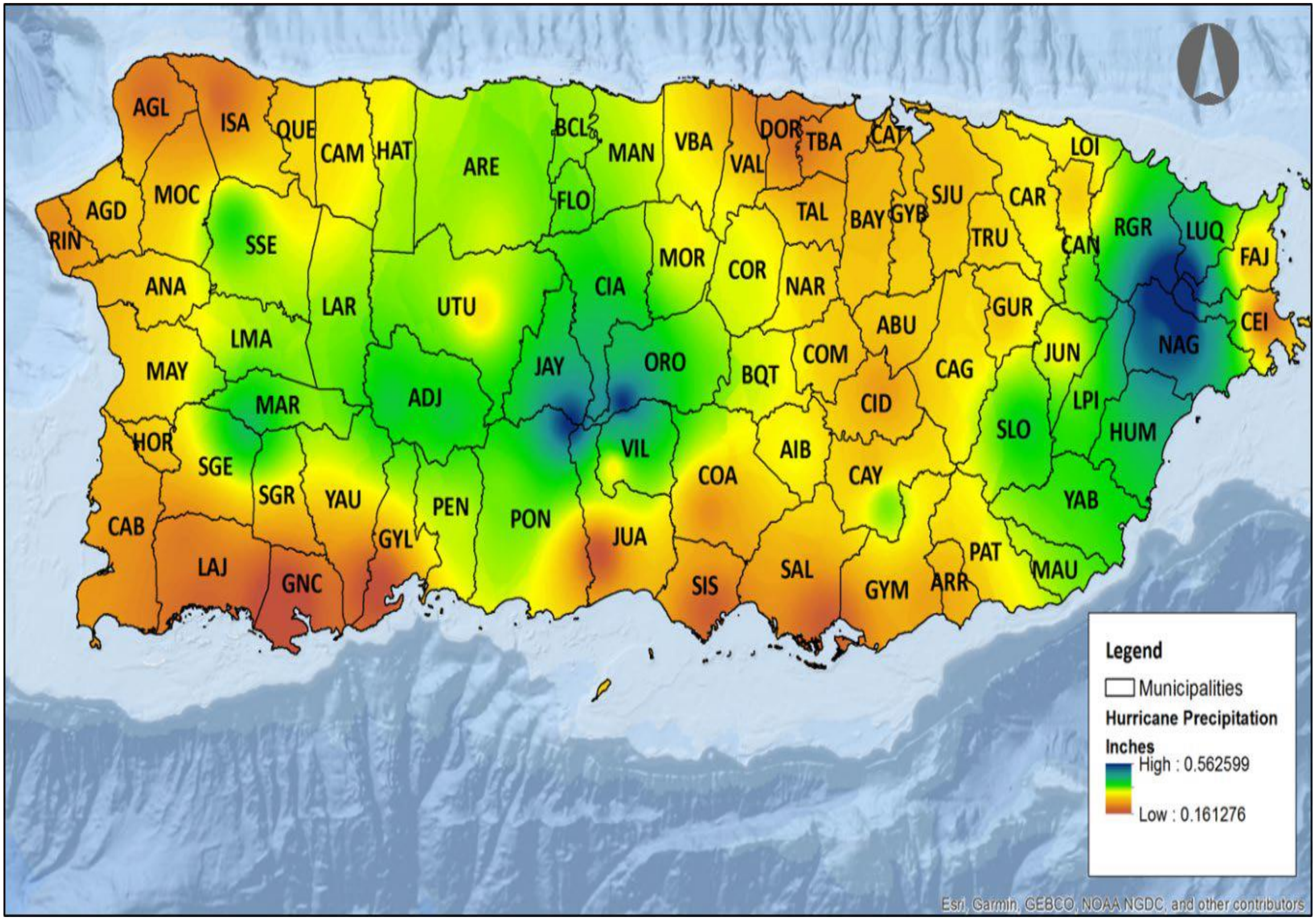
The resulting maps are shown in Figures I.13 through I.15; note that the scale is different in each map and therefore colors do not represent the same rain intensity. The units are shown in inches per day.

Figure I.13: Average Daily Precipitation



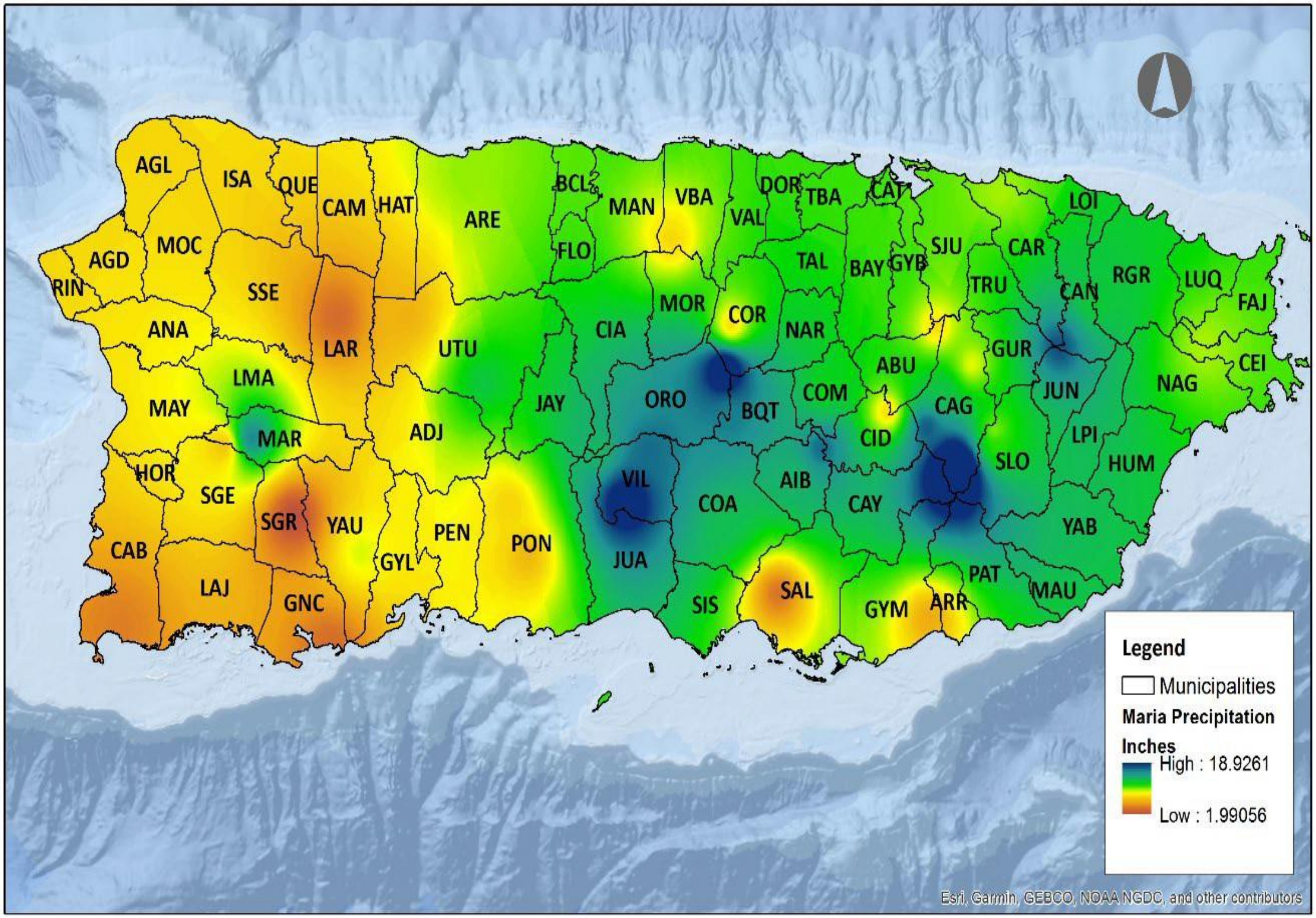
Source: SDG based on information from the National Weather Service.

Figure I.14: Hurricane Season Average Daily Precipitation



Source: SDG based on information from the National Weather Service.

Figure I.15: Hurricane María Average Daily Precipitation



Source: SDG based on information from the National Weather Service

After obtaining daily precipitation levels, it was evident that the rainfall occurred during Hurricane Maria Season is an extreme event that is difficult to compare with the other periods of study. For this reason, a normalization process was necessary, and so all precipitation levels were divided by the maximum value of the Hurricane Season Daily precipitation (0.57 inches/day). After this, the Average season represents the lowest level of precipitation, Hurricane season represents a medium and Hurricane María season the maximum effect.

Flood Hazard

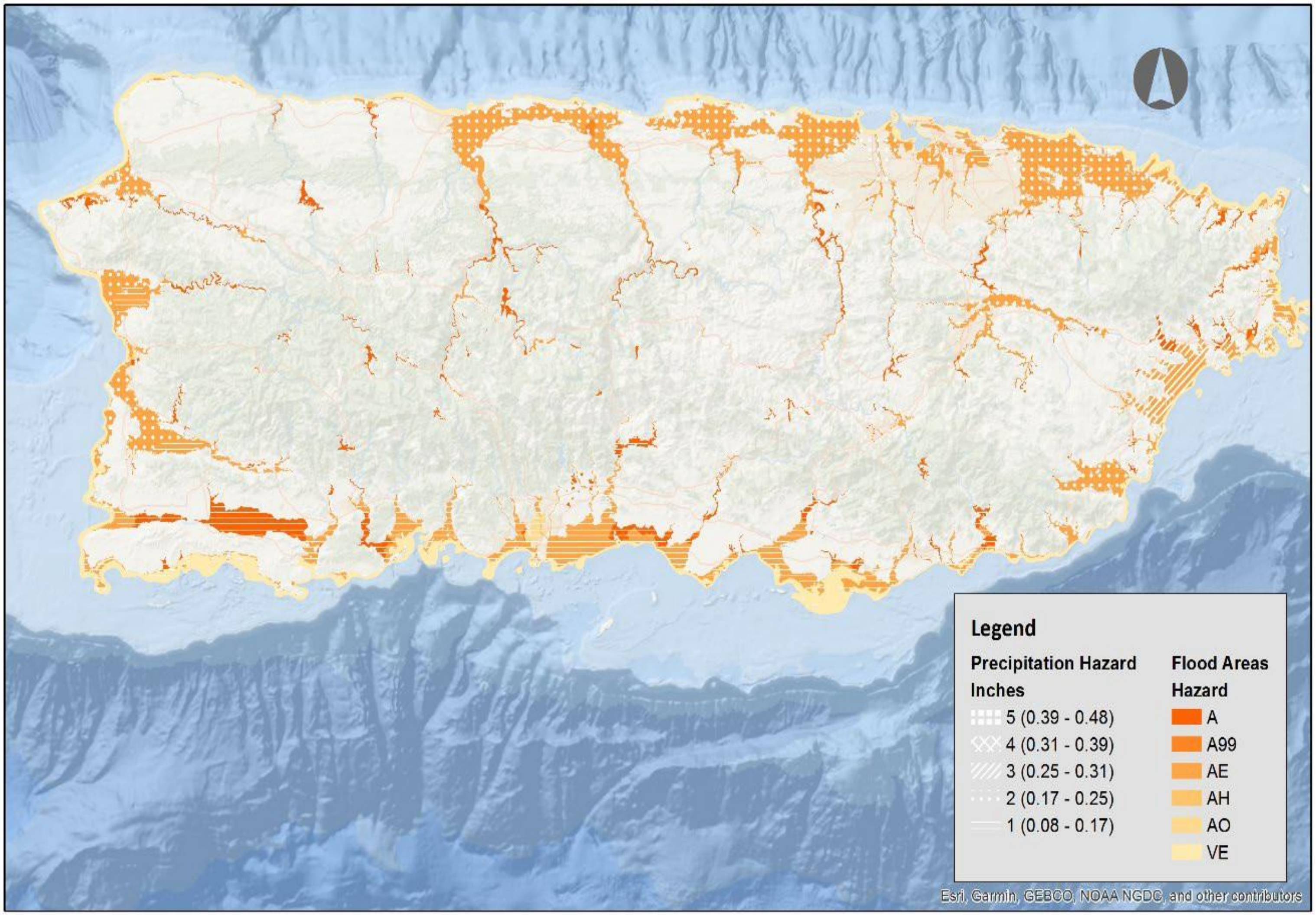
The flood zones identified by FEMA as Flood Insurance Rate Map (FIRM), shown in the previous section, is intersected with the rainfall maps, creating three scenarios of flooding. It was possible to create a standard scale between all three periods of study; however, even the minimum scale for the Hurricane María season was higher than any value in the other periods of study. This condition accentuates the amount of rain withstood by all the areas of the island, even those that are usually dry and whose infrastructure might not be prepared to these extreme events.

Furthermore, this extreme situation has ranges that cannot be compared with the Hurricane or the Average season. The result of this process was a level of hazard according to the precipitation levels in each season, where “1” corresponds to the areas with the lower probability of occurrence and “5” the areas with higher probability of being affected by high precipitation levels.

As it was discussed before, the flood hazard was not defined solely by the precipitation levels, but as a conjunction with the FIRM map. Accordingly, a map was created to join the hazard level of precipitation created by this study with the flood areas defined by FEMA.

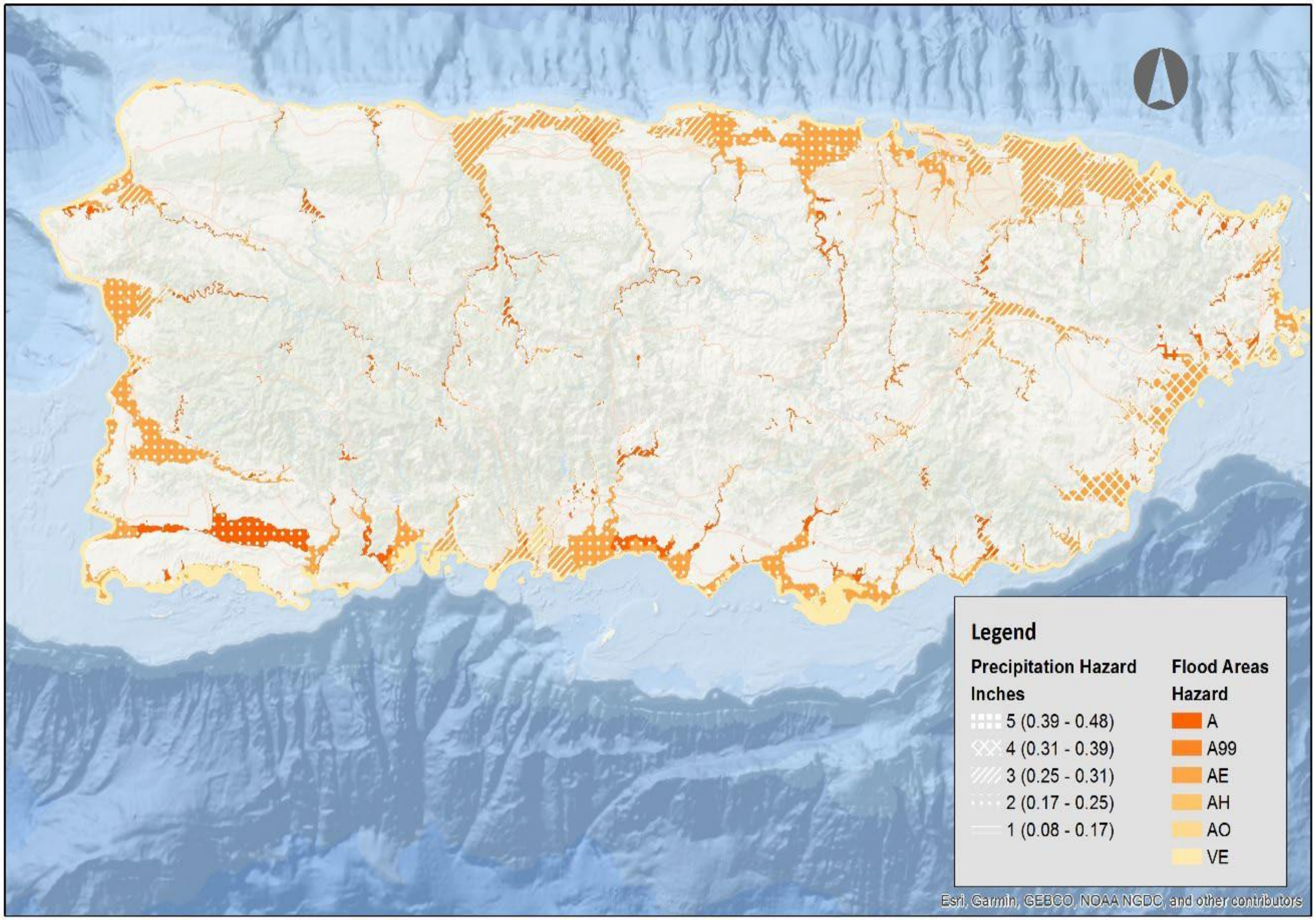
The corresponding maps for each period of study are shown in Figures I.16 through I.18.

Figure I.16: Average Flood Hazard



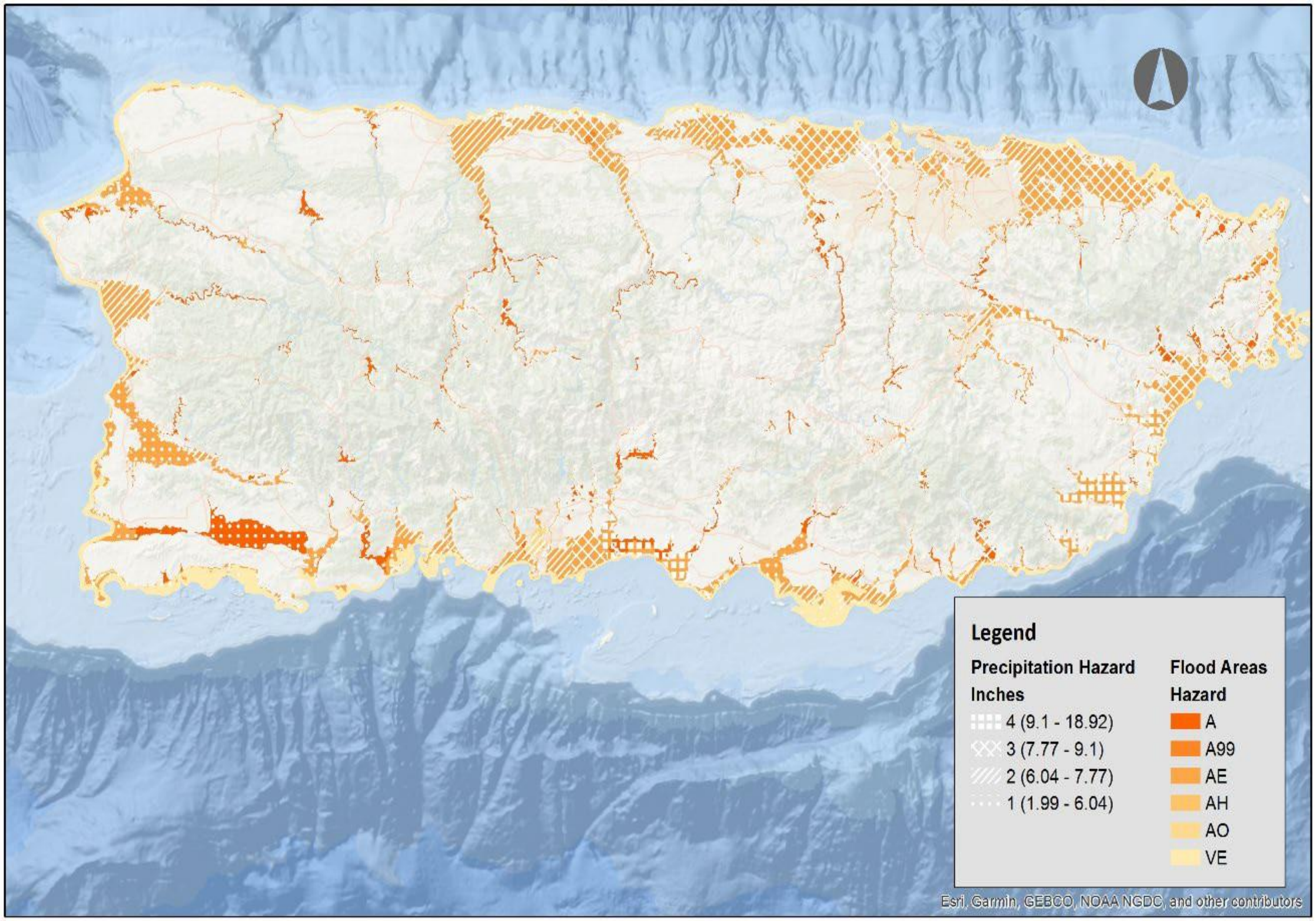
Source: SDG based on information from the National Weather Service and FEMA.

Figure I.17: Hurricane Season Average Flood Hazard



Source: SDG based on information from the National Weather Service and FEMA.

Figure I.18: Hurricane María Average Flood Hazard



Source: SDG based on information from the National Weather Service and FEMA.

Landslide Hazard

For the regression analysis, the entire island of Puerto Rico was divided into cells with an area of 100x100 meters, being each cell the unit of study that includes the information of the variables contained. For this reason, the Hurricane María Landslides data, obtained from the National Weather Service and used in this study as the observed landslides occurred by this event, were georeferenced to create a shapefile in raster format (see Figure I.8 from the Data Compilation section).

Similar to the flood hazard analysis, the one for landslides was based on two periods of study: Hurricane María season and the Average season, where the only variable that varies between them is the precipitation levels (the same used for the flood hazard analysis). The remaining triggering variables depends on characteristics of the terrain that were constant during the period of study.

The first step of this process was the preparation of the input data for the model. The slope indicators were obtained from the processing of the Digital Elevation Model (DEM) of Puerto Rico. This variable was created from the entire island in degree units ranging from 0° to 89.3°. On the other hand, the proximity to rivers was obtained by a spatial process that determines if a cell (unit of analysis) is intersected by a flowing body of water. Finally, the Landslide susceptible zones and the Land Use data were rasterized, to have all the variables in the same format of 100x100 meters cells.

The shapefile with the Land use information has a classification methodology that summarizes land uses into 17 categories. For this reason, it was necessary to simplify data to the level of detail needed to represent landslide hazard. Therefore, six classes were obtained, in which the higher value is a more vulnerable land use (for landslides) and the smallest value is a less vulnerable land use (see Table I.1.)

Table I.1: Reclassified Land Use Values

Reclassification value	Normalized Land Use Classes	Data base Land Use Classes
1	Common Rustic Land	7. Common Rustic Land
2	Protected Land	Specially protected rustic land Rustic ground specially protected from landscape Specially protected ecologically protected rustic Land Rustic ground specially protected ecological and hydric Specially protected rustic ecological and landscape land Specially protected rustic water land
3	Urban Land	Urban Land Land for development not programmed Programmable land for development
4	Road System	Road System
5	Agricultural Land	Specially protected rustic agricultural land Rustic land specially protected for agriculture and water Rustic land specially protected for agriculture and landscape Rustic land specially protected for agriculture and ecology Rustic land specially protected ecologically and agriculturally

Reclassification value	Normalized Land Use Classes	Data base Land Use Classes
6	Water Body	Water Body

Source: SDG

Finally, all the triggering data defined in terms of different categories, depending on the level of criticality that each of them represent in terms of landslide. The variable, classification, rank value and source are summarized in the Table I.2 below.

Table I.2: Variables Summary

Variable		Rank Values	Classes	Data Source
Dependent	Hurricane María Landslides	1 2 3	No Landslides Less than 25 per Sq Km More than 25 per Sq Km	National Weather Service
Topology	Slope	1 2 3 4 5	Very gentle slopes (< 5°) Gentle slopes (5° - 15°) Moderately steep slopes (15° - 30°) Steep slopes (30° - 45°) Escarpments (> 45°)	DEM provided by Highway and Transportation Authority
Geology	Landslide Susceptibility	1 2 3 4	Area of low susceptibility to land sliding Area of moderate susceptibility to land sliding Area of high susceptibility to land sliding Area of highest susceptibility to land sliding	Landslide Susceptibility from the Planning Board
Hydrology	Proximity to rivers	0 1	Not close to a river Close to river	Flow River shapefile provided by Highway and Transportation Authority
Land Cover	Land use	1 2 3 4 5 6	Common Rustic Lands Protected Land Urban Land Road system Agricultural Land Water body	Lands Use from the client
Climate	Precipitation for Hurricane María (inches/day)		Min: 1.99 Max: 18.93	National Weather Service

Variable		Rank Values	Classes	Data Source
	Precipitation for Average Season (inches/day)		Min: 0.081 Max: 0.48	National Weather Service

Source: SDG

The data collected could be divided in two groups: evidence (concentration of landslides during Hurricane María) and triggers (i.e., topology, geology, hydrology, land cover and climate). Therefore, it was possible to create a model under the conditions of Hurricane María and use it to predict the resulting landslides for other seasons.

For this analysis, the landslide variables were divided into two groups: training data for the construction of the model and testing data for accuracy evaluation. The prediction model was estimated using a binomial logistic regression for the Hurricane María Season to extract the coefficients of all causative variables for each class of the observed landslide in this period of study. Accordingly, a model for each respond in the Hurricane María Season (“No landslides”, “Less than 25 per Sq Km”, and “More than 25 per Sq Km”) was created. The result of each model indicates de probability of being in the corresponding class, as the following equation indicates:

$$PP = \frac{1}{1 + JJ^{-oo}}$$

where SS is a linear combination of independent variables using the estimated coefficient for each model.

The model for the “No landslides” class is the following:

$$PP_1(xx_1, \ldots, xx_6) = \frac{1}{1 + JJ^{\sum_{ii}(ww_{1ii}xx_{ii}) + bb_1}}$$

The model for the “Less than 25 per Sq Km” class is the following:

$$PP_2(xx_1, \ldots, xx_6) = \frac{1}{1 + JJ^{\sum_{ii}(ww_{2ii}xx_{ii}) + bb_2}}$$

The model for the “More than 25 per Sq Km” class is the following:

$$PP_3(xx_1, \ldots, xx_6) = \frac{1}{1 + JJ^{\sum_{ii}(ww_{3ii}xx_{ii}) + bb_3}}$$

The corresponding weights for each model are shown in Table I.3.

Table I.3: Logistic Regression Models’ Coefficients

Related variable	Coefficients for model “No landslides”	Coefficients for model “Less than 25 per Sq Km”	Coefficients for model “More than 25 per Sq Km”
Intercept (b)	5.87059	(5.72394)	(6.91072)
Slope	(3.02466)	2.76992	2.36195
Landslide Susceptibility	(6.20830)	0.81184	2.60127
Proximity to rivers	(0.38143)	0.35103	0.26701
Land use	(1.00084)	0.81184	1.90019

Related variable	Coefficients for model "No landslides"	Coefficients for model "Less than 25 per Sq Km"	Coefficients for model "More than 25 per Sq Km"
Precipitation for Hurricane María (inches)	(1.96749)	2.14350	(1.02239)

Source: SDG

The misclassification error of each model was evaluated comparing the quantity of predicted values within the class and the quantity of observed values in the corresponding class defined as:

$$EEJJJJJJJ_{tt} = 1 - \frac{\sum_{jj \in NN} 1_{SS>0.5}(PP_{tt}(xx_{jj}))}{NN}$$

where NN is the number of observations and PP_{tt} is the regression model for class TT.

The misclassification error was calculated for training data and for testing data. The former is known as the training error and represents how well the model adjusts to the data given to construct the model. The latter is known as the generalization error and represents how well the model can classify new given data.

The results for the misclassification error for each model show their ability to explain the areas classified as "Less than 25 per Sq Km" and the areas classified as "No landslides"; however, due to the extreme events during Hurricane María, the current variables are not sufficient to explain all the conditions that lead to "More than 25 per Sq Km" class and it was not possible to have an acceptable accuracy for this category. See Table I.4.

Table I.4: Misclassification Error for Each Landslide Model

Landslide class	Training Error	Generalization Error
No Landslides	0.2737	0.2733
Less than 25 per Sq Km	0.2863	0.2875
More than 25 per Sq Km	1	1

Source: SDG

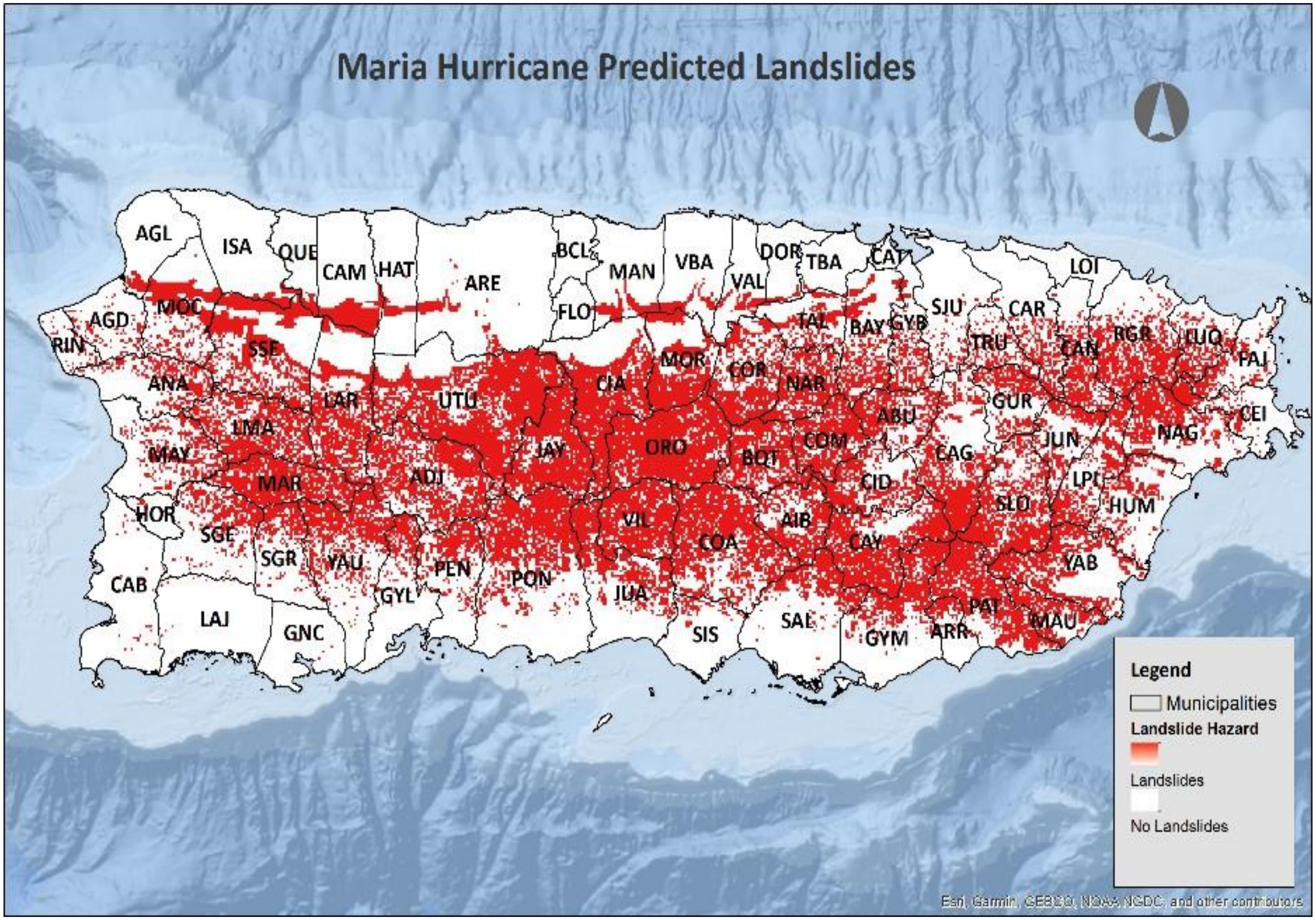
The multiclass model is a combination of the previous models, as the class with the higher probability given the vectors of each independent variable ($xx_1, \ldots, xx_6$):

$$PP_{TTPPmmbbttPPPPoo} = DDJJWWTTDDxx(PP_1, PP_2, PP_3)$$

Once the prediction model was obtained, the testing data was input to the model. Where, the resulting landslide class of each cell was the one with the maximum probability comparing the results from the three models. With these results an accuracy of 0.741 was obtained.

The predicted hazard map for Hurricane María is shown in Figure I.19 below. As it can be seen, this map differs from the original data gathered for the actual landslides occurred shown in Figure I.8. This classification errors might be due to the lack of explanatory variables or very specific conditions that occur during Hurricane María. For the scope of this study, that is a screening level, the accuracy given by the prediction model is believed to be sufficient and appropriate.

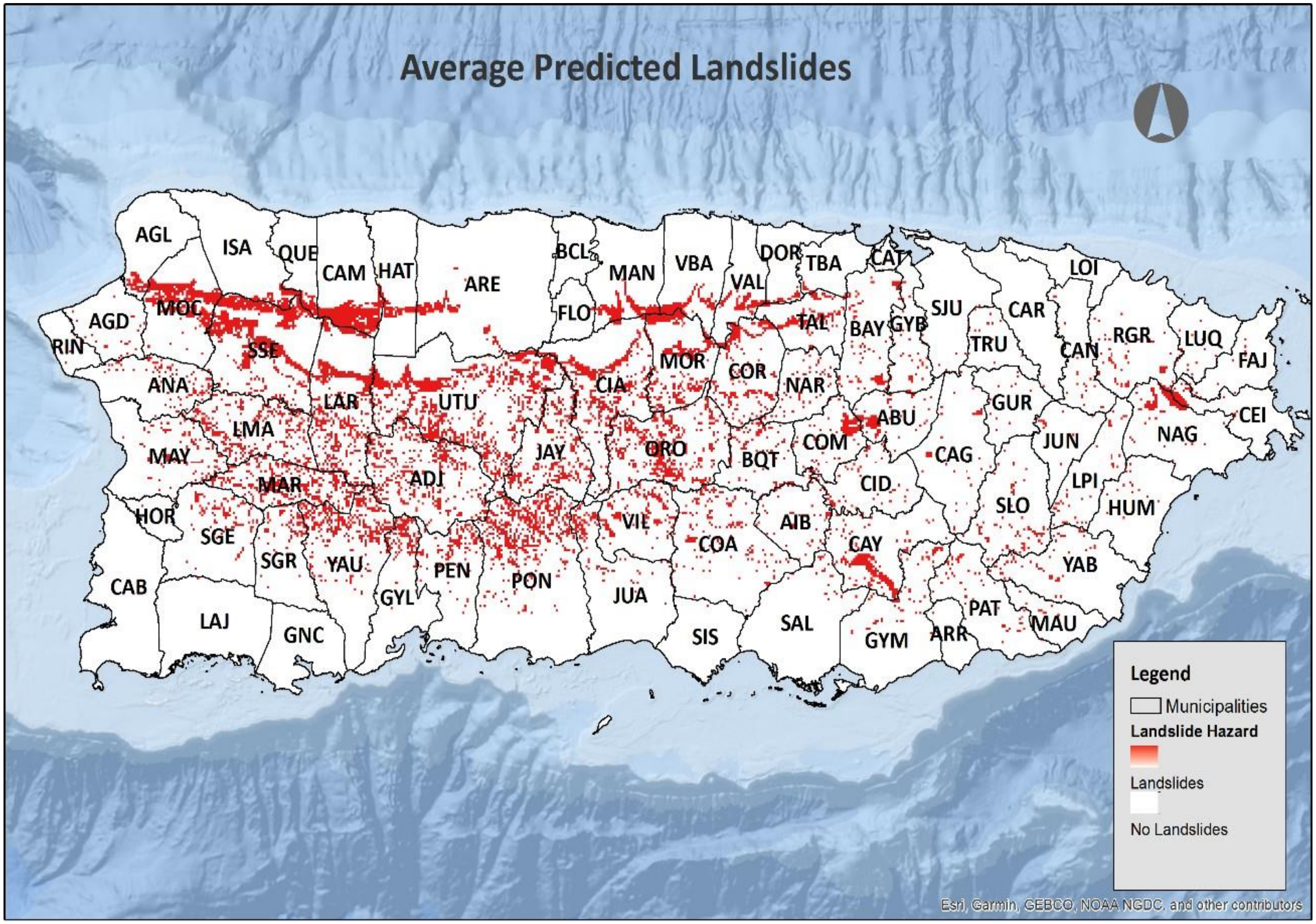
Figure I.19: Hurricane María Predicted Landslides



Source: SDG

Once the classification model is built, it is possible to estimate the landslides for the Average season, changing the data for precipitation levels for its corresponding study period. The remaining variables were the same to the Hurricane María Season as they do not change with time (under the period considered). The resulted map is shown in Figure I.20.

Figure I.20: Average Predicted Landslides



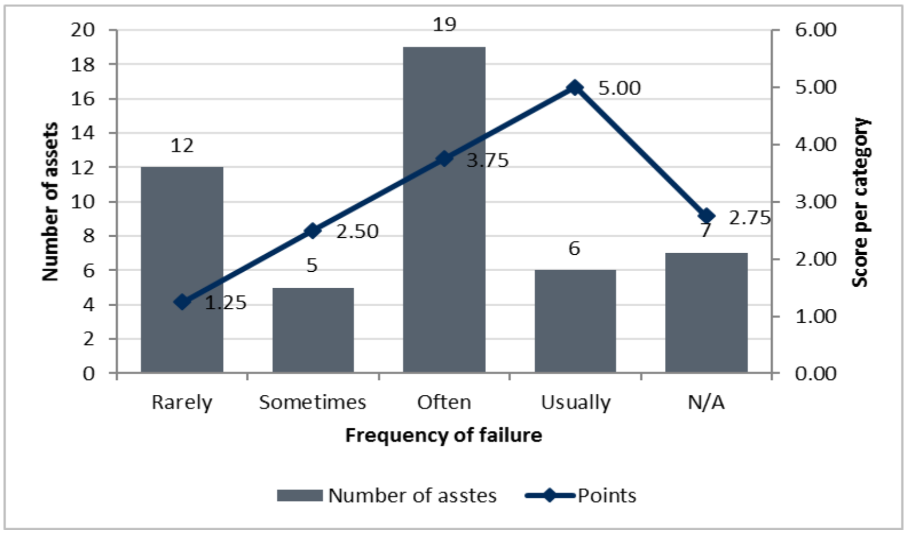
Source: SDG

Sensitivity

Asset State

As mentioned before, the results of frequency of failure were used as a measure of the state of the asset and each category were given a score for measuring how "sensitive" is the asset to the identified hazard. Four different categories were identified from the answers provided by the stakeholders (rarely, sometimes, often and usually), therefore a scale from 1 to 5 was divided into these categories. Assets with highest frequency were given a score of "5", while the lowest frequency was given a score of "1.25". An additional intermediate score was given to segments which frequency of failure was uncertain or not provided by stakeholders (i.e., N/A), as shown in the Figure I.21 below.

Figure I.21: Frequency of Failure

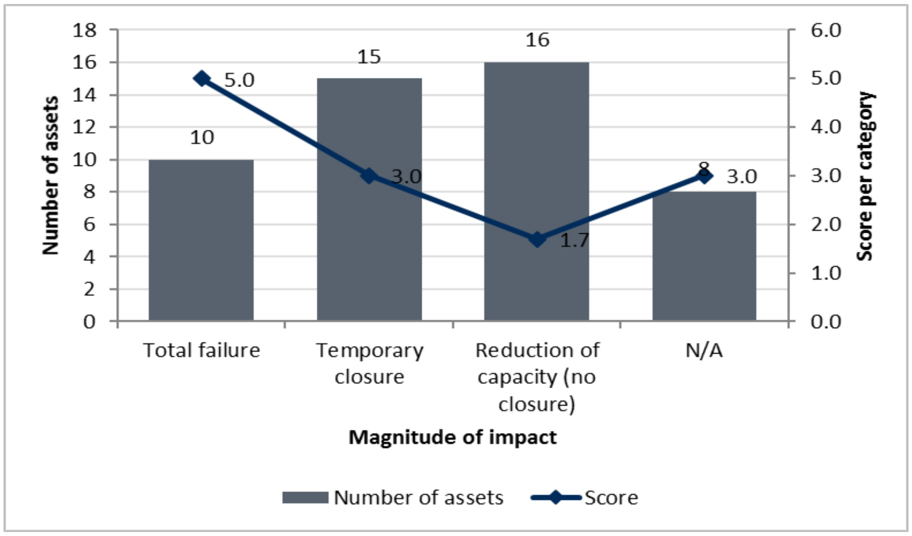


Source: SDG based on results from Stakeholders' survey.

Reduction Input

The magnitude of failure was used as a measure of the reduction of asset's functionality when affected by a hazard. Like the asset state, for each category of magnitude of failure a score from 1 to 5 was given. In this case, the uncertainty (i.e., N/A) was given an intermediate score of "3", since there were only three categories, and assigning a different value might result on underestimate or overestimate uncertainty. See Figure I.22.

Figure I.22: Magnitude of Failure



Source: SDG based on results from Stakeholders' survey.

Criticality Index

A criticality analysis is used to identify the most relevant assets in an infrastructure system. This criticality analysis can be developed from any perspective: supply, demand, risk, vulnerability, connectivity, etc. For this analysis the criticality index aims at representing the transportation model information (e.g., capacity, volume, free-flow speed and congested speed) as part of the Sensitivity and the Adaptive Capacity measure.

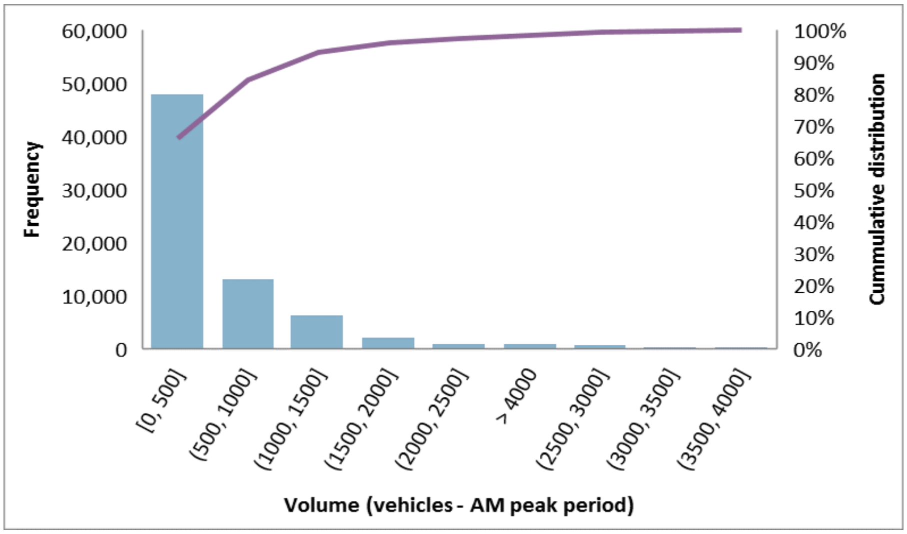
Even though the criticality analysis is used to help practitioners identify the most critical assets to perform the vulnerability analysis (Federal Highway Administration, 2017) it can also be used to complement the vulnerability analysis, especially when there is not enough information gathered about g the asset state and/or when the identified assets are not easily comparable. In this case, the identified segments have different characteristics (i.e., length, location, type of mitigation strategies, etc.) and the calibrated transportation model can provide additional and comparable input regarding the Sensitivity of each asset.

Conceptually, the criticality index should highlight those segments of the network that are part of most of the users' trips, i.e., highly demanded segments. Because this model represents a period (AM peak), the volume in each segment is not the only measure of high demand. The conditions to be considered as a critical segment are any of the following:

- High volume of vehicles (>95% of segments)
- Critical volume/capacity ratio (>1) in conjunction with low speed (compared to free-flow speed), which means congestion

To define an index able to capture the above concept, first it is necessary to characterize the current conditions of the links. The distribution of total volume assigned to each in the transportation model is shown in the following Figure I.23. By analyzing the results, only 5% of the links have a traffic volume above 2,500 vehicles during the AM peak (7:00 – 9:00).

Figure I.23: Distribution of Total Assignment Volume in Transportation Model



Source: SDG

With the above analysis, the criticality index was defined as:

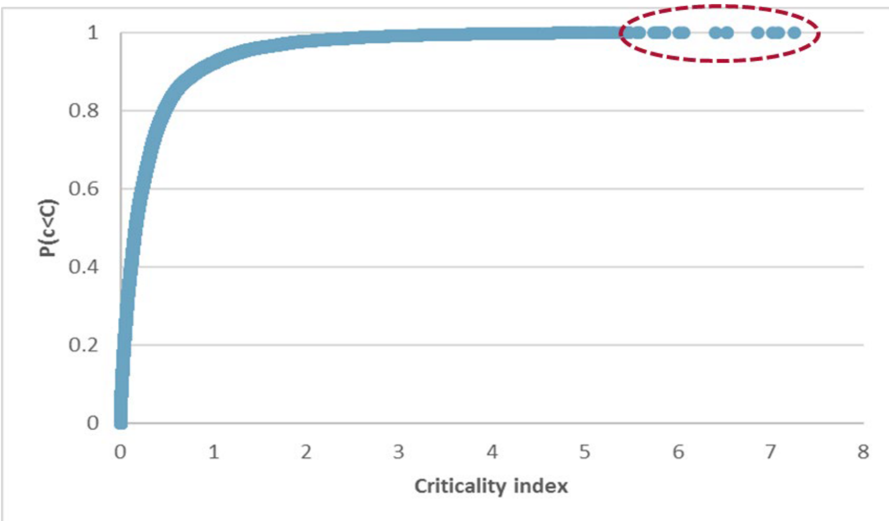
$$tt = \frac{VV}{2500} + \frac{VV}{CC}\left(1 - \frac{DD_{TTPPPPAA}}{DD_{FFFF}}\right)$$

where VV is the total traffic volume of a link (in vehicles during the AM peak), CC is the total capacity of the link (in vehicles for AM peak period), $DD_{TTPPPPAA}$ is the congested speed (in mph) and DD_{FFFF} is the free-flow speed (in mph).

With this equation, critical links obtain the highest score. The resulting distribution for the criticality index is shown in the Figure I.24 below. As it can be seen, the criticality index ranges between 0 and 8, where “0” is the least critical links and “8” is the most. Also, in the figure the top critical links are highlighted in the dashed-circle.

Also by the shape of the cumulative distribution, it is noticeable that most of the links have low criticality index (below “1”) and only few have high criticality index. This characteristic is highly expected by this type of measure, since the decision-maker need it to identify only the most critical and the criticality measure should be able to differentiate the top critical segment from the rest.

Figure I.24: Cumulative Distribution of Criticality Index



Source: SDG

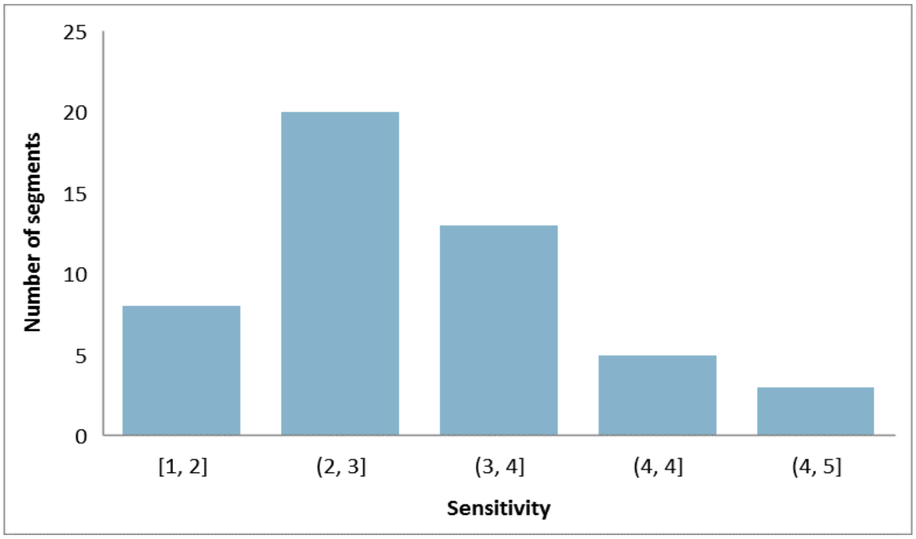
Finally, to compare this measure with the rest of the Sensitivity, the criticality index is normalized to fit a scale between 1 to 5.

Sensitivity Measure

The final measure for Sensitivity is a combination of the three components: asset state, reduction input and criticality index. Since the three measures are equally important and complement one another, the Sensitivity was defined as the average. The distribution for the identified segments are shown in the following Figure I.25.

Most of the selected segments scores a medium-low Sensitivity measure (i.e., '2') which supports the previous findings regarding low magnitude of failure and only few critical segments. These results show that there are few segments which are less likely to be able to withstand a future hazard.

Figure I.25: Distribution for Sensitivity



Source: SDG

Adaptive Capacity

The final component of the vulnerability analysis is the Adaptive Capacity. This is a system-level measure and aims at measuring how a failure in one element of the system reflects in the overall performance. There are two possible approaches for this measure:

- Direct: Using the transportation model, each segment is removed from the network and the model demand is assigned again. Using performance statistics of the transportation model (e.g. average volume/capacity ratio), the effect of the removal of such link is measured.
- Indirect: Using graph theory, the transportation model is represented by a weighted-directed graph and a centrality statistic (before and after removal) is used to measure the effect of a link failure in the system.

The direct measure solves the assignment optimization problem and gives the distribution of traffic volume in each link of the network. Even though this is as exact as it can be possible with a computational modelling tool, the results of the general performance are not easily captured, and the effect of a link removal might only be reflected locally, but in a general measure it can be hidden. Also, since this is an exact measure, every assignment of the transportation model is a time-consuming task.

On the other hand, the indirect measure is a simplification of the transportation model; it runs all the possible shortest paths, but it does not consider users decision problem or even the number of trips for each OD pair. Therefore, the weighted value assigned to each link should already consider traffic. However, it is a fast methodology for high-level decision-making and the centrality measures successfully captures the global effect of a change in the network topology (e.g., removal of a link). Considering the abovementioned conditions, it was decided to use graph theory to capture the effect in the system given by the failure of a segment of the network.

Several statistics of a node have been defined for measuring the relevance of a link in graph theory, among the most used ones are:

- Degree: number of adjacent nodes, i.e. sum of links connected to it Cesar Ducruet, 2017
- Closeness: it is a measure of how close is this node to the rest of the nodes, i.e. the sum of the length (or weight) of the shortest paths between the node and all other nodes in the graph (Bavelas, 1950) Cesar Ducruet, 2017
- Betweenness: "measure of accessibility that is the number of times a node is crossed by shortest paths in the graph"[21] Cesar Ducruet, 2017
- Eigencentrality: It is a measure of the importance of the node relative to the network, and it depends on the number of connected components and the relative importance of them Cesar Ducruet, 2017 and
- PageRank: is a variation of eigencentrality, used by Google search engine to rank the pages in a web search, by representing them as nodes and its references to other pages as links.

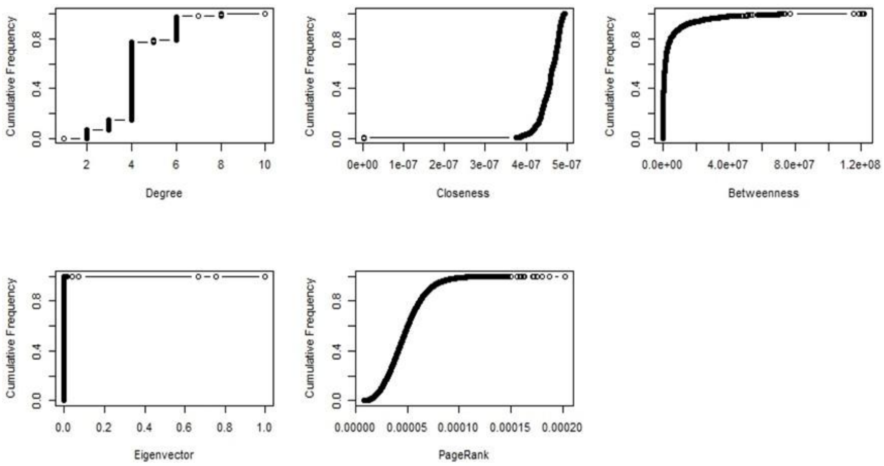
A summary of cumulative distribution of possible centrality measures for the network are shown in the Figure I.26 below. As mentioned before, it is ideal to have an index that highlights the most important elements of the network, so that when the network topology is changed, it reflects it.

From the merely connectivity standpoint, in the degree distribution graph most of the nodes in the network have four or less connections. This behavior is usually presented in transportation networks since most of intersections only connect two different roads. However, nearly 20% of the nodes have more than six connections, which makes them stand from the rest. On the other hand, closeness measure for Puerto Rico's transportation system shows an even distribution of links' length in combination of similar degree, since most of the links have a measure between $4 * 10^{-7}$ and $5 * 10^{-7}$. The eigencentrality measure shows that only five nodes present a relative importance (measured from its eigenvalues) that is significantly higher than the rest. These nodes are principally very congested intersections in the metropolitan area.

The betweenness and Page-rank measures show a more gradual distribution, where the elements of the network can be differentiated, i.e., there are few nodes with high centrality and the rest of them with smaller centrality value. However, the behavior shown by betweenness centrality measure is the one that best fits what we look for: highlight the most critical elements of the network.

[21] Cesar Ducruet, 2017.

Figure I.26: Centrality Measure for Puerto Rico Transportation Network

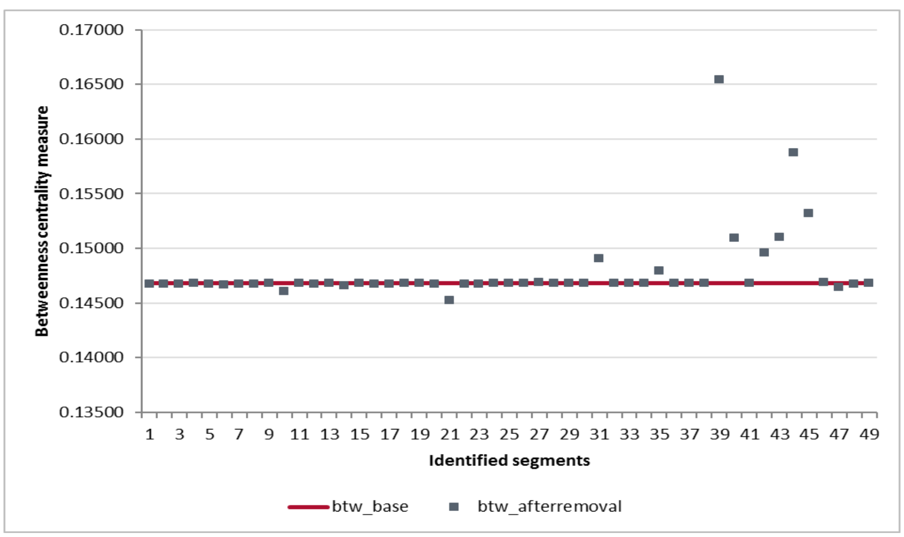


Source: SDG

Once the centrality measure is selected, it is calculated for the whole network as the baseline to compare. Then, for each identified segment, the corresponding links were removed and the centrality measure is again estimated. According to the difference obtained, all the segments that caused a reduction in betweenness centrality (i.e., they caused a negative effect system-wise) are assigned a score of "5", while all the segments that caused an increment or no change in the betweenness centrality (i.e., they are not as relevant in a system-level) are assigned a score of "1".

The Figure I.27 below shows the results for all identified segments.

Figure I.27: Betweenness Centrality After Removal



Source: SDG