A geospatial analysis platform for infrastructure risk assessment and resilient investment prioritisation in Jamaica

Final technical report on methodology and implementation of the Jamaica Systemic Risk Assessment Tool (J-SRAT) prepared for the Planning Institute of Jamaica (PIOJ)

University of Oxford, Environmental Change Institute

July 2022

Issue	**Status**	**Author(s)**	**Reviewed by**	**Issue Date**
1	Final report	Raghav Pant Olivia Becher Robyn Haggis Aman Majid Tom Russell Jasper Verschuur Edson Williams Anaitée Mills Ardith Grant	Tim Fowler Jim Hall	15/07/2022

This report may be cited as follows:

Pant, R., Becher, O., Haggis R., Majid, A., Russell, T., Verschuur, J., Williams, E., Mills, A., Grant, A. Fowler, T. and Hall, J.W. (2022). Final technical report on methodology and implementation of the Jamaica Systemic Risk Assessment Tool (J-SRAT). Environmental Change Institute, Oxford University, UK.

This report was produced as part of the project “A geospatial analysis platform for infrastructure risk assessment and resilient investment prioritisation in Jamaica” which was funded by the UK Foreign Commonwealth and Development Office (FDCO) as part of the Coalition for Climate Resilient Investment (CCRI). The views expressed and recommendations set out in this report are the authors’ own and do not necessarily reflect the position of the FCDO, CCRI or any public or private stakeholder in Jamaica.

Contents

Summary 1
1 Introduction 2
1.1 Background 2
1.2 The need and opportunity for infrastructure risk and resilience assessment 2
1.3 Project objectives and impact 5
2 Methodology development and implementation steps 7
2.1 Types of assessments done through J-SRAT 7
2.2 J-SRAT framework details and risk calculations 8
2.2.1 Risk estimation framework 8
2.2.2 Adaptation assessment and calculations 10
2.3 Output metrics 12
2.4 Implementation steps of the J-SRAT methodology 14
3 Model assumptions and data assembled for implementing J-SRAT 15
3.1 Generic methodology assumptions 15
3.2 Hazard data assembly 17
3.3 Socio-economic model and data assembly 19
3.3.1 Population data creation 19
3.3.2 Economic activity assigned to building footprints 21
3.3.3 Land-use data with economic activity assignment 24
3.4 Infrastructure asset and network model and data assembly 25
3.4.1 Energy systems model and data 25
3.4.2 Water systems models 29
3.4.3 Transport systems model 35
3.5 Adaptation options data 40
4 Implementation of J-SRAT tool through a use case 42
Appendix A: Vulnerability curves for infrastructure assets in Jamaica 45
Appendix B: Hazard models 53
B.1 Fluvial and pluvial flood models 53
B.2 Coastal flood model 53
B.3 Tropical cyclone model 54
B.4 Drought model 55
Appendix C: Infrastructure network flow models for failure analysis 56
C.1 Generalised network representations 56
C.2 Energy system model 56
C.3 Water systems models 60

C.3.1 Potable water demand assembly and disruption analysis 60
C.3.2 Irrigation demand mapping and disruption analysis 61
C.4 Transport system model 62
C.4.1 Transport flow allocation 62
C.4.2 Transport flow disruption analysis 69
Appendix D: Spatial disaggregation of economic activity at buildings and area levels 71
D.1 National accounting of GDP by economic sectors and subsectors 71
D.2 Disaggregation of GDP to buildings 74
D.3 Disaggregating GDP to agriculture areas 75
D.4 Disaggregating GDP to mining and quarrying areas 76

Summary

This document describes the methodology, data and implementation for the development of the Jamaica Systemic Risk Assessment Tool (J-SRAT). The focus of this report is to:

1. Provide a background of the project;
2. Provide a detailed overview of the methodology and the component models;
3. Outline the modelling assumptions made in the analysis;
4. Describe the datasets collected and finalised in implementing the methodology;
5. Show the process of implementation of the methodology through a use case example.

This is a *technical document* which is meant to explain the theory and concepts behind the spatial risk analysis and component models being developed in Jamaica. The *main target audience* of this report include climate risk and infrastructure modellers and technical experts who would be interested in understanding the detailed working of the J-SRAT.

1 Introduction

1.1 Background

The Coalition for Climate Resilient Investment (CCRI) was launched at the UN Secretary General's Climate Action Summit in September 2019, representing a commitment from the global private sector towards the development of practical analytical and investment solutions for decision-making that better incorporate climate risk. At a national level, CCRI will advance the assessment and protection of social and economic value from the growing incidence of physical climate risks, driving a shift toward a more climate resilient economy for all countries, including the most vulnerable. Building the economic and financial case for climate resilient investments will mobilise capital into resilient infrastructure and foster a more resilient financial industry.

This project forms part of the CCRI's collaboration with the Government of Jamaica (GoJ), with grant funding made available by the Foreign, Commonwealth and Development Office (FCDO), United Kingdom. The project was implemented in collaboration with the Planning Institute of Jamaica (PIOJ), with the support and collaboration from multiple government agencies in the GoJ, including the Office of the Prime Minister (OPM), Ministry of Finance and the Public Service (MOFPS), the Ministry of Transport and Mining (MTM), Ministry of Economic Growth and Job Creation (MEGJC), Ministry of Energy, Science and Technology (MSET), the National Water Commission (NWC), the National Works Agency (NWA), the Climate Change Division (CCD), the National Environmental Planning Agency (NEPA), the Office of Disaster Preparedness and Emergency Management (ODPEM), the University of the West Indies (UWI), the Statistical Institute of Jamaica (STATIN), Jamaica Social Investment Fund (JSIF), Public Investment Appraisal Branch (PIAB), National Spatial Data Management Division and other relevant Divisions within the GoJ.

The project technical development was led by the Environmental Change Institute (ECI) at the School of Geography and Environment (SoGE) in the University of Oxford as well as experts employed in Jamaica, with support from experts in the United Nations Office of Project Services (UNOPS) and the Smith School of Enterprise and Environment (SSEE), SoGE, University of Oxford.

1.2 The need and opportunity for infrastructure risk and resilience assessment

Infrastructure systems, including energy, transport and water supply networks, are particularly vulnerable to the impacts of climate change. Infrastructure is often disproportionately exposed to climate change: ports are inevitably going to feel the consequences of sea level rise; dams and reservoirs will have to cope with the implications of changing patterns of rainfall; thermoelectric power plants are usually located on the coast or next to large rivers because they need access to cooling water. The impacts of climatic extremes can be propagated through infrastructure networks far away from the places where the extreme event hit. Repairing and replacing infrastructure after a disaster can take months or even years, denying people of essential services and adding to the financial burdens on governments and communities.

In common with other Caribbean islands, Jamaica is exposed to a range of climate-related hazards, including hurricanes that have the potential to do the most widespread damage to the population and to infrastructure, as was demonstrated in hurricanes Gilbert in 1988 and Ivan in 2004. The most recent hurricane season in 2020 was considered one of the most severe with back-to-back tropical storms Zeta and Eta causing widespread devastation to people and infrastructure in the country[1]. Floods, which are linked with severe weather systems, frequently occur. Coastal areas are exposed to storm surges associated with cyclonic conditions, which will be exacerbated by sea level rise.

Jamaica has a long history of devasting damage from natural hazards to infrastructure, which is projected to increase in future[2]. Total damage from 9 hurricane events between 2001 and 2010 was estimated at J$111 billion. Of this, the infrastructure sector accounted for J$51.7 billion, or 46 % of the overall costs, with the transport (roads and bridges) incurring J$44.4 billion in damage costs[3]. For example, during Hurricanes Emily and Dennis the direct damage to infrastructure was estimated at J$3.7 billion, including 100,000 electricity customers being disrupted, damage to water supply systems, and major damage to roads[4].

Through its recently announced Infrastructure Development Programme[5], since 2019 the Jamaican government has taken some significant steps in planning for climate resilience in the infrastructure design process. This includes the national scale master drainage plan that identifies the gaps in the existing drainage systems in the country and suggests plans for reducing flood risks in the country[6]. These efforts are part of large-scale investments of J$500 million marked for bridges and roads in country over the next 12 years[7]. The Jamaica National Development Plan, which sets out the vision for 2030, outlines the aspirations for strong economic infrastructure as a national outcome stating that "Vision 2030 Jamaica will ensure the development of world-class transport, telecommunications, water supply and sanitation infrastructure that contributes to the competitiveness of our producers and improved quality of life for our people"[8].

While expansion and modernization of infrastructure systems almost always accompany economic development, infrastructure investments lock in patters of development for decades to come. It is estimated that US$80 trillion of investment in new and existing infrastructure is required worldwide over the next 15 years[9]. Plans, designs and investments made in the next few years will feel the full brunt of climate change. Especially in a small island like Jamaica, where space is limited, investments made in hazard prone areas cannot be avoided. It is therefore essential that climate change is factored into infrastructure planning right from the outset. Moreover, like most countries, Jamaica has a large stock of existing infrastructure which has mostly not been designed to cope with the threat of climate change. The impacts of climatic extremes on energy, transport and water infrastructure networks are already being felt worldwide. For example, in analysis for the World Bank[10] and Global Centre on Adaptation[11] estimate that more than 200,000km of roads are currently exposed to climate-related hazards

[1] https://www.miamiherald.com/news/nation-world/world/americas/article247095932.html
[2] UNCTAD https://sidsport-climateadapt.unctad.org/wp-content/uploads/2018/07/Jamaica-Case-Study.pdf
[3] Jamaica Institute of Engineers https://www.jiejamaica.org/presentations/Assessing%20the%20Costs%20of%20Disasters%20on%20Jamaica's%20Infrastructure.pdf
[4] PIOJ https://web.archive.org/web/20151125174915/http://www.pioj.gov.jm/portals/0/sustainable_development/dennis%20emily%20report.pdf
[5] https://jis.gov.jm/significant-investment-in-infrastructure-in-2020-21/
[6] https://jis.gov.jm/master-drainage-plan-completed-for-the-entire-island/
[7] https://opm.gov.jm/news/greater-infrastructure-development-programme-to-follow-midp/
[8] PIOJ. https://sustainabledevelopment.un.org/content/documents/1501jamaica.pdf
[9] http://newclimateeconomy.report/2016/wp-content/uploads/sites/4/2014/08/NCE_2016Report.pdf
[10] https://openknowledge.worldbank.org/handle/10986/31805
[11] https://cdn.gca.org/assets/2019-12/GCA-Infrastructure-background-paperV11-refs_0.pdf

worldwide, which could increase to 237,000km by 2050 because of climate change, without considering the new highway construction that will take place in that period[12].

Most investment needs for new and more climate resilient infrastructure are often focussed on steel and concrete infrastructure projects. There is a growing recognition that infrastructure resilience need not be provided only by traditional 'grey' infrastructure – the concrete barriers and steel pipes that perhaps one first thinks of when talking about flood protection, drainage or irrigation. Alternatively, 'green infrastructure' or 'nature-based solutions' (NbS) can improve resilience to climate change impacts while slowing further warming, supporting biodiversity and securing ecosystem services[13]. Flood protection, drainage and water storage can be provided by NbS like wetlands, mangroves and forests which are increasingly being designed to enhance the resilience of coasts, estuaries, rivers and cities in the face of climate change. The great thing about nature-based solutions is that, if they are well designed and properly cared for, they can provide multiple benefits – not just protection against climatic extremes but also enhancing biodiversity, capturing carbon in trees and the soil, and providing recreation opportunities and improvements to people's health and wellbeing. Studies have estimated that protecting coastal reefs in Jamaica could help avoid US$46 million damages to properties in coastal areas[14]. But making the economic case for the benefits of NbS remains a challenge as their full potential is not realised in most climate resilience investment planning processes[15].

All the above discussion shows that getting infrastructure right is a question of making the right choices – myriads of choices relating to investment prioritisation, planning, design, maintenance and rehabilitation. Good decision making is required to ensure that existing systems efficiently provide essential services even though they are threatened by climate change. And the right choices need to be made about prioritisation and investments in new infrastructure. This is all in the context of inevitably limited public resources and the private sector's attitude to risk. For Jamaica these issues are most relevant in the face of increasing extreme climate risks and limited budgets and investments constraints.

Making infrastructure decisions is a complex process. The tools of cost-benefit assessment have been widely used, though they raise problems of properly valuing all of the benefits and impacts of infrastructure investments. This is particularly challenging because infrastructure acts as systems which deliver services through networks. The impacts of infrastructure failure are not just felt locally but propagate widely across the economy and society. Infrastructure decision making is also challenging because of the complexity of infrastructure assets (for example their reliability and physical deterioration) and the hazards to which they are exposed – like flooding and land-sliding.

Over the past decades, it has become widely recognised that spatial risk analysis provides a rigorous way of analysing the benefits of investments in networks to improve their resistance to climatic hazards. The decision-making problem relies on being able to analyse risks first without, and then with, a given investment intervention. In recent years there have been rapid

[12] Koks, E.E., Rozenberg, J., Zorn, C., Tariverdi, M., Vousdoukas, M., Fraser, S.A., Hall, J.W., Hallegatte, S. A global multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications,* 10(1) (2019): 2677. DOI: 10.1038/s41467-019-10442-3

[13] Seddon, N., Chausson, A., Berry, P., Girardin, C.A., Smith, A. and Turner, B., 2020. Understanding the value and limits of nature-based solutions to climate change and other global challenges. *Philosophical Transactions of the Royal Society B*, *375*(1794), p.20190120.

[14] https://www.insuresilience.org/wp-content/uploads/2020/05/The-Value-of-Reefs_TNC_UCSC_InsuResilience-Integrated-Approaches-WG_20052020.pdf

[15] https://publications.iadb.org/publications/english/document/Nature-based_Solutions_Scaling_Private_Sector_Uptake_for_Climate_Resilient_Infrastructure_in_Latin_America_and_the_Caribbean.pdf

advances in the capability to provide high resolution information not only on asset-level exposure and vulnerability to natural hazards (which is achieved with catastrophe models), but also to model how infrastructure assets interact as systems supporting trade and other economic activities. This analysis enables calculation of indirect and wider economic losses from infrastructure failure[16]. When combined with information on repair/replacement costs, it can be used to target and prioritise ex ante adaptation actions. When combined with more information about the duration of recovery[17], it can be used to make the economic case for enhanced investment in ex post recovery strategies, including disaster risk finance.

In light of increasing climate risks to existing and potential new infrastructures in Jamaica this project comes at an opportune moment when climate adaptation planning and sustainable development priorities need to be urgently aligned at national and global scales.

1.3 Project objectives and impact

Notwithstanding several recent significant initiatives in policy and science, the development of a robust analytics platform for infrastructure risk and resilience assessment has not yet been achieved. The *vision of this project* is of an innovative open-source platform populated with Jamaica specific information (and completed with global datasets wherever necessary), which form the starting point for any national analysis, which can be progressively refined to provide dependable information at national and sub-national scales. This will provide a multi-purpose platform that can be adapted to several different use cases.

The *objectives* of the project are to:

1. Develop a decision support platform for Jamaica which enables risk analysis of climate risks to infrastructure networks (including transport, energy and water) and evaluation and prioritization of policies and options to reduce losses and enhance infrastructure resilience.
2. Build capacity within the Government of Jamaica and other relevant public and private stakeholders for infrastructure risk analysis and adaptation decision making.
3. Take a significant step on the journey towards an infrastructure risk and resilience analytics platform that can be applied throughout the world, thus contributing to the CCRI's work programme and to the adaptation goals of COP26.

The project aims to have *impact in Jamaica* by:

1. Providing new evidence to enable the prioritization of scarce resources that are available to strengthen, enhance, replace and add to infrastructure networks in Jamaica.
2. Bringing together relevant datasets, formatting them in a way that is interoperable, filling some gaps and highlighting priorities for data collection.
3. Providing insights into a full range of adaptation options, including disaster risk finance, nature-based solutions, and the resilience benefits of decarbonizing energy, transport and water supply networks.
4. Assessing the scale of macro-economic risks from infrastructure failure which will assist with assessment of fiscal risks and contingent liabilities for the Government of Jamaica.
5. Providing evidence that will help to make the case for adaptation finance assistance to the Government of Jamaica.

[16] Koks, E., Pant, R., Thacker, S., Hall, J.W. Understanding business disruption and economic losses due to electricity failures and flooding, *International Journal of Disaster Risk Science*, 10(2019): 421–438. DOI:10.1007/s13753-019-00236-y
[17] Zorn, C.R. and Shamseldin, A.Y. Post-disaster infrastructure restoration: A comparison of events for future planning, *International Journal of Disaster Risk Reduction*, 13(2015): 158-166. DOI: 0.1016/j.ijdrr.2015.04.004.

6. Properly quantifying climate risks to infrastructure investments, which will help private sector infrastructure investors to quantify risk and will incentivize adaptation in their investments.
7. Building capacity amongst staff in the Government of Jamaica and other stakeholders to use the analysis platform that is developed.

2 Methodology development and implementation steps

2.1 Types of assessments done through J-SRAT

The focus of this study is to create and implement a risk and climate adaptation assessment framework for energy, transport and water infrastructure networks in Jamaica. The implementation of this framework has led to the creation of the Jamaica Systemic Risk Assessment Tool (J-SRAT).

The J-SRAT tool comprises:

1. A methodology framework for spatial climate risk and adaptation analysis described in this report.
2. A geospatial database of climate hazards, energy, transport and water networks, population, buildings with economic activities, and different land use dataset created for Jamaica.
3. Open-source implementation codebase executed in Python programming language, available at: https://github.com/nismod/jamaica-infrastructure and https://github.com/nismod/JEM.
4. A web-based visualisation tool of all underlying datasets and different risk and adaptation outputs from the analysis, available at: https://jamacia.infrastructureresilience.org.

The tool is capable of producing different types of system-of-systems assessment useful for decision-making, which include:

- **Vulnerability assessment** – *Vulnerability* is defined as the propensity or predisposition of exposed elements such as infrastructures assets, human beings and economies to suffer adverse effects when impacted by hazard events[18]. We measure vulnerability of infrastructures terms of the negative *impacts or consequences* suffered due to failures induced by external hazard shocks[19].
- **Criticality assessment** – *Criticality* is defined as a measure of an infrastructure assets' importance and disruptive impact on the rest of the network[20]. Criticality assessment results in ranking network elements based on their relative impacts on the serviceability of the networks[19].
- **Risk assessment** – Climate *risks* are measured as the product of the probabilities of hazards, exposures and vulnerabilities summed over all possible hazard and network failure and disruption scenarios. Climate risk evaluations rely on the use of climate projections, derived from Global (or Regional) Climate Models (GCMs and RCMs), which introduce large uncertainties associated decision making at the infrastructure-level[21].
- **Adaptation assessment** – Climate *adaptation assessment* is the process of anticipating the adverse effects of climate change and evaluating the relative success of specific actions

[18] Cardona, O.D., M.K. van Aalst, J. Birkmann, M. Fordham, G. McGregor, R. Perez, R.S. Pulwarty, E.L.F. Schipper, and B.T. Sinh. 2012. Determinants of risk: exposure and vulnerability. In: *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 65-108.

[19] Pant, R., Hall, J.W. and Blainey, S.P. 2016. Vulnerability assessment framework for interdependent critical infrastructures: case-study for Great Britain's rail network. *European Journal of Transport and Infrastructure Research*, *16*(1).

[20] Arga Jafino B. Measuring Freight Transport Network Criticality: A Case Study in Bangladesh. TU Delft; 2017.

[21] Gersonius, B., Ashley, R., Pathirana, A. and Zevenbergen, C., 2013. Climate change uncertainty: building flexibility into water and flood risk infrastructure. *Climatic change*, *116*(2), pp.411-423.

aimed at reducing climate vulnerabilities[22]. Climate adaptation involves comparing the costs of the specific options with the benefits of avoided risks, realized over a time horizon and climate scenario.

2.2 J-SRAT framework details and risk calculations

2.2.1 Risk estimation framework

The different components in the J-SRAT framework that produce the *climate vulnerability and risk assessment* are shown in Figure 2-1. This framework has been created in a generic way in order to be applicable to a wide range of hazard and infrastructure datasets. We next explain the methodological steps in this system-of-systems framework, and focus on the generic nature of the component models and datasets involved in the analysis:

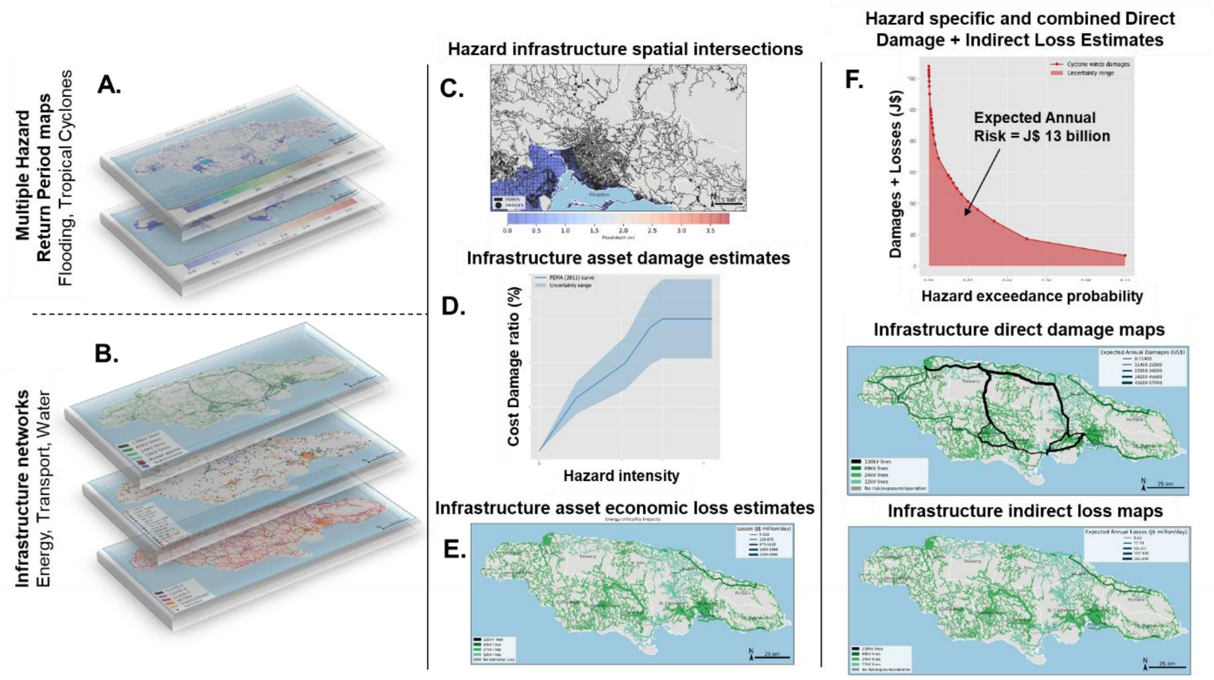


Figure 2-1: Framework for Jamaica Systematic Risk Assessment tool.

A. **Hazard assembly** – In this study we have assembled information on different types of flood hazards (fluvial, pluvial and coastal flooding) and tropical cyclones. We have also created a model for drought estimation, applied only to potable water assets. Every type of hazard (flooding, tropical cyclones and droughts) in our model is represented and quantified through *static hazard maps* that capture the following parameters: (a) spatial extent; (b) magnitude; (c) return period or the annual exceedance probability; (d) climate scenario; and (e) time epoch. Details of these terms and the hazard datasets assembled in this project are given in Section 3.1.

B. **Networks assembly** – We have created spatial representations of energy, transport and water infrastructure by assembling data on point and line assets to create topologically connected networks with attributes necessary for failure and damage analysis. In this study this means collecting or inferring all location information of point assets (railway stations, power plants, water treatment work, etc.) and geometries of line and polygon assets (roads,

[22] Möhner, A. 2018. The evolution of adaptation metrics under the UNFCCC and its Paris Agreement. In Christiansen, L., Martinez, G. and Naswa, P. (eds.) *Adaptation metrics: perspectives on measuring, aggregating and comparing adaptation results*. UNEP DTU Partnership, Copenhagen.

railway lines, electricity cables, pipes, ports, airports etc.), inferring structural condition of assets (e.g., paved or unpaved roads), and associating damage functions with different asset types, getting rehabilitation costs of assets. We have also developed models for mapping and modelling the services provided by networks to people and the economy. This involves understanding the supply capacities and demands associated with the usage of network assets. For example, the volumes of freight transport through ports, airports, roads, railway lines in tons/day; power plant capacities in MW, voltages of substations and transmission lines in kV; water demand in megalitres/day. Their measures are used in the estimation of socio-economic metrics of infrastructure service use, which include measures of the number of people and economic activity to network assets. Details of each network model are provided in Section 3.2 – 3.4.

C. **Exposure analysis** – Following the assembly of spatial hazard and infrastructure network datasets, we undertake an exposure analysis, which is done by performing spatial intersections of hazards and network assets. This involves overlaying each hazard map layer with each asset (point, line, polygon) and estimating: (a) the magnitude of the hazard at the location of the asset; (b) the extent of the line and polygon assets that are within the hazard areas given by the hazard map layer. The process of exposure analysis results in compiling hazard levels and spatial extents affecting each infrastructure asset across all return periods, climate scenarios, and time epoch of every hazard type. This leads towards the estimation of direct and indirect risks associated with assets and network failures.

D. **Direct damages estimation** – Following the exposure analysis, estimation of *direct damages* (or *direct damage costs*) to assets is done to quantify the *rehabilitation costs* (in J$ or US$) of assets subjected to different hazard shocks across current and future climate scenarios. The direct damage estimation is done by: (a) selecting a level of hazard that might cause physical damage to assets such that they will be a need to rehabilitate them; (b) looking up fragility or vulnerability functions, which quantify the percentage (or fraction) of damage sustained by an asset for a given magnitude of a hazard. In our analysis we also combine the uncertainties of vulnerability functions and asset unit costs, to quantify a range of direct damage costs to assets exposed to hazards.

E. **Indirect economic loss estimation** – This involves measuring the service and socio-economic losses that are associated with the damaged and hence failed assets. This is done by incorporating the effects of disruptions to infrastructure networks' overall performance and services, following direct damage assessment of individual (or groups of) assets. The effects of network-wide disruptions are measured in terms of disrupted customers or users of the network services, which include households and businesses. These user-disruption metrics are common across all networks and provide a systemic understanding of the importance of different networks and services at a larger regional or national scale. A more complete loss assessment is done by estimating the economic losses to businesses and the wider economic supply chains affected by infrastructure failures and disruptions. Such *indirect economic losses* are calculated at macroeconomic scales by translating the business and supply chain disruptions to Gross Domestic Product (GDP) and trade losses in J$/day (or US$/day). Infrastructure network specific models for estimation of indirect economic losses are described in further detail in Section 3.2 – 3.4.

F. **Different risk outcomes** – Risks at the asset-level are estimated as a function of the hazard annual exceedance probabilities and the total impacts (direct damages plus indirect losses). Due to the uncertainties associated with hazard events and climate scenarios, asset fragilities, and disruption impacts the risks associated with an individual failure scenario are not expressed as a single estimate, but rather a range of values. In this study we estimate two risk metrics:

a. **Expected Annual Damage (EAD)** – This is the measure of the average damage costs (in J$ or US$) incurred for an asset in any given year due to a given hazard type for a given time epoch and climate scenario. For a given asset and hazard, EAD at the asset level is estimated by first constructing the damage-probability curve, which is done by estimating the direct damages $d_1, \ldots, d_m$ associated with increasing annual exceedance probabilities $p_1, \ldots, p_m$. The EAD is estimated as the area under the damage-probability curve, which is described in Equation (1).

$$EAD = \frac{1}{2}\sum_{k=1}^{m}(p_{k+1} - p_k)(d_k + d_{k+1}) \qquad (1)$$

b. **Expected Annual Economic losses (EAEL)** – This is the measure of the average economic losses (in J$ or US$) incurred for an asset in any given year due to a given hazard type for a given time epoch and climate scenario. For a given asset and hazard, EAEL at the asset level is estimated by first constructing the loss-probability curve, which done by estimating the economic losses $l_1, \ldots, l_m$ associated with increasing annual exceedance probabilities $p_1, \ldots, p_m$. The EAEL is estimated as the area under the loss-probability curve multiplied by an assumed duration of disruption τ for the asset, which is described in Equation (2).

$$EAEL = \frac{1}{2}\tau\sum_{k=1}^{m}(p_{k+1} - p_k)(l_k + l_{k+1}) \qquad (2)$$

From the estimate of EAD and EAEL we get the asset level *total risk* = EAD + EAEL. There are different ways in which the risk estimates can be presented, either through the damage (loss)-probability curves or as a network map highlighting the most critical assets across the country in terms of value of EAD and EAEL estimates (see panel F in Figure 2-1).

2.2.2 Adaptation assessment and calculations

After having done an estimation of asset level risks across multiple hazards, climate scenarios, time epochs, we can do an adaptation assessment with respect to a set of adaptation options. The aim of this study is to quantify the effectiveness of adaption options with estimated costs for building resilience (to climate shocks) of individual assets and networks. This is done through a cost-benefit analysis of a chosen option, where the costs of an adaptation option are compared with the benefits due to reduced or avoided risks. The estimating of costs, risk reduction benefits and co-benefits of adaptation options leads towards prioritisation of investment interventions, which is done by evaluating different options and ranking them by their benefit-cost ratios. Section 3.5 describes the specific types of adaptation options considered in the J-SRAT tool. Here we focus on the general process of quantifying the effectiveness of any adaptation option irrespective of climate hazard or infrastructure network.

The effectiveness of any adaptation option is evaluated and compared through a Cost-Benefit Analysis (CBA), which is a well-established technique to compare the costs of an option with its benefits[23]. The planning for an adaptation option is done on an annual time-scale $t_0, \ldots, t_T$, starting at the time t_0 when the adaptation option is implemented and continues over its planned time horizon T. Assuming r is the rate for discounting costs and benefits over time in %, and j

[23] Pearce, D., Atkinson, G. and Mourato, S., 2006. *Cost-benefit analysis and the environment: recent developments*. Organisation for Economic Co-operation and development.

is the count for the years over which the value of adaptation is evaluated, the effectiveness of this adaptation option is quantified in terms of the:

1. *Costs* – which includes the initial cost of investment (CI_{t_0}) of implementing the adaptation option at the start year t_0, and the costs of routine (CR_{t_j}) and periodic maintenance (CP_{t_j}) investments needed to maintain the adaptation option over the time horizon. The total net present value of the investment cost of the adaptation options over the asset timeline is therefore given by Equation (3).

$$NPV\ Cost = CI_{t_0} + \sum_{j=0}^{j=T} \frac{CR_{t_j} + CP_{t_j}}{\left(1+\frac{r}{100}\right)^j} \qquad (3)$$

2. *Benefits* – which include the avoided losses, in terms of the expected reduction in direct damage risks ($\Delta EAD_{t_j} = EAD_{t_j} - \widehat{EAD}_{t_j}$) and the indirect economic losses($\Delta EAEL_{t_j} = EAEL_{t_j} - \widehat{EAEL}_{t_j}$), without ($EAD, EAEL$) and with ($\widehat{EAD}, \widehat{EAEL}$) the adaptation option implemented. Over time the EAELs are also assumed to grow (or decline) based on annual % GDP growth rates ΔGDP_j over the years. The total net present value of the benefits over the implementation of the adaptation option timeline is therefore given by Equation (4).

$$NPV\ Benefit = \sum_{j=0}^{j=T} \left(\frac{\Delta EAD_{t_j} + \left(1+\frac{\Delta GDP_j}{100}\right)^j \Delta EAEL_{t_j}}{\left(1+\frac{r}{100}\right)^j} \right) \qquad (4)$$

3. The *benefit-cost ratio* (BCR) of adaptation given as:

$$BCR = \frac{NPV\ Benefit}{NPV\ Cost} \qquad (5)$$

The above CBA analysis helps identify the effectiveness of adaptation options at the asset level, which can also be used to prioritise assets and locations for investments by either focusing on all assets with BCR≥1 or only targeting the few assets with the highest BCR. At the aggregated regional levels, we can use this analysis to estimate the total budget needed for investing in climate adaptation for assets with BCR≥1.

Figure 2-2 shows one adaptation assessment result from the J-SRAT web-visualisation platform, where the given adaptation option to ‘Build protective wall’ of height 1 meter around an electricity substation, in order to reduce flooding risks, is estimated to produce a BCR of 9.05. Details of the calculations are described in Section 4.

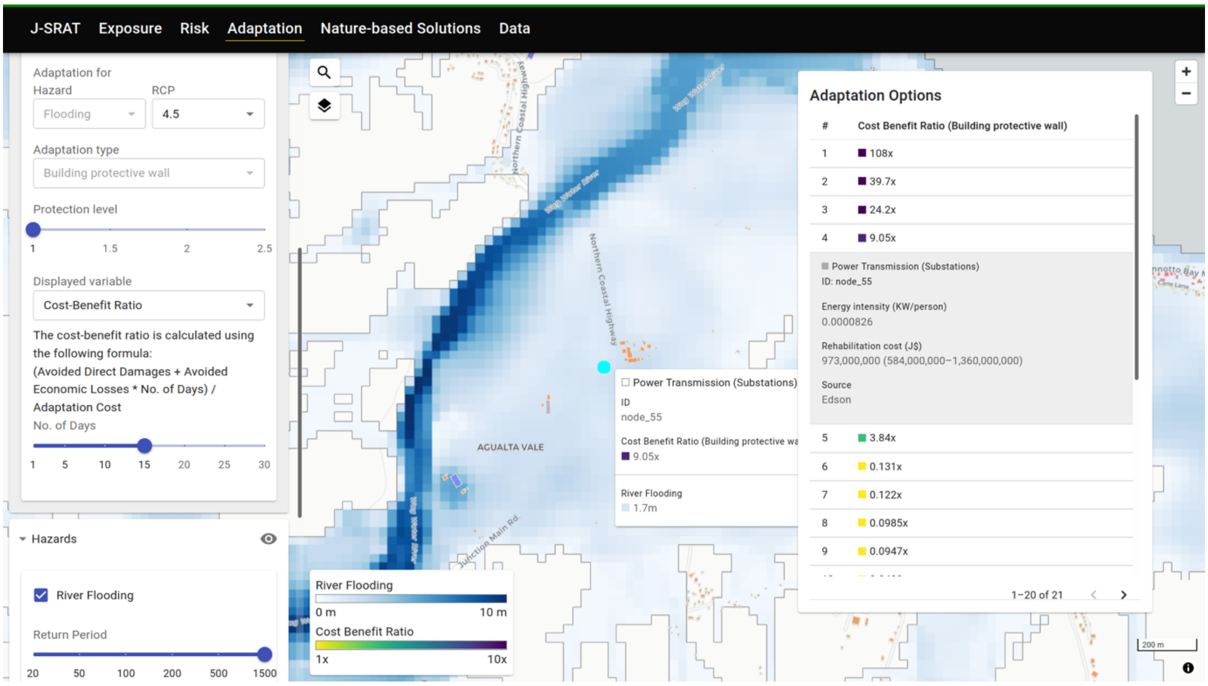


Figure 2-2: Visualisation demonstration of adaptation assessment output produced by J-SRAT tool.

2.3 Output metrics

A summary of the main output metrics developed in this study, their associated units, and types of results, are shown below in Table 2-1. These output metrics can be presented at different spatial scales:

1. **Infrastructure asset scale** – where the particular individual infrastructure assets are identified, and their systemic metrics are estimated.
2. **Regional scale** – where the metrics are aggregated at regional scales within Jamaica by adding up the asset level values. For example, the Parish level damages and losses of energy assets due to flooding can be estimated by adding up the value for each asset within the Parish boundaries.
3. **National scale** – where aggregated metrics are presented at the scale of the whole of Jamaica by adding up the asset level values.

Table 2-1: Overview of metrics that are produced from the J-SRAT implementation.

Stage	Type of metric	Metric descriptions	Unit
Hazard exposure	Numbers	Number of assets exposed to every hazard layer	-
	Lengths and Areas	Lengths and areas of assets exposed to every hazard layer	m and m^2
Vulnerability and criticality assessment	Direct damages	Rehabilitation costs for an asset damaged by each hazard layer	US$ or J$
	Indirect economic loss – Energy/water	GDP disruptions to household and businesses due loss of network service following an asset damaged by a hazard	US$/day or J$/day
	Indirect economic loss – Transport	Trade and passenger flow losses on network due to an asset damaged by a hazard	US$/day or J$/day
	Population/User disruptions	Number of people/households disrupted due to loss of network services	People/day
Risk assessment	Expected annual damages (EAD)	Direct risks	US$ or J$
	Expected annual economic losses (EAEL)	Indirect risks	US$ or J$
Adaptation assessment	NPV costs	Total cost of adaptation over an implementation timeline	US$ or J$
	NPV benefits	Total benefit of adaptation over an implementation timeline	US$ or J$
	BCR	Benefit-Cost Ratio	-

2.4 Implementation steps of the J-SRAT methodology

As noted previously, the J-SRAT analysis is implemented in a Python programming environment. Here, we summarise the overall sequence of steps in implementation of the J-SRAT risk and adaptation assessment methodology.

Table 2-2: Implementation steps of the J-SRAT methodology.

Step 1	Collect climate hazard layers with: • Annual exceedance probabilities (1/return periods) • Magnitudes • Spatial area coverage • Climate scenarios • Time epochs
Step 2	Assemble and create spatial population, economic activity and land-use data and models with: • Populations assigned to areas • Buildings assigned to specific economic sectors • Areas of agriculture, mining, and other types of activities • GDP associated with buildings and land-use activities
Step 3	Assemble and create spatial energy, transport and water infrastructure asset and network data and models with: • Locations and geometries of points, lines and polygons • Information on network connectivity • Asset and sector relevant attributes – e.g. asset types, capacity, dimensions • Rehabilitation costs • Network service flow allocation to locations of populations, buildings and land-use to determine location specific GDP dependent upon infrastructure assets
Step 4	Assemble information on hazard and asset specific vulnerability curves with: • Hazard and asset type • Hazard magnitude • Percentage damage to asset for given hazard magnitude
Step 5	Intersect hazards and assets and estimate the direct exposure statistics – numbers, lengths, areas of assets exposed to each hazard layer
Step 6	Estimate the set of assets damaged by each hazard layer, and estimate the direct damages from the exposures, vulnerability curves and rehabilitation costs
Step 7	Estimate the economic losses for damaged assets by implementing sector specific network models that quantify the network losses in terms of the population and GDP disrupted by asset failures
Step 8	Collect the asset specific damages and losses for each hazard return period, climate scenario, time epoch
Step 9	Calculate EAD and EAEL, from Equations (1)-(2), for each hazard, climate scenario, time epoch
Step 10	Assemble adaptation options data with: • Type of hazard specific option • Effectiveness of option in reducing hazard • Initial investment costs and maintenance costs and schedules over time • Discounting rates, GDP growth factors over timeline for implementation of option
Step 11	Repeat Steps 5-9 to calculate new asset level risks corresponding to the hazards with the adaptation options in place
Step 12	Estimate the NPV of adaptation costs, NPV of benefits and BCR values from Equations (3)-(5)
Step 13	Integrate results of the analysis into J-SRAT visualisation tool

3 Model assumptions and data assembled for implementing J-SRAT

To implement the J-SRAT methodology a number of different types of model assumptions and datasets are needed, and the confidence in the outputs depends heavily on the quality of the underlying datasets. In this project, all infrastructure and socio-economic datasets have been assembled from existing information compiled by ministries, government departments and other agencies managing data on energy, water, transport systems in Jamaica. We have leveraged upon high quality hazard datasets derived from global products for the analysis. There are also many model generalised model assumptions made in the risk assessment process, which are derived from previous studies in Jamaica or other studies relevant to the Caribbean region. Here we describe the underlying model assumptions and data created in the study.

3.1 Generic methodology assumptions

The following assumptions are applied in a generalised sense in the implementation of the risk and adaptation calculations.

1. The current (baseline) year for estimation of risks is chosen to be 2019. All rehabilitation cost estimates of assets and the economics statistics data used are in 2019 J$ values.
2. Where cost information was available in US$ it was converted to J$ by assuming the conversion rate of 1U$ = 150 J$.
3. In the adaptation options assessment the timeline of an option is assumed to be from the current year = 2019 to the end of century = 2100. This very long timeline is chosen simply because some of the climate change driven hazard datasets give future values until 2100.
4. In the adaptation cost-benefit analysis calculations the discount rate = 10%, which comes from previous projects data in Jamaica[24].
5. The assumed GDP growth rate trajectory for Jamaica till the end of the century is shown in Figure 3-1. The historical data and forecasts till 2025 are from the International Monetary Fund (IMF)[25], while further projection of constant GDP rate profile with lower and upper bounds are our own estimates.

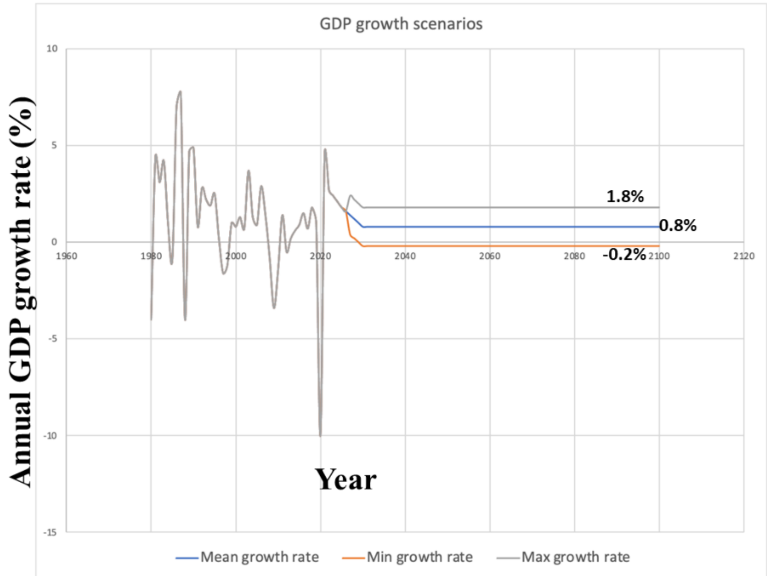


Figure 3-1: GDP growth rate forecasts for Jamaica showing the historic rates and projection till 2025 from IMF data (grey line), while further projections from 2025-2100 are done by assuming a constant mean rate (blue line) with a lower (orange line) and upper (grey line) bound.

[24] St. Elizabeth Water Supply Parish Plan – October 12 2011 - National Water Commission
[25] https://www.imf.org/external/datamapper/NGDP_RPCH@WEO/JAM

6. It is assumed that not all hazard types will cause damage to infrastructure assets even if there are known exposures to these hazards. Table 3-1 shows the assumed cases of hazard exposures that could potentially lead to failures of different types of assets with infrastructure sectors. For example, from Table 3-1 we can infer that in our analysis it is assumed that energy transmission lines and poles will not be affected and damaged by flooding while road and railway assets will not be physically damaged by extreme winds.

Table 3-1: All assumed instances of types of hazards exposures, which could lead to infrastructure asset damages for the assets considered in Jamaica (Y=Yes, N=No).

Sector	Sub-sector	Fluvial, Pluvial and Coastal Flooding	Tropical Cyclone Winds
Energy	Generation & Substations	Y (excluding solar and wind plants)	Y (excluding solar and wind plants)
	Transmission & Distribution Poles and Lines	N	Y
Transport	Airports	Y	Y
	Ports	Y	Y
	Railways	Y	N
	Roads	Y	N
Water	Potable water	Y	Y
	Irrigation	Y	N
	Wastewater	Y	N

7. It is assumed that damage to infrastructure assets will occur only when the hazard magnitude affecting them would be above a certain threshold value. This is done in order to avoid over-estimation of damage due to exposures, since assets would generally be built to withstand lower magnitudes of hazards. For example, 0.1 meters of flood depth might not be severe enough to cause any damage to assets. Table 3-2 shows the assumed failure threshold values for the magnitudes of each hazard type, where the flood depth threshold values are chosen based on previous studies in Jamaica[26] and the tropical cyclone wind speed threshold is chosen based on the Saffir-Simpson Hurricane wind speed scale in which a category 1 hurricane wind speeds have a lower bound close to 30 m/s and can potentially cause damage to overhead lines and poles in electricity networks[27].
8. The infrastructure vulnerability curves with respect to flooding and cyclone hazards are explained and shown in detail in Appendix A. Flood vulnerability curves are generally created for freshwater flooding (fluvial and pluvial), while coastal flooding due to storm surges can be more corrosive due to saltwater. Previous flood damage assessment studies

[26] Glas, H., Jonckheere, M., Mandal, A., James-Williamson, S., De Maeyer, P., & Deruyter, G. (2017). A GIS-based tool for flood damage assessment and delineation of a methodology for future risk assessment: case study for Annotto Bay, Jamaica. *Natural Hazards*, *88*(3), 1867-1891.
[27] https://www.nhc.noaa.gov/aboutsshws.php

in Jamaica assumed damages due to saltwater flooding were 12% higher than freshwater for the same flood depths[26], which we adopt. Table 3-2 shows how the 12% increase in vulnerability for coastal flooding exposures is accounted for through an uplift factor, which is a parameter multiplied to the vulnerability curve to scale it up or down.

Table 3-2: Hazard specific thresholds and vulnerability uplift factors assumed for direct damage assessment of assets in Jamaica.

Hazard type	Failure threshold value	Vulnerability curve uplift factor
Coastal flooding (flood depths)	50 cm	1.12
Fluvial flooding (flood depths)	50 cm	1
Pluvial flooding (flood depths)	50 cm	1
Tropical cyclones (wind speeds)	30 m/s	1

3.2 Hazard data assembly

In this study we are looking at infrastructure risks due to climatic hazards such as flooding (coastal, river (fluvial), surface water (pluvial)), tropical cyclones and droughts. For flood and tropical cyclone hazards we have static hazard layers that show the hazard outlines, intensities, and exceedance probabilities (or return periods), for present and future climate scenarios. We note that for flooding and tropical cyclone hazards we have not created any hazard models ourselves, so we rely on the hazard datasets and model outputs created by other organisations. Appendix B.1- B.3 describes the models behind the flooding and tropical cyclone datasets.

All the flooding and tropical cyclone datasets have the following information.

1. **Spatial extent** – The area over which the hazard exists.
2. **Magnitude** – The value that captures the severity of the hazard over an area. For example, flood depth in meters or wind speeds in m/s.
3. **Return period (or 1/occurrence probability)** – The probability or chance that a hazard might occur in any given year is expressed in terms of the return period[28]. For example, a 100-year return period hazard has a 1/100 or 1% chance of occurring in any given year.
4. **Climate scenario** – The climate scenarios associated with a hazard map show how the hazards might change in the future based on Representative Concentration Pathways (RCPs) as defined by the Intergovernmental Panel on Climate Change (IPCC)[29].
5. **Time epoch** – These are specific slices of time in years that show representative hazard maps corresponding to the climate scenario induced changes. Generally, climate scenario induced changes are seen in time scale of decades. Hence, the time epochs are represented in the hazard maps in some long-term future year rather than the current baseline year (example 2030, 2050, 2080).

For droughts we built our own model, which involved collecting data of daily stream flows (in m^3/s) at specific river gauge locations in Jamaica and creating a timeseries of current and future stream flows under changes to temperature and precipitation driven by different climate scenarios. Appendix B Section B.4 describes the model in further detail.

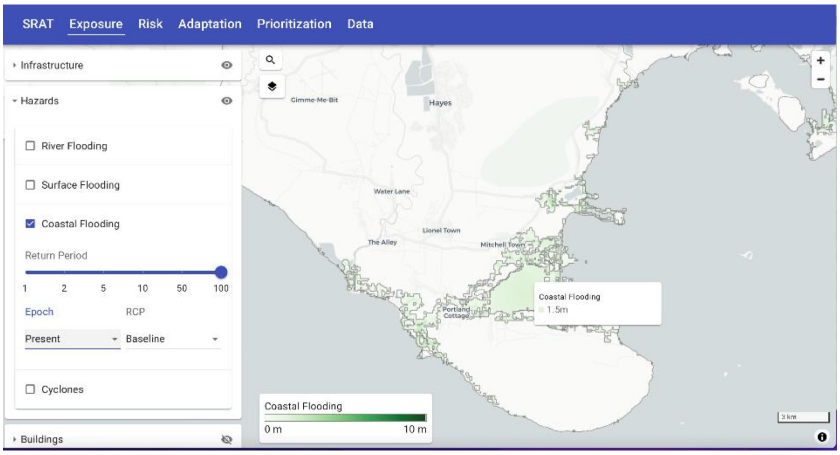
[28] https://niwa.co.nz/natural-hazards/faq/what-is-a-return-period
[29] https://coastadapt.com.au/infographics/what-are-rcps

Table 3-3 describes the details of the hazard datasets compiled for this study and Figure 3-2 shows the sample outputs for coastal flooding maps in present and future time epochs.

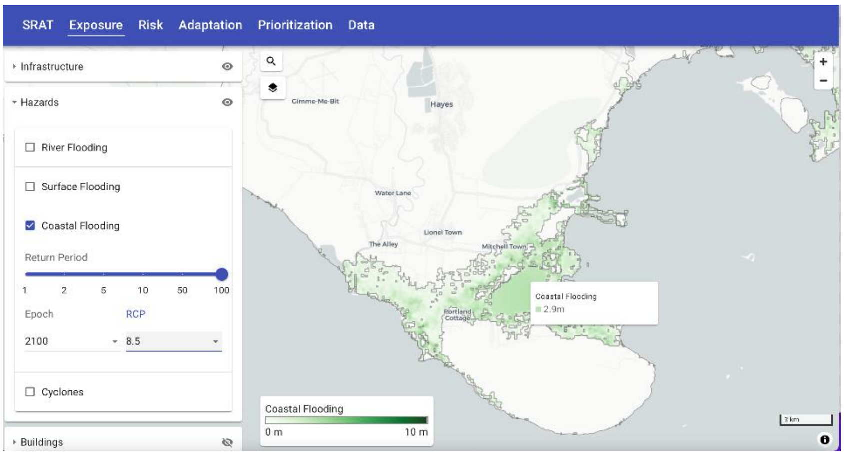
Table 3-3: List of hazard datasets assembled for the study.

Hazard type (data source)	Annual exceedance probabilities (1/return periods in years)	Magnitudes and spatial extents	Climate scenario information	Time epochs
Fluvial (river) flooding (JBA global flood map product[30])	1/20, 1/50, 1/100, 1/200, 1/500, and 1/1,500	Flood depths in meters over 30m grid squares.	• 1 current + 2 future climate model outputs • RCP 2.6, 4.5 & 8.5 emission scenarios	Current (2019) + future maps in 2050 and 2080
Pluvial flooding (JBA global flood map product[30])				
Coastal flooding (Deltares global flood map[31])	1/1, 1/2, 1/5, 1/10, 1/50, 1/100	Flood depths in meters over 90m grid squares.	• 1 current + 1 future climate model output • RCP 2.6, 4.5 & 8.5 emission scenario	Current (2019) + future maps in 2030, 2050, 2070 and 2100
Tropical cyclones (STORM IBTrACS model[32])	26 different exceedance probabilities from 1/1 to 1/10,000	10 minute sustained maximum wind speeds in m/s at 10km grid squares.	• 1 current + 1 future climate model output • RCP 4.5 & 8.5 emission scenario	Current (2019) + future maps in 2050 and 2100
Droughts (our own model)	No recurrence probabilities	Daily streamflow in m^3/s	• 1 current + 1 future climate model output • RCP 2.6, 4.5 & 8.5 emission scenario	Current (till 2019) + future climate scenario timeseries output till 2100

[30] https://www.jbarisk.com/flood-services/maps-and-analytics/global-flood-maps/
[31] https://microsoft.github.io/AIforEarthDataSets/data/deltares-floods.html
[32] https://opendap.4tu.nl/thredds/catalog/data2/uuid/779b9dfd-b0ff-4531-8833-aaa9c0cf6b5a/catalog.html



(a)



(b)

Figure 3-2: Sample map representation of coastal flooding model outputs in Jamaica showing the spatial extents and magnitudes for 1/100-year return periods for (a) Present day flooding under baseline climate conditions; and (b) Future flooding in 2100 under RCP 8.5 climate scenario.

3.3 Socio-economic model and data assembly

For economic loss analysis, we have assembled and created population and economic activity datasets that we use with every infrastructure sector model in this study.

3.3.1 Population data creation

The most spatially disaggregated population data for Jamaica was available at 5,776 Enumeration District (ED) levels, which was created by the Statistical Institute of Jamaica (STATIN) using 2011 census population estimates[33], which was the last detailed census recorded in Jamaica. From this dataset we get estimates of two quantities: (1) total number of people within an ED and (2) total working population within an ED, which we assume to be people in the age group 19 – 79 years.

We also use data from STATIN on the total annual population at the Parish level from 2011-2019[34], which give estimates for 2019 (the baseline year for our analysis) as shown in Table 3-4. We estimate the percentage change in population between 2011 and 2019 levels at the

[33] https://statinja.gov.jm/maps.aspx
[34] https://statinja.gov.jm/Demo_SocialStats/PopulationStats.aspx

Parish level and assume the total and working populations for all ED levels within a Parish also change by the same rate. Figure 3-3 shows the distribution of the 2019 population estimates at the ED levels.

Table 3-4: Jamaica Parish level population changes between 2011 and 2019 estimated from STATIN data.

Parish	2011	2019	Percentage change (%)
Kingston	89,275	90,544	1.42%
St Andrew	573,566	571,947	-0.28%
St Thomas	94,071	94,391	0.34%
Portland	81,669	80,921	-0.92%
St Mary	113,850	115,090	1.09%
St Ann	172,814	177,054	2.45%
Trelawny	75,559	78,487	3.88%
St James	184,619	191,737	3.86%
Hanover	69,929	72,519	3.70%
Westmoreland	144,874	149,857	3.44%
St Elizabeth	150,597	151,911	0.87%
Manchester	190,308	191,720	0.74%
Clarendon	245,488	247,112	0.66%
St Catherine	516,284	520,804	0.88%
Total	**2,702,903**	**2,734,093**	**1.15%**

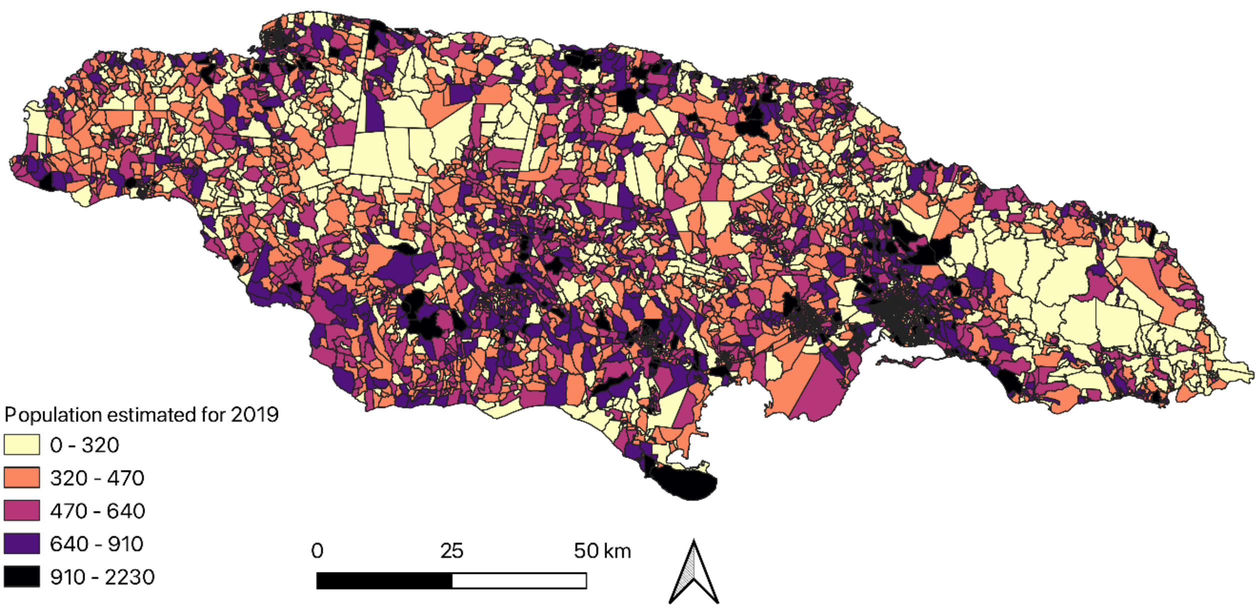


Figure 3-3: Map visualisation of population distribution at the ED level in Jamaica.

3.3.2 Economic activity assigned to building footprints

In Jamaica there are no datasets that provide information on spatial economic activity below national level statistics. We therefore created a first-of-its-kind spatial economic activity dataset at the level of 995,984 buildings in Jamaica. The aim of this dataset is to: (1) represent the type of buildings in Jamaica as residential and different types pf non-residential; (2) assign economic activities to non-residential buildings in terms of the GDP/day that might be generated by them; (3) map the buildings to different infrastructure networks to infer the dependence of economic activities on infrastructure services and (4) estimate the value of economic activity disrupted when the buildings lose their access to infrastructure services due to infrastructure damage.

To create the final building level economic outputs in GDP/day, data was gathered from the following organisations:

- OpenStreetMap (OSM)
- Humanitarian OpenStreetMap Team (HOT)
- National Environment and Planning Agency (NEPA)
- National Land Agency (NLA)
- Forestry Department (FD)
- The Nature Conservatory (TNC)
- Office of Disaster Preparedness and Emergency (ODPEM)
- Parish Municipal Corporations (PMC) – Manchester, Portland, St. Elizabeth, Clarendon, Kingston and St. Andrews
- National Spatial Data Management Division (NSDMD)
- Statistical Institute of Jamaica (STATIN)

The process of economic activity assignment involved geotagging buildings as residential and belonging to specific macroeconomic sectors in Jamaica. Based on data from STATIN we followed the Jamaica Industry Classification (JIC) 2005 nomenclature[35] to identify buildings belonging to macroeconomic sectors described in Table 3-5 and Appendix D Table D-1. We note the following:

1. A more recent JIC 2016 system does exist[36], but detailed macroeconomic statistics are still provided according to the JIC 2005 system. Hence, we adopted the JIC 2005 system to group buildings into macroeconomic sectors.
2. We have excluded the infrastructure specific macroeconomic sectors from the classification below, since GDP associated with infrastructures was estimated using the non-building dataset described in Section 3.4.
3. We note that we have also excluded some sectors, such as Private Households with Employed Persons, in our data because it was not possible to infer which buildings they could be assigned to.
4. A more detailed industry breakdown of the JIC 2005 sectors into further sub-sectors with Gross Value Added (GVA) and total GDP at current prices for the year 2019 was provided by STATIN[37]. This is reported in Appendix D Table D-1, from which we assigned sector and subsector specific GDP values to the building levels.

[35] https://statinja.gov.jm/Jamaica%20Industrial%20Classification%20Structure%20Revised%20-%202005.pdf
[36] https://jic.statinja.gov.jm/
[37] https://statinja.gov.jm/NationalAccounting/Annual/NewAnnualGDP.aspx

Table 3-5: Jamaica Industry Classification (JIC) 2005 based codes and names of macroeconomic sectors.

JIC code	JIC sector name
A	AGRICULTURE, HUNTING AND FORESTRY
B	FISHING
C	MINING AND QUARRYING
D	MANUFACTURING
F	CONSTRUCTION
G	WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES, MOTORCYCLES AND PERSONAL AND HOUSEHOLD GOODS
H	HOTELS AND RESTAURANTS
I	TRANSPORT, STORAGE AND COMMUNICATIONS (POSTAL SERVICES)
J	FINANCIAL INTERMEDIATION
K	REAL ESTATE, RENTING AND BUSINESS ACTIVITIES
L	PUBLIC ADMINISTRATION AND DEFENCE, COMPULSORY SOCIAL SECURITY
M	EDUCATION
N	HEALTH AND SOCIAL WORK
O	OTHER COMMUNITY, SOCIAL AND PERSONAL SERVICE ACTIVITIES

The first operation of simply geotagging buildings involved the following steps:

1. The baseline buildings polygon datasets were obtained from OSM and HOT, which are open and free datasets[38,39]. Within these datasets several buildings were already tagged in terms of their usage. For example, several schools, hospitals, hotels, etc. were geolocated and tagged in the data, to which we could then assign the correct JIC sector codes (M, N, H, etc.).
2. Several datasets from an NSDMD database also provided locations of known schools, hospitals, institutions, industrial and manufacturing sites in Jamaica, which was spatially intersected and mapped onto the buildings polygons to further infer the building usage and assign JIC sector codes.
3. Land parcel datasets from NLA, NEPA, ODPEM and PMC helped identify large numbers of buildings within areas designated for specific types of construction, and especially separate out residential areas from non-residential ones. Figure 3-4 shows an example of buildings overlaid with different land planning classes, from which we know that all areas coloured in pink are designated residential areas and so all buildings within pink areas will be residential.

[38] https://download.geofabrik.de/central-america/jamaica.html
[39] https://data.humdata.org/dataset/hotosm_jam_buildings?

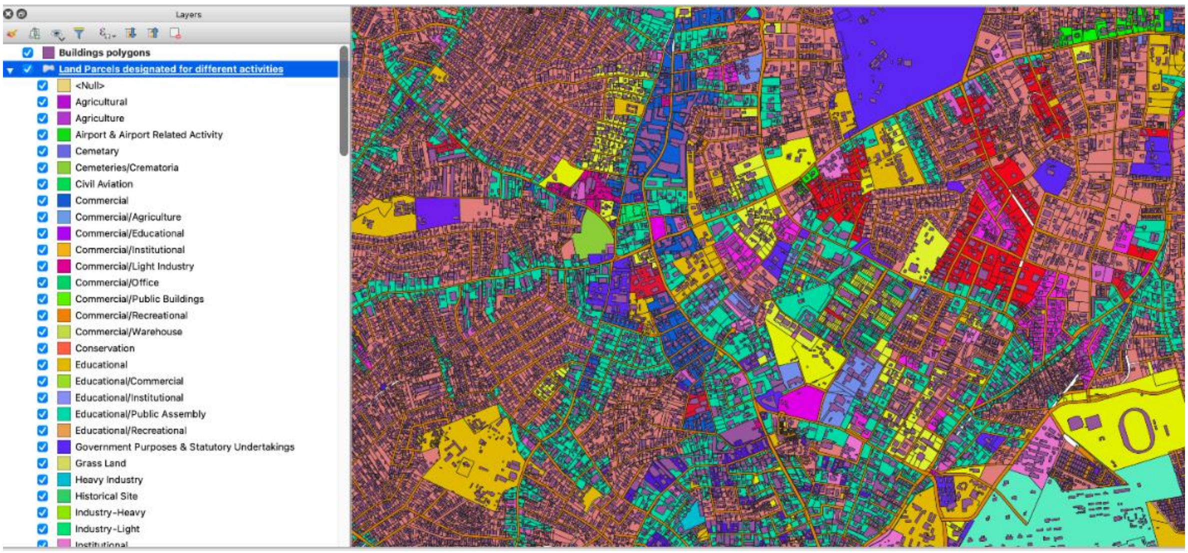
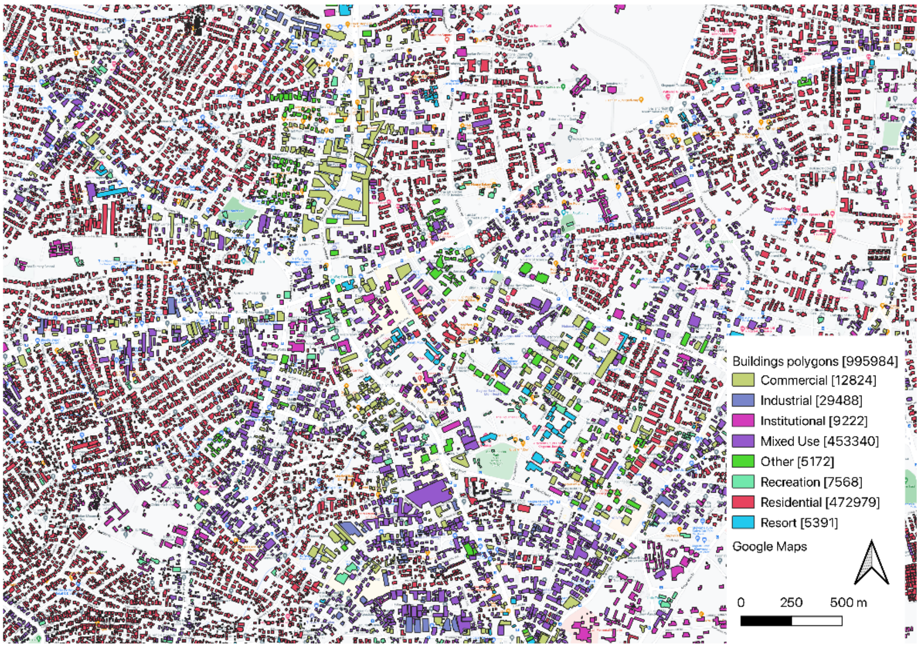


Figure 3-4: Screenshot of the buildings overlaid with different planning land parcels with designated types of developments assigned to them.

4. The remaining buildings, especially those belonging to agriculture, fishery and mining sectors were tagged based on different land use datasets from NEPA, TNC, and FD.

Figure 3-5 shows a zoomed in map representation of the final result of geotagging all buildings in Jamaica, where the different types denote the primary usage of the buildings as shown in the figure.



Type	Meaning	Type	Meaning
Commercial	Sector G	Other	No sector mapped
Industrial	Sector A, B, C, D	Recreation	Sector O
Institutional	Sector L, M, N	Residential	Residential only
Mixed Use	More than one type	Resort	Sector H

Figure 3-5: Map representation of different building types zoomed in over an area in Jamaica. The map legend shows the total numbers of different building types mapped over the whole country.

Following the creation of the sector specific geotagged buildings, we disaggregated the national scale GDP estimates (given in Appendix D Table D-1) to the building stock mapped to each sector and subsector. For buildings assigned to sectors D – O we applied the method described in Appendix D Section D.2, which gave us the GDP/day for each building.

3.3.3 Land-use data with economic activity assignment

Economic activity assigned to the Agriculture (A), Fishery (B) and Mining (C) sectors in Jamaica in GDP/day/area was done over areas where these activities were taking place, instead of building scale. If buildings were located within these areas, then the GDP/day over the areas of the buildings was then estimated. For creating these estimates, data was gathered from the following organisations.

- Forestry Department (FD)
- The Nature Conservatory (TNC)
- National Spatial Data Management Division (NSDMD)
- International Food Policy Research Institute (IFPRI)
- Statistical Institute of Jamaica (STATIN)

The process of assigning GDP/day to agricultural areas is explained in detail in Appendix D Section D.3. In general, we aimed to create approximate estimates of the concentration of agricultural output over different areas in Jamaica. No such data exists in Jamaica or if it does then we were not made aware of it. To estimate spatial agriculture output, we use the land-use datasets from FD and TNC to first identify the areas designated as agricultural land and different crop types, and then - using gridded datasets of crop level agricultural output estimates from IFPRI - we map the intensity of agricultural outputs (in US$/m^2) over the agriculture land areas for different crops. Finally, the overall agriculture sector and subsector GDP estimates (from Table D-1) are spatially disaggregated in proportion to the intensity of agriculture output estimates. Figure 3-6 shows the final agriculture layer with the GDP/day/area values.

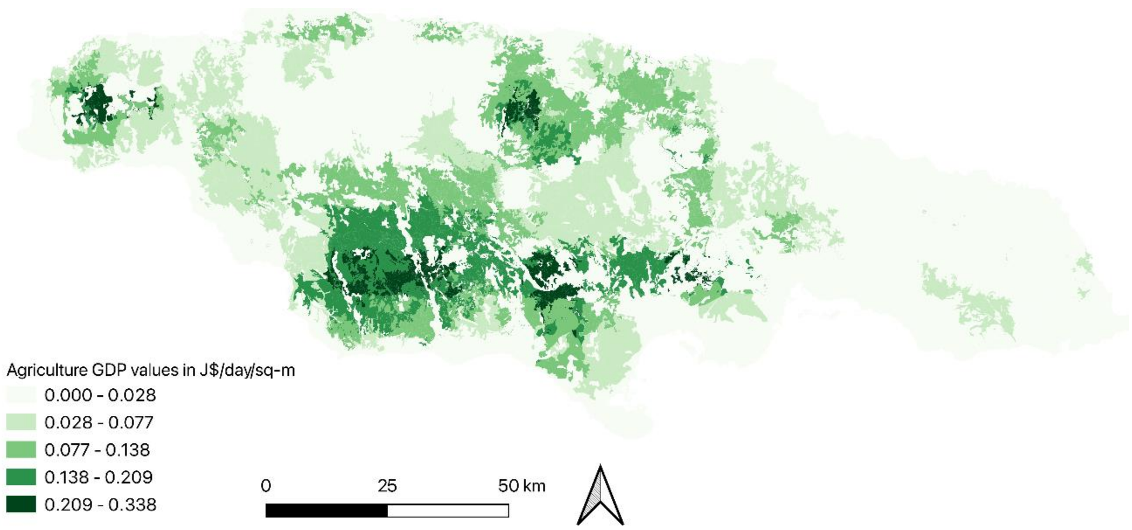


Figure 3-6: Map representation of the estimated agriculture sector GDP intensity associated with different areas in Jamaica.

For assigning Fishery sector GDP spatially across Jamaica we used a dataset on Aqua Farms compiled in the NSDMD database (and originally from Fisheries Division, Mona Geoinformatics), which gave information of the size of farm lots in terms of the acres devoted to fisheries production. We used this information to assume that the whole fishery sector GDP was assigned to each farm area in proportion to its size.

The process of assigning GDP/day to mining and quarrying sector is explained in detail in Appendix D Section D.4. Mining and quarrying sector GDP was spatially disaggregated over areas of mining and quarrying land-use from the FD and TNC datasets, through port statistics on tonnages of mining and quarrying produce sent out for export. Figure 3-7 shows the final mining layer with the GDP/day/area values.

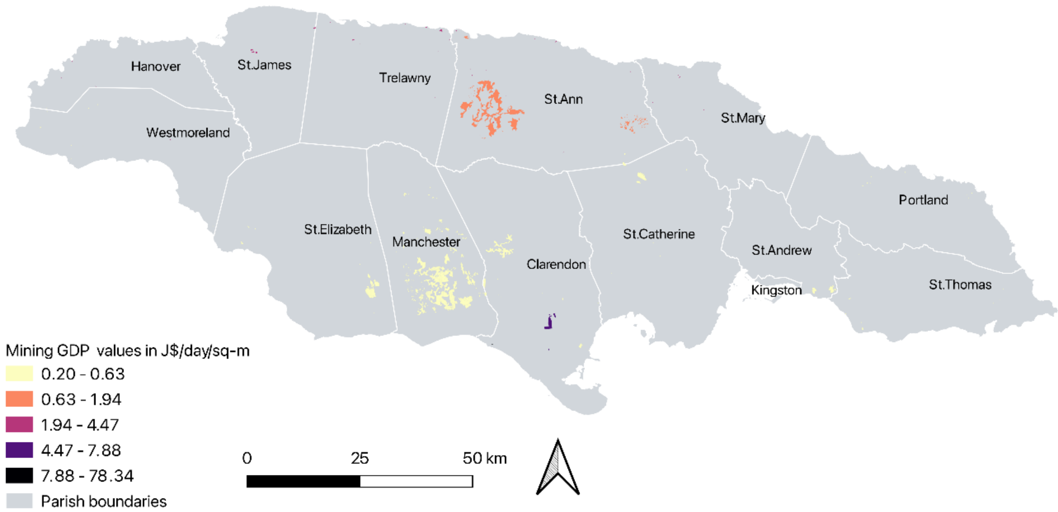


Figure 3-7: Map representation of the estimated mining and quarrying sector GDP intensity associated with different areas in Jamaica

3.4 Infrastructure asset and network model and data assembly

The energy, transport and water infrastructure systems being analysed in this study are conceptualised as spatial network models. A network is a collection of points (or polygon) assets called *nodes* or *areas* (power plants, railways stations, ports, dams) connected by line assets called *edges* (electricity lines, railway tracks, pipelines). The term asset is also used to refer to a node, area or edge. Appendix C Section C.1 explains the general network formulation adopted in this study.

3.4.1 Energy systems model and data

In this project we have created a Jamaica Energy Model (JEM), which is a power systems model which aims to: (1) create a high-level representation of Jamaica's electricity network; (2) represent how electricity would flow across Jamaica from locations of supply to meet demands across the country; (3) quantify the network flow losses due to asset damage from climatic hazards; and (4) provide risk outcomes that feed into the overall J-SRAT process to help identify the assets and regions that are most vulnerable to current and future climatic hazards.

Appendix C Section C.2 describes the technical details of the JEM. The JEM is a high-level optimal power flow model, which computes energy balances across the system, using defined supply and demand curves. It uses a mass-balance formulation, which is solved with an underlying network linear programming (optimisation) algorithm. JEM has been implemented in Python with the codebase available at: https://github.com/nismod/JEM.

Figure 3-8 shows the spatial network representation of the Jamaica energy system, which was built using data obtained from the sources below.

- National Spatial Data Management Division (NSDMD)
- Jamaica Public Service Company (JPS Co.)
- Ministry of Science, Energy & Technology (MSET), Energy Division
- Office of Utilities Regulation (OUR)
- OpenStreetMap (OSM)

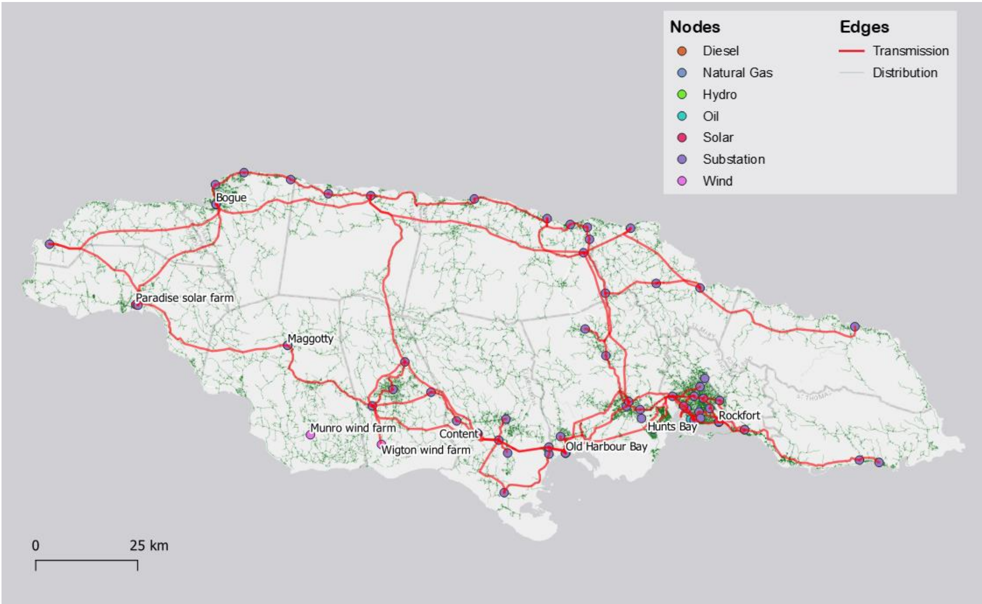


Figure 3-8: Map of Jamaican electricity network as modelled within JEM. Nodes and edges represent physical assets within the system.

Table 3-6 describes the data attributes and source for the different type of sub-systems within the energy system.

Table 3-6: Summary of data collected and required for the energy system.

Type	Network category	Asset	Attributes	Source
Generation	Node	Power stations (solar, wind, hydro, gas, diesel)	Latitude, longitude, fuel type, capacity, baseload factor	NSDMD/JPS/MSET/OUR
Distribution	Edge	High voltage (69 kV – 138 kV)	Geometry, voltage, capacity	NSDMD/JPS/MSET/OUR
		Mid-voltage (24 kV)		
		Low voltage (12 kV)		

Type	Network category	Asset	Attributes	Source
	Node	Substations	Latitude, longitude, capacity	NSDMD/JPS/MSET/OUR
		Power poles	Latitude, longitude, capacity	OSM*
Demand**	Node	Consumer demand	Load	JPS/MSET/OUR

* Poles were added to the data either through OSM data or by introducing them at the ends of voltage lines.
** Demand nodes were inferred to exist where the low-voltage lines terminated.

The other assumptions made in the JEM include:

1. That electricity flow in all high-voltage transmission lines is bidirectional, whereas mid-voltage and low-voltage distribution lines are unidirectional.
2. The model only considers optimal load flow analysis and does not incorporate power system constraints such as AC and DC power flow analysis.
3. To estimate the direct damages to assets due to hazards, rehabilitation costs were assigned to different node and edge assets from different sources as shown in Table 3-7 and Table 3-8. Direct damage curves for assets are shown in Appendix A Figure A-1.

Table 3-7: List of node asset types and their rehabilitation costs estimates used for Jamaica's energy system.

Node type	Node numbers	Capacity (MW)	Rehabilitation unit costs	Cost unit
Diesel	2	40 – 68	1,106,069 – 3,000,219[40,41]	US$/MW
Gas	2	120 – 194	1,179,503 – 3,370,503[40,41]	US$/MW
Hydro	1	13 – 13	2,780,352 – 9,733,017[40,41]	US$/MW
Solar	2	20 – 51	2,517,638 – 3,489,415[40,41]	US$/MW
Wind	2	34 – 62	2,178,693 – 12,253,971[40,41]	US$/MW
Substation	59	8.4 – 96	80,000 – 180,000[40,41,42]	US$/MW
Pole	29,934	8.4 – 96	1,000 – 5,000[43]	US$
Demand	14,037	8.4 – 48	1,000 – 5,000[43]	US$

[40] https://documents1.worldbank.org/curated/en/474111560527161937/pdf/Final-Report.pdf
[41] 360° Resilience: A Guide to Prepare the Caribbean for a New Generation of Shocks – Overview of Engineering Options for Increasing Infrastructure Resilience in the Caribbean (English). Washington, D.C.: World Bank Group. http://documents.worldbank.org/curated/en/260061635280496287/360-Resilience-A-Guide-to-Prepare-the-Caribbean-for-a-New-Generation-of-Shocks-Overview-of-Engineering-Options-for-Increasing-Infrastructure-Resilience-in-the-Caribbean
[42] Olave-Rojas, D., Álvarez-Miranda, E., Rodríguez, A., & Tenreiro, C. (2017). An optimization framework for investment evaluation of complex renewable energy systems. *Energies*, *10*(7), 1062.
[43] https://polesaver.com/blog/why-do-wooden-utility-poles-fail/

Table 3-8: List of edge types and their rehabilitation costs estimates used for Jamaica's energy system.

Edge Voltage	Length (km)	Capacity (MW)	Rehabilitation unit costs	Cost unit
138kV	362	96	746 – 3,318[40,41]	US$/MW/km
69 kV	830	48	746 – 3,318[40,41]	US$/MW/km
24 kV	8,032	16	1,491 – 6,636[40,41]	US$/MW/km
12 kV	2,205	8.4	1,491 – 6,636[40,41]	US$/MW/km

To model the supply and demand balance in JEM, data on annual electricity usage in MWh/year was obtained from JPS. Due to data security reasons this data is not reported here, and the interested reader can contact JPS for details. The demand data was provided as an aggregated statistic at the Parish level, which we disaggregated to the demand node level as following:

1. It was assumed that each demand node within a Parish would service a unique area of customers (households and businesses) closest to it, which was represented by a Voronoi polygon. This technique of creating Voronoi Polygons is a very well-known method, which assumes that infrastructure assets services will be allocated to their closest customer because that is the most cost-effective option[44,45].
2. For each demand node the total population within its Polygon area was estimated and the Parish level demand estimate from JPS was then disaggregated in proportion to the population associated with each demand node. This assumes that more electricity would be needed where more people would be concentrated.

Figure ***3-9*** shows the map visualisation of the process of population allocation to the electricity demand nodes in the Kingston area. This result is taken to estimate the demands in MW at each demand node which is then balanced by the capacity values assigned to the power plant nodes in Jamaica, by implementing the JEM.

[44] Thacker, S., Pant, R., & Hall, J. W. (2017). System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures. *Reliability Engineering & System Safety*, *167*, 30-41.
[45] Thacker, S., Barr, S., Pant, R., Hall, J. W., & Alderson, D. (2017). Geographic hotspots of critical national infrastructure. *Risk Analysis*, *37*(12), 2490-2505.

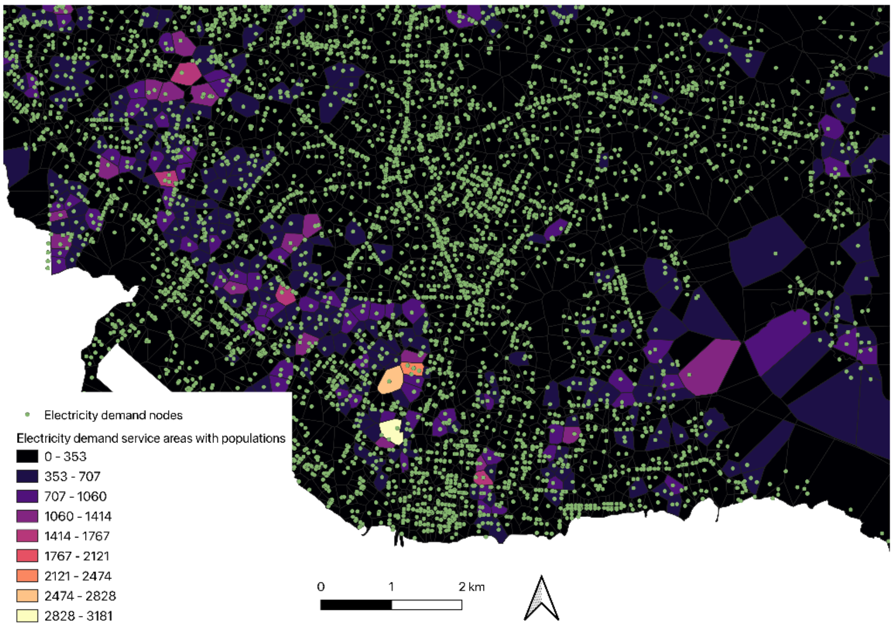


Figure 3-9: Map visualisation of the Voronoi polygon service areas created around electricity demand nodes and the assigned population within each area.

By solving the JEM, we are able to estimate how electricity would flow from power plants to demand nodes in Jamaica. When we introduce a hazard event to the electricity network, we remove the nodes and edges that would suffer direct damages from that hazard. We then rebalance the supply and demand on the network by resolving the JEM for the disrupted network. This will result in following cases:

1. The network might still be able to match supply with demand at the pre-disruption levels, which would not lead to any network losses. Hence, in this case there would be no economic losses due to network failures.
2. There might be locations where demand will not be met due to either loss of capacity in the network or due to the network service unable to reach the demand nodes. This would lead to economic losses.
3. Economic losses due to electricity outages are estimates estimated in terms of the sum of GDP disrupted from electricity sector and the GDP associated with buildings and other infrastructure using electricity within the service areas of demand nodes affected by network failures. This is explained in more detail in Appendix C Section C.2.

The outputs of the JEM feed into the Step 7 of Table 2-2, where the J-SRAT implementation steps are explained.

3.4.2 Water systems models

In this project we have modelled the water system comprised potable water, wastewater and irrigation. The aim of the water systems model is to: (1) create a high-level representation of Jamaica's different water networks; (2) represent how potable water and irrigation systems would spatially meet demands for water from households and industries across the country; (3) quantify the network losses to due to assets damage from climatic hazards; (4) quantify the effects of droughts on potable water supply and demand; and (5) provide risk outcomes that feed into the J-SRAT process to help identify the assets and regions that are most vulnerable to current and future climatic hazards.

The potable and wastewater networks are owned and operated by the National Water Commission (NWC), which supplies drinking water and wastewater services to 70% and 15% of Jamaica's population, respectively. The NWC produces in excess of 90% of Jamaica's total potable water supply and the rest of the water supply services are provided by the Parish Councils and a small number of private water companies, servicing private residential developments. The NWC supplies approximately 190 million gallons of potable water daily to consumers island-wide from river, spring and groundwater sources. The remaining portion of the population is supplied with drinking water from smaller private utilities, standpipes, trucks, rainwater harvesting, or direct access to rivers or streams[46]. The vast majority of people who are not connected to the sewer network use pit latrines. The National Irrigation Commission (NIC) provides irrigation services over approximately 50,000 Hectares across 15 irrigation schemes as well as drainage services in the Black River area.

We note that:

1. Potable supply schemes operated by Rural Water Supply Limited and non-formal forms of water supply (e.g., private well/spring sources and tanker trucks) are not included in our study.
2. Catchment tanks owned by the NWC are also not included.
3. Water supply and wastewater management systems that serve individual agricultural or industrial schemes are not included in the analysis.
4. We do not consider any economic losses for wastewater asset damages. Propagations of disruptions to users and other assets is less relevant for the wastewater network in comparison to the other networks considered because users would not be affected by wastewater treatment plant failures. This is discounting the flood risk posed by sewer network overflows and the environmental consequences.

The water systems models are built using data obtained from following sources, as described in Table 3-9 and shown in Figure 3-10.

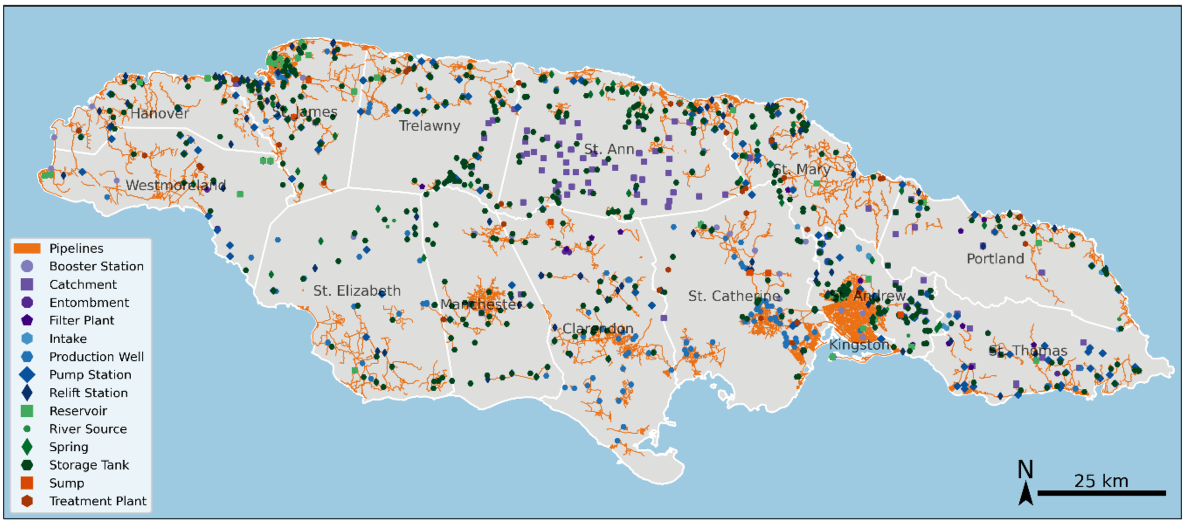
- National Water Commission (NWC)
- Mona Geoinformatics Institute (MGI)
- National Spatial Data Management Division (NSDMD)
- National Irrigation Commission (NIC)
- Water Resources Authority (WRA)

Table 3-9: Summary of data sources for the water systems model.

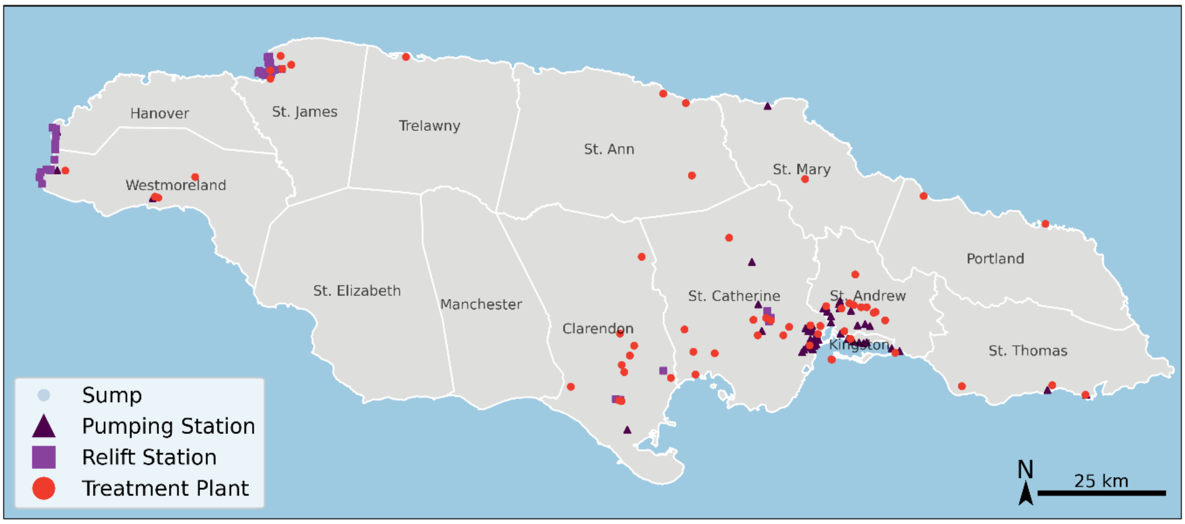
Data type	**Name**	**Source**
Asset locations and attributes	Potable facilities	NWC
	Potable Pipelines network	NWC
	Water Supply Zone	NWC
	Wastewater facilities	NWC
	Irrigation pipelines network	MGI/NSDMD

[46] Statistical Institute of Jamaica (2010) *Census of Population and Housing - Jamaica*.

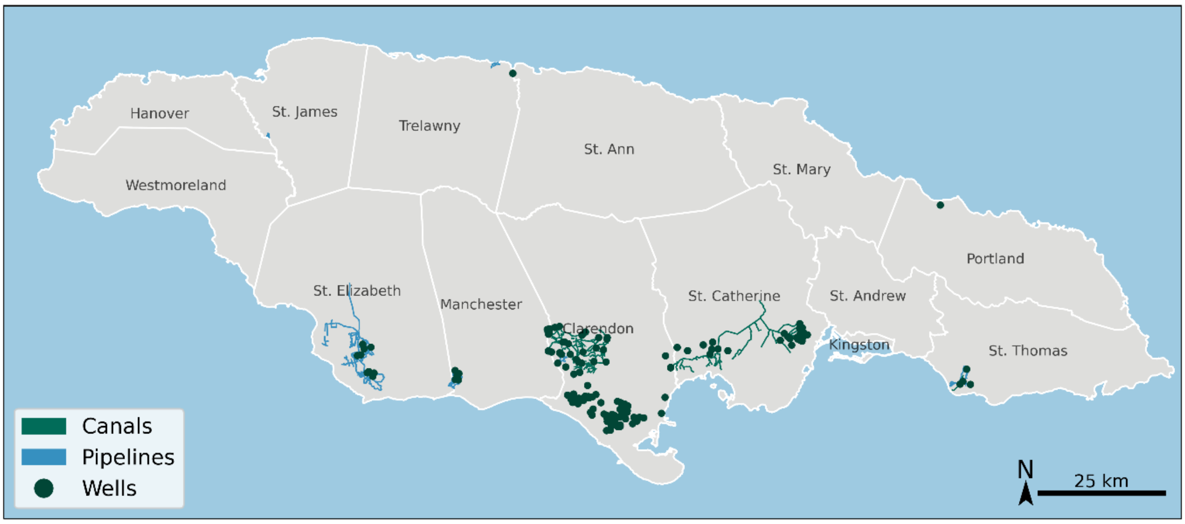
Data type	Name	Source
	Irrigation canal network	MGI/NSDMD
	Irrigation well sites	NIC
Scheme/System attributes	Parish Water Supply Plans	NWC
	Disruption Notices	NWC
	Irrigation Scheme Attributes	NIC
Abstraction	Monthly Abstraction for NWC potable supply systems	WRA
Hydrology	Daily Streamflow	WRA
	Sub management Catchments	WRA



(a)



(b)



(c)

Figure 3-10: (a) NWC owned and operated potable water supply assets and piped network; (b) NWC owned and operated wastewater treatment assets; and (c) NIC owned and operated wells, canals and pipelines.

Table 3-10 shows the assembled list of different assets types, and their assumed rehabilitation costs for damage assessment. We note that where there are no cost estimates, those types of assets are assumed to be not damaged by the given climatic hazards considered in this study for Jamaica. Damage curves for water assets as shown in Appendix A Figure A-1.

Table 3-10: Asset types, counts and rehabilitation cost estimates for water system assets in Jamaica.

Potable nodes	Asset count	Rehabilitation unit costs	Cost unit	Source
Booster Station	36	5 – 20	J$ million/asset	NWC Parish Plans[47]
Catchment	100	N/A*	N/A*	
Entombment	14	N/A*	N/A*	
Filter Plant	23	200 – 300	J$ million/Mgal*	
Intake	14	N/A*	N/A*	
Production Well	145	70,000	J$/asset	
Pump Station	130	5 – 20	J$ million/asset	
Relift Station	126	5 – 20	J$ million/asset	
Reservoir	40	N/A*	N/A*	
River Source	13	5 – 15	J$ million/asset	
Spring	51	5 – 15	J$ million/asset	
Storage Tank	477	N/A*	N/A*	

[47] Parish Water Supply Plans from 2010/11 - https://www.nwcjamaica.com/uploads/document/

Potable nodes	Asset count	Rehabilitation unit costs	Cost unit	Source
Sump	6	5 – 15	J$ million/asset	
Treatment Plant	33	200 – 300	J$ million/Mgal**	
Potable edges	**Length (km)**	**Rehabilitation unit costs**	**Cost unit**	
Pipelines	10,544	2,00 – 5,000	J$/mm-m***	
Wastewater nodes	**Asset count**	**Rehabilitation unit costs**	**Cost unit**	
Sump	1	5 – 15	J$ million/asset	
WW Pump Station	55	5 – 20	J$ million/asset	
WW Relift Station	36	5 – 20	J$ million/asset	
WW Treatment Plant	59	200 – 300	J$ million/Mgal**	
Irrigation nodes	**Asset count**	**Rehabilitation unit costs**	**Cost unit**	NWC Parish Plans[47], NIC financial accounts[48]
Well	178	70,000	J$/asset	
Irrigation edges	**Length (km)**	**Rehabilitation unit costs**	**Cost unit**	
Canal	248	60,000 – 70,000	J$/asset	
Pipeline	220	10,000 – 20,000	J$/asset	

* No cost estimates for these assets because they are assumed to not be damaged by climate hazards in Jamaica
** Mgal – Million gallons
*** Costs are in terms of pipe diameter in mm and length in m

For potable water assets, the mapping of demand in terms of population and business numbers, economic values (GDP) and locations to water nodes are done in order to estimate the indirect economic losses due to asset damages. The result of this process is shown in Figure 3-11 for population served numbers assigned to each node in the network, which is explained in more detail in Appendix C Section C.3.1. Once we know the population and GDP assigned to every node (and edge) we assume that the damage to the node (and/or edge) results in those population and GDP being disrupted. The outputs of this process then feed into Step 7 of Table 2-2, where the J-SRAT implementation steps are explained.

[48] NIC financial accounts - https://www.nicjamaica.com/wp-content/uploads/

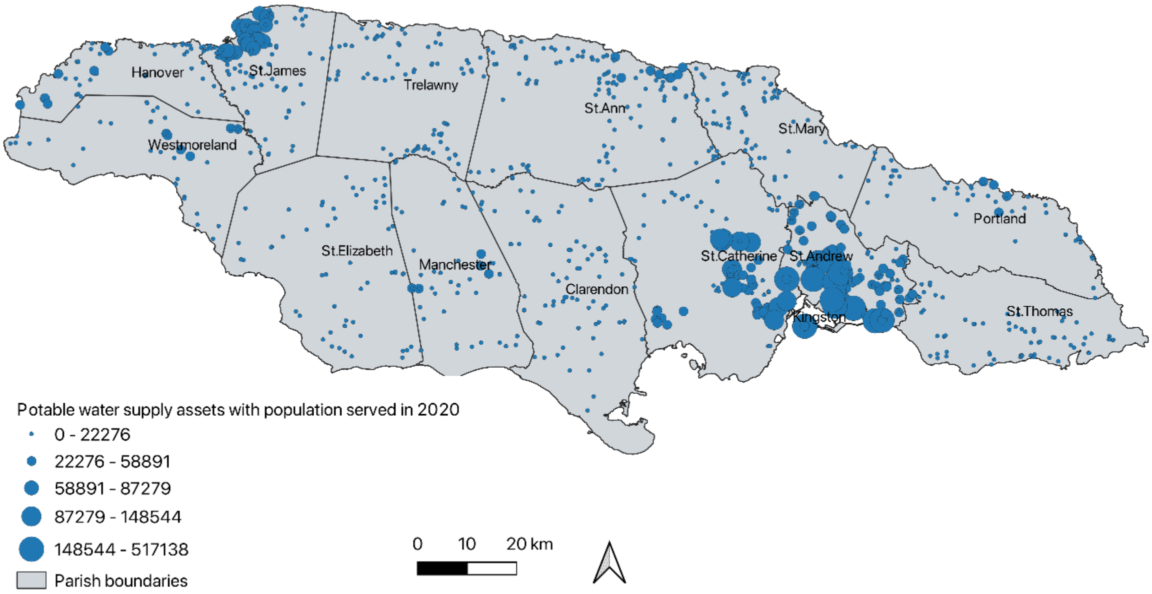


Figure 3-11: Map visualisation of the population served by different assets in the potable water network of Jamaica.

For the irrigation system we map the GDP associated with agriculture areas that are supplied by the irrigation network. This is done by finding the agriculture GDP within the different irrigation schemes (agriculture land areas being irrigated) and associating that GDP with the irrigation assets. This process is shown in Figure 3-7, and further explained in Appendix C Section C.3.2. Once we know the GDP assigned to every asset we assume that the damage to the asset results in that GDP being disrupted. The outputs of this process then feed into Step 7 of Table 2-2.

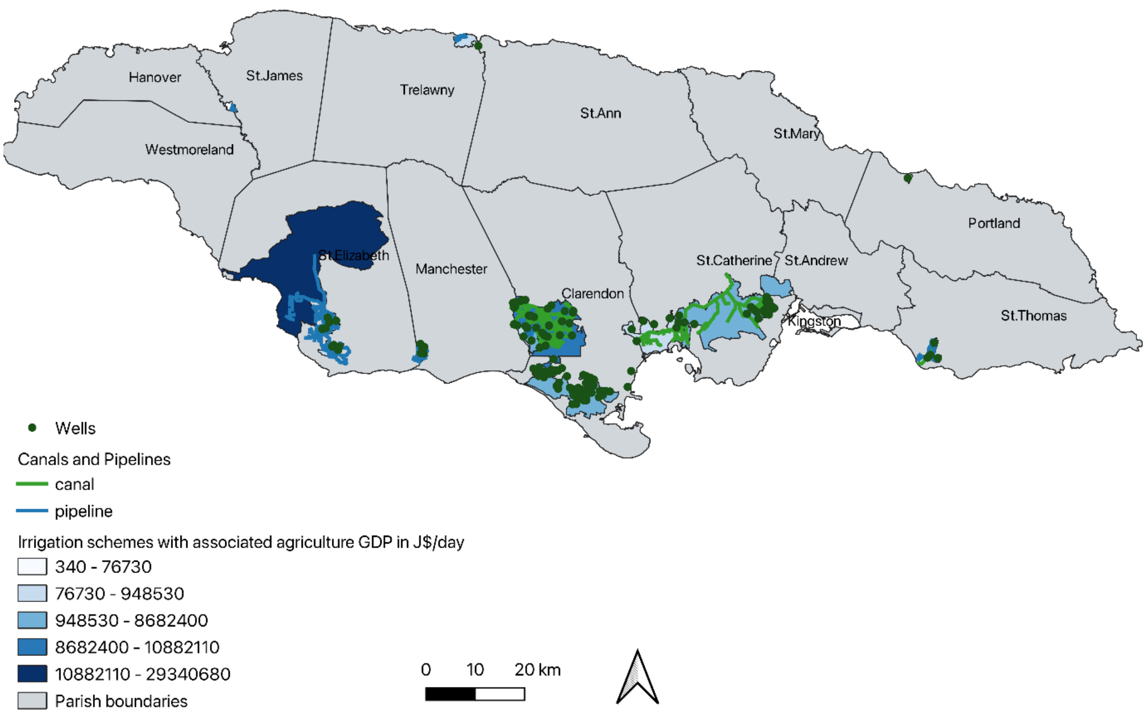


Figure 3-12: Map visualisation of the agriculture GDP in J$/day associated with irrigation schemes in Jamaica, which are mapped to irrigation assets.

3.4.3 Transport systems model

The transport model developed in this project is an integrated model of multi-modal systems composed of roads, railways, ports and airports systems. The aims of the transport model are to: (1) create detailed topological networks of each mode of transport; (2) quantify passenger/commodity/industry flows on transport links to understand how socio-economic flows take place in Jamaica; and (3) estimate the disruptive impacts of transport asset damage in terms of its effects on network flows.

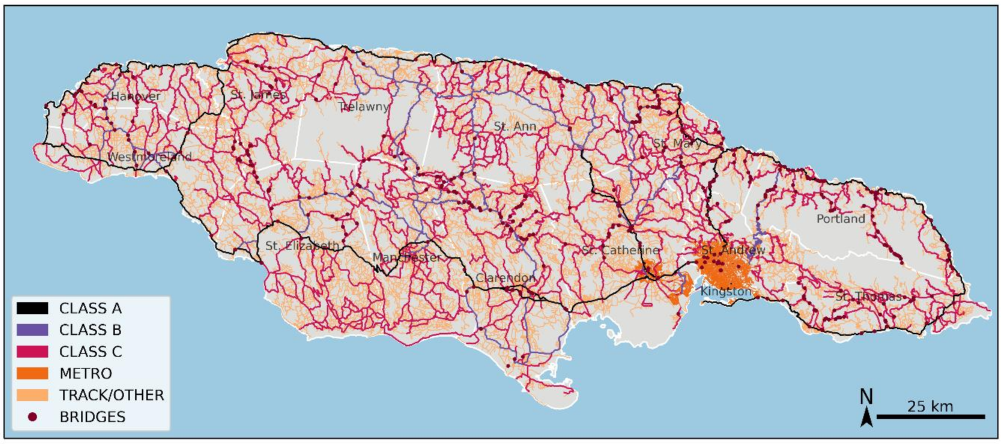
The spatial network location, connectivity and asset attributes information for the transport network model have been assembled using data obtained from different sources, as described in Table 3-11 and shown in Figure 3-13.

- National Spatial Data Management Division (NSDMD)
- National Works Agency (NWA)
- National Road Operating and Construction Company (NROCC)
- Ministry of Transport and Mining (MTM)
- Port Authority of Jamaica (PAJ)
- Airports Authority of Jamaica (AAJ)
- OpenStreetMap (OSM)

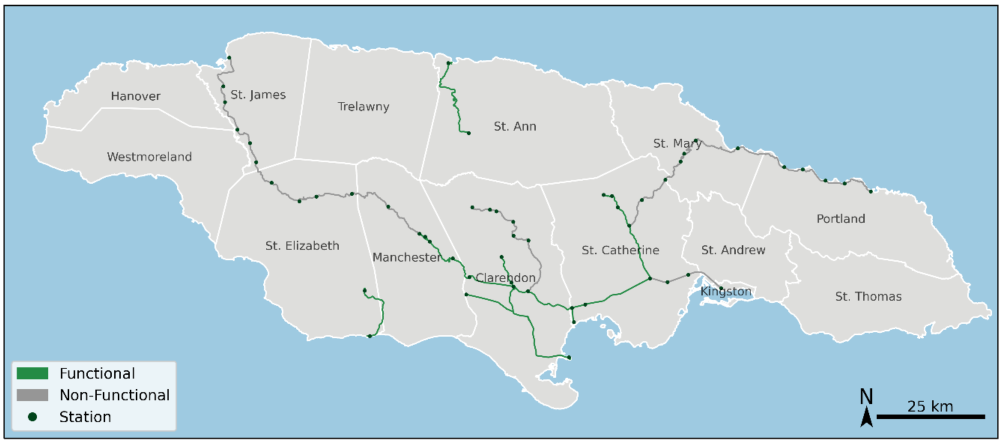
Table 3-11: Summary of data collected and required for the transport systems.

Mode	Asset	Attributes	Source
Roads	Links	Geometry, Road class, Road name, Pavement type, Road width, Lanes, Traffic Count	NSDMD/NWA/NROCC
	Bridges	Latitude, longitude	
Rails	Stations	Latitude, longitude, Name, Operational status	NSDMD/MTM
	Rail lines	Geometry, Name, Operational status	NSDMD/MTM
Ports	Ports	Polygon areas, Name, Passenger, numbers, Freight tons	OSM/PAJ
Airlines	Airports	Polygon areas, Name, Passenger numbers, Freight tons	OSM/AAJ

We note that in this study we have considered a much wider road network than the one owned and operated by the NWA, although due to lack of data, some roads are missing from the modelled road network. The rail network of Jamaica includes all routes and stations that are no longer functional, which seems to be a substantial part of the network. We have also only considered the main ports and airports in the country through which most of the passenger and freight transport takes place, hence ignoring smaller ports and airstrips whose use might be more limited.



(a)



(b)

(c)

Figure 3-13: Map visualisations of different transport systems for Jamaica showing (a) road network with different road classes and bridges; (b) rail network with operational and non-operational stations and routes; and (c) main ports and airports considers in this study.

Several assumptions were taken in gap filling data for each transport sector. We note that these assumptions could be improved if better quality of data was available.

Roads

The road network created for this study is a combination of a network of CLASS A/B/C roads for the NWA and a bigger network within the NSDMD database containing additional METRO and local roads. Most information for road attributes was available for CLASS A/B/C roads in NWA data, but most of it was missing in the NSDMD data. Also, the connectivity between road geometries was very poor in the data, which was fixed through meticulous data cleaning. The following assumptions were made in assigning attributes to roads:

Road pavement types – This information was useful in determining the fragility (vulnerability) curves of roads in a broader sense (see Table 3-12 and Appendix A Figure A-4), as there was no other way to determine the quality of roads in terms of their ability to perform under different hazard loading conditions. It was assumed that most roads in Jamaica were surface dressed if there was no information on the road pavement type in the original NWA or NSDMD data.

Table 3-12: Estimate of lengths of different road pavement types and their assigned road fragility curve for the road network of Jamaica.

Road pavement type	Road fragility curve	Length (km)
Asphaltic Concrete	Asphalt	859
SD & AC		468
Surface Dressed		21,733
SD & Unasphalted	Non-asphalt	32
Unasphalted		71
Unasphalted & SD		31
Gravel		3
TOTAL		**23,199**

Road widths – This information was useful in determining adaptation costs. Based on the communications within Jamaica the general design lane width in Jamaica for CLASS A/B/C roads was 3.65 m and for all other roads it was 3.048 m.

Road lanes – This information was useful in determining damage costs. If no lane information was provided in the data we assumed that roads had 2 lanes.

Speeds – This information was useful in assigning flows to roads. It was assumed that road speeds for CLASS A/B were 110 km/hr, CLASS C were 80 km/hr, and rest of the roads had speeds of 50 km/hr.

Road rehabilitation unit costs – Based on communications within Jamaica, the average rehabilitation costs for roads in Jamaica was estimated to be 0.75 US$ million/km/lane. We assumed that there was a 20% uncertainty involved in these cost estimates, which meant that in our analysis the road rehabilitation unit costs were between 0.6 – 0.9 US$ million/km/lane.

Railways

The main attributes for the railway assets are shown in Table 3-13. In addition, we assumed that the rail track speeds were 120 km/hr for assigning flows. Rail damage curves are shown in Appendix A Figure A-4.

Table 3-13: Estimates of rehabilitation unit costs assigned to railway assets in Jamaica.

Asset type	**Status**	**Asset count**	**Rehabilitation unit cost**[49]	**Cost unit**
Station	Functional	20	400,000 – 600,000	US$/asset
	Non-Functional	34	-	-
Asset type	**Status**	**Length (km)**	**Damage cost**	**Cost unit**
Tracks	Functional	201	1.0 – 1.2	US$ million/mile
	Non-Functional	236	-	-

Ports

The list of ports and their attributes used in this study as shown in Table 3-14. Port damage curves are shown in Appendix A Figure A-3.

Table 3-14: List of ports with passenger and freight statistics and estimates of rehabilitation unit costs.

Name	**Area (m^2)**	**Passenger numbers (annual)**[50]	**Transhipment tonnes (annual)**[50]	**Export tonnes (annual)**[50]	**Import tonnes (annual)**[50]	**Rehabilitation unit costs (US$/$m^2$)**[51]
Falmouth	46,662	564,267	-	-	-	560 - 1,040
Kingston	674,948	-	-	-	-	489 - 1,560
Kingston Freeport Terminal	1,066,516	-	1,113,607	185,650	1,203,044	770 - 1,430
Kingston Wharves	238,612	-	710,257	164,228	4,609,340	840 - 1,560
Montego Bay	313,900	368,886	-	1,413	832,328	489 - 1,560
Ocho Rios	54,460	577,486	-	12,890	-	560 - 1,040
Petrojam	325,853	-	-	-	1,747,723	489 - 910
Port Esquivel	302,203	-	-	439,242	-	489 - 1,040
Port Kaiser	98,613	-	-	500,576	-	560 - 1,040

[49] All cost estimates from report: Development Bank of Jamaica (2021). Privatization of Commercial Railway Services – JRC Commercial – Business Case (Draft), Version 1.0. Jamaica.
[50] All passenger and freight estimates from Port of Jamaica 2019 statistics: http://www.portjam.com/index.php/statistical-report
[51] All cost estimates from World Bank Investment database: https://ppi.worldbank.org/en/ppi

Name	Area (m^2)	Passenger numbers (annual)[50]	Transhipment tonnes (annual)[50]	Export tonnes (annual)[50]	Import tonnes (annual)[50]	Rehabilitation unit costs (US$/$m^2$)[51]
Port Rhoades	468,612	-	-	3,584,184	-	840 - 1,560
Rio Bueno	112,727	-	-	-	-	560 - 1,040
Rocky Point	176,626	-	-	1,038,806	-	560 - 1,040
Wherry Wharf	61,765	-	-	-	-	560 - 1,040

Airports

The list of airports and their attributes used in this study are shown in Table 3-15. Airport damage curves are shown in Appendix A Figure A-4.

Table 3-15: List of airports with passenger and freight statistics and estimates of rehabilitation unit costs.

Name	Area (m^2)	Passenger numbers (annual)[52]	Freight tonnes (annual)[52]	Rehabilitation unit cost (US$/$m^2$)[51]
Ken Jones Airfield	32,516	-	-	87 - 262
Kirkvine Airfield	17,575	-	-	87 - 262
Negril Aerodrome	21,692	-	-	87 - 262
Norman Manley International Airport	737,275	1,700,000	17,000	87 - 262
Sangster International Airport	864,496	4,300,000	6,500	87 - 262
Tinson Pen Aerodrome	51,307	-	-	87 - 262
Vernam Airfield	93,106	-	-	87 - 262

For economic loss estimation due to transport failures we developed a flow and failure estimation model for Jamaica that quantifies: (1) the value of trade flow in J$/day that goes between ports and important business locations in the country; (2) the volume of workforce commuting to locations of economic activities; (3) the value of trade and workforce disruption in J$/day due to increased time for rerouting of flows following failures to transport links; (4) the value of trade lost in J$/day when transport links are cut off following failures.

Appendix C Section C.4 describes the transport flow allocation and flow disruption models and results in extensive detail. We note that these models are based on several assumptions about locations of trade flows and workforce travel patterns, for which we did not have any observable data in Jamaica. We have based our analysis on a thorough understanding of import-export data, port freight data, and spatial disaggregation of economic activity in Jamaica. The

[52] All passenger and freight estimates are from Airport Authority of Jamaica 2019 statistics: https://airportsauthorityjamaica.aero/annual-report/

outputs of the transport disruption analysis feed into the Step 7 of Table 2-2, where the J-SRAT implementation steps are explained.

3.5 Adaptation options data

The data on adaptation options and their cost estimates is shown in Table 3-16, where the chosen options apply to enhance resilience of specific assets that are vulnerable to specific hazards. These values feed into Step 10 of Table 2-2.

We note that one of the key challenges in this study was obtaining adaptation options and costing information from within Jamaica. Hence, we relied on studies done in other countries (see sources reference in Table 3-16) and used their options and costs. Our options and costs are not meant to be prescriptive in nature and they merely aim to provide the J-SRAT user with information of how the adaptation analysis is done in the J-SRAT tool. If better information on options and costs are available in Jamaica, then they could replace our chosen options and costs.

1. We have considered more options that protect assets against flooding, because most assets in Jamaica were found to be vulnerable to flood risks.
2. To adapt to flooding risks most of the options relate to increasing the elevation of assets or building flood protection defences around assets, which is aimed at preventing flood water to overtop assets. Our chosen options result in increasing the flood depth thresholds of assets to levels higher than 50 cm (see Table 3-2).
3. We consider some very expensive options to upgrade roads to standards that eliminate all flood risks. These options are based on estimates of high quality roads built in Jamaica, which are less prone to flooding.
4. We have considered measures to upgrade wooden electricity poles to steel ones, in order to improve the resistance of poles to higher wind speeds. Our chosen option results in increasing resistance of poles to wind speeds up to 53 m/s[53] from 30 m/s (see Table 3-2).

[53] Salman, A. M., & Li, Y. (2016). Age-dependent fragility and life-cycle cost analysis of wood and steel power distribution poles subjected to hurricanes. *Structure and Infrastructure Engineering*, *12*(8), 890-903.

Table 3-16: List of adaptation options and their cost estimates applied to improve resilience of assets against hazards in Jamaica.

Hazard	Sector	Asset details	Adaptation option	Option cost unit	Initial investment	Periodic cost	Routine cost	Periodic intervals (years)	Routine intervals (years)	Source
Flooding	Transport	Roads-2L	Upgrade concrete mix, upgrade mortar mix, upgrade rubble masonry wall, increase number of drainage structure	US$ million/km	1.5	0.3	0.015	5	1	NWA
		Roads-4L	Upgrade concrete mix, upgrade mortar mix, upgrade rubble masonry wall, increase number of drainage structure	US$ million/km	5	1	0.05	5	1	
		Roads - Bridges	Upgrade the bridge	US$ million	5	1	0.05	5	1	
		Roads - All	Elevate the roads	US$ million/km/meter	3.5	0.7	0.035	5	1	Dasgupta et al. (2011)[54]
		Rail - Tracks	Elevate the tracks	US$/km/meter	80,000	16,000	800	5	1	
		Airport Areas	Sea dike around airport	US$ million/km/m	27		0.27		1	Aerts (2018)[55]
		Port Areas	Elevate main terminal areas	US$/$m^2$/m	178		1.78		2	Becker et al. (2017)[56]
	Water	Potable water treatment works	Flood defence around asset	GBP/m	1,000,000		5,000		1	Mott McDonald [57]
		Potable pumping station	Flood defence around asset	GBP/m	50,000		250		1	
		Irrigation wells	Flood defence around asset	GBP/m	50,000		250		1	
		Wastewater treatment works	Flood defence around asset	GBP/m	1,000,000		5,000		1	
	Energy	Electricity substation	Building protective wall	GBP/m	500,000		2,500		1	Thacker et al. (2018)[58]
		Power plant	Building protective wall	GBP/m	500,000		2,500		1	
Tropical Cyclone		Poles	Upgrade wooden poles to steel	$US	4,300	4,300	21.5	25	1	Salma and Li (2016)[53]

[54] Dasgupta, S., Huq, M., Khan, Z. H., Sohel Masud, M., Ahmed, M. M. Z., Mukherjee, N., & Pandey, K. (2011). Climate proofing infrastructure in Bangladesh: the incremental cost of limiting future flood damage. *The journal of environment & development*, *20*(2), 167-190.
[55] Aerts, J. C. (2018). A review of cost estimates for flood adaptation. *Water*, *10*(11), 1646.
[56] Becker, A., Ng, A. K., McEvoy, D., & Mullett, J. (2018). Implications of climate change for shipping: Ports and supply chains. *Wiley Interdisciplinary Reviews: Climate Change*, *9*(2), e508.
[57] https://www.wessexwater.co.uk/-/media/files/wessexwater/corporate/strategy-and-reports/business-plan/0401a--mott-macdonald-flood-risk-assessment--published.pdf
[58] Thacker, S., Kelly, S., Pant, R., & Hall, J. W. (2018). Evaluating the benefits of adaptation of critical infrastructures to hydrometeorological risks. *Risk Analysis*, *38*(1), 134-150.

4 Implementation of J-SRAT tool through a use case

We demonstrate the J-SRAT tool through an example use case, which involves going through the steps of the J-SRAT methodology (outlined in Table 2-2), data creation and implementation. Here we use the J-SRAT visualisation platform to present the results of the analysis. The use case involves looking at a single infrastructure asset and understanding how the climate risk and adaptation analysis was done for this asset. Each of the results and output metrics from the risk assessment process are available to explore in detail in the J-SRAT online tool.

Our selected use case is an electricity substation in the power transmission network of Jamaica, which is at risk due to extreme fluvial flooding as shown in Figure 4-1.

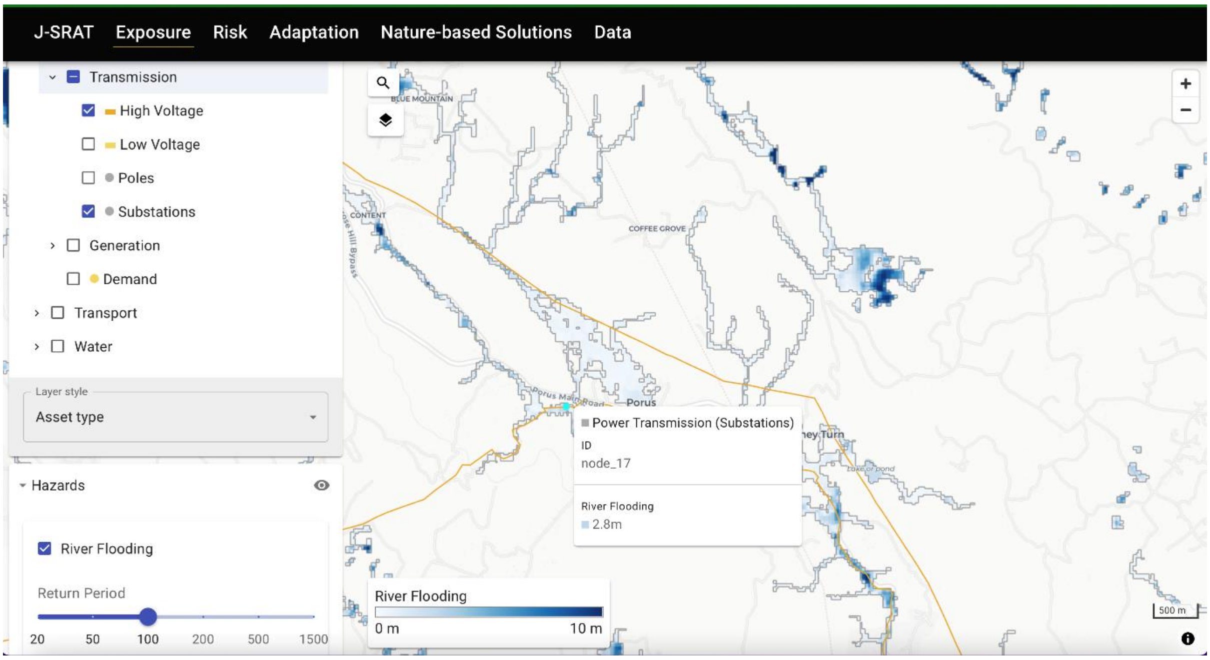


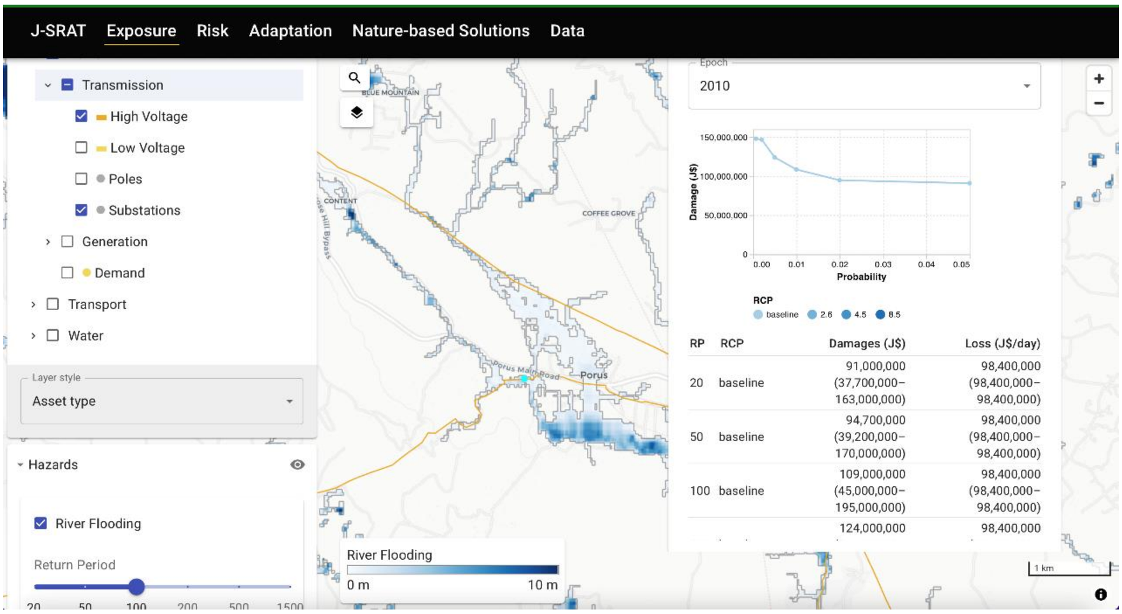
Figure 4-1: Fluvial flooding exposure of the use case substation demonstrated in the J-SRAT visualisation platform.

Through the creation of the energy network data and the implementation of the JEM, we estimate that this substation has the attribute values as shown in Table 4-1.

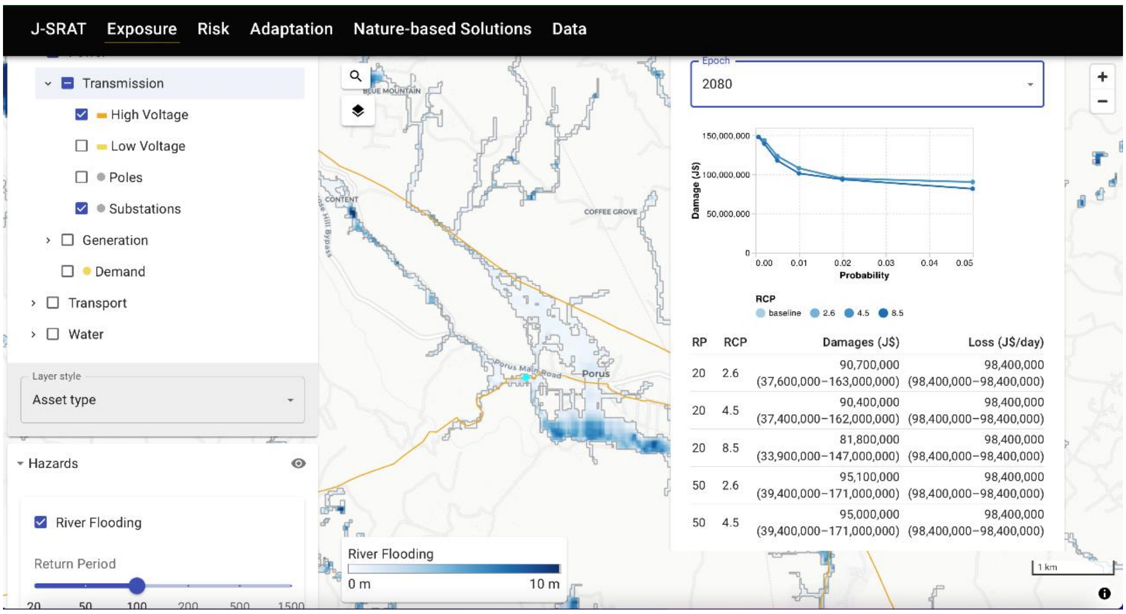
Table 4-1: Attributes and values for estimating the direct and indirect risks for the use case in J-SRAT.

Attribute	**Value**	**Comment**
Rehabilitation cost (for 100% damage)	973 (584 – 1,360) J$ million	Mean (Min – Max) estimates from the data described in Table 3-7.
Flood depth vs damage curve	See Figure A-2(b)	We test a range of curves within the lower and upper bounds of the Figure A-2(b) values.
Economic loss	98.4 J$/day million	Economic loss due to disruptions of telecoms, potable water, and buildings. Estimated from the JEM network disruption analysis.

By intersecting the substation with different fluvial flood outlines under baseline and future climate scenarios, we estimate the direct damages and indirect economic losses. These results are shown in Figure 4-2, where the plots show how the damages vary for different hazard return periods (or annual exceedance probabilities). We note that the future losses shown here are later factored by the compound effect of the GDP changes (from Figure 3-1) when we do the adaptation assessment.



(a)



(b)

Figure 4-2: Demonstration of the results of the direct damage and indirect loss estimations under (a) baseline, and (b) future climate scenarios following the flood exposure and failure analysis for the J-SRAT use case example.

The direct and indirect risk calculations follow the direct damage and indirect economic loss estimations, which result in the EAD and EAEL estimates shown in Figure 4-3. Again, we note that the future EAEL values shown here are later factored by the compound effect of the GDP changes when we do the adaptation assessment. For example, the mean EAEL in 2080 will be about 7.89 J$ million/day, with a minimum – maximum range of 4.6 – 13.44 J$ million/day, when we factor in the future GDP growth rate forecasts shown in Figure 3-1.

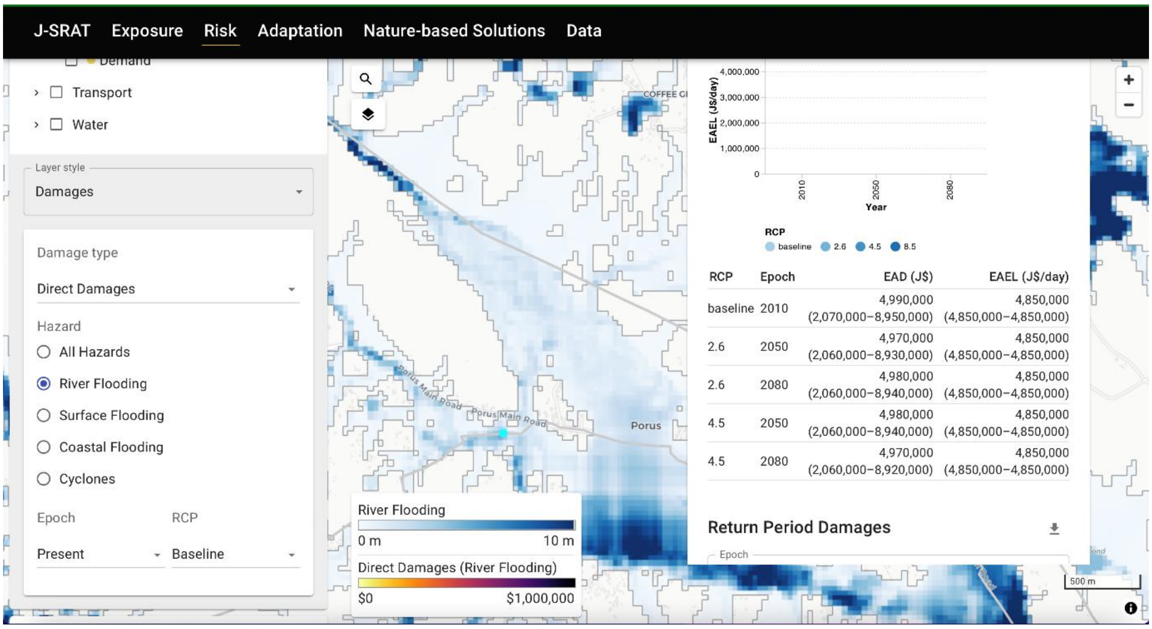


Figure 4-3: Demonstration of the results of the direct and indirect fluvial flood risks across climate scenarios for the J-SRAT use case example.

Once all the climate risks have been estimated, we implement a chosen adaptation option for this substation, which is to build a protective wall that prevents flood waters from inundating the asset. The option and its unit cost estimates are described in Table 3-16. We test different heights of flood protection walls and estimate the NPV cost, NPV benefits (avoided risks), and BCR values for each case as shown in Figure 4-4. Here we see that building a protective wall that is 1-meter high would incur an NPV cost of 110 J$ million over time and result in avoiding mean NPV risks of 807 (min. 761 – max. 863) J$ million under RCP 2.6 flooding scenario, which results in BCR of 7.32 (6.91 – 7.83). Hence, for this asset the chosen adaptation option presents a robust case for investment as the BCR > 1.

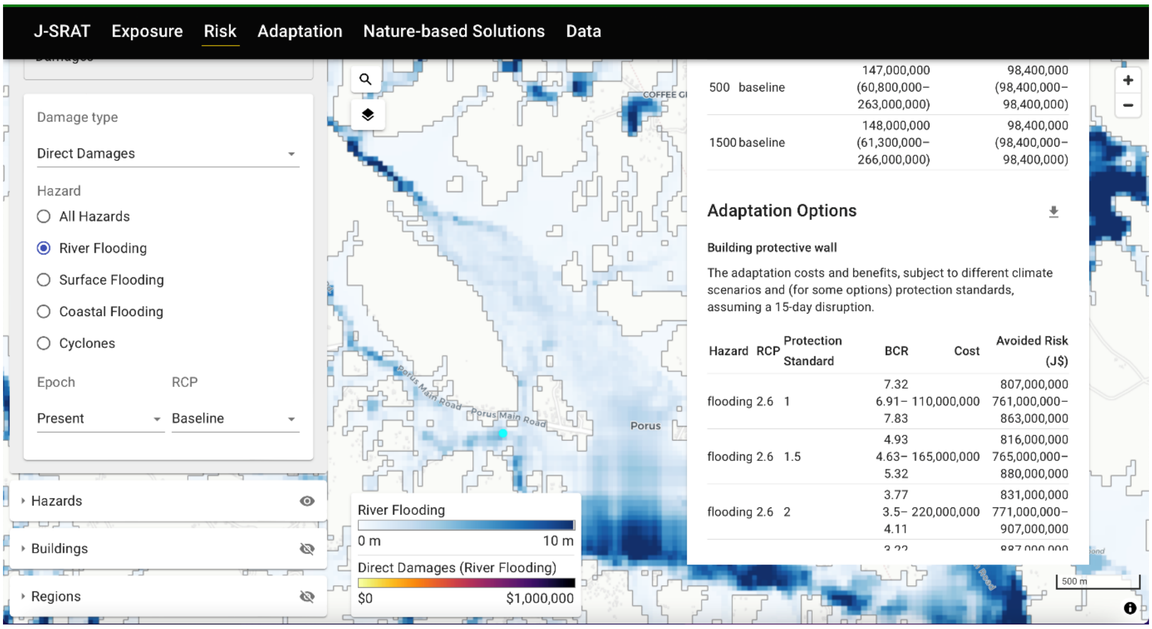


Figure 4-4: Demonstration of the results of the adaptation assets for the J-SRAT use case example.

Appendix A: Vulnerability curves for infrastructure assets in Jamaica

In creating hazard damage curves, we make the following assumptions:

1. The damaged state of an asset is defined as being extensively damaged and damaged beyond repair. The damage curves are used to quantify the percentage (or fraction) of the physical asset that is in such a damaged state.
2. Only certain types of assets in each infrastructure network are assumed to be vulnerable to damage when exposed to extreme flooding and winds. Our assumptions are in line with damage assessments around the world (FEMA 2011, Miyamoto 2019, van Ginkel et al. 2020).
    a. *Water* – Wells, pumping stations, water treatment plants, wastewater treatment plants, and irrigation canals are all assumed to be vulnerable to flooding, while only water treatment plants are considered to be assumed to be vulnerable to extreme winds. Most underground infrastructure such as pipelines are not considered to be damaged by extreme floods or winds.
    b. *Energy* – Electricity substations and power stations are considered to be vulnerable to extreme floods and winds, while overhead lines and poles are considered vulnerable to extreme winds only. We have not considered assets such as solar and wind farms to be vulnerable to any hazards. Evidence suggests that the Clarendon solar farm was able to withstand floods and winds during Hurricanes Irma and Maria in 2017, as it is designed for extreme weather resilience (Jamaica Observer 2018).
    c. *Transport* – Within the transport sector; road, rail, and airport assets are assumed to be damaged by floods but not affected by extreme winds. We note that extreme winds can stop the functions of roads and rail lines, by depositing debris on them but they are not considered to be physically damaged. Ports are assumed to be susceptible to both floods and extreme winds.
3. Most of the flood damage studies and curves in literature have been derived for freshwater flooding, which is generally fluvial and pluvial flooding. Coastal flooding due to storm surges causes greater damage to assets due to the much more corrosive nature of saltwater. Previous flood damage assessment studies in Annotto Bay, Jamaica assumed damages to concrete structures due to saltwater flooding were 12% higher than freshwater for the same flood depths (Glas et al. 2017). Flood insurance claims data for residential building damages in the US from 2001-2014 show building damage ratios were 1%-15% higher for saltwater flooding in comparison to freshwater flooding for flood depths between 6-9 feet (Tonn and Czajkowski 2018). In our study we assume that there is a 12% uplift in damage ratios due to coastal flooding from storm surges, keeping in line with the assumption made in the previous study in Jamaica. Hence, we increase the damage ratio values for all freshwater flood damage curves shown later from Figure A-1 – Figure A-4 by 12% when quantifying coastal flood risks.

Table A-1 shows the list of all infrastructure assets that are considered vulnerable to flooding and wind damage, along with the literature sources from which the damage curves for these assets are derived. Most water and electricity asset damage curves are derived from studies done by the Federal Emergency Management Agency (FEMA) in the United States (FEMA 2011, Miyamoto 2019), while transport damage curves are derived from studies done in Europe (Snuverink et al. 1998, Kok et al. 2005, Huizinga et al. (2017, van Ginkel et al. 2020). Several studies from Jamaica have also used a combination of damage curves from United States and Europe (Burgess et al. 2015; Glas et al. 2017; Ortega et al. 2019; He and Cha 2021).

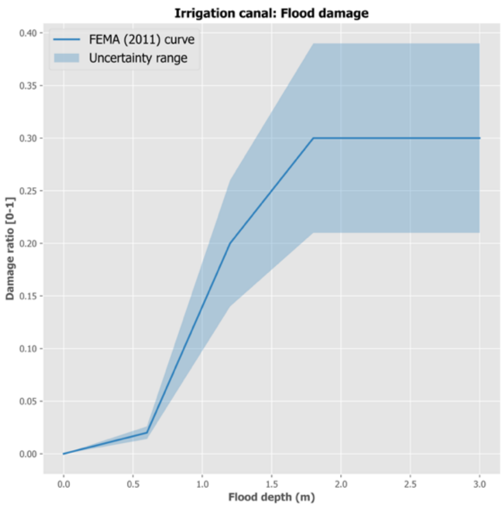
Table A-1: List of infrastructure assets considered damaged with respect to flood and wind hazards in Jamaica.

Sub-sector	Asset	Flood depth damage curve	TC wind damage curve
Water	Wells	FEMA (2011)	-
	Water treatment plants	FEMA (2011)	Miyamoto (2019)
	Pumping stations	FEMA (2011), Kok et al. (2005)	-
Wastewater	Wastewater treatment plants	FEMA (2011)	-
	Pumping stations & Retention tanks	FEMA (2011)	-
Irrigation	Irrigation work canals	FEMA (2011)	-
Electricity	Power stations	FEMA (2011)	FEMA (2011), Miyamoto (2019)
	High/Mid/Low Voltage	-	
	Substations	FEMA (2011)	
	Power poles	-	
Airports	Terminal	Kok et al. (2005)	-
	Runway	Snuverink et al. (1998)	-
Ports	Container terminal	Snuverink et al. (1998)	Miyamoto (2019)
	Industrial areas	Huizinga et al. (2017)	Miyamoto (2019)
	Silos	Snuverink et al. (1998)	Kameshwar and Padgett (2018
	Break	Snuverink et al. (1998)	Miyamoto (2019)
Railways	Track sections	Kok et al. (2005)	-
Roads	Road sections	van Ginkel et al. (2020), Glas et al. (2017)	-
	Bridges		

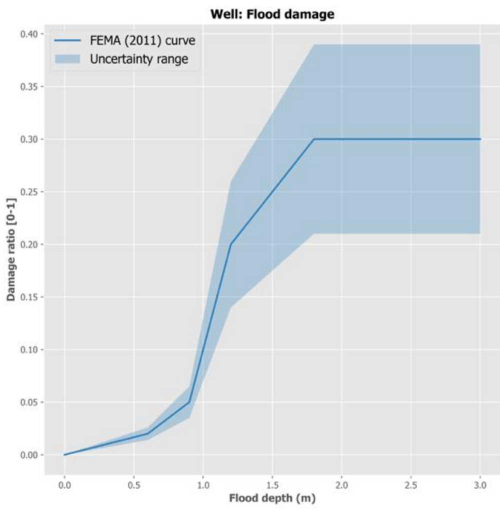
The damage curves obtained from these studies generally give deterministic estimates of the percentage (or fraction) of damage sustained by an asset exposed to a certain magnitude of the hazard (flood depth in meters or wind speed in m/s). In reality this is not the case, as every asset will have its own unique response to a hazard depending upon its physical properties, age, condition etc. To account for uncertainties in asset damage responses to hazard exposures, we have hence made the following assumptions:

1. For a given asset, if we have only one damage curve from literature, we assume a ±30% uncertainty in our estimate and produce multiple estimates of damages bounded with the ±30% uncertainty range. Generally, there is a lot of uncertainty in hazard damage curve data, with some studies in Europe showing the 40%-50% uncertainty in damage curves for buildings based on empirical data (Freni et al. 2010). Also, there are even bigger uncertainty when damage curves from one location are applied to another, as analysis shows ranges of variations from 5%-360% in damage estimates between empirical data and those predicted by known damage curves (Scorzini and Frank 2017).
2. If for a given asset, we have more than one damage curve (generally two) we use these two curves to create lower and upper bound estimates of damages and produce multiple estimates of damages bounded with the two curves. For example, this is done for water pumping stations where the lower bound damage estimates are derived from FEMA (2011), while the upper bound estimates are derived from European codes (Kok et al. 2005).

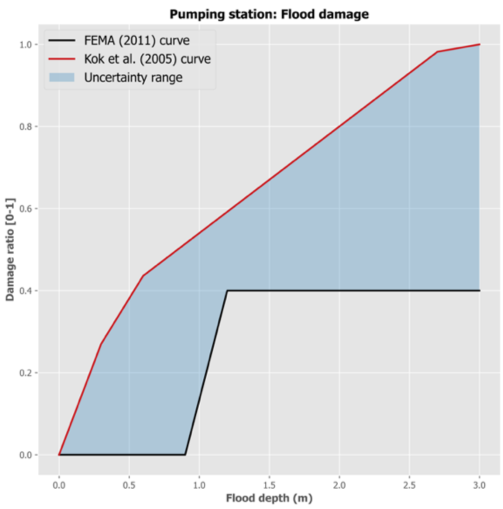
Figure A-1 shows the hazard damage curves for all water assets considered to be exposed to flood and wind hazards and susceptible to damage, Figure A-2 shows similar information for energy assets, and Figure A-3 for port assets. Airport, roads and rail assets are only considered damaged by floods, for which the damaged curves are shown in Figure A-4.



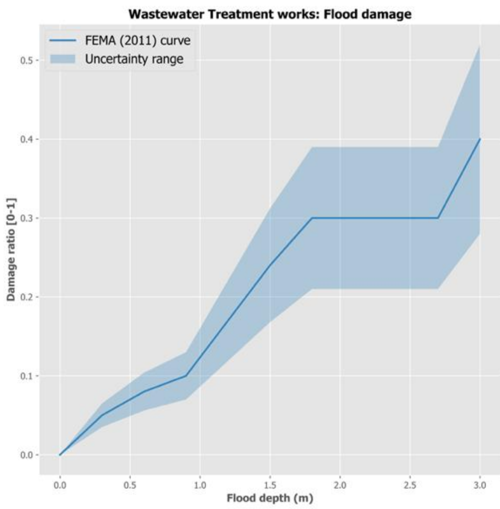
(a)



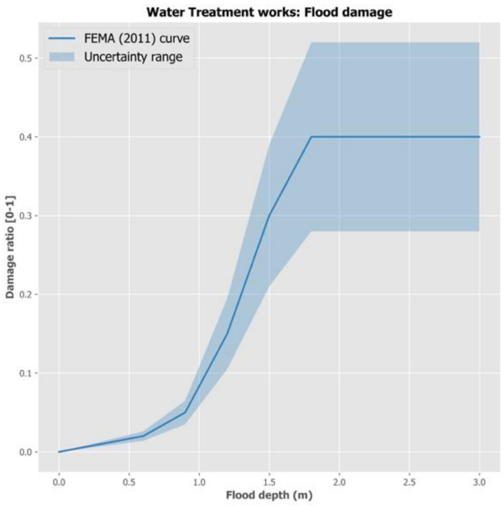
(b)



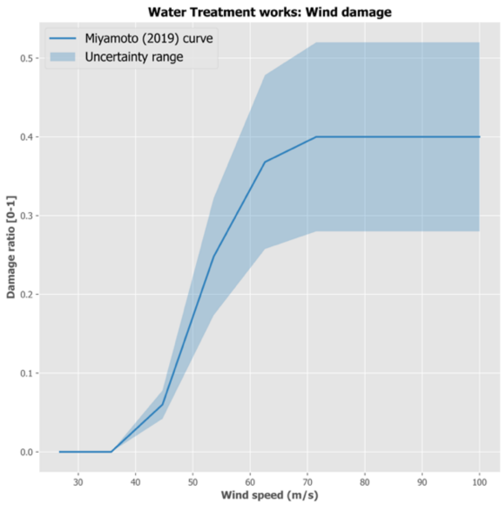
(c)



(d)

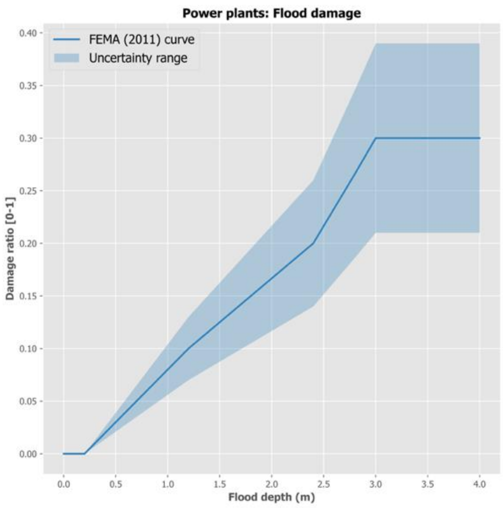


(e)

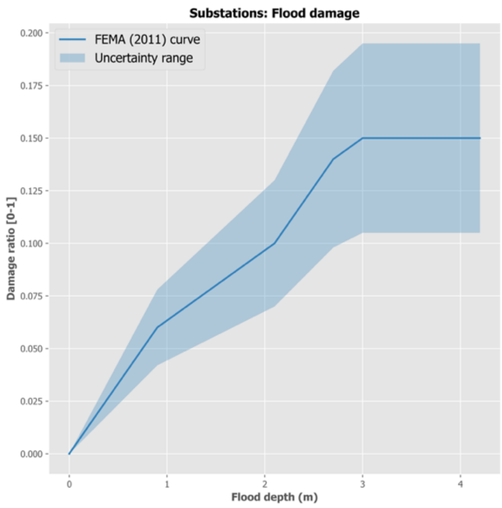


(f)

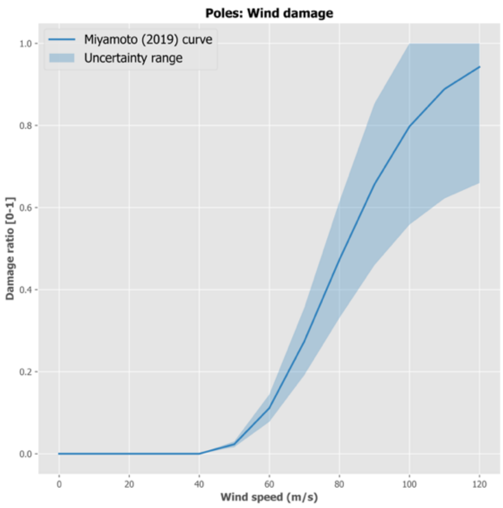
Figure A-1: Flood and wind hazard damage curves for different water assets considered in the study.



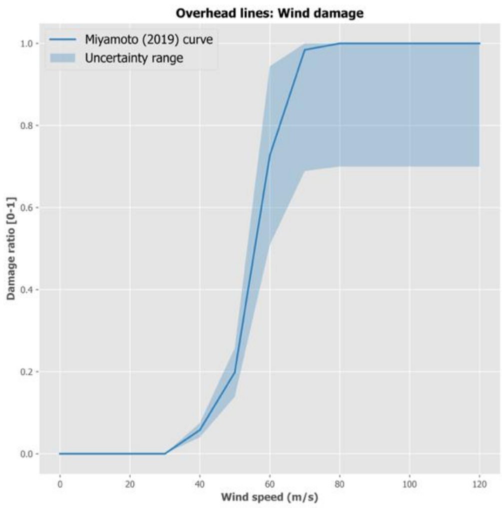
(a)



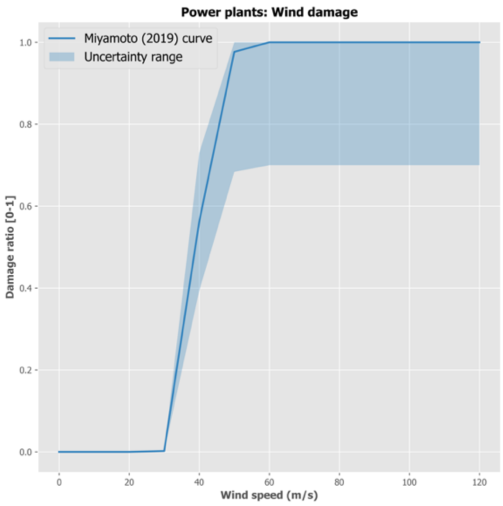
(b)



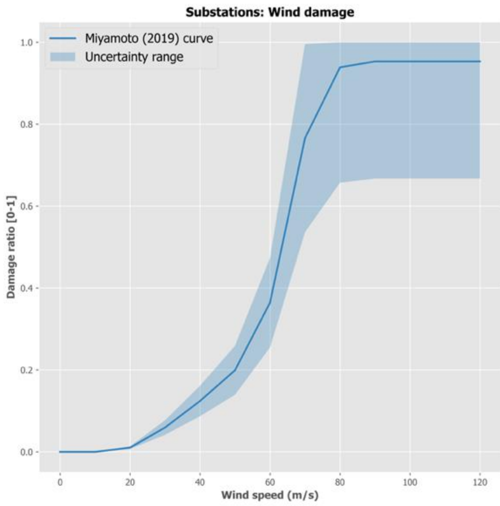
(c)



(d)

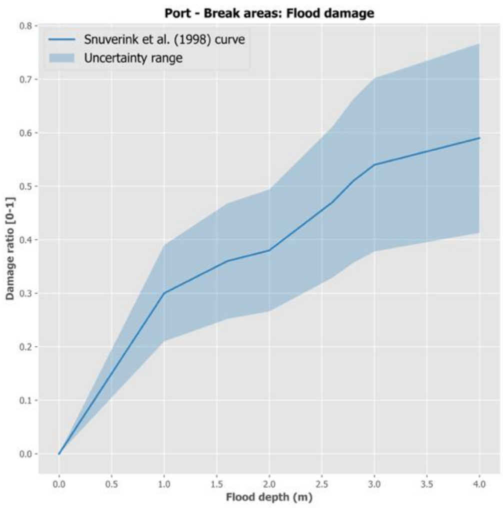


(e)

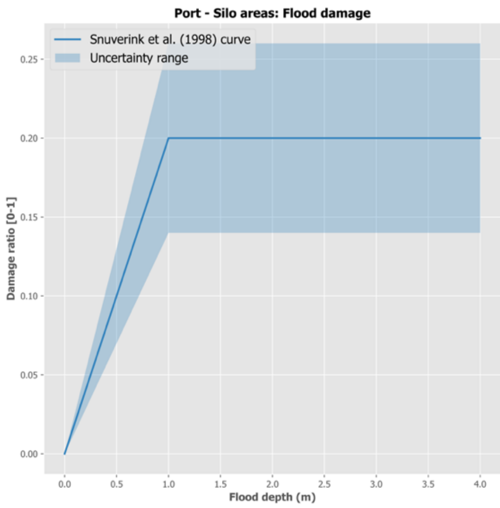


(f)

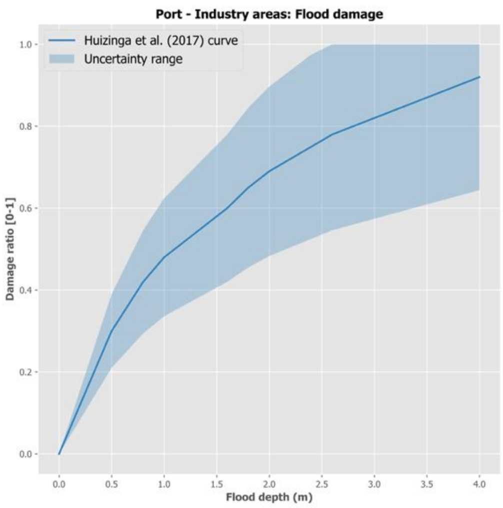
Figure A-2: Flood and wind hazard damage curves for different energy assets considered in the study.



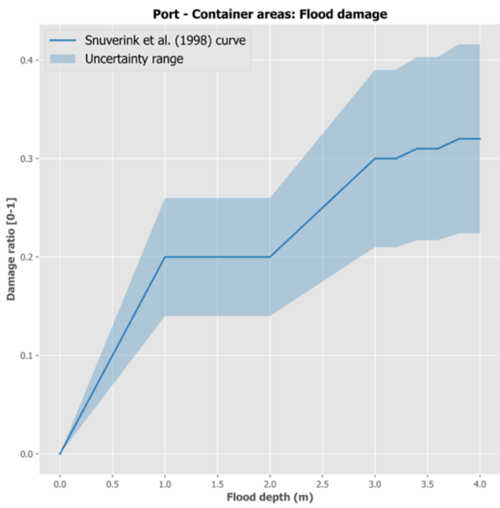
(a)



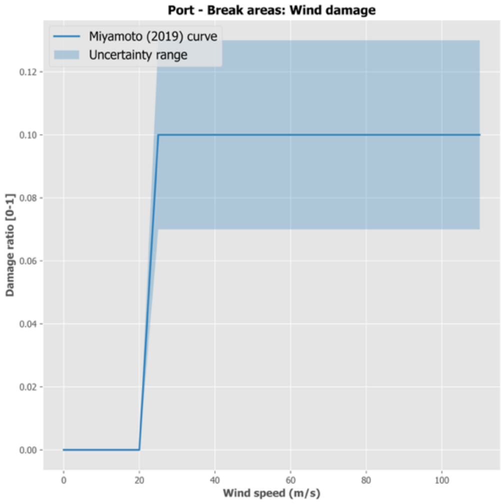
(b)



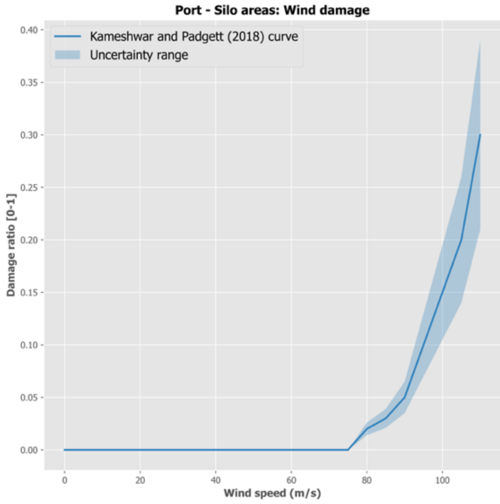
(c)



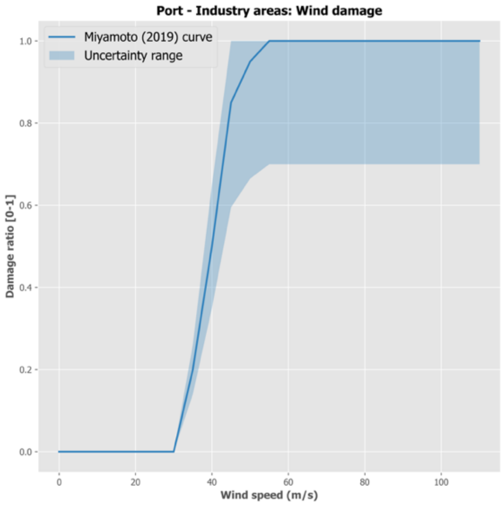
(d)



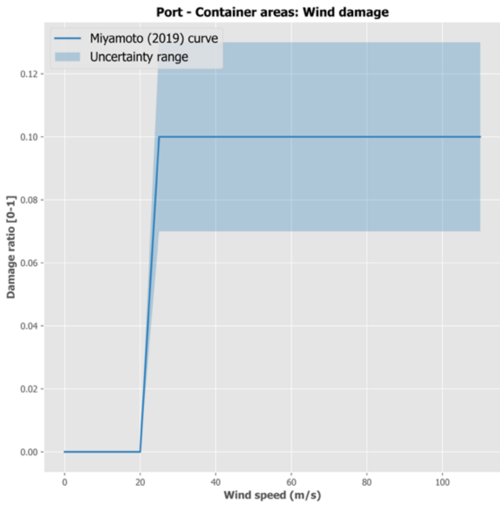
(e)



(f)

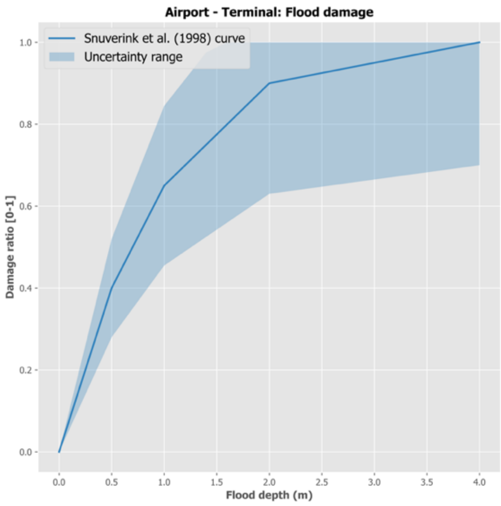


(g)

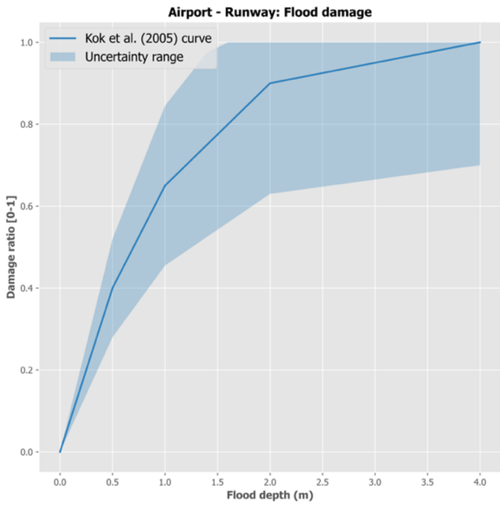


(h)

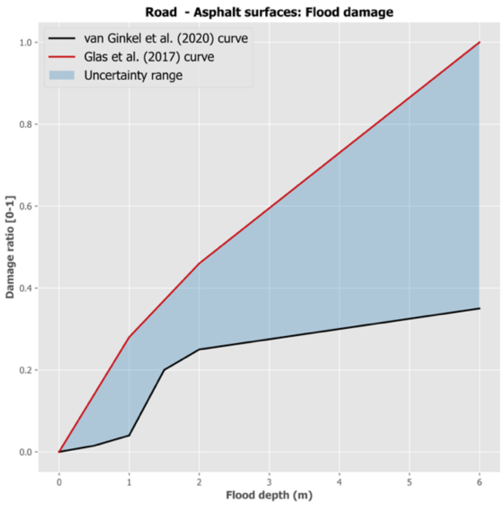
Figure A-3: Flood and wind hazard damage curves for different port assets considered in the study.



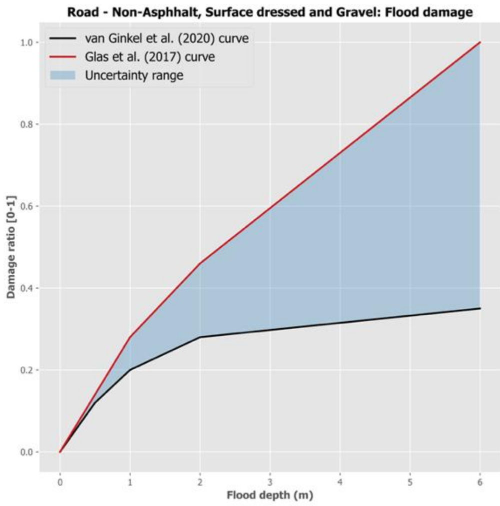
(a)



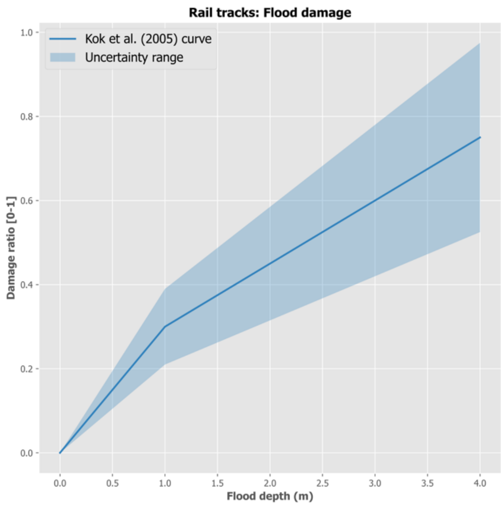
(b)



(c)



(d)



(e)

Figure A-4: Flood hazard damage curves for different airport, road and rail assets considered in the study.

References

Burgess, C. P., Taylor, M. A., Stephenson, T., Mandal, A., and Powell, L. (2015). A macro-scale flood risk model for Jamaica with impact of climate variability. *Natural Hazards*, *78*(1), 231-256.

FEMA. (2011). Multi-hazard loss estimation methodology, Hurricane model: Hazus-MH2.1 technical manual. Washington, DC: FEMA.

Freni, G., La Loggia, G., & Notaro, V. (2010). Uncertainty in urban flood damage assessment due to urban drainage modelling and depth-damage curve estimation. *Water Science and Technology*, *61*(12), 2979-2993.

Glas et al. (2017). A GIS-based tool for flood damage assessment and delineation of a methodology for future risk assessment: case study for Annotto Bay, Jamaica. Natural Hazards.

He, X., and Cha, E. J. (2021). Risk-Informed Decision-Making for Predisaster Risk Mitigation Planning of Interdependent Infrastructure Systems: Case Study of Jamaica. *Journal of Infrastructure Systems*, *27*(4), 04021035.

Huizinga et al. (2017), Global flood depth-damage functions. Methodology and the database with guidelines, JRC.

Jamaica Observer. (2018). Clarendon solar farm withstands heavy rains, hurricane winds. url: https://www.jamaicaobserver.com/environment-watch/clarendon-solar-farm-withstands-heavy-rains-hurricane-winds_130178 (Last accessed September 21, 2021).

Kameshwar and Padgett (2018), Fragility and resilience indicators for portfolio of oil storage tanks subjected to Hurricane, ASCE.

Kok et al. (2005), Standaard method 2004 Schade en Slachtoffers als gevolg van overstromingen, HKV lijn in water.

Miyamoto (2019), Overview of Engineering Options for Increasing Infrastructure Resilience.

Ortega, S. T., Losada, I. J., Espejo, A., Abad, S., Narayan, S., & Beck, M. W. (2019). The Flood Protection Benefits and Restoration Costs for Mangroves in Jamaica.

Scorzini, A. R., and Frank, E. (2017). Flood damage curves: new insights from the 2010 flood in Veneto, Italy. *Journal of Flood Risk Management*, *10*(3), 381-392.

Snuverink et al. (1998), Schade by inundatie van buitendijkse industry, Tebodin Consultants and Engineers, Rijkswaterstaat.

Tonn, G., and Czajkowski, J. (2018). *An analysis of US tropical cyclone flood insurance claim losses: Storm surge vs. freshwater*. Risk Management and Decision Processes Center, The Wharton School, University of Pennsylvania.

van Ginkel et al. (2020), Direct flood risk assessment of the European road network: an object-based approach, NHESS.

Appendix B: Hazard models

B.1 Fluvial and pluvial flood models

The fluvial and pluvial flood maps and flood event sets for Jamaica are derived from JBA's Global Flood Model, which is a global probabilistic river and surface model. The flood event set generation process follows three stages as shown in Figure B-1. The rainfall and rainfall-runoff are simulated at Observation Points (OPs), which are the locations of the calibration (observed) data and additional locations in ungauged river catchments. Discrete flood events are defined from the continuous rainfall and rainfall-runoff time-series simulated at every OP. The output for the rainfall-runoff modelling is a synthetic streamflow time series in units of mm/day equivalent precipitation (defined using catchment area). The resulting simulated daily precipitation and river discharge data are then converted into return period estimates using extreme value theory, and events are extracted from this to form the final event set.

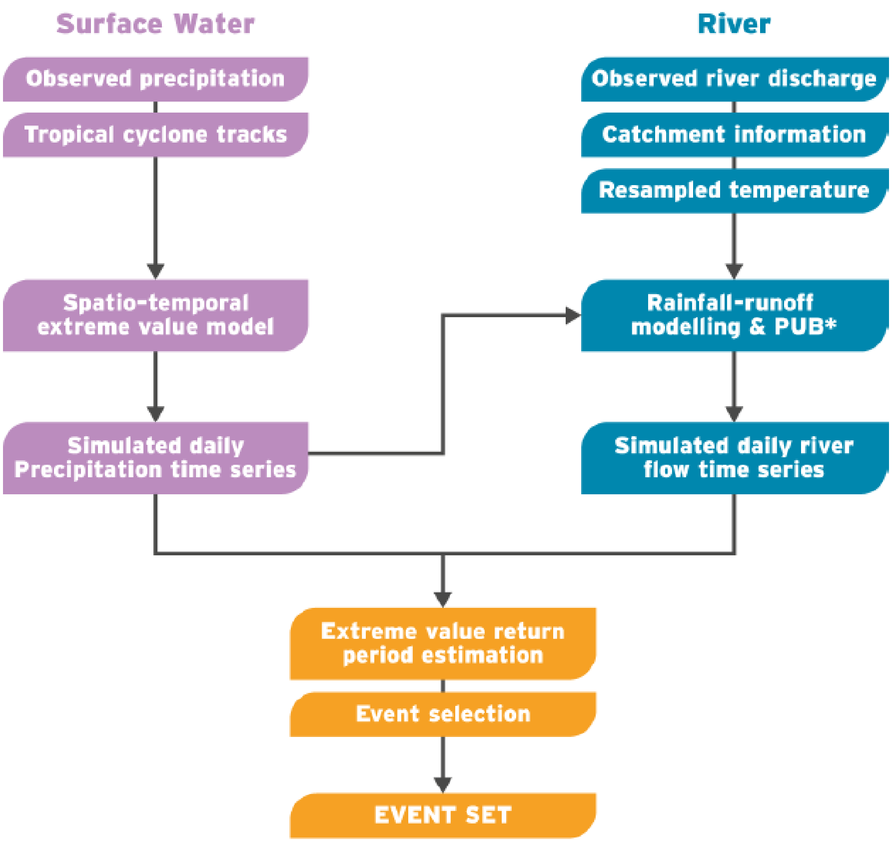


Figure B-1: Methodology for creating event sets in the JBA Global Flood Model.

B.2 Coastal flood model

The storm surge data is derived from a number of global data sources. For Jamaica, no local Digital Elevation Model (DEM) was available, so the Multi-Error Removed Improved-Terrain (MERIT) dataset[59] was used in this study. To model inundation, an extreme water level times series was constructed. The values of the extreme water levels were based on the Global Storm

[59] http://hydro.iis.u-tokyo.ac.jp/~yamadai/MERIT_DEM/

and Tide Model (GSTM)[60], which provided storm+tide return periods for the six return periods. For the future scenarios, no change in the storm+tide was considered apart from sea level rise. Wave setup was added to the dataset as well. Time series of local wave data (36 years) were extracted from a global reanalysis dataset[61]. Every 5km a transect was considered, and for every transact a reduction factor was estimated based on the incoming wave direction and the angle of the coast, which captures the wave sheltering effect of islands. Extreme wave return periods were estimated based on these statistics (using a Peak-over-Threshold methodology) and the wave setup was found by assuming that setup is equal to 0.2 times the corrected offshore wave height. No change in wave conditions is assumed for the future scenarios.

For estimating flood depths, a physics-based inundation model was used, the SFINCS model (Super-Fast Inundation of CoastS model)[62], which is a reduced-physics solver for large-scale flood modelling. The transect data was linearly interpolated on a grid constructed around the island, which was used for the inundation modelling. Storm duration was schematized by a triangular hydrograph with the duration equal to eight times the storm surge plus a factor ten (D = 8 * surge + 10). To construct future storm surge projections, the effect of sea level rise was taken into consideration by extracting likely local sea level rise estimates for two scenarios and four time slices. Local sea level rise estimates were extracted from Vousdoukas et al. (2018)[63]. All data was rasterized to a 90-meter grid in line with the resolution of the DEM.

B.3 Tropical cyclone model

To estimate tropical cyclone (TC) wind speed, we use the 10,000 synthetic cyclone database STORM, developed by Bloemendaal et al. (2020)[64]. The STORM database contains 10-meter 10-minute sustained maximum wind speeds at 10km resolution globally for 26 return periods (ranging from 1 year to 10,000 year). Both the mean and 5-95th percentiles of the return periods are included in the data, with the uncertainty reflecting the uncertainty in the fitting parameters of the extreme value distribution (Weibull distribution). We readily adopt this data for Jamaica and use this as the baseline extreme wind conditions.

We create two future time slices, a mid-century and end-century time period, and use a scaling factor to correct the wind speed based on the expected change in extreme wind. We do this for two climate scenarios (RCP4.5 and RCP8.5). In this analysis, we only change the maximum wind speed, as these results are robust across models, and do not alter the frequency of certain TCs occurring, as there is little consensus on this for the North Atlantic TC basin[65]. Based on a review of the studies projecting changes in cyclone wind speed in the North Atlantic basin, we identify six relevant studies that use CMIP5 models for their evaluation. The end-century ranges provided by these studies are 4-6% increase for RCP4.5 and 6.3-10.5% for RCP8.5. We use this range and multiple the mean wind speed per return period with 5% for RCP4.5 and 8.4% for RCP8.5, while multiplying the 5th and 95th percentiles with the lower and upper range.

[60] Muis, S., Apecechea, M.I., Dullaart, J., de Lima Rego, J., Madsen, K.S., Su, J., Yan, K. and Verlaan, M., 2020. A high-resolution global dataset of extreme sea levels, tides, and storm surges, including future projections. *Frontiers in Marine Science*, *7*, p.263.
[61] Giardino et al. (2020), Assessing the impact of sea level rise and resilience potential in the Caribbean, Technical Report, Deltares, the Netherlands.
[62] https://sfincs.readthedocs.io/en/latest/
[63] Vousdoukas, M.I., Mentaschi, L., Voukouvalas, E., Verlaan, M., Jevrejeva, S., Jackson, L.P. and Feyen, L., 2018. Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard. *Nature communications*, *9*(1), pp.1-12.
[64] Bloemendaal, N., Haigh, I.D., de Moel, H., Muis, S., Haarsma, R.J. and Aerts, J.C., 2020. Generation of a global synthetic tropical cyclone hazard dataset using STORM. *Scientific data*, *7*(1), pp.1-12.
[65] Knutson, T., Camargo, S.J., Chan, J.C., Emanuel, K., Ho, C.H., Kossin, J., Mohapatra, M., Satoh, M., Sugi, M., Walsh, K. and Wu, L., 2020. Tropical cyclones and climate change assessment: Part II: Projected response to anthropogenic warming. *Bulletin of the American Meteorological Society*, *101*(3), pp. E303-E322.

For the mid-century scenario, we assume that the increase is approximately linear, resulting in a mean increase of 2% under RCP4.5 and 3.5% under RCP8.5 (while adopting a similar approach for the 5 and 95th percentiles).

B.4 Drought model

- Annual hydrological balance per major catchment
- REGCM4 present day and future climate change projections

Analysis steps:

1. Find relationship between mean annual rainfall, evaporation, and surface water (SW)/groundwater (GW) supply
2. Find annual variations in temperature and precipitation now and in future (RegCM4)
3. Factor surface water and groundwater with respect to variations in precipitation and temperature
4. Obtain annual sectoral demand from groundwater and surface water

Data sources:

- Parish supply plans: 2010 production limit[66], leakage rates and demand

Analysis steps:

1. Assign Water Supply Zones (WSZ) to each major catchment
2. Find NWC water production limit, leakage rates and demand per major catchment per source based on parish plans
    a. Divide parish production limit in proportion to WSZ population served
    b. Apply leakage constantly across schemes in parish
    c. Determine which schemes are SW and which are GW, if both, assume 50:50 split
3. Find frequency of annual demand shortages for drinking water supply:
    a. Shortages occur when water input – leakage < demand
    b. Where SW/GW supply – environmental flow ≥ production limit:
        i. water input = production limit,
    c. Where SW/GW supply – environmental flow < production limit:
        i. water input = SW/GW supply - environmental flow
    d. Where environmental flow = Q20 basin flow for SW[67]
4. Find total population disrupted per return period and per climate change scenario
5. Disaggregate annual water shortage to find population disrupted per system

[66] the maximum volume of water produced by NWC supply assets
[67] groundwater supply available represents renewable portion

Appendix C: Infrastructure network flow models for failure analysis

C.1 Generalised network representations

All infrastructures are modelled as networks. The network topology is represented as a graph $G = (N, E)$ with nodes $N = \{1,2, \dots, n\}$ and edges $E = \{e_{ij} = (i, j)\ \forall i, j \in N\}$, where the relationship $e_{ij} = (i, j)$ shows that edge e_{ij} connects from node i towards j. All network edges are assumed to be directed, that is $e_{ij} \neq e_{ji}$, to distinguish between the direction and volumes of flows imposed on certain edges. Since all nodes and edges in the graph G represent physical assets, we denote this collection of assets as $G = \{g_1, \dots, g_n\}$.

The infrastructures have evolved into large spatially distributed networks that generally exhibit multi-scale hierarchical structures[68]. Broadly there are three types of nodes layers in an infrastructure network: (1) sources – where resources are generated, (2) intermediate/junctions – where resources are transformed or transmitted towards sinks, and (3) sinks – which connect to direct final users of resources. Generally, the asset sizes might diminish, and asset numbers might increase from the source towards the sink layers. Figure C-1 shows the generalised network formulation and hierarchical representation conceptualised for this study.

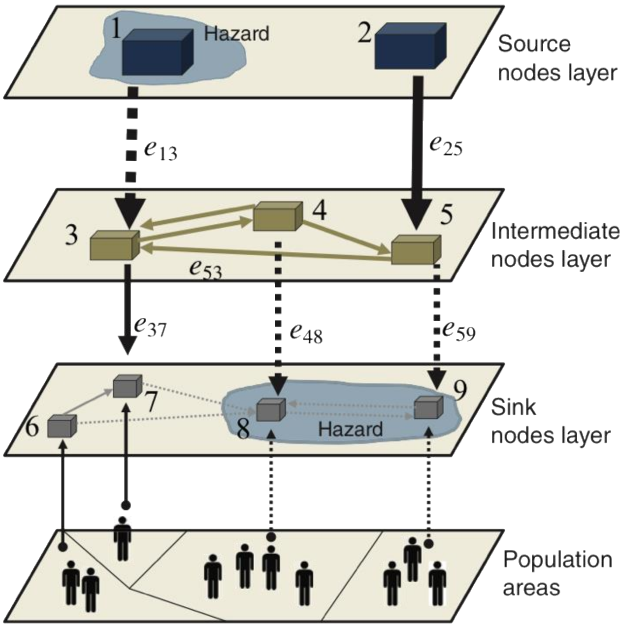


Figure C-1: Hierarchical network representation showing nodes and some edge notations of a generalised infrastructure network as conceptualised in this study (source: Pant et al. 2016[69]).

C.2 Energy system model

The model of the energy system is formulated as a directed graph *G* comprised of nodes $n \in N$ and edges $(i, j) \in A$. Nodes in the network represent physical electricity assets such as power

[68] Thacker, S., Pant, R. and Hall, J.W., 2017b. System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures. *Reliability Engineering & System Safety*, *167*, pp.30-41.

[69] Pant, R., Thacker, S., Hall, J.W. and Alderson, D. (2018). Critical infrastructure impact assessment due to flood exposure. *Journal of Flood Risk Management*, *11*(1), pp.22-33. Doi http://dx.doi.org/10.1111/jfr3.12288.

plants and transformers, but also represent aggregated demands associated with a particular region. Meanwhile, edges in the network represent transmission lines that carry electricity between nodes. There are three types of nodes in the network: (i) sources, (ii) sinks, and (iii) junctions. Source nodes *supply* electricity and as such are comprised of generation assets such as power stations. Sink nodes *demand* electricity and hence are representative of a city or a large industrial consumer (*e.g.*, water treatment plant). Meanwhile, junction nodes neither supply nor demand electricity and instead transform or split flows of electricity (*e.g.*, transformer). Figure C-2 shows a schematic of the source-sink energy flow model.

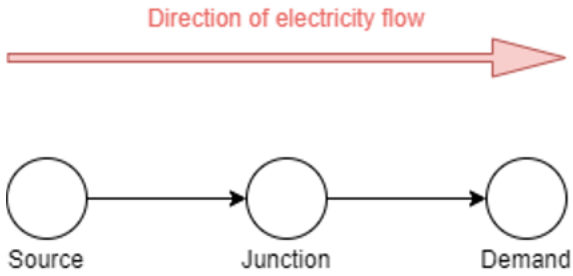


Figure C-2: Schematic of the edge-node energy flow model.

JEM requires two main data inputs:

- **Spatial Data** – Spatial datasets are generated to create a geographical representation of the Jamaican power grid. The spatial network is composed of a set of points (nodes) and lines (edges) that capture the locations of physical assets within the system. These data are used to define node types (e.g., generation, distribution, demand) and their network and asset categories. Nodes also require specific attributes such as capacity, losses, and efficiencies.
- **Temporal Data** – Temporal data describe the supply and demand associated with source and sink nodes, respectively. A unique time series is assigned to each source and sink node at an hourly resolution. Table C-1 shows a small sample of this data.

Table C-1: Example of time series nodal supply/demand data.

Time [h]	Supply/Demand [MWh]		
	Bogue Power Plant	Kingston Demand	Wigton Wind Farm
1	1000	250	0
2	1000	260	0
3	1000	270	0
4	1000	300	10
5	1000	310	20

A network linear programming (NLP) optimisation algorithm is used for the simulation model. The formulation of the algorithm can be generally expressed as:

minimise:	Cost of flows across the network
subject to:	(1) Supply
	(2) Demand
	(3) Conservation of energy
	(4) Energy system operational rules

The objective of the NLP optimisation routine is to minimise the total cost of electricity supply and distribution *C* across the simulation period such that:

$$\min_{x}. C = \sum_{t=1}^{T} x_t c_t \quad \text{(C.1)}$$

where x_t is the flow of electricity across a given edge at time *t* and c_t is the unit cost of electricity along the edge. The cost of flow along each edge is a function of the distance of the power line. The supply constraint denotes that the flow from a supply node i to node *j* cannot exceed the generation S_i at a given time step such that:

$$\sum_{j:ij\in A} x_{ij,t} \leq S_{i,t} \;\forall\; (i,j) \text{ and } t \quad \text{(C.2)}$$

Meanwhile, the demand constraint denotes that demand at node *j* must be met for each time step, such that:

$$\sum_{j:ij\in A} x_{ij,t} = D_{j,t} \;\forall\; (i,j) \text{ and } t \quad \text{(C.3)}$$

In cases where demand cannot be met by the system, supply is drawn from a 'hidden' network layer known as the *super source*. The super source node can provide an infinite amount of supply at any given time step but is only used if no other supply is available. This serves to ensure model feasibility and helps to quantify the supply shortage. A conservation of energy constraint is also set to indicate that the total energy input into a node must equal the total energy output, such that:

$$\sum_{j:ij\in A} x_{ij,t} - \sum_{j:ij\in A} q_{ji,t} x_{ji,t} = 0 \;\forall\; (i,j) \text{ and } t \quad \text{(C.4)}$$

In the equation above, the parameter $q \in [0,1]$ indicates the total losses from a given power line. Flows along each edge are subject to minimum and upper bound constraints (h and u, respectively). That is, the total transmission along a given edge cannot exceed its capacity and must be above the minimum transmission (if applicable), such that:

$$h_{ij,t} \leq x_{ij,t} \leq u_{ij,t} \;\forall\; (i,j) \text{ and } t \quad \text{(C.5)}$$

The output from electricity generation sites is subject to the ramping constraint μ of the given technology. For example, natural gas plants have a higher ramping rate as compared to coal-fired power plants. As such, the following constraint is imposed:

$$x_{ij,t} - x_{ij,t-1} \leq \mu_i \;\forall\; (i,j) \text{ and } t \quad \text{(C.6)}$$

For the economic loss calculations due to electricity failures, we estimate the GDP disrupted at the sink (demand) nodes in the network. When the source and sink nodes fail in the electricity network we trace the network effects of their failures to the demand nodes, as explained in Section 3.4.1. This demand node GDP disruption is a combination of the GDP directly generated by the electricity sector and the GDP of other infrastructures and businesses that are indirectly dependent on electricity. The following method is applied:

1. We first spatially disaggregate the GDP/day (henceforth referred to as GDP) estimates from the electricity sector (Section E 401 from Table D-1) to the demand nodes, by assuming that this spatial distribution of GDP is proportional to the population served by each demand node. This gives us the directly generated electricity sector GDP at the demand node level.
2. We map all the commercial buildings within the electricity demand service areas (see Figure ***3-9***) to find all the GDP associated with non-residential buildings (see Section 3.3.2 and 3.3.3) that would be indirectly disrupted when electricity is disrupted.
3. We assume that two other infrastructure sectors are also dependent upon electricity – telecoms and potable water and telecoms.
    a. We collect data from the water sector (NWC disruption notices) to infer where electricity outages are causing water disruptions, and use this information to identify the locations of water nodes connected to electricity demand nodes. This helps us simulate disruptions in the potable water network to find the water sector GDP disrupted for all households and buildings using water (described in the next section).
    b. We obtain a Jamaica wide dataset on 2,526 telecom masts spread across the island from the NSDMD database (the original data sources are from NEPA, Digicel, Mona Geoinformatics Institute).
        i. We assume at the telecom masts within the service area of each electricity demand node are getting their electricity supply from that demand node. Hence, the GDP generated by these telecoms mast would be dependent upon the electricity demand node, and disrupted if the demand node is disrupted.
        ii. We assume that these telecom masts serve the whole population of Jamaica and the service areas of each mast is estimated using Voronoi polygons to map nearest population to each mast. Using the GDP estimates of the post office and telecoms sector (I 640 from Table D-1) we estimate that 84.3% of this GDP is generated from the telecoms sector only[70].
        iii. We then disaggregate the telecoms sector GDP to each mast in proportion to the customers served by each mast.
4. We only counted the unique set of buildings disrupted due to electricity or water disruptions in order to avoid double counting the building GDP that is dependent upon electricity and water supply.
5. From step 1-2 we can estimate the GDP/day disrupted (direct electricity + indirect from telecoms, potable water and non-residential businesses) due to electricity demand node disruptions.
6. We note that we have excluded transport assets due to lack of an understanding of the specific assets that are connected to the electricity nodes.

[70] MSET (2009). Vision 2030 Jamaica – Information and Communications Technology (ICT) Sector plan 2009 - 2030: https://www.mset.gov.jm/wp-content/uploads/2019/09/ICT-Sector-Plan-Complete.pdf

C.3 Water systems models

C.3.1 Potable water demand assembly and disruption analysis

The potable supply network of Jamaica was conceptualised as a network of nodes and edges (pipes). The nodes were classified in three categories of: (i) *sources* – these were assets where the water supply was introduced into the network and included assets such as entombments, filter plants, intakes, production wells, reservoirs, river sources, springs, treatment plants ; (ii) *intermediaries* – these were assets which transmit the water further along the network and included assets such as booster stations, pump stations, relift stations; and (iii) *sinks* – these were assets from which the water supply would be finally linked to customers (households and businesses) and included assets such as reservoirs and storage tanks. Figure C-3 shows an example of the directed network graph of the water network.

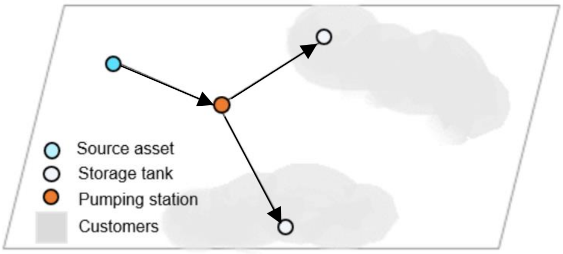


Figure C-3: Graphic representation of a directed sub-system in the Jamaica potable water network.

The Jamaica potable water network was found to be a collection of smaller networks or sub-systems, which operate independently of each other, and each sub-system had at least one source, intermediary and sink nodes. These sub-systems were first identified by associating them with known Water Supply Zones (WSZ) that showed areas in Jamaica receiving water supply from the NWC. This was done through:

1. Data from the Water Service Plans (WSPs) and disruption notices from the NWC, which provided information on all source, intermediary and sink nodes supplying water to each WSZ;
2. For nodes not identified in the WSPs we assigned them to the WSZ that they were located inside of. Some WSZs did not have assets or sources, which may be because the asset data we had was outdated and new assets were missing.

Once all the sub-systems were identified, we assigned customers (population and businesses) to them and did the disruption analysis in following steps:

1. We intersected the WSZ areas with the population areas of Jamaica to infer total number of people within each WSZ. Based on data from the Parish Supply Plans on fraction of customers serviced within Parish in 2010 and projections for 2030, we were able to estimate the number of water customers serviced within each WSZ in 2019 or for any future projected year. We assumed that the GDP generated by the potable water supply sector (Section E 410, see Table D-1) was spatially disaggregated to the WSZs in proportion to the population within each WSZ.
2. We also intersected the WSZ areas with the building footprints of commercial buildings in Jamaica and associated each building's GDP (see Section 3.3.2) with each WSZ.
3. We next disaggregated the customers (population and/or businesses) served per WSZ to each asset by assuming:
    a. Each source node served the entire WSZ it was associated with. This is a conservative estimate as we don't know the proportionate contribution if multiple sources served the same WSZ.

b. Each intermediary node also served the entire WSZ it was mapped to.
c. Sink nodes equally serve their allocated WSZs, which meant that the fraction of WSZ customers assigned to each sink node was equal to (1/number of sinks in WSZ)×(served population of WSZ).

4. We assigned each pipeline to the closest node and assigned customers served by that node to the pipeline. Some WSZs did not have a piped network, which may be because assets have been built since the database was created or because they are missing.
5. From steps 1-4 we found the total population and GDP (from water household customers + buildings dependent on water) served by each water asset by adding up its contribution to each WSZ it was supplying to.
6. For disruption analysis we assumed that:
   a. If one node or edge failed, the customers and GDP served by that asset are all disrupted.
   b. If multiple nodes or edges failed, we take the maximum customers disrupted in a WSZ across all failed assets in order to avoid multiple counting.

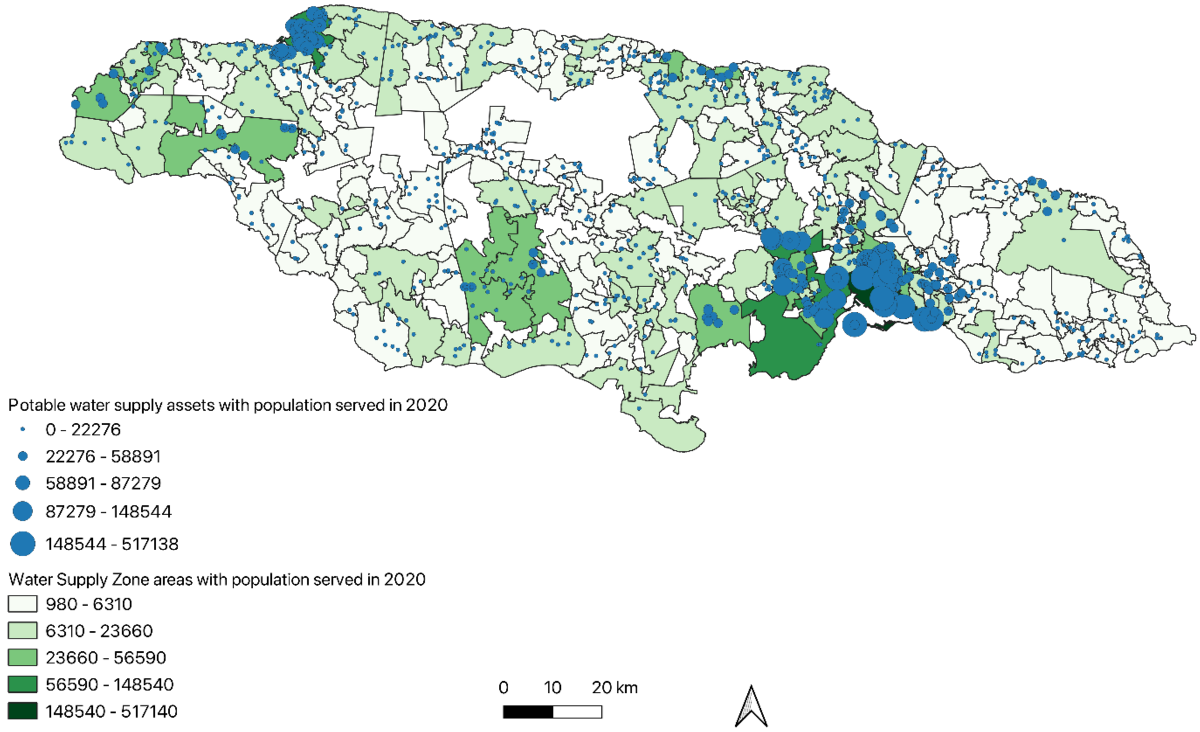


Figure C-4: Map visualisation of the estimated population served with WSZs assigned to potable water supply assets in Jamaica.

C.3.2 Irrigation demand mapping and disruption analysis

The irrigation asset demands were estimated in the following steps:

1. Allocate irrigation assets (wells, canals and pipelines) to different irrigation schemes.
2. Intersect the irrigation scheme area with the agriculture GDP areas (see Section 3.3.3) and estimate the agriculture GDP/area associated with each irrigation scheme.
3. Find fraction of scheme served by each irrigation asset type by applying following rules:
   a. Area served per well = 1/number of wells per scheme. This is a conservative estimate because we do not know the contribution from surface water sources.

   b. Area served per pipe = (pipe size)/(sum of pipe sizes). The grid network structure of the pipes provides a high level of redundancy, meaning that other pipe networks are unlikely to be cut-off if one fails.
   c. Area served per canal = either known value or in proportion to the length of the canal. It is unknown how water sources combine along the canal and how much is extracted from each section, therefore we assume water is abstracted proportionally to canal length.
4. For disruption analysis we assumed that:
   a. If one node or edge failed, we assumed the area the asset served was disrupted and hence the GDP over that area was disrupted.
   b. If multiple nodes or edges failed, we summed the areas and the GDP over those areas to get the combined effect of all failed assets.

C.4 Transport system model

C.4.1 Transport flow allocation

The transport system is modelled as a multi-modal network graph composed of roads, railways, airports and ports. The multi-modal linkages are created by identifying the linkages from rail stations to their nearest road nodes, the linkages that exist between ports and key rail stations and ports and their nearest road nodes, and the linkages that exist between airports and their nearest road nodes.

Commodity and industry flows on the transport network are estimated from the import-export trade flow statistics of Jamaica, compiled from STATIN[71,72]. These statistics are shown for exports in Table C-2 and for imports in Table C-3, where the sector code and subsector code mapping has been created by us to match commodities to specific industries as per the JIC 2005 system (see Table 3-5 and Table D-1). We converted these statistics from annual estimates to daily estimates by dividing by 365 to obtain values in J$/day.

Table C-2: Annual export statistics for main commodities being exported from Jamaica.

Commodity	2019 (J$'000)	Sector code	Subsector code
TOTAL DOMESTIC EXPORTS	201,385,696	ALL	ALL
AGRICULTURE:	8,932,010	A	ALL
Vegetables	130,794	A	011-7
Yams	3,764,995	A	011-6
Other Root Crops	814,039	A	011-6
Banana	77,499	A	011-2
Papayas	265,156	A	011-7

[71] https://statinja.gov.jm/Trade-Econ%20Statistics/InternationalMerchandiseTrade/newtrade.aspx
[72] https://statinja.gov.jm/Trade-Econ%20Statistics/InternationalMerchandiseTrade/newtrade.aspx

Commodity	**2019 (J$’000)**	**Sector code**	**Subsector code**
Other fruits and beverage crops	674,234	A	011-8
Coffee	1,597,516	A	011-4
Herbs & Spices	1,107,592	A	011-5
Animal & Fish	183,978	B	050
Other Agriculture Exports	316,207	A	011-5
MINING AND QUARRYING:	106,813,486	C	ALL
Bauxite	12,784,971	C	132
Alumina	93,478,964	C	132
Other Mining	549,551	C	141
MANUFACTURE:	83,461,415	D	ALL
FOOD, BEVERAGES & TOBACCO:	37,305,799	D	SUB
Meat & Meat Preparations	1,159,574	D	151-1
Fish & Fish Products	1,165,957	D	154-3
Ackee (canned)	2,638,015	D	154-3
Dairy Products	1,089,369	D	152
Processing of Other fruits & vegetables	1,818,006	D	151-2
Sugar	1,404,178	D	154-2
Baked products	2,871,991	D	154-1
Sauces	3,200,133	D	154-3
Other Food exports	4,847,365	D	154-3
Rum	7,471,026	D	155
Alcoholic Beverages (excl. Rum)	7,268,585	D	155
Other beverages & tobacco exports	2,371,600	D	160
OTHER MANUFACTURE PRODUCTS:	46,155,615	D	SUB
Refined Petroleum Products	39,272,461	D	240
Chemical & Chemical Products	4,236,781	D	240
Other manufactured products	2,646,373	D	360

Table C-3: Annual import statistics for main commodities being imported into Jamaica.

Commodity	2019 (J$'000)	Sector code	Subsector code
TOTAL IMPORTS	851,749,148	ALL	ALL
CONSUMER GOODS:	209,860,958	G	SUB
Food (incl. Beverages) Mainly for Household Consumption	113,228,672	G	500-1
Non-Durable Goods	48,242,384	G	500-1
Semi-Durable Goods	25,243,579	G	500-1
Durable Goods	23,146,322	G	500-1
RAW MATERIALS/INTERMEDIATE GOODS:	247,396,846	SUB	SUB
Food (incl. Beverages) Mainly for Industry	19,557,937	D	154
Industrial Supplies	132,172,350	D	360
Construction Materials	57,943,441	F	450
Parts and Accessories of Capital Goods (except Transport Equip.)	37,723,117	G	500-1
FUELS AND LUBRICANTS:	228,997,929	C, D, G	ALL
Crude Oil	85,824,640	C, D, G	132,240,500-2/3
Motor Spirit	32,582,836	G	500-2/3
Other Fuels and Lubricants	110,590,454	C, D, G	132,240,500-2/3
TRANSPORT EQUIPMENT:	68,975,266	G	SUB
Passenger Motor Vehicles	49,677,071	G	500-1
Parts and Accessories of Transport Equipment	18,195,495	G	500-2/3
Non-industrial Transport Equipment	1,102,700	G	500-2/3
CAPITAL GOODS (EXCL. MOTOR CARS):	96,152,284	G	SUB
Capital Goods (except Transport Equipment)	77,636,883	G	500-1
Industrial Transport Equipment	18,515,400	G	500-1
GOODS NOT ELSEWHERE SPECIFIED:	365,866	G	500-1

From the commodities and industries mapped above we are able to map trade flows in following steps:

1. We infer that the main exports out of Jamaica are in Agriculture (Sector A), Fisheries (Sector B), Mining (Sector C), Manufacturing (Sector D).
2. The main imports into Jamaica are in Retail and Trade (Sector G), Construction (Sector F), and Fuels which are used by Mining (Sector C), Automobile trade (Sector G) and Manufacturing (Sector D).
3. We assume that all the export-import trade flows have to pass through the ports in Jamaica, for which we know the annual tonnage statistics and main commodity goods being shipped through the ports (see Table C-4).

Table C-4: Export-import statistics of shipping through ports of Jamaica in 2019 (source PAJ[50]).

Name	Export tonnes (annual)	Import tonnes (annual)	Commodity/Industry being shipped
Kingston Freeport Terminal	185,650	1,203,044	Dry bulk, Break bulk, Liquid bulk & container (Sector A, Sector B, Sector D, Sector F, Sector G)
Kingston Wharves	164,228	4,609,340	
Montego Bay	1,413	832,328	
Ocho Rios	12,890	-	
Petrojam	-	1,747,723	Fuels
Port Esquivel	439,242	-	Alumina (Sector C)
Port Kaiser	500,576	-	
Rocky Point	1,038,806	-	
Port Rhoades	3,584,184	-	Bauxite (Sector C)

4. Once we identify the ports, and their industries we assume that the export and import of a particular industry through a port would be in proportion to the tonnage volume of that industry's export and import handled at the port. For example, from Table C-4 we estimate that Sector A, B, D, F, G exports will be shipped through mainly four locations in Jamaica, with Kingston Terminals handling 96% of the cargo, 3.6% will be handled at Ocho Rios port and 0.4% at Montego Bay port. Hence, we assume that the export trade values in J$ (from Table C-2) shipped for each industry to these ports will also be in same proportion.
5. Once we identify the ports we estimate the locations within Jamaica from and to which the commodities will be shipped for exports and imports. Exports will be sent from within the country towards the ports and imports will arrive at the ports and sent within the country.
    a. We assume that only the mining industry exports will be sent via rail and road to the ports handling mining products. For all other industry exports, we assume that only roads will be used to transport commodities to the ports handling those commodities.

b. We assume that all imports will be sent from ports to location within the country via the road network only.

c. We assume that the locations of exports and imports within Jamaica by industry are based on the different areas and buildings designated to those industries.

    i. All agriculture (sector A) commodity exports would be from the locations of the agriculture areas assigned to specific crops, as described in Section D.3.

    ii. All mining (sector C) exports would be from the locations of the mining areas identified in the country and connected to ports, as described in Section D.4.

    iii. All fishery (sector B) exports would be from the locations of the aquatic farms identified in the country, as described in Section 3.3.3.

    iv. For the other sectors of manufacturing (sector D), construction (sector F) retail and trade (sector G) the exports and imports would be between locations of buildings assigned to these sectors, based on the building footprint data described in Section 3.3.2.

    v. We assume that all fuel imported within the country would be arriving at three types of locations[73]: 64% at the Petrojam port facility, 21% at other ports from where it will be shipped to automobile parts shops (sector G), and 15% to the ports connected to the mines.

6. After the locations of export-import are identified, we assign the value of trade between these locations and ports in the following steps:

    a. We identify the least-time route connecting each port to any location of economic activity identified for different sectors from Step 5 above). This results in estimating which locations would be connected to their most preferred ports, and the route to those ports.

    b. Once we have identified all the least-time connectivity routes, we disaggregate the value of trade (export and import) assigned to the port (from Step 4 above) to the routes. This is done in proportion to GDP assigned to the locations connecting to the ports. For example, if we know all the mines connected to the ports, the export trade share of each port (e_i) and the GDP associated with each mine (GDP_j) (see Section D.4), then we assume that the value of trade assigned to a mine (j) and its route to the port (i) will be equal to $e_i\, GDP_j / \sum_j GDP_j$ where the summation is over the GDP of each mine connected to the port. The same principle is applied to all other sector trade routes value allocations.

Figure ***C-5*** shows the result of the implementation of the Step 1-6 outlined above, which is represented here in terms of the total value of daily trade in J$/day along edges of rail and road networks.

[73] Based on information from the Ministry of Science, Energy and Technology (MSET): https://www.mset.gov.jm/wp-content/uploads/2020/06/JAMAICA-ENERGY-STATISTICS-2020.pdf

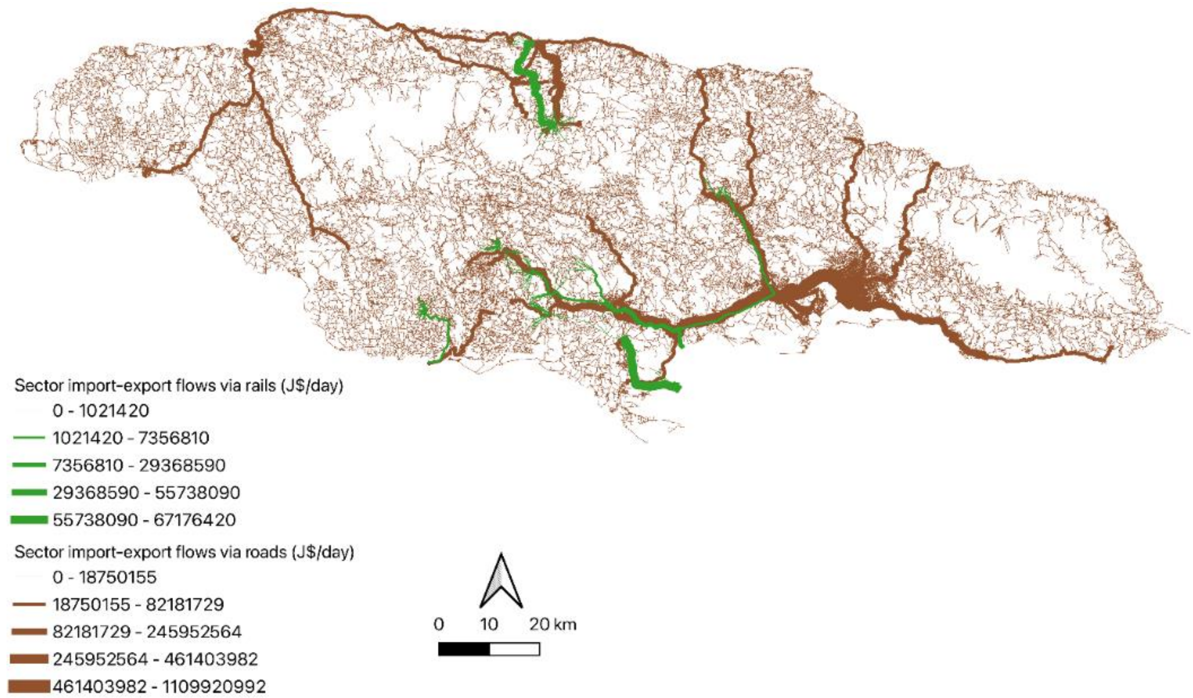


Figure C-5: Result of the trade flow allocation to rail and road network route connecting to ports in Jamaica.

In addition to the allocation of trade values, we also allocate clusters of working populations to clusters of business activities via the road network. We assume that the GDP associated with non-residential buildings will depend upon the ability of the workforce to access these buildings. Hence, we build a road flow assignment model to find routes from locations where working populations are concentrated to locations where GDP is concentrated. To do such a road flow assignment we implement the following steps:

1. We take the Enumeration District (ED) level working population data (see Figure 3-3) and disaggregate it to the residential buildings with each ED. We assume that the allocation to residential buildings is done in proportion to the areas of the buildings.
2. We find the nearest road node to each residential building and aggregate the total number of working populations to their nearest road nodes.
3. We also take all the non-residential buildings in the country and find the nearest road nodes to each building, to estimate the aggregated GDP assigned to its nearest road node.
4. Once we have identified all the road nodes where labour is concentrated and where GDP is concentrated, we implement a radiation model for estimating the commuter patterns along roads. This is a well researched problem in transport modelling, where radiation models have been developed to quantify such movements[74,75]. The overall aim of such models is to understand how likely are people to travel to work based on employment opportunities in surrounding areas, which depends on the concentration of populations, workforce and GDP. We create a radiation model, which is a variation of the model proposed by Pivoni et

[74] Simini, F., González, M. C., Maritan, A., & Barabási, A. L. (2012). A universal model for mobility and migration patterns. *Nature*, *484*(7392), 96-100.
[75] Ren, Y., Ercsey-Ravasz, M., Wang, P., González, M. C., & Toroczkai, Z. (2014). Predicting commuter flows in spatial networks using a radiation model based on temporal ranges. *Nature communications*, *5*(1), 1-9.

al. (2018)[76]. According to our radiation model, the working population e_i at an origin location i on the road network is likely to travel of another destination location j within a distance (or travel time) of d_{ij} based on the GDP opportunities GDP_i and GDP_j at the locations i, j and all other opportunities GDP_{ij} within the travel distance between the two locations. The number of working people w_{ij} who will move from location i to location j to seek employment is estimated as shown in Equation C.1.

$$w_{ij} = e_i \frac{GDP_j/(GDP_i + GDP_{ij})}{\sum_k GDP_k/(GDP_i + GDP_{ik})} \qquad \text{(C.1)}$$

w_{ij} also indicate how much of the working population 'flow' will happen along the road network between the locations i, j, which we assign to the least-cost route connecting the two locations[75,76].

5. The implementation of Equation C.1 is done as following:
    a. We assume that the working population would look for employment opportunities which are within 1 hour of travel time from them, i.e., $d_{ij} = 1$ hour.
    b. We implement a least-cost route assignment algorithm developed in Python.
6. We also estimate how much of the GDP is associated with each route, as per Equation C.2.

$$GDP_{ij} = GDP_j \frac{w_{ij}}{\sum_i w_{ij}} \qquad \text{(C.2)}$$

Figure C-6 shows the result of the implementation of the Step 1-6 outlined above, which gives the value of daily GDP in J$/day along edges of the road networks.

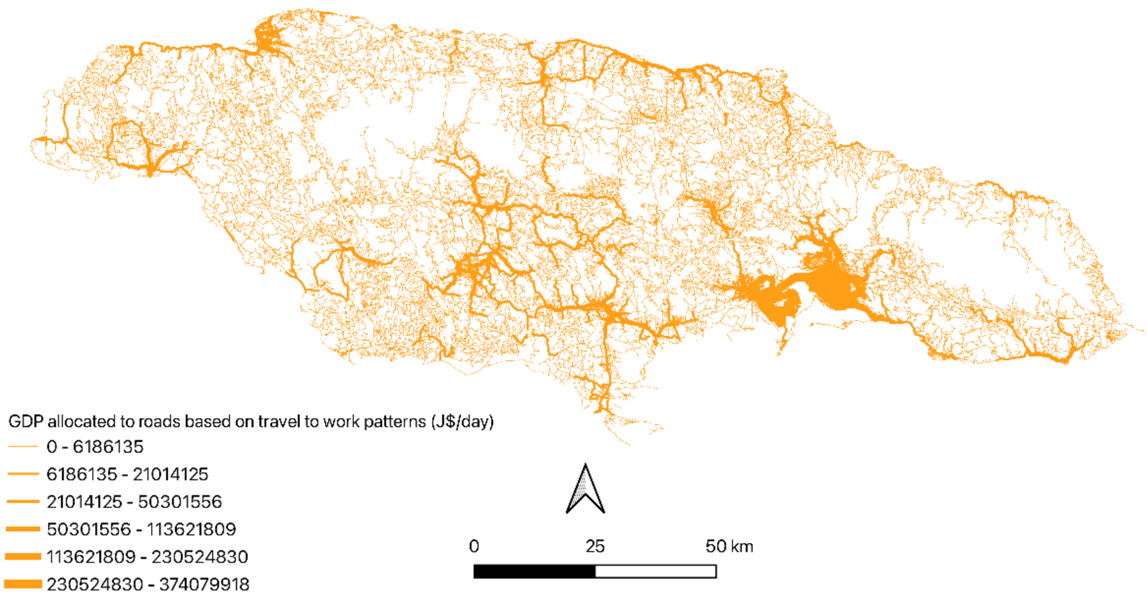


Figure C-6: Result of the GDP flow allocation to road network based on estimations of commuting patterns of working populations in Jamaica.

[76] Piovani, D., Arcaute, E., Uchoa, G., Wilson, A., & Batty, M. (2018). Measuring accessibility using gravity and radiation models. *Royal Society open science*, *5*(9), 171668.

C.4.2 Transport flow disruption analysis

From the flow assignment analysis, leading to Figure ***C-5*** and Figure C-6, we are able to create a large set of origins-destinations, travel routes, value of trade and GDP in J$/day. The transport failure and disruption analysis that follows this flow assignment analysis, involves the following steps:

1. We first assemble the set of transport nodes and edges that are considered damaged due to a hazard event. Here a set includes at least one node or edge.
2. We remove the set of damaged transport assets from their networks.
3. We find all the travel routes that include the damaged assets, which are assumed to now be disrupted due to transport damages.
4. We re-run the flow assignment for these disrupted routes to find the next best routes based on least-cost (least-time) assignment along the remaining network. This is called the process of rerouting flows.
5. From the rerouting process we get two possible outcomes for each route:
    a. There is an alternative route along the network, which is now assigned to complete the trip between the origin-destination pair. But this comes at a higher cost of transport, which we estimate in terms of the increased time to travel. Assuming that the increased travel time between origin-destination (OD) pair i, j is Δt_{ij} in hours, the associated pre-disruption trade flow is f_{ij} in J$/day, the number of workers commuting before disruption are w_{ij} then the rerouting loss associated with the OD-pair is estimated as:
    $$l_{ij} = 0.02\Delta t_{ij} f_{ij} + 136.82\Delta t_{ij} w_{ij} \qquad \text{(C.3)}$$
    Where the value 0.02 or 2% is based on the study of Hummels and Schaur (2013)[77], who studied United States and global trade data and found that each hour of delay to imports results in 2% loss of value of trade. The 136.82 is the estimate of wage losses in J$/person/day, which is estimated by assuming the average basic hourly rate of employees in Jamaica from STATIN statistics of 2009 was 235.25 J$/hour[78], adjusted to 2019 values by assuming 45.4% inflation from 2009-2019[79] and each hour of delay in travel results in 40% loss of wages[80]. We note that the network losses associated with labour rerouting will only apply for the road network disruptions, as we assume rail networks are only used for trade flows of mining products.
    b. There is no alternative route along the network, which means that due to asset damages the network flows have been cut-off resulting in loss of the trade and GDP assigned to that origin-destination journey. In this case we add up all the trade and GDP values due to all trips lost, to get the economic loss in J$/day attributed to failed nodes and edges.
6. The implementation of Step 5 above gives us the estimate of the economic losses due to transport disruptions along each disrupted journey. For a given failure scenario of damaged nodes and edge we can find the sum over all OD routes that incur rerouting and flow cut-off losses.

We note that in the above methodology we have not estimated economic losses due to disruption to airports. Unfortunately, there is very little information on freight data patterns and

[77] Hummels, D. L., & Schaur, G. (2013). Time as a trade barrier. *American Economic Review*, *103*(7), 2935-59.
[78] https://statinja.gov.jm/BasicHourlyRateOfHoursRatedWageEarnessinLgEstMIG.aspx
[79] https://www.statista.com/statistics/527084/inflation-rate-in-jamaica/
[80] https://www.vtpi.org/tca/tca0502.pdf

employment for airports in Jamaica. However, we know the passenger estimates for airports in Jamaica from AAJ data (see Table 3-15), and we have estimates that suggest that airports in Jamaica on average generate 35 US$ per passenger revenues[81]. Hence, if an airport is disrupted we estimate the economic losses (in US$/day) associated with the disruption to be equal to 35US$×(number of annual passengers/365).

[81] https://jamaica-gleaner.com/article/business/20211121/jamaica-city-airports-earn-us75m-nine-months-travel-recovery-slow

Appendix D: Spatial disaggregation of economic activity at buildings and area levels

The spatial disaggregation of the economic activity in Jamaica involved taking national-scale statistics and creating methods to disaggregate them to individual buildings and areas. The steps involved in the process are described in the following sections.

D.1 National accounting of GDP by economic sectors and subsectors

1. We first obtained the national accounts of sector specific Gross Value Added (GVA) and total GDP for 2019 as reported by STATIN (https://statinja.gov.jm/NationalAccounting/Annual/NewAnnualGDP.aspx, see Table D-1).
2. From the STATIN data we can see the GVA + TAX = GDP, and hence we can estimate the percentage of TAX added to GVA to get GDP. From Table D-1

$$\text{TAX} = 23\% \text{ of GVA} \qquad \text{(D.1)}$$

3. We assume that the TAX contribution to each sector to the economic is in the same percentage, which implies that for a given sector *s*:

$$(1 + 0.23)\times \text{GVA}_s = \text{GDP}_s \qquad \text{(D.2)}$$

4. From Equation (D.1) we obtain the GDP of each sector and subsector shown in Table D-1. This is the annual estimate, which we convert to a daily estimate by dividing by 365.

Table D-1: Detailed values of industry sector specific GVA and final GDP estimates for Jamaica in 2019 from STATIN.

JIC sector name	JIC sector code	JIC subsector code	GVA 2019 (J$ million/year)
AGRICULTURE FORESTRY & FISHING	**A**	**ALL**	**148,144**
Traditional Export Agriculture	A	SUB	14,879
Sugar Cane	A	011-1	1,998
Other Traditional Exports	A	011-2,011-3,011-4,011-5	12,881
Other Agricultural Crops	A	SUB	99,063
Root Crops	A	011-6	37,207
Other Domestic Crops	A	011-7,011-8	61,856
Animal Farming	A	12	22,691
Post-Harvest Crop Activities & Agricultural Services	A	14	1,658
Forestry and logging	A	20	979

JIC sector name	JIC sector code	JIC subsector code	GVA 2019 (J$ million/year)
Fishing	**B**	**50**	**8,875**
MINING & QUARRYING	**C**	**ALL**	**37,734**
Bauxite & Alumina	C	132	34,594
Quarrying incl. Gypsum	C	141	3,141
MANUFACTURING	**D**	**ALL**	**163,315**
Food Beverages & Tobacco	D	SUB	97,001
Food excl. sugar	D	151-1,151-2,152,153-1,153-2,154-1	67,617
Sugar and molasses	D	154-2	1,578
Alcoholic Beverages & Tobacco Products	D	155,160	19,350
Non-Alcoholic Beverages	D	154-3	8,456
Textiles & Wearing Apparel	D	180	1,282
Leather Leather Products & Footwear	D	190	242
Paper & Paper Products Printing & Publishing	D	210	7,369
Refined Petroleum Products	D	240	18,918
Chemicals Chemical Products Rubber & Plastic Products	D	250	13,355
Non-Metallic Mineral Products	D	260	11,811
Metals Fabricated Metal Products; Machinery & Equipment	D	280	8,035
Furniture & Products of Wood Cork & Straw	D	200	4,701
Other Manufactured Goods	D	360	601
ELECTRICITY & WATER SUPPLY	**E**	**401/410**	**61,185**
Production & Distribution of Electricity	E	401	43,537
Water & Sanitation Services	E	410	17,648
CONSTRUCTION	**F**	**450**	**144,100**
WHOLESALE & RETAIL TRADE; REPAIRS; INSTALLATION OF MACHINERY & EQUIPMENT	**G**	**ALL**	**330,623**
Wholesale & Retail Trade	G	500-1	300,352
Repair of Motor Vehicles Household & Personal Goods; Installation and Maintenance of Machinery & Equipment	G	500-2/3	30,271

JIC sector name	JIC sector code	JIC subsector code	GVA 2019 (J$ million/year)
HOTELS & RESTAURANTS	**H**	**ALL**	**84,159**
Hotels & Other Short -Stay Accommodation	H	550-1	61,108
Restaurants Bars Canteens & Mobile Stands	H	550-2/3	23,052
TRANSPORT STORAGE & COMMUNICATION	**I**	**ALL**	**137,151**
Transport	I	600	35,740
Auxiliary Activities to Transport	I	600	54,983
Post & Telecommunications	I	640	46,428
FINANCE & INSURANCE SERVICES	**J**	**ALL**	**189,821**
Monetary Institutions (incl. Central Bank)	J	650	99,847
Other Financial institutions & Financial Services	J	650	44,186
Insurance & Pension Funding (incl. Auxiliary Activities)	J	650	45,788
REAL ESTATE RENTING & BUSINESS ACTIVITIES	**K**	**ALL**	**187,065**
Operating of Owner-Occupied Dwellings	K	701	55,462
Rental of Residential Buildings	K	701	23,420
Other Real Estate Activities	K	740	29,656
Business Activities incl. Renting of Machinery & Equipment	K	710	78,526
PRODUCERS OF GOVERNMENT SERVICES	**L**	**ALL**	**220,728**
Central Government (incl Agencies & Departments)	L	750	217,628
Local Government	L	750	3,101
OTHER SERVICES	**OTHER**	**ALL**	**112,721**
Private Education	M	800	21,418
Private Health & Social Services	N	850	9,915
Recreational Cultural & Sporting Activities	O	920	43,358
Community Social & Personal Services n.e.c.	O	920	24,830
Private Households with Employed Persons	P	ALL	13,199

JIC sector name	JIC sector code	JIC subsector code	GVA 2019 (J$ million/year)
Less Financial Intermediation Services Indirectly Measured (FISIM)	FIN	FIN	102,234
TOTAL GROSS VALUE ADDED AT BASIC PRICES	**GVA**	**GVA**	**1,714,513**
TAXES LESS SUBSIDIES ON PRODUCTS	**TAX**	**TAX**	**395,919**
GROSS DOMESTIC PRODUCT AT MARKET PRICES	**GDP**	**GDP**	**2,110,433**

D.2 Disaggregation of GDP to buildings

1. For the sectors D – O, listed in Table 3-5 and Table D-1, we created the geotagged buildings database described in Section 3.3.2. We assume that the total sector GDP will be disaggregated to these buildings.

2. The amount of GDP associated with a building is estimated to be a function of the location of the buildings in proximity with working populations and the area of the building. The proximity to working population is a measure of the attractiveness of the area where the building is located and the area is a measure of the capacity of the building in accommodating more workforce.

3. To estimate the attractiveness of the area where a building is located we used the Enumeration District (ED) level total and working population estimates, from the data described in Section 3.3.1. We then apply the radiation model (introduced in Section C.4) to infer how mobility patterns will determine concentrations of GDP. For the collection of ED areas in Jamaica we know the total populations p_i, p_j and employed populations e_i, e_j between two ED-pairs (i, j) located within a distance (or travel time) of d_{ij}. The number of people T_{ij} who will move for ED-area i to ED-area j to seek employment is estimated from a radiation model[76] as shown in Equation D.3. Here e_{ij} is equal to the employed population within the radius defined by the travel distance d_{ij}.

$$T_{ij} = p_i \frac{e_j/(e_i+e_{ij})}{\sum_k e_k/(e_i+e_{ik})} \qquad \text{(D.3)}$$

   The total attractiveness of an ED is then estimated by Equation D.4, which is then normalised as per Equation D.5.

$$T_j = \sum_i T_{ij} \qquad \text{(D.4)}$$

$$\bar{T}_j = \frac{\bar{T}_j}{\sum_j \bar{T}_j} \qquad \text{(D.5)}$$

   The implementation of the above formulations is done as following:

4. We found the centroid of each ED as a reference point for population concentration in that ED.

5. We assumed that the people in an ED would look for employment opportunities which are within 10 km from them, i.e., $d_{ij} = 10$km.

6. For each ED i we created a 10 km radius around the centroid and located every other ED j within that radius, which gave us the values of e_{ij}. We repeated this calculation for each ED in Jamaica to find $e_{ik} \forall k$, which then solved Equations D.3 – D.5.
7. The process outlined in Step 3 allowed us to assign a weight to each ED in Jamaica to signify how likely the working population would be concentrated within that ED, and hence be likely to work in the buildings within that ED. We assumed that the spatial disaggregation of GDP of a sector would be proportional to the working population attracted to EDs, which meant that the GDP of a sector s assumed to be concentrated within an ED i, GDP_{si}, was estimated as:

$$GDP_{si} = \bar{T}_i GDP_s \tag{D.6}$$

8. Within a given ED we then looked at all the buildings of that sector and assumed that GDP of sector s assigned to building b in ED i was estimated from Equation D.7, where a_{sib} denotes the area of the building tagged to sector s and within ED i.

$$GDP_{sib} = \frac{a_{sib}}{\sum_b a_{sib}} GDP_{si} \tag{D.7}$$

D.3 Disaggregating GDP to agriculture areas

1. We estimate national scale GDP values from the steps outlined in Section D.1, for the agriculture sector and subsectors with codes A 011-1 – 011-8, A 12, A 14, A 20 shown in Table D-1.
2. We use the FD and TNC land-use datasets to find all land-use types that can be mapped to the agriculture sector and subsector classes. For example, these datasets show the areas where plantation crops such as sugarcane and bananas are grown, which means we can map those areas to sector and subsector code A 011-1 and A 011-2 and later on disaggregate the GDP of these sectors to these areas.
3. We use the IFPRI Map Spatial Production Allocation Model (MapSPAM)[82] data estimates from 2010 to estimate the total value for different crops values produced in Jamaica. MapSPAM provides estimates production values in annual tonnages and US$ for 42 crops globally at a 5km gridded resolution[83]. Using this data, we map the crops to the agriculture subsectors for Jamaica and then estimate the total subsector production values per areas from 2010 in US$/m^2 disaggregated at 5km gridded resolutions.
4. We intersect the land-use datasets (step 2 above) with the 5km gridded MapSPAM data layers (step 3 above) and assign the production values per area of the specific sectors to the land use areas.
5. We assume that the overall subsector GDP value (step 1 above) will be disaggregated to areas in proportion to the estimated production values in US$/m^2 estimated for these areas. Hence, we are using the 2010 estimate as weights to spatially disaggregate 2019 GDP estimates. We note that there is an assumption here that agriculture production patterns and intensity in 2019 will be similar to those in 2010, which is made in the absence of any other data on spatial agriculture production.

[82] https://www.mapspam.info/
[83] https://www.mapspam.info/methodology/

D.4 Disaggregating GDP to mining and quarrying areas

1. We estimate national scale GDP/day values from the steps outlined in Section D.1, for the mining and quarry subsectors with codes C 132 and C 141 shown in Table D-1.
2. We use the FD and TNC land-use datasets to find all land-use types that can be mapped to the mining and quarrying area. For example, these datasets show the areas where mining and quarrying activities are taking place, which means we can identify all areas where the GDP associated with sectors C 132 and C 141 are coming from.
3. We do not have any information on the mining and quarrying outputs (in tonnages or J$) produced from specific locations of the mining and quarrying areas we have identified.
4. For quarrying we assume that the quarrying outputs and hence GDP is disaggregated in proportion to the areas of the quarrying locations identified from the FD and TNC data. Since, we do not have any information on the intensity of output from each quarry in Jamaica. we are simply assuming the same output/area for each quarry.
5. For mining we know the total tonnages of bauxite and alumina (C 132) being exported from ports in Jamaica as per statistics published by Port authority of Jamaica (PAJ)[84] shown in Table D-2. We assume that Using the transport network of roads and railways we map the mines to the ports, which allows us to know which mines are contributing to the total export tonnages to specific ports.

Table D-2: Annual tonnages to bauxite and alumina from specific ports in Jamaica (source PAJ).

Port Name	Exported Commodity	Total tonnage (2019)
Port Rhoades	Bauxite	3,584,184
Port Esquivel	Alumina	439,242
Port Kaiser	Alumina	500,576
Rocky Point	Alumina	1,038,806

6. We assume that the contribution of a mine to a port is in proportion to its area, and hence we can estimate the total tonnage outputs of specific mines connected to each port in Jamaica.
7. From the estimate of total tonnages allocate to each mine, we assume that the total GDP of the sector C 132 is disaggregated to the mines in the same proportion.

[84] https://www.portjam.com/stat-report/Monthly_Statistical_Publication_February_2020.pdf