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YSSP Report

Young Scientist Summer Program

Urban System Resilience to Floods in Greater Jakarta

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ABSTRACT

This report presents a framework for assessing physical disruption of critical infrastructure accessibility using an example of Greater Jakarta, a metro area of the Indonesian capital. The goal is to inform decision makers and general public on the community's social-physical vulnerability. The first pillar of the framework is damage quantification from the real major flood. Within this pillar, system states before and soon after the flood were compared. The results suggest that in a result of flood access to facilities for people has been significantly hindered, the transportation connectivity has distorted, and the system has become more vulnerable to compound attacks. Poverty is found to be associated negatively with surface elevation, which suggests that urbanisation of flood-prone areas has happened. The second pillar of the report is flood simulation. 140 simulations allow to identify places and clusters that are more vulnerable to floods. Finally, the report proposes a modified method for testing vulnerability of inhabitants' access to services, which is based on percolation technique. The whole framework could be applied to other cities and urban areas and adjusted to account for other disasters that physically affect urban infrastructure. Most importantly, this work has demonstrated feasibility of damage quantification and vulnerability assessment with sole reliance on open publicly available data and tools. Satellite data of flood occurence timely shared by space agencies will allow rapid ex-post examination of social-physical consequences of a disaster. This framework will save resources as the analysis can be run by a single person. Ex-ante vulnerability assessment will help communities, urban planners, and emergency personnel better prepare for the future shocks.

Keywords

Access to critical facilities, Flood, Physical-social vulnerability assessment, Urban resilience, Geographic information systems, Network analysis, Simulation, Percolation.

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1 Introduction

Since the early history of civilizations, the mankind has had to cope with disastrous events (Gerrard, Forlin, and Brown 2020). Cities, as places of high concentration of population and resources, played a major role in advancement of disaster management systems. Urban areas attracted people for numerous reasons, be it presence of religious places, proximity to markets of goods, access to vital natural resources, protection from bandits, search for financial opportunities, or education (Gurevich 1984). Along with benefits of living in cities there were costs, such as higher exposure to cascading events and negative feedback loops. If something went wrong with the supply chain, the city could run out of food, which, in turn, would worsen a criminal situation. During the plague outbreak, the rate of contagion would increase manifolds in cities due to higher population density. Most of the time, the benefits outweighed the costs, therefore cities maintained their attractiveness.

In the modern society, cities still play a special role. The revised projections estimate that by 2050 at least 68 percent of world's population will live in cities (UNDESA 2018). This exposes even more people to the risk of experiencing extreme events. The United Nations New Urban Agenda pledged to integrate disaster risk reduction into the *"urban and territorial development and planning processes, including greenhouse gas emissions, resilience-based and climate-effective design of spaces, buildings and construction, services and infrastructure, and nature-based solutions."* (UN 2017).

Urban infrastructure is crucial to the operation of a city and required for efficient emergency response. Risk reduction strategies should ensure safety of infrastructure to make it possible for facilities, such as hospitals, educational institutes, police, fire stations, communication systems, energy systems, as well as transportation systems, continue providing services when they are needed the most. The importance of infrastructure is recognized by the Sendai Framework for Disaster Risk Reduction (2015-2030).

The framework of this report presents city as a complex living, self-regulating system (Forrester 1969), consisting of a number of components that are compicated to such an extent that we consider them systems within a system. Urban infrastructure together with social organisation represent an ensemble of such systems, therefore we define the city as a hybrid social-physical system or a network, where all components are embedded into its simplified topological structures.

Growing number of facilities and installed devices and large-scale expansion of transportation infrastructure make vital components of the city more dependent on each other. Crippling one road junction may mean a transportation collapse for the city's larger part. Over-relience on various sensors and centralised data collection and decision-making mechanisms will lead to serious issues during any minor power outage. One can conlcude that the more complicated the city is, the more vulnerable it is (Vale and Campanella 2005). The discussion of vulnerability inevitably brings us to the concept of resilience.

Resilience is studied from the perspective of both disaster risk reduction and systemic approaches, where it is the ability of a system together with its components to anticipate, recover, and improve from the effects of extreme events that have shattered infrastructure and disrupted societies. I accept the definition of resilience provided by the Intergovernmental Panel on Climate Change, which stated that resilience is *"the ability of a system and its component parts to anticipate, absorb, accommodate or recover from the effects of a hazardous* *event in a timely and efficient manner, including through ensuring the preservation, restoration or improvement of its essential basic structures and functions"* (2018). Thus, urban system resilience is this ability of a city to effectively prepare for a catastrophe, withstand it, recover from its consequences, and get better in the aftermath.

In view of extreme events that happen in cities and shift their normal system state into a catastrophic state, we can highlight the phenomenon of *tipping point*. The tipping point definition was adopted from physics. It can be explained as the moment when the system passes a critical threshold and shifts to another state (Mrotzek 2011). For example, a disaster happens and urban infrastructure is destroyed; when a critical share of valuable infrastructure is nonoperating, a whole system ends up heavily distorted—this very moment we call the tipping poing. Epidemics are another example. A number of sick people is growing, but for the time being health facilities are able to cope with the inflow of patients. At some point, the tipping point, the system, however, overheats. That ruins healthcare sector, drives up the crime levels, and destabilises the political situation.

All this significantly increases interest of researchers, decision makers and practitioners to resilience of urban systems to crises and disasters. Particular attention is given to floods. Although flood is a natural phenomenon, which is important to the life cycle of a number of organisms, including humanbeings, the uncontrollable urbanisation of floodplains has led to huge problems involving material and financial losses and has taken numerous human lives (Casale and Margottini 1999).

The research framework that is proposed in this report attempts to quantify damage to social-physical system of the city caused by the real flood case and assess vulnerability of critical infrastructure and communities to the future catastrophes. *Jabodetabek*, the Jakarta metropolitan area in Indonesia, also known as Greater Jakarta, is my geographical focus. The disaster that the report quantifies is *2020 Jakarta major flood*, which has led to displacement of sixty thousand people and claimed the lives of eighty people.

Setting up the scene, we should identify form and context for this framework. The *context* defines the problem, and the *form* provides a solution to the problem (Alexander 1964). In our case, the context suggests that the very human background implies the need for safety. The social-physical environment, where safety is enabled by emergency sites and social structures, is the form.

The report raises and answers four major questions.

Research question 1. How did 2020 flood in Greater Jakarta affect urban structure? Which types of objects and facilities suffered the most? What share of population ended up without access to services?

Research question 2. What is relationship between loss of access, poverty, and elevation in Greater Jakarta?

Research question 3. What is spatial social-physical vulnerability of Greater Jakarta to future floods?

Research question 4. How robust is in general access of population in Greater Jakarta to specific services?

The structure of the report is the following. The *Background* section represents a brief literature review with description of a flood-related situation in Jakarta. The *Data* section lists sources of data and discusses specificities of data collection and cleaning, and data reliability. *Methods* explain my approaches towards data analysis. *Results* discuss outcomes of this research and their limitations. The *Discussion* part draws the way forward. The report ends with *Conclusions*.

2 Background

The risk of catastrophes is related to power-law distribution, where the probability of event is in inverse relationship with its size, i.e. the larger the catastrophe, the less likely it occurs (Page 2018), therefore there is a large number of minor catastrophes, and a relatively small number of large ones.

The power law also governs the outcome of disasters. It is difficult to predict the occurence of the event and it is even more difficult to guess its catastrophic outcome (Taleb 2012; Cimellaro 2016; Blečić and Cecchini 2017; Blečić and Cecchini 2019). Taking this into account, one should focus on preparadeness rather than prognostication. When a disaster hits, the affected community requires immediate help to save as many lives as possible, and later it needs resources to quickly recover. If the community is prepared, it is less vulnerable, hence resilient (Cimellaro 2016).

This part briefly discusses major concepts related to system ability to cope with shocks, gives an overview of selected papers that investigate floods in a way that is relevant to my framework, and describes the flood, the impact of which I quantify.

2.1 Concepts

2.1.1 Vulnerability, robustness, resilience, antifragility

Researchers still struggle to clearly define system characteristics related to its ability to withstand shocks. Vulnerability is usually understood as the degree of susceptability to negative implications from disaster (Fuchs and Thaler 2018). If a system is vulnerable, it can be easily damaged. UNDRO defines vulnerability as "the degree of loss to a given element, or set of elements, within the area affected by a hazard" (UNDRO, 1980 in Fuchs and Thaler, 2018.

Transition of a system from a vulnerable state to a robust state means that it is no longer that easy to break or damage the system. The system becomes more durable to any tension. The accumulated damage from a hazard, however, may still become a tipping point and shift the whole system into a broken state. The question is how quickly this will happen. In my framework, robustness is the ability of a system to withstand damage of the flood and continue to provide access to critical services for population.

The next quality level in system states is resilience. Resilience is a vague concept with dozens of definitions that significantly differ one from each other. There are two major dimensions of resilience definitions—*disaster and crisis management* view and *hybrid social-physical* perspective.

This paper concerns social-physical dimension. Studying sociotechnical systems, i.e. combining physical systems research with examination of communities and individuals, it is possible to apply a relatively holistic approach. The roots of this approach lie in the post-World War II practices with large restoration projects initiated. Current research on sociotechnical systems focuses on networks of information and action, required for their sustainability (Newman 2018). In this approach, physical and social systems are interdependent. Without the technology, society faces limits, without society there is no technology at all.

In the majority of papers, resilience is understood as the system ability to quickly recover from stress. It is essentially different from robustness. The papers focus on minimisation of time and resources to bounce back to the initial state. But is this resilient state of a system an ultimate goal for practicioners and theoreticians? Can we imagine something exceeding resilience? The book *Antifragile: things that gain from disorder* proposes an answer. The antifragile system does not only resist shocks and quickly recovers; it goes beyond—it becomes stronger in a result of imposed damage (Taleb 2012). I was tempted to use the term *antifragility* of urban systems instead of *resilience*, but to avoid confusion, I utilise a more popular concept of resilience, given the fact that the IPCC definition of resilience cited in the *Introduction*, already includes the phrase "through ... improvement of its essential basic structures and functions".

A number of methodologies has been developed in an attempt to assess resilience of settlements to disasters and crises. There are three types of resilience assessment: *indices*, *scorecards*, and *tools & models*. Indices aggregate multiple indicators into a single value. Scorecards are usually the checklists that evaluate current performance or progress towards the resilient state. Models use mathematical language to simplify real world to allow some extent of understanding of complex events. This framework employs the *tools & models* type of assessment.

2.1.2 City as a hybrid social-physical network

Infrastructure is widely considered multilayer networks and studied jointly (Bianconi 2018). Interconnectedness is observed, for example, between the layers of oil & gas infrastructure (fuel and supply, compression stations), electric power (power plant, supply, substations), communication (end office, switching office), emergency services (fire stations, ambulances, call centers), transportation, and water (reservoir substation). Examination of interdependence between these layers is crucial when assessing efficiency, robustness and resilience of the systems (Buldyrev et al. 2010).

Though the researchers of interconnected infrastructure are mostly focused on robustness and resilience, yet there is no complete understanding of the response of complex systems to damage. It has been revealed that the more networks are interdependent, the more fragile they are, because they become more prone to cascading failures (Bianconi 2018).

Brummitt, D'Souza, and Leicht 2012 found that it is beneficial to some extent to improve connectivity between parts of networks as this gives the alternative paths. Higher levels of connectivity, however, result in negative outcomes, because the system is more vulnerable to cascades of failure. For instance, destruction of an increasing fraction of nodes leads to dismantling of the whole interdependent multilayer network, which in case of isolation would still remain functional (Brummitt, D'Souza, and Leicht 2012). Their main conclusion is that the probability of large avalanches is related to a number of interlinks between layers. In particular, a larger probability of interlinks increases the probability of more catastrophic cascades. Lee, Goh, and Kim 2012 showed that multiplexity influences fragility of high-degree nodes.

In addition, critical infrastructure and cascadial failures are examined by a particular line of research (Rinaldi, Peerenboom, and Kelly 2001; Grubesic and Matisziw 2013; Pinnaka, Yarlagadda, and Çetinkaya 2015; Cheng 2017; Mao and Li 2018; W. Wang et al. 2018). Possible scenarios for improving robustness and resilience of networks were proposed in D.

Zhou et al. 2013, Y. Zhou, Sheu, and J. Wang 2017 and Radicchi and Bianconi 2017. Sun, Bocchini, and Davison 2020 review resilience metrics and measurement for transportation infrastructure.

Currently there is a limited number of papers that consider the urban system as a whole, which implies taking into account not only transport or critical infrastructure, but also communities, socieconomic topographical characteristics, and urban space. One of the research lines proposes and develops a network approach that transforms each of the urban system element into nodes and edges and uses methods for complex network analysis (Cavallaro et al. 2014; Bozza, Asprone, and Manfredi 2015; Bozza, Asprone, Parisi, et al. 2017).

Barthelemy 2019 attempted to model urban complex systems to try predicting their behaviour. The author notes that a possibility to identify such generic behaviours is limited. The author, however, believes that with help of machine learning it will soon become practicable. Rise of big data, and increasing number of data sources (such as monitoring sensors in cities) open a potential to improve our predictive abilities and inform urban designers and planners more efficiently (Batty 2016).

2.1.3 Percolation as robustness measure of the network

Percolation theory from statistical physics and mathematics inspired many researchers in network science to apply it to their studies of robustness properties of various networks. The inverse percolation transition helps identify the impact of node failure on the overall integrity of a network (Barabási and Pósfai 2016). In classical applications, the giant connected component (GCC) is used as an indicator of the state of network functionality. Recently researchers focused on the analysis of multimodal transportation systems (Yadav, Chatterjee, and Ganguly 2020), critical facilities (Dong et al. 2020), power grid (Smith et al. 2019), and universal models of resilience (Gao, Barzel, and Barabási 2016; Duan et al. 2019) potentially applicable to different types of networks. In addition to examination of robustness to failure, researchers look for optimal attack strategies and post-failure recovery and restoration approaches.

Abbar, Zanouda, and Borge-Holthoefer 2016 claim that using percolation theory in complexity science it is possible to generate a classification of fragility and service geographical distribution imbalances in cities. They analyse robustness of road networks and services in 54 cities relying solely on publicly available data. The authors believe, it is possible to develop objective methods for measuring urban resilience but there is more work to do. Yadav, Chatterjee, and Ganguly 2020 urge researchers to examine various infrastrucural failures jointly, not in separation from each other. They say that, given nowadays cyber-physical threats, intentional targeted attacks on top of random failures during ongoing crises will aggravate the severity of a situation.

Applying this method to real networks, however, one should demonstrate distinguished accurateness, as it is generally known that spatial networks with real topologies significantly differ in their properties from non-embedded networks. I address relevant concerns about percolation usage for studying cities in the *Methods* section.

2.2 Floods

2.2.1 Related literature

My framework is most closely situated within the following three papers.

Dong et al. 2020 developed an approach for assessing city's physical vulnerability to floods in terms of community's ability to access critical facilities and tolerate access disruption. The authors utilised a method of percolation, calculated disruption tolerance index, and revealed spatial clusters of vulnerability in Houston, Texas. The critical facility type they considered was hospitals. They found that vulnerable areas form spatial clusters. The information that their framework reveals is of practical essence and is important for city planners and emergency managers.

Yadav, Chatterjee, and Ganguly 2020 in their paper analysed urban transport network-of-networks and developed the framework for its resilience assessment. They considered five failure scenarios—*flood*, *random*, *random-local*, *targeted*, and *compound failure* (a series of targeted attacks after flood failure), and two recovery methods – *centrality-based* and *greedy algorithm*. They find that it is more important to maximise robustness rather than efficiency, as the network with maximised efficiency is more vulnerable to compound crises and cascading failures.

Budiyono et al. 2016 assessed future river flood risk in Jakarta under scenarios of climate change, land subsidence, and change of land use. They simulated floods and calculated economic losses with view of prospective sea level rise and precipitation change. The authors developed probabilistic risk scenarios.

2.2.2 Greater Jakarta case: 2020 major flood

This report works with the real-world data and considers the flood case that occured in Greater Jakarta in January 2020.

The major problem of the Jakarta metropolitan area is that its significant portion is low-lying (ALOS 2021); large populated areas are located below sea level, which is the result of uncontrollable urbanisation (Energydata.info 2020). In the case of January 2020 flood, the heavy rainfall intensity coincided with high tides. The water was pushed into low-lying areas from the side of the ocean and from the upland areas, which caused severe flood. The drainage system did not manage the inflow, and flood occured even in higher-lying areas. The hazard caused power outages and transportation system collapse. In a result, 10000 people in rural areas and 6000 in Jakarta city were displaced. 80 people died.

3 Data

The framework of this research relies on availability of data. To successfully quantify implications of flood on the network, we require high-resolution raster or detailed vector data for topology of urban systems and flood occurence.

Despite the fact that more and more satellite data are becoming available, there is still a limited number of high-quality sources depicting catastrophes. Major sources for these data currently are Maxar, the U.S.-based space technology company, Copernicus, the EU Earth observation programme, and Sentinel Asia, the Earth observation initiative for Asia-Pacific region. Maxar within its Open Data Program provides optical satellite imageries of a number of catasrophes across the world. Copernicus as well as Sentinel Asia give access to both optical and radar satellite data. Some cases have vector data with information about the asessed damage from catastrophes. In this research, I use publicly available vectorised data of flood occurence provided by SentinelAsia 2020.

Data	**Year**	**Source**
Physical		
Elevation	2020	ALOS GDSM
Flood	2020	Sentinel Asia
Road	2020	Humanitarian OSM
Fire station	2020	Humanitarian OSM
Police station	2020	Humanitarian OSM
Hospital	2020	Humanitarian OSM
Pharmacy	2020	Humanitarian OSM
Shelter	2020	Humanitarian OSM
Grocery store	2020	OpenStreetMap
School, college, university	2020	OpenStreetMap
Social		
Population density	2015	Energydata.info
Poverty severity in Jakarta	2010	Open Data Jakarta
Poverty severity in Jakarta Metro	2020	Open Data Jabar
Poverty severity in Jakarta Metro	2020	Badan Pusat Statistik
Hospital capacity	2020	Humanitarian OSM

Table 1: Overview of data types and sources

Besides disaster and damage-related sources, I must possess data on urban systems. For that, I utilise free and open platform OpenStreetMap 2020, which is a project that unites thousands of volunteers who digitise physical objects on surface. An additional source of specialised data based on OSM platform is the HumanitarianOpenStreetMap 2021. These sources are the treasury for analysts. It should be noted, however, that both professionals and amateurs make their inputs to the platforms, which raises just questions like *are these sources reliable?*

Researchers and GIS experts judge accurateness of OSM. For instance, Herfort et al. 2015 assess the quality of OSM database, concluding that critical asset types are well represented.

Ludwig et al. 2019 estimated accurateness of public green spaces in OSM and found that the spaces are mapped with a high degree of completeness. Sauter, Feldmeyer, and Birkmann 2019 report that "the spatial indicators deduced from points, lines and areas are able to mirror socio-economic characteristics", and they believe that OSM possesses important capacities and assets for urban resilience assessment.

Returning to this report, it is known that the surface elevation plays important role in flood occurence, therefore I use ALOS Global Digital Surface Model (ALOS 2021) to add the elevation dimension to my framework. Social characteristics of Greater Jakarta were extracted from Energydata.info 2020 (population density) and OpenDataJakarta 2018, OpenDataJabar 2021 and BadanPusatStatistik 2020 (poverty severity). Poverty severity is the index explainin a share of population below a minimum income threshold disaggregated by district. Population density is initially a raster dataset for the whole country.

The data types and sources are summarised in the Table 1.

4 Methods

Christopher Alexander in his brilliant book *Notes on the synthesis of form* described fit as the absence of misfit. To assess the object, it is possible to name all its good qualities, but likely the list will be long. A more efficient way to do this is to make a list of detrimental qualities—the qualities that are not only unfavourable but are severly harmful. "... it is through misfit that the problem originally brings itself to our attention. We take just these relations between form and context which obtrude most strongly, which demand attention most clearly, which seem most likely to go wrong" (Alexander 1964).

This is why children are better off having antiheroes instead of heroes (Taleb 2012). One hero cannot encompass all superior characteristics (unless she is infamous Mary Sue, which is of no help to us), therefore picking one positive person as the prime example does not provide a comprehensive guide to the moral ideal. Almost all Bible's Commandments instruct on what not to do. Probably, it is also not a coincidence that in the adolescense my favourite book was Mikhail Lermontov's *Hero of our time* featuring Pechorin, a constellation of the worst man's traits in the society.

My research framework revolves around the same principle. I analyse and reveal what is wrong or what will go wrong, instead of focusing on some best practices.

In summary, I assess vulnerability of people's access to critical infrastructure in the event of flood and quantify damage from 2020 flood in Greater Jakarta, identifying its implications for the system. I search for relationships between loss of access to services, poverty, and elevation. I run 140 simulations of floods of various degrees to identify the most vulnerable places. Finally, I conduct my modified version of percolation to test robustness of access to every type of facilities. This framework is the combination of two major quantitative methods–geographic information systems and network analysis.

The urban systems selected for this report are listed below. The selection is based on review of literature and availability of open data.

1. TRANSPORTATION SYSTEM
   (a) Road infrastructure
2. EMERGENCY SYSTEM
   (a) Police stations
   (b) Hospitals (with capacity)
   (c) Fire stations
   (d) Shelters
3. TRANSFORMABLE SYSTEM (public facilities convertable into shelters)
   (a) Schools, colleges, and universities
4. SOCIO-ECONOMIC SYSTEM
   (a) Approximate population count with poverty information
   (b) Grocery stores

5. ENVIRONMENTAL SYSTEM

   (a) Land surface elevation

4.1 Geographic information systems

This method concerns data preparatory stage of research, and it is the most time-consuming part. Road topography from OpenStreetMap usually requires simplification and cleaning from geometrical errors. Initially all urban systems (facilities, roads, population) represent an independent dataset or layer of data. Our task is to create a single dataset that embodies all individual layers. This unification is done based on the road network. All other elements are joined to the nearest road segment in the form of a vector's attribute (See Figure 1 and 2 in Annex).

The same is done with flood occurence. Flood becomes a boolean property of each road segment indicating 0, when there is no flood, and 1, when flood occurs on a segment.

I use other GIS techniques, such as fixing geometries, raster vectorization, joining attributes by location, when necessary. The utilised software is `QGIS`, free and open desktop GIS application (QGIS Development Team 2021).

4.2 Network statistics

The cleaned geospatial data are then transformed into a two-dimensional graph (network), consisting of vertices and edges. Thus, road infrastructure becomes a network of road segments (edges) that are connected to each other through road junctions (vertices). Critical facilities, surface elevation, population density, and poverty data are embedded into the network as the edge properties.

The mathematical formulation of the network is as follows. Let $G = (V, E)$ be an undirected network of an urban transportation system, where V is a set of vertices representing road junctions (intersections) and E is a set of edges representing parts of the road that link those junctions. Each edge (u, v) in G has a corresponding feature vector ϕ_{uv} that indicates the closest to an edge physical object (critical facility) or relevant surface elevation, or associated with this edge social characteristic (population number, poverty). V_d and E_d are the sets of vertices and edges affected by the flood. Let $G' = (V', E')$ be a copy of the initial network with all vertices from V_d and edges from E_d removed.

Using Python `NetworkX` (Hagberg, Swart, and S Chult 2008) and `graph-tool` (Peixoto 2014) specialised modules, I obtain basic network statistics and do all other calculations.

Number and share of roads and services of certain type. I collect data on what types of roads there are (e.g. trunk, primary, secondary, residential), what is a total share of affected edges of each type, how many and which critical services are available, what is a fracture of disabled services due to disasters.

Population without access to facilities. A share of population left with no access to critical facilities is calculated for the global system and for each district.

Betweenness centrality of edges. The edge betweenness centrality denotes a number of shortest paths that go through an edge in the network. Knowing betweenness of edges will help to see how important the roads that are damaged during catastrophes are. If, for example, some critical amount of important roads are prone to disaster, vulnerability of the whole system should be our concern. If the most important roads are still available or some other roads can take their function even in case of a major catastrophe, then this may be the indication of system robustness.

Average betweenness. We can also take the average of edge betweenness as one of the network robustness measures. Intuitevely, the smaller the average is, the more robust the network is. Average betweenness is the linear function of the average distance.

Highest betweenness. This is the value of the top edge in the betweenness centrality distribution. One also wants this number to be as low as possible.

Comparison of network states. Summarising all the collected statistics, I compare two networks: the initial network $G = (V, E)$ and the network affected by the flood $G' = (V', E')$.

4.3 Relationship identification

This concerns running linear regressions to reveal associations between loss of access and poverty, loss of access and elevation, and elevation and poverty.

4.4 Flood simulation

Having confirmed existence of negative relationship between flood damage and elevation, I run flood simulations based on surface elevation level. Overall, I have fourteen intervals of elevation degrees (from elevation lower than 0.62 meters to elevation lower than 3.78 m), and for each interval I run ten simulations. For each simulation I create a new feature vector in the network that describes weight attributes assigned based on certain occurence probabilities. Probabilities in an individual simulation are distributed as follows:

- $p = 0.95$ of flood occurence for lower cap elevation level
- $p = 0.90$ of flood occurence for higher cap elevation level
- $0 < p < 0.1$ for all the rest elevation values

Recorded weighted probabilities help us construct a spatial vulnerability map.

4.5 Percolation

The idea of percolation is to test system robustness. Edge by edge or vertex by vertex we disintegrate the system, applying certain strategies. The most common strategies are failure (removal of a random element) and attack (targeted removal of an element based on its properties). The majority of papers use size of a giant connected component (GCC) as the main measurement of network robustness in the course of inverse percolation. The elements are removed and the GCC slowly or rapidly decays. Although this approach is sufficient in certain situations, GCC is not relevant or informative for some types of networks. We are in this position with urban systems.

During a catastrophe, a city sometimes ends up being broken into parts (e.g. try disabling the Danube bridges in Budapest). When we have two parts of a city (Buda and Pest), and one is slightly larger (Pest), we will not give up on the smaller part (Buda) if the misfortune comes. Both parts are equally important to us and we want them to function independently as fine as they do together.

To account for this GCC limitation, I have adjusted the methodology of robustness assessment. Instead of recording what happens solely in GCC, at each step I record the population number that loses access to particular services in every disconnected part of a network. I iterate through each disconnected part and algorithmically ask—is this part still supplied with at least one service of a certain type? If the population of that island has access to at least one service of the selected type, it is considered to be fine and nothing is recorded. If the part is not supplied, I record the number of people living on that disconnected island. In a result, the sum of population with no access to services is what in my model percolates at each step. In other words, the problem is defined as follows. Let $C(n)$ be a set of connected components at an attack step n. The robustness of the network is measured by the rate at which the population loses access to critical services in the course of edge destruction. To capture that, the population number with no access to at least one service inside each connected component c at each step n is calculated and summed up.

In this report, I consider only the worst-case scenario, when destruction of the network is done by targeted attacks on the edges with the highest betweenness centrality. This way I destroy about 2.5 percent of the network and see how quickly the population of Greater Jakarta loses access to critical facilities.

5 Results

5.1 System state description: before and after 2020 Greater Jakarta flood

5.1.1 Global level

Table 2 summarises statistics for two systems—Greater Jakarta network before the flood (J_0) and Greater Jakarta network after the flood (J_1). n_e describes the number of edges. One can see that the hazard directly affected 9.6 percent of the studied area. Completeness of the network is represented by the parameter κ that indicates a number of connected components within the whole system. The first network is the monolythic unaffected network, therefore it has only one component. After the event the system breaks down into 62772 individual components.

Table 2: Network information and robustness properties

	n_e	κ	P	F_e	F	$b_e^{\max}$	$\overline{b_e}$
J_0	995074	1	100	10739	2363*	0.207	0.000254
J_1	899628	62772	87	10035	2231*	9.506	0.005946
δ	-9.6%	6277100%	-13%	-6.6%	-5.6%	4492%	2241%

* except groceries

The share of population P with access to all critical facilities is 100 percent in the first case and 87 percent in the second. F_e and F correspond to the number of facility edges and facilities. The reason why we distinguish facility edges from facilities is grounded in the way the edge properties have been assigned. Figures 5 and 6 in Annex explain how an individual facility is embedded into its nearby edges, constituting a multiedge-facility. Comparison of F_e in two systems shows how many edges regardless of their facility attachment are flooded. This may or may not mean that a certain facility is flooded. Comparison of F suggests how many facilities are completely flooded, which happens only when all facility-edges, attributed to a certain facility, are affected by the flood. For example, if a multiedge-facility consists of five edges and of these five four edges are disabled, the facility is still considered functional, although we assume that access to it is to some extent hindered.

Betweenness centrality comparison allows us to see how importance of the edges is redistributed after the flood. Edges high in betweenness centrality tell us that their positionhas significant influence on connectivity in the whole graph. It may be a case when the street has a little number of connections, but it is located in such a way that, if it is taken out, some large parts of the graph will be disconnected. We want this measure to be as small as possible, because a small number is a sign of less dependancy on certain edges. Here we observe a dramatic increase in both highest ($b_e^{\max}$) and average betweenness centrality ($\overline{b_e}$), which suggests that after the tipping point the system has become more vulnerable. This assumption finds support in Yadav, Chatterjee, and Ganguly 2020, who demonstrate how natural hazards make technical system increasingly more fragile to compound attacks.

Table 3: 2020 flood direct impact on road infrastructure, number of edges

	J_0	J_1	δ
Trunk	9199	8795	4.4%
Primary	23156	22177	4.2%
Secondary	21365	19935	6.7%
Tertiary	45115	41851	7.2%
Residential	675285	601080	11%
Other	220954	205790	6.9%
Bridge	18093	17008	6%

Table 3 shows flood effect on the types of roads. The roads that suffered the most from flood occurence are residential, tertiary, and secondary. Trunk and primary roads are usually of a paramount importance in the urban transportation system, therefore even 4.2-4.4 percent of damage is considered a significant loss.

The direct impact of flood disaggregated by services is shown in Table 4.

Table 4: 2020 flood direct impact, number of facility edges (in parentheses—facilities)

	J_0	J_1	δ
Hospital	6753 (1393)	6356 (1308)	5.9% (6.1%)
Police station	597 (178)	559 (173)	6% (2.8%)
Fire station	283 (96)	254 (91)	10% (5.2%)
Pharmacy	287 (98)	254 (88)	11.5% (3.4%)
Shelter	45 (21)	43 (20)	4.4% (2.2%)
Public space	670 (577)	628 (551)	6.3% (4.5%)
Grocery store	2104	1941	7.7%

In Table 5, I show indirectly affected population and total population left without access to all services. The population that was directly affected by the flood and, in a result, lost access was equal to 2082678, which amounted to 9.22 percent. I calculate P_{total} simply adding up directly affected population and indirectly affected population. All services are ranked from 1 to 4. The smallest share of population lost access to hospitals, the largest share ended up without access to police stations, fire stations, pharmacies, and shelters. Figure 1 visualises edges that were flooded, edges that lost access to at least one service, and a robust fully functional component.

5.1.2 District level

To get a more detailed picture of the flood implications on the urban system I conduct calculations for each district in Greater Jakarta. Table 6 shows comparison of population share with access to all services P, poverty severity index S, number of facility edges F_e, and number of facilities F before and soon after the flood.

Figure 2 is the illustration of access variability across districts with background layer of the surface elevation. The access is excellent in the districts coloured in green, and it is

Table 5: Approximate population and its share left without access to facilities in a result of indirect and both direct and indirect impact from 2020 flood

	$P_{indirect}$ (%)	P_{total} (%)	Rank
Hospital	678120 (3)	2760799 (12.22)	4
Police station	778468 (3.44)	2861147 (12.66)	1
Fire station	772541 (3.42)	2855220 (12.64)	1
Pharmacy	768178 (3.49)	2850857 (12.62)	1
Shelter	789672 (3.47)	2872351 (12.71)	1
Transformable	721112 (3.19)	2803790 (12.41)	3
Grocery store	743529 (3.29)	2826208 (12.51)	2

difficult in the districts coloured in red. The lighter (whiter) areas of elevation correspond to lower sea levels and dark areas—to higher sea levels. One can see that the northern part of the city is situated on the low grounds. We might assume that elevation and flood vulnerability are interrelated. To do this, we need to fit those distributions, which will be done in the next subsection of the report.

Table 7 is a closer look at the access to all facility types. Here I show poverty severity index with population share with access to all facilities of a certain type. To give some idea about availability of services within the district, I calculate the number of facilities of certain types per 10000 persons.

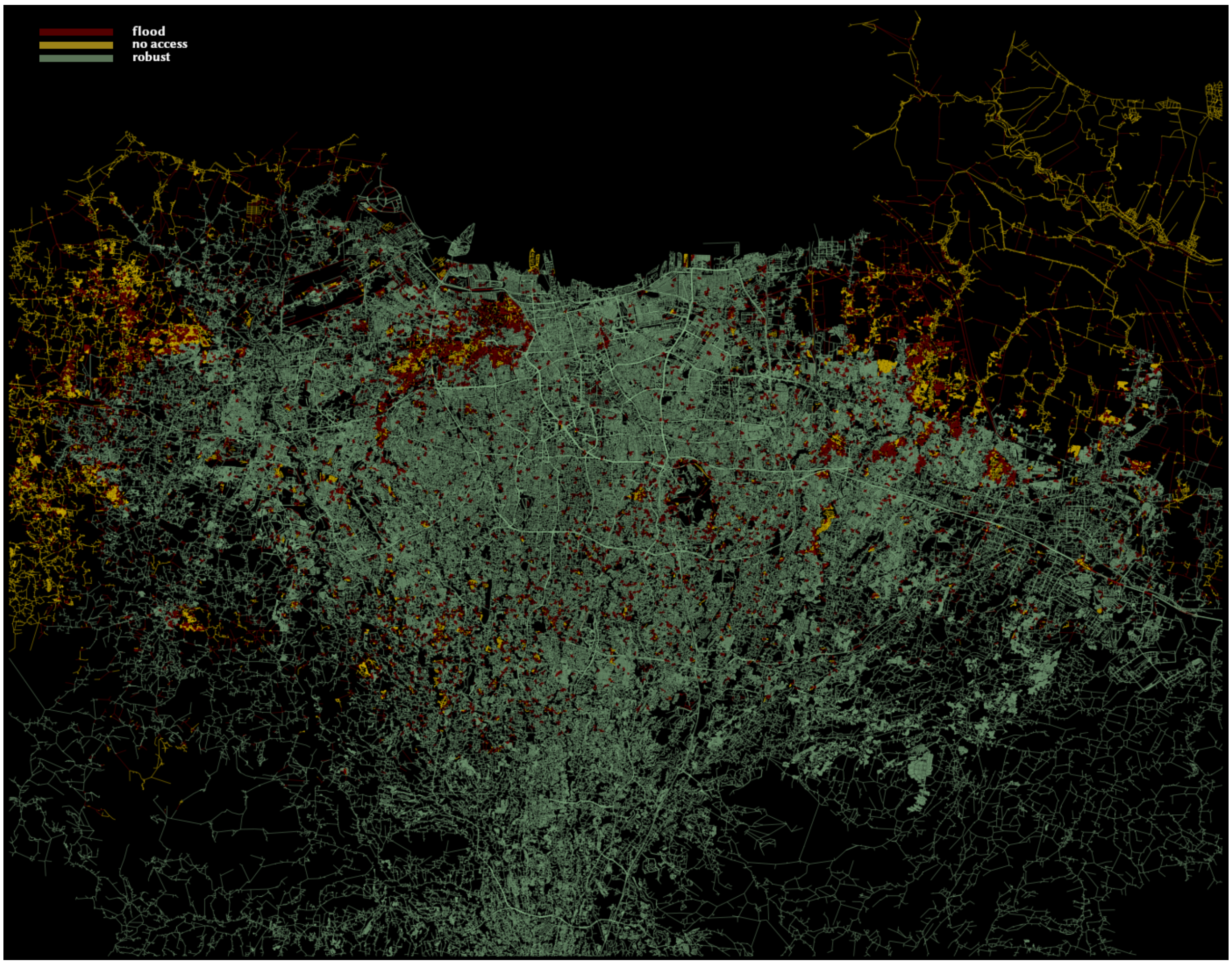

Figure 1: Greater Jakarta network after major flood in January 2020: flooded edges, edges with no access to services, and robust edges

Table 6: Network statistics and robustness properties by district before and after the 2020 flood

	P	S	F_e	F
Kota Jakarta Utara (0)	100		1210	356
Kota Jakarta Utara (1)	89.9	0.26	1129	337
Kota Jakarta Barat (0)	100		1326	278
Kota Jakarta Barat (1)	76.4	0.18	1143	246
Kota Jakarta Pusat (0)	100		977	212
Kota Jakarta Pusat (1)	95.5	0.31	935	205
Kota Jakarta Selatan (0)	100		1582	408
Kota Jakarta Selatan (1)	94.2	0.18	1523	392
Kota Jakarta Timur (0)	100		1615	384
Kota Jakarta Timur (1)	91.5	0.07	1494	358
Tangerang* (0)	100		404	67
Tangerang* (1)	62.5	0.22	328	61
Kota Tangerang (0)	100		440	106
Kota Tangerang (1)	89.5	0.15	419	102
Kota Tangerang Selatan (0)	100		590	89
Kota Tangerang Selatan (1)	91.1	0.08	570	89
Karawang* (0)	100		191	82
Karawang* (1)	28.8	0.25	184	76
Bekasi (0)	100		346	68
Bekasi (1)	77.5	0.18	298	57
Kota Bekasi (0)	100		589	79
Kota Bekasi (1)	85.7	0.15	563	76
Kota Depok (0)	100		728	114
Kota Depok (1)	90.3	0.06	710	112
Bogor* (0)	100		309	64
Bogor* (1)	96.3	0.11	307	64
Kota Bogor* (0)	100		429	78
Kota Bogor* (1)	100	0.26	429	78

* incomplete network

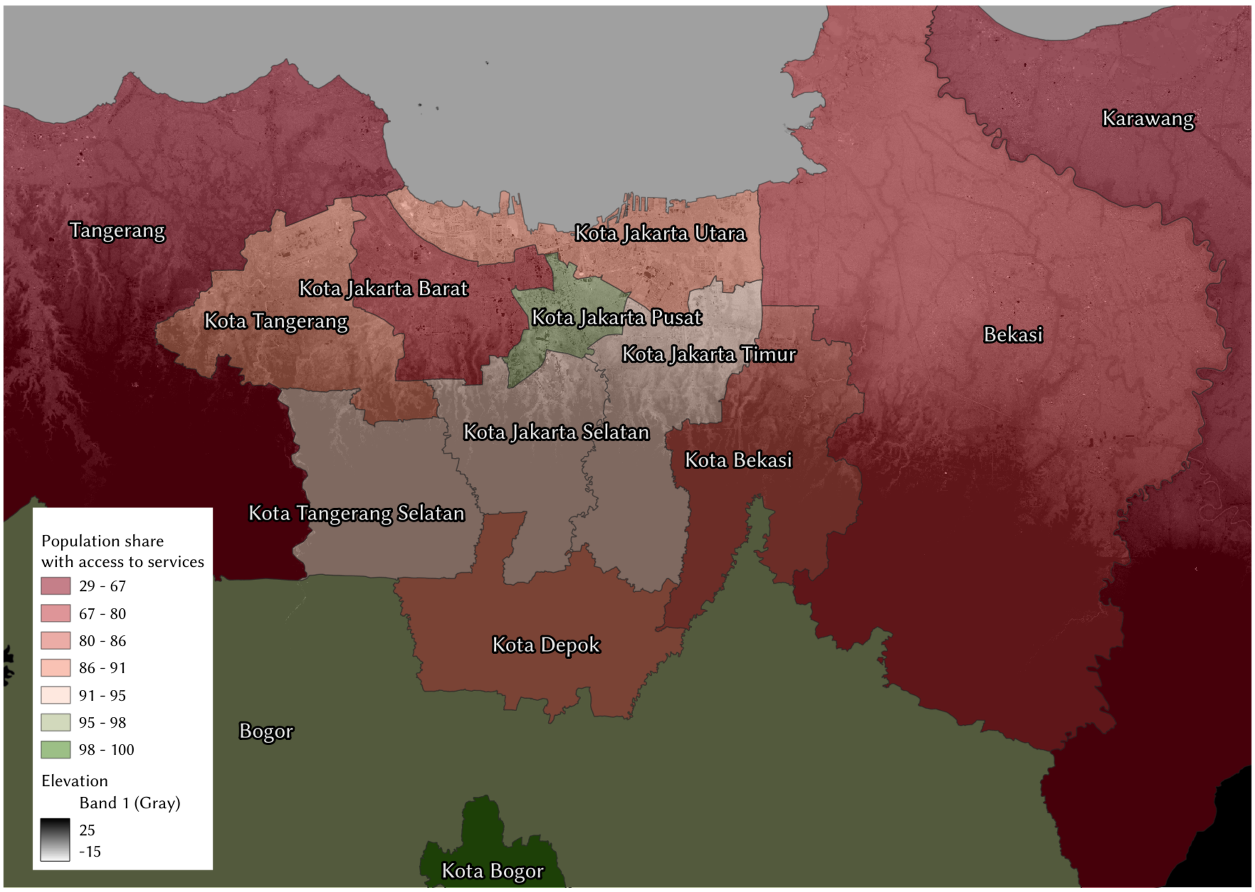

Figure 2: Share of population with access to all services after the flood in January 2020

Table 7: Access to and availability of facilities by district after the flood in January 2020

	S	h_p	h_f	ps_p	ps_f	fs_p	fs_f	ph_p	ph_f	sh_p	sh_f	t_p	t_f	g_p
Kota Jakarta Utara	0.26	90.21	0.374	89.97	0.069	89.81	0.035	89.66	0.071	89.72	0.008	89.66	0.042	89.66
Kota Jakarta Barat	0.18	77.41	0.172	76.7	0.046	76.96	0.021	76.95	0.01	76.41	0.003	77.05	0.023	76.4
Kota Jakarta Pusat	0.31	95.51	0.296	95.51	0.069	95.51	0.03	95.51	0.012	95.51	0.002	95.55	0.081	95.51
Kota Jakarta Selatan	0.18	94.21	0.366	94.15	0.039	94.15	0.017	94.15	0.012	94.15	0.008	94.15	0.017	94.15
Kota Jakarta Timur	0.07	91.79	0.243	91.55	0.022	91.57	0.022	91.55	0.009	91.55	0	91.55	0.018	91.55
Tangerang*	0.22	65.37	0.054	62.45	0	62.45	0	63.07	0.006	62.45	0.002	65.99	0.082	65.99
Kota Tangerang	0.15	89.62	0.04	89.54	0.001	89.62	0	89.62	0.009	89.54	0.003	89.54	0.103	89.59
Kota Tangerang Selatan	0.08	91.1	0.088	91.08	0.002	91.08	0	91.08	0.004	91.08	0	91.08	0.063	91.08
Karawang*	0.25	91.15	0	28.85	0	28.85	0	28.85	0	28.85	0	94.94	15.208	28.85
Bekasi	0.18	79.27	0.065	77.51	0	77.51	0	77.51	0.012	77.51	0	77.65	0.042	77.79
Kota Bekasi	0.15	85.67	0.036	85.67	0	85.67	0	85.67	0.001	85.67	0	85.69	0.037	85.71
Kota Depok	0.06	90.36	0.048	90.35	0	90.35	0	90.35	0.003	90.35	0.001	90.35	0.108	90.35
Bogor*	0.11	96.35	0.035	96.34	0	96.34	0	96.34	0	96.34	0.002	96.34	0.069	96.34
Kota Bogor*	0.26	100	0.138	100	0	100	0	100	0	100	0	100	0.26	100
Total – Greater Jakarta	0.15	87.78	0.618	87.34	0.079	87.36	0.043	87.38	0.043	87.29	0.009	87.59	0.256	87.49

* incomplete network

S – poverty severity index
h_p – population share with access to hospitals
h_f – number of hospitals per 10000 person
ps_p – population share with access to police stations
ps_f – number of police stations per 10000 person
fs_p – population share with access to fire stations
fs_f – number of fire stations per 10000 person
ph_p – population share with access to pharmacies
ph_f – number of pharmacies per 10000 person
sh_p – population share with access to shelters
sh_f – number of shelters per 10000 person
t_p – population share with access to transformable facilities (public buildings)
t_f – number of transformable facilities (public buildings) per 10000 person
g_p – population share with access to grocery stores

5.2 Poverty, lack of access, elevation. All related?

To understand better the relationships between poverty, population's lack of access to facilities in a result of a flood, and elevation, I run simple linear regressions.

I find that there is the negative significant association between elevation and poverty. This tells us that in Greater Jakarta poor people tend to settle in the lowland areas (Figure 7), which is confirmed by a visual check of the map (Figure 2). The association between loss of access to services and elevation also exists; it is negative and statistically significant (Figure 8). These two findings suggest that elevation in case of Jakarta is an important indicator and can be used as the defining parameter when running flood simulations.

A test on the existence of relationships between loss of access and poverty is less successful. Though the association is positive and significant, the R^2 value is weak (Figure 9).

One more attempt to identify relationships between these two uses 14 observations on access to facilities and poverty severity from the Table 6. The relationships appear to be negative but insignificant (Figure 10).

5.3 Vulnerability simulation

Table 8 summarises 140 flood simulations conducted on the real Greater Jakarta network. The simulations were based on the lower cap of elevation value in meters (with 95 percent probability of failure), higher cap (with 90 percent probability of failure), and any elevation failure (with probability of failure varying from 1 to 10 percent).

Table 8: Simulation results

	$\overline{P}$	$\overline{S}$	I	W
sim_1	98.33	0.1707	$< 0.31 < 0.62$	0.5
sim_2	98.32	0.1703	$< 0.48 < 0.96$	0.2
sim_{30}	96.44	0.1729	$< 0.6 < 1.22$	0.1
sim_{40}	96.46	0.1725	$< 0.73 < 1.47$	0.05
sim_5	96.46	0.1724	$< 0.9 < 1.81$	0.02
sim_6	94.17	0.176	$< 1.03 < 2.07$	0.01
sim_7	92.79	0.1719	$< 1.15 < 2.33$	0.005
sim_8	91.39	0.1686	$< 1.32 < 2.67$	0.002
sim_9	91.38	0.1682	$< 1.4 < 2.82$	0.0013
sim_{10}	89.92	0.1666	$< 1.45 < 2.93$	0.001
sim_{11}	86.8	0.1704	$< 1.52 < 3.08$	0.0007
sim_{12}	85.19	0.1682	$< 1.58 < 3.18$	0.0005
sim_{13}	83.4	0.1661	$< 1.74 < 3.52$	0.0002
sim_{14}	81.6	.0164	$< 1.87 < 3.78$	0.0001

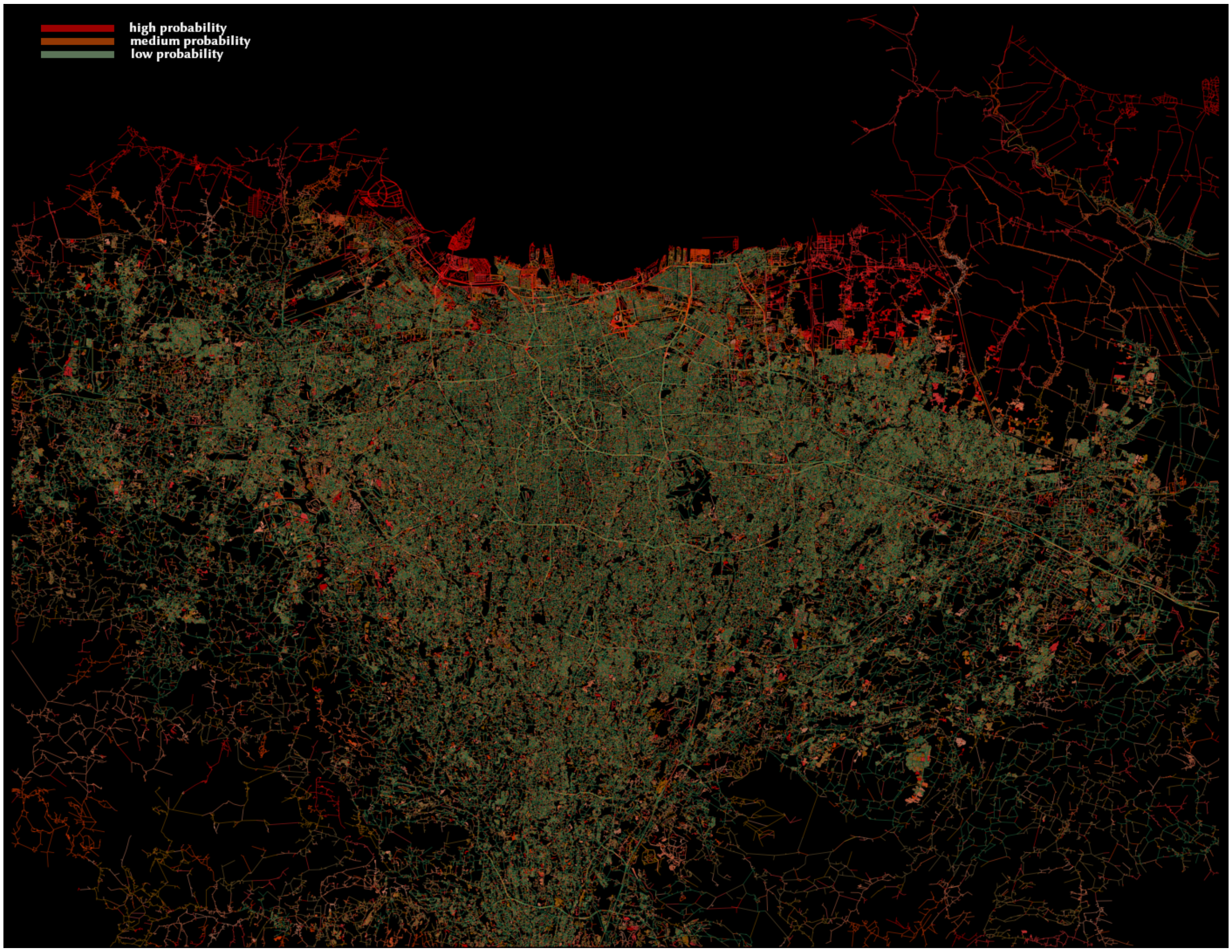

Figure 3: Greater Jakarta vulnerability map based on simulated flood occurence probability accounted for elevation and random failure

In the table, the average for ten simulations within each elevation interval is calculated for population share with access to all facilities and for poverty severity index in the affected edges. The third column of the table presents the higher and lower elevation caps (in meters). The last column is the weight. Having this information, it is possible to create a vulnerability map (Figure 3) that depicts probabilities of failure in the spatially-embedded network. Bright red gradient colours present the edges that are very likely to fail during floods, orange colours indicate medium probability, and grey colours mean low probability. There are also edges of green colour. They are supposedly safe, however, they are not that numerous.

5.4 Robustness of community access to critical infrastructure

Finally, I apply my modified percolation technique to test robustness of access to each service (Figure 4). Approximately 2.5 percent of the network is destroyed. The population with no access to certain services at the end of all attacks varies at about 4.5-5 percent.

Looking at the plotted lines, we observe how access is more or less stable for all services

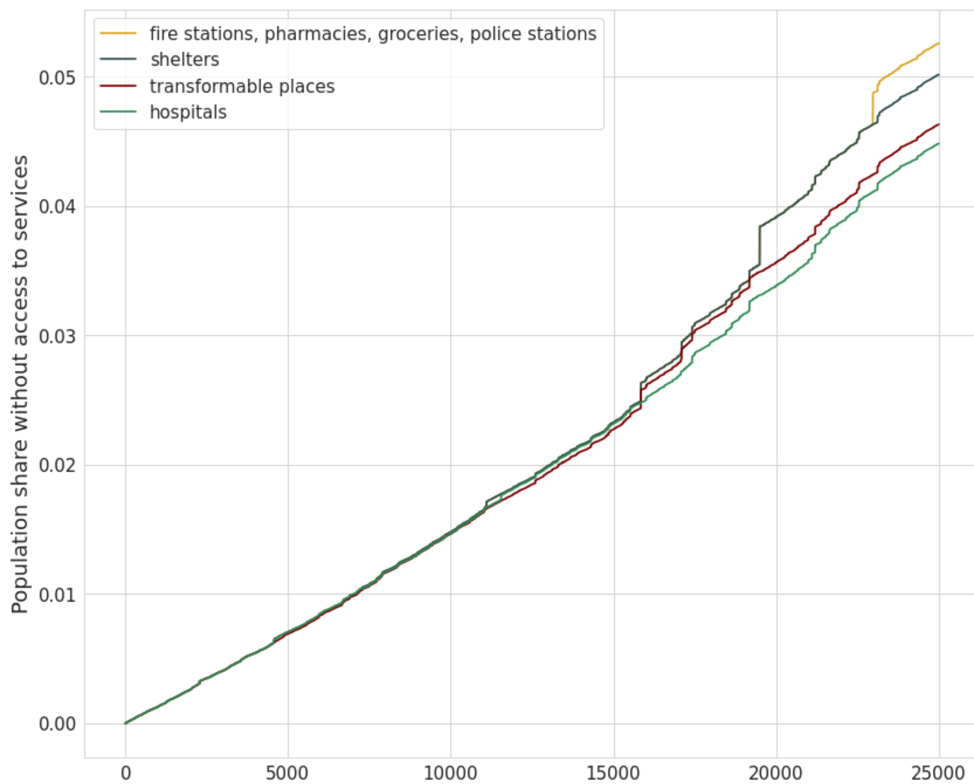

Figure 4: Percolation of population share that loses access to services in a result of attacks on the most central edges.

for the first 15000 steps. Then the lines begin to deviate from each other. By the end of percolation, the difference is sound. To quantify this difference, I calculated slopes of fitted lines between the pairs of each service type with hospitals (Table 9). The access to hospitals was the most stable, therefore I used it as the reference point.

The results suggest that the most robust access for population is provided to hospitals. The least robust access is ensured for fire stations, police stations, pharmacies, and groceries.

Let us compare this ranking to the ranking from the Table 5. It is curious that, except for access to shelters, the rankings are identical. This stimulates me to investigate this method more. In the report, I use only one percolation technique—betweenness centrality attack—and only for a limited number of steps (2.5 percent of the network). Further application of this method may reveal more information about system robustness.

Table 9: Slope comparison for fitting decay of access to hospitals vs decay of access to all other types of services

	Slope	Rank
Hospitals	1	4
Transformable places	1.01175007	3
Shelters	1.03087868	2
Groceries	1.03408133	1
Pharmacies	1.03467889	1
Police stations	1.03469094	1
Fire stations	1.03469094	1

6 Discussion

This report is only a segway to a wider discussion of resilience of urban systems. In the *Background* section, I have mentioned vulnerability, robustness, resilience, and antifragility. So far my framework has covered only vulnerability and robustness stages; and these all are the matter of future research—strategies for restoration of a crippled network, time and resources required for restoration, strategies for not simply bouncing back to the initial condition but rather for building back better, pursuit for constant improvement and utilisation of shocks as opportunities to rise from the ashes in the form of a more robust, more resilient, and antifragile system.

The framework that considering access to facilities vulnerability also opens the door to a discussion on facility placement under uncertainty and facility location problem in general.

The major challenge with this research was computation. Working with this size of a network was intriguing. Certain chunks of code had been running for more than a hundred hours. It is not, however, a bottleneck for users and researchers. The code can be improved and rewritten in the lower-level programming language, which will shorten the process substantially. Apart from that, in the world there are still not many metro areas of size of Greater Jakarta. Smaller cities will be assessed in a matter of minutes and hours.

The framework has generated data for many more insights that have been covered here. The simulations can be improved, accounting for more flood factors—environmental, social, and technological, although, simulations are not that important, as it is always more beneficial for the system to prepare for a hit from any direction.

7 Conclusion

Major flood in Jakarta that occured in January 2020 was the devastating catastrophe that affected lives of hundreds thousands of people. The proposed in this report framework allowed to quantify direct and indirect damage to physical infrastructure and loss of population's access to critical facilities. It was found that 9.6 percent of all edges were flooded. The hazard broke the urban network into dozens of thousands of disconnected components, drove the betweenness centrality up, making the whole system more vulnerable for potential compound attacks, and significantly distorted road connectivity and people's access to critical facilities. Both important and less important roads were affected (among those residential streets the most). The damage to trunk and primary roads was enough to cause transportation collapse in other major streets. All types of facilities were directly affected.

From 12.22 to 12.71 percent (more than 2.7 million people) of population lost access to at least one critical facility in a result of a disaster. Access to police stations, fire stations, pharmacies, and shelters was hindered the most.

The tests show that poor people, on average, settle more in the lowland areas, which confirms the hypothesis of uncontrollable urbanisation of flood-prone zones in Greater Jakarta. The positive relationship exists between poverty and loss of access, although one cannot make any predictions based on that.

The flood simulations have shown that northern coastal areas and all suburban areas are most vulnerable to floods. The simulation model, used for calculations, however, is too simplistic—it relies on the elevation data, but many more factors should be taken into account. Currently, the produced risk map does not reflect vulnerability of Kota Depok and Kota Bekasi, and it does not explain large occurences of real flood in Kota Jakarta Barat, as well as it does not explain why low-lying poor Kota Jakarta Pusat is relatively safe.

The novel percolation technique that takes into account what happens in all connected components instead of focusing on only one giant connected component generated some curious results. The calculated robustness of access to facilities is to a large extent congruent with access loss to relevant services in the real 2020 flood. The results suggest that in Greater Jakarta the least robust access is provided to fire stations, pharmacies, groceries, and police stations. The most robust access is provided to hospitals.

Geospatial data transformation into a network and embeddedness of social-physical characteristics into this network in the form of edge properties with consequtive analysis provides a simplified enough (*simple but not simpler*) framework for quantification of damage from disasters, assessment of vulnerability of access to services, and discussion of robustness and resilience. This framework relies solely on the open publicly available data and will be interesting for urban planners, decision makers, and emergency specialists as the tool for rapid quantification of hazard implications without the necessity for ground surveys and for preliminary assessments of access to critical facilities vulnerability.

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Annex

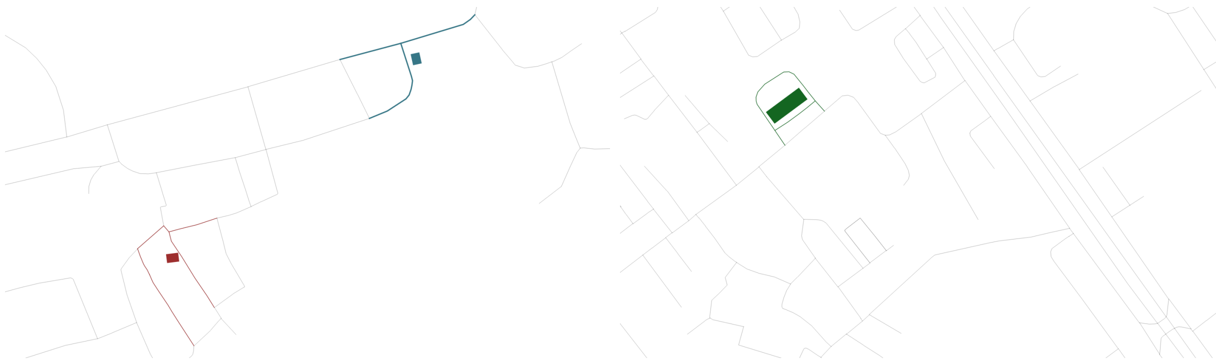

Figure 5: Approach for embedding critical facilities into the network

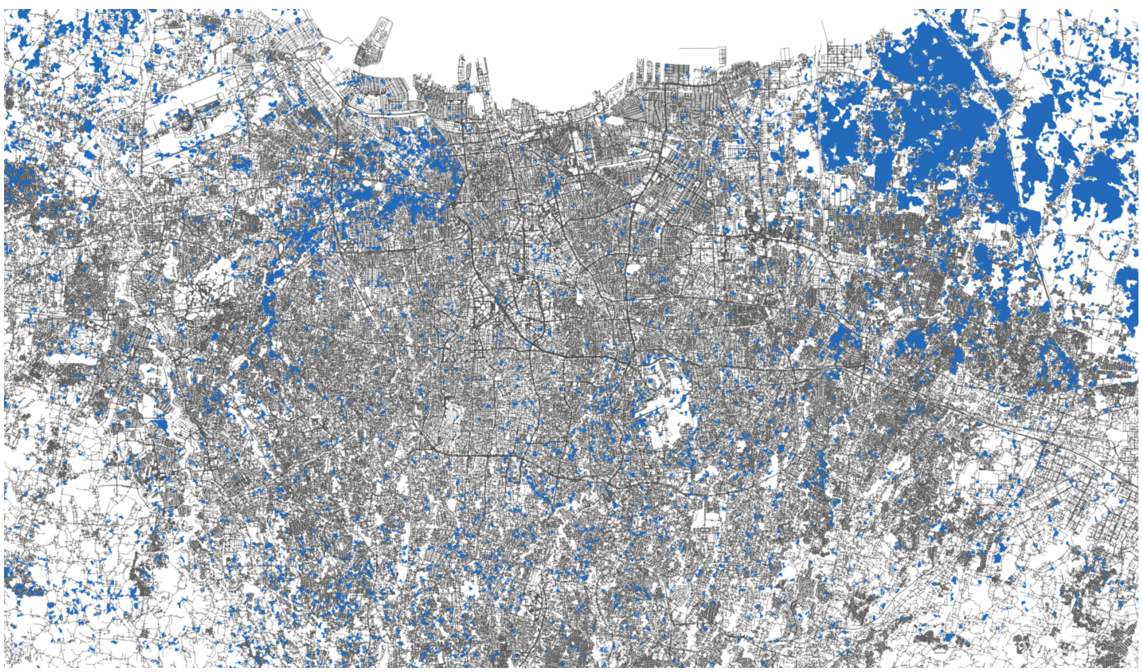

Figure 6: Flood occurence in Greater Jakarta, January 2020. Data: SentinelAsia 2020, OpenStreetMap 2020

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.084
Model:                            OLS   Adj. R-squared:                  0.084
Method:                 Least Squares   F-statistic:                 9.157e+04
Date:                Di, 28 Sep 2021   Prob (F-statistic):               0.00
Time:                        09:48:57   Log-Likelihood:             1.3803e+06
No. Observations:              995074   AIC:                        -2.761e+06
Df Residuals:                  995072   BIC:                        -2.761e+06
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1694   8.08e-05   2096.996      0.000       0.169       0.170
x1            -0.0004   1.19e-06   -302.600      0.000      -0.000      -0.000
==============================================================================
```

Figure 7: Linear regression – elevation vs poverty

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.042
Model:                            OLS   Adj. R-squared:                  0.042
Method:                 Least Squares   F-statistic:                 4.412e+04
Date:                Di, 28 Sep 2021   Prob (F-statistic):               0.00
Time:                        09:48:22   Log-Likelihood:            -5.3015e+06
No. Observations:              995074   AIC:                         1.060e+07
Df Residuals:                  995072   BIC:                         1.060e+07
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         49.5669      0.055    907.041      0.000      49.460      49.674
x1           -28.3359      0.135   -210.037      0.000     -28.600     -28.071
==============================================================================
```

Figure 8: Linear regression – loss of access vs elevation

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.023
Model:                            OLS   Adj. R-squared:                  0.023
Method:                 Least Squares   F-statistic:                 2.358e+04
Date:                Di, 28 Sep 2021   Prob (F-statistic):               0.00
Time:                        09:49:29   Log-Likelihood:             1.3481e+06
No. Observations:              995074   AIC:                        -2.696e+06
Df Residuals:                  995072   BIC:                        -2.696e+06
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1490   6.84e-05   2176.634      0.000       0.149       0.149
x1             0.0259      0.000    153.565      0.000       0.026       0.026
==============================================================================
```

Figure 9: Linear regression – loss of access vs poverty

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.067
Model:                            OLS   Adj. R-squared:                 -0.010
Method:                 Least Squares   F-statistic:                    0.8651
Date:                Di, 28 Sep 2021   Prob (F-statistic):              0.371
Time:                        22:38:19   Log-Likelihood:                 16.851
No. Observations:                  14   AIC:                            -29.70
Df Residuals:                      12   BIC:                            -28.42
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.2669      0.100      2.662      0.021       0.048       0.485
x1            -0.0011      0.001     -0.930      0.371      -0.004       0.001
==============================================================================
```

Figure 10: Linear regression – population access to services index vs poverty severity index