Assessing the vulnerability of pumping stations to trash blockage in coastal mega-cities of developing nations

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Assessing the vulnerability of pumping stations to trash blockage in coastal mega-cities of developing nations

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Abstract

Pumping stations are important flood mitigation infrastructure used in coastal cities to remove accumulating floodwater from low-lying areas, where drainage is naturally poor due to very low slope gradient. In coastal mega-cities situated in developing nations, these pumping stations are often vulnerable to trash blockage as a result of frequent dumping of solid waste in water bodies. Given that blocked pumps are common causes of drainage infrastructure failure, the inability to identify the most vulnerable pumping stations can lead to inefficient allocation of limited resources for preventative maintenance of the drainage system. This study proposes an approach for measuring and ranking the vulnerability of pumping stations to trash blockage. In this approach, a trash blockage vulnerability index (TBVI) is developed based on the concepts of exposure, sensitivity and resilience. Using a graph-based network analysis technique, the proposed TBVI is applied to assess and rank the vulnerability of pumping stations in one of the most representative coastal mega-cities - Jakarta, Indonesia. The results show that TBVI can point to the pumping stations that are most vulnerable to trash blockage. Such information are vital to decision makers when planning and prioritising infrastructure to be serviced or upgraded as part of flood preparedness in coastal cities.

Keywords: vulnerability, network, mega-cities, coastal cities, Jakarta, trash blockage, flood, pump, solid waste, graph theory

1. Introduction

Coastal mega-cities in developing nations are facing ever-increasing challenges, including rapid urbanisation, inadequate infrastructure and the lack of basic amenities to meet the demands of an increasing population (Gasper et al., 2011; Li, 2003). The geography of these coastal mega-cities makes them vulnerable to natural hazards, particularly flood events (Dewan, 2013). It has been shown that the average number of victims from natural hazards, including

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flooding, is 150 times greater in developing countries and economic losses are around 20 times higher than those in developed nations (Wenzel et al., 2007). Furthermore, many of the densely populated coastal cities in developing nations lack affordable housing and sanitation facilities for low-income households (Alam, 2014). As a result, there is an uncontrolled sprawl of informal settlements or slums, many of which expand into flood plains and unprotected areas situated along the waterside (De Sherbinin et al., 2007; Laronne and Shulker, 2002; Li, 2003). Without access to adequate waste collection and handling facilities urban trash often end up in waterways (De Sherbinin et al., 2007; Laronne and Shulker, 2002). Consequently, solid wastes flow freely into the drainage network to further aggravate the flooding problem by reducing the carrying capacity of the channels and clogging the pumping infrastructure (Bankoff, 2003; Laronne and Shulker, 2002).

When a pumping station is blocked, its functionality in the flood mitigation process is jeopardised, leaving the possibility of flooding (Bankoff, 2003), particularly in low-lying areas where drainage is difficult without the use of a pump (Tingsanchali, 2012). Clogged pumps are common causes of drainage infrastructure failure in various coastal mega-cities, with resultant inundation claiming human lives, damaging urban property and disrupting economic activities (Bankoff, 2003; Li, 2003). This challenging problem, if not effectively addressed will leave these coastal mega-cities continuously trapped in a reinforcing cycle of infrastructure fragility and flood-related losses (Gasper et al., 2011).

The key challenge in addressing this problem stems from the fact that governments of developing nations lack adequate funding to cater for the basic needs of many of their urban residents including provision and maintenance of a functional drainage system (Gasper et al., 2011; Laronne and Shulker, 2002). Similarly, the use of engineering interventions for combating pump blockage (e.g. trash screens, channel dredging, etc.) have not been particularly effective due to poor maintenance arising from the mismanagement and inefficient targeting of limited resources allocated for the upkeep and upgrade of the drainage infrastructure system (Laronne and Shulker, 2002; Wallerstein and Arthur, 2012). Hence, in planning for maintenance and upgrade of the drainage infrastructure system, there is need for a structured solution that facilitates informed decisions on where limited resources should be judiciously spent in order to prevent pump blockage (Ogie et al., 2016b). Ideally, such resource allocations and investment decisions should be effectively targeted at the pumping stations that are most vulnerable to trash blockage (Kumar, 2007).

A quantitative assessment of vulnerability can enable decision makers to highlight, and therefore prioritise their efforts towards the most vulnerable components within a system (Balica et al., 2012). However, no standardised processes yet exist for ranking pumping stations according to their vulnerability to trash blockage. The lack of a standardised process of finding suitable metrics (Balica et al., 2012), combined with the data scarcity in developing nations (Brecht et al., 2012) complicate this task.

To address this issue, this study proposes a graph-based network approach for measuring and ranking the vulnerability of pumping stations to trash blockage. The graph theory approach is considered suitable because it provides a rigorous mathematical basis for computing vulnerability (Dunn and Wilkinson, 2012; Dunn et al., 2013), using very little data obtainable at the time and allowing for further improvement from the initial results as additional data becomes available in the future (Bunn et al., 2000). In exploring this approach, a general equation for computing the vulnerability of pumping stations to trash blockage is first established, based on the concepts of exposure, susceptibility and resilience. The derived equation is then implemented in a case study application to assess and rank the pumping stations in the city of Jakarta, Indonesia, according to their vulnerability to trash blockage.

The remainder of this paper is organised as follows: In Section 2 the methods followed to derive the equation for computing the Trash Blockage Vulnerability Index (TBVI) of pumping stations are presented, including the use of the Jakarta's study area as a demonstration of the activities leading to network construction and application. Section 3 presents the application of the underlying equation to compute TBVI for Jakarta's pumping infrastructure. In Section 4, the results are presented and their implications discussed. Section 5 concludes the paper and presents major limitations. Finally, Section 6 provides suggestions for future research.

2. Methods

This section presents the methods followed to derive the equation for computing the Trash Blockage Vulnerability Index (TBVI) of pumping stations. It includes the use of the Jakarta's study area as a demonstration of the activities leading to network construction and application. In this application, suitable metrics for implementing the equation are systematically derived using the constructed spatio-topological network model of the city's drainage infrastructure system. The results of the application are TBVI values representing the degree to which each pumping station in the city of Jakarta is vulnerable to trash blockage failure. The computed TBVI values are stored in a PostGIS database table (Obe and Hsu, 2015) and accessible for visualisation using geographical information system software (e.g. Quantum GIS or QGIS for short) (Gray, 2008). Such detailed analysis results are useful to decision makers in coastal communities when planning and prioritising infrastructure maintenance and resource allocation for flood preparedness.

In this paper, we narrow our scope to focus solely on fluvial (or riverine) flooding as this is the most likely to impact or aggravate trash interference to the pumping stations. Many coastal cities are also impacted by pluvial (or surface water) and coastal flooding (Douglas et al., 2010). Pluvial flooding occurs during intense rainfall as a result of surface water runoff associated with low permeability in urban areas that may be lying above and far from coastal and river floodplains (Douglas et al., 2010). Considering that pluvial floods are normally only a few centimetres deep, pumps are not often used to mitigate such type of floods (Yin et al., 2016). Coastal flooding is associated with high

tides / waves, storm surges and sea-level rise that result in overtopping or breaching of coastal defences and the consequent inundation of areas lying on the coast of the sea or ocean (Wolf, 2008). Coastal floods happen less frequently than fluvial or pluvial floods and pumping stations have limited use in this scenario because they are not as effective as traditional coastline defences (e.g. dunes, groynes or seawalls) (Bates et al., 2005). However, pumping stations play a crucial role in defending against fluvial floods (Quan, 2014). This type of flooding is caused by inundation from river flows and can occur either due to intense, high velocity flash floods or excessive rainfall that causes river channels to overflow their banks (Fernandez et al., 2015). During fluvial flooding events, pumping stations are often used to pump out water from low-lying urban areas into storage basins or drainage channels flowing to larger water bodies such as the sea (van Andel et al., 2010). Therefore, fluvial flooding is the most likely to be catalysed and aggravated by trash flowing in rivers. On the one hand, the flow of trash in rivers reduces their carrying capacity and increases the likelihood of fluvial flooding during days of extensive rainfall (Laronne and Shulker, 2002). On the other hand, the clogging of pumping stations by trash can result in their failure to defend low-lying urban areas against the impact of fluvial flooding (Bankoff, 2003). Hence, given that this study focuses on trash and their blockage to pumping stations, further reference to flooding, including for purpose of analysis will be based on fluvial floods.

2.1 Trash blockage vulnerability index (TBVI)

Vulnerability is the degree to which a system is susceptible to and is unable to cope with hazards (Adger, 2006). Its measurement depends on a number of factors within and outside the given system, which often appear to be complicated and with many dimensions that are difficult to capture in a single metric (Adger, 2006). These factors often vary from one system to another. They may also vary according to the conceptualisation of vulnerability, a term that seems to defy consensus usage (Adger, 2006; Few, 2003). In this study, the vulnerability of pumping stations to trash blockage (i.e. Trash Blockage Vulnerability Index, *TBVI*) is conceptualised as being made up exposure, *E*, sensitivity (or susceptibility), *S*, and resilience, *R* (modified from: Balica et al., 2012). This relationship is represented mathematically using the general formula (Eq. 1).

$$TBVI = \frac{E*S}{R} \tag{1}$$

2.1.1 Exposure

Exposure, a key element of vulnerability, is the degree to which a system is in contact with, or subject to perturbation (Gallopín, 2006). In the context of flood hazards, pumping units are exposed to blockage from trash in all river reaches that flow from upstream to the given pumping station. In this regard, longer and large-size rivers or drainage channels pose greater risk to downstream pumps because they have more room and avenue for trash uptake. Given that the

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number of channels that flow from upstream towards a given pumping station can range from 1 to q, the length, l weighted by the size or width, w for each of these channels can be summed to determine the exposure, E, of the pumping station to trash blockage. Mathematically, this can be represented as shown in Eq. 2.

$$E = \sum_{i=1}^{q} (l_i * w_i) \tag{2}$$

Nonetheless, a more accurate estimation of exposure, E can be obtained by further considering the transport mechanism of trash through river channels. An accurate analysis of flow and trash transport in a river reach can be a difficult task depending on whether the channel is straight or meandering (Shams et al., 2002). In narrow, straight reaches, high shear stresses, deep flows, and limited bar development cause trash to flush through quickly towards pumping stations located downstream (Braudrick and Grant, 2001). However, in meandering reaches, the process is far more complicated and trash movement to pumping stations is much more retarded (Shams et al., 2002). Unlike a comparable straight reach, the change of flow direction in a bend introduces an additional energy loss, concentrated in the zone of greatest curvature (Jeffries et al., 2003; Langbein and Leopold, 1966). Each time a moving piece of trash encounters such bends, its velocity is reduced and momentum is extracted (Braudrick and Grant, 2001).

In addition, naturally occurring persistent obstacles such as large woody debris, boulders, and other immobile pieces of rubbish tend to deposit on the outside of bends, forming log jams (Braudrick and Grant, 2001; Daniels and Rhoads, 2003). These log jams may trap other moving trash or profoundly obstruct their flow towards downstream pumping stations (Braudrick and Grant, 2001; Daniels and Rhoads, 2003). The trapped rubbish may eventually find their way to downstream pumping stations after been potentially entrained during the piece-to-piece collisions with other trash (Braudrick and Grant, 2001). In reality though, this process of trash transport in river reaches is far more complex and cannot be accurately predicted, particularly because it depends on a wide range of factors that are difficult to measure in real world. These factors include trash characteristics (i.e. size, roughness, shape), channel characteristics (i.e. depth, width, sinuosity or curviness, roughness), and flow rate, amongst other hydrological conditions (Braudrick and Grant, 2001). Furthermore, in considering the length of waterways as a determinant factor for calculating exposure, E, this study accounts for the effect of energy loss or retardation in trash movement along curved channels by computing the degree of sinuosity of each river reach and using that as a weighting factor to determine the effective contribution of the meandering length to the pump's exposure. In essence, for each channel length, l_i, the effective channel length, l_i^e, can be represented mathematically as shown in Eq. 3, where d_i is the Euclidean or straight line distance between the start and end of the channel (Fig. 1), $(l_i - d_i)$ is its meandering length, and d_i/l_i is the degree of sinuosity or curviness. The effective length, l_i^e of a channel is the fraction of its physical length that can be used for

computing exposure, having taken into consideration the effect of energy loss or retardation associated with trash movement along meanders.

$$l_i^e = d_i + (l_i - d_i) * \frac{d_i}{l_i} \qquad (3)$$

Hence, to attain more accurate estimation of exposure, E, the channel length, l_i in Eq. 2 can be substituted with the effective channel length, l_i^e, to obtain Eq. 4.

$$E = \sum_{i=1}^{q}(l_i^e * w_i) \qquad (4)$$
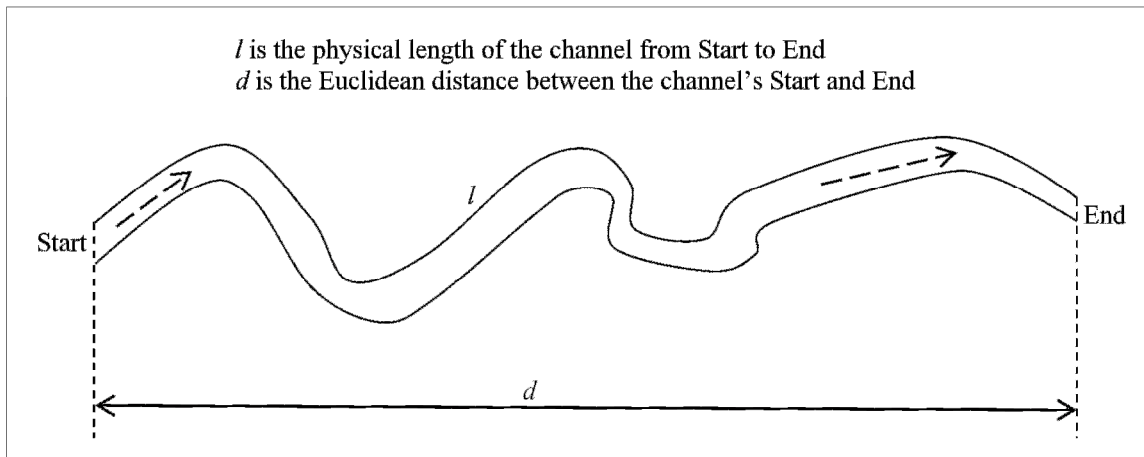
Fig. 1. Illustrating channel length in a meandering reach.

2.1.2 Susceptibility

Susceptibility is a function of the intrinsic characteristics or specific features of a system that makes it prone to hazards (Ostrowska, 2013). For example, in landslide studies, susceptibility can be determined as a function of the terrain characteristics (e.g. distance from tectonic lines, altitude, slope angle, land use, etc.) that influence its proneness to slope failures (Poli and Sterlacchini, 2007). Similarly, in social vulnerability studies, susceptibility can be considered to be a function of the demographic characteristics of the population such as age, gender, financial capacity, etc. (Cutter and Emrich, 2006). In this study, susceptibility is considered an intrinsic characteristic which determines the degree to which the operation of the pumping station is affected by the impact of trash (Balica et al., 2012). In this regard, the capacity of the pumping station is used as a measure of susceptibility to trash blockage. Pumps with high capacity are normally fitted with high-horsepower motors and large diameter piping (Fipps, 1995). When exposed to solid waste flowing from upstream channels, a pump with high capacity is considered less susceptible to trash blockage compared to one with lower capacity because the excessive pumping force generated by the high-horsepower pump can cause trash to flush through its large diameter discharge pipe with less likelihood of being trapped. This is a reciprocal

relationship, as such the susceptibility, S of a given pumping station decreases as the capacity, C_g increases. This relationship can be represented mathematically as shown in Eq. 5.

$$S = \frac{1}{c_g}$$ (5)

2.1.3 Resilience

Resilience is another important factor that determines the vulnerability of pumping stations to trash blockage. The term resilience does not have a commonly accepted definition, mainly because it has been conceptualised in many different ways within different disciplines and contexts (Lizarralde et al., 2015). In the context of this study, resilience is a measure of the persistence of the pumping stations and can be defined as the ability to absorb, cope, and recover from a disturbance such as trash interference and still maintain form or state without significant damage (Cutter et al., 2008). A resilient pumping station is less vulnerable to trash blockage compared to one that is non-resilient (Gallopín, 2006). Cutter et al. (2008) reported that it is not obvious what leads to resilience or what variables should be utilized to measure it, particularly because of its multidimensional properties. The properties of resilient infrastructure include robustness, redundancy, resourcefulness, and rapidity (Chang and Shinozuka, 2004). Together, these properties are referred to as the four Rs of resilience (Chang and Shinozuka, 2004; Panteli and Mancarella, 2015). Robustness is the strength or ability to withstand a given level of stress or disturbance without suffering degradation or loss of function (Chang and Shinozuka, 2004). Redundancy measures the availability of substitutable components that can be activated when a disturbance occurs (Chang and Shinozuka, 2004). Resourcefulness is an indication of the capacity to mobilise material and human resources in response to a disturbance while rapidity is the capacity to function in an agile and timely manner in order to minimise losses and prevent the reoccurrence of the disturbance in the future (Chang and Shinozuka, 2004). Due to the multidimensional nature of resilience, a broad model that includes all four properties of resilience is yet to be empirically tested (Cutter et al., 2008). However, it is rather common to measure resilience based on one or more of these properties, subject to the availability of data (D'Lima and Medda, 2015; Venkittaraman and Banerjee, 2014).

In this study, resilience, R is derived mainly as a function of redundancy. For each pumping station in the drainage network, there are one or more pumping units, all of which may not always be engaged at the same time. Redundant pumping units which are not turned on at a given time provide some level of resilience to the pumping station because they serve as backup pumps that can be activated when any of the pumping units in use fails or when a worsening flood condition demands extra pumping capacity. Therefore, it is assumed that the more pumping units there are to a pumping station, the higher the redundancy and ultimately, the higher the resilience. This relationship can be represented mathematically as shown in Eq. 6, where R is the total resilience of the pumping station, R_j^m is the material

resilience (i.e. robustness) of each pumping unit, *j* based on the physical property of its material, *n* is the total number of available pumping units in the station, and $(n-1)$ is the redundancy. For purpose of computation, the material resilience, R_j^m of each pumping unit can be determined using historical data about its failure rate and performance under previous hazardous conditions. In this sense, pumps with history of impressive performance and low failure rate can be considered as being robust or having high material resilience.

$$R = \sum_{j=1}^{n} R_j^m + (n-1) \tag{6}$$

By substituting Eq. 4, 5, and 6 into Eq. 1, a general equation (Eq. 7) is obtained for estimating the TBVI for pumping stations.

$$TBVI_{local} = \frac{\sum_{i=1}^{q}(l_i^e * w_i)}{C_g(\sum_{j=1}^{n} R_j^m + (n-1))} \tag{7}$$

2.2 Local and global TBVI values

In this paper, two values of TBVI are calculated for each pumping station in the network to account for its "local" and "global" vulnerability. The "local" TBVI value is defined as the vulnerability of a pump to trash entering the system between it and the next pump upstream and is calculated using Eq. 7. Whereas, the "global" TBVI captures the total vulnerability of the pumping station to trash entering a point anywhere upstream of the pump. To calculate this "global" TBVI we modify Eq. 7 to consider the total exposure to all upstream routes, resulting in Eq. 8, where l_{total} is the total length of upstream river. It is acknowledged that trash is more likely to be trapped by an upstream pump. However, this may not always be the case. For example, in high capacity upstream pumps, the use of large diameter pipes combined with the excessive pumping force generated by the high horsepower motors can cause trash to flush through without being trapped in their piping. Trash may also be pushed through an upstream pump by human intervention.

$$TBVI_{Global} = \frac{\sum_{i=1}^{q}(l_{i,total}^e * w_i)}{C_g(\sum_{j=1}^{n} R_j^m + (n-1))} \tag{8}$$

Fig. 2 is a hypothetical network that illustrates how the computation of local TBVI and global TBVI differ. In calculating the local TBVI for the pumping stations, P1 and P2 shown in Fig. 2, the exposure of P1 is determined using the length of all the waterways flowing in Section 1 towards P1 while that of P2 is computed based on the length of the waterway in Section 2 only, i.e. the waterway flowing between P1 and P2. To calculate the global TBVI for the pumping stations, the length of waterways used to determine exposure of P1 remains unchanged from that used for

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computing its local TBVI. This is because there is no other pumping station located upstream of P1 and the total length of all the waterways flowing from upstream towards P1 are the same as those in Section 1. However, in computing the global TBVI for P2, exposure is determined using the length of all the waterways flowing in Sections 1 and 2, i.e. the total length of all the waterways flowing from upstream towards P2.
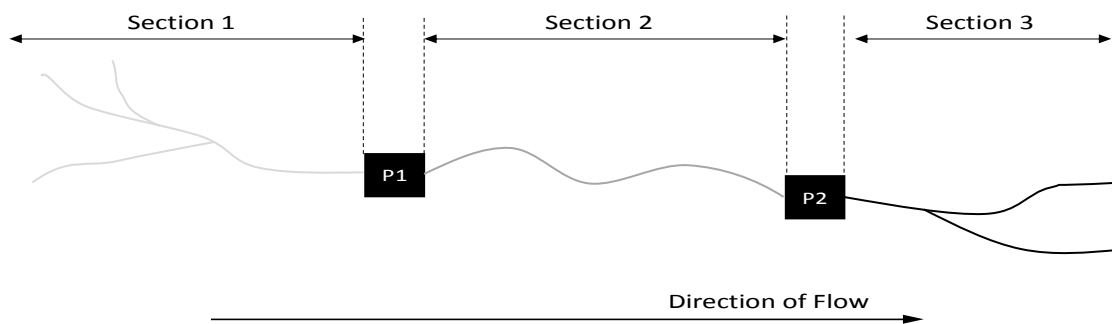
Fig. 2. Showing an illustrative section of waterways (shown as grey lines) and pumping stations (indicated by the black squares).

The application of Eq. 7 to a real-world network will produce index values for the two scenarios of local and global vulnerability considered. These index values represent the degree to which the pumping stations are comparatively vulnerable to failure arising from trash blockage. For each scenario, the index values obtained (i.e. TBVI) will be normalised to numbers ranging from 0 to 1, where 0 represents the value with the lowest vulnerability and 1 points to the value with the highest vulnerability in the dataset.

2.3 Description of activities leading to network construction and application: The case of Jakarta's drainage network

2.3.1 Study area

Jakarta, the capital of Indonesia, is a coastal conurbation covering a land area of approximately $662 km^2$ and home to over 14 million people, making it one of the most densely populated cities in the world (Brown-Paul and Ross, 2014; Holderness and Turpin, 2015). Its position as a low-lying delta city served by 13 rivers exposes it to the damaging impacts of extensive rainfall and associated flooding during the annual monsoonal season that typically occurs between November and March (Ogie et al., 2016). Like many coastal mega-cities situated in developing nations (Li, 2003), Jakarta struggles with population explosion and rapid urbanization, which plant the seeds that exacerbate flooding: inadequate housing, poverty, illiteracy and the lack of sanitation facilities that result to solid waste disposal in rivers,

amongst others (Akmalah and Grigg, 2011; Padawangi et al., 2016). These factors combine to make Jakarta an ideal study area for this paper.

Notable amongst these factors are the issues of inadequate housing and the lack of sanitation facilities that result to solid waste disposal in rivers (Steinberg, 2007). Over the years, Jakarta has experienced an influx of migrants, and the demand for affordable housing and social infrastructure such as sewage and sanitary facilities has outgrown the capacity of the government to provide same for its residents (Costa et al., 2016). As a result, excess wastes are often dumped in unauthorized areas near or within water bodies, potentially leading to undesirable outcomes such as polluted rivers and flooding during the monsoon season (Pasang et al., 2007). In a previous study, by Texier (2008), dumping of solid waste in rivers was reported as the second cause of Jakarta floods after rainfall from upstream, followed by the encroachment of squatter settlements on river banks. When excessive waste accumulates within the drainage network (Fig. 3), it reduces the carrying capacity of the river channels and also causes trash blockage to Jakarta's ageing and poorly maintained pumping stations (Akmalah and Grigg, 2011; Ogie et al., 2016). These conditions increase the likelihood of hydrological infrastructure failure and associated flooding, particularly in low-lying areas where drainage is difficult without hydraulic pumping (Steinberg, 2007).

Fig. 3. Trash build-up in Jakarta's waterways, as maintenance is conducted near one of the cities pumping stations in North Jakarta (Image credit T. Holderness). This pumping station is Pump 57, highlighted in Fig. 6.

The consequences of extensive flooding in Jakarta are devastating to the people and often have high economic cost for the government (Hartono et al., 2010). For example, the 2002 monsoon flood inundated nearly 20% of the total area of Jakarta (Firman et al., 2011), resulting in the death of 25 people (Brinkman and Hartman, 2008; Ogie et al., 2016), US$788 million in damage to urban infrastructure and at least US$22 million in damage to roads (Akmalah and Grigg,

2011). Worse still, the 2007 monsoon flood inundated approximately 40% of the city, resulting in the death of 80 people, displacement of 340,000 people (Brinkman and Hartman, 2008; Ogie et al., 2016), 190,000 cases of flood-related illness (Akmalah and Grigg, 2011), direct economic losses of US$453 million (Ward et al., 2011) and approximately US$998 million in total losses (Akmalah and Grigg, 2011).

In responding to this problem, the government's first objective is to fight floods by using structural measures such as pumps and floodgates to control the flow of waters from surrounding hills and mountains, through the city towards the Java Sea (Akmalah and Grigg, 2011; Hartono et al., 2010; Texier, 2008). Constrained by the shortage of funding, this approach deemphasises the socio-economic support for the poorest communities who are considered by the government to be living illegally in slums (Texier, 2008). To some, this approach of prioritising the technical measures over the people is considered a fight of flood hazards, by fighting the poorest and most disadvantaged people (Texier, 2008). In spite of this, the government continues to focus its limited resources on technical measures, with some components of the drainage infrastructure still remaining highly vulnerable to trash blockage (Texier, 2008). This situation calls for a structured method of highlighting the components that are most vulnerable to trash blockage, in order for the government to effectively target limited resources towards their maintenance.

2.3.2 Data collection

For the purpose of this study, data regarding the locations of rivers, canals and streams in the city of Jakarta were gathered using ground survey, GPS locations and aerial imagery analysis. The output from the data collection is a series of spatial vector data representing the river/canal network and the location of pumping stations in the city of Jakarta. The pumps vector data file is a point geometry representation constituting a total of 71 pumping stations within the city of Jakarta (Turpin and Holderness, 2015). The waterways vector data file is a line geometry representation of rivers, canals and streams in the city of Jakarta (Turpin and Holderness, 2015b). The waterways dataset consists of 209 rows and attributes include river name and geometries representing geographical locations of the line features. All of the datasets acquired for this study were stored in spatial database tables within the PostgreSQL and PostGIS Relational Database Management System (Obe and Hsu, 2015) for ease of data management and analysis. The next subsection explains the preprocessing steps undertaken on the acquired data.

2.3.3 Data preprocessing

The data preprocessing activity involves the removal of locational and topological errors in the survey data such as aerial imagery tracing. For instance, point geometries in the pumps vector file which slightly missed from intersecting a line geometry in the mapped waterways dataset were programmatically snapped to the nearest waterway. Similarly, to

avoid errors in network analysis results such as shortest distance computation, the presence of undershoots and overshoots introduced in the digitisation of location data were removed. Overshoots are topological errors in which lines extend beyond other connecting lines while undershoots are topological errors in which lines fall short of connecting to neighbouring lines (Fig. 4) (Maraş et al., 2010). The overshoots and undershoots in the waterways file were fixed using the toolset for cleaning topology of vector map, known as "v.clean.snap" within the GRASS plugin in the Quantum GIS (Geographical Information System) software (Neteler et al., 2012). The GRASS plugin within QGIS is considered useful in fixing the topological errors because in addition to being an open source software, sufficient documentation exist for anyone with basic GIS skills to be able to replicate the process on different datasets (Athan et al., 2011; Neteler et al., 2012). Furthermore, edges in the waterways data were programmatically split into separate line features where they intersected point features (i.e. pumping stations) or self-intersected. This is to ensure that when the drainage network is constructed, junctions are created where they actually exist.
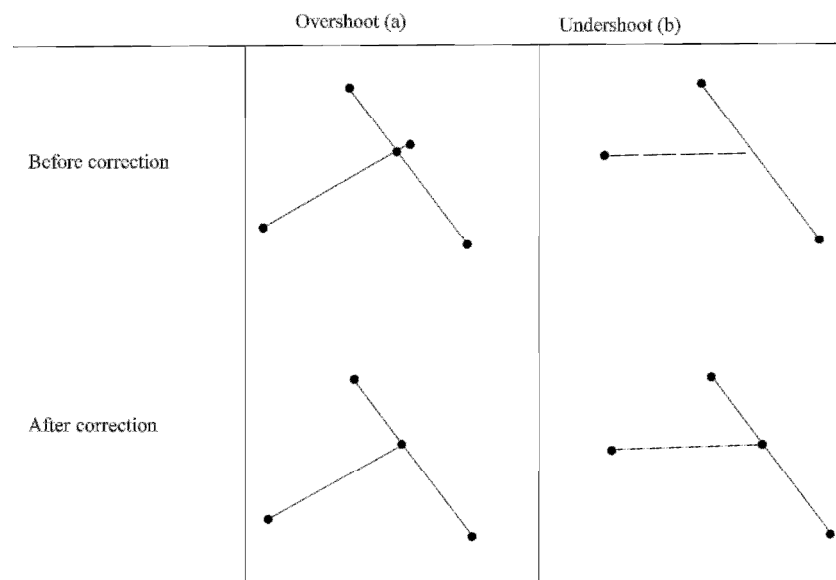

Fig. 4. Example of topological errors: overshoot (a) and undershoot (b)

2.3.4 Construction of a spatio-topological model of Jakarta's drainage network

The construction of the graph-based spatio-topological network model of Jakarta's pumping infrastructure was carried out using the PostGIS spatial database schema and coupled Python interface to the NetworkX graph analysis package developed by Newcastle University (for detail of this software, see Barr et al., 2012). This software was extended to support the proposed graph type, known as multidigraph or directed multigraph (Ogie et al., 2016). The rationale for modelling the drainage network as a multidigraph is based on the topology of Jakarta's waterways, in which two separate watercourses or channels are often found to flow from the same source node to the same target node (see

diagrammatical illustration in Fig. 5). A multidigraph is a directed graph in which multiple edges are permitted to share the same source and target nodes (Biwas et al., 2013). A multidigraph, *G* can be represented as an ordered pair (*V*, *E*) where *V* is a set of vertices, points, or nodes which are connected by a set of relationships, lines, or edges, *E* as shown in Fig. 5 (Biwas et al., 2013). In applying graph theory to model Jakarta drainage network, point features such as pumping stations were represented as nodes while line features such as waterways (e.g. rivers, canals, streams, etc.) were represented as edges.
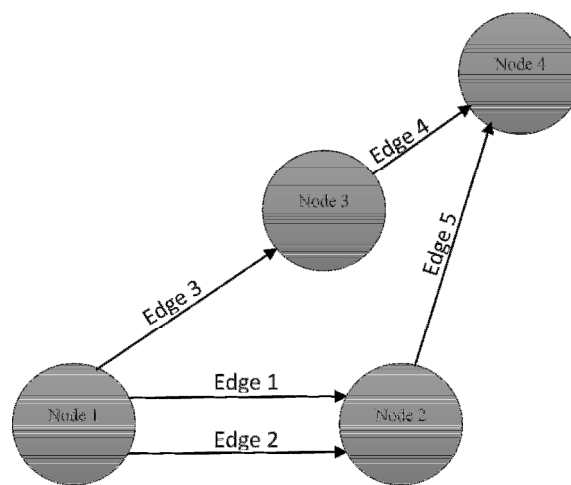

Fig. 5. Diagrammatic representation of a multidigraph

The integrity of the network topology was maintained by using a system of unique node and edge primary keys encoded within the data. In hydrology, flow direction of waterways is normally based on digital elevation models (DEM) (Tarboton, 1997). In the absence of accurate and high resolution digital elevation data, the flow direction of each river or drainage channel was modelled into the network using expert knowledge of the study area in combination with actual field observations of water flow in the city of Jakarta. This knowledge was used as a basis for edge orientation or encoding of flow direction for each linestring representing a channel segment in Jakarta waterways dataset. Subsequent corrective adjustments were then made based on actual field observations of water flow in the city of Jakarta. Constrained by issues of safety, accessibility, and availability of resources, field observations could not be carried out several times per day at a city-scale level to obtain more accurate results that account for the effect of tidal flow.

On completion, the constructed network comprised of 606 edges representing Jakarta's rivers and drainage channels, with a total geometric length of 1092 km. The network also comprised 538 nodes, with 71 of them

representing actual pumping stations and the remainder being network junctions (e.g. river confluences). Fig. 6 shows the locations of the pumping stations in the drainage network.
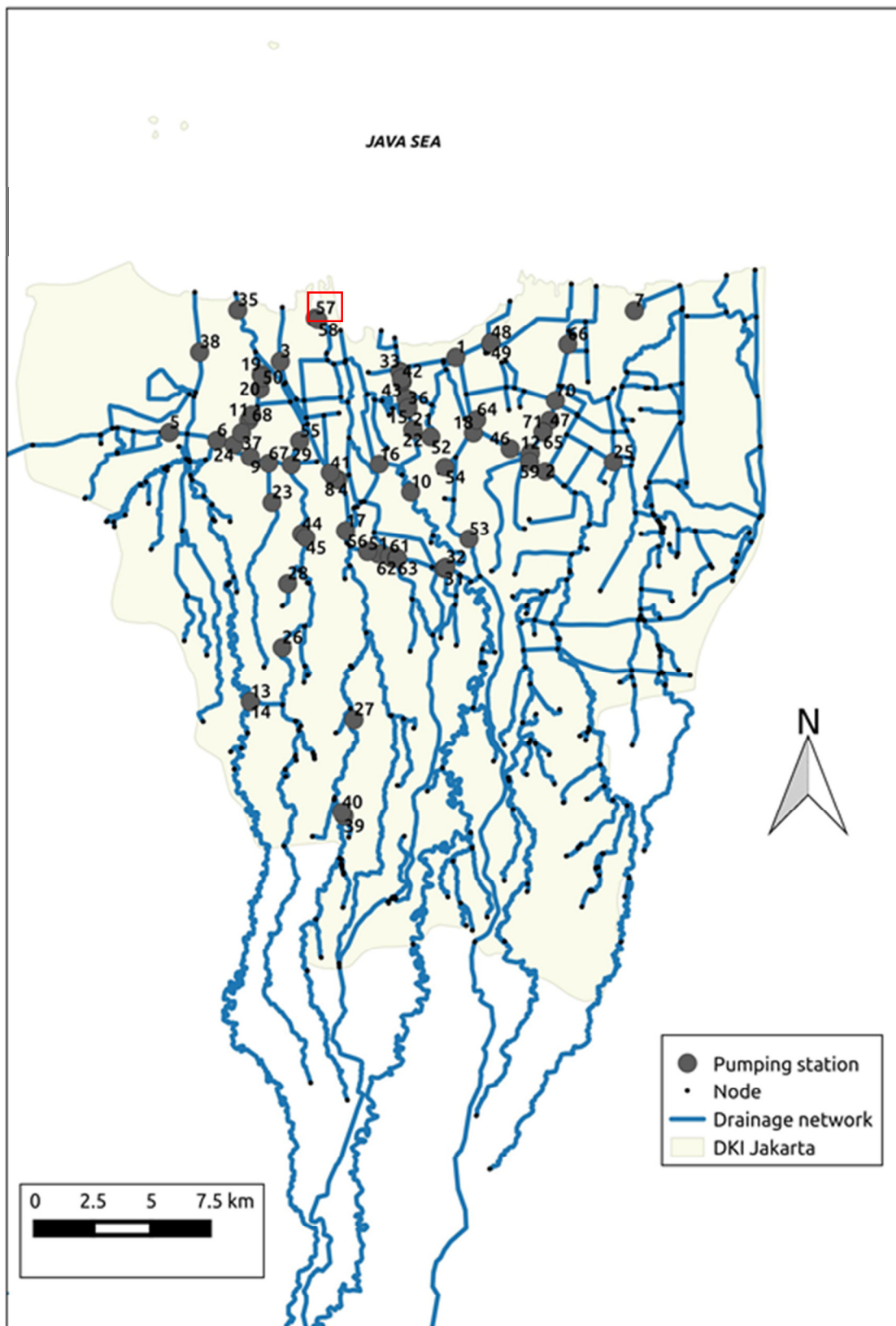

Fig. 6. Showing the locations of pumping stations within Jakarta drainage network

3. Computation of TBVI for Jakarta's pumping stations

On successfully constructing the network, Eq. 7 and Eq. 8 were applied to compute the local and global TBVI values for all 71 pumping stations in the city of Jakarta. In applying these equations, certain assumptions were made. First, in the absence of historical data to calculate robustness or material resilience, this parameter (i.e. $\sum_{j=1}^{n} R_j^m$) was assigned an arbitrarily small positive constant value of 1 for each pumping station in the network. This approach to applying Eq. 7 and Eq. 8 ensures that in scenarios where the number of pumping units, n is 1 and redundancy, (n-1) is 0, the total resilience, R will still have a non-zero value, technically avoiding null results associated with division by zero (Cao et al., 2012; Howarth and Rüger, 2005). Secondly, following Eq. 7 and Eq. 8, exposure is considered a function of the effective length, l_i^e and size or width, w_i of upstream waterways. In the absence of data about the precise width or size of the different waterways in Jakarta, a channel classification scheme was used as an estimate of river size. In this classification, channels with higher flow rates were given greater weighting as follows: 550 m3/s and more = 1, less than 550 m3/s and more than 100 m3/s = 0.5, less than 100 m3/s = 0.33, and all other smaller watercourses and ditches = 0.25. The classification used was derived based on empirical observation of water flow in the network.

The task of computing the local and global TBVI values for all 71 pumping stations in the city of Jakarta was carried out using the NetworkX Python library. Furthermore, with the use of the Pandas Python library, the computed data was organised in a structured table, and then exported into a PostGIS database (Obe and Hsu, 2015), where it was stored and made accessible for visualisation using a geographical information system software such as Quantum GIS (or QGIS for short) (Gray, 2008) . In computing local vulnerability, exposure is determined based on the immediate upstream channels. In other words, consideration is given to only the trash in all upstream river reaches before the next connected upstream pumping station. In practical terms, the local TBVI of a pumping station measures its vulnerability to the trash that are directly within its local surrounding and are therefore likely to affect it before any other pumping station in the network. Fig. 7(a) shows an example of pumping station (i.e. pump 22) in the network, clearly highlighting the upstream channels that would be considered for computing exposure, E, in the case of local vulnerability. However, in the case of global vulnerability, the computation of exposure, E, is determined based on all upstream channels that flow to the given pumping station. The global TBVI of a pumping station represents its vulnerability under worse-case scenarios. In worse-case scenarios, it is assumed that during heavy flow conditions such as intense rainfall events, trash in distant upstream channels will eventually get washed to the pumping station. Fig. 7(b) shows the same example of pumping station but highlights the upstream channels that would be considered for computing exposure, E, if the interest was to determine its global vulnerability.
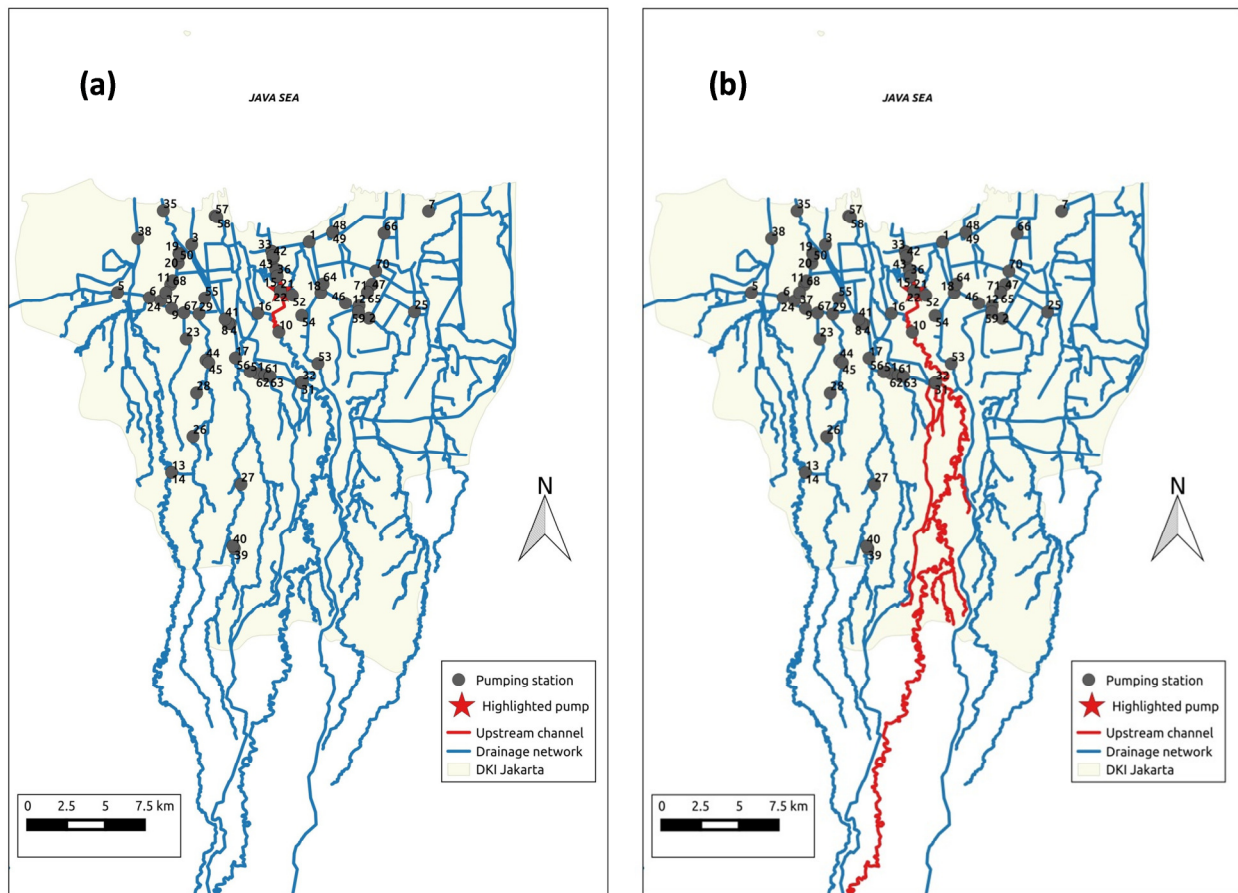
Fig. 7. Showing (a) the length of waterway used in the calculation of the local TBVI for the highlighted pump and (b) the length of waterway used in the calculation of the global TBVI.

4. Results and discussions

In this section, the results of the vulnerability assessment of 71 pumping stations to trash blockage in the city of Jakarta are presented and their implications discussed. The results of the computed TBVI are index values representing the degree to which the pumping stations are comparatively vulnerable to failure arising from trash blockage. For each scenario considered (i.e. local and global vulnerability), the index values obtained are normalised to numbers ranging from 0 to 1, where 0 represents the value with the lowest vulnerability and 1 points to the value with the highest vulnerability in the dataset.
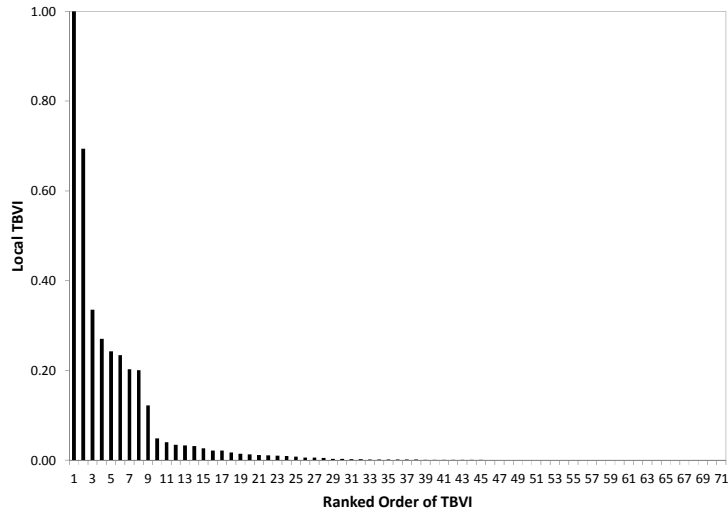
4.1 Local vulnerability

The aim of the local TBVI vulnerability assessment is to highlight the pumping stations that are most vulnerable to blockage failure on the basis of their exposure to the trash in the neighbouring or immediate upstream channels. In other words, the local vulnerability of a pumping station is based on the trash in all its upstream river reaches before the

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next connected upstream pumping station. Following this approach, TBVI values are computed for all pumping stations in the city of Jakarta. Fig. 8 is a cartographic visualisation of the results, clearly highlighting the spatial locations of the most vulnerable infrastructure in the network. The results show a step-wise trend (Fig. 9) in an ordered ranking of the pumping stations according to their degree of vulnerability. From Fig. 9, it is observed that the top two most vulnerable pumping stations ranked very high in comparison to other infrastructure components, with TBVI values of 1 and 0.69. These are followed by another 7 pumping stations (approximately 10% of the entire sample), which recorded close values of TBVI ranging from 0.12 – 0.34. All other pumping stations (87% of the entire sample) ranked comparatively very low in their degree of vulnerability, with TBVI values within the range of 0 – 0.049. This approach shows the TBVI ranking of each pumping station in the network, clearly demonstrating the usefulness of graph theory in comparatively assessing the vulnerability of urban infrastructure components to environmental hazards. In the context of developing nations where limited funding is available to mitigate flooding, such vital information about infrastructure vulnerability ranking can facilitate prioritised and efficient allocation of scarce resources for the maintenance and upgrade of the urban drainage system.
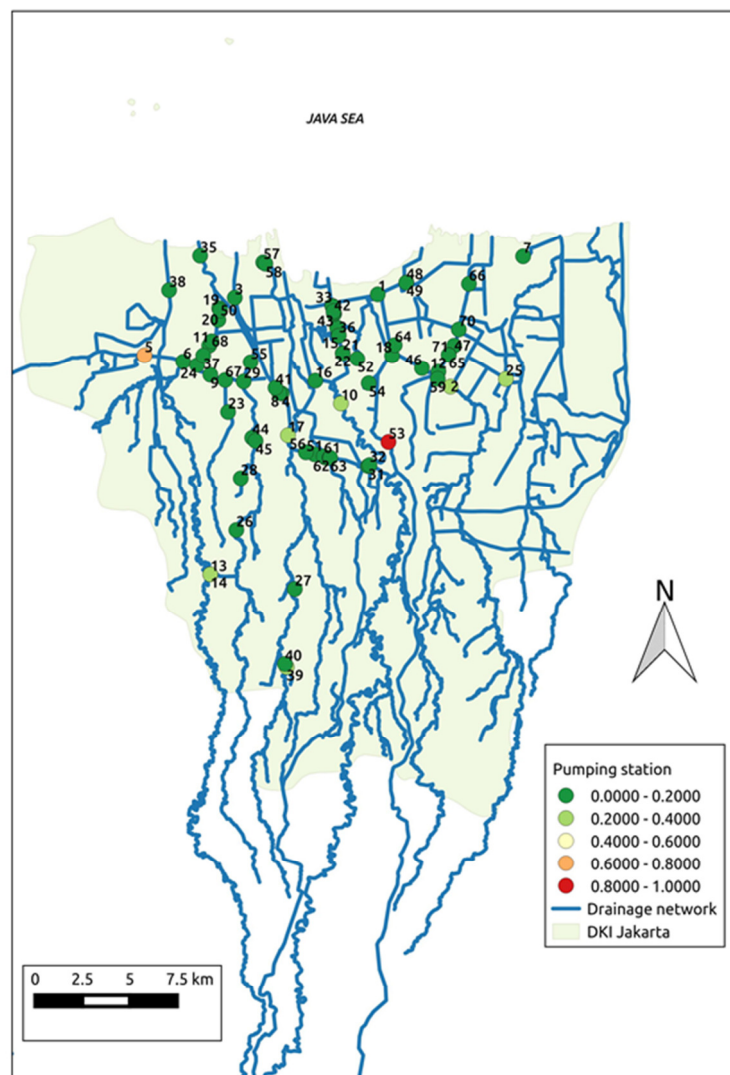
Fig. 8. Highlighting the vulnerable pumping stations, using the local TBVI values (shown on a red-green scale).
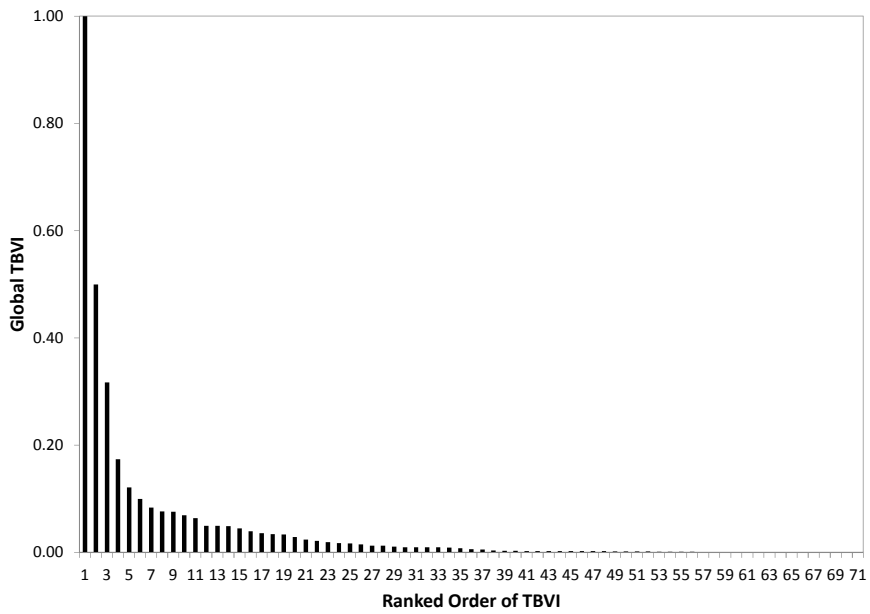
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Fig. 9. Plotting the ranked values of local TBVI for all 71 pumping stations in Jakarta, in order of highest to lowest vulnerability.

Further analysis of the results shows that Pump 53 and Pump 5 with TBVI values of 1 and 0.69 ranked as the top two most vulnerable pumping stations because of their significant exposure to trash in 182.09 km and 124.34 km length of waterways respectively. These levels of exposure can be considered to be very high when compared to the 7.09 m length of waterways to which the least vulnerable pumping station (i.e. Pump 47) is exposed. The relatively low exposure of Pump 47, in addition to its low susceptibility make it the least vulnerable to trash blockage. The low susceptibility of Pump 47 can be attributed to its high pumping capacity of 9900 gallons per minute. Interestingly, the results also show that it is common to find pumping stations with similar values of TBVI, but with significantly different values in one or more of the key components (i.e. exposure, susceptibility, and resilience) considered in computing vulnerability. For example, despite the fact that Pump 60 is approximately 5 times more exposed to trash blockage compared to Pump 41, its proportionately lower susceptibility and higher resilience give it a TBVI value of 0.0112, which is similar to 0.0114 computed for Pump 41. This fine level of vulnerability attribution can be useful to urban decision makers who require detailed justification for allocation of limited resources to the most vulnerable components in the infrastructure network.

4.2 Global vulnerability

In computing global TBVI vulnerability, the estimation of exposure of any given pumping station was not limited to its local or neighbouring upstream waterways, but rather extended to include all upstream channels that can potentially convey trash towards it. The results show an exponential decay (Fig. 10) in an ordered ranking of the pumping stations according to their degree of vulnerability.

Fig. 10. Plotting the ranked values of global TBVI for all pumping stations in Jakarta, in order of highest to lowest vulnerability.

The top three most vulnerable pumping stations (i.e. Pump 32, Pump 33, and Pump 24) showed significant gap in computed TBVI, with values of 1, 0.50, and 0.32 respectively. Afterwards, the TBVI of the remaining pumping stations decayed steadily to the value of 0. Further observation of the results indicates that in addition to high susceptibility and low resilience, the lengthy trash-carrying waterways to which the top three most vulnerable pumping stations are exposed mostly influenced their high TBVI values. This situation can potentially trigger an argument that in the global vulnerability assessment approach, higher TBVI values are always a result of exposure to longer rivers or drainage channels especially because the technique takes into account all upstream waterways. However, a plot of the global TBVI values versus the exposure, E, shows no correlation and therefore dismisses any grounds for such argument (Fig. 11). From Fig. 11, it can be seen that there is a cluster of pumping stations highlighted as hollow diamonds, which have very high exposure but comparatively low TBVI values. In these cases, the high TBVI values are mostly a result of the combination of very low susceptibility and very high resilience.

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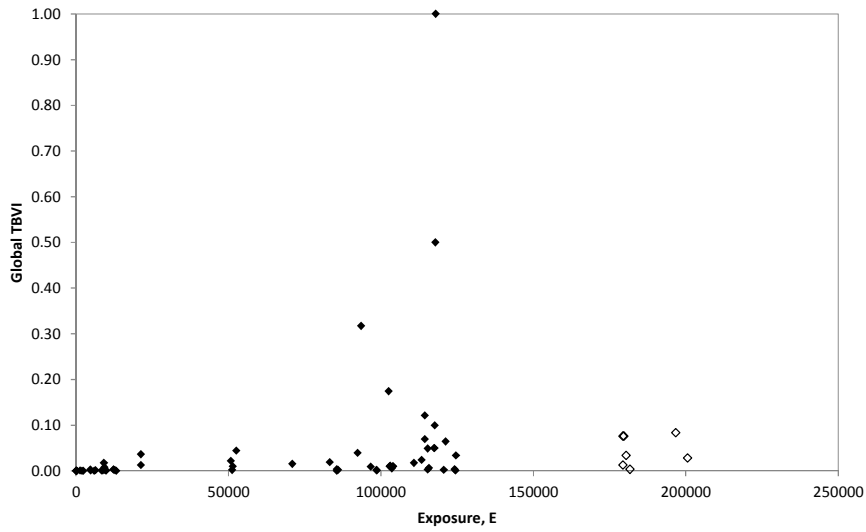
Fig. 11. Plotting the exposure, E, against the calculated values of Global TBVI for all 71 pumping stations in Jakarta, where the hollow diamonds are used to highlight a group of pumping stations with relatively low TBVI values but high exposure.

4.3 Comparison of results from local and global vulnerability

Fig. 12 shows the ranking of each of the 71 pumping stations in terms of computed values of both local and global vulnerability, ordered by their local TBVI values from highest to lowest. Pumping stations are referenced by their unique id in the dataset. The results show that although many pumping stations (e.g. Pumps 15, 47, 57, 62, 4, and 40) ranked low in both scenarios, there is apparently no correlation between the TBVI values of local and global vulnerability. The pumping stations that ranked as the most vulnerable using computed local TBVI are not necessarily the same that recorded the highest global TBVI values.
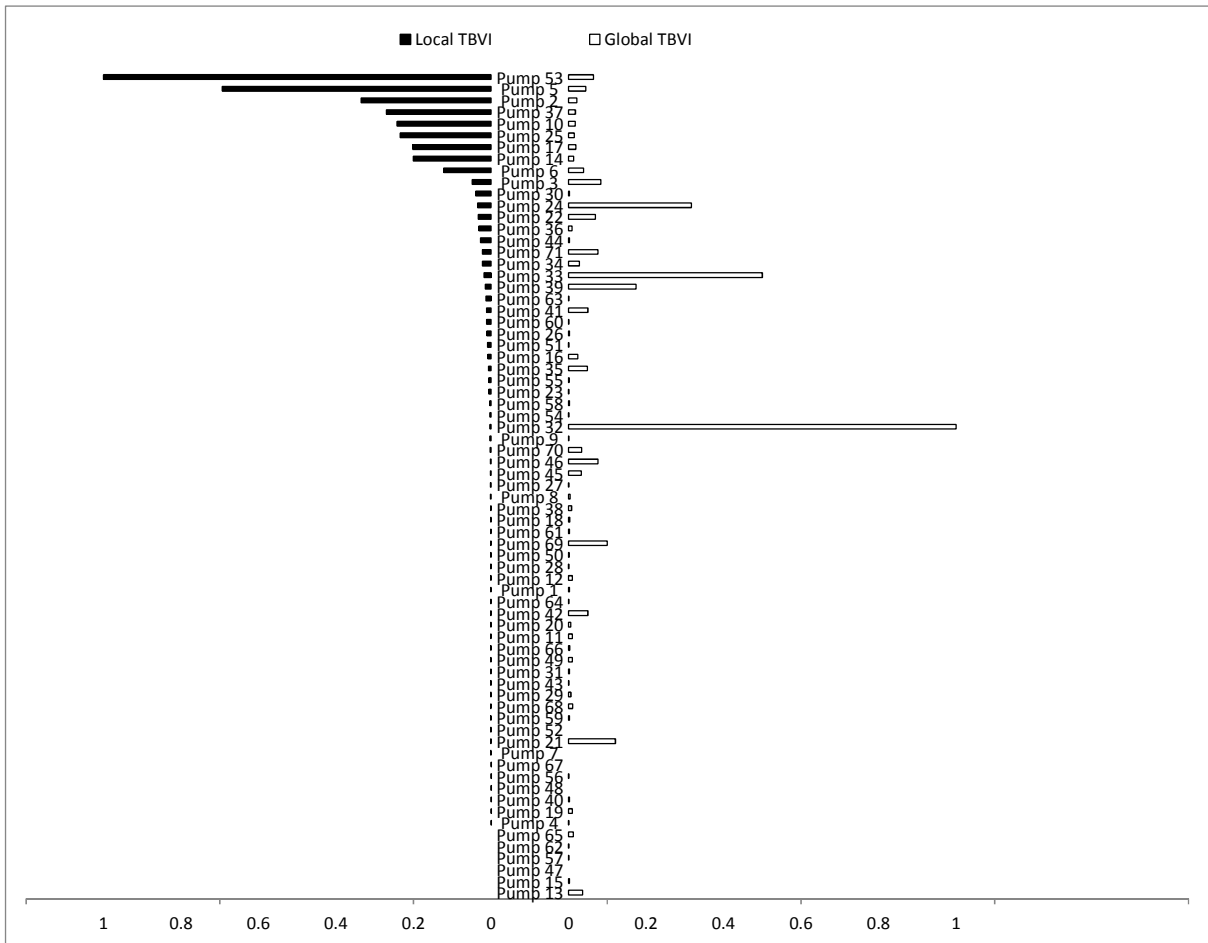
Fig. 12. Plotting the ranked local TBVI values against the global TBVI values for the same pumping station, where the pump number is shown alongside.

The variance in results between the computed values of local and global vulnerability is justified considering the fact that the two scenarios address significantly different infrastructure vulnerability conditions, both of which are important to decision makers in urban coastal communities of developing nations. The local TBVI values point to the pumping stations that are most likely to be clogged by trash flowing freely in the nearby upstream channels that are local to the pumping stations. Under normal flow conditions such as during moderate rainfall events, trash in nearby upstream channels may likely find their way to the pumping stations to cause pump blockage. Pumping stations with high TBVI values should therefore be prioritised for immediate infrastructure maintenance when allocating limited resources for flood preparedness. Typical maintenance activities could involve the dredging of local upstream drainage channels and the repair or replacement of faulty trash screens. Interestingly, the approach proposed in this study also highlights the upstream drainage channels that are local to each pumping station (Fig. 7a), making it easy for municipal authorities to promptly and accurately target limited resources for dredging activities on the most critical waterways.

Similarly, global TBVI identifies the pumping stations that are most likely to experience disruption to their operations as a result of trash interference, particularly under heavy flow conditions such as during intense rainfall events. Unlike local TBVI that focuses on neighbouring upstream channels, global vulnerability considers all connected upstream waterways because it assumes that during intense flow conditions, trash in far upstream channels will eventually get washed to downstream pumping stations. Coastal communities in developing nations should therefore keep watch on pumping stations with high global TBVI values because they are most likely to experience maximum disruption from trash interference during heavy flow conditions. To minimise the vulnerability of such pumping stations, limited resources can be judiciously spent on increasing their pumping capacity by using bigger piping and higher horsepower motors and/or improving their resilience by installing additional pumping units where possible. No doubt, the outcome of this study will be useful to coastal communities in developing nations as well as external funding bodies who often require structured techniques that facilitate transparent and efficient decisions on where limited resources can be invested to minimise the failure of key components of the drainage infrastructure.

5. Conclusions

Many coastal mega-cities in developing nations are vulnerable to natural hazards, particularly flooding events. Flooding within these densely populated cities can have devastating and long-lasting impacts to infrastructure, communities and the economy. As part of engineering interventions, coastal mega-cities often rely on pumping stations to mitigate the impacts of flood hazards, particularly in low-lying areas where drainage would be otherwise difficult. However, as a result of inadequate sanitation and garbage pickup services to properly collect and dispose solid wastes from various parts of these cities, particularly those from squatter settlements erected near water bodies, there can be an issue with trash entering the drainage channels and blocking the pumps. This situation can potentially exacerbate flooding conditions if the highly vulnerable pumping stations are not identified and prioritised for preventative maintenance. This paper therefore developed a methodology to quantify the vulnerability of pumping stations to blockage from trash entering the waterways.

The methodology calculates a vulnerability rating, TBVI value, for each pumping station in a network, based upon its exposure, susceptibility and resilience. These values were then normalised on a scale of 0 to 1 and used to highlight the pumping stations that are the most vulnerable to trash blockage. In this paper, two measures of TBVI were calculated, namely the "local" and "global" values. The local TBVI, calculated by considering exposure to only the waterways between the given pumping station and the next upstream station is representative of the vulnerability of the pump to trash that are local to it and therefore are most likely to affect it. Whereas the global TBVI, calculated using

the exposure to trash in all upstream waterways is representative of a pump's vulnerability under worse-case scenarios that assume trash will be pushed through upstream pumps.

In this paper, the proposed methodology which is based on graph-theoretic analysis has been applied to a real-world drainage network (i.e. Jakarta, Indonesia), consisting of 71 pumping stations. The analysis has highlighted the pumping stations that are particularly vulnerable to trash blockage, when considering their local TBVI values. However, when the global TBVI value is considered, it is interesting to note that these pumping stations do not show a large vulnerability relative to others in the network. This lack of correlation between the local and global TBVI values is similar for most pumping stations in the network and can be attributed to the disproportionate changes in the exposure of pumping stations from one scenario to the other.

Importantly, the proposed methodology provides a quantifiable framework for the owners, operators and decision-making authorities responsible for the maintenance of urban drainage network to assess and rank the vulnerability of pumping stations within their system. This vulnerability ranking information can then be used to guide decision making on where limited monetary and nonmonetary resources available for the maintenance and upgrade of the urban drainage network can be judiciously spent in order to minimise the failure of pumping stations. For example, decisions could be made to either add more pumping units to increase redundancy and therefore resilience, or replace smaller pumps with those of higher capacity. It is worth noting that whilst this methodology has been applied to the Jakarta case study in this paper, it is transferable to other areas and could be used to highlight vulnerable pumping stations in other coastal mega-cities.

The main limitation of this study is the lack of additional data such as channel depth, roughness coefficient, nearness to dumpsites, etc. to accurately model flow of trash in waterways. When available, future work will explore the use of such data to further refine and improve the accuracy of the computed TBVI value for each pumping station in the network.

6. Future work

Future work should seek to integrate additional data about population density, nearness of waterways to dumpsites, channel depth and roughness coefficient in order to obtain more accurate results with improved modelling of trash flow in open channels. Hydraulic computations of flows in open channels often require an evaluation of roughness characteristics (Azamathulla and Jarrett, 2013). In computing exposure, the roughness coefficient of a river channel can be used as an indication of the resistance to flow of trash in the channel (Arcement and Schneider, 1989; Azamathulla and Jarrett, 2013).

Additional data regarding the precise width and depth of each river channel could improve the accuracy of quantifying the exposure, E of pumping stations. In the absence of complete dataset to compute exposure, the current study used values derived based on river classification as proxy for the size or width, w_i of waterways. Assuming that the river channels are mostly rectangular in shape, then by obtaining the precise depth, u_i and width, w_i of each channel, the exposure, E of a pumping station can be more accurately determined as a function of volume, i.e. the product of effective length, l_i^e, width, w_i, and depth, u_i of waterways flowing to the pumping station. The assumption is that the higher the volume of a river channel, the larger the quantity of trash that can be accommodated and therefore, the greater its contribution to the exposure of a connected downstream pumping station. This is particularly important for coastal cities situated in developing nations as evidence from news reporters (Winn, 2016) and a recent shocking video (Dunn, 2016) have revealed that large rivers with high volume for accommodating trash are frequently being targeted by poorly trained, low-paid garbage truck drivers who in a bid to save time and fuel take short cut to dump trash in water bodies.

Furthermore, the location and spatial distribution of dumpsites relative to the different waterways and pumping stations in the city can be considered in computing exposure. In this regard, waterways to which there are closely located dumpsites can be considered to be in higher risk of experiencing high volume intake of trash as compared to those in which the dumpsites are situated farther away. Similarly, the population density of people living upstream and alongside each waterway (e.g. slums) can also be obtained and used as a weighting factor when determining the contribution of different waterways to the exposure of a pumping station. The assumption is that the higher the population density, the higher the volume of trash that could find their way into the waterways. Future work can also consider the age of pumping stations as one of the determinants of susceptibility. In this sense, well-aged pumping stations can be said to be more susceptible to failure when exposed to hazards as compared to ones that are new.

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