Geographical Hotspots of Critical National Infrastructure

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Abstract

Failure of critical national infrastructures can result in major disruptions to society and the economy. Understanding the criticality of individual assets and the geographic areas in which they are located is essential for targeting investments to reduce risks and enhance system resilience. Within this study we provide new insights into the criticality of real-life critical infrastructure networks by integrating high-resolution data on infrastructure location, connectivity, interdependence and usage. We propose a metric of infrastructure criticality in terms of the number of users who may be directly or indirectly disrupted by the failure of physically interdependent infrastructures. Kernel Density Estimation is used to integrate spatially discrete criticality values associated with individual infrastructure assets, producing a continuous surface from which statistically significant infrastructure criticality hotspots are identified. We develop a comprehensive and unique national scale demonstration for England and Wales that utilises previously unavailable data from the energy, transport, water, waste and digital communications sectors. The testing of 200,000 failure scenarios identifies that hotspots are typically located around the periphery of urban areas where there are large facilities upon which many users depend or where several critical infrastructures are concentrated in one location.

1. Introduction

Critical National Infrastructures (CNIs) support society and the economy by providing essential services to households and industries. Examples of CNIs include electricity, water, transportation, gas, digital communications and waste networks. Motivated by economies of scale and unequal distributions of national resources and economic activity, modern CNIs have evolved into large spatially distributed systems with multiple interdependencies.

Such complexity provides the conditions for failure at a particular location to have disproportionate consequences. In the United Kingdom (UK), a number of recent events have highlighted this systemic vulnerability: In 2009, flooding in Cumbria [1] resulted in a bridge failure that not only caused disruptions to local transportation systems, but also to water, electricity and telecoms utilities that were co-located on the bridge. In 2011, power failure at a major exchange in Birmingham resulted in the loss of broadband connection for hundreds of thousands of users across the UK [2]. On Christmas Eve 2013, the flooding and subsequent failure of three electricity sub-stations at Gatwick airport contributed towards the disruption of 13,000 airline passengers [3]. Motivated by historic failure events and the threats posed to the CNI from a changing climate and human threats, understanding this vulnerability for the purpose of targeting investments to reduce risks and enhance resilience, has become a national priority [4-8].

In order to effectively target investments we are required to identify 'critical' infrastructure assets "the loss or compromise of which would leave to severe economic or social consequences or to loss of life" [9]. Given the 'interconnectedness' of modern infrastructure systems, we are required to think beyond traditional sectorial silos and consider infrastructure as a system-of-systems [10-12]. One major source of interconnection is established through the physical flow of resources between infrastructures, classified as physical interdependencies [13].

A second form of interdependency proposed by Rinaldi et al. [13] is geographic, where the spatial proximity between assets results in their exposure to similar local environmental conditions. Co-location can occur because of physical necessity (i.e. the assets physically depend upon one-another) or because sites are geographically attractive e.g. on the periphery of urban areas where land is cheaper and may be designated for industrial purposes. In the context of failures, co-location can result in correlated events, which are considered common-cause failure mechanisms [13]. These include: weather related hazard events such as ice storms [14], flooding [15], heat waves [16] or hurricanes [17]; geo-hazards such as earthquakes [18], volcanic activity [19] and subsidence [20]; co-location related infrastructure asset failures [2] and targeted attacks [21,22]. Considering this form of interdependence, we extend our understanding of criticality beyond the scale of an individual asset to identify geographic areas that are in themselves critical.

Methods and tools from the study of complex networks provide an intuitive means to explore the behaviour of CNIs [23-25]. Using this approach, the spatial organisation and topological connectivity of CNI assets are explicitly represented by nodes and edges [26]. A variety of complex network based modelling and simulation tools have been developed to study failure propagation within physically interdependent CNIs. This includes topology-based methods, such as from Bashan et al. [27] and Shekhtman et al. [28] that explore network vulnerability and robustness through the removal of individual components. Despite the advancements that these studies provide, care should be taken when applying practical insights to real CNIs such as the power grid [29,30]. Detailed physics based models can capture many details of CNIs and CNI failures; however, the data and computational costs of such analyses are prohibitive to large-scale studies [31,32]. Functional network models such as proposed by Johansson & Hassel [33], Poljansek et al. [34], Zio & Sansavini [35] and Hernandez-Fajardo & Dueñas-Osorio [36] quantify failure and disruption propagation using functional connectivity and network-path based techniques that replicate the most salient behaviour of CNIs without excessive data and computational costs.

In a recent review of modelling and simulation approaches for interdependent infrastructure systems undertaken by Ouyang [32], it was recognised that applied studies are limited to two or only a small number of CNIs - therefore potentially underestimating the consequences of failure. In order to compare the disruptive impacts of different assets from multiple interdependent CNI sectors, an informative, universal metric for physically interdependent CNIs is required. Casalicchio & Galli [37] identify that in order to support decision-making for protection and resilience planning, "core metrics" such as those that act at the asset level are required. To this end, Zimmerman & Restrepo [38] developed a ratio of the temporal disruptions to the supporting and dependent infrastructure, however, despite its universal quality, this metric does not incorporate the magnitude of user disruptions that result from failure events. Johansson and Hassel [33] and Thacker et al. [39] provide a universal metric of infrastructure service losses (user disconnections) applied to individual sectors, however this does not, at the asset level, explicitly incorporate the impacts of indirect disruptions that manifest through nth-order interdependency effects.

Through the removal of infrastructures co-located within previously determined square grid cells, Johansson and Hassel [33] identify critical geographic locations. This work performs an application of the 'cell-space' method that was demonstrated for a university campus [40] and a road network [41]. Two major limitations of this technique are identified in Wilson [42]: (i) that all infrastructure locations are considered to be evenly spread across a cell, resulting in a loss of spatial information; (ii) Due to the distribution of point assets in space, the choice of grid cell shapes and locations can have a large impact of outcomes, this is otherwise know as the Modifiable Areal Unit Problem [43]. Kernel Density Estimation (KDE) is a technique that has been developed to produce a single density surface from spatially distributed observations [44].

The KDE creates a continuous surface, any point of which integrates a number of observations (infrastructure assets) within a certain distance that are weighted using a specified kernel function. This addresses the limitations of the cell-space method by explicitly incorporating the distances between infrastructure assets, preserving detailed spatial information and secondly, providing a continuous (overlapping) kernel function across the entire surface, reducing the impacts of cell boundary choice. Statistical methods such as those proposed by Ord & Getis [45] provide a means by which to analyse this continuous surface, identifying 'hotspot' locations that are considered as statistically significant outliers.

We present novel methodology and applied analysis that incorporates physical and geographic interdependencies to identify '*infrastructure criticality hotspots*' for risk and adaptation planning. In doing so this study makes a number of unique contributions to the literature, these include: (i) Methodology to calculate infrastructure asset *user criticality* as a universal disruption metric, allowing assets from different sectors to be compared directly with one another. The metric incorporates the potential direct and indirect user disruptions that can result from the failure of the infrastructures through physical interdependencies; (ii) The use of Kernel Density Estimates (KDEs) and statistical testing to calculate geographic hotspots of infrastructure criticality. Hotspots identify concentrations of critical infrastructure that might not otherwise be identified as being critical; (iii) The presentation of a comprehensive and unique national-scale infrastructure criticality assessment for England and Wales that tests 200,000 failure scenarios by integrating data from the energy, transportation, water, waste and digital communications sectors.

The remainder of this paper is organised as follows: Section 2 outlines methodology to identify geographic hotspots of critical national infrastructure; Section 3 provides a detailed description of an application of the methodology for England and Wales; Section 4 highlights results and findings from the applied analysis. Finally, Section 5 offers conclusions from the study.

2. Definition of critical infrastructure hotspots

(a) Infrastructure asset criticality

Consider $Q \subset \mathbb{R}^2$ the set of all two-dimensional coordinates of geographical locations within the boundaries of a spatial extent such as a country. Users residing within Q rely upon a variety of essential services that are delivered by the collective function of physical infrastructure assets that make up the national infrastructure. Such assets include electricity power stations, gas compressor stations and water pumps. Though service delivery also relies on non-physical assets (such as human control), the focus of this study centres on physical infrastructures only.

We collect all assets, a, belonging to the national infrastructure to form the set $A = \{a_1, \dots, a_n\}$. Assets belonging to a specific infrastructure type can be collected to form the set $A^k \subseteq A$. For example, A^e contains all the electricity assets, A^g contains all the gas assets and A^w is the set of all the water assets. The number of users P dependent on a single infrastructure system A^k is given as $P^k \subseteq P$.

Infrastructure assets perform different functions in order to satisfy the users dependent on them. To describe this functionality we characterise three different asset types: sources – where services are generated, intermediate – where services are transmitted to other assets, and sink - which distribute services directly to users. This arrangement forms a functional hierarchy where, at the lowest level, demands for services are placed on sink assets and at the highest level, services are generated at source assets. Intermediate assets support the distribution of services between sources and sinks and in doing so establish directionality of flows within the hierarchy.

We consider each sink asset to serve a unique (non-overlapping) geographic area. As such, the set A^k of assets classified as sinks divide the space Q into disjoint partitions. Assuming there are m sink assets in the set A^k which divide the space Q into disjoint partitions $\{Q_1, \ldots, Q_m\}$, we can estimate the number of users within each partition, we define this as the assets *user footprint*. Denoting the number of users associated with the sink node of infrastructure A^k serving the space Q_l as P_l^k, we can construct the sets of all unique subsets of users $\{P_1^k, \ldots, P_m^k\}$ on the infrastructure A^k. Beyond sink assets, the exact demand placed by the users on the intermediate and source assets depends upon a range of factors that include: which sinks they are connected to, as well as other capacity and functional constraints of the system.

For any give asset (source, intermediate or sink) $a_j \in A^k$ we can assemble the set S^k of all sink assets of the same infrastructure type that it is supplying to. The *direct demand* placed on a_j is denoted by $P_j^{dir} = f(\bigcup_{\forall a_l \in S^k} P_l^k)$, where the function f depends upon the capacity of the asset to serve the total demand $\bigcup_{\forall a_l \in S^k} P_l^k$ of all sinks in the set S^k. Since assets are also connected across infrastructures (through physical dependencies), there is an indirect demand places on each asset a_j that is supplying resources to another infrastructure type. So for example, gas users place an indirect demand on electricity assets due to the existence of a physical dependency between the gas system and the electricity system. We calculate the *indirect demand* P_j^{indir} in a similar way to estimating P_j^{dir}. $P_j^{indir} = g\left(\bigcup_{S^v \neq S^k} \bigcup_{\forall a_l \in S^v} P_l^v\right)$, where the function g depends upon the capacity of the asset to serve the total demand $\bigcup_{\forall a_l \in S^v} P_l^v$ of all sinks in the sets S^v belonging to other infrastructures.

For the purpose of targeting investments, we are interested in identifying critical assets, the failure of which can have disproportionate consequences. In developing this analysis we seek to compare the criticality of all assets within A irrespective of which individual infrastructure system they belong to. To do this, we propose the universal metric: *user criticality c_j that we define as the total number of users who are directly or indirectly dependent on infrastructure asset*

a_j: $c_j = \left|P_j^{dir}\right| + \left|P_j^{indir}\right|$. In the context of infrastructure asset failure, this would be the number of users without service.

Figure 1 provides a simplified illustrative example to demonstrate infrastructure asset user criticality that can arise through direct and indirect user demands that manifest through physical infrastructure interdependencies. The national infrastructure system A (Part A of Figure 1) consists of assets from the electricity system $A^e = \{a_1, a_2, a_3, a_4, a_{5,}\}$ and the gas system $A^g = \{a_6, a_7, a_8\}$. The arrows highlight the direction of service flows through the hierarchy, from source to sink assets to meet user demands. As well as supporting electricity demands, electricity assets also indirectly enable gas users due to a physical dependency established between the infrastructures. In Part B of Figure 1 the user criticality calculation for a_3 is given as the total sum demand imposed due to service flows through the network in supporting the direct user footprint established at electricity sink nodes a_4 and a_5 and indirect user footprints established at gas nodes a_7 and a_8.

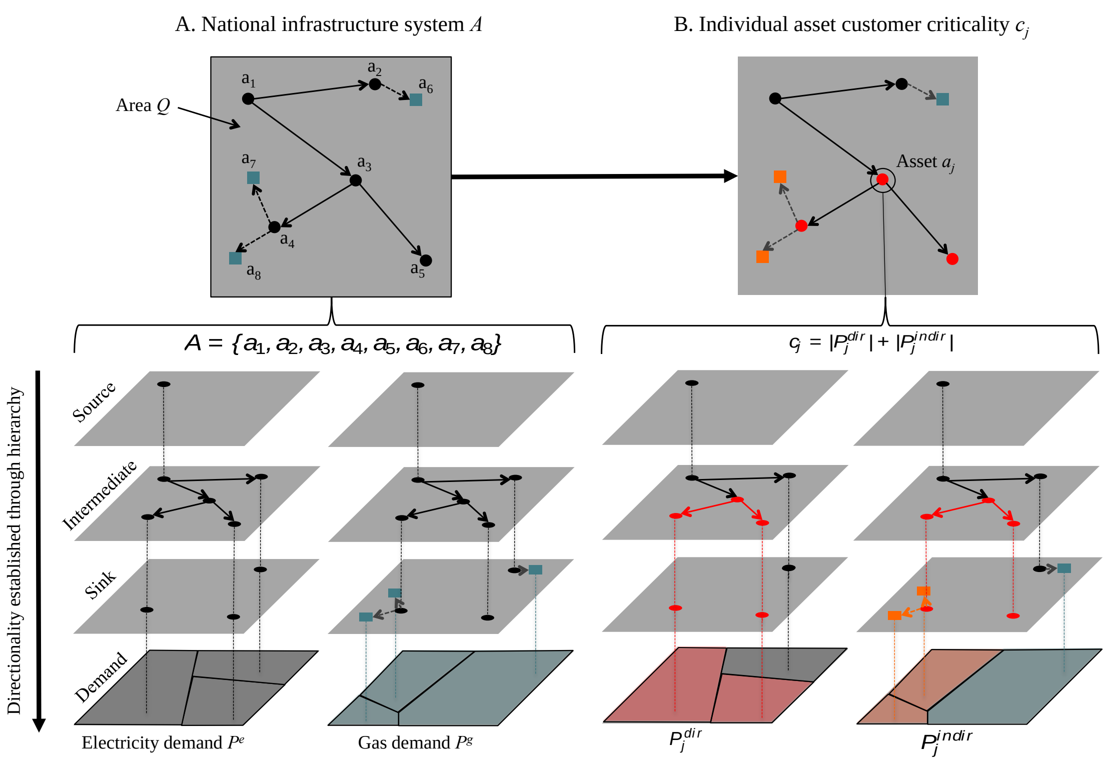


Figure 1: The calculation of individual infrastructure asset user criticality values from the mapping of infrastructure systems and their physical interdependencies and the summation of direct and indirect user demands

(b) Geographical location of critical infrastructure hotspots

The disruptive consequences associated with infrastructure asset failures that are geographically interdependent provide motivation to look beyond the scale of individual assets and identify geographic areas that are in themselves characterised as critical. To address this we propose the concept of an *infrastructure criticality hotspot* - that we define as *a geographic location where there is a concentration of critical infrastructure, measured according to the number of users directly or indirectly dependent on the infrastructure in that location*.

The identification of statistically significant 'hotspot' areas requires us to calculate the infrastructure user criticality values at all locations within the geographic area being tested. To do this we use KDE, which incorporates discrete assets locations and criticalities to produce a continuous 'surface' for which a criticality density value is available at any location. Using a weighted KDE approach the density $g(x_i)$ at location x_i is given by

$$g(x_i) = \begin{cases} \sum_{j=1}^{n} \left\{ [w_j c_j] \frac{1}{\pi h^2} K\left(\frac{d_{ij}}{h}\right) \right\}, & if\ 0 < d_{ij} < h \\ 0, & otherwise \end{cases} \qquad 1$$

where w_j is the weight associated with infrastructure asset a_j, c_j is the *user criticality* associated with infrastructure asset a_j, h is the bandwidth of the density estimation (the search radius around the location) and $K\left(\frac{d_{ij}}{h}\right)$ is the kernel applied to point i. Multiple kernel functions can be selected based on a theoretical, empirical or other functional reason for its use [42].

The resulting 'surface' can then be analysed to identify spatial concentrations of critical infrastructures that constitute statistically significant hotspots (high magnitude outliers) of infrastructure criticality. The Getis & Ord Gi* measure [45] provides a statistical z-score significance test that compares locally calculated values with global values, thus providing a significance test across the whole study area. The Gi^* value for the location i is given by

$$Gi^* = \frac{\sum_{j=1}^{n} w_{ij}\, g(x_j) - \bar{g} \sum_{j=1}^{n} w_{ij}}{\sigma \sqrt{\frac{n \sum_{j=1}^{n} w_{ij}^2 - (\sum_{j=1}^{n} w_{ij})(\sum_{j=1}^{n} w_{ij})^2}{n-1}}} \qquad 2$$

where w_{ij} is the spatial weight between feature i and asset a_j, $g(x_j)$ is the KDE value of the attribute of interest at location j, $\bar{g}$ is the global mean of attribute of interest and σ is the standard deviation of the attribute. z-score significance testing provides a means to identify both hot and cold spots for the analysis.

Figure 2 Part A. highlights the key elements of the KDE and how it is used to calculate a continuous criticality density surface. Part B. of the figure shows how statistical significance testing of the criticality surface can be used to identify geographic hotspot locations.

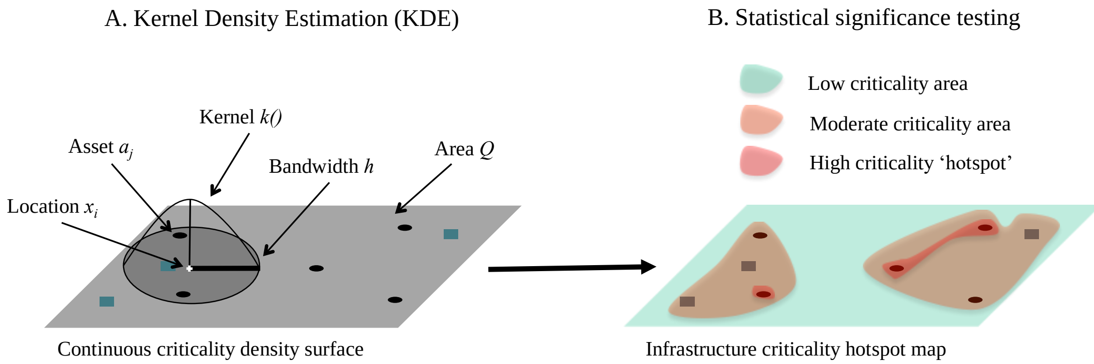


Figure 2: Part A. Shows the elements of the Kernel Density Estimation (KDE), which is used to create a continuous criticality surface. Part B. highlights how the statistical significance testing is used to derive infrastructure criticality hotspots from the criticality surface.

The infrastructure criticality hotspot methodology can be implemented in a number of ways to provide different insights into criticality. These are summarised below:

- *Single sector assets only:* Identifies hotspots using only the locations of assets from a single sector
- *Multiple sector assets only:* Identifies hotspots using the locations of assets from multiple sectors that are all mapped in the same space
- *Single sector with direct users:* Identifies hotspots using locations and direct user weightings for only a single sector
- *Multiple sector with direct users:* Identifies hotspots using locations and direct user weightings from multiple sectors that are all mapped in the same space
- *Single sector with direct and indirect users:* Identifies hotspots using locations and user criticality weightings (direct and indirect demand) for only a single sector
- *Multiple sector with direct and indirect users:* Identifies hotspots using locations and user criticality weightings (direct and indirect demand) from multiple sectors that are all mapped in the same space

The choice for implementation of the analysis will depend upon the questions that drive the analysis and practical constraints, such as lack of available data or computational constraints. The incorporation of increasing levels of data into the analysis (such as the analysis of multiple sectors and user criticality values) promotes the identification of geographic locations that might not otherwise have been identified.

In the following sections we provide a demonstration of this methodology for England and Wales using data from multiple sectors. We use direct and indirect demands to estimate asset user criticalities and produce hotspot maps for individual and multiple sectors to draw out important insights into national infrastructure criticality and vulnerability.

3. Application to critical national infrastructure in England and Wales

(a) Overview of the analysis

We provide a comprehensive national scale demonstration of the methodology for England and Wales utilising unique data from the energy, transport, water, waste and digital communications sectors. For each sector, direct user estimates are used to derive asset user criticality values. The integrated electricity network is central to the national infrastructure provision, with all other sectors physically dependent on electricity for their operation. Given its importance, we characterise the user criticality of electricity assets based on direct and indirect users that are established due to this dependency. Geographic interdependency is characterised through the derivation of infrastructure criticality hotspots using KDEs.

The following sub-sections provide a detailed account of the methods and data used in the analysis, this includes: (b) *Infrastructure asset representation:* the integration of highly detailed data on infrastructure location, interconnectivity and interdependence to build a national infrastructure representation; (c) *Infrastructure criticality calculation:* applied methodology and data for calculating asset criticalities using user estimates derived from usage statistics, spatial density estimates and network-based path assignment techniques and (d) *Infrastructure criticality hotspot identification:* details for implementation of the KDE and statistical significance testing for the purpose of hotspot identification.

(b) Infrastructure asset representation

In order to calculate asset criticality values we first map all infrastructure assets from the national infrastructure within the area of the study. Table 1 presents the real infrastructure asset data from multiple sectors that have been used in the analysis. This includes a representation of the integrated electricity network, where nodes are used to represent generation facilities and electricity substations and edges are used to represent overhead lines and underground cables. Figure 3 (a) provides a representation of this network, showing the different voltage levels at which connections to generators and other infrastructures are made. Other network infrastructures include the national road network, where nodes represent junctions and edges represent different road segments. Similarly, the national railway network in comprised of nodes that represent junctions and stations and edges represent track segments.

The location of airports, ports, water towers, wastewater treatment plants and telecommunication towers are represented as single point assets, identified by nodes. Each asset of these specific types is dependent on electricity for its operation. In many cases, the nature of the physical connection between the dependent asset and its supporting electricity asset is unknown. We build a dependency edge between the asset and its nearest (geographically closest) electricity asset of appropriate voltage. Figure 3 (b) provides an example of this, showing the physical connections that are established between gas take-off points and the 33kV electricity substation assets.

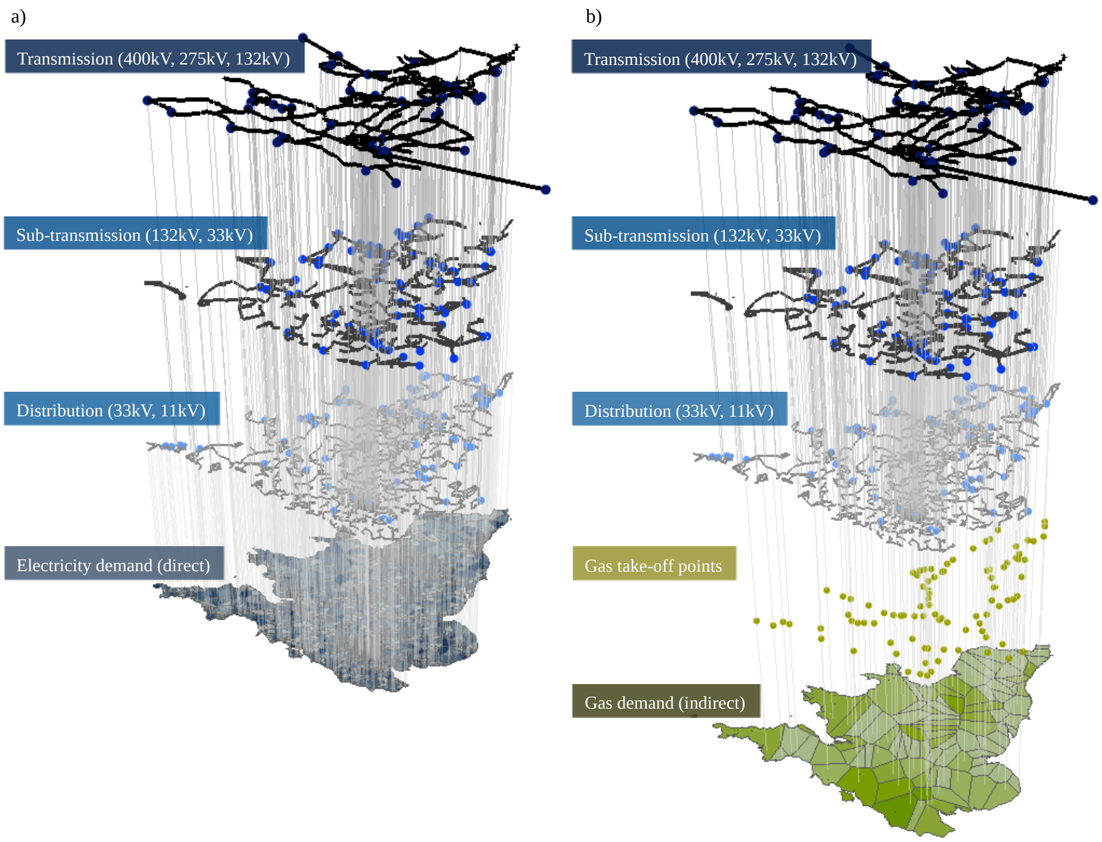


Figure 3: A representation of the integrated electricity network for England and wales; consisting of the electricity power generation, transmission, sub-transmission, distribution sub-systems. (a) Shows how domestic electricity users at distribution sub-stations place a direct demand. (b) Shows how gas users, connected through a dependency link between the gas and electricity infrastructure place an indirect demand on electricity assets.

(c) Infrastructure criticality calculation

Having mapped the assets within England and Wales, we next calculate their criticality. The first step of this process is to calculate the numbers of users directly dependent on all assets. Table 1 provides details for how users are allocated to infrastructure assets from different sectors. In summary: Point assets representing airports are derived from annual flight statistics and are calculated as the total number of terminal passengers for an average day in 2009 [46]. Similarly, average daily port users were derived using 2009 national port usage statistics [47].

In the absence of data for the gas take-off points, electricity distribution substations, water towers, wastewater treatment plants and telecommunication towers assets, we estimate these using a Voronoi decomposition technique [34,39]. Assignment of users is a two part process comprising: (i) deriving infrastructure asset footprints to estimate spatial area of influence around each distribution level asset, and (ii) assigning user counts to each distribution level asset based on a spatial union of asset footprint with census derived population estimates (that we take as an estimate for domestic demand). This method assumes each asset provides an equally weighted service and assets influence only the closest space around them. Figure 4 (a)-(h) highlights the process of user assignments and provides results (with user counts highlighted on a colour scale) derived for wastewater treatment works, gas off-take points, telecommunication masts and water towers respectively.

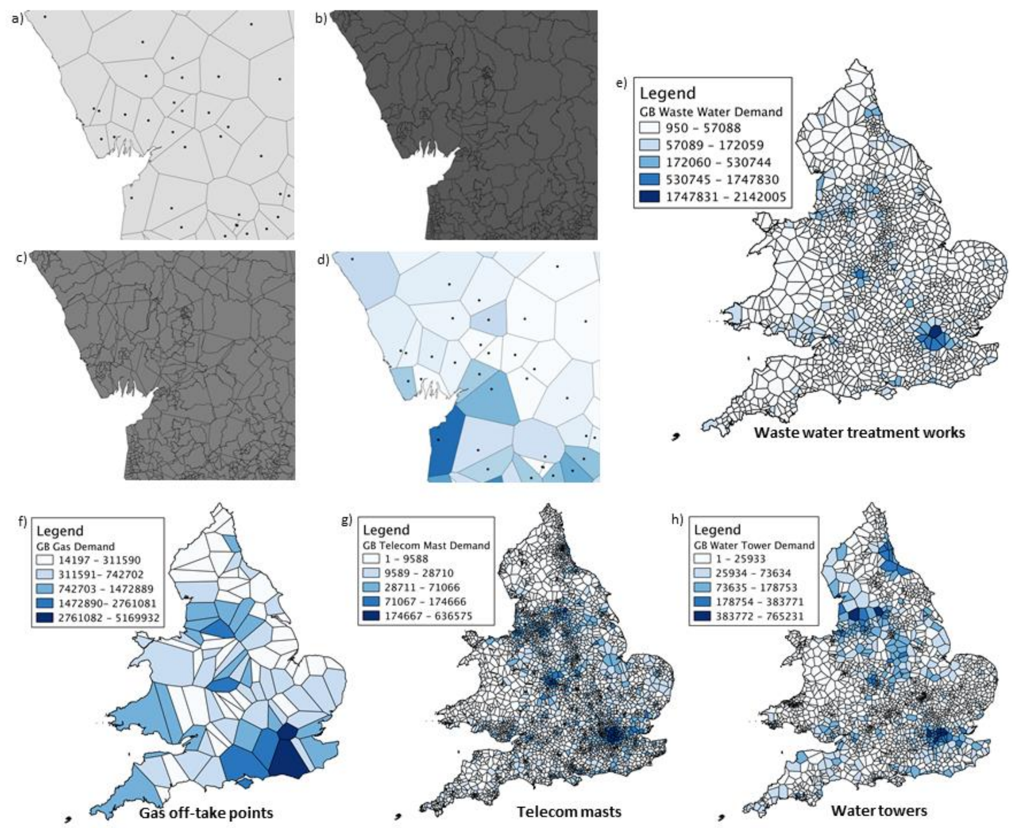
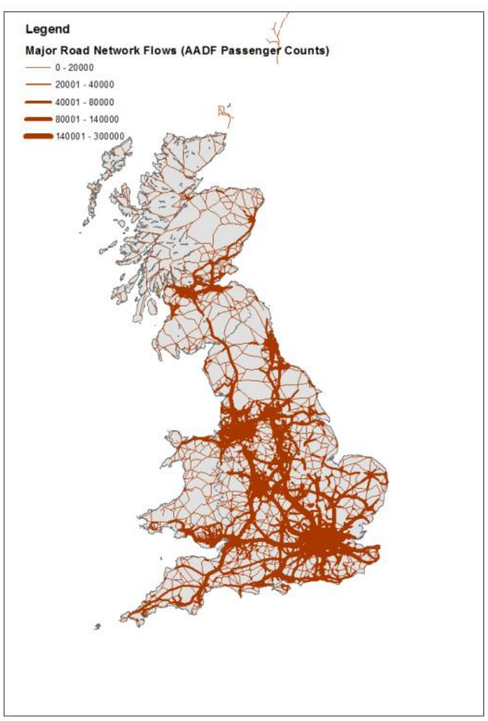


Figure 4: Stages in assigning users to assets; (a) introduces a set of asset footprints. (b) Provides a view onto ward level population data. (c) Represents the union of both the asset footprint and the bounded population data. (d) Gives user estimates transferred to asset footprints (e), (f), (g) and (h) provide user assignments, with user magnitude highlighted on a colour scale derived for waste water treatment works, gas off-take points, telecom masts and water towers respectively

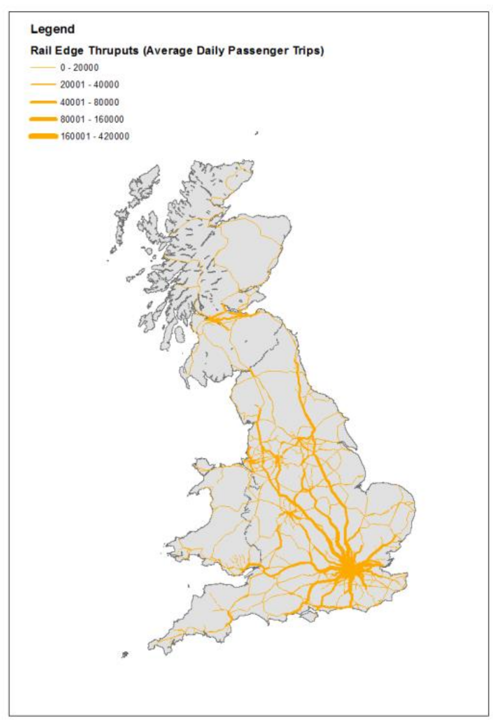
Direct (electricity) and indirect (non-electricity) user demands that are concentrated at sink nodes are then allocated to intermediate and source nodes within the integrated electricity network. Due to the lack of availability of user demand data for these assets, allocations are made on the assumption that electricity flows are established along a path of least resistance within capacity constraints. To achieve this we perform an application of the capacity constrained location-allocation method as outlined in Thacker et al. [39]. In summary: The method calculates the set of shortest paths between source and sink nodes in the network that are required to satisfy user demand within generation availability constraints. Users are aggregated at assets within paths between sink and sources and these aggregations correspond to asset criticality values.

User demands for the major road network were derived from Department for Transport Average Annual Daily Flows (AADF) usage statistics [48] which give aggregated estimates of number of vehicles of different types (two-wheelers, cars, taxies, buses, coaches, light goods vehicles and heavy goods vehicles) along major roads in Great Britain. We have converted these to passenger counts by multiplying the vehicle numbers by passenger occupancy factors provided by transport analysis guidelines handbooks [49]. Figure 5 (a) shows the major road network with edges weighted based on traffic flows.

Usage of the railway network was derived from a rail trip distribution model developed in previous work by Pant et al. [50]. The model uses information from train timetables and station usage statistics to estimate trips being made between station pairs. The results are aggregated as origin-destination (O-D) daily trip assignments of passengers in the railway network. Figure 5 (b) represents the flows of all passengers through stations and along routes for the national railway network of Great Britain.



(a)



(b)

Figure 5: (a) Illustration of the average annual daily flows (passenger numbers) along links on the major road network from Great Britain. (b) Edge Criticality: which represent the passenger throughputs at each railway network edge (track section).

(d) Hotspot identification

A 1km sampled spatial lattice was constructed across all of England and Wales. The individual points in the lattice formed the sample locations at which KDE estimation was performed to obtain an estimate of the spatial density of infrastructure occurrence and related user density per infrastructure sector. The output units of the KDE analysis were density per-km^2

For each location in the lattice a spatial density estimate was derived using a weighted intensity KDE approach as presented in EQ. 1. A Gaussian kernel of the form $K\left(\frac{d_{ij}}{h}\right) = \left\{\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{d_{ij}^2}{2h^2}\right)\right\}$ was selected to incorporate the decay in spatial influence that is associated with a sampled location. For each infrastructure sector considered in Table 1 KDE surfaces were derived both in terms of the spatial frequency of infrastructure assets (i.e., without any measure of associated user criticality such that c_j was set to $1 \forall j \leq h$) and also in terms of user criticality, with c_j set to the user counts associated with a particular infrastructure asset j. A weighting of W_a = 1 for all infrastructure types, establishing no preference for a particular infrastructure systems type. All KDE surfaces were derived for a bandwidth (h) set to 5km by experimentation.

To recognize statistically significant spatial hotspots of infrastructure criticality the Getis and Ord Gi^* spatial hotspot statistical test was employed. Formally, the Getis and Ord Gi^* value for a location i is calculated using EQ.2. where in the case of this study, each 1km sampled lattice location in an infrastructure sector formed the locations i. To test for statistical significant hotspot locations, the Z-score of each location i was threshold at a 99% significance level ($Gi^* > 2.6$).

4. Results

(a) Non-transport asset criticality

Figure 6 (a) shows the estimated spatial density of non-transport infrastructure assets for England and Wales (electricity transmission Grid Supply Points (GSP), gas transmission take-off points, water towers, waste water treatment works and telecom towers/masts). Large density values occur in south-west Wales, south-east Midlands and also in the west of England. However, in terms of criticality, the spatial density and subsequent hotspots are focused on the major urban conurbations of England and Wales Figure 6 (b); namely, London with a tapering to the surrounding south-east region, Liverpool and Greater Manchester, Birmingham and Leeds areas.

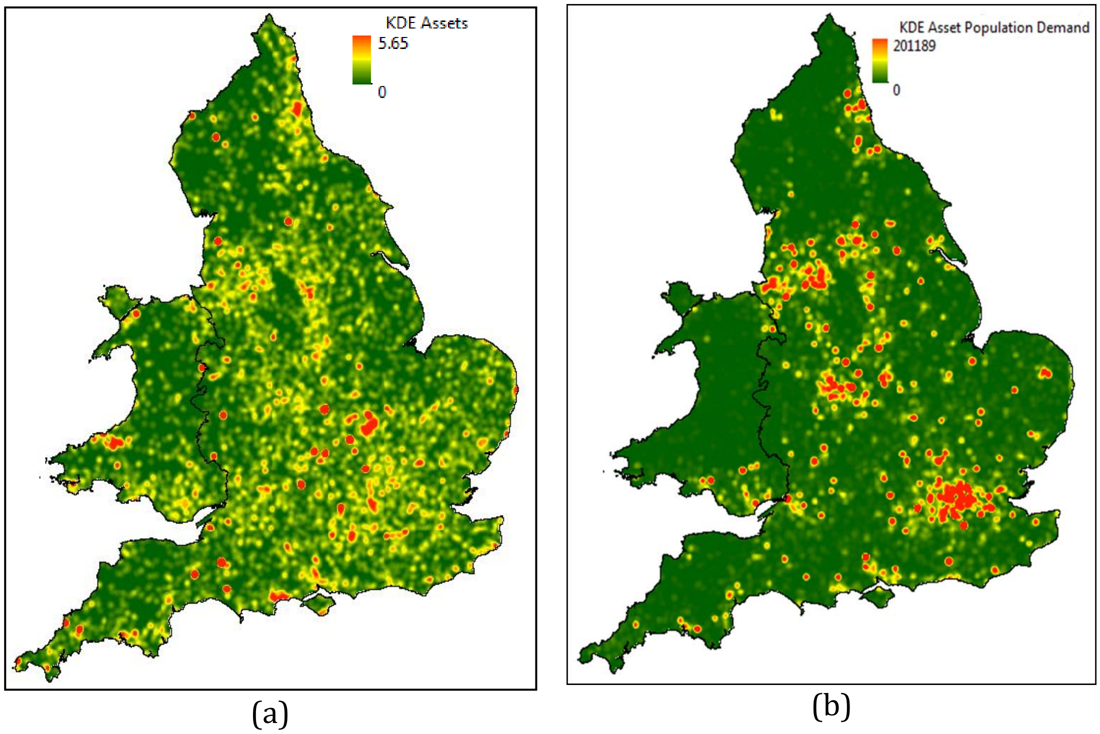
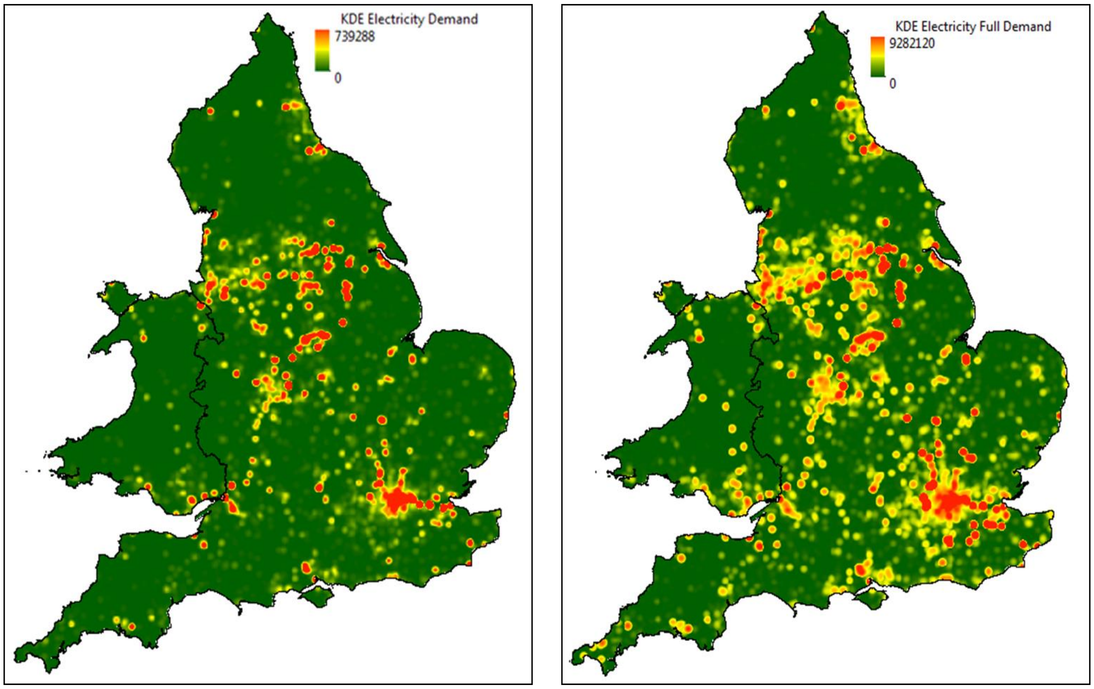


Figure 6: (a) Kernel density estimated infrastructure asset spatial density (GSP, gas, telecoms, water and water treatment assets). (b) Kernel density estimated infrastructure asset user demand (GSP, gas, telecoms, water and water treatment assets).

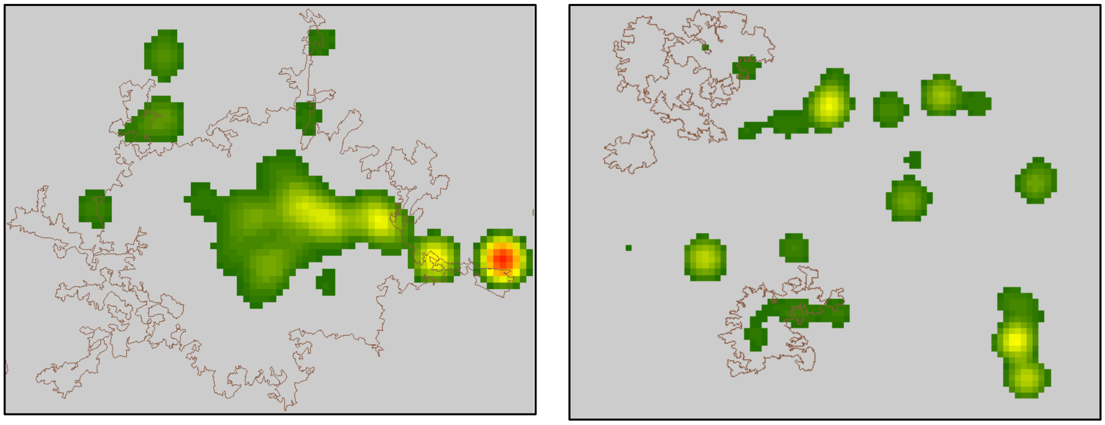
The criticality metric based on direct users of electricity network assets is shown in Figure 7 (a). Not surprisingly the major urban conurbation of England and Wales form the major demand hubs for electricity infrastructure network assets. Indirect user dependence due to the dependence of of the GSP, gas, telecoms, water and water treatment assets on the electricity network is shown in Figure 7 (b). When physical interdependence is taken into account, the map of critical asset density is more spatially dispersed than when just considering the direct usage of electricity infrastructure. The overall electricity results suggest that a relatively small number of key geographical locations play a major role in satisfying electricity demand within England and Wales, particularly with respect to the dependence of other non-transport infrastructures on the electricity network.



(a) (b)

Figure 7: (a) Kernel density estimated electricity user demand (no dependent demand). (b) Kernel density estimated full electricity user demand including GSP, gas, telecoms, water and water treatment assets dependency

The major spatial focus of this critical infrastructure lies to the east of London Figure 8 (a). It is worth noting that the actual largest magnitude hotspot of electricity demand in the south-east fall to the east of the Greater London Authority (GLA), showing the key role that large regional grid supply points play in satisfying the electricity demand of London and the south-east. This relationship of large non-urban regional electricity infrastructure assets satisfying urban users is more evident outside of London. For example, Figure 8 (b) shows the hotspots in South Yorkshire between Leeds and Sheffield. Similar non-urban demand hotspots are found running north to south through the east Midlands and also to some extent in the Liverpool to Manchester corridor in the north-west.



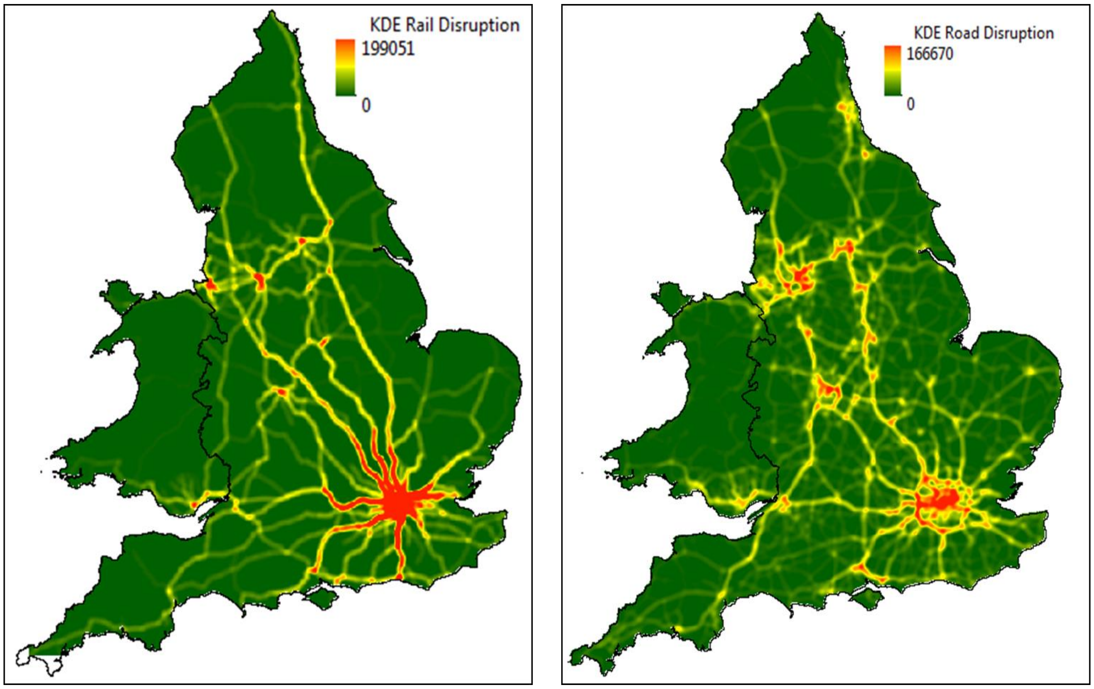
(a) (b)

Figure 8: (a) London's electricity infrastructure asset user demand hotspots at a 99% significance level (Z-score > 2.56). (a) Electricity infrastructure asset user demand hotspots at a 99% significance level (Z-score > 2.56) for South Yorkshire.

(b) Transportation asset criticality

KDE results Figure 9 (a) show that there are only a small number noticeable hotspots of criticality outside London. In the case of London, disruption radially propagates along the mainline rail connections into the south-east. The result is a large hotspot for London and the mainline rail corridors connecting it, with only four other much smaller (both spatially and in terms of magnitude) hotspots occurring at Liverpool, Greater Manchester, Birmingham and Leeds.

A slightly more complex relationship exists between road assets and related criticality compared to rail. Larger more significant densities of criticality are found outside London Figure 9 (b). Resulting hotspots of criticality are focused around principal motorways, in particular the M25, M1, M6 and the local motorways of Greater Manchester and Leeds, including the M62.

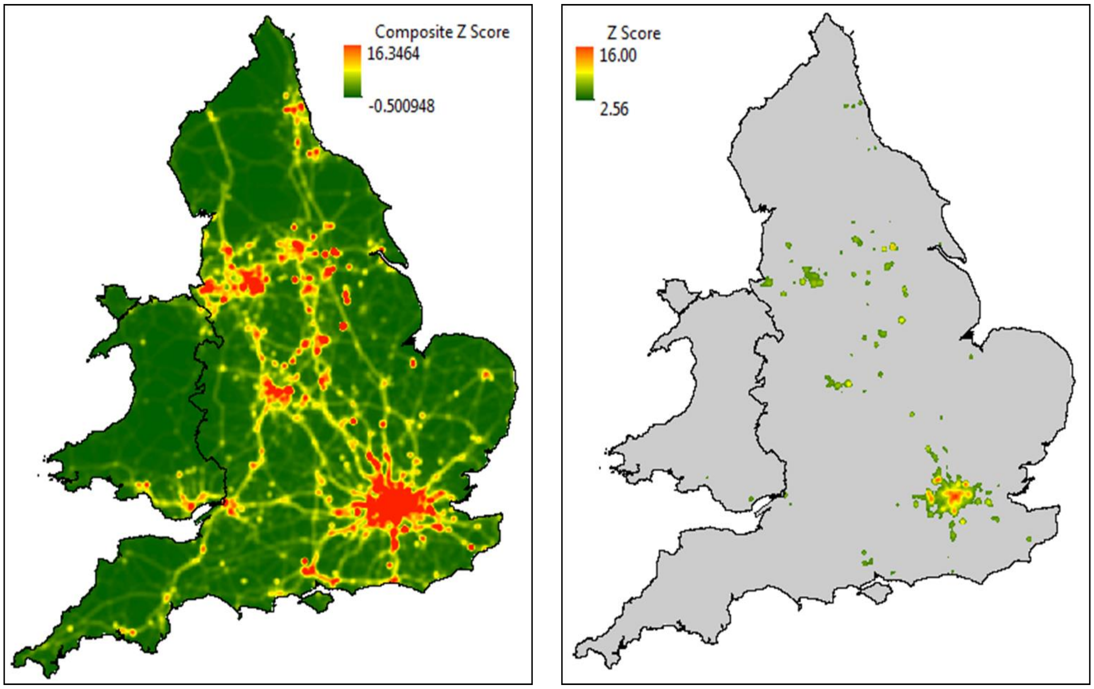


(a) (b)

Figure 9: (a) Kernel density estimated rail disruption (stations and track). (b) Kernel density estimated road network disruption on the basis of passengers

(c) Composite asset criticality

The composite criticality hotspots analysis Figure 10 (a) and Figure 10 (b) shows the major role that the large urban areas of England and Wales have both in terms of the demand for infrastructure services and also in terms of spatially accommodating these. The composite analysis (combination of criticality for individual assets, interdependence with the electricity network and transport disruption) shows that London is a major focus of criticality; it has a spatially continuous hotspot with multiple peaks that covers a spatial extent of approximately 2,331 sq-km 63 km west-to-east and 37 km north-to-south; Other composite hotspot locations are found in or around Greater Manchester, Liverpool, Leeds and Birmingham. However, the magnitude of these is lower than the London and the spatial extent significantly smaller (e.g., the largest hotspots are 256 sq-km Manchester, 115 sq-km Liverpool, 110 sq-km Leeds and 153 sq-km Birmingham. A cluster of smaller hotspots (between approximately 8 and 26 sq-km) are found in the Sheffield, Derbyshire and Nottinghamshire, and Humberside areas which are a result of the strong hotspots previously noted in these regions relating to electricity assets meeting user demand.



(a) (b)

Figure 10: (a) Composite Z scores of user demand and disruption of assets, electric network, rail and road (b) Statistically significant composite hotspots at a 99% significance level (Z-score > 2.56).

5. Conclusions

In this study we have developed methodology that incorporates both physical and geographic infrastructure interdependencies to identify infrastructure criticality hotspots. The methodology has been applied at the national scale for a range of infrastructure types in England and Wales.

Through application of the methodology to a real-world system we were able to highlight areas of infrastructure criticality in England and Wales that can be targeted for investment to reduce risks and enhance resilience. Results highlight the importance of evaluating criticality as a function of direct and indirect infrastructure users, rather than infrastructure asset concentrations. Although many locations rather intuitively correspond to areas of high user density, other, non-intuitive locations are also highlighted. These typically exist on the peripheries of cities where dependence is focused onto a small selection of infrastructures located outside of urban areas.

The general methodology developed in this paper is not only applicable to different geographic areas, but also to a broad range of infrastructure types, providing a means to explore the relationships that exist between different infrastructures at a variety of operational and spatial scales. There are many natural extensions to this work that include, (i) the development of methodology and applied analyses to incorporate logical and information interdependencies [13] into a single framework with physical and geographic interdependencies; (ii) the development of risk assessment that integrates a mapping of infrastructure criticality with a spatial representation of hazard likelihood and quantification of the consequences of failure in economic or other terms; (iii) The incorporation of hotspots into a decision making framework designed to inform prioritization of investment in system resilience.

Assembling the data for such an analysis represents a significant challenge. This is not only because of the variety of data needed from different sectors, but also because information on infrastructure users are often restricted due to matters relating to privacy, security or commercial sensitivity. Due to these complexities, where data have not been available, we have adopted an approach that allocates users to assets through Voronoi decomposition and network path based assignments. A dynamic approach for estimating users would be a valuable extension to this work, though the data and computation requirements to facilitate such an analysis may prove prohibitive.

In conclusion, the methodology and analysis presented herein provides a range of decision makers with the ability to identify infrastructure criticality hotspots. Such an analysis provides useful evidence and insights for assessing the vulnerability of modern interconnected infrastructure systems.

Ethics statement

The research reported within this paper does not raise any issues relating to ethics.

Data accessibility statement

The data and its sources used within this paper are fully documented within the main text, references and in the Table 1 of the Appendix.

Competing interests statement

We have no competing interests.

Authors' contributions statement

ST, SB and RP participated in the design of the analysis, in data analysis and in drafting the article. JH participated in the design of the analysis and in drafting the article. DA participated in data analysis and data preparation. All authors gave final approval for publication.

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References

[1] Miller, J.D., Kjeldsen, T.R., Hannaford, J., Morris, D.G. 2013. A hydrological assessment of the November 2009 floods in Cumbria, UK.

[2] BBC. 2011. BT suffers huge broadband failure. Retrieved October 3rd 2011, from www.bbc.co.uk/news/technology-15154020

[3] McMillan, D. 2014. Disruptions at Gatwick Airport – Christmas Eve 2013. Report by David McMillan to the Board of Gatwick Airport Limited

[4] CST. 2009. A National Infrastructure for the 21st Century. Council for Science and Technology.

[5] POST. 2010. Resilience of UK Infrastructure. POSTNOTE. Number 362. October 2010. Parliamentary Office of Science and Technology.

[6] DEFRA. 2011. Climate Resilient Infrastructure: Preparing for a Changing Climate. Department for Environment, Food and Rural Affairs.

[7] Cabinet Office. 2011. Keeping the Country Running: Natural Hazards and Infrastructure.

[8] ASC. 2014. Managing climate risks to well-being and the economy. ASC progress report. Adaptation Sub-Committee.

[9] Cabinet Office. 2010. Strategic Framework and Policy Statement on Improving the Resilience of Critical Infrastructure to Disruption from Natural Hazards.

[10] Kröger, W. 2008. Critical infrastructures at risk: a need for a new conceptual approach and extended analytical tools. Reliability Engineering & System Safety, 93(12), 1781–1787.

[11] Eusgeld, I., Nan, C., & Dietz, S. 2011. System-of-systems approach for interdependent critical infrastructures. *Reliability Engineering & System Safety*, 96(6), 679–686.

[12] Tran, M., Hall, J. W., Hickford, A.J., Nicholls, R.J., Alderson, D., Barr, S., et al. 2014. National infrastructure assessment: Analysis of options for infrastructure provision in Great Britain, Interim results. Oxford, GB, Environmental Change Institute, University of Oxford, 104pp.

[13] Rinaldi, S. M., Peerenboom, J. P., Kelly, T. K. 2001. Identifying, understanding, and analyzing critical infrastructure interdependencies. Control Systems, IEEE 21 (6), 11–25.

[14] Chang, S. E., McDaniels, T. L., Mikawoz, J., Peterson, K. 2007. Infrastructure failure interdependencies in extreme events: power outage consequences in the 1998 ice storm. Nat Hazards 41:337-358

[15] Pitt, M. 2008. Learning lessons from the 2007 floods. Pitt Review.
[16] McColl, L., Palin, E. J., Thornton, H. E., Sexton, D. M., Betts, R., Mylne, K. 2012. Assessing the potential impact of climate change on the UK's electricity network. Climatic change 115 (3-4), 821–835.
[17] Loggins, R. A., Wallace, W. A. 2015. Rapid assessment of hurricane damage and disruption to interdependent civil infrastructure systems. ASCE Journal of Infrastructure Systems 10.1061
[18] Dueñas-Osorio, L., Craig, J. I, Goodno, B. J. 2007. Seismic response of critical interdependent networks. Earthquake Engineering and Structural Dynamics 36:285-306
[19] Wilkinson, S. M., Dunn, S., Ma, S. 2012. The vulnerability of European air traffic to spatial hazards. Natural hazards, 60(3), 1027-1036.
[20] Prichard, O. G., Hallett, S. H., Farewell, T. S. 2013. Soil movement in the UK – Impacts on critical infrastructure. ITRC working paper series. http://www.itrc.org.uk/wordpress/wp-content/PDFs/Soil-movement-impacts-UK-infrastructure.pdf
[21] Chernick, H. 2005. Resilient city: the economic impact of 9/11. Russell Sage Foundation Publications.
[22] Prager, F., Beeler Asay, G. R., Lee, B., von Winterfeldt, D. 2011. Exploring reductions in London underground passenger journeys following the July 2005 bombings. Risk Analysis 31 (5), 773–786.
[23] Strogatz, S. H. 2001. Exploring complex networks. Nature 410 (6825), 268–276.
[24] Newman, M. 2010. Networks: An introduction. Oxford University Press.
[25] Lewis, T. G. 2011. Network science: theory and applications. John Wiley & Sons.
[26] Barthelemy, M. 2011. Spatial Networks. J.physrep. 499:1-101
[27] Bashan, A., Berezin, Y., Buldyrev, S. V., Havlin, S. 2013. The extreme vulnerability of interdependent spatially embedded networks. Nature Physics 9(10), 667-672.
[28] Shekhtman, L. M., Berezin, Y., Danziger, M. M., Havlin, S. 2014. Robustness of a network formed of spatially embedded networks. Physical review E 90, 012809
[29] Hines, P., Cotilla-Sanchez, E., Blumsack, S. 2010. Do topological models provide good information about electricity infrastructure vulnerability. CHAOS 20 033122
[30] LaRocca, S., Johansson, J., Hassel, H., Guikema, S. 2015. Topological performance measures as surrogates for physical flow models for risk and vulnerability analysis for electricity power systems. Risk Analysis 35 (4) 608-623
[31] Brummitt, C. D., Hines, P. D. H., Dobson, I., Moore, C., D'Souza, R. M. 2013. Transdisciplinary electric power grid science. PNAS 110(30) 12159
[32] Ouyang, M. 2014. Review on modelling and simulation of interdependent critical infrastructure systems. Reliability Engineering & System Safety, 121, 43-60.

[33] Johansson, J., Hassel, H. 2010. An approach for modelling interdependent infrastructures in the context of vulnerability analysis. Reliability Engineering & System Safety 95 (12), 1335–1344.
[34] Poljansek, K., Bono, F., Gutierrez, E. 2010. GIS-based method to assess seismic vulnerability of interconnected infrastructure: A case of EU gas and electricity networks. EU JRC 24275.
[35] Zio, E., Sansavini, G. 2011. Modelling interdependent networks systems for identifying cascade-safe operating margins. IEEE transactions on reliability 60 (1) 94-101
[36] Hernandez-Fajardo, I., Dueñas-Osorio, L. 2013. Probabilistic study of cascading failures in complex interdependent lifeline systems. Reliability Engineering & System Safety 111 (0), 260 – 272.
[37] Casalicchio, E., Galli, E. 2008. Metrics for quantifying interdependencies. Critical Infrastructure Protection II. Chapter 16. Springer.
[38] Zimmerman, R., Restrepo, C. E. 2006. The next step: quantifying infrastructure interdependencies to improve security. Int. J. Critical Infrastructures 2(2/3) 215-230
[39] Thacker, S. Pant, R., Hall, J. W. 2014. Characterizing the vulnerability of future configurations of Great Britain's electricity network infrastructure to climate-related hazards. Vulnerability, uncertainty and risk: pp. 648-657.
[40] Patterson, S. A., Apostolakis, G. E. 2007. Identification of critical locations across multiple infrastructures for terrorist actions. Reliability Engineering and System Safety 92, pp. 1183-203
[41] Jenelius, E., Mattsson, L-G. 2008. The vulnerability of road networks under area-covering disruptions. In: proceedings of INFORMS annual meeting, Washington, DC.
[42] Wilson, R. 2012. Using kernel density estimation to examine changes in voucher density over time. Cityscape: A journal of policy development and research Volume 14 Number 3.
[43] Openshaw, S. 1994. The Modifiable Areal Unit Problem. London, UK: Geo Books.
[44] Silverman, B. W. 1986. Density estimation for statistics and data analysis. New York: Chapman and Hall.
[45] Ord, J. K., Getis, A. 1995. Local spatial autocorrelation statistics: distributional issues and an application. *Geographical Analysis* 24(3).
[46] Civil Aviation Authority (CAA). 2010. Civil Aviation Authority: UK Airport Statistics.
[47] Department for Transport (DfT). 2012a. UK Department for Transport: Maritime and Shipping Statistics.
[48] Department for Transport (DfT). 2014. Road traffic statistics: http://www.dft.gov.uk/traffic-counts/
[49] Department for Transport (DfT). 2012b. Tag Unit 3.5.6 – Values of Time and Vehicle Operating Costs. London, UK.
[50] Pant, R., Hall, J.W., Blainey, S. 2015. Vulnerability assessment framework for interdependent critical infrastructures: case study for Britain's rail

network. Special Issue on Climate Adaptation and Infrastructure of European Journal of Transport and Infrastructure Research. Accepted.
[51] Department of Energy and Climate Change (DECC). 2012. Digest of UK Energy Statistics (DUKES).
[52] National Grid. 2012. Electricity Ten Year statement, UK electricity transmission. National Grid, UK.
[53] Ordnance Survey. 2015. OS MasterMap Topography. Ordnance Survey, UK.

Appendix

Table 1: List of assets included in the spatial criticality analysis. Detailing the data sources used to complete the spatial topological network representations and the capacity and demand data used to estimate the functional path set and assign user demands.

Sector	Spatial and Topological Attributes	Capacity and Demand Attributes
Electricity generation • Owners: Multiple • Nodes: 207	Generator node locations derived using DECC 2012 DUKES data [51]	Individual generator capacity values derived using DECC 2012 DUKES data [51]
Electricity transmission • Owners: National Grid • Nodes: 437	Transmission network derived from National Grid maps [52]	User demands derived using capacity constrained location allocation – detailed in paper, based on Thacker et al. [39]
Electricity sub-transmission • Owners: Multiple DNOs • Nodes: 4798	Sub-transmission network derived from OS MasterMap topography layer node and edge data [53]	User demands derived using capacity constrained location allocation – detailed in paper, based on Thacker et al. [39]
Electricity Distribution • Owners: Multiple DNOs • Nodes: 164,069	Distribution network derived using OS MasterMap topography layer node and edge data [53]	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. [39]
Gas transmission • Owners: National Grid • Nodes: 625	Gas network derived from National Grid maps [52]	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. [39]
Airports • Owners: Multiple • Nodes: 32	Airport locations derived from OS MasterMap topography layer node data [53]	User demands derived from CAA 2010 flight statistics [46]
Ports • Owners: multiple • Nodes: 66	Port locations derived from OS MasterMap topography layer node data [53]	User demands derived from DfT 2012 maritime statistics [47]
Water towers • Owners: multiple • Nodes: 2566	Water tower locations derived from OS MasterMap topography layer node data [53]	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. [39]
Waste-water treatment • Owners: multiple • Nodes: 1563	Waste-water treatment locations derived from OS MasterMap topography layer node data [53]	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. [39]
Telecom masts • Owners: multiple • Nodes: 5226	Telecom mast locations derived from OS MasterMap topography layer node data [53]	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. [39]
Railways • Owners: multiple • Nodes: 3941	Railway locations derived from OS MasterMap topography layer node data [53]	Passenger demands from a rail trip distribution model, documented in Pant et al. 2015 [50]
Roads • Owners: multiple • Nodes: 24071	Road locations derived from OS MasterMap topography layer node data [53]	Passenger demands from DfT AADF usage statistics [48] and DfT loading factors [49]