Assessing Urban Critical Infrastructure Using Online GIS and ANN: An Empirical Study of Bucharest City (Romania)

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Abstract. Critical infrastructure (CI) assessment is becoming a prominent topic for smart city, as it supports economic activity, governance and determines the quality of life. Due to their interdependence, the geographic location and effectiveness of CI components definitely determine the overall performance of urban system, so that any internal or external disturbance of one CI component could generate cascading failure and impact the whole urban activity. Nowadays, the explosion of urban infrastructure, the increased volume of extant data and technological advancements in ICT foster emerging smart critical infrastructure assessment solutions, adapted for various smart city requirements.

While information related to CI is heterogeneous and multi-dimensional, it is a lack of studies exploring the potential of combined data-sources in modelling and assessing urban interconnected CIs.

In this context, to better understand the holistic approach of CI and to support decision makers this paper proposes a framework for CI assessment, based on Geographic Information System (GIS) technology and artificial neural-networks (ANN) modelling. This framework envisages identifying urban sub-regions profiles as the first step in assessing resilient capacity of different urban areas.

A case study of CI assessment accomplished for Bucharest city from Romania, is included.

Keywords: Critical infrastructure · Artificial neural networks · Smart city · Geographic Information System

1 Introduction

Nowadays, the urban system is the result of complex natural, physical, social, political and economic processes and their dynamic interactions, where attributes such as urban critical infrastructure plays a major role in city activities and evolution. According to the United Nations' forecast about 66% of World's population is expected to settle in urban areas by 2050. As a consequence, the complexity of urban system and its infrastructure even high will increase more.

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Cities are complex and interdependent systems, extremely vulnerable to threats, from both natural hazards and terrorism. In the recent years, the occurrence of various shocks and stressors has increased and disproportionately affected regions and cities. In this respect, identifying specific profile of various geographic areas of an urban area, from various perspectives, is a foremost subject for smart city research area.

The urban infrastructure is defined as a network of physical, cyber and organizational independent and mostly privately-owned systems and processes that collaboratively and synergistically operate to produce and distribute a continuous flow of essential products and services, to ensure citizens' protection and to support economic, social and administrative activities of the city [1, 2]. Even though it is no agreement on what components of urban subsystems infrastructure deemed to be the critical infrastructure [3], according to [4, 5] this includes those systems whose incapacity or damage would have a debilitating impact on the defense, economic security, public health and safety or any combination of these matters.

Urban infrastructure sub-systems are mutually dependent and interconnected into a network through which goods, services, people and information flow, supporting activities within the city. In this context, modeling and assessing of interdependent Cis in a holistic manner is a prominent research topic for smart city governance nowadays. Moreover, advancements in ICT support smart cities development, but withal modern solutions bring in also new risks and cyber threads.

Most of the extant papers evaluating CIs mainly focus on classic CI systems, like: telecommunications, energy systems, water supply, emergency and transportation services, but more recently [2, 6] have included economic related systems, like: banking, finance and government services in their critical infrastructure assessments as they have a major impact on smart city evolution.

As the economic related infrastructure is considered of a critical importance in mitigating and recovering from disasters [7], this paper attempts to provide a comprehensive understanding of interconnected CIs in a holistic manner.

To better understand CIs and to support decision makers, this paper proposes a new framework that combines GIS analysis with ANN to profiling and assess the available urban CIs, considering not only traditional critical infrastructure, but also economic components like: banking, financial, governmental and commercial facilities.

To exemplify the holistic approach of urban critical infrastructure assessment and proposed framework effectiveness, a case study of Bucharest city, from Romania is included. A web geographic information system has been designed to illustrate spatial distribution of some urban system assets, relevant for urban resilience assessment.

The paper is organized as follows: Sect. 2 depicts in a holistic manner, the main attributes of urban CIs to support urban policy-makers. Section 3 introduces the novel framework developed using ANN modelling for urban CIs assessment. Proposed model applied as a case study designed for Bucharest city, from Romania is presented in Sect. 4. The 5th section concludes the findings of this research and proposes future research directions.

2 Urban Critical Infrastructure Functions to Support Urban Resilience

Critical infrastructures are complex urban systems of a high importance for the quality of humans' life, for providing essential services to households and economic activities, and the functioning of which is dependent on various internal and external factors, occurring continuously or randomly, which can cause cascade failures of the interconnected assets. Traditional CIs include electricity, water, transportation, gas and waste networks. Motivated by economies of scale, digital technologies and unequal distributions of resources and economic activities, current CIs have included communication and information systems, bank and finance systems, emergency services (police, fire rescue, medical rescue) and local administration also [6]. Nowadays, CIs have been interconnected and have evolved into large spatially distributed systems, with multiple interdependencies.

From various perspectives, CIs are considered both dependently and interdependently. Whereas dependency refers to the unidirectional relationship, interdependency infers bidirectional interactions [8]. The acknowledged types of interdependency are: physical, cyber, logical, functional, spatial, geographic, informational, policy, market and economic. Such complexity provides the conditions for generating disproportionate consequences, when particular CIs asset from one location fails.

Considering this form of interdependence, the infrastructure criticality should be analyzed beyond the scale of an individual asset. Moreover, critical geographic areas of a city have to be identified.

Spatial diversity in all dimensions, including CIs diversity, is considered an important property of a city for fostering urban resilience whereas it assures risks diffusion and shapes up learning opportunities [9]. However, two apparently contradictory views that determine the role of urban infrastructure spatial diversity exist, namely: the socio-ecological view that considers diversity helpful in reorganization of processes and systems once disrupted and the socio-technical approach in which spatial diversity is seen as a costly and inefficient strategy to develop resilience, as it could affect critical infrastructure performance, but it can mitigate the risk of damaging circumstance occurrence. Since most of the urban activities are geared towards communities residing in specific geo-locations, spatial diversity, spatial clusters and connectivity are considered determinants of urban infrastructure resilience [9].

Each urban community is unique and has its own local context, experiences, resources and beliefs regarding the prevention, protection, response and recovery mechanism from different types of disturbances. Function on the adopted standpoint and the strategy considered to foster urban resilience, each approach can be considered appropriate.

In addition, the amount and diversity of gathered data related to CIs have mostly increased due to advances in ICT technologies for acquiring, storing, processing and mining both spatial and non-spatial data. Since this data usually encapsulates hidden or hardly detectable relationships, using traditional statistical methods, a new appropriate approach is to apply spatial data mining methods that integrate artificial intelligence, machine learning and spatial statistics to identify and extract knowledge from large and heterogeneous datasets [10].

Additionally, Internet-of-things, cloud computing and embedded operational technologies are some of the areas which may cause serious disruptions in critical infrastructures, critical information infrastructures, and essential services for urban society.

In this context, a framework aiming to identify regional clusters, to assess urban CIs and to benchmark various resilient-specific measures is definitely valuable.

An increased number of research papers emerged in the past few years, attempting to better understand the CI systems diversity and their impact on urban activities and resilience, but as notice [11], among others, more research needs to be done in this direction. This paper aims to fill this identified gap in the smart city research area.

Furthermore, while there is a significant number of studies that model critical infrastructure system performance, due to their complexity, it is a big challenge to assess their resilience and their contribution to economic development [11]. This paper aims to fill this gap and introduces a new framework for CIs assessment, as the first step in the attempt to model CIs resilient conditions.

3 A Modelling Framework for CIs Assessment in Smart City Context

This section introduces the novel framework for assessing urban CIs that brings to light the extant cluster type agglomerations of CIs from the urban area.

The assessment of urban system infrastructure spatial diversity is not only a precondition for developing comprehensive methods of measurement and techniques for analyzing urban resilience, but also boost the understanding of society as part of the urban system resilience.

One challenge of this scientific approach is to identify spatially neighboring urban areas, characterized by similar features in respect to CIs, owing to the prominent complexity of CIs and the lack of fine-grained administrative datasets.

Clusters identification has been used in various studies related to smart city research area, such as: disaster analysis [12], criminology [13] and critical infrastructures [11], to explain reasons for occurrence of one phenomenon in a particular geographic area.

To account for spatial dependence among heterogeneous CIs related data, to extract pattern from available data and to identify homogeneous urban areas, from CIs standpoint, the following methodology has been designed:

1. All infrastructural assets were mapped and a spatial distribution of CIs has been accomplished. To reveal the geographic density of CI features a heat map was built up for each significant critical infrastructure sub-system. Relevant critical infrastructure assets considered for this study are: public transportation infrastructure, road network, emergency infrastructure: hospitals, police office, bank services: bank establishments, ATM, public administration establishments, and other point of interest: parks, schools and commercial centers.
2. To discover multivariate clusters from unstructured CIs data, a self-organizing map, namely the GeoSOM method was employed.

Self-organizing map (SOM) artificial-neural networks method uses unsupervised learning approach for training and discovering data patterns with the aim to mitigate data-dimensionality and to generate a two-dimensional representation of input datasets, while maintaining the input datasets topology. Unlike other ANN methods, which use error-correction learning approach, SOM method employ competitive learning that maintains the topological properties of the input datasets, including spatial characteristics [14].

Even there is a significant number of algorithms available for clustering analysis, only very few neural network related clustering algorithms consider spatial characteristic of data. The most prominent adaptation of self-organizing network algorithm is Geo-Self-Organizing Maps (GeoSOM) [15].

GeoSOM is a proximity-aware alternative algorithm of the standard SOM. GeoSOM uses geo-coordinates to establish the geographic tolerance parameter, which is used to maintain the geographic vicinity of similar data objects, by mapping them to neurons. GeoSOM spatial clustering method groups neighboring observations into clusters, to maximize similarity within cluster, while the similarity between clusters is minimized [14]. The method is available as part of the SPAWNN [15] toolkit.

For this research purpose, the CIs related data was mapped onto 8×12 neural network, and such generating a two-dimensional matrix of 96 neurons. Considering the observation number (3994) the resulting feature map is considered medium-size [15], and such multiple data observations could be mapped to each neuron, generating regions with more general characteristics.

The output of the GeoSOM algorithm is an attribute map that group items with similar attribute values into neighboring regions of neurons. A correlation analysis can be further performed, to identify and evaluate the associations between different attributes of the CI datasets.

As spatial distribution is a prominent characteristic of CIs components, GeoSOM method is appropriate for this research purposes.

3. Finally, the outcome of modelling process is linked back to urban geographic space providing a comprehensive understanding of the extant CIs. The pairwise difference between and within identified clusters is evaluated to ensure clusters validity. So that the identified sub-regions maintain both spatial continuity and similarity of non-spatial attributes of CIs. Modeling infrastructure allows to systematically evaluate the consequence associated with the loss of infrastructure components and to benchmark the impact of various policy measures.

4 CIs Assessment - Empirical Study of Bucharest City

The aim of this section is to evaluate Bucharest city's CIs by applying the proposed model to identify homogenous city sub-regions or clusters [16]. Data sets used for this case study were provided by ESRI Romania and include geographic coordinates of points of interest (POI).

Besides typical critical infrastructure, this case-study has considered so-called infrastructure for economic and administrative activity also. So that, a total of 3994 POIs have been included in the analysis, namely: public transportation stations (including maximum capacity in each point), bank system establishments (bank, ATM), governmental institutions (public institutions, Police office), schools, parks, hotels, hospitals and commercial centers.

Firstly, each type of critical infrastructure was evaluated considering spatial distribution of infrastructure assets. Figure 1 exemplifies public transportation infrastructure distribution for Bucharest city, where the green dots represent spatial distribution of public transportation stations considering both geo-location and the maximum capacity available in each station. The CIs features heat map presented in Fig. 4 distinguishes urban areas that holds spatial density of each CI resources.

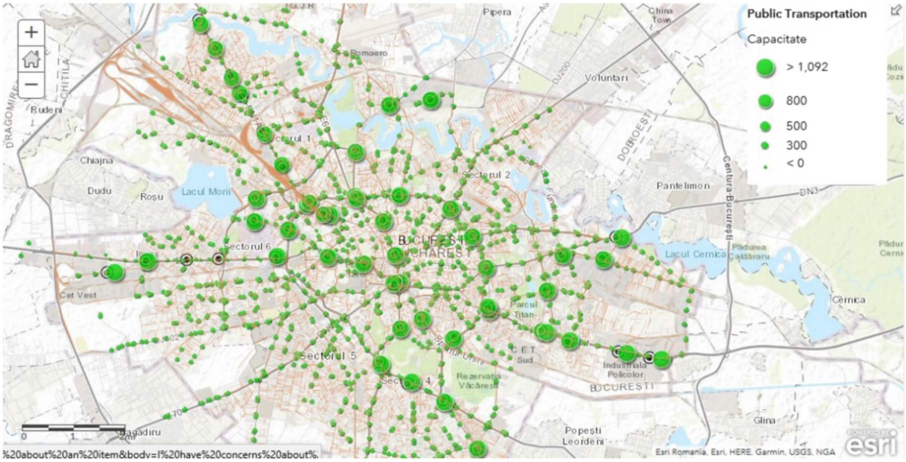

Fig. 1. Public transportation infrastructure (bus, tram and metro stations) – including available transportation capacity (Color figure online)

Secondly, ANN modelling was performed for the interconnected CI systems. Geo-SOM ANN method was applied and Fig. 2 presents the aforementioned method outcomes. The resulting output matrix reveals ten clusters of CIs, with different sizes.

Ten CIs clusters have been identified, mapped and laid out in the online GIS application, as depicted in Fig. 3. Each of the resulting urban sub-regions is characterized by internal homogeneity with regard to the non-spatial feature of CIs.

Due to the great diversity of data patters, only 501 out of 3994 CI features could be clustered. Figure 3 depicts discovered clusters in the Bucharest city and represents urban regions characterized by similar feature values across all variables of CIs, using various colors. Geo-coordinates are used to define the proximity of observations and the contiguity of urban clusters.

The largest identified cluster is figured in Fig. 3 as C1 and could be generally described as a region with a dense and high-capacity public transportation network, holding mixed points of interest like: commercial centers, public schools, hospitals, parks. The second is the cluster named C2, mainly holding both very big financial network and public transportation infrastructure. On the 3rd place is C3 cluster with numerous public and financial institution establishments. The C4 cluster is on the 4th position; it

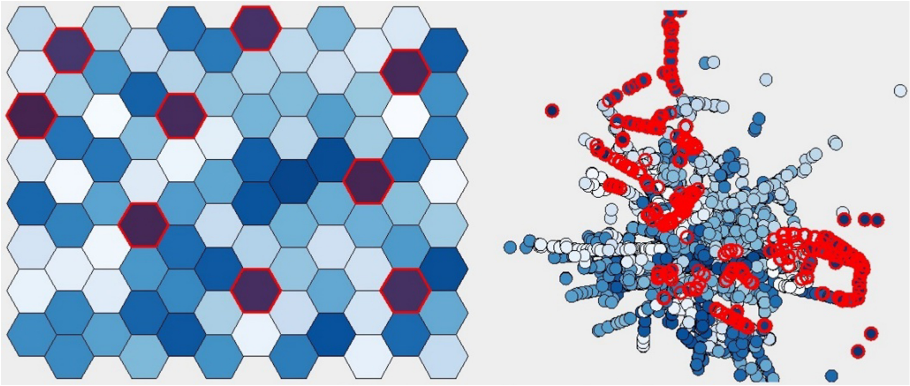

Fig. 2. Distance matrix and cartographic map of the GeoSOM algorithm and SPAWNN tool

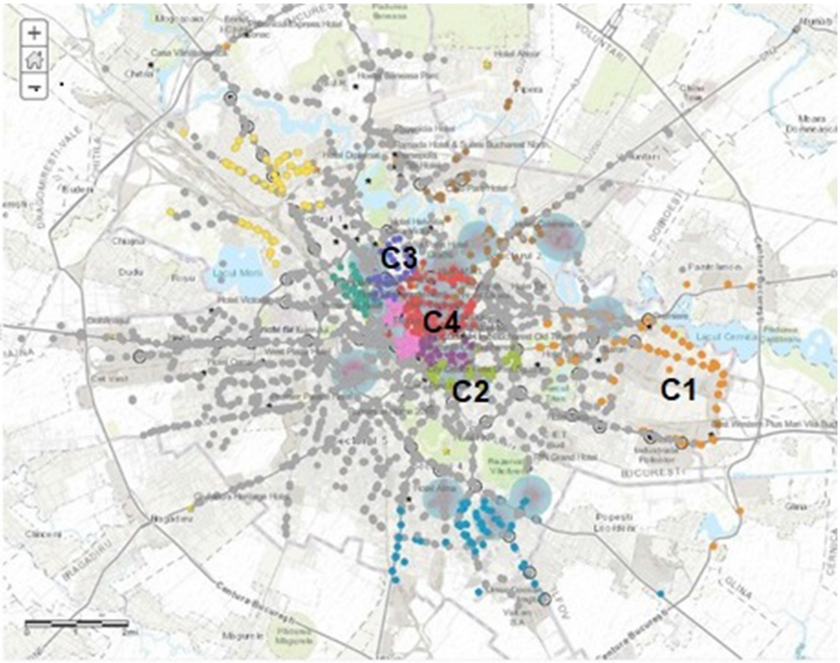

Fig. 3. City sub-regions resulting from the projection of the GeoSOM clusters onto the geographic space of Bucharest

is located in the very center of the city and it hosts mainly a combination of financial institutions, hotels and public transportation features. Definitely, future research needs to be done to determine the influence of each cluster on urban resilience and economic development of the city.

The resulting urban clusters reflect various dimensions of CIs, both geographically and indicate neighboring urban areas where infrastructure components with similar characteristics are available in a large extend.

Figure 4 introduces a snapshot of online GIS application developed to assist policy-makers and analysts to support their decisions as it can be helpful in identifying dependencies between local critical infrastructures.

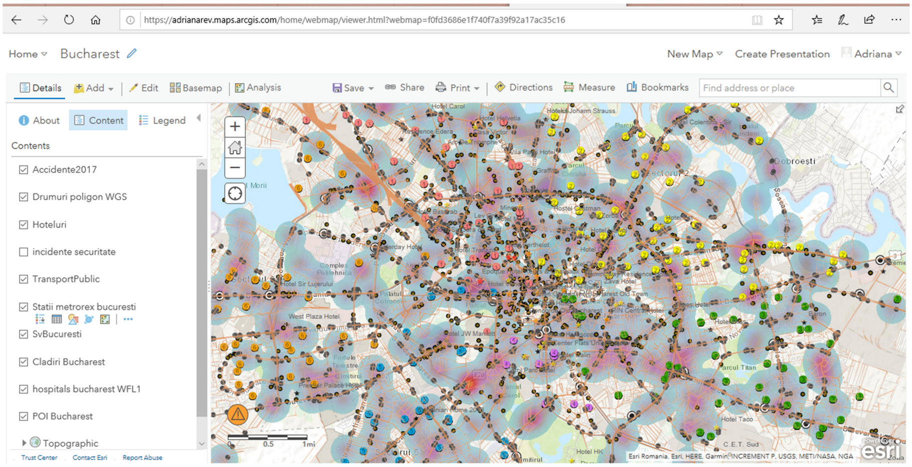

Fig. 4. A snapshot of online ArcGIS solution CIs assessment

Although the focus of this paper is on supporting interaction between local critical infrastructure within the Bucharest city this framework can be correspondingly customized and used for other urban areas.

5 Conclusion and Future Research Direction

As smart city well-being is dependent on critical infrastructure security, the subject of this paper is a prominent topic for smart city and governance research area, nowadays.

The contribution of this paper is twofold. Firstly, using the lens of GIS and ANN this paper proposes a novel theoretical model for assessing extended critical infrastructure of an urban area, using clustering modeling of spatial and non-spatial characteristics of CIs. The model can be extended and other urban resources can be included to determine the profile of urban-sub regions. This is an essential approach towards urban resilience aiming to enrich the available methods for urban resources assessment.

Secondly, this paper proposes a practical framework, including both online GIS and machine learning model techniques, to identify homogeneous sub-regions in a city.

This paper highlighted the importance of CIs clustering in heterogeneous urban areas towards setting-up appropriate resilient policy. The findings of this paper can be valuable for policy makers in their attempt to benchmark and develop appropriate resilient measures and to prioritize the financial resources available.

Further research will investigate if the identified homogeneous urban areas can be considered significant predictors of urban resilience.

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