FP7 2013 Cooperation Work Programme
Theme 6: Environment (Including Climate Change)

Novel indicators for identifying critical
*INFRA*structure at *RISK* from Natural Hazards

Deliverable D6.5

The wider economic impact of a natural hazard: An agent based approach

Primary Author	Francesca Medda, Miao Wang/University College London (UCL)
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Project Coordinator:

Professor Eugene O' Brien
Roughan & O’ Donovan Limited
eugene.obrien@rod.ie

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Partners:

Roughan & O’ Donovan Limited, Ireland

Eidgenössische Technische Hochschule Zürich, Switzerland.

Dragados SA, Spain.

Gavin and Doherty Geosolutions Ltd., Ireland.

Probabilistic Solutions Consult and Training BV, Netherlands.

Agencia Estatal Consejo Superior de Investigaciones Científicas, Spain.

University College London, United Kingdom.

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Ritchey Consulting AB, Sweden.

University of Southampton (IT Innovation Centre), United Kingdom.

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Executive Summary

This report develops a methodology to estimate the wider economic impacts of road network disruption caused by natural hazards. In this report, an agent-based model is developed to simulate the indirect consequences of the natural hazard to the transport infrastructure system. By making novel use of the origin-destination travel demand data, a connection between travel demand and regional productivity is set up for the purpose of quantitatively estimating the indirect economic impacts such as economic loss caused by business, production and consumption interruptions due to the natural hazard.

Our findings demonstrate that the disruption of the road network in a natural disaster area has significant economic impacts on the non-disaster exposure area, where no direct impact such as road, building and property damages can be observed. The degree of economic impacts not only depends on the intensity of the natural hazard and cities' distance to the disaster exposure area but also the cities' economic status as well as the recovery time of road network, the time period from the occurrence of the natural hazard to the time when roads network fully recovered its functionality . This confirms that an earthquake significantly impacts on regional economies as well as the national economy as a whole through the disruption of the road network.

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1.0 INTRODUCTION

1.1 The context

Natural hazards have costly and long-lasting social and economic effects on societies (National Research Council, 1999). In relation to climate change, more frequent extreme natural hazard events have intensified the consequences regarding negative social and economic impacts (Ash and Newth, 2007). Moreover, not only is the natural hazard exposure area itself significantly impacted, but also are geographical areas reaching far beyond the impact zone. Take for an example; evidence shows that the Great East Japan Earthquake impaired 90% of companies in non-affected areas through inter-company transactions (Carvalho et al., 2014; Yukiko, 2012).

In the infrastructure context, given its structural and functional interdependencies, natural hazards have the capacity to trigger a sequence of 'secondary hazards' (Buzna et al., 2007), and therefore causes the indirect consequences. For example, on 11 March 2011, a 9.0 magnitude earthquake followed by a 100-foot tsunami hit the coast of Japan. As a consequence, the giant wave severely damaged the Fukushima nuclear power plant. The chain of calamity now known as the 'Triple Disaster,' killed more than 18,000 people, caused approximately $US 360 billion in building damages, and resulted in a 6-8% reduction in Japan's total production (Matanle, 2011).

In relation to infrastructure management, Kelly (2015) credits the importance of quantifying the economic impacts of the indirect consequences of natural hazards. Researchers have, for example, analysed the indirect economic impact on the transport system. In particular, using regional Input-Output tables, Buyck (2008) estimated the economic loss of a transport corridor due to an unexpected event. Similarly, Xie et. al. (2014) through the use of a computable general equilibrium (CGE) model, quantified the indirect economic impact triggered by disrupted transportation in the Hunan province after the Great 2008 Chinese Ice Storm. hese studies follow the established methods for post-event natural hazard impact investigation (Carrera et al., 2015; Rose, 2004; Rose et al., 1997; Tsuchiya et al., 2007), but a noteworthy limitation of this research approach is that they focus mainly on a specific natural hazard and a circumscribed disaster exposure area. The indirect economic impact in *non-disaster-affected* areas, however, remains largely unexplored. In our context, the indirect economic impact of natural hazards that includes the indirect economic impact at the non-disaster affected area is defined as the wider economic impact.

1.2 Deliverable Objective

The objective of this deliverable is to evaluate the wider economic impacts of a natural hazard on road infrastructure. Specifically, taking Italy as a case study, we analyse the wider economic impacts of an earthquake event in Bologna on Italy's road infrastructure system. The research is developed by three main questions:

1. How can the indirect consequences for a road infrastructure system due to a natural hazard be presented?
2. How can we calculate the wider economic impacts of the Italian road infrastructure system under a natural hazard scenario in a specific area?
3. How does the delaying of the individual road infrastructure component restoration affect the regional and national economy?

To address these objectives, we integrate an agent-based infrastructure response simulation model with an economic model. We examine the wider economic impacts under different scenarios of varied individual infrastructure components' restoration time.

1.3 Structure of the study

Figure1.1 sets out the general framework of the study, consisting of data, models, and applications.

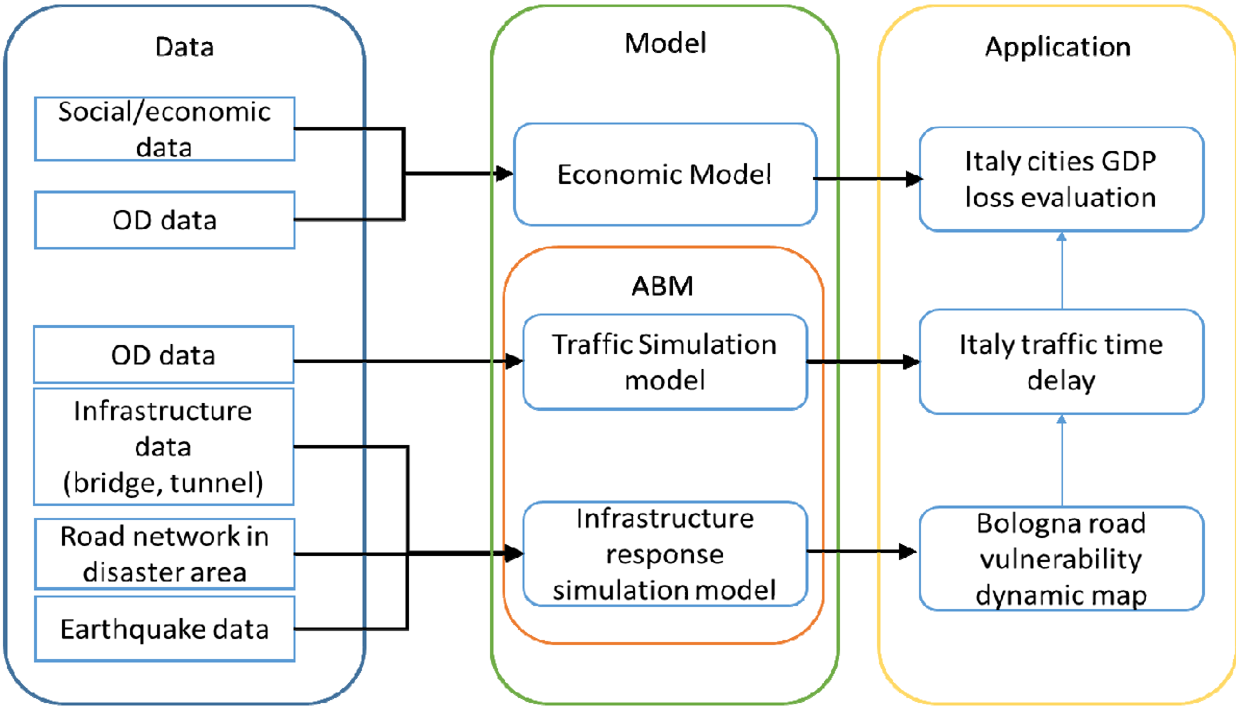


Figure 1.1: Structure of the study

The data for the study includes both the geographical, socio-economic data and infrastructure data of the study area, which will be described in detail in Chapter 2.

The model is comprised of the agent-based model (ABM) and the economic model. Applying ABM is because such a model can simulate the scenarios of the earthquake event's indirect consequences. The economic model can estimate the wider economic impacts of the earthquake event. The ABM consists of two sub-models: (1) Infrastructure response simulation model and (2) Traffic simulation model. The Infrastructure response simulation model is fundamental because it provides the physical road network condition after the earthquake event, thus giving the background for the post-event road network traffic simulation. Whereas the Traffic simulation model replicates traffic conditions after an earthquake. As a result, the travel times between cities (of each OD link) can be estimated. We use the estimation of travel time delay of each OD link in the economic model to calculate the wider economic impacts of the earthquake-induced road disruption. The activity of the 'Model' phase is introduced in Chapter 3.

The model developed is applied to an example of an earthquake scenario in Bologna, for which the results and analysis are demonstrated in Chapter 4.

Our analysis is structured such that we carry out the economic assessment for scenarios of different disaster management options, and in doing so, we return to our three basic questions.

In order to analyse the indirect consequences of an earthquake on the Italian road system, it is assumed that the response behaviour of each component of the infrastructure system (bridges, tunnels, road traffic) to the earthquake would induce road network disruption. We then calculate the traffic delays caused by the earthquake-induced road network disruption. We presume that the traffic delay will not only appear in the disaster exposure area, where direct damage and losses due to the natural hazard can be observed, but it will also occur in the non-disaster affected areas spanning the connected road network.

To answer question two, we examine any changes in GDP due to the travel time delay after a natural hazard. We hypothesise that cities near the disaster area have a higher travel time delay due to a natural hazard and thus will result in higher GDP loss.

To address our third question, we conduct a sensitivity analysis on the restoration duration of individual bridges and tunnels in order to see how the network elements' restoration duration will affect GDP loss. We hypothesise that the longer the restoration duration of the individual components is, the larger the economic loss will be. However, the entire network system's recovery time is nonlinear to the increase of restoration time and therefore the increase of economic loss along with the restoration time is/will be non-linear too.

Our next steps are to elaborate the research specification and data, introduce the development of ABM and the economic model, and describe how the model is applied to an example study of an earthquake in Bologna, Italy.

1.4 INFRARISK work package connections

The study is for INFRARISK work package 6: Stress tests for multi-risk scenarios. Specifically for WP6.5 A toolkit for scenario analysis. The tool kit for scenario analysis first should be able to simulate multi-hazard scenarios and at the same time have the function of assessing the consequences of multi-hazard scenarios. The ABM model developed in this research is capable of simulating multi-hazard scenarios for the purpose of stress testing. Furthermore, a novel economic indicator named wider economic impact is established for assessing the consequences of multi-hazard scenarios.

The research follows INFRARISK work package 4's terminology and risk assessment framework.

For developing –multi-hazard scenario simulation model, we use the research result of INFRARISK work package three relating to infrastructure fragility function and general restoration function. We also use the traffic model methodology from INFRARISK work package 5 for simulating traffic conditions after a natural hazard under different operation assumptions.

This study is mainly focusing on testing a new methodology for analysing the wider economic impact of natural hazards for the project case study in INFRARISK work package 8, in which a complete stress testing under multi-hazards scenarios would be presented.

2.0 DATA

2.1 Data collection

The data for our research is at both urban and national level. At the urban level, as shown in Fig. 2.1, Bologna is considered as an earthquake-prone area. Related geographical data, road network, and bridges and tunnels data are integrated for simulating the Bologna road network disruption scenario under a seismic load. At the national level shown in Fig. 2.2, traffic data of Italy's 90 cities (listed as Eurostat NUTS 3 cities) (ETIS-PLUS, 2012b) are used to simulate Italy's post-event traffic conditions. The earthquake's wider economic impacts on Italy's 90 cities and 8100 Origin-Destination links are estimated according to the cities' economic data. In Section 2.2, we will first describe the area of Bologna. In doing so, we will examine: (a) economic city context, (b) earthquake data, (c) road network data, and (d) bridge and tunnel data. We will thereafter describe the data at the national level in Section 2.3.

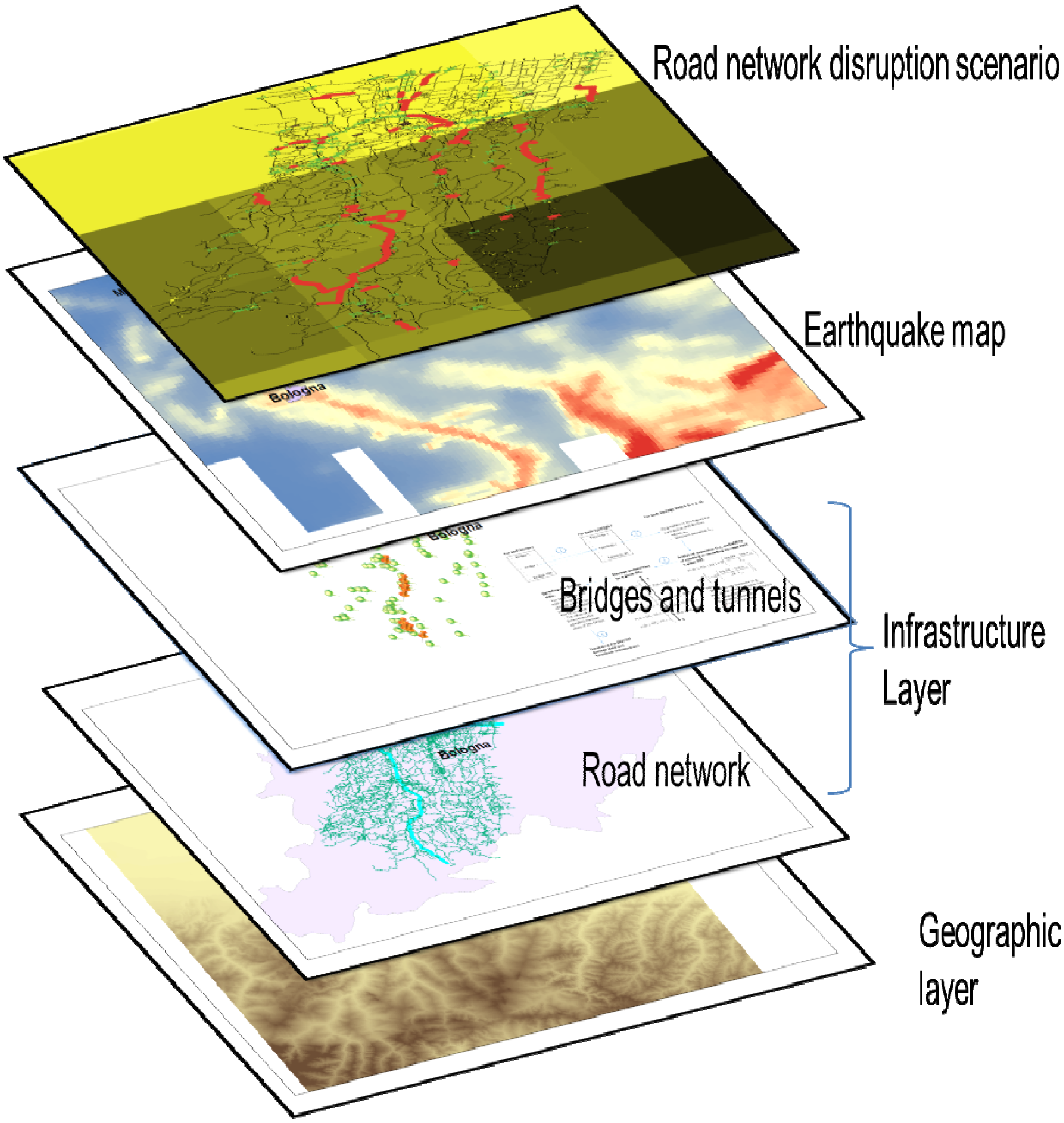


Figure 2.1: Simulation of Bologna road network disruption scenario

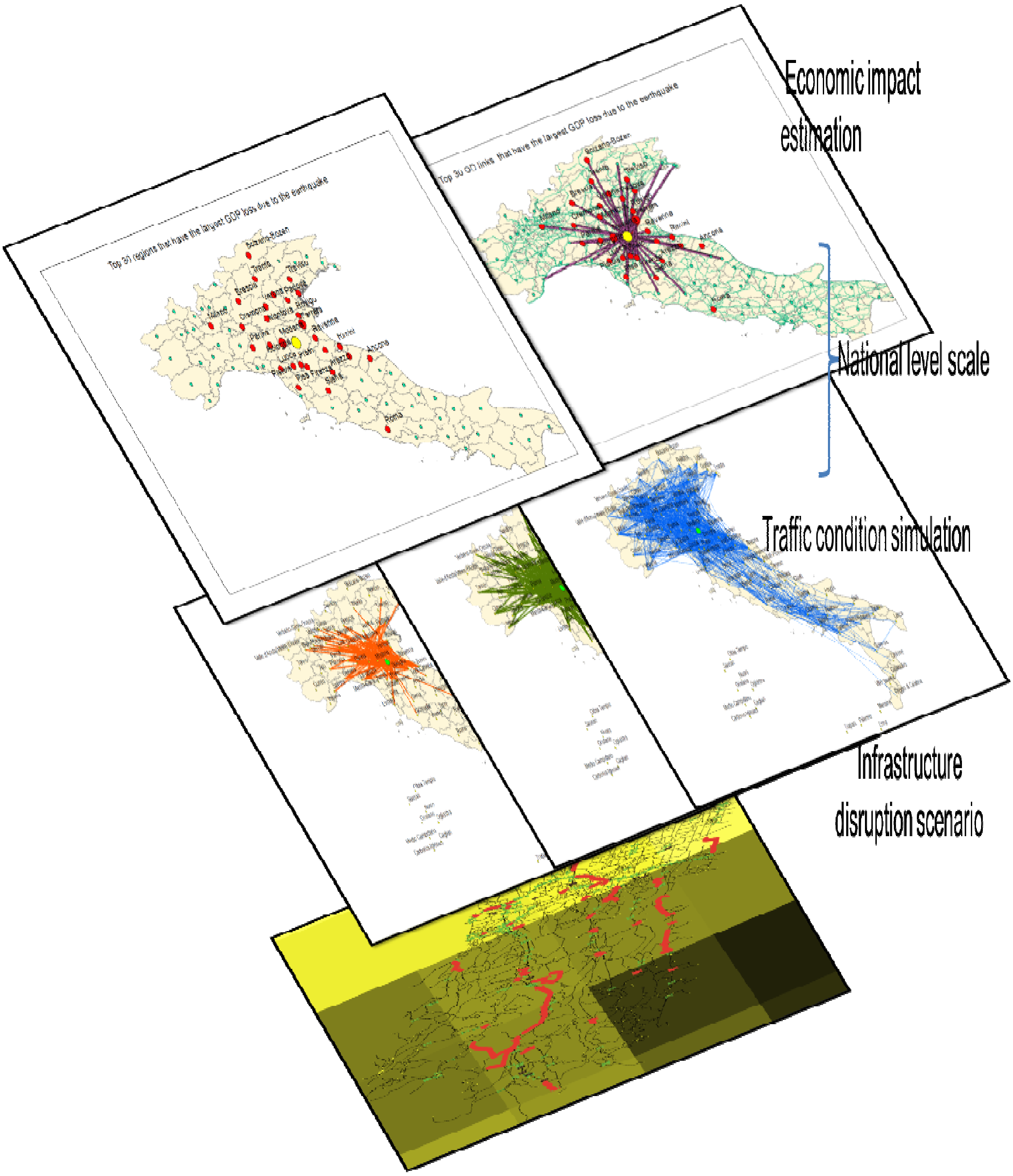


Figure 2.2: Traffic condition simulation and wider economic impact evaluation in Italy at the national level

2.2 Bologna data

2.2.1 Economic city context

The metropolitan city of Bologna is situated in the region of Emilia-Romagna in north central Italy. Bologna is bounded by the province of Ravenna to the east, the province of Ferrara to the north, and the province of Modena to the west. The metropolitan city of Florence, the province of Prato, and the province of Pistoia are in the south. The territory of Bologna covers an area of 3,702 km^2 with a population of 1.004,615 in the year 2015 (Bologna City Council, 2015).

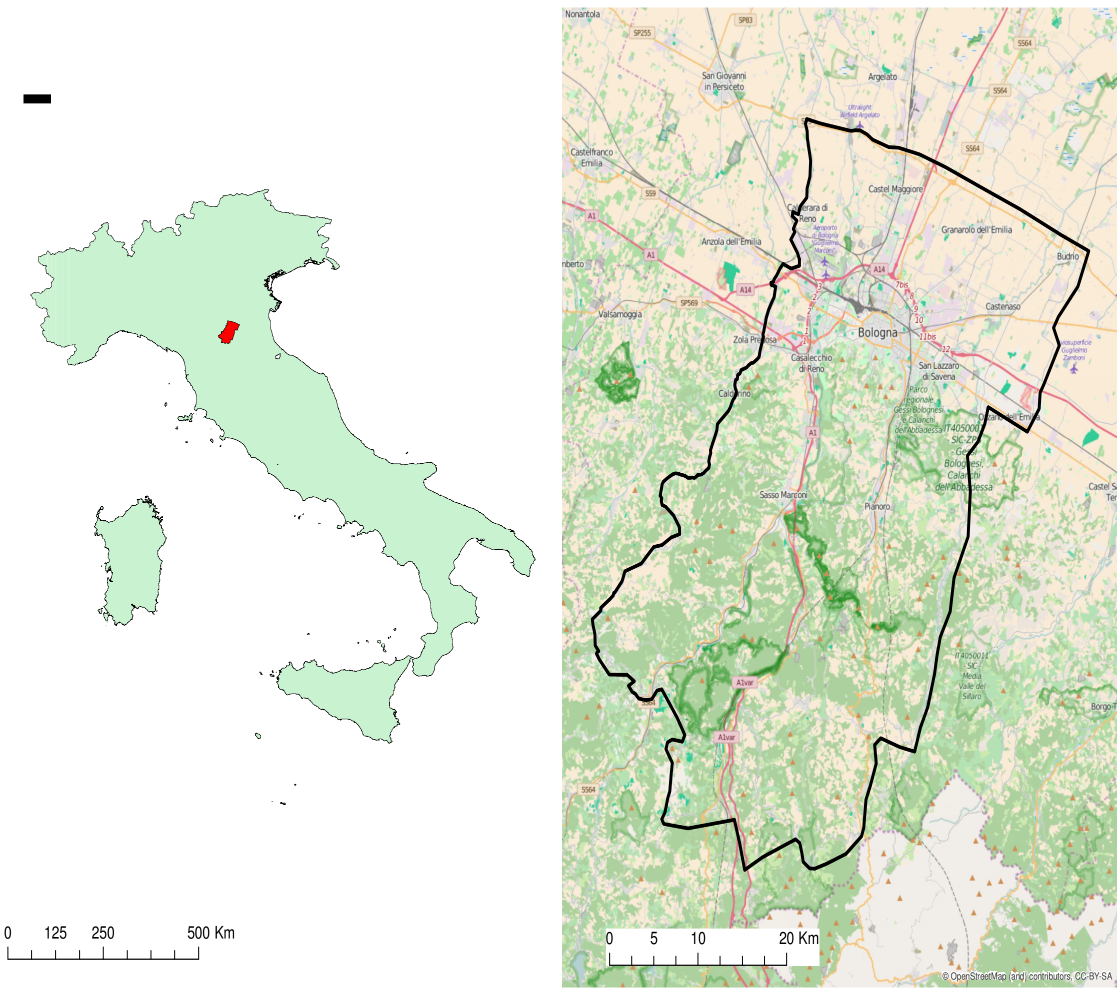


Figure 2.3: The location of Bologna in Italy

The city of Bologna has a strategic position in Italy. As an important cultural centre, it has the oldest university in the world. Education levels have reached significant figures, both as a percentage of total citizens with school graduation (60%), and regarding a university degree (26.2%). Bologna was also declared the 'city of music' by UNESCO in 2006 and the 'European capital of culture' in 2009. Bologna is also one of the wealthiest cities in Italy, often ranking at the top. Regarding quality of life in the country, it ranked 1st out of 107 Italian cities in 2011.

Alongside its cultural tradition, Bologna is one of the most important business cities in northern Italy. Its economy is based on key industries of manufacturing, business such as mechanics, textiles, food production, and engineering, particularly automated machinery. The city itself is known as an important centre for business and hosts numerous international exhibitions, ranging from motor shows to fashion and architecture. There is considerable retail and wholesale trade based around the CenterGross, a large-scale organised trading district for entrepreneurs and small businesses, particularly those in clothing and fashion. Bologna is also a popular tourist destination. It has the second-highest per capita GDP in Italy (€34,458), which accounts for an estimated one-third of the Emilia-Romagna region's GDP (EUROCITIES-NLAO, 2011). Bologna's GDP is ranked 6th highest of all major cities in Italy (Fig. 2.4).

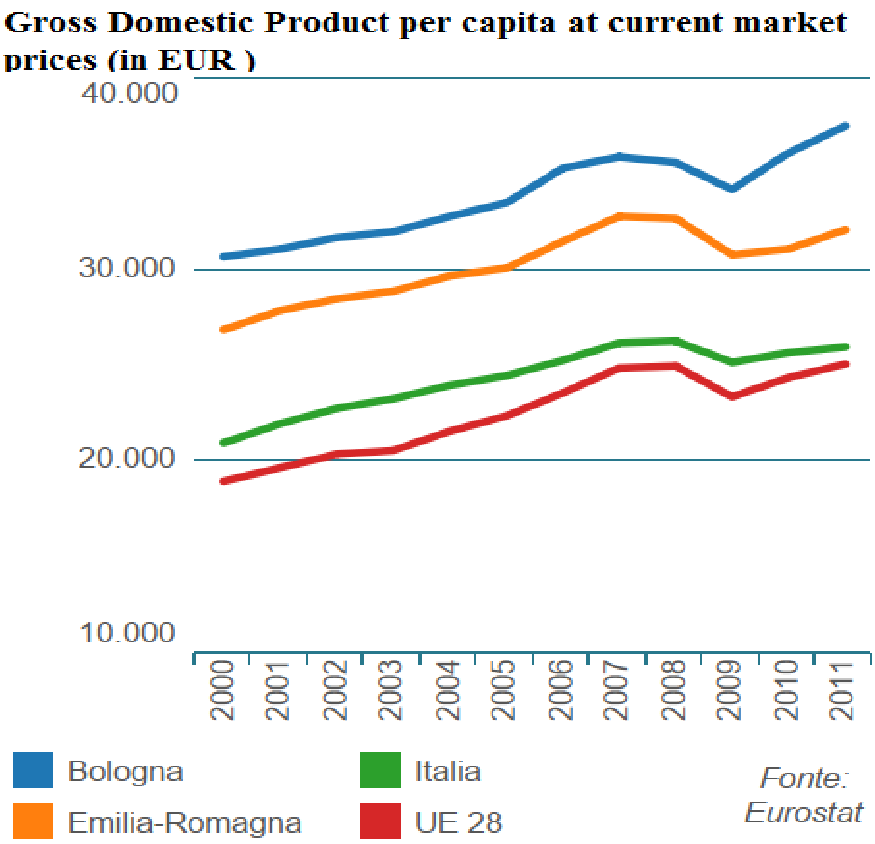


Figure 2.4: Bologna GDP per capita at current market prices (in Euros) (Bologna City Council, 2014)

2.2.2 Earthquake data

Italy has a long history of earthquakes due to its being situated at the meeting point of the Eurasian Plate and the African Plate, where considerable seismic and volcanic activity takes place. Northern Italy is not the most active in terms of earthquakes, but Bologna has experienced noteworthy earthquakes over the years, such as in May of 2012, when Bologna suffered two major earthquakes of magnitude 5.9 and 5.2 (USGS, 2012). The strong and unusually shallow earthquakes resulted in 26 losses of life and the destruction of 14,000 people's homes.

The earthquake data used in the present deliverable is based on the seismic hazard map accessed from the European Commission FP7 SHARE project, which has produced a seismic hazard map for the whole of Europe (Giardini et al., 2014). Figures 2.5 shows, respectively, the seismic zone map and the 10% probability of exceedance within the next 50 years on a 15 km resolution grid. The map indicates that, although Bologna is not in the highest seismic risk area (represented by the colour red), a medium level of earthquake risk is nevertheless indicated in this area. We will apply the seismic map as the seismic load for the simulation scenarios.

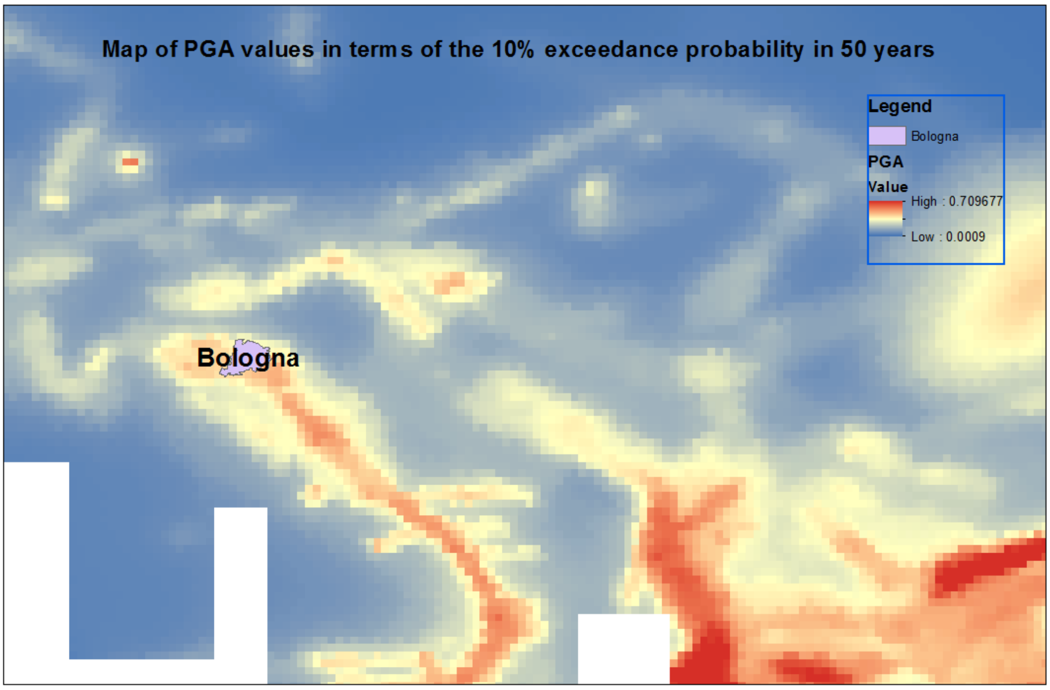


Figure 2.5: Map of PGA values regarding the 10% exceeding probability in 50 years (The PGA value, Peak ground acceleration , is the measurement of the intensity of an earthquake) (Giardini et al., 2014)

It has to be mentioned that, this study focuses on exploring the methodology for evaluating the wider economic impact of a natural hazard, here we take SHARE Project PGA map as an example. Actually, in INFRARISK project, a special earthquake scenarios simulation tools has been developed shown in INFRARISK work package 3.1. In INFRARISK work package 8.2, a holistic probabilistic earthquake risk analysis on Bologna case will be presented.

2.2.3 Road network data

Bologna is an important juncture for goods and people in Italy due to its central location between Milan, Venice and Florence. Bologna is crossed by five major rail routes and four motorways and is a vital national and European freight transport hub. The city is situated on the North-South line of traffic, i.e. 75% of goods transiting between the North and South of Italy pass through Bologna (Promo Bologna, 2010). Bologna also carries 35% of goods passing through Italy and 16% of the ever-increasing flows of Continental traffic (Interporto Bologna, 2010). Regarding logistics-related activities, 90% are dedicated to road transport (Promo Bologna, 2010).

Following on the INFRARISK research on Italy case study relating to natural hazard and transport modelling (WP5), the study area in this research comprises a 989 km² region of Emilia-Romagna, surrounding the city of Bologna, intersected by the Autostrada del Sole, Autostrada Bologna-Padova and Autostrada Adriatica. The main road network is the Italian Motorway, which forms part of the European TEN-T network. The TEN-T network has been identified by the European Union as a vital component of the transport network. Our road network data has been accessed from Open Street Map (Haklay and Weber, 2008).

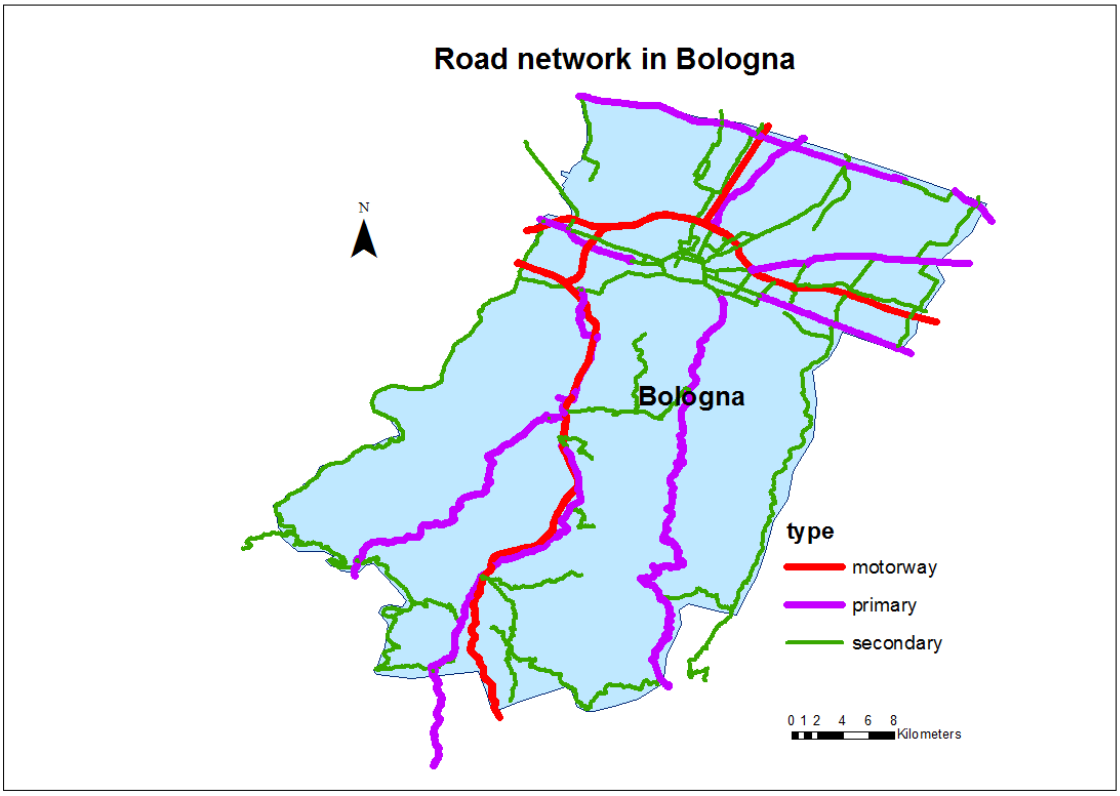


Figure 2.6: Road network in the province of Bologna (Haklay and Weber, 2008)

2.2.4 Bridge and tunnel data

The infrastructure of the road system, 340 bridges and 30 tunnels, depicted in Fig. 2.7 has been extracted based on Open Street Map, more details of the bridges and tunnels extraction can be found in Deliverable WP8. The typology of bridges and tunnels is an important variable deciding the damage states of bridges and tunnels under a given seismic load. These typologies are provided INFRARISK sampling database (Gavin and Martinovic, 2014).

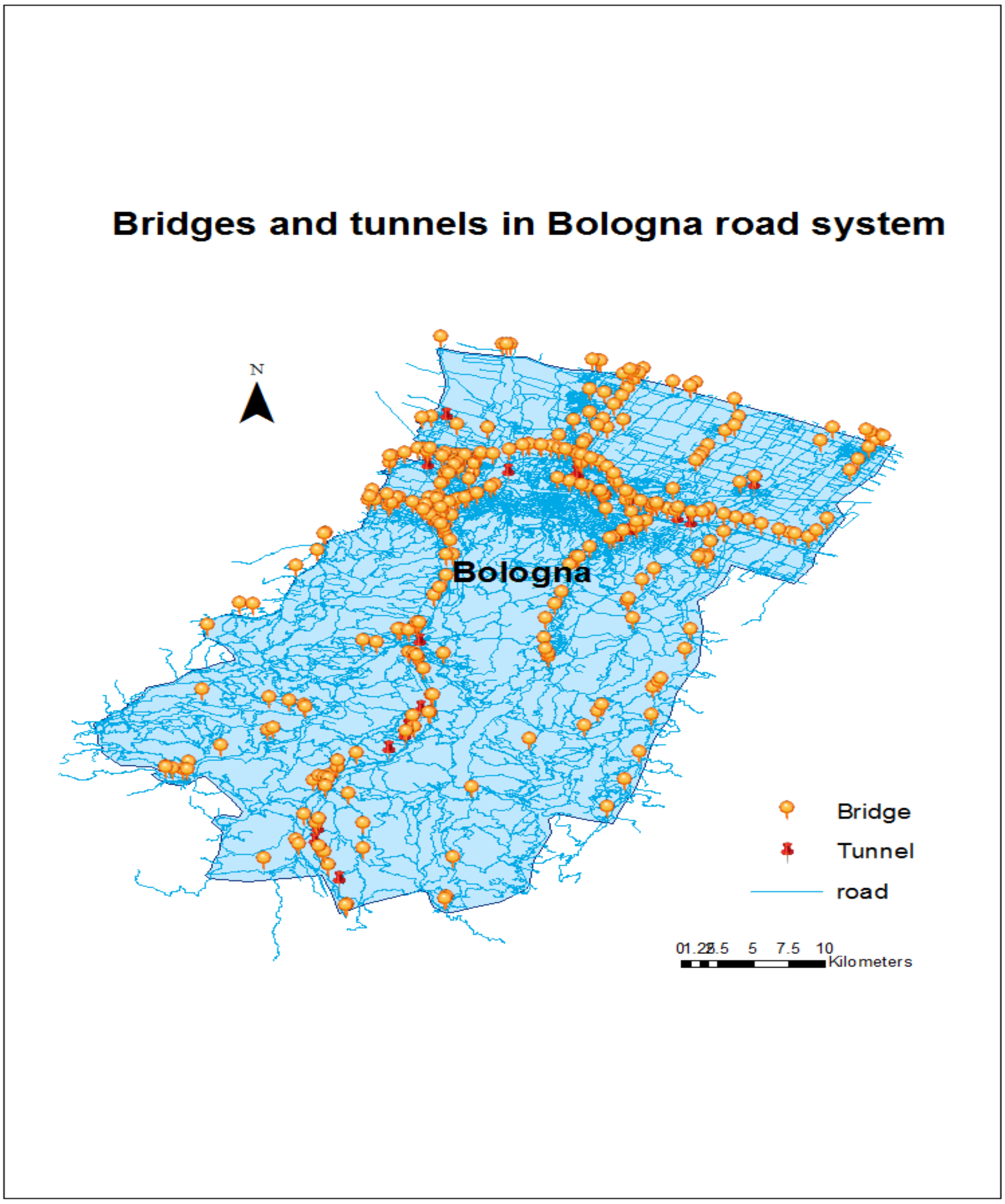


Figure 2.7: Bridges and tunnels in the Bologna road network (Gavin and Martinovic, 2014)

2.3 National level data

To include the wider economic impacts of an earthquake we have assumed that the earthquake will impact areas beyond the disaster exposure area, so we estimate the wider economic impact at national level and for this purpose Italian road network and economic data are collected.

2.3.1 Italian road network

Data on the national road network (Fig. 2.8) is accessed from the ETIS-plus European FP7 project, which aims to provide good quality, integrated transport data for the whole of Europe (ETIS-PLUS, 2012a). A detailed description of the national road network data can be seen in INFRARISK Deliverable 5.3.

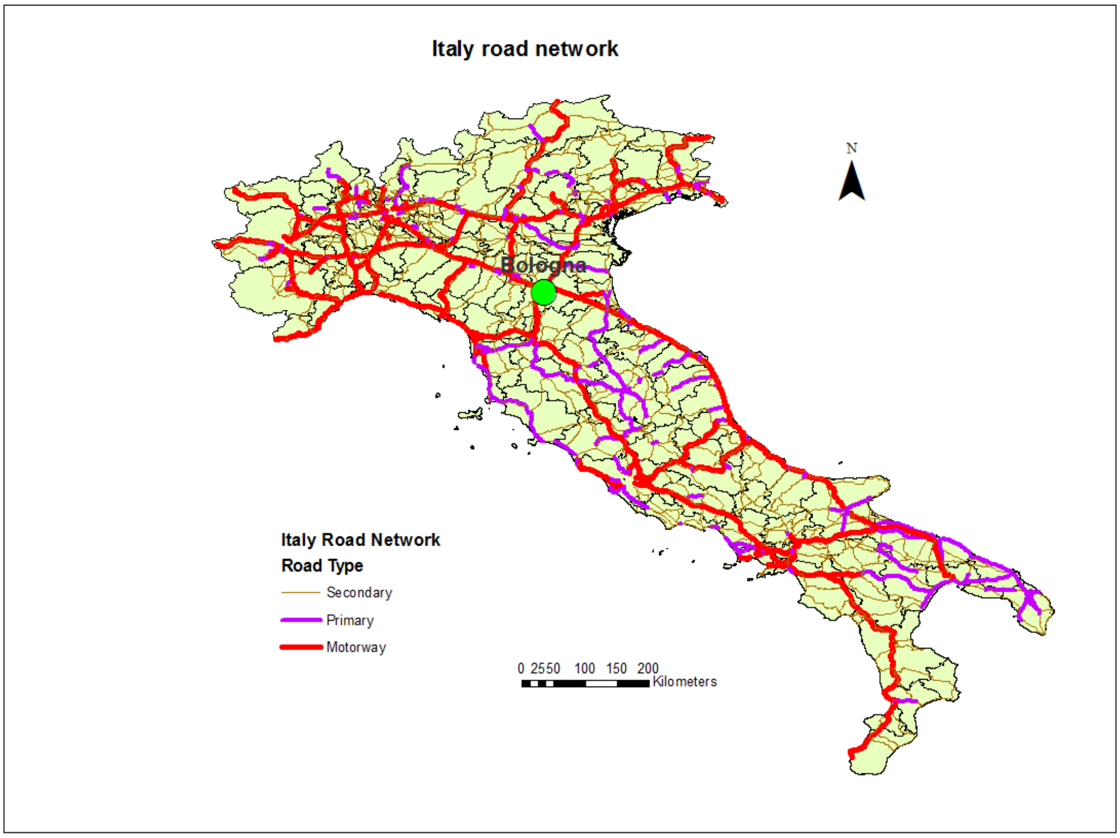


Figure 2.8: The Italian road network

2.3.2 ETIS Origin-Destination Data

We introduce Italian roads at a national scale in order to examine the consequences of disruption to the network using a traffic equilibrium model. This modelling approach requires traffic data details of origin and destination of journeys and number of journeys taken between these same origins and destinations. Our traffic data consists of Origin-Destination (OD) information between cities in Italy. In the ETIS dataset (ETIS-PLUS, 2012b) 90 cities are situated in mainland Italy (Fig. 2.9).

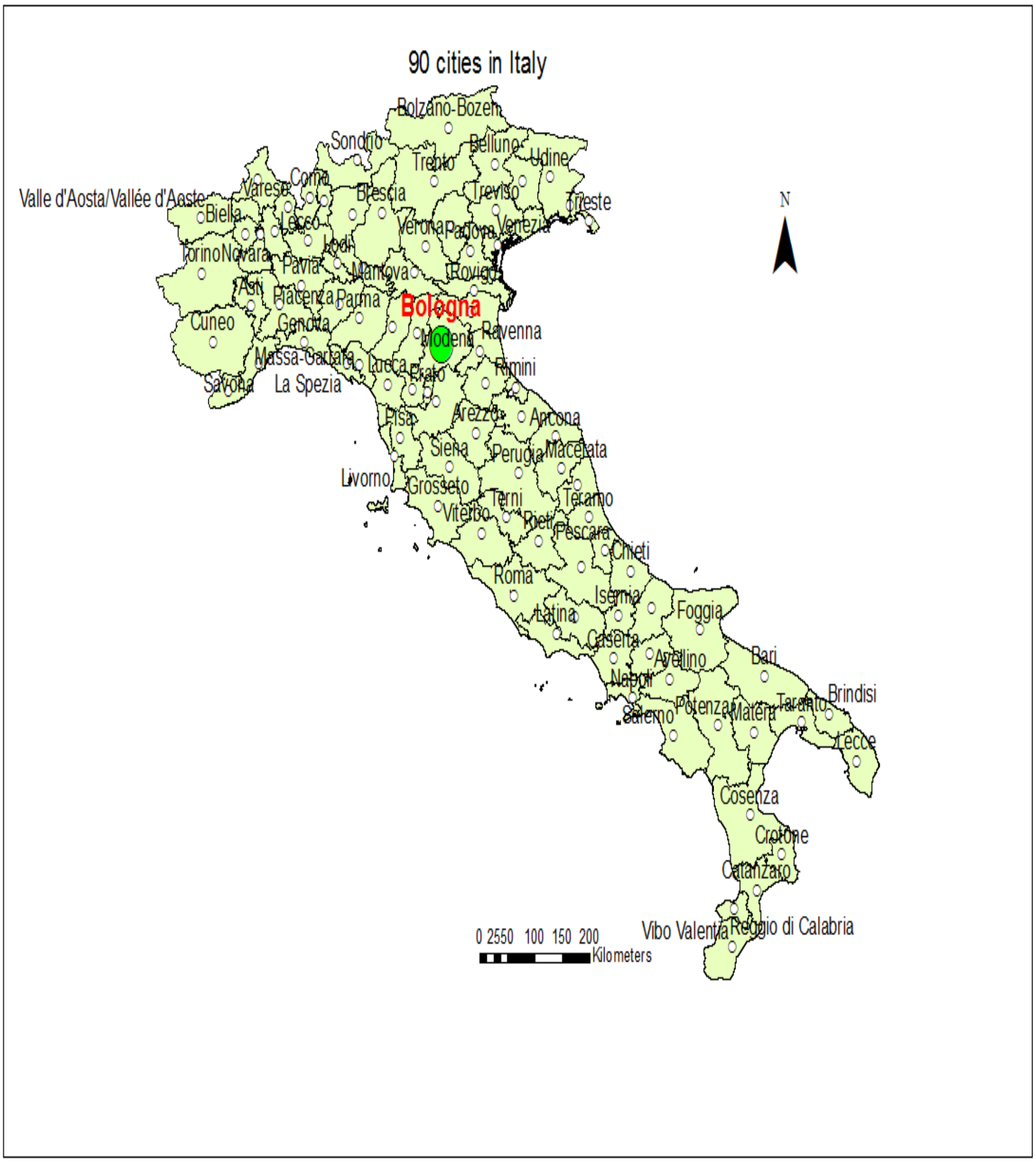


Figure 2.9 The 90 Italian mainland cities included in the Origin-Destination dataset Source: (ETIS-PLUS, 2012a)

Our data is observable in the form of an OD matrix with trips distributed between cities (zones), a detailed description of the OD data can be found in INFRARISK Deliverable 5.3.

2.3.3 ETIS city social, economic data

ETIS-Plus provides the social and economic data of 90 cities in the year 2010, including city GDP and population (Table 2.1).

ID	City Name	Region	GDP (million Euro)	Population (thousand)
1	Milano	Lombardia	144833.1	3854.1
2	Roma	Lazio	124491.6	3820
3	Torino	Piemonte	61725	2239.9
4	Napoli	Campania	48305.1	3089.7
5	Brescia	Lombardia	35426.6	1175.8
6	Bologna	Emilia-Romagna	31229.3	947.1
7	Bergamo	Lombardia	30869.7	1028.1
8	Firenze	Toscana	29119.4	966.4
9	Bari	Puglia	27035.4	1594.7
10	Padova	Veneto	26288.1	886.8
11	Verona	Veneto	25452.6	865.5
12	Vicenza	Veneto	24279.3	835
13	Treviso	Veneto	24154	844
14	Venezia	Veneto	23689.1	830.9
15	Varese	Lombardia	23412.2	845.9
16	Genova	Liguria	22565.2	883.3
17	Modena	Emilia-Romagna	20489.1	662.6
18	Salerno	Campania	17508	1090.4
19	Cuneo	Piemonte	16439.2	570.9
20	Bolzano-Bozen	Provincia Autonoma Bolzano-Bozen	15078.8	479.9
21	Perugia	Umbria	14831.9	636.4
22	Reggio nell'Emilia	Emilia-Romagna	14741.6	490.6
23	Como	Lombardia	14401.7	563.9
24	Trento	Provincia Autonoma Trento	14202.2	500
25	Udine	Friuli-Venezia Giulia	13839.4	529
26	Caserta	Campania	13238.9	883.1
27	Pavia	Lombardia	12558.7	513.1
28	Parma	Emilia-Romagna	12477.9	415
29	Ancona	Marche	12165.4	462.9
30	Mantova	Lombardia	12005	392.3
31	Lecce	Puglia	11822.9	806.4

ID	City Name	Region	GDP (million Euro)	Population (thousand)
32	Latina	Lazio	11757.7	522.2
33	Cosenza	Calabria	11115	731.5
34	Alessandria	Piemonte	10968.5	430.2
35	Pisa	Toscana	10618.2	395.4
36	Forlì-Cesena	Emilia-Romagna	10575.6	373
37	Frosinone	Lazio	10453.9	490.2
38	Ravenna	Emilia-Romagna	10267.8	367.4
39	Novara	Piemonte	9667.1	354.5
40	Lucca	Toscana	9616.2	379.7
41	Foggia	Puglia	9592.9	685.6
42	Taranto	Puglia	9570	580.6
43	Cremona	Lombardia	9161.9	347.3
44	Lecco	Lombardia	9043.4	323.6
45	Reggio di Calabria	Calabria	8899	565.7
46	Ascoli Piceno	Marche	8817.8	379.8
47	Ferrara	Emilia-Romagna	8804.6	350.6
48	Pesaro e Urbino	Marche	8758.3	367
49	Livorno	Toscana	8546.7	333.4
50	Pordenone	Friuli-Venezia Giulia	8423.7	299
51	Arezzo	Toscana	8386.1	334.4
52	Rimini	Emilia-Romagna	7934	288.4
53	Chieti	Abruzzo	7881.7	391.3
54	Piacenza	Emilia-Romagna	7382	274.8
55	Macerata	Marche	7300.5	314.1
56	Savona	Liguria	7078	282.1
57	Siena	Toscana	7051.7	261.4
58	Avellino	Campania	6959.4	437.5
59	Trieste	Friuli-Venezia Giulia	6853.9	237.6
60	Pistoia	Toscana	6783.6	278
61	Potenza	Basilicata	6744.1	391.1
62	Prato	Toscana	6378.2	240.7
63	Catanzaro	Calabria	6360.8	368.3
64	Pescara	Abruzzo	6250.9	309

ID	City Name	Region	GDP (million Euro)	Population (thousand)
65	Viterbo	Lazio	6170.9	301.2
66	Rovigo	Veneto	6059.3	244.7
67	Brindisi	Puglia	5973.6	402.5
68	Teramo	Abruzzo	5897.7	297.4
69	Belluno	Veneto	5883.9	212.2
70	L'Aquila	Abruzzo	5842.7	304.6
71	La Spezia	Liguria	5402.6	219.5
72	Lodi	Lombardia	5331.2	210.6
73	Grosseto	Toscana	5098.2	218.8
74	Asti	Piemonte	4924.8	213.8
75	Sondrio	Lombardia	4741.6	179.4
76	Biella	Piemonte	4731.5	187.9
77	Imperia	Liguria	4721.5	216.3
78	Terni	Umbria	4713.8	227
79	Vercelli	Piemonte	4584.7	177.2
80	Benevento	Campania	4287.5	289.3
81	Massa-Carrara	Toscana	4224.5	200.7
82	Campobasso	Molise	4068.2	231.6
83	Gorizia	Friuli-Venezia Giulia	3578.7	140.9
84	Valle d'Aosta/Vall?e d'Aoste	Valle d'Aosta/Vall?e d'Aoste	3543.9	123.4
85	Verbano-Cusio-Ossola	Piemonte	3481.2	161.6
86	Matera	Basilicata	3405.8	204.2
87	Rieti	Lazio	2956.7	153.8
88	Crotone	Calabria	2566.9	172.7
89	Vibo Valentia	Calabria	2473.9	168.7
90	Isernia	Molise	1616	89.8

Table 2.1: GDP and population data of 90 Italian cities in 2010 (*Eurostat)*

As shown in Table 2.1, Bologna has the 6th highest GDP; it is situated in the region of Emilia-Romagna along with other cities with high GDP, including Modena, Reggio nell'Emilia and Parma. Using these social and economic data, we can develop our economic model for estimating the wider economic impacts of disruption to the Bologna road network for 90 cities in Italy. In the next chapter, we describe our research methodology.

3.0 METHODOLOGY

In the chapter, given our objectives, we describe the methodology developed. We apply a combination of two models: an ABM infrastructure response model and an economic model for quantifying the wider economic impacts of natural hazards.

3.1 Agent-Based Model

The research tends to follow the general framework of scenario-based risk analysis (Le Sage, 2013). In risk analysis it is common practice to run computer simulations on various possible risk scenarios. Here the agent-based model (ABM) is selected to analyse (potential) impacts/consequences of a hazard under different disaster management measures (Borrion and Bouhana, 2012).

The Agent-Based Model (ABM) is a robust and commonly-used model for the simulation of complex systems (Batty, 2007; Bonabeau, 2002; Farmer and Foley, 2009). ABMs view a system by simulating individual component (agent) behaviours and their interrelationships. These agents are assigned various attributes and decision-making rules then released and allowed to interact with a defined digital simulation environment. Macro-level patterns are not predefined, but rather emerge as a consequence of these (multitudinous) interactions (Bollinger, 2011). It has been claimed that agent-based models can better capture the emergence of socio-economic structures (Downing et al., 2000). Furthermore, it has been suggested that they offer the potential for improved validation (Moss et al., 2001).

Specifically, in the field of infrastructure risk analysis, the AB model is often used to simulate the interrelationships of components within transport systems (Gómez et al., 2014; Kaegi et al., 2009; Lian et al., 2007; Ouyang, 2014). Agent-based modelling has also been applied in road network vulnerability and reliability studies (Takama and Preston, 2008; Wu and Lin, 2012; Waizman et al., 2013; Zolfpour-Arokhlo et al., 2014; Fares and Gomaa, 2015; Wang et al., 2015).

We, therefore, deem ABM as appropriate for analysing a complex system such as the road network (Jenelius et al., 2006), which includes both the physical road network and traffic flows. The components of the physical road network consist of bridges, tunnels, roads, land. Traffic flow consists of travellers and freight. The performance of the physical road network will change when a natural hazard occurs, and as a consequence, traffic flows will vary when the capacity of the physical road network changes. ABMs simulate the behaviour of the components of the road network, their responses to the natural hazard, and the indirect consequences of the natural hazard to the entire road infrastructure system.

The ABM model includes two sub-modules, the Infrastructure response model and the Traffic model. The Infrastructure response model is based on disaster-area data at city level; the Traffic model is based on the road network at the national level. In conjunction with the ABM, we will also apply available transport data to assess the wider economic impacts of an extreme natural hazard on the road infrastructure system in Italy.

3.1.1 Infrastructure response model

The Infrastructure response model focuses on depicting a natural hazard's impact on the road network by simulating the responses of each network component to the earthquake. As the result, the physical damage of the road network in the earthquake area can be visualised.

3.1.1.1 Agents

In the infrastructure response model, the agents are (1) bridges, (2) tunnels, (3) roads, and (4) land.

The agents that will decide the physical performance of the road network in the model are the bridges and tunnels. Each bridge or tunnel agent has a fixed location, and both are identified with their different typology attributes which contribute to their susceptibility to earthquakes, the bridge and tunnel typologies and their fragility functions are described in INFRARISK Deliverable D3.2.

Each bridge and tunnel are linked with a physical road represented by a road agent in the model. The road has its geographical location attribute, grade, and capacity attribute. As described in INFRARISK D3.2, road capacity will decrease if bridges and tunnels on the road are damaged due to the earthquake, but it will gradually recover as bridges and tunnels on it are restored.

Another component we examine is the environment, which is represented by the agent 'land '. The land cell has the attributes geographic coordinates and PGA value (Peak ground acceleration**,** the measurement of the intensity of the earthquake). All road, bridge and tunnel agents are related to land cells. GIS data is imported into the ABM to identify each land cell's geographic coordinates. The ground motion map that describes the earthquake intensity is imported to give each land cell a PGA value.

3.1.1.2 Behaviour rules of agents

The behaviour rules for agents to respond and behave during and after the hazard event includes two aspects: (1) the initialization of the agents, which identifies the initial status of the agents, and (2) the scheduling of the agents, which decides the agent's behaviour at each time step.

The initialisation of the agents relies on spatial data of the area and the provided fragility sampling as described in INFRARISK D3.2. The initial status is used as a proxy for the regular road network status before the earthquake.

The temporal resolution of the model is in days. Each time step of the simulation represents one day. We assume that, at time step one, the earthquake occurs. The simulation ends when the road network recovers to its initial status, in which there are no traffic disruptions caused by the physical damages of road network elements.

The bridge and tunnel agents' scheduling behaviour rules are shown in Fig. 3.1. Their behaviour at each time step is split into two parts**: '*Hazard response*' and '*Restoration*'.**

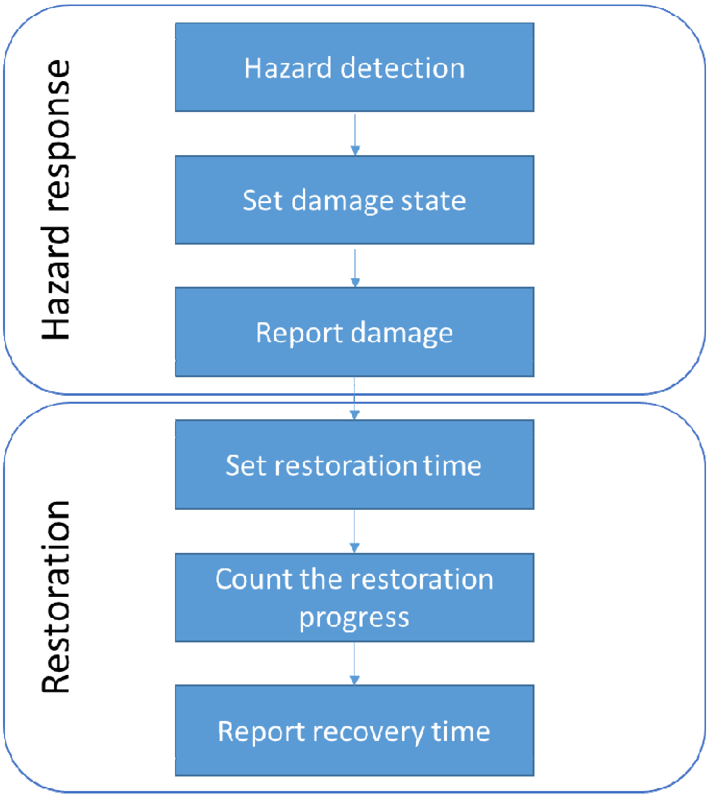


Figure 3.1 Agent behaviour at each time step

3.1.1.3 Hazard response

The ***Hazard response*** involves agents' responsive behaviour to the earthquake event. At the beginning of the simulation, the earthquake scenario is applied to the transport network in the study area. Bridge and tunnel agents' response to the natural hazard includes: (1) Hazard detection, (2) Set damage state, (3) Report damage. The ***hazard detection*** is the bridge and tunnel agent's behaviour of detecting PGA value of the land cell it situates.

In ***Set damage state*** behaviour each bridge and tunnel identify its damage state according to the land cell's PGA value. The process is elaborated in Fig. 3.2.

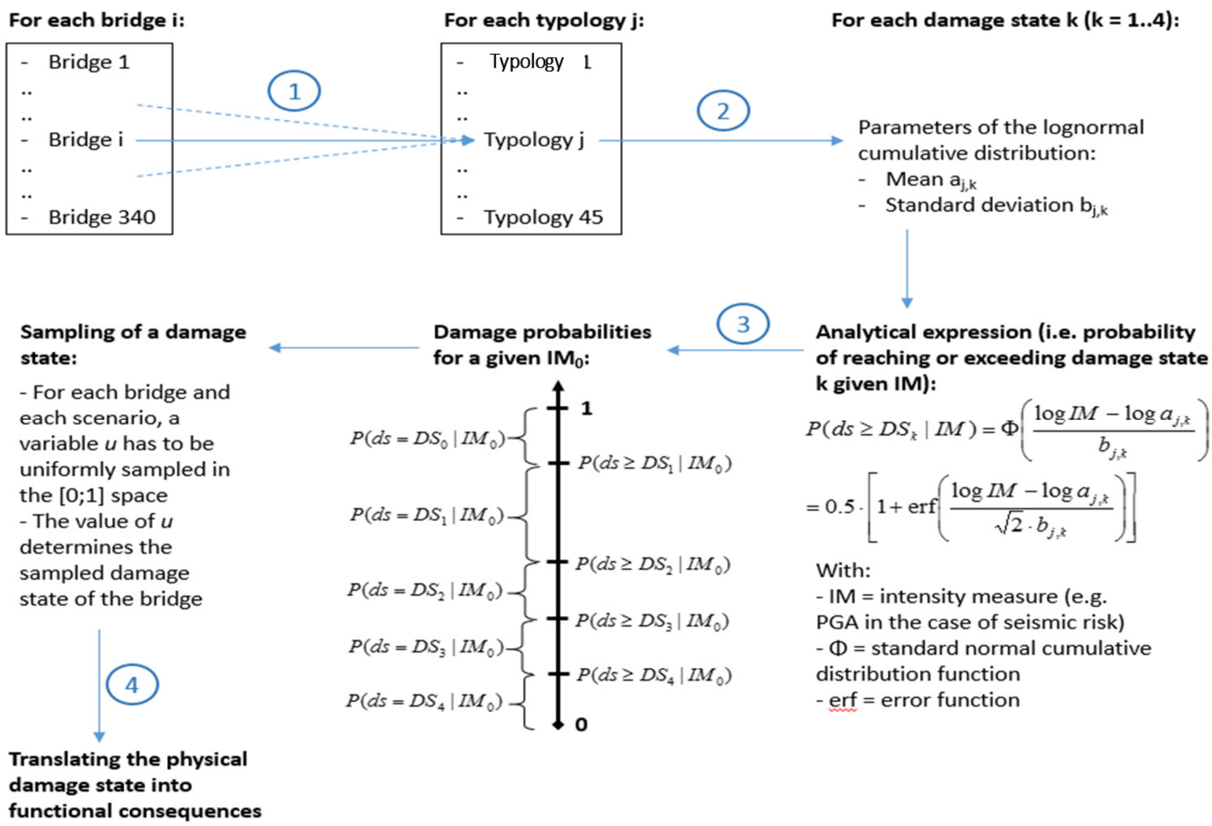


Figure 3.2: The process of identifying bridges' global damage states, based on the fragility curve

As shown in Fig. 3.2, there are five possible states for a bridge or a tunnel, (DS0-DS4).DS0 is the state of no damage, DS1 is the lightest damage, and DS4 is the most severe damage. The bridge and tunnel agent's damage state is decided by three parameters (1) the PGA value of the land cell where the bridge is located *IM,* (2) The typology of the bridge j, and (3) the random variable μ uniformly sampled in [0,1]. Details of how the damage state is calculated can be found in INFRARISK WP3 D3.2.

The third behaviour, ***Report damage***, is a step that bridge and tunnel agents convey the damage states information to its linked road so that the road will reduce or increase the traffic capacity according to the bridge and tunnel damage states.

3.1.1.4 The Restoration

The ***Restoration*** includes bridge and tunnel agents' behaviour during the restoration process. Bridge and tunnel agents' sequential behaviour in this phase includes: (1) Set restoration time, (2) Count the restoration progress and (3) Report recovery time.

The ***Set restoration time*** is the key behaviour of the restoration phase. Restoration time refers to the duration of the restoration period of a damaged bridge or tunnel after an earthquake (D'Ayala et al., 2015). For a bridge or tunnel agent, its restoration time is decided by its damage state. Details of how the restoration time is identified can be found in INFRARISK Deliverable D3.2.

Count the restoration progress is bridge and tunnel agents' behaviour of counting down the restoration time. When the time is due, the bridge and tunnel will change their state from 'Being damaged' to 'normal'. Accordingly, the associated road's capacity also returns to normal.

Lastly, ***Report recovery time*** is bridge and tunnel agents' behaviour of calculating the road network recovery time. The time step at which all damaged bridges and tunnels are restored is the whole road network's recovery time.

3.1.1.5 Model development on NetLogo platform

The Infrastructure response model is achieved on an ABM platform NetLogo (Wilensky, 1999). Figure 3.3 gives an example of the spatial-temporal simulation result obtained from the Infrastructure response model. The window on the right shows the locations of bridges and roads that are most likely to be damaged (vulnerable bridges and roads are in red). The window on the left shows a dynamic change damaged bridges numbers at each time step: the time when all the bridges are restored is known as the road network recovery time.

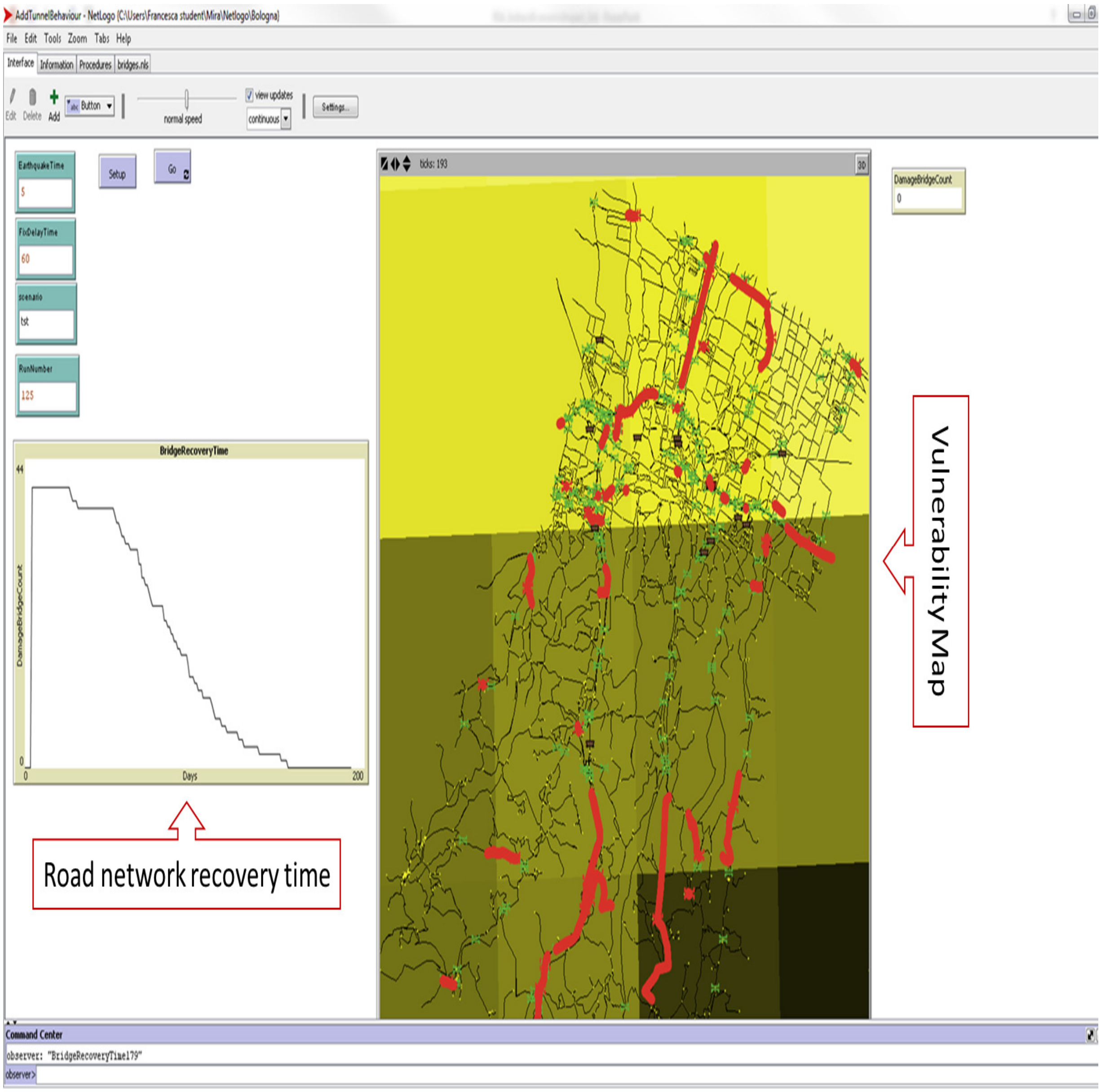


Figure 3.3: A snapshot of ABM simulation result showing the spatial locations of damaged bridges and impacted roads as well as the recovery time of the road network

The simulation result is then imported into the Traffic model so that we may simulate the traffic condition after an earthquake.

3.1.2 Traffic simulation model

To explore the earthquake event's indirect consequences on the Italian road network at the national level, the traffic model is next applied to simulate Italy's national road network's traffic condition after the earthquake. The traffic model can estimate travel times between Italy's 90 main cities. A detailed description of the traffic model can be seen in INFRARISK Deliverable D5.3. The traffic model is capable of representing the indirect consequences of the earthquake on the entire road network system measured by travel time delay.

Our next step is to evaluate the wider economic impacts of the earthquake. The economic model is exactly for this purpose.

3.2 The Economic Model

To achieve our main objective, an economic model based on Italy's Origin-Destination data and Italian cities' Gross Domestic Product (GDP) is developed.

In this section we elaborate on our choice to use GDP loss as the measurement of wider economic impacts. We thereafter explain why transport OD data is used. Lastly, we describe how we set up the production function and the travel demand elasticity function in the Economic model.

3.2.1 Wider economic impacts

As discussed in the introduction section, the economic consequences related to the indirect consequences of a natural hazard in non-disaster-affected area is defined as the 'wider economic impacts'. In this definition, the indirect, wider and macroeconomic impacts of natural hazards are stressed. These may be considered as the "full cost or loss to the society" (Carrera et al., 2015). The wider economic impacts are depicted in Fig. 3.4.

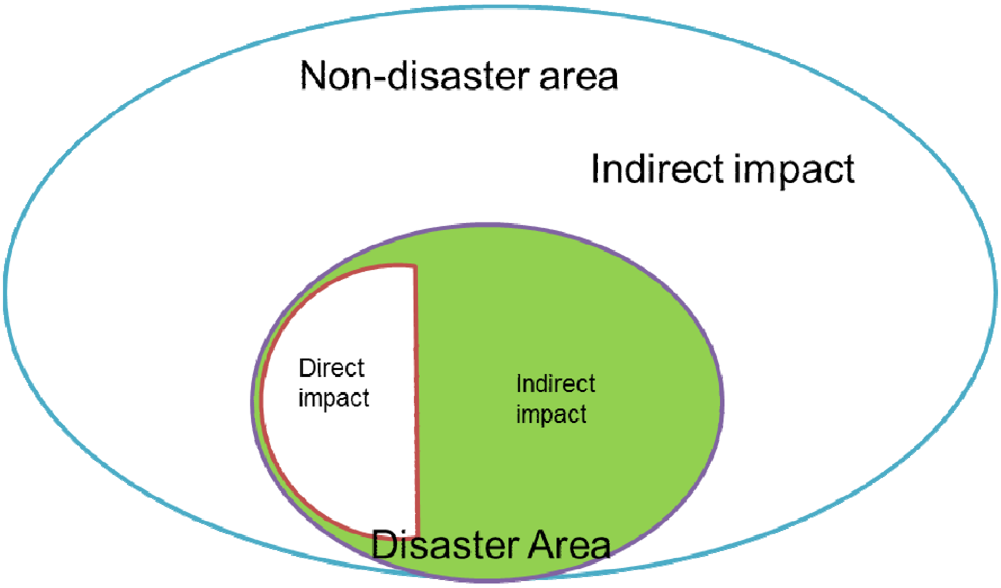


Figure 3.4: The composition of the wider economic impacts

In Figuew 3.4, a natural hazard's indirect economic impacts may include business interruption costs or adjustments in production and consumption patterns (Lazzaroni and van Bergeijk, 2014) not only in the disaster area but also in the non-disaster area; these are all taken into account in the wider economic impact evaluation.

3.2.2 GDP as a measurement of wider economic impact

In order to analyse the wider economic impacts of natural hazards, we set up an Origin-Destination traffic data based economic model. Traditionally, the transport literature reflects the view that traffic volumes, especially those of road traffic, are strongly connected to Gross Domestic Product (GDP) (Seo et al., 2015). In most cases, GDP per capita or GDP growth rates are the indicators of the economy. The measurement of traffic volumes is used in many different contexts: from port handling capacity (PHC) (National Research Council, 1999); freight index (Gao et al., 2016); vehicle miles of travel (VMT) (Liisa Ecola and Wachs, 2012); and road passenger numbers (Zorn and Shamseldin, 2015), but their conclusions are quite similar; traffic volumes indeed have a very close relation to GDP (Ash and Newth, 2007; Liu et al., 2016).

Local/national GDP is used as the indicator for regional or national economy in research on indirect impacts assessment, in particular in Computer General Equilibrium (CGE) models (Tsuchiya et al., 2007), I/O models (Rose et al., 1997), and agglomeration research (Vickerman, 2007).

For our purposes here, and because the wider economic impact emphasizes the indirect economic impact to an area's economy, we use city GDP as an area's economic indicator. The cities' GDP loss will represent the wider economic impact of natural hazards.

3.2.3 Relationship between GDP and travel demand

Travel demand is essential the demand for travel (McFadden, 1974). The transport system provides the services of moving goods and people from one place to another. As the demand side of this service, travel demand has been explored extensively (McFadden, 1974; Murthy and Mohle; Transportation Research Board, 2012). Travel demand is represented by key traffic volume indicators, such as average trips (Transportation Research Board, 2012); VMT (Vehicle miles of travel) (Liisa Ecola and Wachs, 2012) etc.

It is well known that the economy has a close relationship with travel demand (Gao et al., 2016; Stead, 2001; Tapio et al., 2007; Yu et al., 2012), and that a change in travel demand will impact on the GDP of an area. Bayliss (2008) explains that this close positive correlation between GDP and travel demand is a 'two-way process' because more economic activities will enhance people and goods movement. More money being brought into an area is likely to encourage people to participate in economic activities across a wider range, and broader range travel would boost the economy.

Furthermore, it has long been recognised that regional travel demand is elastic to the travel time (Graham and Glaister, 2004), but the assessment of 'how a decrease in travel demand due to a traffic system disruption will affect the GDP' remains unclear. Therefore, by observing statistics on travel demand and GDP, we are able to construct a model that connects travel demand change and GDP change.

Using regional OD data from Italy describing average trips between cities and EuroStats NUTS 3 cities GDP data in 2010, we plot the relationship between cities' GDP per capita and travel demand measured by the incoming traffic flow trips for Italy (Figure 3.5).

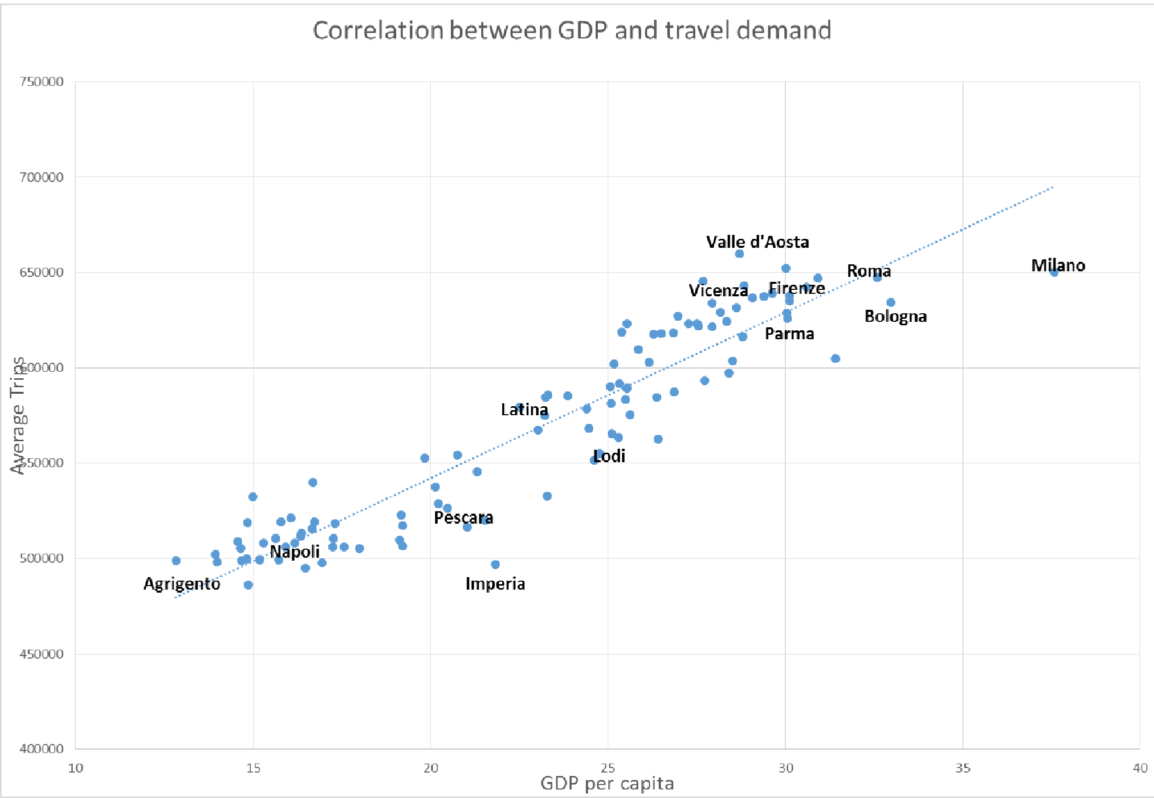


Figure 3.5: Correlation between regional productivity and travel demand

Figure 3.5 indicates that GDP for Italian cities is significantly positively associated with city travel demand. A univariate linear cross-country regression of average incoming trips accounts for about 81% of the variance in GDP. Our observation of GDP and travel demand of 90 Italian cities coincides with Bayliss's theory.

Following the analysis of Ecola and Wachs (2012), we express city GDP as a function of local travel demand; a linear regression function between GDP and in Italy cities travel demand (Tr) is as follows:

$$GDP = a * Tr + b, \quad \textbf{(1)}$$

where a = 0.0099, b= -31.05.

This equation is known as the productivity function.

According to Eq. 1, the change in a city's GDP can now be expressed as

$$\Delta GDP = a * \Delta Tr \quad \textbf{(2)}$$

Assuming that the incoming trips of a city *j* are the sum of incoming trips from all OD links *i* to the city j, Eq. (3) can then be expressed as

$$\Delta GDP_j = a * \sum_i \Delta Tr_{ij}. \quad \textbf{(3)}$$

Here, ΔGDP_j is the GDP per capita change caused by the change in the travel demand ΔTr_{ij}.

Equation (3) can now be applied to estimate the wider economic impacts of an earthquake if there is a travel demand change due to the earthquake-induced road network disruption. The travel demand elasticity function thus developed, aims to calculate this travel demand change caused by the natural hazard event.

3.2.4 Relationship between travel demand and time delay in a natural hazard event

Travel demand is sensitive to travel time (Dueñas-Osorio and Vemuru, 2009; Graham and Glaister, 2004; Li et al., 2015; Litman, 2013). Moreover, it has been observed that travel demand will decrease due to the time delay.

The travel demand's elasticity with respect to time η describes how travel demand decreases due to the time delay (Graham and Glaister, 2004).

$$\eta = \frac{\%\Delta Tr}{\%\Delta Time}, \quad \textbf{(4)}$$

Where:

η is the demand elasticity

ΔTr is the changing of travel demand

$\Delta Time$ is the change of travel time.

De Jong and Gunn (2001) conducted a large-scale review for Europe of available evidence concerning elasticities of private car travel demand with respect to time and cost changes. Their results show that when travel time increases between 20%-50%, travel demand elasticity will range between 0.09 and 0.62, depending on country and purpose of car use. This result has often been used to estimate the economic loss of traffic congestion or to evaluate the economic benefits of a new road project (Graham and Glaister, 2004). In these analyses, travel demand elasticity is regarded as a linear function. However, the accuracy of the linear function has been questioned, and an arc elasticity is recommended if the travel time change is significant (Litman, 2013).

A natural hazard will disrupt the road network and subsequently induce travel time delays (Argyroudis et al., 2015; Bono and Gutiérrez, 2011; Chang and Nojima, 2001; Ouyang and Wang, 2015).

In an earthquake event, an arc elasticity curve is applied, as can be seen in Fig. 3.6. The arc elasticity curve is non-linear and the travel demand sensitivity to time varies. We use the arc elasticity curve because, in an earthquake event, travellers already have the expectation that an extreme natural hazard is likely to incur severe travel delays and that the restoration time taken after the natural hazard will therefore be slow. When a travel time delay reaches a threshold (*H*), the travel demand elasticity weakens or even disappears due to the expectation that there is no difference between 'very bad travel conditions' and 'even worse travel conditions'.

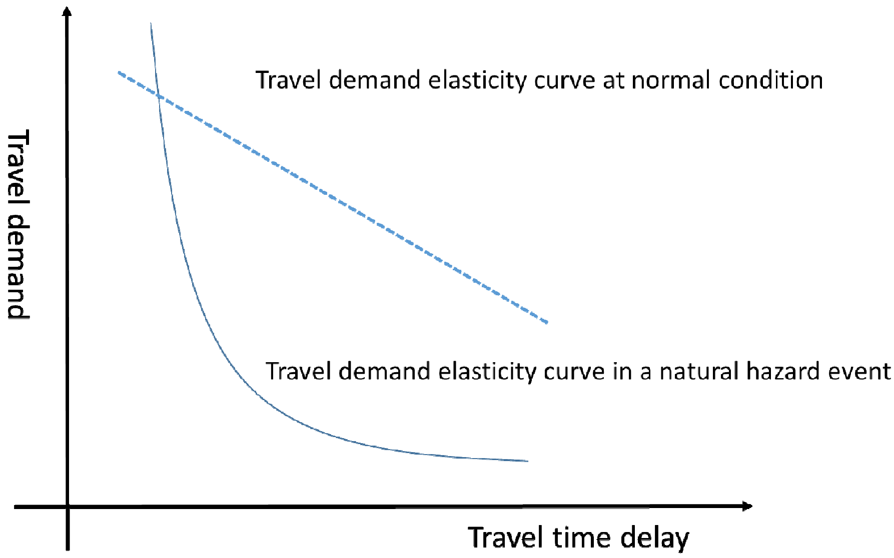


Figure 3.6: Travel demand elasticity in a natural hazard event

To simplify the model, we set up the travel demand elasticity function describing day travel demand change due to a natural hazard $\Delta DayTr_{ij}$, as a function of travel time delay:

$$\Delta DayTr_{ij}(x) = \begin{cases} DayTr_{ij} * \eta * x & x \leq H \\ \Delta DayTr_{ij}(H) & x > H' \end{cases} \quad (5)$$

where :

$\Delta DayTr_{ij}$ is the day travel demand change due to a natural hazard at OD link between city i and city j

η is the point elasticity of travel demand

x is the travel time delay.

In Eq. 5, *H* represents the threshold at which the travel demand elasticity becomes weak or even disappears. In a natural hazard event, ΔTr_{ij}, the travel demand change caused by travel time delay at the OD link between i and *j*, can be expressed as:

$$\Delta Tr_{ij} = \int_{t_0}^{t_{recovery}} \Delta DayTr_{ij}, \tag{6}$$

where:

t_0 is the time when an earthquake occurs

$T_{recovery}$ is the time for the road network to recover to its normal capacity after the earthquake event, counted in days.

3.2.5 Summary

In this section, we have introduced the methodology applied for the research and given detailed descriptions of the agent-based (AB) and economic models used for evaluating the wider economic impacts of natural hazard-induced road network disruptions. Our next step in Chapter 4 will be to estimate the GDP change induced by an earthquake, using in Bologna, Italy as the disaster area. We will calculate the travel demand change resulting from time delays and the recovery time to see how much GDP loss the traffic delay will incur.

4.0 RESULT AND DISCUSSION

After having described the methodology applied in this study, we can now discuss the results. The obtained results will be examined in relation to the three objectives.

4.1 Representing an earthquake's indirect consequences on the transport network

The indirect consequences associated with a natural hazard relate to its capacity to trigger a sequence of secondary hazards due to the structural and functional interdependencies. The indirect consequences to transport system due to natural hazards relate to the damaged road network that would cause the travel time delay.

Given the first sub-objective, we are going to study the traffic delay caused by the earthquake-induced road network disruption. We hypothesise that the traffic delay should not only appear in the disaster exposure area but also the nondisaster affected areas through the connected road network.

In order to test the hypothesis, we first use the ABM hazard simulation model to produce a road network damage scenario when the earthquake occurs. Then we simulate the Bologna road network dynamic restoration process. Based on each week's road network damage status, the traffic model is applied to the Italian road network in order to estimate the travel time delay between the major cities.

4.2 Infrastructure physical damage of the earthquake

The ABM model can dynamically present the infrastructure network's physical damage condition after an earthquake scenario.

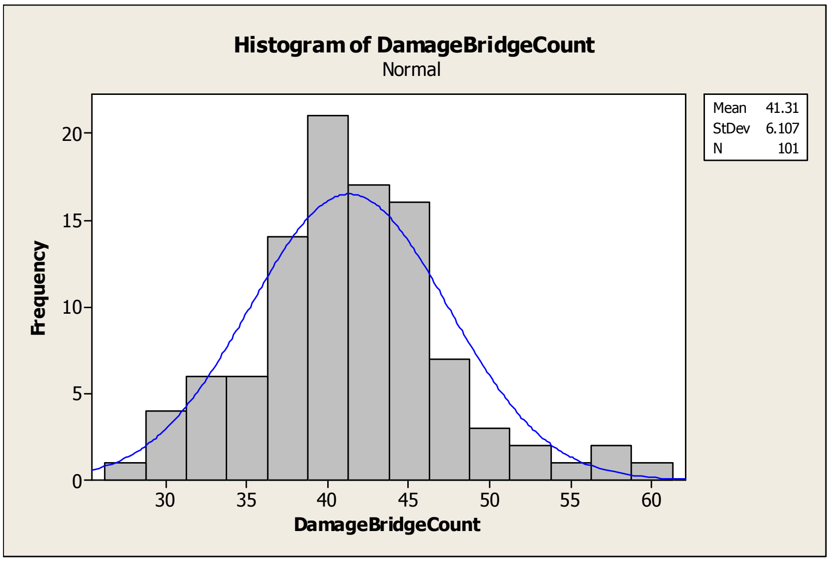


Figure 4.1: Simulation result of damaged bridges in an earthquake

For the given earthquake PGA map, no tunnel is in a damaged state. As shown in Figure 4.1, there are 41 bridges on average that have DS3 or DS4 states. This simulation result can be applied to estimate the direct economic damage for the emergency management, which however is not the objective of this study.

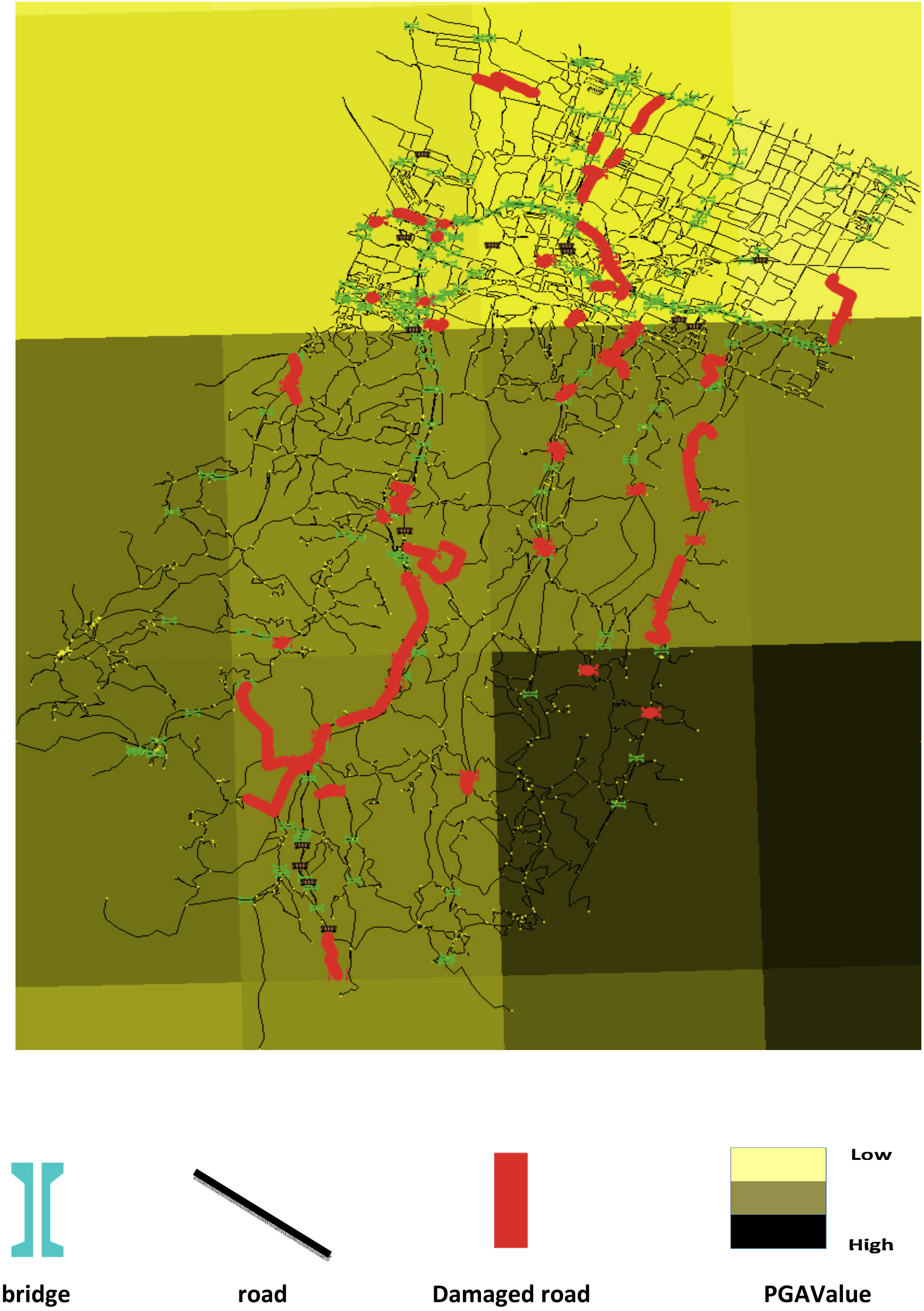


Figure 4.2: Bridges and roads vulnerability map for a given seismic load

Figure 4.2 shows the spatial distribution of the 41 bridges that are the most likely to be damaged in the earthquake, here we call it as the 'classic scenario .' For a given seismic load, three roads are most impacted: A1 road between Sasso Marconi and Stazione; A13, SS64 and E45 roads within Bologna; SP7 road between Mercatale and Pizzano. This indicates that the main roads connecting Bologna to the south, east, north (Ferrara direction) are all heavily impacted.

4.2.1 Recovery process simulation

The infrastructure physical damage map produced by the ABM model is used as the background of the dynamic simulation of Bologna road network restoration process.

Figure 4.3 shows a snapshot of bridge recovery process over the period of an earthquake event. The horizontal axis is the time in days, a vertical axis is a number of damaged bridges. The ABM model simulates the restoration behaviour of each bridge and tunnel after an earthquake and counts the number of damaged bridges and tunnels every time step. The road network recovery time is from the time the earthquake occurs to the time when all individual bridges and tunnel are restored.

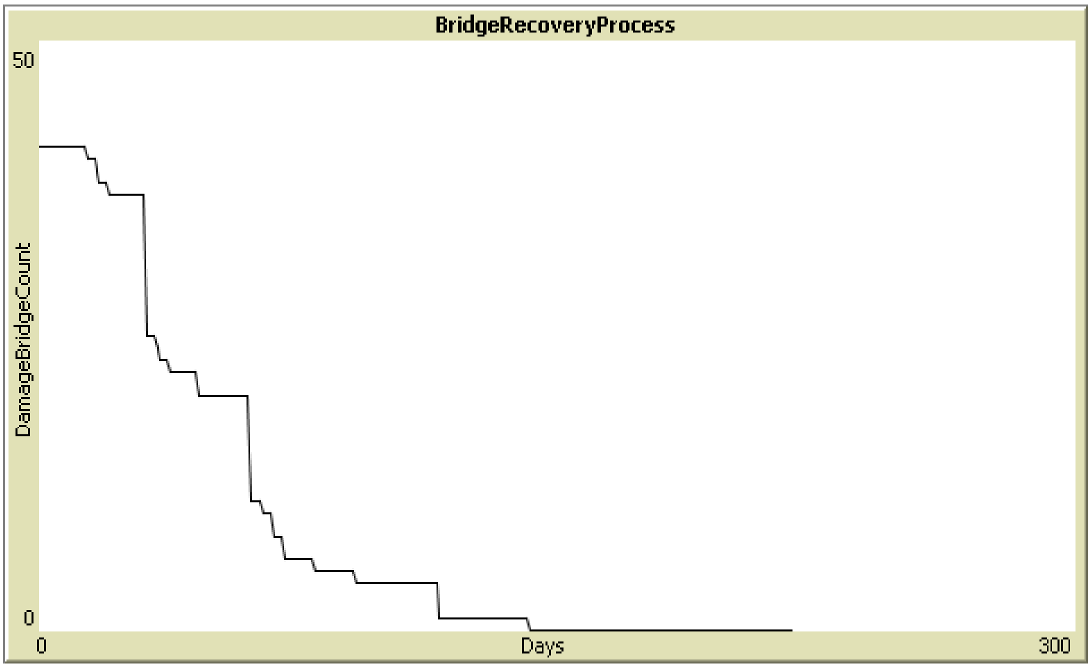


Figure 4.3 An example of the result of road network recovery time

100 times simulation statistics show (Figure 4.4) that the mean recovery time of Bologna road network is about 136 days for the given seismic load.

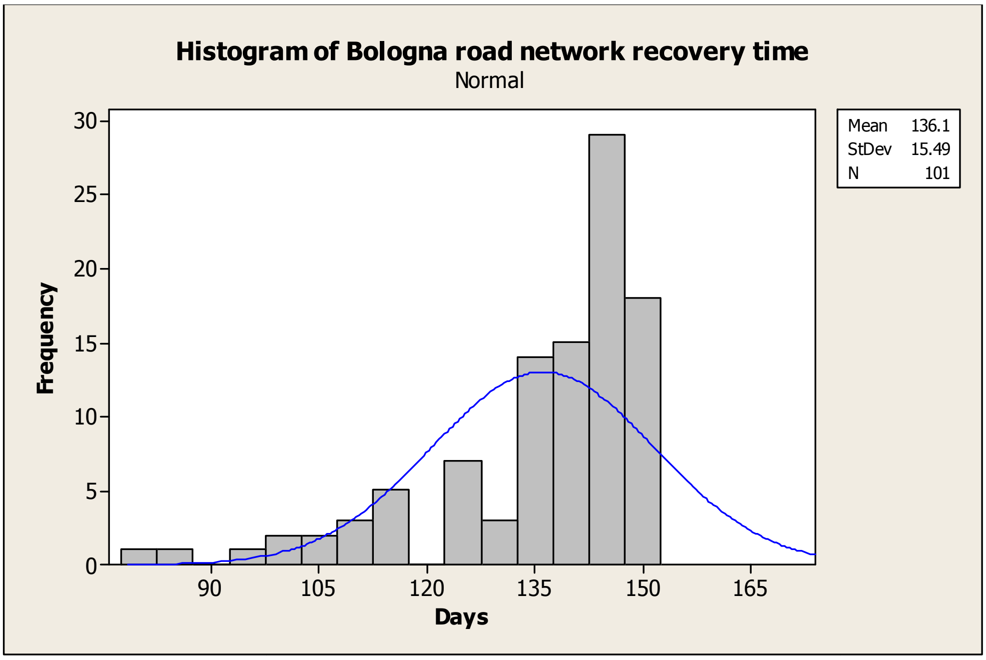
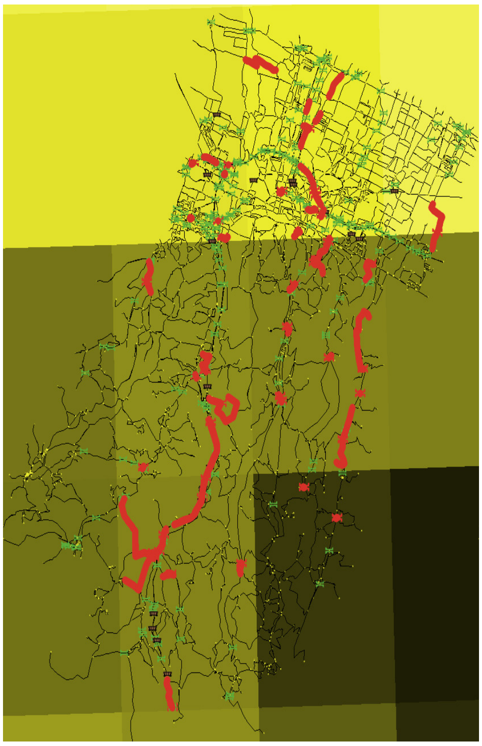
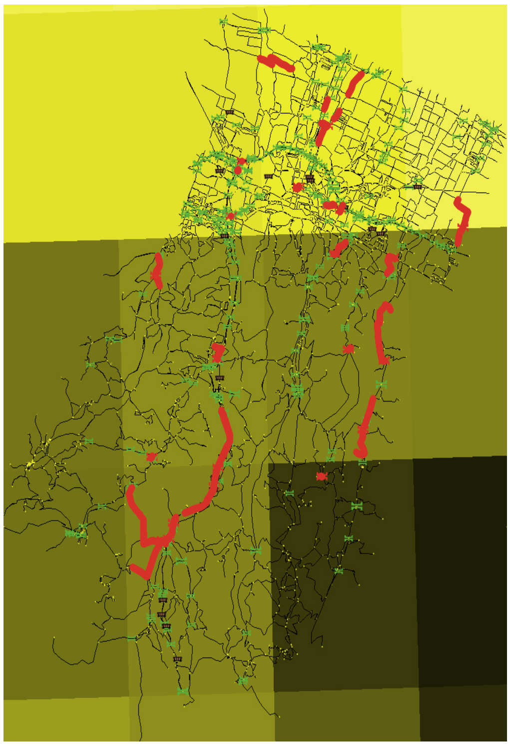


Figure 4.4: Histogram of Bologna road network recovery time for 100-time simulation

The road network recovery dynamics during the earthquake event can be seen in Figure 4.5. Figure 4.5 (a) shows the road network disruption situation when the earthquake occurs. In the week five as shown in Figure 4.5 (b), there is an improvement, but the three main highway road: A1 road between Sasso Marconi and Stazione; A13, SS64 and E45 roads within Bologna; SP7 road between Mercatale and Pizzano are still in a severely damaged condition. In week 8, the damaged roads in Bologna ring road are considerably restored. The roads that need the longest time to repair is the A1 road between Sasso Marconi and Stazione; it is restored on the 16th week as shown in Figure 4.5 (c,d,e).The whole road network recovers after 19 weeks.



(a)Week-1



(b)Week-5

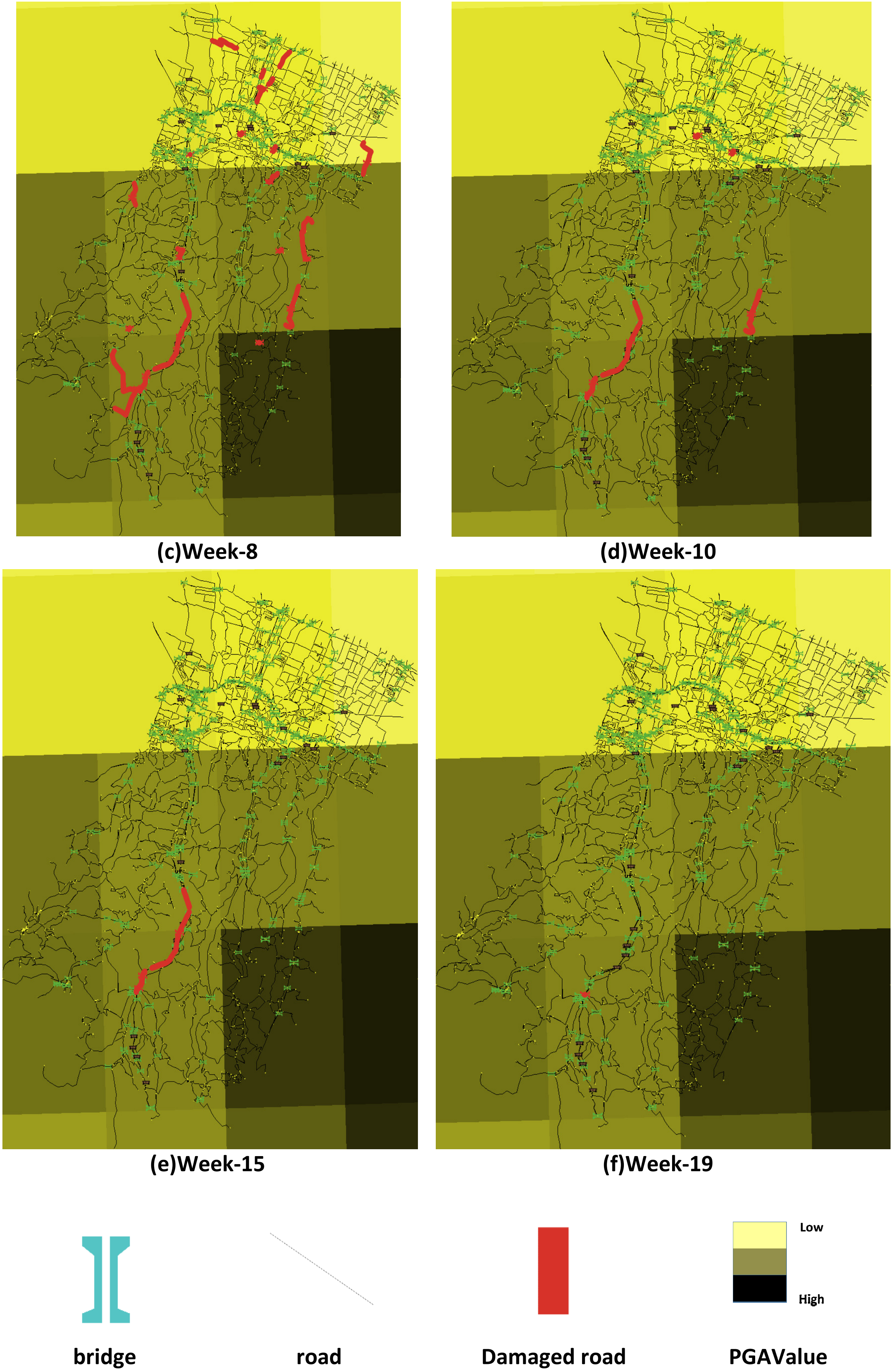


Figure 4.5: Bridges and roads vulnerability maps at different week

The restoration process simulation is vital in the research because it visualises the dynamic change of the road network's accessibility during the earthquake event. As a result, the travel time delay at each week can be estimated.

4.2.2 Traffic delay on Italy road network

An open source traffic simulation tool NeXTA is applied to simulate the regional travel time delays caused by the earthquake-induced road network disruption. Figures 4.6 shows the heavily –medium-slightly delayed OD links in Italy after the earthquake. It illustrates that heavily delayed (>50% time delay than average travel time) OD links are mainly at the northern part of Italy. The most impacted OD links are Bologna related OD links such as Bologna to Parma, Bologna to Cremona, Bologna to Verona or OD links that are quite close to Bologna such as Brescia to Rimini, Mantova to Rimini. The medium delayed (between 10-50% time delay than average travel time) OD links covers a vast area of Italy, the furthest medium suspended OD links includes OD links from the north to Roma, Latina, and Teramo. Even OD links in the further south such as Reggio di Calabria, Valentia and Crotone, their travel time are also slightly delayed (<10% time delay than average travel time) due to the earthquake in Bologna. The impacted OD links in the southern part of Italy are those connecting large cities such as Rome and Napoli.

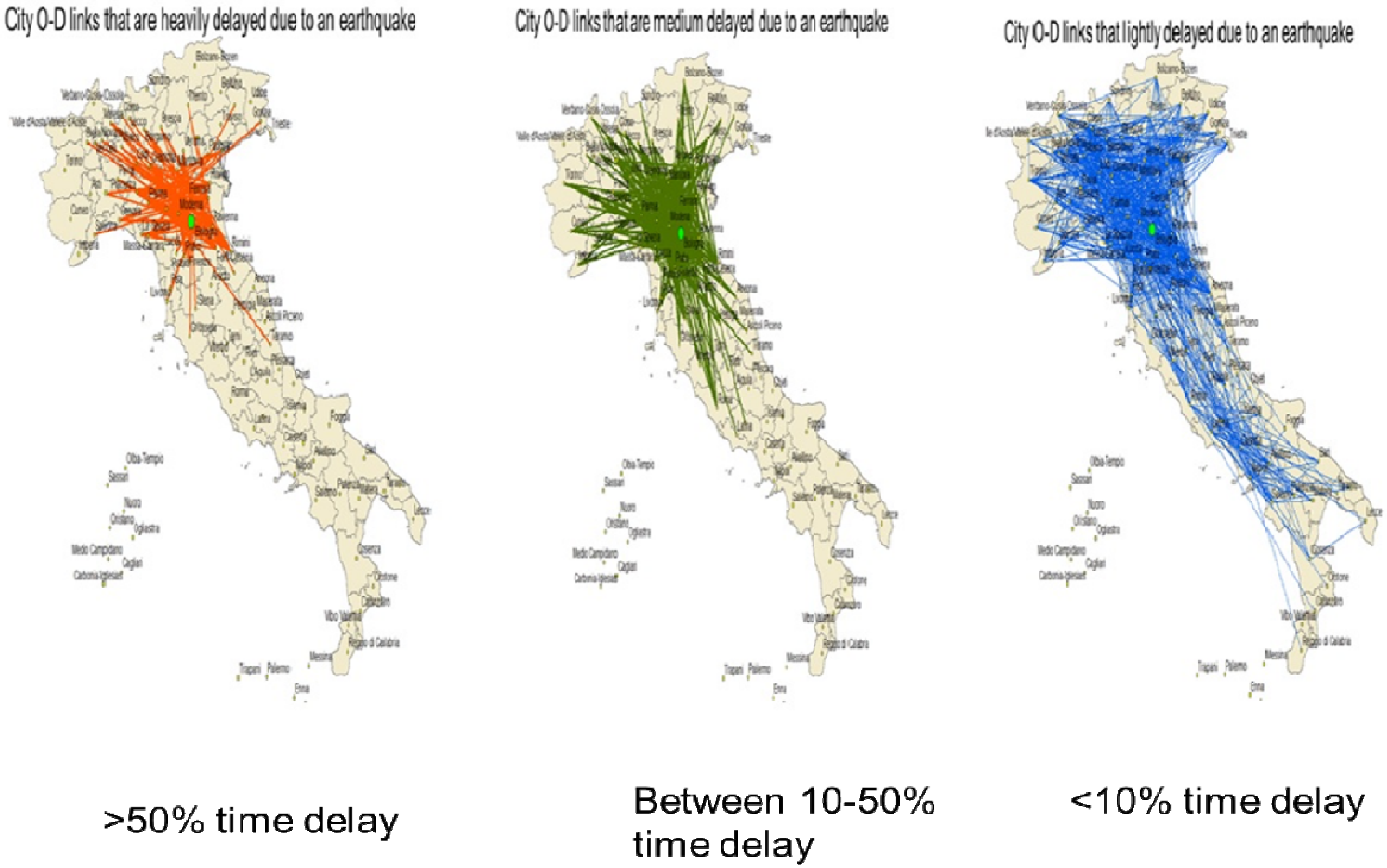


Figure 4.6: O-D links that are delayed due to an earthquake in Bologna earthquake

The post-event travel time delay estimation proves the hypothesis: Natural hazards not only affect the disaster exposed area but also unexposed area's transportation is valid.

The next question is how much these travel time delay would cost? The economic model is designed to solve this problem.

4.3 Economic evaluation

For the 2nd objective, we are going to examine the GDP change of 90 Italian major cities due to the travel time delay after an earthquake event in Bologna. The hypothesis is that the city that has a higher travel time delay during a natural hazard will have higher GDP loss.

For each earthquake scenario, the GDP loss per capita at each OD link and each city can be calculated following the economic model identified the previous section. Here we first analyse the GDP loss per capita of OD links between 90 Italian major cities and then we will focus on cities GDP loss.

As mentioned in Section 3.2, it is assumed that the GDP loss is related to travel demand decreasing, the travel demand reduction occurs between t_0 and $t_{recovery}$, therefore, the GDP loss is the sum of GDP loss during t_0 to $t_{recovery}$.

4.3.1 Evaluation of OD links GDP losses

As shown in Figure 4.6, OD links have different travel time delay. Therefore, the GDP loss of each OD link can be estimated by the linear regression function developed (in Section 3.2).

Figure 4.7 shows the spatial locations of the top 30 O-D links that have the greatest GDP loss per capita due to the earthquake. Table 4.1 shows the economic estimation to these links.

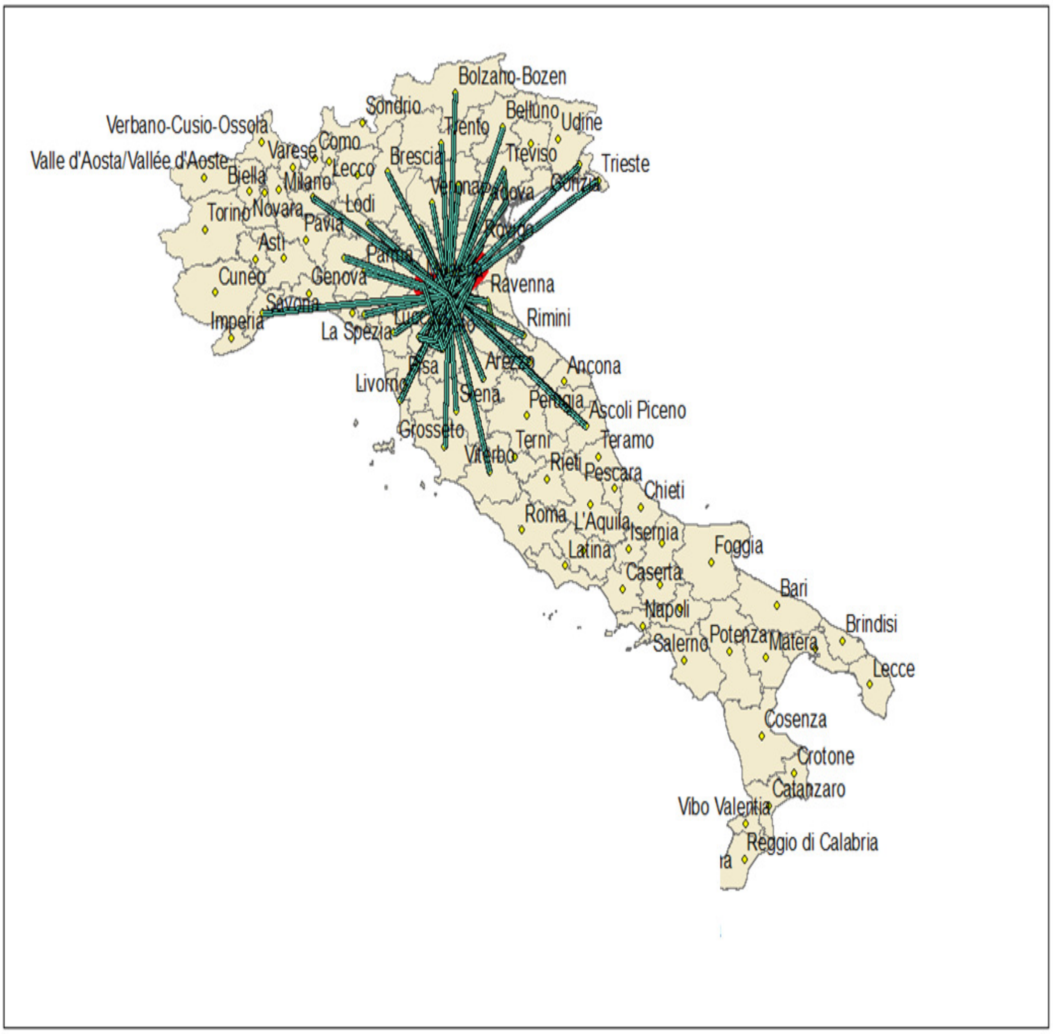


Figure 4.7: Spatial location of top 30 OD links with greatest GDP loss per capita

Rank	Origin	Destination	Loss of GDP per Capita (Euro)
1	Ferrara	Bologna	392.86
2	Modena	Bologna	379.01
3	Bologna	Modena	241.86
4	Bologna	Ferrara	154.41
5	Ravenna	Bologna	78.98
6	Forlì-Cesena	Bologna	63.25
7	Bologna	Ravenna	48.44
8	Rovigo	Bologna	46.2
9	Prato	Bologna	42.29
10	Reggio nell'Emilia	Bologna	41.77
11	Bologna	Firenze	35.32
12	Bologna	Forlì-Cesena	31.85
13	Pistoia	Bologna	31.38
14	Rimini	Bologna	31.06
15	Firenze	Bologna	25.41
16	Mantova	Bologna	23.54
17	Parma	Bologna	22.57
18	Bologna	Prato	20.21
19	Bologna	Reggio nell'Emilia	19.6
20	Bologna	Rimini	17.48
21	Bologna	Padova	14.16
22	Bologna	Pistoia	12.51
23	Bologna	Rovigo	12.43
24	Padova	Bologna	12.03
25	Pesaro e Urbino	Bologna	9.58
26	Pistoia	Firenze	9.51
27	Venezia	Bologna	8.74
28	Verona	Bologna	8.49
29	Arezzo	Bologna	8.18
30	Venezia	Treviso	7.97

Table 4.1: Top 30 O-D Links of GDP loss per capita

The most affected OD links are the links that connect to Bologna city such as the link from Ferrara to Bologna, for which the estimated GDP loss per capita is about 392.86 Euros. The OD links between Ferrara and Bologna, Modena and Bologna, have higher GDP Loss than other OD links, since they all have GDP loss more than 150 Euros. Other OD links that have significant GDP loss are OD links that connect Bologna with the cities in Emilia-Romagna such as Ravenna, Forlì-Cesena, Reggio nell'Emilia, Rimini, Parma, the GDP loss of these links ranges from 78.9-17.4 Euros. The OD Links that connect Bologna with other cities that have large GDP loss are links to or from Rovigo, Prato, Pistoia, Firenze, Venezia, Verona, Arezzo, Padova, etc. These are cities in the north and are quite near Emilia-Romagna region. It is interesting that two OD links not connected to Bologna links between Venezia and Treviso, Pistoia and Firenze are also listed at the top. This might be because Firenze and Venezia are main cities with lots of economic activities. As shown in Figure 4.7, most of the top impacted OD links are in the middle of Italy and near Bologna. But it is noticed that Links from northern cities (Trieste, Belluno, Gorizia, Venezia, Rovigo) to Rome are also seriously economically impacted.

For the OD links that are not related to Bologna, the top 30 ODlinks with the greatest GDP loss are listed in Table 4.2. The spatial locations of these OD links are shown in Figure 4.8.

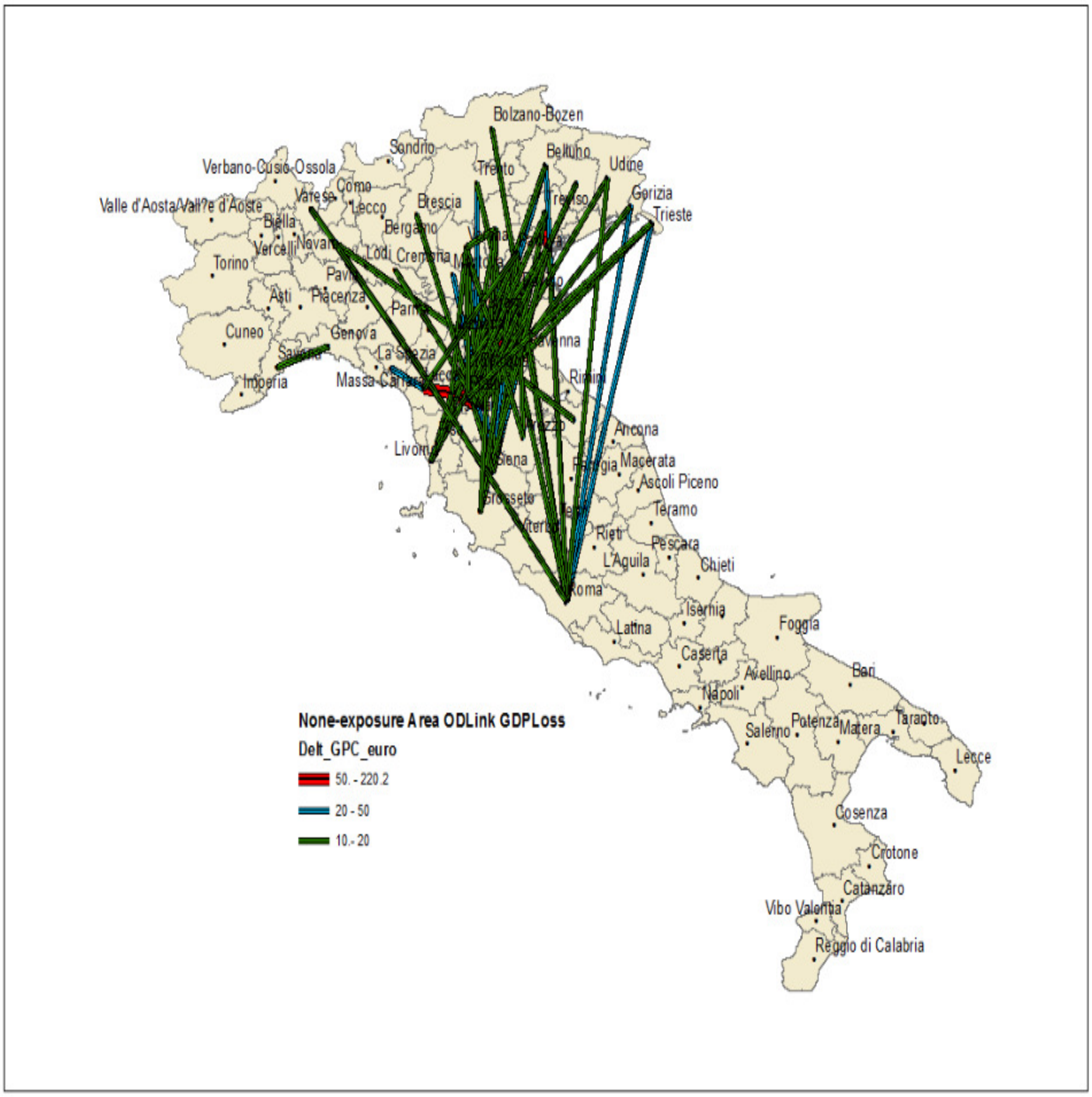


Figure 4.8: Spatial locations of the top 30 O-D links in non-disaster area with the largest GDP Loss Per Capita

Rank	Origin	Destination	Loss of GDP per capita(Euro)
1	Pistoia	Firenze	9.51
2	Venezia	Treviso	7.97
3	Pistoia	Prato	5.51
4	Rovigo	Firenze	2.41
5	Pistoia	Lucca	2.3
6	Trieste	Roma	1.79
7	Prato	Firenze	1.43
8	Siena	Padova	1.35
9	Lucca	Massa-Carrara	1.34
10	Mantova	Firenze	1.33
11	Siena	Firenze	1.28
12	Belluno	Roma	1.2
13	Prato	Padova	1.18
14	Belluno	Firenze	1.17
15	Rovigo	Prato	1.01
16	Firenze	Padova	0.96
17	Verona	Firenze	0.95
18	Siena	Verona	0.94
19	Pistoia	Padova	0.92
20	Gorizia	Roma	0.9
21	Venezia	Firenze	0.88
22	Trento	Firenze	0.88
23	Siena	Venezia	0.88
24	Venezia	Roma	0.85
25	Genova	Savona	0.81
26	Gorizia	Firenze	0.78
27	Rovigo	Roma	0.77
28	Rovigo	Pistoia	0.76
29	Siena	Rovigo	0.75
30	Pistoia	Pisa	0.75

Table 4.2: Top 30 O-D Links in non-disaster area with greatest GDP loss per

The GDP loss of the OD links in the non-disaster area are far less than that of the disaster area, the highest GDP loss of non-disaster OD links is only 9.51 Euros per capita, and for the majority, OD links GDP loss are under 2 Euros per capita.

The OD links outside the disaster area with the greatest GDP loss are mainly North-south trend OD Links in the northern and middle part of Italy. The results highlight the significant role Bologna plays within the dynamics of the Italian economy.

4.3.2 Evaluation of GDP loss of Italian major cities

The GDP loss of a city is identified as the sum of the GDP loss of all the OD links to the city in the research. This assumes that damaged bridges are repaired immediately. The wider economic impact to Bologna, Emilia-Romagna region, and cities in other area are estimated according to Table 4.3

Area	**GDP Loss （Euro）**	**% of total GDP Loss**
Bologna	633475878	44.6
Emilia-Romagna region	535451312.6	37.8
Other area	250350416.6	17.6
Total	1419277607	100

Table 4.3: Wider economic impact to Bologna, Emilia-Romagna region and other regions in Italy regarding GDP loss

In general, there is an overall 1.4 billion Euros GDP loss for all the 90 major cities in Italy. The disaster area Bologna's general domestic productivity is affected most, the traffic delay causes about 0.63 billion GDP loss, which contributes 44.6% of the total GDP loss of all 90 cities. For other cities in Emilia-Romagna region, where Bologna locates, the GDP loss is about 0.54 billion, which occupies 37.8% of the total GDP loss of all 90 cities in Italy. If Bologna GDP loss is included, Emilia-Romagna region's GDP loss will reach to 1.17 billion, which contributes 82.4% of the total GDP loss of all 90 cities. For the cities in another area, The GDP loss induced by the Bologna earthquake is about 0.25 billion, which occupies 17.6% of the total GDP loss of all 90 cities in Italy.

4.3.2.1 Bologna area wider economic loss calculation

With the simulated travel time delay result and the linear regression function developed, Bologna's GDP loss at each week during the earthquake event is estimated as shown in Table 4.4 and Figure 4.9.

Bologna	**Weekly1 GDP Loss per Capita (Euro)**	**%of Weekly GDP per Capita**
Week1-2	110	17.3
Week4	98.94	15.6
Week5	60.21	9.5
Week6	59.06	9.3
Week7-8	42.18	6.7
Week9-18	4.5	0.7
Week19	2.33	0.4
	Annual GDP per capita Loss (Euro)	**% of Annual GDP per Capita**
Total	668.86	2

Table 4.4: Weekly GDP loss per capita in Bologna

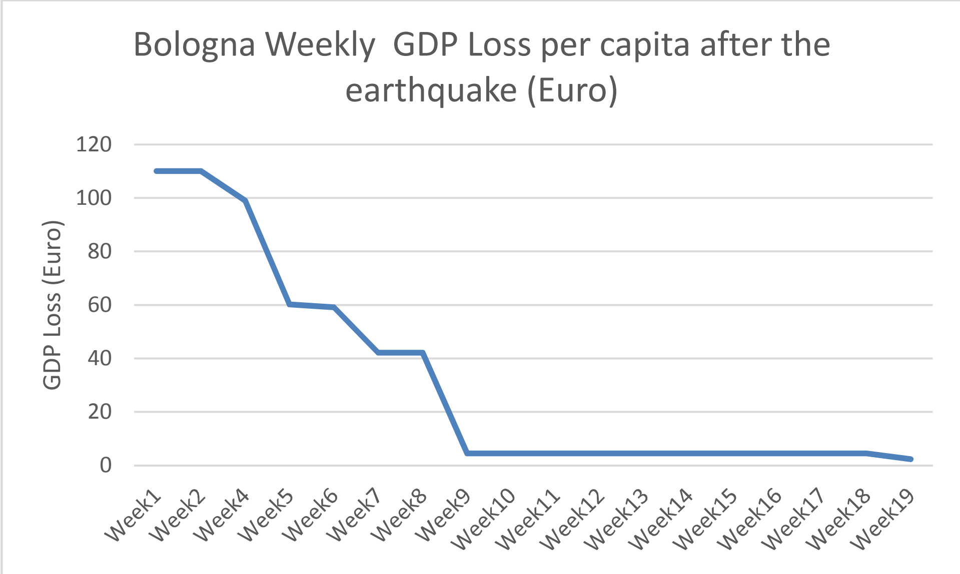


Figure 4.9: Bologna Weekly GDP Loss per capita

Figure 4.9 shows that the aggregate GDP loss during the earthquake event can be divided into 3 phases. From Week 1 to Week 4, the GDP Loss is high, which is over 10% of the normal weekly GDP. From week 5 to week 8, the GDP loss is reduced. From week 9 to week 19, the GDP loss dropped to a very low level， which is less than 1 % of the average weekly GDP. The damage, therefore, lasts for a period spanning ten weeks. In general, the GDP loss caused by the earthquake-induced transport disruption would lead to an annual GDP loss per capita of 668.86 Euros, which occupies about 2 % of annual GDP of Bologna. Our result on Bologna area's indirect economic impact is in line with the analysis developed for Memphis earthquake (Rose et al., 1997).

4.3.2.2 Wider economic loss of Emilia-Romagna region

Emilia-Romagna region is the area where Bologna locates. Except for Bologna, Emilia-Romagna region also includes the cities of Modena, Ferrara, Ravenna, Forli-Cesena, Reggio-Nell'Emilia, Rimini, Parma, and Piacenza. Emilia-Romagna's GDP loss at each week during the earthquake event is estimated as shown in Figure 4-10.

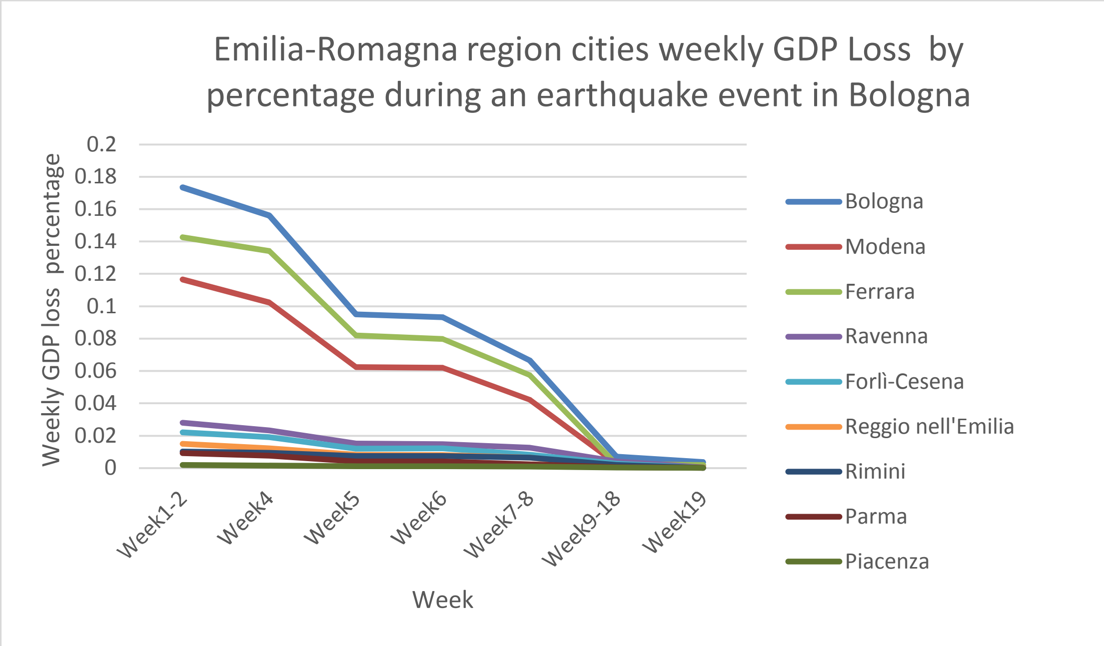


Figure 4.10: Emilia-Romagna region cities weekly GDP Loss by percentage during an earthquake 'event in Bologna

Figure 4.10 illustrates that Modena, Ferrara have significant GDP losses and have a similar dynamic trend with Bologna. Other cities' GDP losses are lower. The GDP losses dropped to a low level after Week 5. The estimation of the cities' total GDP loss is shown in Table 4.5.

City	GDP Loss(Euro)
Bologna	633475878
Modena	266393720.1
Ferrara	144787206.5
Ravenna	39408627.17
Forlì-Cesena	30769059.76
Reggio nell'Emilia	26286082.04
Rimini	13391398.17
Parma	12418045.31
Piacenza	1997173.638

Table 4.5: Emilia-Romagna Cities total GDP loss estimation

Table 4.5 shows that Modena and Ferrara's GDP loss due to the earthquake-induced road network disruption is 266.4 million and 144.8 million. Ravenna, Forli-Cesena, Reggio nell'Emilia, Rimini and Parma cities endure GDP losses over 10 million Euros. Piacenza is the least impacted city by the earthquake in Bologna.

4.3.2.3 Cities in other areas wider economic impact estimation

The GDP loss of cities in other regions in Italy during the earthquake event is shown in Figure 4.11.

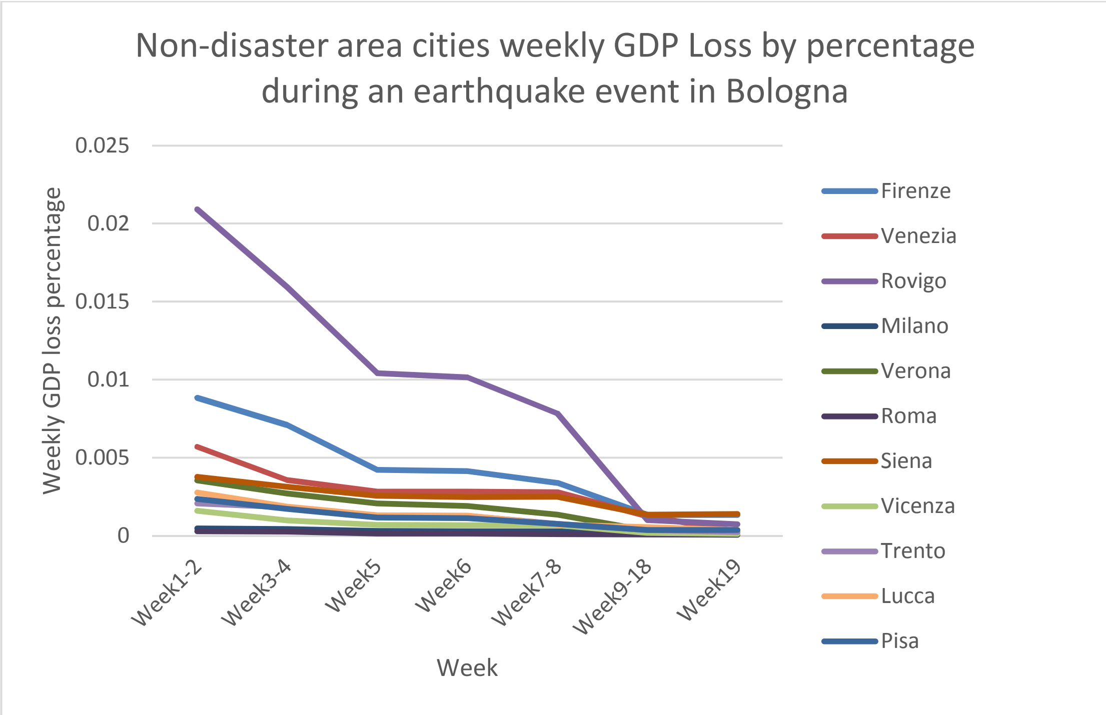


Figure 4.11: Non-disaster area cities weekly GDP Loss during an earthquake event in Bologna

Figure 4.11 indicates that the percentage of weekly GDP loss per capita, Rovigo is the highest among the cities, and it shows a similar dynamic trend with Modena, Ferrara. In the first week, the GDP loss of Rovigo reaches 2% of its average weekly GDP. But other cities first week GDP loss are all less than 1%. Week 5 is also a critical time point when the GDP loss decreased sharply.

City	Annual GDP reduction(%)	GDP Loss(Euro)
Firenze	0.00118772	34585691.53
Venezia	0.000818523	19390070.3
Pistoia	0.002415159	16383470.67
Rovigo	0.002320078	14058047.83
Prato	0.00217542	13875264.9
Padova	0.000519641	13660362.02
Milano	7.99168E-05	11574596.36
Mantova	0.00094748	11374491.47
Verona	0.000436775	11117068.07
Roma	5.0309E-05	6263051.814
Pesaro e Urbino	0.000658717	5769240.066
Siena	0.000748229	5276286.054
Brescia	0.000138866	4919549.958
Arezzo	0.000551127	4621808.862
Vicenza	0.000190177	4617375.516
Trento	0.000307281	4364068.428
Cremona	0.000391342	3585438.054
Lucca	0.000369724	3555335.214
Pisa	0.000310809	3300227.496

Table 4.5: Top 20 cities in other regions that have the largest GDP loss

The GDP loss of all the weeks during the earthquake event is summed, and an estimation of the cities' total GDP loss caused by the earthquake can be estimated. The total GDP loss indicates natural hazards' overall economic impact to the cities the result is shown in Table 4.5. The GDP loss of the cities in other cities occupies a small portion to the city annual GDP. The city with the highest economic loss is Firenze; its GDP loss is about 34.6 million Euros, nearly 15 million more than the second-highest city Venezia, with 0.12% of its annual GDP. The cities with the GDP loss over 10 million are Pistoia, Rovigo, Prato, Padova, Milano, Mantova, Verona.

As shown, the northern cities such as Rovigo, Mantova, Brescia, Vicenza, Cremona are the most seriously impacted cities by the earthquake of Bologna. But there are also cities in the middle and south of Italy which suffer relevant GDP loss such as Rome, Napoli.

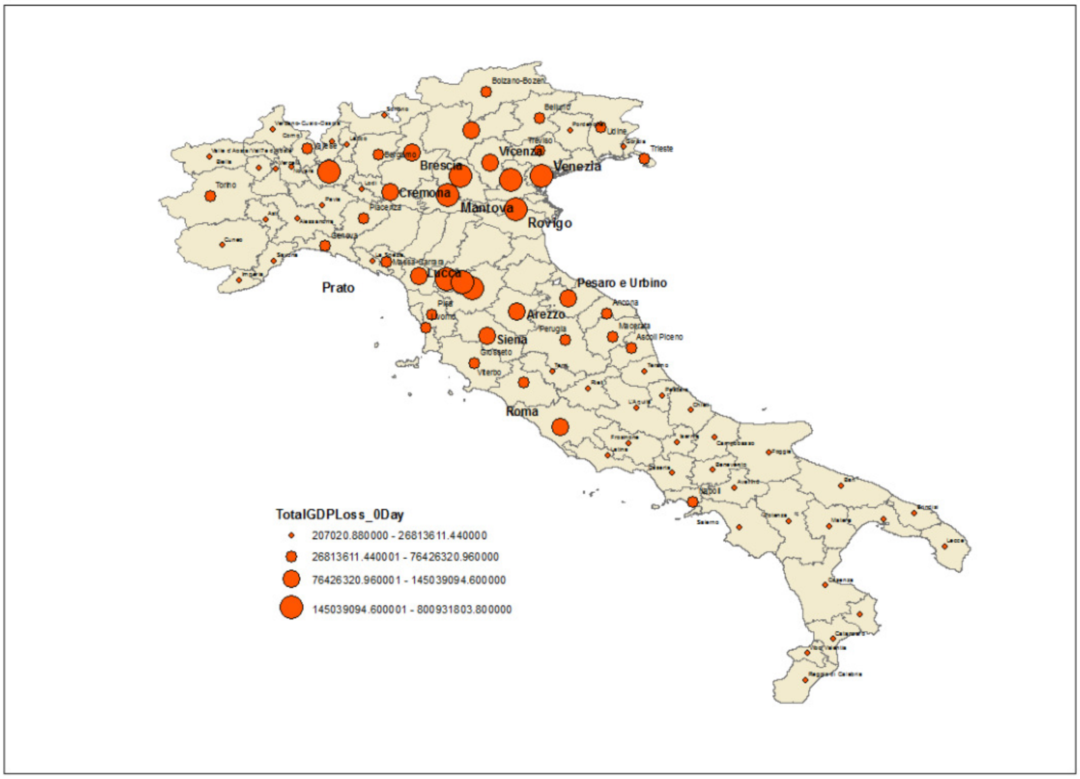


Figure 4.12: Top 20 cities that have the largest GDP loss due to the earthquake

The results obtained prove our hypothesis that the cities close to Bologna area have higher travel time delay have the larger economic loss. However, there are some special cases such as Prato and Rome. The commercial and industrial clusters might also be a factor that influences the economic loss.

4.4 Model application on evaluating hazard's wider economic impact

For the third sub-objectives, we will have a sensitivity analysis on the recovery time of individual bridges and tunnels to test how the repair time of bridges and tunnels will affect GDP loss. We hypothesise that the longer is the restoration time of the individual components, the larger is the economic loss. However, the whole system's recovery time is not linear to the increasing of restoration time and therefore, the increasing of economic loss along with the restoration time is non-linear either.

In the previous economic estimation, we assumed that damaged bridges are repaired immediately. However, it is not the situation in reality. The restoration of damaged bridges is often delayed due to the lack of labour or organisation deficiency. In the simulation, we set a parameter named 'Bridge restoration delay' to represent the time delay of a bridge restoration process. The simulation shows that the road network recovery time varies according to different bridge restoration delay as shown in Figure 4.13.

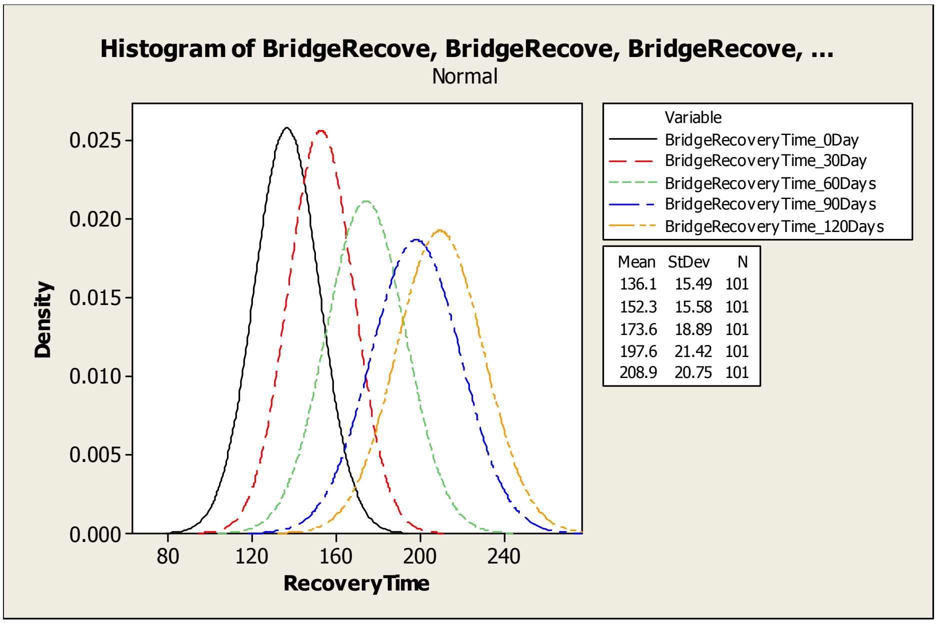


Figure 4.13: Statistics of road network recovery time given no bridge restoration delay and 30, 60,90,120 days delay.

Figure 4.13 shows that, if every bridge restoration process starts immediately, the whole road network needs 4-5 months to be fully recovered. The longer the individual bridge restoration delay, the longer the recovery time for the overall system needs, reaching 6- 8 months. Meanwhile, larger variation of the recovery time can be observed when to increase the bridge restoration delay; This refers that the longer individual bridge's restoration delay, the larger uncertainty for the road network recovery.

Based on the estimation of the road network recovery time, overall GDP loss of cities under five scenarios of giving different bridge restoration delay time (0day, 30days, 60days,90,120 days) is calculated. The calculation results for the cities in Emilia-Romagna region and other area are shown in Figure 4.14 and Figure 4.15.

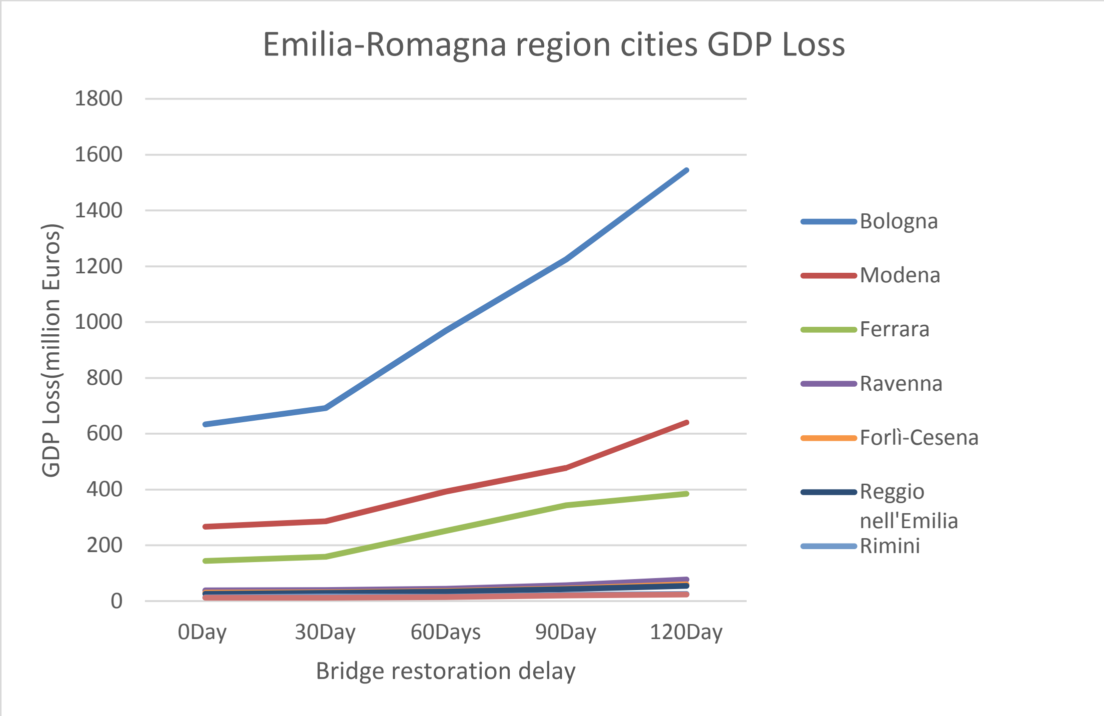


Figure 4.14: Emilia-Romagna regional GDP loss comparison at different bridge restoration delay level

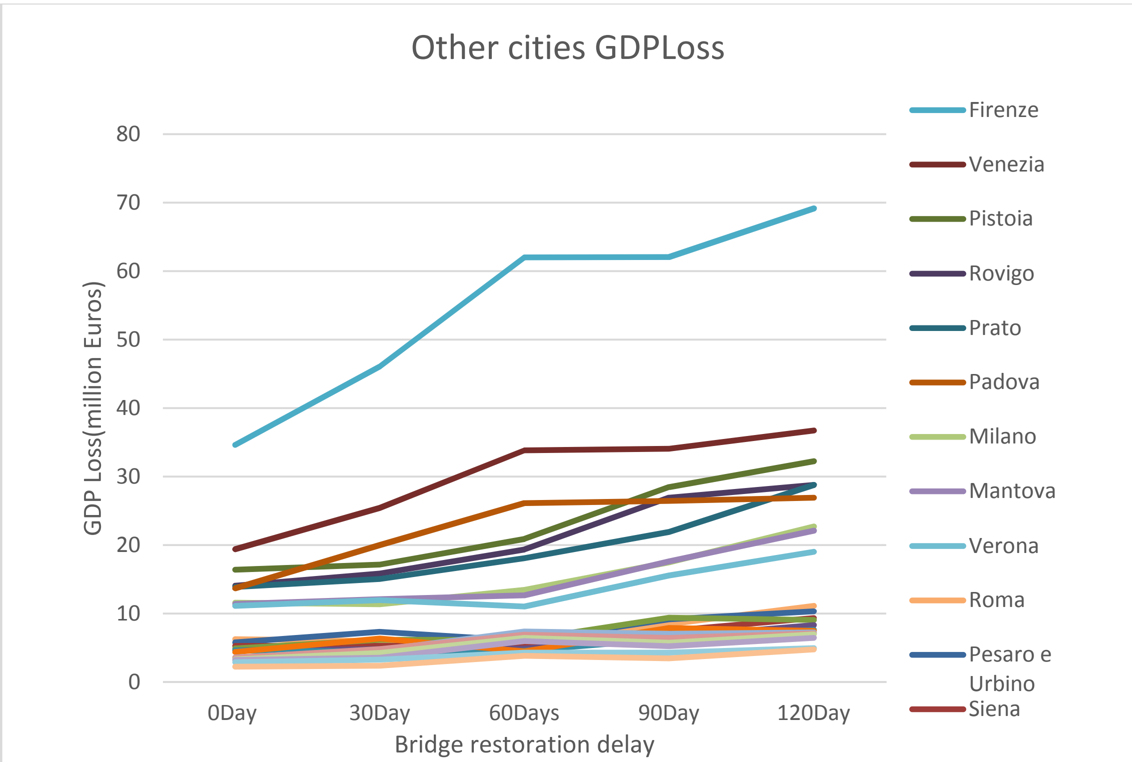


Figure 4.15: Regional (non-disaster exposure area) GDP Loss comparison at different bridge restoration delay level

Based on the research on the Italy case, it implies that the longer restoration delay of the individual components, the larger economic loss will be, and the increase of the GDP loss is non-linear. In the disaster exposure area, the GDP loss sharply increases when the individual bridge restoration delay is longer than 30 days. Comparing different cities, it is quite obvious that the closer distance the city has to Bologna, the sharpest increase of the GDP loss. For example, Modena and Ferrara have a sharper increase than the city such as Firenze.

4.5 Results Summary

In this section, we present the research result obtained for evaluating the wider economic impact of an earthquake event in Bologna to the road network in Italy.

Firstly, the result of the simulating the disaster scenario and the dynamic restoration process after the natural hazard is presented. Then the traffic delay of all the 90 major cities is estimated. It is found that the earthquake in Bologna impacts not only the disaster area but also the non-disaster area cities.

Secondly, the economic model successfully estimates the wider economic impact of the earthquake in Bologna to the national transport system. The estimation of all the 90 cities wider economic loss due to the earthquake-induced transportation disruption shows that the cities that are close to Bologna area have higher travel time delay and have a larger economic loss. ’s wider economic loss of the cities in Emilia Romagna region occupies 82% of the total wider economic loss in Italy. The total GDP loss reaches to 250 million Euro.

Finally, the sensitivity analysis on the restoration time of individual bridges and tunnels is carried out to see how the restoration time of bridges and tunnels will affect GDP loss. The result shows that the GDP loss would double if the bridge restoration delay is longer. For the cities in Emilia-Romagna, 30 days is a key time point, if the bridge restoration delay time is long than 30 days, the wider economic loss will increase sharply. While for other cities, 60 days is a threshold of bridge restoration delay time, beyond which, would lead to a sharp increase in GDP loss. It proves that the longer restoration time of the individual components, the larger economic loss, however, the whole system’s recovery time is none linear to the increasing of restoration time.

5.0 CONCLUSION

In this deliverable, the wider economic impact of a natural hazard to the regional and national economy through transport infrastructure system disruption has been investigated. We set out to solve the problem from three perspectives:

1. To investigate the indirect consequences of a natural hazard to transport infrastructure
2. To quantitatively evaluate the indirect economic value of transport disruptions.
3. To measure how infrastructure restoration time impacts on the economic context.

Based on previous research, an ABM model is developed to simulate the indirect consequences of a natural hazard event. The model was then combined with an economic model that can estimate the GDP loss with transport OD data.

This research confirms that a natural hazard not only impacts on the disaster exposure area but also the non-disaster exposure area. We also show that recovery time is a critical issue about the economic loss due to a natural disaster. For an earthquake event in Bologna, the cities that are close to Bologna area and have higher travel time delay all have a large economic loss. However, there are some special cases such as Prato, Rome, which indicates that the economic industry structure might also be a factor that influences the economic loss. As anticipated, the longer restoration time of the individual components, the larger economic loss, and the increase of the GDP loss is non-linear. In the disaster exposure area, the GDP loss sharply increases when the individual bridge restoration delay is longer than 30 days.

One significant innovation of this research is the application of ABM model for simulating the indirect consequences of a natural hazard. This enables us to transfer the research result on individual infrastructure fragility curve and restoration curve into the road network vulnerability and resilience study. Additionally, the integration of ABM traffic model allows us to study the resilience at regional and national level. These simulation models can be applied for the emergency planning to predict the location of the vulnerable infrastructure as well as the resources needed for the organising emergency restoration process. Another important characteristic of this research is the use of transport OD data to estimate the indirect economic loss.

The research result displays a possible number and locations of infrastructure physical damages given an extreme earthquake happens in Bologna. The most impacted roads and how long time the roads system can be recovered are all visualised. Furthermore, the economic loss caused by this earthquake to all the cities in Italy can be estimated. This can give Italy road planners, Bologna, and other cities a practical guide on how to improve the restoration process and reduce the economic loss to the lowest level. We also show that recovery time is a key issue about the economic loss due to a natural disaster, and therefore the operation management measures such as shortening post-event infrastructure restoration can reduce the economic loss according to the result of the economic model.

One important question that has not been addressed in this research is that the OD data has not been divided by travel mode and travel purpose. If travel mode and travel purpose can be classified, there should be a more rigorous economic estimation.

Certainly, we can argue that to have a post-disaster travel behaviour survey will allow for a better understanding of how sensitive the travel demand reacts to a natural hazard.

Nevertheless, given the limitation of our data, we can conclude that natural hazards end in particular economic losses due to natural hazards impacts on the areas and people beyond the geographical disaster exposure area. It is, therefore, necessary to examine the problem at local and national and transnational level in order to reduce and recover the possible economic losses.

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