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RISK-BASED NETWORK-WIDE ROAD SAFETY ASSESSMENT. A NEW METHODOLOGICAL APPROACH.

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List of contents

Abstract

Although EU roads are among the safest in the world, the burden of road crashes is still too high, so that the road safety targets set for 2020 were far from being achieved. Road Infrastructure Safety Management (RISM) procedures aim at evaluating, monitoring, and improving the safety performance of the road network, over its whole life cycle. Specifically, Road Network Screening (RNS) is the first step of the procedure, and it is applied to a wide scale to identify those most critical segments that require further investigation. Recently, the European Commission has updated the former RISM Directive (2008/96/EC) and expanded its scope beyond the TEN-T Network, by specifically upgrading the RNS procedure (Art. 5). More precisely, according to a proactive approach, a *risk-based network-wide safety assessment* and a *risk mapping* have been introduced. However, no technical nor methodological specification has been provided on how to perform such tasks, which are mandated to the Member States by 2024.

RNS represents the starting point for developing the new risk-based assessment procedure. However, despite the valuable insights provided by previous research on such topic at the theoretical and practical level, looking thoroughly at the past literature some gaps persist. For instance, available road network segmentation methods strongly depend on the availability of accurate spatial crash locations to work properly. A structured and common formulation of *road crash risk* (*i.e.,* the combination of crash occurrence, severity, and exposure) was not clearly found. Indeed, just a handful of studies tried to formalise a risk-based analysis, which however was just partially explained. Finally, most used ranking methods rely on a fixed threshold, instead of a multi-level ranking scale.

The present research aims at providing practitioners and road safety authorities with a flexible and easy-to-apply scheme that supports their work and responds to the new EU requirements. More precisely, it proposes a new methodological approach for the implementation of a risk-based network-wide road safety assessment. Building on the basic procedure of the RNS and applying the widely shared definition of risk (*i.e.,* the combination of crash occurrence, severity, and exposure), an operational and flexible framework is devised, which integrates different raw data sources (*i.e.,* road infrastructure, operational, environmental and context characteristics) and returns an evaluation of an entire road network. Specifically, the evaluation is performed through a *road crash risk prediction model,* in which all the risk components are estimated separately: road crash occurrence probability and road crash severity by mean of a binomial logit model, and crash exposure factor (*i.e.,* traffic volumes) by mean of a multiple linear regression model. The identification of the most critical segment of the network is the main expected output, which is obtained by developing risk maps based on a five-levels ranking scale. Moreover, it is devised in compliance with the ISO 39001:2012 Standards, to facilitate the whole process and enables for qualification.

To assess its applicability and effectiveness, the proposed methodology is tested over the main road network of the Province of Brescia (Lombardy Region - Italy), which represent an emblematic case study. Furthermore, it is compared to the alternative risk formulations retrieved from previous studies. Results highlighted the potential of the proposed methodology, its wide adaptability and easy interpretability. Furthermore, it allows the identification of critical segments of the network that the other assessment procedures are not able to detect.

Keywords: Road network screening; Road crash risk; Road Infrastructure Safety Management; Crash probability; Crash severity; Crash exposure; Data integration.

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Abstract in Italian

Nonostante l’Europa presenti le reti stradali tra le più sicure al mondo, le esternalità dovute all’incidentalità stradale risultano ancora troppo elevate, tanto che gli obiettivi di sicurezza stradale fissati per il 2020 non sono stati raggiunti. Il processo di Gestione della Sicurezza delle Infrastrutture Stradali (GSIS) mira a valutare, monitorare e migliorare le prestazioni di sicurezza di una rete stradale, durante il suo intero ciclo di vita. Nello specifico, la valutazione della sicurezza di rete rappresenta il primo passo dell'intero processo, e viene applicata su larga scala per individuarne quei segmenti più critici che richiedono ulteriori indagini. Recentemente, la Commissione Europea ha aggiornato la precedente direttiva GSIS (96/2008/EC) e ne ha ampliato il campo di applicazione oltre la rete Transeuropea (TEN-T), introducendo, secondo un approccio proattivo, *un processo di valutazione della sicurezza a livello di rete basato sul rischio* oltre alla *mappatura di tali rischi* (Art. 5). Tuttavia, non è stata fornita alcuna indicazione metodologica riguardo come eseguire tale procedura, di cui è invece prevista la realizzazione da parte degli Stati Membri entro il 2024.

La valutazione della sicurezza di rete rappresenta il punto di partenza per lo sviluppo della nuova procedura basata sul rischio. Tuttavia, nonostante i numerosi ed importanti contributi forniti dagli studi precedenti sul tema, sia a livello teorico che pratico, analizzando la letteratura scientifica, rimangono alcune limitazioni. Ad esempio, l’efficacia dei metodi di segmentazione della rete stradale disponibili dipendono fortemente dalla disponibilità di un’informazione accurata riguardo la localizzazione degli incidenti. Non è stata ancora definita una formulazione strutturata e comune per la misura del rischio di incidente stradale (*i.e.,* la combinazione di probabilità di accadimento, severità ed esposizione). In merito, solo pochi studi hanno cercato di formalizzare un'analisi basata sul rischio, che tuttavia hanno permesso di spiegare solo in parte il fenomeno. Infine, i metodi di classificazione più utilizzati sono basati su soglie fisse, anziché su una scala di classificazione multilivello.

La ricerca vuole porsi l’obiettivo di fornire a professionisti del settore e alle autorità della sicurezza stradale un sistema flessibile e di facile applicazione che supporti il loro lavoro e risponda ai nuovi requisiti dell'UE. Più precisamente, essa propone un nuovo approccio metodologico per l'attuazione di una valutazione della sicurezza stradale a livello di rete e basata sul rischio. Applicando la ampiamente condivisa definizione di rischio (*i.e.,* la combinazione di probabilità, gravità ed esposizione), è stata elaborata una procedura flessibile, che integra diverse fonti di dati (*e.g.,* caratteristiche dell'infrastruttura stradale, caratteristiche operative, ambientali e di contesto, etc.) e restituisce una valutazione dell'intera rete stradale. In particolare, la valutazione viene eseguita attraverso un *modello di previsione del rischio di incidente stradale,* in cui tutte le componenti di rischio sono stimate separatamente: probabilità di accadimento e severità dell'incidente mediante un modello logit binomiale, mentre il fattore di esposizione (volumi di traffico) mediante un modello di regressione multipla lineare. L'identificazione del sito più critico della rete è il principale output atteso, che si ottiene sviluppando mappe di rischio basate su una scala di classificazione a cinque livelli. Inoltre, l'intera metodologia è sviluppata in conformità con le norme ISO 39001:2012, per facilitare l'implementazione e consentire la qualificazione.

Per valutarne applicabilità ed efficacia, la metodologia proposta è stata testata sulla rete stradale principale della Provincia di Brescia (Regione Lombardia - Italia), che rappresenta un caso di studio emblematico. Inoltre, è stato proposto un confronto con le formulazioni di rischio alternative desunte dagli studi precedenti per capirne le differenze. I risultati hanno evidenziato le potenzialità della metodologia proposta, la sua ampia adattabilità e facile interpretabilità. Inoltre, ha consentito l'identificazione di segmenti critici della rete che le altre procedure di valutazione non sono state in grado di rilevare.

Keywords: Valutazione di sicurezza stradale; Rischio di incidente stradale; Gestione della Sicurezza delle Infrastrutture Stradali; Probabilità di incidente; Severità di incidente; Esposizione all'incidente; Integrazione dati.

1. Introduction

1.1. Research context and problem statement

Sustainable mobility plays a core role in the worldwide discussion about sustainable development. However, it should not be possible to talk about sustainable mobility without accounting for road safety as an essential element. Indeed, road *unsafety* represents a huge health, social and economic burden that causes approximately 1,3 deaths each year and is recognised to be the leading cause of death for people aged 5-29 (WHO, 2018). In addition, the road crash costs range from 0,4% to 4% of the national Gross Domestic Product (GDP) across countries (WHO, 2018; Wijnen et al., 2019). Conversely, in a sustainable perspective, such resources should be employed more effectively, by implementing proactive strategies to reduce in advance such silent and long-lasting pandemic.

Since its establishment in 1992, the European Union (EU) has shown a strong commitment to ensure all Member States (MS) higher safety standards within the Transport sector (European Union, 1992). Over the years, road safety has largely improved in Europe, also thanks to the several targets that, on a ten-year basis, the EU set intending to halve the number of road deaths and serious injuries towards the ultimate goal of the *Vision Zero*[1] (European Union, 2017; European Commission, 2019). As a result, EU roads are now considered among the safest in the World (European Commission, 2021). Indeed, the absolute number of road deaths dropped on average by 37% in 2020 compared to 2010 among the European Member States, and the one of serious injuries by 14% (ETSC, 2021).

However, the burden of road crashes remains too high. According to the latest available statistics, in 2019, more than 22.000 people lost their lives in a road crash, and about 1,23 million injuries were registered Europewide (Eurostat, 2020). Furthermore, the considerable reduction in road crashes and deaths achieved in 2020 cannot be considered a full positive result. Indeed, it was due to the great reduction in transfers and mobility imposed by the Covid-19 restrictions and not to an overall improvement in road safety (ETSC, 2021). In addition, unless those half-positive result, the target of halving the number of road deaths by 2020 compared to 2010 was missed by most EU Member States[2]. As a result, further effort is required to be prepared for the next *Decade of Action.*

In 2018, the latest EU Strategic Action Plan for Road Safety has been adopted (ETSC, 2018b; European Commission 2018), in which key strategies have been drawn to improve road safety according

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[1] Swedish Government. Vision Zero Initative. Traffic Safety by Sweden. Accessible at: http://www.visionzeroinitiative.com/

[2] Only Greece reached the 50% reduction target.

to a *Safe System* approach[3]. In that perspective, the road safety challenge should assume that road crashes are not just caused by the human-error, but rather that the whole road system is responsible for it (*i.e.,* road infrastructure design, vehicle design and safety, enforcement and education, speed control, post-crash response, etc.). Therefore, a new and more human-oriented thinking should be adopted, to forgive the human error and allow human fallibility and vulnerability. In doing so, layered, and coordinated measures from the several multidisciplinary sectors need to be provided, so that where one may fail, the other can still mitigate road crash severe impacts.

Among all, road infrastructures safety has been included between the biggest road safety challenges by the EU, as roads and roadsides are recognized to be a critical contributing factor to crash occurrence in more than 30% of cases (Elvik, 2009; AIB, 2014). Heading to this goal, the EU have recently updated the EU 96/2008/CE Directive on Road Infrastructure Safety Management (RISM), by upgrading RISM procedures to provide safer roads and roadsides (European Commission, 2008; European Commission 2019). Specifically, a risk-based network-wide mapping and safety ratings have been included as proactive assessments in addition (or better, in place) to the more traditional (and reactive) *high accident concentration sites identification* approach (European Commission, 2020). However, no technical specification has been included in the updated RISM Directive about how to perform such road network assessment and risk mapping, which is expected by 2024 instead. Also, a Key Performance Indicator[4] (KPI) has been set to measure the safety quality of the road network and allow comparison among MS. However, such KPI shows drawbacks in that many MS may not have sufficient data available to compute it and, owing to the absence of a common rating methodology, it may be revised.

In addition, the International Standard (*i.e.,* ISO 39001:2012 about *Road Traffic Safety Management System* - RTSMS) was developed to provide private and public organizations that deal with road traffic in their daily activities, with a system able to support them improving their road safety performances and, specifically, reducing the risk of fatal or severe road crashes (ISO 39001, 2012). More precisely, the Standard provides a general but comprehensive guide on how to implement a RTSMS, but it does not provide any technical requirements for its implementation, nor it strictly define the overall structure of the system itself.

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[3] all the key pillars should be accounted together according to a systemic process, to provide layered solutions to mitigate human mistakes

[4] Percentage of distance driven over roads with a safety rating above an agreed threshold.

Therefore, further work is necessary to set up an effective and common methodology for the risk-based network-wide safety assessment, which includes all the recommendations provided by the new EU Directive 1936/2019 on RISM and accommodate the implementation of the ISO 39001:2012

RISM procedures aim at evaluating, monitoring, and improving the safety performance of a road network over the whole road infrastructure life (*i.e.,* at the planning, project, and operating stage) and at different investigation levels (*e.g.,* at a network-wide or site-specific level) (Elvik 2010; Hauer et al. 2002; Persia et al 2016). Specifically, Road Network Screening (RNS) is the first step of the whole process, and it is applied to assess the safety performance of the entire road network and identify the most critical segments (Elvik 2010; Park & Sahaji 2013; Stipancic et al. 2019). It comprises three main stages, namely (i) network segmentation, (ii) evaluation of the network segments, and (iii) network ranking. As RNS is not a novelty in the scientific field, the literature is quite rich in existing RNS methods, which represent a valuable baseline for the implementation of the new risk-based network-wide safety assessment. However, concerning the newly set objectives (*i.e.,* developing a risk-based network-wide road safety assessment and the related risk mapping), some gaps persist.

Specifically, as for (i), space/feature-related segmentation such as fixed-length sliding windows, homogeneous segment (*e.g.,* Elvik 2007; AASHTO, 2010; Ghadi and Török, 2019) and crash-related segmentation detection such as high crash risk profile (*e.g.,* Elyasi et al., 2016; Boroujerdian et al., 2014) are used, which however can properly work just if an accurate crash location is available. In addition, they may suffer from variability in the segmentation criteria and inconsistencies with the scale of the analysis. As for (ii) several methods are used, which range from a more reactive approach based on the analysis of historical road crash data (*e.g.,* Gupta & Bansal 2018; European Road Assessment Program 2020, Borghetti et al. 2021), to more proactive approaches, which rely on the inherent safety characteristics of the network instead, and use composite indicators (*e.g.,* Yannis et al. 2013; Viera Gomes et al. 2018), or apply Crash Prediction Models (CPMs) (*e.g.,* AASHTO, 2010, 2014; Wang et al., 2011; Stipancic et al., 2019). As for the latter, such methods are preferable as they can return both a quantitative and qualitative estimate of the expected outcome (*e.g.,* the frequency and the severity of crashes). In this way, more targeted and cost-effective interventions can be performed to fix potential safety drawbacks in advance (Yannis et al. 2016; Ambros et al. 2018). However, according to the most widely shared risk formula, which can be defined as the combination of three main dimensions (*i.e.,* crash occurrence, severity, and exposure), few studies have included an explicit risk-based structure in their analysis. More precisely, all previous studies addressed crash occurrence by mean of a frequency measure, severity by a probability estimation, while no studies introduced the exposure factor as an independent variable and modelled it. As for (iii), most previous studies identified critical segments based on a fixed threshold, instead of ranking segments according to a multiple level scale (which is required by the Directive instead).

1.2. Research objectives

To bridge the previous gaps, the present research focuses on the road infrastructure safety management sector and proposes a new methodological approach for *the implementation of a risk-based network-wide road safety assessment*. More precisely, the major goal of the research is to provide an effective, flexible, and widely applicable operational framework that returns an evaluation of an entire road network based on a *road crash risk prediction model.*

Existing and widely-applied road safety prediction models (*i.e.,* road crash occurrence and severity prediction models) and exposure models (*i.e.,* Average Annual Daily Traffic – AADT – extimation) are combined in an innovative way to be consistent with the definition of risk. The identification of the most critical sites of the network is the main expected output, which is obtained by developing risk maps based on a five-levels ranking scale.
In addition, a further effort was made to ensure the overall framework wider applicability (both in terms of practical implementation and transferability to other contexts), interpretability (*i.e.,* ease in understanding the model outputs), adequate flexibility (*i.e.,* to return an adaptable-scale analysis), by also unbinding the network segmentation process from the availability of accurate crash location data (*e.g.,* spatial coordinates).

In doing so, it aims at (i) responding to the new 1936/2019 EU Directive requirements, (ii) embracing the proactive approach, and (iii) assuring compliance with the ISO 39001:2012, which facilitates the whole process and enables for standard qualification.

1.3. Research contributions

The present research aims at contributing to both theory and practice.

On the theoretical side, it sheds light on a research area that has not been completely addressed so far. More precisely, it contributes to the field of RNS theory as it proposes alternative methods for network segmentation and network evaluation. In addition, although it relies on well-known crash prediction and mathematical models, it expands the theoretical understanding and application of crash risk in a manner that was not explored yet by previous research, to the author's knowledge.

From a practical perspective, it provides road safety authorities and practitioners with an effective decision support tool, which can help them in (i) identifying most critical road sites, (ii) prioritising interventions, and (iii) defining the most appropriate measure to mitigate the effect of the crash risk components, according to a proactive approach. In addition, this also makes it possible to assess crash risk in the road infrastructure planning stage, in other words, to assess the expected impact that a new (or restored) road may show, based on its characteristics. Moreover, the models selected to perform such analysis are among the most widely applied and easy to perform, so that their implementation and interpretability is fostered also among those who do not have a broad statistical and econometric knowledge.

To assess its applicability and effectiveness, the proposed methodology will be tested over the main road network of the Province of Brescia (Lombardy Region - Italy), which represents an emblematic case study. Indeed, it represents an important residential, industrial, commercial, and touristic hub, whose road network is interested in high traffic volumes. In addition, the road network covers a wide territory, and it consists of a wide variety of roads and environments. As a result, it can be assumed as a representative case study for all the surrounding areas.

1.4. Research outline

The reminder of the thesis is structured as follows: in chapter 2, the state of the art is analysed, by providing an in-depth discussion of the main elements underlying RNS definition and implementation. More precisely, starting from an overview of the road infrastructure and safety policies, a focus on risk formulation, road network screening procedures and crash prediction models are provided. Then, in chapter 3, a thorough description of a new methodological approach for a risk-based road network-wide safety screening is provided. Next, the case study is presented in chapter 4, as well as the application of the overall methodology and the results obtained, which are discussed later in chapter 5. Finally, some conclusive remarks are drawn in chapter 6, with a focus on the research limitations and future perspectives.

2. State of the Art

2.1. Outline of topics

Road safety is a wide and multidisciplinary topic so that extensive research has been produced over the last decades. To help the reader focus on the background rationale of this thesis and understand the link across the several topics, a flowchart of the contents treated in the *State of the Art* is provided in Figure 1 and briefly described in what follows.

First, **road safety policies and directives** have been studied at the international and European level, to provide an overview of the strategies developed over the years to improve road safety, with a focus on road infrastructure safety. Specifically, the more recent directives, which are expected to be transposed by the Member States by the next years, aims at moving forward from the traditional approach by relying on **risk-based evaluations** and promoting **proactive approaches** (*i.e.,* to take actions to mitigate crash occurrence and consequences before it occurs).

Then, a review of the concept of risk has been proposed, to assess how **risk has been evaluated** in the past literature and – mainly – how it has been formalised for a quantitative measurement. Indeed, risk represents an extremely relevant decision-support and decision-making parameter to be applied to any management process, and so to the Road Infrastructure Safety Management (RISM) process.

In this perspective, **Road Network Screening** (RNS) plays a core role, being the first step of the RISM process to be applied for the identification of the *high crash risk sites.* Therefore, the opportunity to apply a measure of risk in the evaluation of the safety performance of the whole road network would result in an effective identification of the riskiest sites. The measure of risk to be applied depends on how RNS is performed: employing a reactive or a proactive approach.

As for the **proactive approach -** which should be preferred relative to the reactive one – crash prediction models have been investigated, representing efficient tools able to return both a qualitative and quantitative measure of the road safety performance. Specifically, a focus on those studies that proposed crash frequency and severity combined models is provided.

To conclude this chapter, some gaps in the literature have been highlighted and thoroughly described along with the contributions that the present research aims to bring to the scientific and professional field.

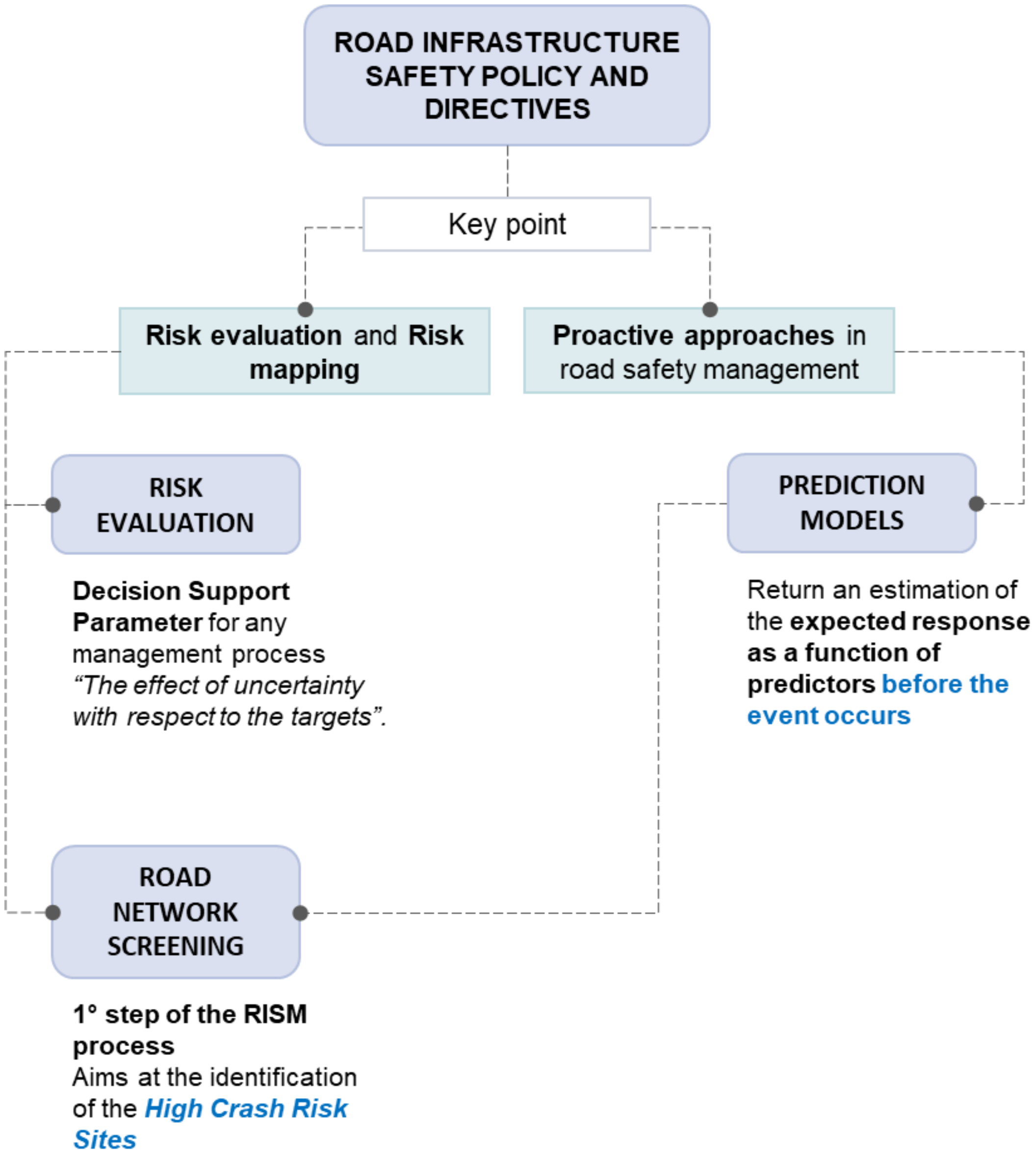

Figure 1 – Outline of the topic addressed in the State of the Art.
Source: Author own elaboration

2.2. Road infrastructure safety policies and Directives

At the international and European levels, a great commitment was put in the definition of specific strategies to provide greater road safety standards for all road users.

As previously mentioned, road safety is a multi-disciplinary subject, that requires coordinated and comprehensive measures from different sectors, such as the health, engineering, and behavioural etc. ones. Moreover, it is necessary to shift from a crash-oriented to a human-oriented mindset to properly fight road *unsafety*. In other words, such approach should anticipate and forgive human error and account for its fallibility and vulnerability (Wegman and Aarts, 2006; Larsson and Tingvall, 2013; European Commission, 2018). As a result, all the elements of the road system (*i.e.,* road infrastructure design, but vehicle design, enforcement and speed management, post-crash response as well) play a core role, as they aim at a layered combination of measures to prevent people from dying and/or got seriously injured. Taken together, they should form layers of protection that ensure that, if one element fails, another one will compensate human error and vulnerability to prevent the worst outcome. In these regards, the Safe System Approach is an innovative approach with respect to the previous road safety approaches.

Although all the components of road safety should be considered as a whole, in this research a focus is provided related to road infrastructure design and safety management. Specifically, road infrastructures play a core role in the road safety challenge as they are a critical contributing factor in more than 30% of crashes (Elvik, 2009; AIB, 2014). For this reason, roads and roadsides have been accounted among the five road safety pillars, as shown in Figure 2. In addition, there is the urgent need to respond to the updated EU Directive, to provide MS (but mainly road authorities and practitioners) with effective methodologies to compute road crash risk and perform a risk mapping analysis.

Figure 2 - Road Safety Pillars.

Source: Author own elaboration

However, when dealing with road infrastructure safety, the sole technical perspective (*e.g.,* defining the most appropriate engineering-related interventions) is not enough. Indeed, road safety is to be intended also at the network level, so that also the management perspective is a key component. The opportunity to provide defined and systematic road infrastructure safety management practices is of utmost importance, as it allows to plan a well-structured monitoring process to control, verify, and improve road safety over the whole network. As a result, specific directives and guidance have been delivered over the years to provide countries with a systematic and common tool to implement effective road infrastructure safety management procedures. In this section, a brief overview of such directives is provided, with a focus on the European level.

2.2.1. EU Directive 96/2008/CE and EU Directive 2019/1936

The EU Directive 2008/96/CE of the European Parliament and of the Council on *Road Infrastructure Safety Management* represents the first main reference Europewide for the implementation of a common Road Infrastructure Safety Management (RISM) system (European Commission, 2008).

The scope of the Directive was that of providing Member States (MS) with shared guidance on how to manage and monitor road infrastructure safety performance from the planning to the operating stage. More precisely, according to Art. 2, the following RISM process was identified:

- *Road Safety Impact Assessment* (RSIA), thus the accurate analysis of the impact of new road infrastructure - or a considerable modification to the existing road network - on the safety performance of the road network.
- *Road Safety Audit* (RSA), thus the detailed, systematic, and technical safety check of the design characteristics of a road infrastructure project (*i.e.,* still non-existing road), from the planning to the early operation stage.
- *Ranking of high road crash concentration sections,* thus a method to analyse the operating road network (at least for more than three years), and then identify and rank those sections registering a too high number of fatal accidents in proportion to the traffic flow have occurred.
- N*etwork safety ranking,* thus a method for identifying, analysing, and classifying parts of the existing road network according to their potential for safety development and accident cost savings (*i.e.,* the Safety Potential).
- *Road Safety Inspection* (RSI), thus the ordinary and periodical check of the road characteristics aimed at identifying defects that require interventions.

For what concerns the operating stage of the road network, Art. 5 of the EU Directive 2008/96/CE was dedicated to the definition of "*Safety ranking and management of the road network in operation",* which were founded on the identification of the *high road crash concentration sections* and specific criteria set out in Annex III of the Directive. The EU Directive 2008/96/CE, which was expected to be transposed by all Member States by 2010, required the implementation of the RISM procedures over the Trans-European Network (TEN-T), while the application on other roads was just recommended as a set of good practices.

Over the years, the EU monitored the effectiveness of the RISM Directive and found that further improvements and efforts were necessary to achieve the new interim targets that were set within the Valletta Declaration (European Union, 2017). Specifically, the major needs were to extend the scope of the former Directive also to those roads not belonging to the TEN-T Network, which was also highlighted by the ETSC (2018a) in their *Joint Statement*. Indeed, Member States which applied RISM procedures to their national roads beyond the TEN-T network achieved much better results, in terms of fatalities and severe injuries reduction, than the MS which did not. In addition, a clear reference to vulnerable road users was required to pay greater attention to such crash types, which represent the most of more severe injuries and deaths.

As a result, in 2020, the EU Commission published the *EU Road Safety Policy Framework 2021-2030* Staff Working Document, with the aim of setting out new strategies to cope with the road safety requirements (European Commission, 2019). Specifically related to the "Infrastructure" Pillar, the EU set clear intention to move towards more *proactive* approaches that rely on risk-based assessment. According to those targets, the European Parliament and the European Council have delivered the new *Directive 2019/1936*, which amended the former Directive on RISM to put such procedures to a higher level and enlarge the application matter of the Directive. Major amendments were related to (i) the extension of the scope of the Directive, (ii) the introduction of a network-wide road safety assessment procedure, and (iii) the inclusion of a specific article to guarantee higher safety standards for vulnerable road users – for the first time. With a focus on the amendments related to the operating stage of road infrastructure RISM, Table 1 reports a comparison among the major amendments and integrations provided by the new Directive,

Table 1 – Major amendments to the Road infrastructure safety management Directive[5].

Article - Topic	EU Directive 2008/96/CE	EU Directive 2019/1936
The subject matter (Art. 1)	It requires the establishment and implementation of procedures relating to road safety impact assessments, audits, inspections, and **the management of road network safety**.	It requires the establishment and implementation of procedures relating to road safety impact assessments, audits, inspections, and **network-wide road safety assessments**.
Scope (Art. 1)	It shall apply to roads that are part of the **trans-European road network (TEN-T)**, either at the design, construction, or operation stage. It may be also applied **to other national road infrastructures as a set of good practices**.	It shall apply to roads that are part of the **trans-European road network, to motorways and to other primary roads**, either at the design, construction, or operation stage. It shall also apply to **roads projects situated outside urban areas**, which do not serve properties bordering on them and which are completed using Union funding.

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[5] Reframed from EUR-Lex website. Full texts of the Directives are available at: https://eur-lex.europa.eu/homepage.html

		Low-risk primary roads may be exempted from the Directive, via communication and justification to the European Commission. ** primary road: road outside urban areas that connects major cities or regions, or both, belonging to the highest category of road below the category "motorway" in the national road classification.*
Road network assessment and ranking (Art. 5)	The ranking of **high accident concentration sections** and the network safety ranking is carried out based on reviews, at least every three years, of the operation of the road network. Remedial treatments should be targeted at the road sections that show **higher priority in terms of benefit-cost ratio**.	A network-wide road safety assessment should be carried out on the entire road network in operation, which shall evaluate **accident and impact severity risk**, based on: (a) primarily, a visual examination, either on-site or by electronic means, of **the design characteristics of the road** (**in-built safety**). (b) an analysis of sections of the road network which have been in operation for more than three years and upon which a large number of serious accidents in proportion to the traffic flow have occurred. Based on the results of the assessment, and for the purpose of prioritisation of needs for further action, **all sections of the road network should be classified in no fewer than three categories according to their level of safety**.
Follow-up of procedures for a road in operation (Art. 6a)	-	The findings of network-wide road safety assessments should be followed up either by targeted road safety inspections or by direct remedial action. Remedial actions should be targeted **primarily at road sections with low safety levels** and which offer the opportunity for the **implementation of measures with high potential for safety development and accident cost savings**. A risk-based prioritised action plan should be prepared and regularly updated to track the implementation of identified remedial action.

Rearranged from EU Directive 2008/96/CE and EU Directive 1936/2019

It is evident that the introduction of the advanced procedure of the network-wide road safety assessment is a core element of the amended Directive and represents a key management tool for achieving the road safety targets Europewide. However, unless no specific common methodology has been provided for such a new procedure, Member States shall ensure that the first network-wide road safety assessment is carried out by 2024 at the latest. In addition, to carry out the network-wide road safety assessment, Member States may consider the indicative elements set out in the updated Annex III.

Specifically, it provides a long list of elements related to *e.g.,* the road design, operational, maintenance, features that should be accounted into a road safety analysis. However, difficulties may arise when trying to collect all those data to cover the whole road network. Indeed, some of the elements included in the long list may be too detailed or not easy to retrieve for such a wide level of analysis. However, the long list of elements represents rather a suggestion, than a requirement.

2.2.2. ISO 39001:2012 Road Traffic Safety Management

The 39001:2012 International Standard was developed by the International Organisation for Standardisation (ISO) to provide private and public organizations, that deal with the road traffic system in their daily activities, with a system able to support them improving their road safety performances and, specifically, reducing the risk of fatal or severe road crashes (ISO 39001, 2012). More precisely, the Standard provides a general but comprehensive guide on how to implement a **Road Traffic Safety Management System** (RTSMS), but it does not provide any technical requirements for its implementation, nor it strictly defines the overall structure of the system itself.

The aim of the Standard is to make the Organization able to recognize in advance all the shortcomings of its activities and processes (hence, something which is fully under the Organization's control) which can affect the road safety performances for employees, products or services and lead to a road crash.

The Standards relies on two core concepts: (i) the holistic approach (*Safe System Approach*) and (ii) the systematic approach of the *Plan-Do-Check-Act* (PDCA) methodology. As for (i), the Standard wanted to stress the importance of tackling the road safety issue from a different perspective, by accounting for all the different areas involved in the road safety challenge (*e.g.,* infrastructure and design, behaviour, traffic management, post-crash response, etc.). As for (ii), the overall system should be focused on a continuous improvement of the Organization's performances and optimal use of resources to reach the road safety target. Indeed, all the general requirements of the Standards are systematically associated with one of the PDCA steps.

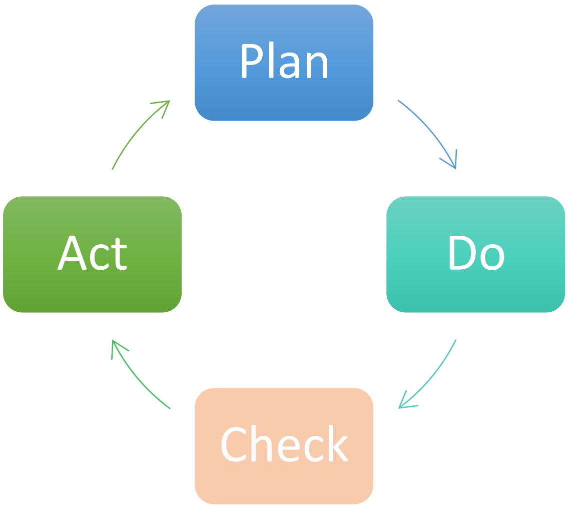

Figure 3 – Scheme of the Plan-Do-Check-Act process (i.e., the Deming Cycle).
Source: Author own elaboration of the Plan-Do-Check-Act cycle of the ISO 39001:2012 Standard

Plan-Do-Check-Act (PDCA) methodology

Plan. The Organization must identify its role within the Road Traffic Safety (RTS) system and all the functions or processes related to its activities that can impact RTS. The Organization must also identify all the parties involved, define the area of applicability of the RTS, and clarify the expected results. This is oriented to the definition of an organization baseline reference for the implementation of the SMS. Moreover, the Organization must adopt a strategic leadership to guarantee that the RTSMS objectives are well integrated and consistent with the ordinary Organization's objectives and assure the availability of resources and commitment to apply and run the RTSMS. In other words, the whole process of the RTSMS must be aligned and included in the ordinary activity process of the Organization. The Organization must also identify risks and opportunities by means of specific performance factors, namely all the safety factors which should be included in the Organization's RTSMS according to its contexts. Such factors must be associated with measurable objectives and monitored throughout the RTSMS process. More precisely, the Organization must identify the Risk Exposure factors, the Final Safety Outcome factors, and the Intermediate Safety Outcome factors.

Do. To make the whole RTSMS work properly, the Organization must coordinate all the parts involved (internal and external) in the most efficient way and train them with adequate expertise and education. To do so, the development of strong communication is key. Moreover, it must guarantee adequate and sustainable resources to set, carry out and maintain the overall RTSMS.

Check. The Organization must monitor and evaluate its Road Traffic Safety performances by means of recurring audits and evaluation processes to check whether improvements or changes may be required to fulfil the objectives. To do so, the Organization must identify clearly what are the factors to be measured and monitored, the methods and procedures to be applied for the monitoring process, and the monitoring schedule. Specific road crash investigations are also warmly recommended, to be able to identify potential threats in the Organization that may lead to a road crash or to a severe consequence.

Act. Based on the results of the monitoring and evaluation process of the RTS performance, the Organization must act to correct and mitigate potential in compliance with corrective actions or, at best, pro-active initiatives. This will lead to a continuously improving process to provide better road safety performance of the Organization.

The RTS performance factors

One of the most important pieces of information that the Standard reports, is the definition of the Road Traffic Safety (RTS) Performance Factors, which account for all the potential elements related to road safety that must be included in the Organization’s RTSMS. Such RTS performance factors are general and widely applicable, and each Organization should consider all the ones falling into the related context. The Standard identifies three main groups of RTS Performance Factor, namely the (i) Risk Exposure factors, (ii) the Final Safety Outcome factors, and the (iii) Intermediate Safety Outcome factors. They will be briefly described in what follows.

Risk exposure factors. Such factors refer to the extent to which the Organization, with respect to its activities and parties, is exposed to road safety risks within the road traffic system. It should also collect data on such factors. Risk exposure factors may be several (e.g., traffic volumes, products or services volume, travel times, etc.). Risk exposure factors may also account for the type of road users (or vehicles) involved.

Final Safety Outcome factors. Such factors represent the road safety indicators to be monitored as final and overall information about the Organization road safety performances. They usually include the road safety outcomes in terms of the number of road crashes, fatalities, or severe injuries but also the measure of the socio-economic or productivity burden resulting from such events.

Intermediate Safety Outcome factors. Such factors can be conceived as measures of potential interventions to improve the final RTS performance, and are related to road infrastructure design and planning, road operational and management measures, road traffic and services regulation, etc. In other words, these factors can be included in the RTSMS to understand the extent to which each factor can affect the overall safety performance of the Organization.

Table 2 – Road Traffic Safety performance factors defined by ISO 39001:2012.

Road Traffic Safety factors	**Description**
Risk exposure factors	Traffic volume, Volume of products and/or services provided Road user type; Vehicles' type
Final Safety Outcome factors	Number of road crashes; Number of road fatalities; Number of road injuries Social costs
Intermediate Safety Outcome Factors	Road design and safe speed, considering traffic/users separation, side areas and intersection design Use of appropriate roads, depending on vehicle type, user, type of cargo and equipment Use of personal safety equipment Using safe driving speed, also considering vehicle type, traffic and weather conditions Fitness of drivers, considering fatigue, distraction, alcohol and drugs Safe journey planning, including the need to travel, the amount and mode of travel and choice of route, vehicle and driver Safety of vehicle, occupant protection, protection of other road users, road crash avoidance and mitigation, roadworthiness, vehicle load capacity and securing of loads in and on the vehicle Appropriate authorization to drive/ride the class of vehicle being driven/ridden Removal of unfit vehicles and drivers/riders from the road network Post-crash response and first aid, emergency preparedness and post-crash recovery and rehabilitation

Rearranged from ISO 39001 (2012)

2.3. The concept of Risk

Being a topic of utmost interest, risk has been widely investigated worldwide in the diverse scientific and professional fields, as it represents an extremely useful decision-support parameter for any management process (Guarascio et al., 2019). Indeed, also road safety policies have moved towards risk-based analysis.

To better understand risk, previous literature tried to provide a general and widely applicable definition of risk (*e.g.,* ISO 31000, 2018), characterise the risk factors, and measure and quantify risk for management purposes (*e.g.,* Fine,1971; Miranda-Moreno et al., 2009; Barabino et al., 2021). However, according to Aven (2012), the concept of risk is open to a great variety of possibilities and, depending on the discipline and specific area of interest, no agreed definition of risk is available. For instance, risk can be defined as *"a measure of the probability and severity of adverse effects"*, *"the combination of the probability of an event and its consequences"*, or *"the triplet made of a given scenario (potential event), the probability of its occurrence, and the potential consequence it may produce"*, etc. As a result, inconsistencies and barriers may result when it comes to return a measure of risk (*i.e.,* quantify), and different mathematical formalisations can be proposed (Aven, 2012). Table 3, which is self-explicative, reports a representative – yet not exhaustive – list of studies, which tried to define risk, provided a mathematical formulation for it, or both.

Table 3 - Definition of risk, risk formulation and components

Authors (year)	**Risk Definition**	**Risk Formulation**	**Risk components**	**Field**
Fine T. (1971)	*Any unsafe condition or potential source of an accident.*	$R = P \cdot C \cdot E$	P = Probability C = Consequences E = Exposure	G
Hauer E. (1982)	*Probability of a potential accident event to result in an accident.*	$R = \frac{S}{E} = \frac{p \cdot C}{E}$	S = System safety p = crash-conflict ratio C = number of conflicts E = system exposure	RS
Crichton D. (1999)	*Probability of a loss, which depends on three elements: hazard, vulnerability, and exposure*	-	Hazard, Vulnerability, Exposure	G
Rumar K. (1999)	-	$I = \frac{A}{E} \cdot E \cdot \frac{I}{A}$	I = number of injured or deaths E = exposure (traffic volume) A/E = crash frequency	RS
UNDRR (1999)	*Potential loss of life [...], which could occur to a system [...] in a specific period, determined probabilistically as a function of hazard, exposure, vulnerability and capacity.*	-	Hazard, Exposure, Vulnerability and Capacity	OSS

Hakkert and Braimaister (2002)	*Risk will be used to mean the probability of an accident occurring. It is the expected road safety outcome (i.e., the number of accidents or victims of a certain type), given a certain exposure.*	$S = R \cdot E$	S = Severity R = Risk E = system exposure (traffic volume)	RS
Lord D. (2002)	*A function of the current safety level of a facility and a measure of exposure.*	$R = \frac{S}{E}$	S = System safety, thus the crash counts E = exposure (traffic volume)	RS
De Leur and Sayed (2002)	*The three fundamental elements used to describe road safety risk include exposure, probability, and consequence.* *Road Safety Risk Index (RSRI)*	$RSRI = E \cdot P \cdot C$	P = Probability C = Consequences E = Exposure	RS
Miranda Moreno et al. (2009)	*Total crash Risk score (TR)*	$TR = \theta \cdot C$	θ = Mean number of crashes C = Expected consequences	RS
UNI ISO 31000 (2018)	*The effect of uncertainty with respect to the targets.*	-	Risk factors, Potential event, Likelihood of the event, Consequence of the event	G
Afghari et al. (2020)	*Weighted Risk Score*	$WRS = C_{rs} \cdot F_s$	C_{rs} = crash cost ratio (cost of a s-severity crash over a reference cost F_s = expected crash counts for the s-severity level	RS
Porcu et al. (2020)	-	$R = F \cdot S$	F = Crash frequency (as a function of exposure) S = Crash severity	RS
Barabino et al. (2021)	-	$R = F \cdot S$	F = Crash frequency (as a function of exposure) S = Crash severity	RS

G = general application field; RS= Road Safety field; SS=Other Specific Sector.

According to Borghetti (2019), risk has been largely misreported as a synonym of hazard, although they are quite different concepts. Indeed, *hazard* refers to the inherent property of an entity to potentially provoke damage. Therefore, the hazard should be intended as an objective potential source of damage. Conversely, *risk* should be not associated with any objective entity, rather with the possibility of specific conditions to occur (favourable or unfavourable) and result in a change of the previous conditions (which, negatively, can lead to damage or loss). Aven (2012) reviewed the development of the definition of risk over time. From their analysis, it emerged that the risk concept evolved from a simple concept of *expected loss* to a definition of *probability of loss*, until an *uncertain probability* of a specific critical scenario to occur and the uncertain probability of the severity of consequence (Aven, 2012).

Although great commitment emerged from the past literature for the identification of a specific and common definition of risk (even by recognized international Institutions such as UNDRR and ISO), looking at Table 3, still a universal and widely accepted definition of risk cannot be found. Conversely, focusing on those studies that provided a formalisation for the quantitative measure of risk and the related risk components, some recurrent and consistent elements can be identified among the several proposals. More precisely, most of them showed that the concept of risk is bound to a (i) hazards or potential sources of risk (*i.e.,* risk factors), (ii) to the uncertainty of the event to occur (*i.e.,* the probability, also expressed in terms of frequency over time), to (iii) some outcomes, which always assumes a negative acceptation as damage or loss (*i.e.,* consequences), and (iv) a measure of exposure to the risk. Indeed, although they may differ from a mere mathematical point of view (*i.e.,* risk components are combined according to different expressions), a common underlying structure can be drawn and so for what concerns the elements included in such formulations. First, it emerges that risk can be expressed as a function of specific factors, which are generally combined by a multiplicative operator. As for the factors, they represent the three main risk components (or risk dimensions), namely:

- The *likelihood* (probability/frequency) of a *potential event (*a specific chain of facts and circumstances*)* to occur.
- The *exposure* (any subject that finds itself in the hazard-prone area).
- The *vulnerability* or *severity* (set of all the conditions that increase the susceptibility of the subjects to the impacts of hazards).

Besides these main factors, also *hazard* (any entity of whatever nature able to cause damage to any extent), and *capacity* (the combination of all the resources available to manage and mitigate the risks and strengthen the resilience of the system) should be accounted to fulfil the risk definition (UNDRR, 1999; ISO 31000, 2018). Therefore, the risk formulation provided by Fine (1971) can be accepted as the baseline for risk computation.

Focusing on the specific road safety sector, this is even more evident as similar risk structures to the one of Fine (1971) were applied (*e.g.,* De Leur and Sayed, 2002; Miranda-Moreno, 2009; Porcu et al., 2020). For instance, Porcu et al. (2021) and Barabino et al. (2021) applied an adjusted formulation to the public transport safety evaluation. However, unlike Fine who attributed fixed and arbitrary values to each risk component, they applied modelling techniques to estimate crash dimensions as functions of explanatory variables.

As a result, the *road crash risk* can be definitively computed as follow. Let:

- P be the likelihood of a road crash to occur, either intended as a probability or a frequency measure.

- E be the exposure, thus the number of *e.g.,* road users that can potentially experience or run into specific hazards (damage sources).
- C be the consequences of the crash, thus the amount of damage to *e.g.,* people or properties.

Then, the road crash risk is computed as:

$$R = P \cdot E \cdot C \tag{2.1}$$

Building on the well-known "*Risk Triangle*" proposed by Crichton (1999)[6], risk can be translated into vectorial dimensions, to explain the physical meaning of Eqn. 2.1. Specifically, as shown in Figure 4, road crash risk can be seen as the resulting vector made by its three components, thus H (crash occurrence), S (crash severity), and E (exposure). Depending on the magnitude of each of the components, different risk vectors can be returned, with different magnitude and directions.

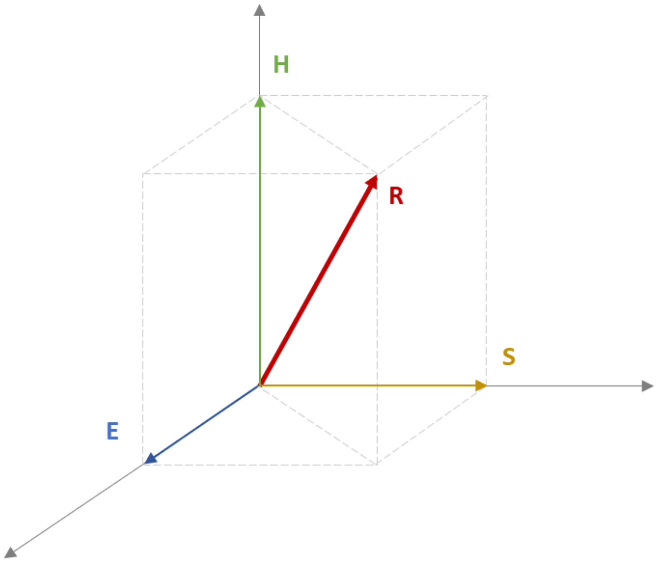

Figure 4 – The risk dimensions and their physical meaning.
Source: Author own elaboration

Following this perspective, as the risk's dimensions vary, also the risk measure does. Likewise, different combinations of the risk's dimensions can return the same values for the measure of risk. In the literature, this fact is known as the *iso-risk concept,* and it is usually represented by *hyperbolic curves* on a multi-dimensional plane (Borghetti, 2019). More precisely, the multi-dimensions

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[6] By mean of a simplification of traditional geometry rules, he compared the area of a generic triangle with the measure of risk, and the dimensions of the triangle's sides with the risk dimensions. As a result, if the area of the triangle depends on the triangles' dimensions, then also the measure of risk depends on the measure of its dimensions.

represent the risk components. Figure 5 aims at providing an example of this concept, by reporting two of the three risk dimensions, for safe clarity. However, it can be easy to expand it to the 3D space.

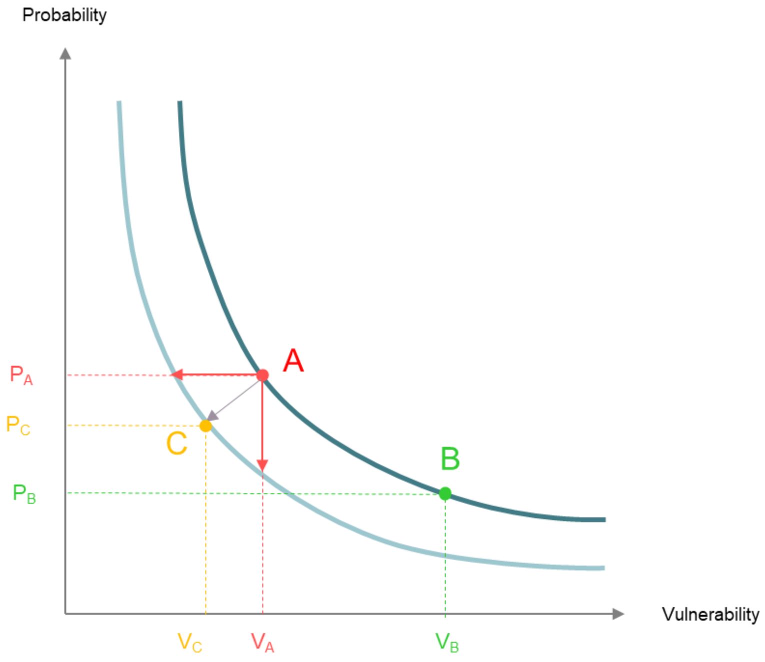

Figure 5 - Iso-risk curves.
Source: Author own elaboration

The two hyperbolic curves (*e.g.,* the light and the dark blue curves) define a different level of risk. Each curve is made by different points (*e.g.,* A and B), which represent the set of all the possible combinations of the risk components (*e.g.,* A (V_A; P_A) or B (V_B; P_B)) that can result in an equal measure of risk. The overall goal of measuring risk is to be able to reduce it, thus, as it raises from Figure 5, to move from the dark blue curve to the light blue one, and go from *e.g.,* A to C. This can be achieved by applying measures that can reduce the extent of the risk's components, namely the probability, the severity, and the exposure of road crashes. To do so, two ways are feasible: reducing at least one of the risk components' contributions by keeping the other unvaried (*i.e.,* moving from A along the vertical or horizontal lines only), or trying to find solutions that allow reducing all of them at once (*i.e.,* moving from A along the transversal line that brings to C). Indeed, the most cost-effective measure to be prioritized is the one that can act over all the risk components.

In addition, as suggested by Wang et al. (2011), Stipancic et al. (2019) and Afghari et al. (2020), it is worthy to account that road crash risk's components should be better studied separately, as they may require different strategies to *e.g.,* reduce the number of crashes and their consequences, respectively.

More precisely, to reduce the crash frequency, it is necessary to act by means of *prevention measures*, thus implementing infrastructural or operational improvements that are meant to prevent the crashes to occur; whereas, to mitigate crash consequences, *protection measures* should be implemented, thus infrastructural or technical interventions that are meant to limit the potential damage caused by a crash.

2.4. Road Network Screening

The Road Infrastructure Safety Management (RISM) System defined by European Directives (European Commission, 2008; 2019) provides a set of tools and procedures to help Road Authorities (RA) and all those responsible for road safety in maintaining and monitoring road infrastructure safety performance (Persia, 2016). Indeed, RISM procedures are meant to (i) evaluate the road infrastructure safety quality over their entire life cycle of roads, (ii) identify design and operational problems, and possibly (iii) provide appropriate measures to solve or – at least – mitigate such drawbacks. Specifically, each procedure is conceived to be applied to a specific stage of the road infrastructure life (*e.g.,* project, operation, etc.), for a defined aim (*e.g.,* monitoring, auditing, etc.), and a specific analysis scale (*e.g.,* network-wide, site-specific, etc.). As a result, depending on those characteristics, the proposed RISM tools differ in terms of data requirements (*e.g.,* the type, quality, and amount of data needed to perform the specific procedure), procedure's protocols, and complexity (*i.e.,* in terms of application and updatability ease) (Elvik, 2010).

When dealing with existing road infrastructures, it is quite common to have few resources available and many problems to be addressed. Hence, it is of paramount importance for Road Authorities and Administrations to have a valid Decision Support Tool (DST) at hand, that helps them in defining intervention priority and directing in-depth analysis in a more cost-effective manner (Park and Sahaji, 2013; Persia et al., 2016; Wang et al., 2021). In this perspective, RISM Directives require that a first-stage safety evaluation of the overall road network should be performed, so that the set of most critical road elements among the others can be detected (*i.e.,* the worst-performing in terms of road safety). Then, such segments can be subjected to further and more detailed inspections, which are generally more time and resource consuming.

Road Network Screening (RNS) is specifically meant for such a task and it represents the first step of the whole RISM process (Park and Sahaji, 2013). More precisely, RSN is applied to a wide scale to the entire road networks (or a part of the network within specific boundaries, or to a specific road class, etc.) to return the first review of its safety performances. In doing so, by also including contained resources and data, RNS identifies the most critical road network elements that require prompt interventions (Elvik, 2010; Hauer et al., 2002)[7]. In other words, as a "*low-cost"* assessment procedure (Elvik, 2010; Hauer et al., 2002; Stipancic et al., 2019), RNS aims at identifying the so-called *"High-Risk Sites", "Hazardous Road Location",* or "*Sites with Promise - SWP*" (Elvik, 2010; Hauer et al., 2002; Stipancic et al., 2019)[8].

RNS is not a novelty in the scientific community: the literature on this topic is quite rich, and several are the approaches proposed by the past research for RNS implementation (Ghadi and Török, 2019; Stipancic et al., 2019; EuroRAP, 2020[9]). However, as reported in Figure 6, across all the many studies available, one can recognize three main steps for the RNS procedure, thus (i) road network segmentation, (ii) application of an evaluation metric to assess the road network, and (iii) ranking and visualisation of the results. Then, based on the specific studies differences may be registered for each of these steps. Figure 6 shows the RNS process which is described in detail in what follows.

Figure 6 - Road Network Screening process

Road network segmentation is the first step of RNS and aims at partitioning the whole road network into basic road units (*e.g.,* segments), thus more manageable elements for the evaluation of road safety performances. Of course, the denser the segmentation, the more detailed the evaluation, but also the higher the quality of data required (which, somehow, contrast the overall sense of RNS). Network segmentation can be performed in different manners (Harwood et al., 2002; Elvik, 2010, 2007; Ghadi and Török, 2019; Persia et al., 2020), which can be grouped into two main categories: (i) space/feature-related and (ii) crash-related segmentation. Space-related segmentation is the simplest one as it splits the entire road network into defined segments whose endpoints correspond to given road

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[7] Elvik (2010) defined Road Network Screening as "*the analytic tools that help government detect emerging safety problems early, that help in locating the most hazardous parts of the road system, that identify the most important factors contributing to road accidents and injuries and that help to estimate the likely effects of specific road safety measures or a road safety programme consisting of several measures*"

[8] Also referred to as *Black Spots, Hot Spots, High Accident Locations (HALs), High Collision Concentration Location (HCCL), High Crash Road Sites (HCRs), Priority Investigation Locations (PILs).*

[9] The European Road Assessment Programme (EuroRAP) has built up a comprehensive and standardised technical protocol for crash risk mapping, which is based on a set of procedures and specifications that ensure wide applicability, consistency of output, and allow comparisons among countries. From a practical perspective, it is based on a step-by-step procedure that follows the three main steps of the RNS: (i) subdivision of the road network and crash, traffic data association; (ii) safety indicator computation; and (iii) crash risk mapping creation. Further information can be found in the *RAP Crash Risk Mapping: Technical Specification Report* (EuroRAP, 2020).

characteristics. More precisely, segment endpoints can be defined by fixed-length segment extension (*e.g.,* 100 metres, 1 kilometre, etc.) (*e.g.,* Elvik, 2007; MIT, 2012) or by the change in design or operational road characteristics. In this case, segments are referred to as *homogeneous* segments, thus road units characterized by consistent features in the cross-section design (*e.g.,* lane width, shoulder presence, median presence, etc.) or in operational characteristics (*e.g.,* constant traffic volumes, etc.) (*e.g.,* AASHTO, 2010; Ghadi and Török, 2019). For instance, according to the EuroRAP protocol, the following requirements should be respected when dividing the road network into road sections: consistency in design features and traffic volumes should be kept as much as possible, while road sections are set with a minimum length's threshold of 5 km for non-motorways national strategic single carriageway roads and 10 km for motorways and dual carriageways roads, respectively (EuroRAP, 2020). Space-related segmentations are the most widespread (Elyasi et al., 2016; Kwon et al., 2013). Among these, *sliding windows* (which consists of a fixed-length road unit that slides along the entire road to detect the Black Spots) are included in many national road safety management guidelines (*e.g.,* SETRA, 2006; Elvik, 2007).

Crash-related segmentation, instead, uses road crash attributes to identify the endpoints of the road unit. For instance, *High Crash Risk Profile* segmentation let a Safety Performance Function (SPF) define the endpoints by comparing predicted vs observed crashes. In addition, Boroujerdian et al. (2014) proposed a method based on the Wavelet Transform theory, which uses crash density as a signal response to identify HCRPs, while Elyasi et al. (2016) proposed a method based on the deviation of a safety index from a fixed threshold between adjacent segments. Other segmentation alternatives are available in the literature based on cluster analysis (*e.g.,* AASHTO, 2010; Ghadi and Török, 2019), thus unsupervised statistical techniques able to identify groups of similar object among a set of observation.

Once the segmentation is performed, the assessment of the safety performance of the road network (*i.e.,* of each road element) must be returned by means of **evaluation criteria**. To do so, different metrics and methods can be adopted, among which mainly respond to a (i) reactive approach or (ii) proactive approach.

As for (i), easy to compute indices-based methods are employed, that however return an evaluation of the road network safety performance based on historical observed crash data. More precisely, previous studies proposed simple or composite indices that express crash frequency or density (*i.e.,* number of crashes per time unit or per space unit, such as crashes/year or crashes/km) or crash rate (*i.e.,* number of crashes per vehicle-km) (*e.g.,* Elvik, 2007; Montella, 2010). For instance, Gupta and

Bansal (2018) proposed a simple crash danger metric defined as the ratio between the number of crashes and the average hourly traffic, multiplied by the severity for all crashes on a road segment. The EuroRAP (2020) technical protocol provides a set of different indicators according to which the analysis can be performed[10]. Almost all such safety indicators are based on a crash rate formula which comprises the number of road fatalities and serious injury crashes, the length of road sections, and the traffic flow, in a way that the main components of risk are accounted in the process. Borghetti et al. (2021) applied a priority-ordered set of indicators (*e.g.,* crash rates, crash frequency, etc.) retrieved from the Italian road safety regulation, and tested it over a major road in northern Italy to identify the most critical segments and then carry out an in-depth in-site investigation to better understand design and operational problems. Being easy to compute, such evaluation metrics are widely employed by most of the national technical guidelines for the implementation of RNS (*e.g.,* SETRA, 2006; MIT, 2012; Mamčic and Sivilevičius, 2013).

As for (ii), indices-based methods or prediction-based models are applied, that return an evaluation of the road network safety performance-based on the inherent *e.g.,* infrastructural and context characteristics of the road environment. In other words, the road safety evaluation is performed by assessing the potential effect of specific risk factors on the road safety outcome (*e.g.,* level of safety, number of expected crashes, etc.). For instance, Yannis et al. (2013) and Gomes et al. (2018) defined a theoretical framework based on a Safety Performance Indicator (SPI) for the road network, drawing on the concept of "*adequate category link*", namely the evaluation of the adequateness of road connections based on their functional and operational characteristics.

Crash Prediction Models (CPM) are considered the primary tool to implement a proactive approach in the road safety analysis. CPM are econometric models developed for road safety analysis that specify an inferential relationship among the road safety performance of a site (*e.g.,* crash frequency, crash severity, etc.) and a set of independent variables, which are expected to explain the phenomenon, such as exposure factors, road design features, and road environment characteristics (Yannis et al., 2016; Ambros et al., 2018). On the one hand, CPM is an extremely powerful tool to be applied to

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[10] Based on the target of the analysis, different crash risk mapping can be obtained: *individual risk*, which is more user oriented, as it expresses the risk to be involved in a severe road crash. In doing so, it is formulated as the ratio of fatal and serious injury crashes over billion vehicle km. Conversely, from the road authority perspective, the *collective risk* can be evaluated. In this term, the overall safety performance of the road section is evaluated, regardless the perceived risk of the single users. In doing so, different formulation can be adopted: (i) crash density: number of fatal and serious injury crashes per km per year; (ii) crash risk by road type: fatal and serious injury crashes per billion vehicle km, relative to the average rate of roads with a similar traffic flow; and (iii) potential accident savings: number of crashes saved if rates on road sections with higher-than-average risk were brought to the average. In addition, it is important to note that the protocol concentrates on fatal and serious crashes, rather than casualties (*i.e.,* the number of people involved), to avoid that such parameter skew the road safety performance. In addition, it is suggested that a minimum number of 20 fatal and serious crashes over a three-year period should be set as a target, to minimise year-to-year variability. In doing so, 3-5 years are recommended as a reference for the assessment time span.

RNS (*e.g.,* Ambros et al., 2018; Persaud et al., 2010; Persia et al., 2016). On the other hand, previous research observed that CPM has not been systematically used by RA and practitioners in the decision-making process, either for implementation or transferability issues (*e.g.,* Yannis et al., 2016; Ambros et al., 2018). Indeed, CPM requires a wide set of observed data for the implementation stage, as calibration is necessary to specify prediction parameters for the application to a specific site.

In addition, too (i) and (ii), other methods have been explored in the literature for the RNS, such as Multi-Criteria-Decision procedures such as the Data Envelopment Analysis (*e.g.,* Fancello et al., 2015, 2020), cluster analysis and classification trees (*e.g.,* Tarko and Azam, 2009; Dell'Acqua et al., 2011), or machine learning techniques (*e.g.,* Fan et al., 2019).

Once all the road network elements have been evaluated according to a selected evaluation metric, a **ranking** is made to identify the ones that recorded unacceptable safety performance scores. How much is the score unacceptable can be defined by the setting of a fixed threshold *e.g.,* in terms of a defined 'quota' of the absolute number of crashes or severe crashes or their frequency (*e.g.,* Thakali et al, 2015; Ghadi and Török, 2019), or by mean of ranking scale, as the one proposed by *e.g.,* the EuroRAP (2020). With regards to this latter case, a five-level ranking scale is defined, which identifies the different level of the crash risk, being lower values associated to higher safety. Specifically, fixed thresholds are set for each level for the different indicators proposed. Then, for comparison purposes, such values need to be normalised. In other words, a scaling factor is computed, which is given by the ratio between the number of fatal and the number of fatal and serious crashes (at the network or, at least, country level). Then the fixed thresholds are multiplied for such factor to return comparable results among countries[11].

Then, a **visualisation of the ranking results** may be provided, to facilitate the interpretation of the results. Indeed, a key factor for the effective analysis of crashes data is to build comprehensible and usable performance reports, which are easily understandable for decision-makers to prioritize interventions. The visualisation may be obtained by using tables, maps, or both. For instance, the EuroRAP protocol provides a five colour bands standardised palette, that ranges from green (low risk) to black (high risk) (EuroRAP, 2020).

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[11] The value of the scaling factor may vary over time, due to a decrease (or increase) of the number of road deaths and serious injuries. Hence, it should be check on a rhythmic cadence to avoid misreporting in the road network ranking.

2.5. Focus on prediction models for RNS

As highlighted in Chapter 2.4, RISM procedures – and specifically RNS – would extremely benefit from the application of CPM. Indeed, they have the potential of providing both a quantitative and qualitative evaluation of the response variable. Specifically referring to the road safety field, they can return the numerical estimate of *e.g.,* the expected crash frequency (thus the expected number of crashes) over a period (*e.g.,* 3 or 5 years in most cases) based on specific conditions. In addition, they also return a measure of the impact that each explanatory variable has over the response variable, both in terms of significance and magnitude. Therefore, they allow identifying potential drawbacks that may lead to unsafe conditions as well as recommendations can be made about which intervention is preferable to get the best result[12].

In addition, they would also contribute to the definition of a risk-based analysis, as they can bring the proactive approach in the estimation of the main risk components. As a result, an overview of crash prediction models is provided in what follows. More precisely, a focus is proposed on that CPM that is meant to return a combined estimation of crash occurrence and crash consequences (*i.e.,* crash severity), namely two of the road crash risk dimensions, according to the definition set in Chapter 2.3. The goal is to understand which types of CPM have been proposed by previous research, how they are structured, and to what extent they have been applied to RNS.
In addition, an overview of exposure prediction models is also reported. Indeed, exposure represents the third risk component.

2.5.1. Crash prediction models

The Highway Safety Manual (AASHTO, 2010) is recognised as the most important reference worldwide for road infrastructure safety management, especially for its well-established road crash prediction procedure. The HSM prediction models rely on the development of the so-called *Safety Performance Function*, thus mathematical equations that return an estimate of the expected crash frequency of a site over a time span, based on segment length and traffic volumes and referred to as base conditions. Then, *Crash Modification Factors* are introduced into the SPF to account for the local and jurisdictional-related characteristics, and for *e.g.,* design, functional, operational differences. Given the high flexibility of the model structure, most of the international literature has focused on

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[12] As suggested by Hauer et al. (2002), the base principle of the whole RISM system is to get the "*most bang of the buck*", thus get the best results out of the limited resources available.

calibrating and transferring the American CPM over different contexts, such as the European one (La Torre et al., 2016; Yannis et al., 2016; Ambros et al., 2018; Bonera and Maternini, 2020). For instance, within the PRACT project, a Europewide CPM was developed to be applied by all Member States over their main road network to perform RISM analysis (La Torre et al., 2016; La Torre et al., 2018). Likewise, research has improved a lot over the years, to outperform the prediction and inferential capabilities (Lord and Mannering, 2010; Mannering and Bhat, 2014) of site-specific CPM, to be applied to road safety assessment procedures. However, past research and practice has mainly focused on the implementation of crash frequency-oriented CPM, while crash severity has been either totally neglected or just partially included in the RNS process (Miranda-Moreno et al., 2019).

Indeed, the sole crash frequency cannot completely characterise the safety level of a road site and decide whether it should be appointed as safe or unsafe: crash frequency explains just one side of the phenomenon, which is merely aimed at defining *"how often"* or *"how many"* crash may occur, given some conditional variables, while no indication is returned about *"how severe"* or *"how much damage could result"* from a crash, given the same specific conditions. Conversely, crash frequency and severity should be both intended to describe the road safety performance of a site, as they help understand and quantify the impact of specific explanatory variables over the model's response (*i.e.,* expected number of crashes, and the expected severity outcome of crashes in terms of damage to people, conditional to the crash occurrence). In addition, recent road safety strategies worldwide are primarily focusing on severity targets, thus *e.g.,* halving the number of road deaths and serious injuries. As a result, over the years, several authors stressed the importance of considering both crash frequency and severity together, when assessing road safety performance (*e.g.,* Hauer et al., 2004; Milton et al., 2008; Aguero-Valverde and Jovanis, 2009; Savolainen et al., 2011).

According to such perspective, road safety research has expanded towards the development and application of combined modelling approaches, which integrate crash frequency and severity modelling in the definition of the overall road safety performance of a site (*e.g.,* entire roads, road segments, intersections, areas, etc.). Research has proven that such models have great potential, in that they can (i) evaluate the two main components of road safety to return a comprehensive result and (ii) provide a cost-effective and reliable valid support for policymakers (Milton et al., 2008; Afghari et al., 2020). Although not exhaustive, Table 4 provides a representative summary of the different modelling alternatives that can be found in the literature for crash frequency and severity integrated estimation. The table contents are critically discussed in the following paragraphs, to investigate the methodological differences and other RNS-related key points. More precisely, the review aims at discussing the several model approaches and forms adopted, the criteria selected for RNS (*i.e.*, the high-risk site identification process), and the explication of a risk formulation.

Table 4 - A summary of crash frequency and severity integrated models

Study Authors (year)	**Country**	**Model approach**	**Model form**	**Model specification**	**Severity levels**	**Evaluation criteria for RNS**	**Risk formulation**	**Analysis scale**
Ma and Kockelman (2006)	USA	Simultaneity	Multivariate model	Bayesian Multivariate Poisson Regression with Gibbs Sampler and M-H algorithm	5	-	-	Micro level
Park and Lord (2007)	USA	Simultaneity	Multivariate model	Multivariate Poisson-Lognormal with MCMC	5	-	-	Micro level
Ma et al. (2008)	USA	Simultaneity	Multivariate model	Multivariate Poisson-Lognormal with Gibbs Sampler and M-H algorithm	5	-	-	Micro level
Aguero-Valverde and Jovanis (2009)	USA	Simultaneity	Multivariate model	Full Bayes Multivariate Poisson-Lognormal	5	Total expected crash cost or Excess crash cost	-	Micro level
El Basyouny and Sayed (2009)	Canada	Simultaneity	Multivariate model	Multivariate Poisson-Lognormal	3	Posterior probability of excess (excessive mean collision frequency)	-	Micro level
Miranda-Moreno et al. (2009)	Canada	Independency	Two-stage model	**F**: Hierarchical Poisson-Gamma and Poisson-Lognormal **S**: Bayesian severity model with multinomial distribution	3	Absolute and Relative TR	Total Risk, TR=θ*C	Micro level
AASHTO (2010)	USA	Independency	Two-stage model	**F**: Negative Binomial **S**: Fixed proportion	3		-	Micro level
Pai et al. (2011)	Hong Kong	Simultaneity	Joint model	NB-Hierarchical and Binomial Logistic / NB-Truncated Poisson joint model	2	-	-	Micro level
Wang et al. (2011)	UK	Independency	Two-stage model	**F**: Full Bayesian spatial model with MCMC **S**: Multinomial Logit and Mixed Logit model	2	Crash rate in terms of monetary costs	-	Micro level
Hosseinpour et al. (2014)	Malaysia	Independency	Two-stage model	**F**: Random-Effect Negative Binomial **S**: Random-Effect Generalized Ordered Probit model	4	-	-	Macro level
AASHTO (2014)	USA	Independency	Two stage Model	**F**: Safety Performance Functions + Crash Modification Factors **S**: Severity Distribution Function	3		-	Micro level

Study Authors (year)	**Country**	**Model approach**	**Model form**	**Model specification**	**Severity levels**	**Evaluation criteria for RNS**	**Risk formulation**	**Analysis scale**
Wang et al. (2017)	USA	Simultaneity	Multivariate model	Multivariate Poisson-Lognormal with INLA	3	-	-	Micro level
Zeng et al. (2017)	Hong Kong	Simultaneity	Multivariate model	Multivariate Random Parameters Tobit model	2 (3)	Crash rate by severity level	-	Micro level
Saleem and Persaud (2017)	USA	Independency	Univariate	Negative Binomial	3	-	-	Micro level
Yasmin and Eluru (2018)	USA	Simultaneity	Joint model	NB-Ordered Logit Fractional Split Joint model	4	Counts by severity levels	-	Macro level
Anarkooli et al. (2019)	USA	Independency	Two-stage model	**F**: Heterogeneous NB, Hurdle Poisson, Hurdle NB and NB **S**: Generalized Ordered Probit Model and fixed proportion	4	-	-	Micro level
Stipancic et al. (2019)	Canada	Independency	Two-stage model	**F**: NB Spatial Latent Gaussian Model with MCMC and INLA technique **S**: Fractional Multinomial Logit model	3	Crash rate in terms of monetary costs (Crash cost per veic-km)	-	Micro level
Xie et al. (2019)	USA	Simultaneity	Multivariate model	Multivariate Autoregressive Model	3	-	-	Micro level
Afghari et al. (2020)	Australia	Simultaneity	Joint model	RPNB and Logit joint model	3	Weighted Risk Score (WRS) based on the cost ratio of severity levels	Weighted Risk Score, $WRS=C_{rs}*F_s$	Micro level
Wang et al. (2021)	USA	Simultaneity	Multivariate model	MVPLN and NB-Generalized Ordered Probit Fractional Split	3	-		Micro level
This research	Italy	Independency	Three-Stage model	**F**: Negative Binomial **S**: Binomial Logit	2	R=H*C*E	R=H*C*E	Macro-level

NB = Negative Binomial.
*In the model specification of two-stage models **F** refers to the ones adopted for frequency estimation, **S** for the one adopted for severity estimation*

2.5.1.1. Model approach, form, and specification

Several model alternatives have been developed over the years, with the aim of identifying the modelling endeavour that better accommodate prediction accuracy and inference power while incorporating crash severity into crash frequency prediction (Anarkooli et al., 2019). To do so, many studies have first tried to classify such models by different criteria, to highlight their potentials and drawbacks: some authors differentiated models based on their mathematical structure (*e.g.,* Ma and Kockelman, 2006; Afghari et al. 2020), others on the way crash severity are meant to be modelled with frequency (*e.g.,* Ma et al., 2008; Pei et al., 2011; Wang et al., 2021). Such classification proposals should be intended as complementary, instead. More precisely, as shown in Figure 7, integrated models for crash frequency and severity can be classified according to a hierarchical structure[13], namely: (i) **model approach**, which defines the underlying relationship among crash severity and frequency modelling; (ii) **model form**, which further defines the computational structure adopted, thus how to crash severity and frequency are integrated into the form; and finally (iii) **model specification,** that further describes to the very specific computational structure selected for the parameters and response estimations.

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[13] In road safety analysis, the classification proposed here also applies to the estimation of crash frequency by specific crash features, such as crash collision type, users' category, etc. For further specification refer to *e.g.,* Ye et al., 2009; Geedipally et al., 2010; Hosseinpour et al., 2018, Bhowmik et al., 2018.

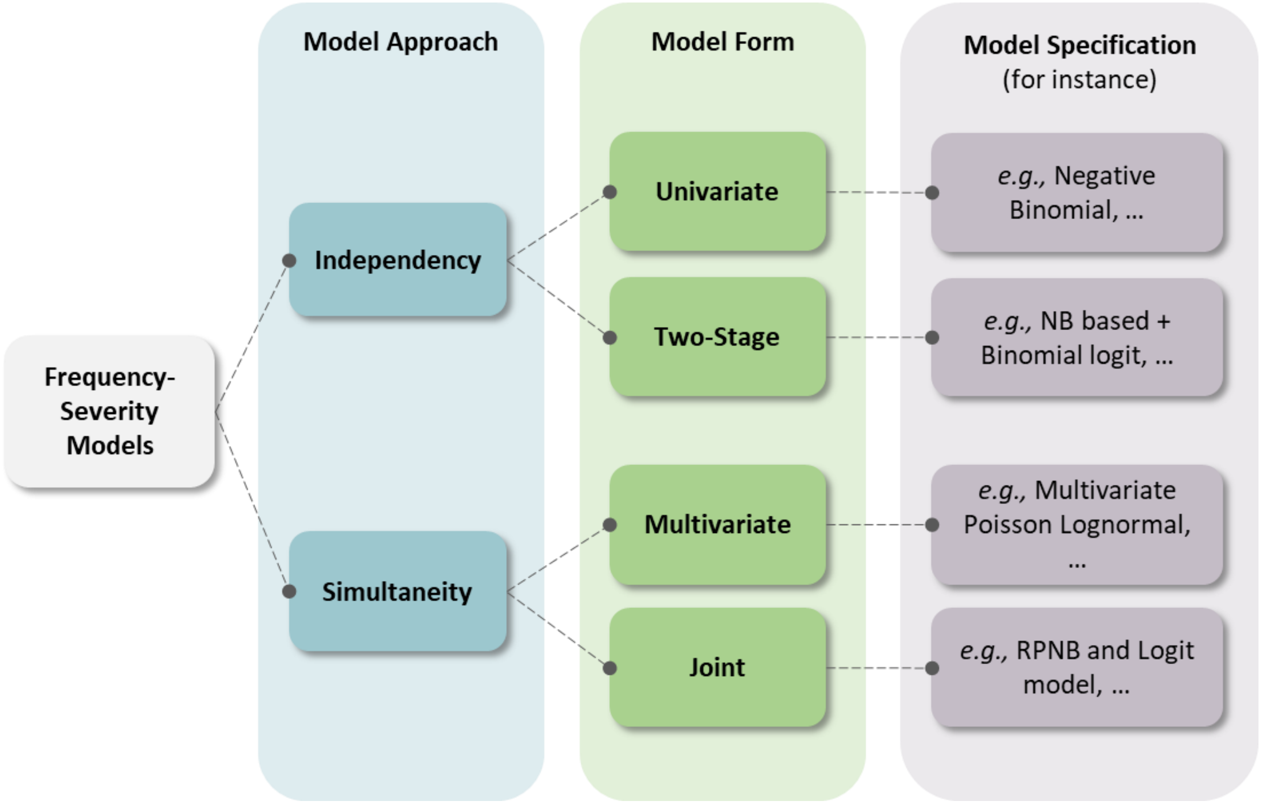

Figure 7 – Hierarchical classification of road crash frequency and severity integrated models

As for the **model approach** to be chosen for estimating crash frequency and severity, two are the main streams recognized in the literature, namely (a) independency modelling approach and (b) simultaneous modelling approach. As for (a), this approach aims at estimating the frequency and the severity levels of crashes by mean of separated models, thus estimating them as distinct quantities (*i.e.,* independently). As for (b), this approach aims at estimating both the frequency and the severity level of crashes by means of a unique model structure, thus estimating them at once (*i.e.,* simultaneously).

As for the **model form**, model approaches can be further classified, based on the overall model structure selected for the estimation of crash frequency and severity. Among independency-based model approaches, the most common model types are univariate and two-steps models. More precisely, univariate models[14] rely on the application of crash frequency regressions to a separated dataset, each one containing crash observation-only related to a single severity level (*e.g.,* non-injury, death, etc.). In this way, a set of frequency estimations is provided, one for each severity level considered. Two-

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[14] Univariate models admit just one-category response variables, while multiple explanatory variables of any type (*e.g.,* discrete or continuous, nominal or ordered, etc.) can be included into the model estimation.

stage models estimate crash frequency and severity separately, by mean of a multiple-stage procedure (*i.e.,* two stages) and by including all the observations. Specifically, the total crash frequency is estimated first, independently from the severity level, which is then estimated by the mean of a probability distribution function. Next, the respective results are combined (*e.g.,* usually by multiplying them). Among simultaneity-based model approaches, the most common model forms are multivariate and joint models. More precisely, multivariate models use crash frequency-based structures to estimate the expected number of crashes for each severity level at once. Indeed, conversely to univariate models, they allow the response variable to have multiple-level categories (*e.g.,* severity levels) to be directly estimated within the frequency model. Joint models still estimate crash frequency and severity at once, but they are recognized to be more flexible with respect to multivariate model types, as the jointed parameters estimation of crash frequency and severity is moderated by the inclusion of a correlation term in the model structure.

Finally, the model form can be further classified with respect to the specific computational structure of the model (*i.e.,* **model specification**), which may be strictly study-related, as it mainly depends on data composition and type.
Among independency-based model approaches, the most widely used model specifications for crash frequency are the ones based on a Negative-Binomial (NB, or Poisson-Gamma) model, which expand the basic Poisson model to account for over-dispersion. Also, Random-Effect NB and Random-Parameter NB are used, as they allow to account for spatial and temporal correlation, and variability of parameters among observations, respectively, compared to simple NB (Lord and Mannering, 2010; Gomes et al., 2012a). Crash severity is generally estimated by the mean of the binomial or multinomial logit model, depending on the number of the categories in the response variables (Savolainen et al., 2011).

Among simultaneity-based model approaches, Multivariate Poisson Lognormal models are the most widely applied, which can be implemented based on Bayesian or Full Bayesian estimation techniques. In addition, they also require simulation procedures such as Markov Chain Monte Carlo (MCMC) or H-M algorithm, for parameter and correlation matrix estimation (Lord and Mannering, 2010). Also, combined structures based on NB models (*e.g.,* ordered NB or Random Parameters NB) and logit models have been used in the development of Joint models.

2.5.1.2. Evaluation criteria for RNS

From Table 4, it is quite noticeable that just a handful of studies directly applied frequency-severity prediction models to the purpose of RNS implementation. Indeed, as highlighted by other authors, while extensive research has tried to outperform existing crash frequency and severity modelling to compare their potential to other alternatives, in the road network screening process few studies have integrated such concept (Miranda-Moreno et al., 2009; Afghari et al., 2020). More precisely, among the studies retrieved from the past literature, the results of the crash frequency-severity models have been generally included in a parameter (*e.g.,* crash rate) serving as the evaluation measure for the site ranking. Conversely, few studies directly applied the model's results in the RNS, to evaluate the safety performance of the network.

For instance, Afghari et al. (2020) investigated the applicability of a joint frequency-severity model to the high-risk site identification process over the state-controlled road segments in Queensland (Australia). More precisely, from the results of the joint model, a Weighted Risk Score (WRS) is computed, thus the crash counts for each severity lever are multiplied by a weighting factor, which represents the ratio between the cost of a crash of a given severity over the cost of a crash of a reference severity level (which is quite like the EPDO approach)[15]. In this way, an economic appraisal is returned to evaluate the safety performance of a site. Then, they adopted and compared two selection criteria for the segments ranking, namely the Potential for Improvements (PFI) with the EB method (*i.e.,* the difference between the EB expected crash counts and the predicted mean of crash counts at a site) and the Excess Weighted Risk Score (EWRS) (*i.e.,* the difference between the observed and predicted WRS for a site). The latter was found to outperform the PFI and return a better and more precise evaluation for the RNS.

Similarly, Stipancic et al. (2019) included the results of their two-stage frequency-severity model into the computation of an adjusted crash rate (*i.e.,* defined as *decision parameter* by the authors), to be used as the ranking metric for the Quebec City (Canada) road network. More precisely, building on the basic formulation of a crash rate, they also included the economic appraisal by accounting for the

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[15] The Weighted Risk Score (WRS) for each segment i is computed as $WRS_i = \sum_{s=1}^{S} cr_s \cdot \mu_s$, Where: cr_s is the ratio of the cost of a crash of a given severity level s and μ_s is the expected crash counts for the s severity level.

cost of a crash at a given severity level[16]. Then, they rank sites by comparing the decision parameter of each site with the per cent deviation.
Also, Wang et al. (2011) performed the RNS of the different segments of the M25 motorway around London (UK) by including their two-stage model results into a crash rate parameter, defined according to the well-established crash rate formula, by also accounting for monetary costs[17]. Then the 20 segments that registered the highest expected crash cost per vehicle-km were accounted as the most critical ones.

Again, Aguero-Valverde and Jovanis (2009) directly applied the results obtained with the Bayesian multivariate model the identification of sites with promise over the road network of District 2-0 in Pennsylvania (USA). However, in the ranking procedure, they also included an economic factor (*i.e., the* crash cost for each severity level) to two indices: the total crash cost (computed as the sum of the expected Poisson rate of crashes at a given severity level multiplied by the relative crash cost) and the excess of crash cost (computed as the difference between the expected excess in injury-severity frequency and the total crash cost). Indeed, the Bayes method allows estimating with precision the expected crash frequency and the excess of crash frequency, by calculating the variance and the standard deviation of the posterior distribution of such parameters. The total crash cost and the excess crash cost were used to rank sites. Then the 40 segments that registered the highest value for both total crash cost and excess crash cost were considered as the most critical.

By accounting for the concept of risk, Miranda-Moreno et al. (2009) wanted to identify the most critical highway-railway crossings in Canada. More precisely, they combined the results of their crash frequency and severity two-stage model into a Total Risk (TR) score[18], which also included the measure of the crash cost at different severity levels. Then, the topmost critical crossings were appointed, by comparing its TR score with a critical value threshold.

Conversely, El-Basyouny and Sayed (2009) chose not to rely on crash cost metrics as they found such approach somehow questionable (*i.e.,* the way crash costs are computed, ethical reasons, etc.). They

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[16] The *decision parameter* proposed by Stipancic et al. (2019) for each segment *i* is computed as: $\delta_{i,model} = \frac{\sum_{s=1}^{m} \mu_i \cdot P(m) \cdot C(m)}{t_i \cdot l_i}$, Where: μ_i is posterior mean expected crash count at the site, $P(m)$ the probability of a crash at the *m* severity level, $C(m)$ the cost of a crash of a given severity level *m,* t_i and l_i a proxy measure of crash exposure and segment length, respectively.

[17] The *cost-crash rate* appliedd by Wang et al. (2011) for each segment *i* is computed as: $\theta_i = \frac{\sum_t \sum_j cost_j \mu_{itj}}{365 \cdot l_i \cdot \sum_t AADT_{it}}$, Where: μ_{itj} is posterior expected crash count at the *j* severity level, $cost_j$ is the cost related to a crash of the *j* severity, l_i the segment length, and $AADT_{it}$ the annual average daily traffic at the site over the *t* year.

[18] The Total Risk (TR) score is computed as follow: $TR_i = F_i \cdot C_i$, where F_i represents the mean number of crashes, and C_i the expected consequences of the crash. More precisely, C is described as a "severity score", thus the combination of the expected number of several outcomes (*e.g.,* fatal, serious, minor injuries, PDO, etc.) and the related equivalent cost.

applied the posterior probability of excess as the parameter for the identification of the most hazardous signalised intersection in the city of Edmonton (Canada). More precisely, intersections were considered hazardous if their multivariate standard normal distribution function exceeds a threshold value arbitrarily selected.

Yasmin and Eluru (2018) and Zeng et al. (2017) directly applied the results obtained from their models to rank sites. More precisely, in the first case, cash count by severity levels was directly generated from the joint model to rank the traffic analysis zones (TAZ) of Florida (USA). In the second case, where the crash rate by severity level was set as the response variable for the multivariate Tobit model, such values were used to rank the road segments of Hong Kong (China).

2.5.1.3. Analysis scale

When discussing the network segmentation process, it is important to define the spatial unit according to which the evaluation of the whole network is returned. Indeed, this parameter defines the scale of the analysis and the detail of the safety performance evaluation of a site. As highlighted by Yasmin and Eluru (2018), different spatial unit formats have been used for either the implementation of crash prediction models or the deployment of an RNS (or both). More precisely, they can be grouped into the two most widely referred scales, thus the (i) micro-scale and the (ii) macro-scale.
The micro-scale refers to road-related defined units, such as road segments or intersections, while the macro-scale usually refers to area-related defined units, such as the Traffic Analysis Zones (TAZs) or more general census tracks.

Therefore, depending on the scope of the analysis, the first scale can be chosen to return a more detailed and road-specific evaluation of the safety performance, while the second one returns an overall evaluation of the road safety condition of an area. In addition, depending on the scale selected, different levels of explanatory variables are used to develop a crash prediction model for consistency: for the micro-scale, road design and operational characteristics of the single road element are generally accounted in the prediction, as they refer to the specific infrastructural characteristics; for the macro-scale, more general information is included, such as socio-demographic factors, road density and provision rates, land use, etc.

As a result, the micro-scale may be preferable when the target is a thorough analysis of the road segments for the identification of the most critical ones (in a delimited area *e.g.,* a single region, county, etc.). In this regard, if a delimited road network is considered, then also a detailed data collection is feasible. Conversely, macro-scale may be preferable when dealing with wide-level comparisons of the road safety performance of Countries or macro-areas, whose target is just an overall evaluation of the general road safety condition (this type of analysis is usually applied by International Bodies responsible for monitoring some Key Performance Indicators – KPIs to rank countries accordingly). In this regard, if a larger spatial dimension is considered (which is not even specifically related to the road network), then also a detailed road-features data collection is pointless. As reported in Table 4, the most of studies used micro-scale.

2.5.2. Data-related issues and methodological barriers for a CPM implementation

As it happens in any other field, input data strictly influence the outcome of the analysis, and data quality and availability represent the major concerns (Imprialou and Quddus, 2019). Specifically referring to the road safety field, while research has improved a lot in terms of modelling techniques, crash data collection does not show the same trend. Indeed, although recommendations have been provided at the international level for a standardised road crash data collection procedure (*e.g.,* CADaS structure, EU Directive 96/2008), still different methods are used, so that inconsistency among data and loss in data transmission are registered (Montella et al., 2019).

On the one hand, data quality is subjective to the aim of the specific use, therefore if a dataset was originally created for other purposes, might not be suitable for other employments. On the other hand, it may happen that the one at hand is the only data source available (Imprialou and Quddus, 2019; Montella et al., 2019). For instance, Police crash reports are mainly aimed at road regulation enforcement, so that although they may register some *e.g.,* infrastructural and context information about the crash is not thoroughly collected. In this regard, crash data are subjected to many uncertainties and inaccuracies, so that temporal and spatial attributes are among the most affected information (Schlögl and Stütz, 2019). However, Police road crash records are the most widespread and available ones, as in most countries, Police bodies are the ones in charge of collecting crash-related information.

As for data availability, problems arise when key variables are missing or are misrecorded, although they may be extremely useful for *e.g.,* the integration of road crash data databases. Specifically, crash location attributes enable the linkage between crash datasets with *e.g.,* environmental, design, and traffic information. However, as highlighted by several authors, the lack of common and comparable location attributes can prevent the integration process (Gupta and Bansal, 2018; Imprialou and Quddus, 2019; Schlögl and Stütz, 2019; EuroRAP, 2020). Indeed, data integration according to crash location is still a challenging task. In addition, although accurate crash location should be recorded for each crash (European Union, 2008), there is still a lack in the collection of this information collection Member States (*e.g.,* in Italy as highlighted by Montella, 2010).

As a result, the choice of the modelling technique to be selected is strictly subjected to two major restraints: the type and nature of the response variable to be estimated, and a set of data-related issues, which may generate methodological questions. More precisely, prediction accuracy (*i.e.,* the model fitting) aims at providing high-performance model estimations, which can return the expected result in a manner as precise as possible (*e.g.,* compared to the observed ones); inference quality aims at producing a strongly reliable and widely applicable understanding of causality, thus the explanation of the impact that contributing factors have over the expected outcome (*i.e.,* crash occurrence, the damage produced, etc.). According to Mannering et al. (2020), it is quite challenging to find the "ideal model" (*i.e., "the one that uncovers causality, has excellent predictive capabilities and is scalable to very large data"*), so that a trade-off between prediction accuracy and inference quality must be met. This, in turn, may have an impact on the model alternative to be chosen. The pursue of such a trade-off clearly emerged from the literature, as many studies focused on the choice of the best model to return high-level predictions, by comparing different model types or specifications in terms of prediction capabilities (*e.g.,* Anarkooli et al., 2019; Wang et al., 2021). Other studies paid major attention to the inference quality, by considering either methodological attribute and/or a different set of explanatory variables to be included in the model to uncover unobserved causality effects (*e.g.,* Park and Lord, 2007; Pai et al., 2011).

Lord and Mannering (2010), Savolainen et al. (2011), and Mannering and Bhat (2014) provided a comprehensive review of all the potential data-related concerns for crash frequency and severity estimations. Table 5, which is self-explicative, summarises those previous findings, by reporting a list of the most common data-related issues, a brief description of the methodological implications, and which among crash frequency and severity (or both) can be affected.

Table 5 - Summary of critical data-related issues in crash frequency and severity modelling

Data-related issue	Description and methodological implications	Frequency	Severity
Under-reporting	The misreporting of crash data is especially related to slight or non-injury crashes (*e.g.,* property damage only crashes) due to reporting procedures or inconsistency with the road-crash definition in force[19]. This might generate distortions in the model estimation and affect the inference results.	x	x
Omitted-variable bias	The missed inclusion of specific explanatory variables in the modelling structure owing to unavailability or misrecording of data. This might generate lower accuracy in the prediction capabilities in addition to a lack of inference results.	x	x
Over- under- dispersion	Given a distribution of observations, over (or under) dispersion occurs when the variance of the distribution is largely higher (or lower) than the mean of the crash counts. This might affect the results of the model if inappropriate techniques are selected (*e.g., the* Poisson model are not recommended), which violate the basic assumption of count-data modelling.	x	

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[19] According to the international definition provided by the Convention on Road Traffic of Vienna (1968), a road crash is conceived as *an event occurred on public streets in which at least one vehicle is involved and generated damage to people or property*. Specifically, in Italy, all road accidents occurring in streets or squares open to public traffic, in which stationary or moving vehicles are involved and that generates damage to people, fall within the field of observation. Road crashes that do not produce injuries to people, those that have not occurred in areas open to public circulation, those that do not include vehicles and those that are recorded as suicides are excluded from recording. In addition, this may be also related to the specific procedure adopted for road crash reporting and the specific bodies responsible for such task (*e.g.,* there might be under-reporting when either the Police or Emergency Services intervention is not required).

Mathematical nature of the response variable	Crashes are recognized to be rare events and their mathematical nature makes them non-negative integers rather than continuous variables. This affects the regression model to be employed, based on the nature of the response variable (*e.g.,* the Ordinary Least Square OLS regression cannot be used for such purpose).	x	
Ordered nature of the response data	Crashes are characterized by a discrete categorical nature (*e.g.,* type of crash, etc.). Crash severity is also characterized by an ordered nature based on the damaged entity (*e.g.,* KABCO scale, MAIS3+ classification of diseases, etc.). If such inherent ordering is overlooked, it may result in prediction bias or it may be difficult to properly identify differences among severity levels.	x	x
Time-dependency of variable	The potential of an explanatory variable to change over time in some characteristics usually remains unconsidered owing to the lack of detailed time-dependent data. This might generate unobserved heterogeneity as well as erroneous parameters estimation.	x	x
Temporal and spatial correlation	The potential of different observations to be somehow correlated in terms of time or space, that may generate unobserved effects in addition to lack of estimation efficiency.	x	x
Low sample mean	Occurrence of the so-called “excess of zeros”, which can derive from a limited observation of crash events at a specific site and over a given period. This might cause an excess of skewed distribution toward zero besides errors in parameters estimation.	x	
Small sample size	The availability of few observations for a given set of data (*e.g.,* more severe crashes), due to data recording issues. This may generate estimation and methodological problems given the limited dimension of the sample on which to produce inference.	x	x
Correlation among severity levels	The possibility to have correlation among different severity levels or crash types in their counts, that may generate errors in the estimation accuracy.	x	x
Endogeneity of variables	The in-build bias of the presence of specific variables just in specific conditions might affect the modelling results.	x	x
Fixed parameter estimation	The assumption of keeping the effect of specific variables over different observations fixed, although the difference may exist due to unobserved heterogeneity. This might generate inaccuracy in prediction performances as well as inference errors.	x	x
Functional form	This defines the type and grade of relationship across the response and the explanatory variables of the model. If incorrect forms are chosen, then errors in parameters estimation and loss of inference results might be returned.	x	

Built on Lord and Mannering (2010), Savolainen et al. (2011) and Mannering and Bhat (2014).

Data-related issues and methodological barriers for frequency-severity CPM

With reference to independency-based model approaches and simultaneity-based model approaches illustrated in chapter 2.5.1.1, Table 6 provides a focus on the main data-related and methodological implications (in terms of the pros and cons). Then, the key issues are discussed in what follows, by comparing the two model approaches over specific pros/cons.

Table 6 - Pros and Cons of independency-based and simultaneity-based models

	Pros	Cons
Independency-based approaches	• Include a separated set of explanatory variables that can be used in the models • Include crash-specific data for severity estimate • Straightforward to interpret • Two-step models require just 2 model development • Two-stage models control *parallel slope assumption*	• Not consider the potential correlation among crash counts for severity level • Univariate models suffer from low sample mean and small sample size • m=n univariate models are required for n severity level
Simultaneity-based approaches	• Consider the potential correlation among crash counts for severity level • Include the same set of predictors for all response variables	• Do not admit crash-specific data for severity estimate • Multivariate models suffer from low sample mean and small sample size • Computationally intensive and not straightforward to interpret • Multivariate models do not control *parallel slope assumption*

According to previous studies, crash frequency and severity should be better studied separately, as they generally require different strategies to reduce the number of crashes and their consequences, respectively (*e.g.,* Wang et al., 2011; Stipancic et al., 2019; Afghari et al., 2020). To identify the most appropriate and effective measures, a better understanding of the causality relationship among predictors and the response variables is required. Independency-based model approaches better respond to this need as they allow a separated estimation for crash frequency and severity but also the inclusion of a different set of explanatory variables for the two modelling procedures. For instance, besides *e.g.,* infrastructural-related attributes, the possibility to employ specific post-crash information (*e.g.,* number and type vehicles involved, people's age, weather conditions, etc.) for the severity estimation help further improve the inference quality (Savolainen et al., 2011; Wang et al., 2011; Hosseinpour et al., 2014).

Conversely, if crash frequency and severity are to be estimated simultaneously (*i.e.,* simultaneity-based approaches), consistency among variables is required. However, not all kinds of data can be included in both estimations: for instance, crash-specific data cannot be considered for frequency estimation, as they mainly refer to post-crash or event-specific conditions. Somehow, this can be intended as a pro, given that data collection requires less effort. However, if non-crash-specific data are used for modelling purposes, then a lacks inference capabilities may be registered. In this regard, past research has highlighted that, while the simultaneous estimation of crash frequency and severity may help in prediction accuracy, the loss in inference quality is greater (Anastasopoulos and Mannering, 2011).

In contrast, independent frequency-severity models do not allow to consider potential correlations across crash counts of different severity levels, which was found to be statistically relevant by several previous studies (*e.g.,* Ma et al., 2008; Yasmin and Eluru, 2018; Xie et al., 2019). Simultaneous frequency-severity models rely on – instead –the assumption that crash data have an in-built multivariate nature, being recorded according to a categorical response attribute (*i.e.,* the injury-severity level, crash type, etc.). In other words, they support that correlations may exist among crash counts of different severity levels and that such information greatly helps in improving prediction accuracy.

Both univariate and multivariate models return the crash counts for given severity levels one at a time or simultaneously, respectively. However, the under-reporting of some slight-severe crashes (*e.g.,* property damage only), or the limited number of more severe crashes (*e.g.,* fatal or disabling) may result in prediction inaccuracies. As a result, if severity subsets of observation are limited in the number or are subjected to small variation among observations, then barriers to a full and correct response prediction may arise. In other words, such models suffer from low sample mean and small sample size (Lord and Mannering, 2010; Hosseinpour et al., 2014; Savolainen et al., 2011). Conversely, *e.g.,* two-stage and joint models can overcome such issues, as the total crash counts are included in the estimation process regardless of the severity levels.

For what concerns the model structure, independent frequency-severity models are more straightforward to develop and interpret. Indeed, the development of two separated models helps in better understanding the single estimation results, in terms of parameter estimates and significance magnitude understanding (Park and Lord, 2007). Also, this flexible structure helps in that also more basic models for crash frequency (*e.g.,* Negative Binomial) and severity (*e.g.,* Binary or multinomial logit) can be applied. Simultaneous frequency-severity models are usually more computation-intensive, given that they are built on a more complex mathematical function that must account for a multivariate response variable. More precisely, they are generally based on Bayesian or Full Bayesian estimation techniques, that require Monte Carlo Markov Chain (MCMC) simulation (*e.g.,* Gibbs Sampler and M-H algorithm, etc.) for the parameters and correlation matrix estimation (*e.g.,* Ma et al., 2008; El-Basyouny and Sayed, 2009; Wang et al., 2011; Wang et al., 2017). In addition, the result is less straightforward to interpret, given that they include two components in one estimation and so the effects of the predictors over frequency and severity may not be immediate.

2.5.3. *Exposure estimation*

From the literature, it clearly emerged that road crash occurrence is strongly influenced by *exposure variables*, besides *e.g.,* infrastructural and context conditions. As road crashes occur - mainly - on roads, road crash exposure is usually expressed in terms of the amount of travel, which represents a surrogate measure of how much users travel (*i.e.,* stay on) the road and so the extent to which they can experience a road crash (*i.e.,* are exposed to a road crash risk) (Jovanis and Chung, 1986; Regev et al., 2018). Therefore, road crash exposure represents an extremely important factor to be included in the road safety analysis. Indeed, both the definition of risk and the RTSM Standard 39001 (2012) stressed the relevance of such factor, by including it as a major risk component, separate from the other influencing terms (*i.e.,* intermediate factors). In addition, many studies proposed exposure-only estimations for road crash frequency, which are defined *safety performance functions* (*e.g.,* Hakkert and Braimaister, 2002; Greibe, 2003; AASTHO, 2010; Vieira Gomes et al., 2012; Bonera et al., in press).

Traffic volume has been widely used as the exposure measure in the road safety analysis. Traffic volume can be expressed in terms of *e.g.,* average daily traffic (ADT), average annual daily traffic (AADT), or vehicle-kilometres travelled (VKM) (Hakkert and Braimaister, 2002). For instance, AADT is defined as the average daily (*i.e.,* over the 24 hours) number of vehicles measured at a location over a year (Castro-Neto et al., 2009). Several methods are available to collect traffic data, which can be mainly classified as fixed or mobile methods (Alonso et al., 2015; Pun et al., 2019; Sfyridis and Agnolucci, 2020).

Fixed traffic counts methods mainly rely on devices that are installed at a specific location either on the roadside (*e.g.,* automatic traffic detectors with microwave radar sensors, video image processing, etc.) or directly drown in the road surface (*e.g.,* inductive, or magnetic loops, piezoelectric sensors, etc.) (Khan et al., 2018). Sometimes, traffic counts records can be still managed by a manual survey. The most used automatic traffic detectors are Permanent Traffic Counter (PTC) stations and Short Period Traffic Counter (SPTC) stations (Alonso et al., 2015). The formers provide a permanent traffic measure at the road section so that they are generally placed at a limited group of strategic points. The latter are short-term counting stations, which are used to collect limited time traffic data (*e.g.,* 24-16h) for specific analysis or intervention. Given that these traffic count methods represent the most traditional alternative, they are greatly employed by road authorities to monitor traffic flows on their networks (*e.g.,* Province of Brescia).

Mobile traffic counts methods mainly rely on the detection of probes vehicles or floating cars by means of GPS signals (Pun et al., 2019).

Although traffic data represent a key input for road safety analysis - but also for many other transportation purposes, such as maintenance planning (Apronti et al., 2016; Shojaeshafiei et al., 2017) traffic data are not generally available for the whole road network, mainly due to economic and operational limitation from the road authority's perspective (Yannis et al., 2008; Park and Sahaji, 2013; Khan et al., 2018; Das and Tsapakis, 2020). Indeed, all the previously mentioned traditional traffic counter devices require great investments to be purchased, installed, and maintained. Hence, that may be unfeasible to provide full network-wide coverage for traffic count monitoring. As a result, traffic count stations are usually located on major arterials or at a strategic point to be controlled (Zhao and Chung, 2001; Fu et al., 2017). In addition, although GPS floating car data detection may be promising, this method suffers from vehicle sampling issues, as it cannot detect all the vehicles circulating on the road but just those that are connected to the system and consent to be monitored (Pun et al., 2019).

Therefore, estimation methods can be applied as a valid alternative to traffic counters, as they can return full-coverage information about road traffic volumes over the whole network. As highlighted by Castro-Neto et al. (2009) and Sfyridis and Agnolucci (2020), two are generally the objectives of a traffic count estimation: (i) current-year traffic estimation, which uses existing traffic counters data to model traffic at a different location where counts are not available, and (ii) future-year traffic estimation, which return for the same location an estimate of short-term future traffic by relying on historical traffic data.

Different techniques have been used in the literature to estimate AADT, such as (i) econometric regression models, (ii) geospatial methods, or (iii) machine learning techniques. Also, travel-demand modelling can be selected as an alternative. Multiple Linear Regression (MLR) models have been largely used to estimate AADT in the literature (see also Zhao and Chung, 2001; Apronti et al., 2016; Das and Tsapakis (2020); Sfyridis and Agnolucci, 2020). MLR mainly relies on a prediction function that return an estimated value of traffic counts (*e.g.,* AADT, VTM, etc.) as a function of context, socio-economic, infrastructural features. Geospatial models (*e.g.,* Geographically Weighted Regression, Spatial Regression models, K-nearest neighbour algorithm, etc.) show the potential of including location characteristics into the estimation result (Pulugurtha and Mathew, 2021).

Machine Learning techniques (*e.g.,* Random Forest, Artificial Neural Network, Support Vector Regression, etc.) are powerful tools that are mainly used for future AADT forecasts.

Table 7, which is self-explicative, provides a comprehensive but not exhaustive summary of studies that dealt with traffic count estimation retrieved from the literature. Some discussion is proposed in what follows.

Table 7 - A summary of traffic volume estimation studies

Authors (year)	Country	Estimation model	Study objective	Variables included	Significant variables	Sample size	Scale
Zhao and Chung (2001)	Florida (US)	Multiple Linear Regression	Estimation of AADT of State roads	Roadway features; socio-economic features; expressway accessibility; accessibility to regional employment centres; Area type.	↑ Road functional class; Number of lanes; Regional accessibility to employment centres; Population density; Employment density. ↓ Network distance to regional mean centres of population	898 count station over principal arterials, minor arterials, collectors, and local roads.	Road level
Castro-Neto et al. (2009)	Tennessee (USA)	Support Vector Regression with Data-dependent Parameters	Estimate AADT for future-year	#NA	#NA	25 counties	County level
Gastaldi et al. (2012)	Venice (IT)	Fuzzy c-algorithm and Neural Networks	Estimate AADT from seasonal traffic counts	#NA	#NA	50 Automatic Traffic Recorders	Road level
Alonso et al. (2014)	Cantabria (ES)	Bi-level Optimization Problem	Determining the best correlation between short period traffic counter and permanent traffic	#NA	#NA	16 PTC and 592 SPTC	Road level
Yang et al. (2014)	North Carolina (USA)	Multiple Linear Regression (with SCAD variable selection)	Test the SCAD criterion for the most significant variables selection	General driving behaviour; Road features; Satellite information; Socio-economic features.	↑ Number of lanes; Housing units; Number of cars; Car density.	243 sections for local roads	Road level
Apronti et al. (2016)	Wayoming (USA)	Multiple Linear Regression and Full Binomial Logistic Regression	AADT estimation for low-traffic roads	Land use; Road surface; Population; Number of households; Highway access; per capita income; Housing units.	↑ Paved roads; Direct access to highways; Population. ↓ Rural and industrial land uses.	19 counties	County level
Fu et al. (2017)	Ireland	Neural network, compared with OLS and log linear regression	Determine the AADT estimation for the national road network and the related polluting emissions	Road class; Local residential density; local working density; average road speed; Region type; Average car ownership ratio; distance to motorways and state roads; population of local settlements.	#NA	96 data points	County level Road level

Shojaeshafiei et al. (2017)	Alabama (USA)	Machine learning vs simple linear regression model and data transformed linear regression model	Determine the quality of the predicted AADT and which model most accurately reflects actual AADT	Number of lanes; Road functional class; Population density (within 0.25 miles); Retail employment (within 0.25 miles); Non-retail employment (within 0.25 miles).	↑ Major roads; Number of lanes; Retail-employment. ↓ Population density; Non-Retail employment.	235 counts collected	Road level
Khan et al. (2018)	South Carolina (USA)	Support Vector Regression and Artificial Neural Network	Develop AADT estimation models to accurately derive AADT from short-term counts	Socio-economic features; Roadway features; Time reference.	↑ Functional class; Area type; Income; Employment; Person below poverty; Vehicles; Housing unit.	164 ATS (83 on interstates, 53 on arterials, 15 on collectors and 7 on local)	Road level
Pun et al. (2019)	Hong Kong	Univariate Models, Multiple Linear Regression and Random Forest	Comparing multiple regression analysis to univariate analysis	Road geometric features; Topological features.	↑ Segment length; Connectivity; Betweeness; Closeness; PageRank; Clustering Coefficient.	216 count stations accounting for the 34% road network	City level
Das and Tsapakis (2020)	Vermont (USA)	Machine learning models	Estimation accuracy and interpretability of AADT	Accessibility to expressway; Population density; Employment density.	↑ Population density; Employment density.	2369 count station in 14 counties	Road level
Sfyridis and Agnolucci (2020)	England and Wales (UK)	Multivariate Linear regression, Random Forest, and Support Vector Regression	Estimate the AADT on existing road based on their characteristics	Road functional and geometric features; Socio-economic features; Public Transport service.	#NA	19000 geocoded count points in the UK	Road level
Pulugurtha and Mathew (2021)	North Carolina (USA)	Ordinary Least Squared (OLS) and Geographically Weighted Regression (GWR)	Model AADT on local road and compare OLS and GWR	Road functional features; Road network features; Land use; Socio-economic features	↑ Road density; Distance from non-local roads; Industrial and commercial areas; Hi-industrial households. ↓ Agricultural and multi-family areas.	10 counties were considered, with a count station number between 55 and 295.	County level

This is a representative, yet not exhaustive, list of reference of frequency-severity prediction models. ↑: variables that have a direct relationship with traffic volumes; ↓: variables that have an inverse relationship with traffic volumes; #NA: Not available Information

2.6. Gaps in the literature

All the previous research about RNS and Prediction Modelling techniques provided significant advancements and insights, both at the theoretical and practical level. However, some gaps persist. From the theoretical perspective, further methodological exploration may help in shedding light on an uncovered research topic. From the practical perspective, still, some issues may prevent the full implementation of RNS procedure and CPM applications.
The major issues will be briefly discussed in what follow. More precisely, the discussion will be structured over the three main steps of the RNS process, to highlight the drawbacks found in the literature related to each of those points. Gaps related to the application of CPMs are included in the "RNS Evaluation Criteria".

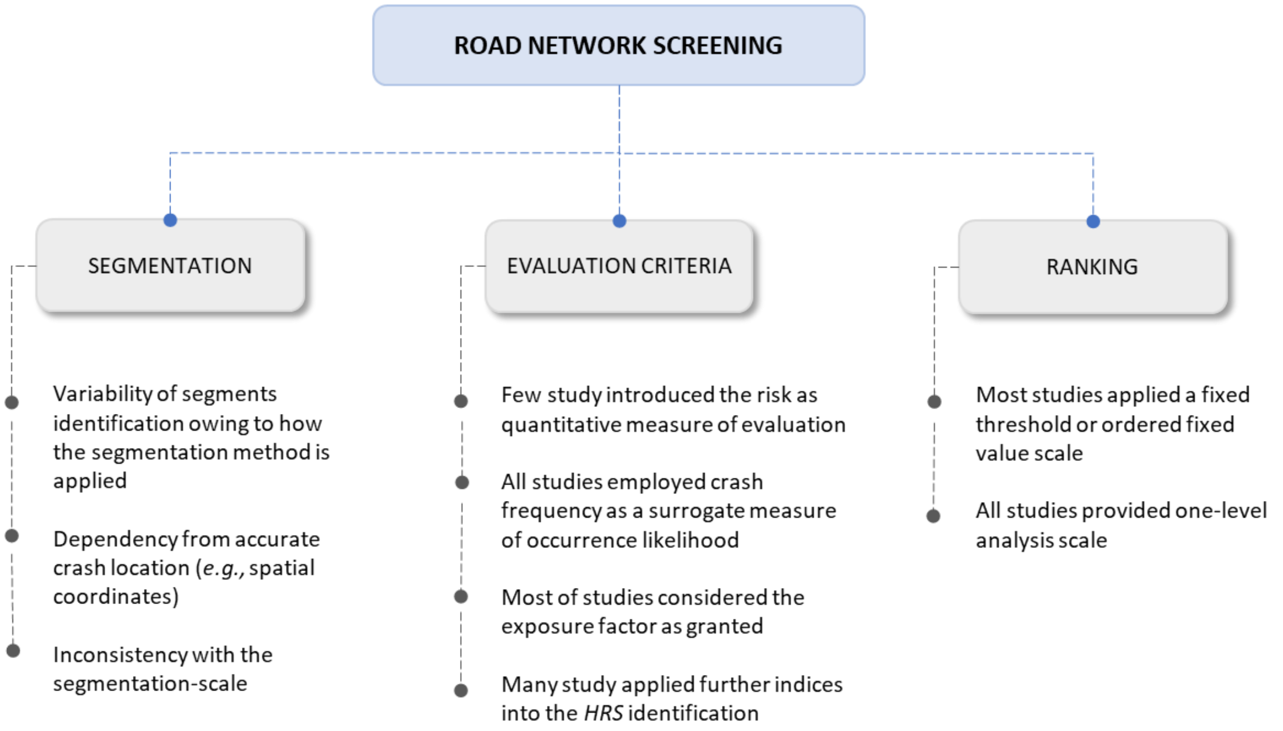


Figure 8 - Scheme of the gaps in the literature

To begin with, existing **road network segmentation** methods present some limitations.

First, fixed-length sliding windows or simple fixed-length segments could generate inaccuracies in the detection of the critical road sites and their extension, given that a fixed extension is imposed by the procedure itself (Elvik, 2007). If *homogeneous segments* or clustering techniques are used for the segmentation, depending on the set of variables selected, different segment types can be detected

(Ghadi and Török, 2019; Montella et al., 2019). Indeed, as a defined agreement over the definition of *homogeneous segment* still misses, variables selection would be challenging: if a too wide range of variables is used for the segmentation, too detailed and too many units might result, with very short average segment lengths. If few variables are included in the segmentation process, the result might lack homogeneity. Last, more sophisticated crash-related segmentation techniques *e.g.,* the ones proposed by Boroujerdian et al. (2014), require greater computational burden.

Second, all those methods strictly depend on accurate crash location availability (*i.e.,* spatial coordinates). Indeed, both sliding windows, homogeneous segments, and crash-related segmentation procedures return a partition of the network based on geometric and road-specific features, which does not include any location specification. Hence, to properly assign crashes their road segment, such methods require precise localization of crashes by means of *e.g.,* geographical coordinates. If an accurate crash location is not available, such methods cannot be fully performed.

Third, existing segmentation methods may return a network partition that may not be fully consistent with the scope and scale of the analysis. Indeed, all the previous methods return a quite thick network partition which may be more appropriate for high-detail analysis. If the evaluation of an entire road network is concerned (*e.g.,* national, regional, etc., that consists of thousands of kilometres), too detailed and short segments may not be suitable. Indeed, if too many and too short segments are returned, then the evaluation of the network will be more time-intensive; in addition, if homogeneous segments are concerned, full coverage of complete data for such segmentation may not be available.

As for **evaluation criteria**, besides two studies, no one introduced the concept of risk in their methodological setting, while talking about "*High-risk sites*" etc. (*e.g.,* Miranda-Moreno et al., 2009; Afghari et al., 2020). However, as also stressed by the international Directives, a risk-based approach should be preferred, as it has proven to return more effective and performing results in the field of road safety analysis. Therefore, further investigation about the application of road crash risk analysis in RNS and in CPM development is required. Specifically, referring to the risk components (*e.g.,* crash occurrence likelihood, crash consequences, and crash exposure) and their estimation, two are the main drawbacks in the literature. First, besides a few attempts (*e.g,* Park and Sahaji, 2013; Theofilatos et al., 2016) crash occurrence likelihood has been mainly addressed in terms of crash frequency. Conversely, crash severity has been widely estimated by means of probability models that return the chance to register the most severe damages. This might be related to the fact that probability models rely on observation-specific information, so that building an appropriate database for crash occurrence probability may be unfeasible in many cases.

In addition, among crash frequency-severity integrated models, multivariate models are the most frequently employed. However, as highlighted previously, they are greatly affected by data-related issues (*e.g., the* low sample mean and small sample size) and have crash data restraints, that may generate an inferential loss. Moreover, their mathematical formulation shows a complex estimation process and further computation (*e.g.,* simulation algorithms) are required for the estimation results. As a result, this can be intended as a barrier to their implementation.

Furthermore, with respect to the studies that applied frequency-severity models directly to RNS, in most cases, the results of the models were then included in the formulation of another index *e.g.,* crash rate, according to which return the evaluation of the safety performance. However, adding a further computational burden in RNS may prevent the implementation of such a procedure by practitioners (Ambros and Sedoník, 2017).

As for the **exposure component**, which is mainly expressed in terms of traffic volumes, most previous studies have included *e.g.,* traffic volumes as input data among the set of explanatory variables, as it was taken for granted. However, this may be questionable for two main reasons.

First, as supported by previous studies, road traffic volumes are not always available for the whole road network (Park and Sahaji, 2013). Hence, the opportunity to estimate the exposure factor for those roads whose traffic data are unavailable may help in bridging such a gap. In addition, given that traffic volumes resulted as a significant variable in almost all the cases when estimating crash frequency and severity, it would be interesting to unveil the factors that could help better regulate and control traffic volumes over specific roads, so that crash occurrence and severity can be mitigated in return.

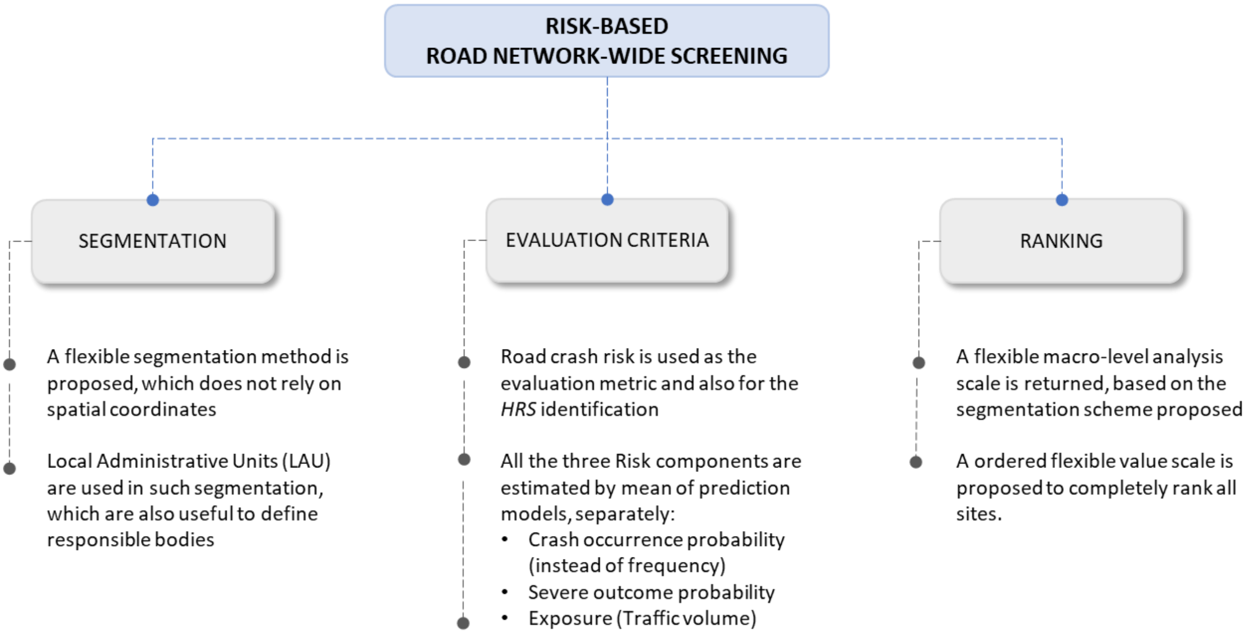
Second, the potential of a road site to register road crashes or generate severe consequences should be evaluated regardless of the extent of the exposure measure. In other words, when estimating the expected crash frequency or severity of a site, just the inherent characteristics of the site itself should be considered as risk factors (*i.e.,* infrastructural, operational, context, etc.), while risk exposure should be treated separately. Indeed, the amount of travel or road users (*i.e.,* the exposure) that interest a specific site should be intended as an amplification factor: starting from the inherent safety performance of a site, the amount of exposure may increase or diminish the extent to which crash and severe consequence are registered.

For what concerns **ranking methods**, in most cases the classification is made by comparing the values obtained for each network unit according to the evaluation criteria selected with a fixed threshold or an ordinal fixed-value scale. In the first case, a summary ranking is returned, which just declare which segments are critical and which are not indiscriminately. In the second case, the full set of units to be evaluated is covered in the ranking, given that they can be assigned to a specific range of the scale depending on the road safety evaluation received. However, if fixed values (*i.e.,* numbers) are used to specify the scale ranges, this may prevent a full transferability of the ranking to other contexts and an uneven comparison among the safety performance of different networks.

Moreover, according to the several studies accounted for in this research, all of them provided a one-level analysis scale, thus just relying on the segmentation units defined. However, when implementing a network-wide safety screening, it may be useful and effective to return a multi-level ranking that allows to first identify the riskiest roads among the others of the network and then, to explore further to detect the most critical segment of those roads.

2.7. Contributions to the literature

Based on the gaps pinpointed in chapter 2.6, this research aims at expanding the existing literature by shedding light on road safety areas that have been slightly explored so far, to the author's knowledge. Specifically, this research proposes the development of a new methodological approach for the implementation of a risk-based network-wide road safety screening. Figure 9, which represents the "complement" of Figure 8, schematically highlights how the methodological proposal aims at replying to the gaps.



A flexible segmentation method is proposed, which does not rely on spatial coordinates

Local Administrative Units (LAU) are used in such segmentation, which are also useful to define responsible bodies

Road crash risk is used as the evaluation metric and also for the *HRS* identification

All the three Risk components are estimated by mean of prediction models, separately:
- Crash occurrence probability (instead of frequency)
- Severe outcome probability
- Exposure (Traffic volume)

A flexible macro-level analysis scale is returned, based on the segmentation scheme proposed

A ordered flexible value scale is proposed to completely rank all sites.

Figure 9 - Scheme of the contribution of the research to theory and practice

In addition, the main underlying points of such methodological proposal are described in what follows. More precisely, the proposed methodology should:

- be based on a flexible structure, which enables a network-wide safety assessment at the macro-scale (entire road) but still provides an evaluation also at the intermediate level (single segment of the entire road). More precisely, depending on the extent of the study area, multiple scales of analysis should be returned, so that both the most critical roads of the entire network (macro-scale) and the most critical segments of such roads (micro-scale) can be identified.
- Use data that are suitable for the wide-level investigation and consistent with the scale of the analysis and specifically to the segmentation of the road network itself. If the segments considered are kilometres long in order of size, then too detailed information may not be

appropriate. Conversely, variables that represent more general characteristics or segment-wide features should be preferred (e.g., road class, number of lanes per direction, presence of median, etc.).

- Rely on the most widespread data and official data sources (*e.g.,* official statistics bodies, Governments, etc.). Indeed, as the whole network should be screened, too detailed information may not be available for all roads, nor their recognition may be feasible (in terms of times and resources consumption) or possible (in terms of data accessibility) data required to perform the investigation should be consistent and standardized for all the roads included into the analysis. This will also foster the replicability and standardization of the whole methodology. Moreover, to make the overall process easy to replicate and less data-intensive, the smaller the set of significant variables to be included the easier the implementation.
- Be independent of geographical coordinates in the data integration process. Indeed, the accurate spatial location (*e.g.,* recorded by GPS system and translated into geographical coordinates) is not always available or correct – even in official sources databases. Hence, an alternative procedure must be implemented, which does not rely on coordinates for location information. Indeed, if spatial coordinates are considered instead, it may happen that a sub-set of a road crash are neglected from the analysis as they cannot be localised on the network.
- Rely on a proactive approach and apply a risk-based criterion for the road safety assessment. To do so, the widely agreed definition of risk (*i.e.,* the combination of road crash occurrence likelihood, consequences, and exposure) can be adopted to return an evaluation metric. In addition, the three components should be estimated by mean of CPM and separately, so that more targeted measures can be proposed to reduce the risk of a road crash.

3. A new methodological approach for a risk-based road network-wide screening

3.1. Overview of the proposed methodological approach

In this section, the proposal of a new methodological approach for the implementation of a risk-based road network-wide screening (RB-RNWS) is presented. Taking the EU Directive 1936/2019 as the reference, a flexible and adaptable framework was devised to perform the RB-RNWS procedure based on three main milestones: (i) the compliance with ISO 39001:2012 Standard, (ii) the formulation of risk, and (iii) the implementation of Road Crash Risk Prediction Model.

The framework, which is shown in Figure 10, consists of three main phases, namely: (I) Data sources, (II) Compliance with ISO 39001:2012, and (III) Road Network-wide Screening. All these phases are further detailed in sub-steps to make the implementation easier and systematic. Specifically, Part III is characterised by three main sub-steps, which correspond to the previously described steps of the RNS, namely: A) Network segmentation, B) Evaluation criteria, and C) Network ranking. Further details are provided in what follows.

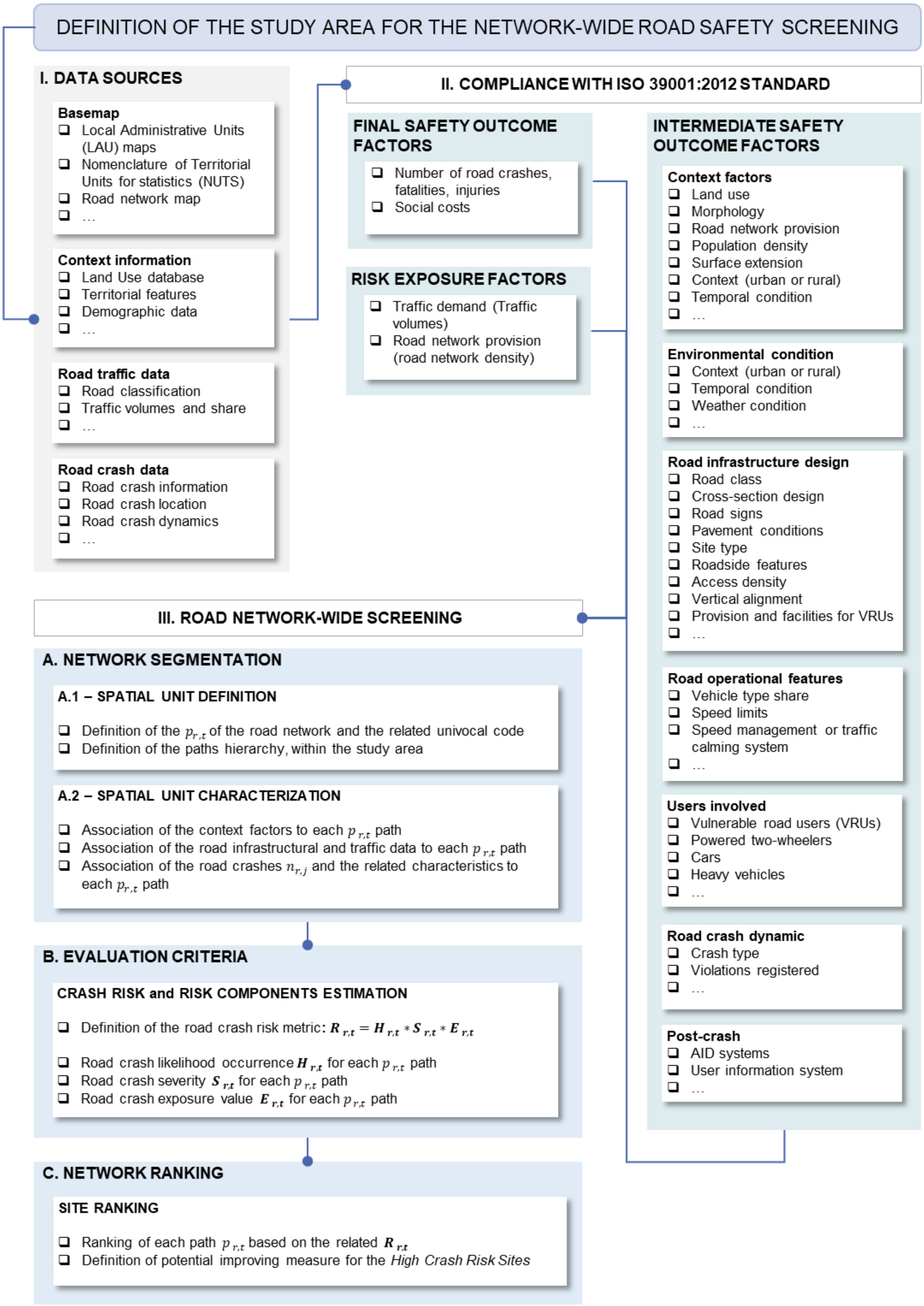


Figure 10 - Framework of the new methodological approach for the risk-based network-wide road safety screening

3.2. Part I - Data sources

Before starting with the implementation of the sequence of steps and sub-steps of the RB-RNWS framework, it is necessary to define the study area and, specifically, the extent of the road network to be analysed. Then, Part I of the framework is devoted to the collection of all the required information and data to be included in the assessment process.

As mentioned before, crash occurrence and consequences can be affected by several variables. However, depending on data availability and according to the scope of the analysis, different data should be collected and to a specific detailed extent.
Given that road network screening reflects a wide-level (macro-level) analysis of the safety performance of a road network – and responds to the first stage of the road infrastructure safety management process, the data used in such procedure must be suitable for the wide-level investigation, consistent with the scale of the analysis, and specifically to the segmentation of the road network itself. For these reasons, few and easy-to-collect data are suggested to be used in this study, and specifically gathered from official sources, to ensure greater data attainability and standardisation. Here below a detailed description of such data is provided.

The "*Data sources*" box contains a reference to the main sources where all the necessary data should be gathered from. In these regards, the long list of *indicative elements of network-wide road safety assessments* reported by Annex III of the EU Directive 1936/2019 should be considered as a reference. However, as mentioned previously, it is believed that, if the whole road network must be screened, less detailed but available data for all the roads can represent a good compromise. For this reason, among the long list provided in Annex III, it is preferable to include in the RB-RNWS those data which are more largely available and retrieved from the main official data collectors. In this manner, data should be available to cover the whole network and should be standardized to facilitate the processing operations. According to such assumption, the main elements to be considered are:

- **Basemap** – This information source refers to the Local Administrative Units (LAUs) of the area considered and to the main digital cartographic support. More precisely, the following are required: the maps showing the physical and/or administrative partition of the territory into the several levels (*e.g.,* national, regional, county, etc.) which will be considered for the network-wide assessment; the information related to the Nomenclature of the Territorial Units for Statistics (*i.e.*, *NUTS*), as they will serve as a reference for the association of the road network to the specific area; the road network map should be retrieved, which represents the whole and complete extension of the road network in the study area. Such data are generally provided as a vector-based file, but also spreadsheets-based files may be available for the related metadata.

- **Context information** – This information source refers to all the data related to the characteristics of the area considered. More precisely, the following are required: the geographical and morphological features of the area, such as the land use information or the territorial types; socio-demographic data should be gathered by the official sources, which comprise the number of inhabitants or population density, and other household information that might be useful for the analysis. Such data can be provided either as a vector-based file or spreadsheets-based file, depending on the type of information (*e.g.,* land use data may be recorded into both formats, while demographic information may be available only as metadata).
- **Road traffic data** – This information source refers to all the data related to traffic demand, traffic share, and road operational characteristics. More precisely, the following are required: traffic volumes data should be collected to have a measure of how many road users and which type of vehicles transit on each road; information related to road and traffic management, such as road classification (both functional and administrative), speed limits, etc. Such information can be collected by means of site measurements or traffic modelling/estimation (and an example will be provided later). Such data are generally provided as a vector-based file (*e.g.,* graphs), but also spreadsheets-based files may be available for the related metadata.
- **Road crash data** – This information source refers to all the data included in the road crash record template. Indeed, all the Police bodies who oversee collecting road crash data are required to fill a standardized form which contains all the main information related to the number of people involved and the damage received (*e.g.,* fatality, severe injury, etc.), crash location (*e.g.,* road design characteristics, road name, etc.), and other data. Such data are generally provided as a spreadsheets file (an example of the Italian official template for road crash data collection is provided in the Appendix).

3.3. Part II - Compliance with ISO 39001:2012 Standard

Once all the required data are retrieved from the official sources, Part II of the framework is devoted to further arranging them in compliance with the ISO 39001:2012 RTSM Standard guidance. More precisely, data should be organized in subsets that correspond to the main risk factors of the 39001 Standard, thus (i) Final safety outcome factors, (ii) Risk exposure factors, and (iii) Intermediate safety outcome factors. Such data refinement is key for two reasons at least.

First, it guarantees that the overall methodology complies with the Standard's requirement, which is mandatory for the methodology to undergo a Standardisation process (*i.e.,* official, and technical certification). Second, such a data organization will facilitate the implementation of the B.2 step of the framework, when computing the road crash risk by means of prediction models. Indeed, it will help identify the role of each element to be included in the estimation process.
Figure 11 helps explain the underlying correspondence among all these components.

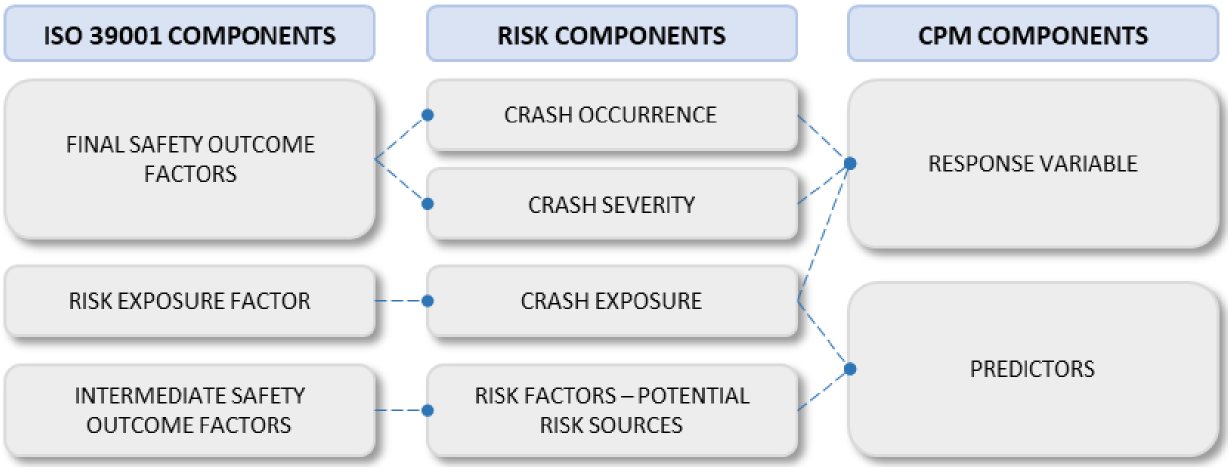


Figure 11 - Correspondence between the components of ISO 39001:2012, Risk, and CPM

The literature has shown that a road crash can be the result of the interaction of several factors *e.g.,* the road context, the infrastructure design, the operational characteristics, etc., (*e.g.,* the long list of *indicative elements* included in Appendix III of the RISM Directive). According to the definition of risk, those are recognized as risk factors, thus the ones that can cause a change in defined condition and that can lead to a potential risk event. Furthermore, according to ISO 39001 (2012), such factors are identified as the *Intermediate outcome safety factors*.

In addition, when dealing with road safety, it is of paramount importance to include in the analysis information that reflects the actual use of the network by road users of all categories. According to ISO 39001 (2012), we define these factors as *Risk exposure factors*.
Therefore, crashes will result from what one can define as a break in the equilibrium that results from the interaction between the *Intermediate safety outcome factors* and the *Risk exposure factors*. In

other words, these main categories of factors can affect both the occurrence and the severity of the crash event, which are then defined as the *Final safety outcome factors*.

Following this flow there can be a link among all the pillars, thus the 39001 Standard, the Risk definition, and the CPM structure. For instance, when referring to the ISO 39001 section, the risk exposure factors can be related to the exposure component of risk, which usually is represented by traffic volumes. Again, those two related elements can be further connected with the corresponding in the CPM structure, which can be intended as either a response variable or a predictor, depending on the modelling structure adopted. Likewise, when considering the intermediate safety outcome factors of the ISO, we can find their counterpart in the risk definition by relating to the risk factors. Then, in the CPM structure, both elements correspond to the predictor components, thus the set of explanatory variables used to explain the response variable.

To facilitate this process, the table reported in Annex 7.4 suggests how the long list of *indicative elements* of Annex III of the RISM’s Directive (which represents the potential risk sources) can be organized according to the three ISO 39001 and CPM components.

3.4. Part III – Road Network-wide Screening

Once Part II has been completed, Part III can be implemented, which is the core of the whole framework. Indeed, it concerns the application of the RNS process by following the sequence of the three main steps (*i.e.,* step A, step B and, step C) and the related sub-steps. A detailed description of all the tasks to be performed is provided in what follows.

A. Network segmentation

Step A is aimed at preparing the road network base map, which will serve as the cartographic reference for all the forthcoming steps. It consists of two sub-steps, namely (A.1) Spatial unit definition, and (A.2) Spatial unit characterization. More precisely, first, the whole road network will be partitioned into several spatial units (*i.e.,* road segments) according to the several scales of the analysis; then, each spatial unit will be associated with the related information (*e.g.,* context, infrastructural design, road crashes) that will characterise their risk components.

Step A.1 – Spatial unit definition

According to Part I and Part II, the overall RB-RNS process is made of a set of different data and information which are generally characterised by different spatial resolutions.

Road crashes are well-defined events in terms of time and space. Indeed, they are geographically identified by a point-based entity, which distinctively refers to a specific location over the map and is represented by *e.g.,* a couple of spatial coordinates or other spatial information (*e.g.,* road names, address, etc.). As a result, punctual information usually best accommodates the spatial dimension of such elements.

The road networks are usually geometrically represented by the mean of a sequence of links (*i.e.,* the road segments) and nodes (*i.e.,* intersections or changes in the cross-section design), which are characterised by a specific design or context attributes or are identified according to their administrative competency limits. The same rationale is used for the spatial representation of road traffic volumes, which are generally returned over a network graph made by links and nodes. In this case, each link is associated with the related traffic volume and is defined by endpoints (*i.e.,* the nodes), which identify a cause of change in the traffic flow. However, road links cannot be expressed by *e.g.,* a single couple of spatial coordinates, being entities characterised by a 2D dimension.

As a result, it is evident that the spatial resolutions through which road crashes and road elements are expressed differently and cannot be directly matched. Therefore, it is necessary to find a different spatial unit to enable a univocal correspondence between road crashes, road segments, and the related characteristics. In addition, considering a network-wide road safety assessment, a point-based location might not be the preferable choice, given the size of the problem. Conversely, an alternative spatial unit should be found, to serve as a *least common multiple* of the location attributes of all the data sources included in the assessment process. In this manner, both road crash data and road network attributes can be referred to the same spatial unit.

To define such a spatial unit, some consideration must be made. First, all the location and spatial resolution attributes (*e.g.,* jurisdiction, road name or code, road chainage, coordinates, address, etc.) among the different data sources need to be identified (*i.e.*, base map data, traffic data and crash data). Then, only the location attributes which are in common to all the sources should be considered. That will be used to build the *least common spatial unit* based on which the road network can be divided and through which all the data can be referred to as the unique spatial resolution.

Unlike road chainage and spatial coordinates, jurisdictions (*i.e.,* the territorial units, which are ascribed a specific code and name) and the road name (or route code) are always reported in all the sources, as they are prior information that characterises the location, even in the road crash data record template. In addition, geographical coordinates or road chainage may not be always recorded, especially in road crash reports[20]. In addition, when dealing with GIS-based formats, data layers that may not contain such information in their metadata can be easily integrated into GIS environment by overlapping e.g., basemap and transfer information by mean of the intersection or joint functions. Therefore, the road network can be partitioned into several units, which are defined by the portion of the road within the administrative boundaries of a given territorial area. Such entity is here defined as **path**. For sake of clarity, in what follows a detailed explanation is provided to help understand this concept. Figure 12 also provides a graphical example.

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[20] For what concerns road crash data location, the EU Directive 2008/96/CE, Annex V, provided a list of information to be included in road crash reports. Specifically, it recommended a *"precise as possible location"* (European Union, 2008). However, in the latest official communication of the Italian Institute for Statistics (ISTAT) to the Police bodies in charge of reporting road crashes, for what concerns road crash location, it is requested to correctly include in the form the road name, the chainage (km and metres) and the road class. Still spatial coordinates are not mandatory but *"to be included, if available"* (ISTAT, 2021).

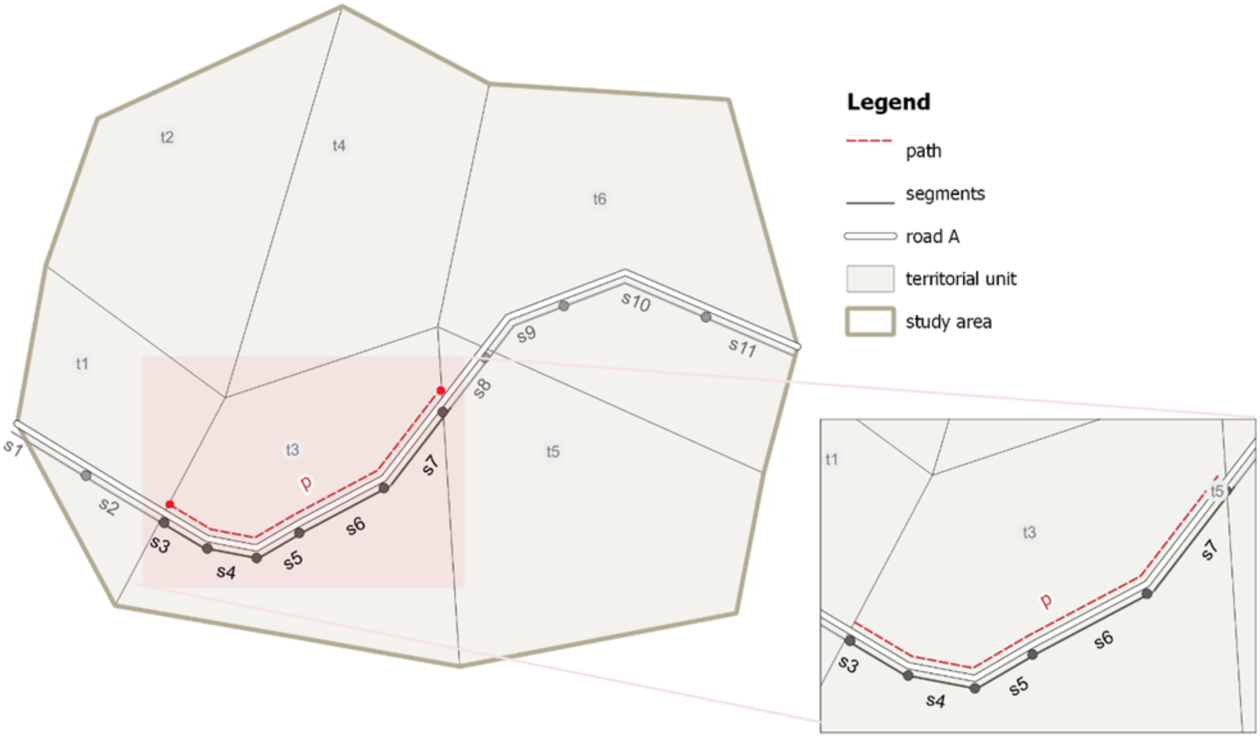

Figure 12 - Conceptual scheme of the network partition and path definition.

Within the study area (*i.e.,* beige bold-line polygon) all the several territorial units are identified (*i.e.,* grey polygons named t1, t2, etc.), which represent the possible administrative boundaries over which the study area can be divided. For instance, a generic t can represent the municipality boundaries in a province or a region. Also, all the roads of the network to be analysed are identified (*i.e.,* the thick white line. For sake of clarity, Figure 12 shows just one road). As mentioned before, each road is usually composed of a sequence of segments that represent the links (*e.g.,* the dark-grey lines named s1, s2, etc.), which are delimited by a defined endpoint that correspond to intersections or changes in the cross-section design (*i.e.,* the dark-grey dots). Hence, by applying the definition, a generic path is represented by the portion of a road (*e.g.,* road A) within a specific territorial unit (*e.g.,* t3), in other words, the segment of the road whose endpoints correspond to the intersection between the road with the boundaries of the specific territorial unit considered (*i.e.,* the red dotted red line, named p, delimited by the red points). In addition, as the road is also composed of a sequence of segments, the path is the sequence of the segments of the road which are comprised within the selected territorial (*e.g.,* from s3 to s7, as reported in the zoom).

Such road network partition provides enough flexibility to investigate the whole road network in a thorough manner. Indeed, the thicker the territorial unit partition, the denser the network partition and the more detailed the network screening. By considering the definition of path, depending on the number and type of territorial units available for the study area, different levels of path can be drawn[21]. If so, then it is necessary to define a hierarchical structure of the level into which the study area can be divided. This will also correspond to the hierarchy of the different levels of paths that can be defined, and – eventually – to the levels of RB-RNS. For instance, if the network partition is made by considering the lowest level of the territorial unit available in the hierarchy, then paths are defined at the lowest level possible. In this case, paths can be defined as "**minimum" paths**.

More formally, let:

- T be the set of all the territorial units into which the study area can be divided, and $t \in T$ be a generic territorial unit.
- $K \subseteq T$ be a generic subset of territorial units into which the study area can be divided, according to a specific level of the hierarchical structure, and $k \in K \subseteq T$ be a generic territorial unit of such level.
- $I \subset K \subset T$ be the set of territorial units into which the study area can be divided at the lowest possible level of the hierarchical structure, and $i \in I \subset K \subseteq T$ be the generic lowest territorial unit.
- $R(t)$ be the set of the roads crossing the $t \in T$ territorial unit, and $r \in R\ (t)$ be a generic road.
- $S(r, t)$ be the set of the road segments of the road $r \in R(t)$, which crosses the territorial unit $t \in \mathrm{T}$, and $s \in S(r, t)$ be a generic segment.
- $P_{r,t}$, be the set of paths, thus the sequence of all segments $s \in S(r, t)$ of the road $r \in R(t)$ crossing $t \in T$, and $p_{r,t} \in P_{r,t}$ be a generic path.

Then, the generic path $p_{r,t}$ is defined as:

$$p_{r,t} = \{s \in S(r,t) \colon r \in R(t) \text{ and } t \in \mathrm{T}\} \tag{3.1}$$

while any intermediate path $p_{r,l}$ and the "minimum" path $p_{r,i}$ are defined, respectively, as:

$$p_{r,k} = \{s \in S(r,k) \colon r \in R(t) \text{ and } l \in K \subseteq T\} \tag{3.2}$$

$$p_{r,i} = \{s \in S(r,i) \colon r \in R(t)\ and\ i \in I \subset K \subseteq T\} \tag{3.3}$$

---

[21] If the road is to be considered over the entire study area (*e.g.,* at the regional or national level), the whole sequence of segment should be selected, from s1 to s11 (*i.e.,* the whole sequence within the beige bold-line polygon). If, instead, the road is to be considered over the territorial unite named t3, path will be defined as the sequence of s9-s11.

The territorial unit partition proposed by Eurostat (European Commission, 2003) can be used as a reference for this aim. Such partition is a geocode standard for referencing the subdivisions of countries for statistical purposes. More precisely, all the system is based on a least territorial unit, which is named Local Administrative Unit (LAU) and generally corresponds to the municipality (or district) administrative level. All the other partitions are conceived as a gradual aggregation of LAUs, depending on the scale considered and the population size. The underlying criteria of such aggregation are based on the existing administrative units, thus a geographical area with specific administrative authority. Table 8 briefly reports the system established by the EU Directive 1059/2003 (European Commission, 2003).

Table 8 – Example of hierarchical territorial units' structure, based on the European NUTS partition (Art. 3 of the EU Directive 1059/2003)

Hierarchy of the territorial unit	Minimum inhabitants	Maximum inhabitants	Correspondent territorial unit
NUTS 1	3 million	7 million	Groups of regions
NUTS 2	800 thousand	3 million	Regions
NUTS 3	150 thousand	800 thousand	Provinces
LAU	-	-	Municipalities
ZIP CODE	-	-	*e.g.*, district

Figure 13 reports an example of such a hierarchical structure for territorial units for the Italian case. More precisely, by referring to the area of the Lombardy Region, the following administrative territorial units are identified, namely: NUTS 2 correspond to the regional's administrative boundaries, NUTS 3 corresponds to the counties' (provinces) administrative boundaries, and LAU corresponds to the municipalities' administrative boundaries.

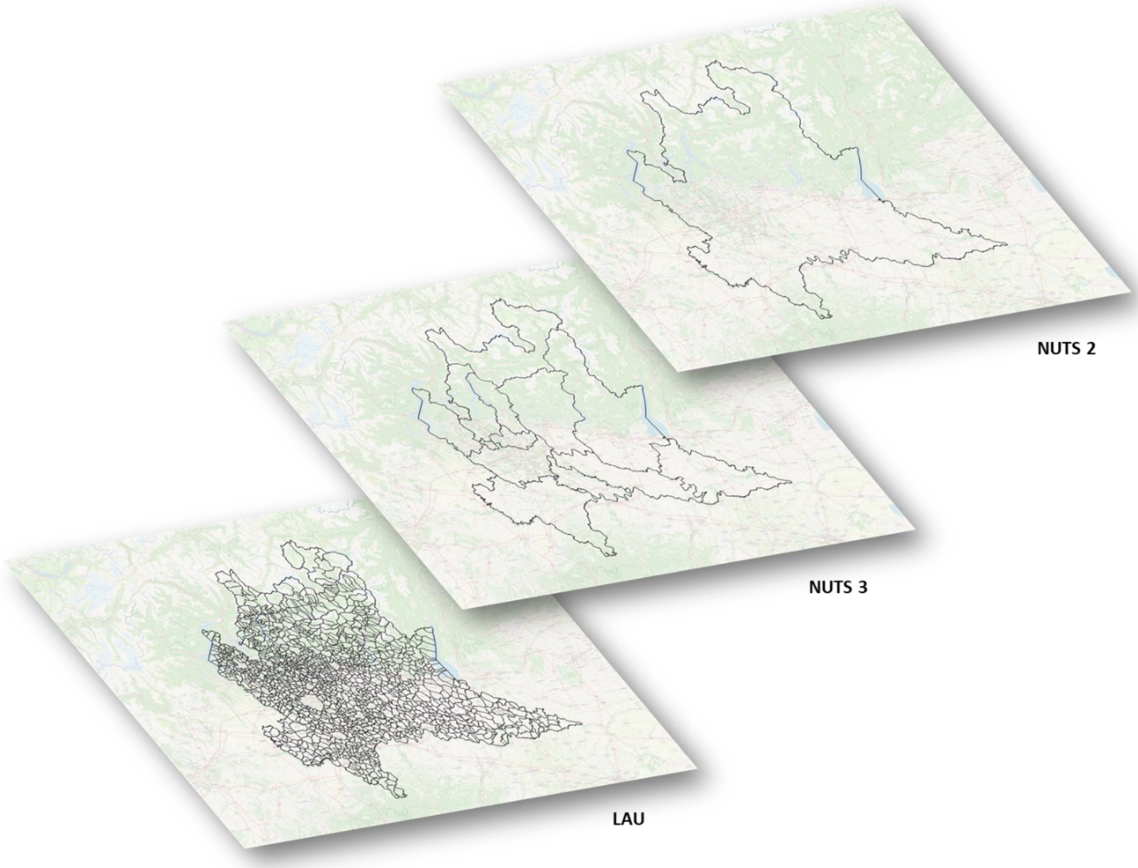

Figure 13 - Hierarchy of the territorial partition based on the NUTS and LAU resolution for Italy (LAU= municipality level; NUTS 3= provinces level; NUTS 2= regions level).

This territorial partition system is an extremely useful criterion to develop the concept of paths. Indeed, such network partition can be related to the definition of the Traffic Analysis Zones (TAZ), which are the most widespread geographical units in conventional transportation planning models. The size of a TAZ can vary but generally, they are constructed by census block information so that the definition of a TAZ can overlap the definition of a LAU.

In addition, the proposed method may be preferable to the existing ones for several reasons. Specifically referring to the spatial-related methods, some differences can be highlighted. First, the spatial-related methods are “user dependent”, as the resulting segmentation is subjected to the features considered in the process. Conversely, census block and administrative boundaries are fixed and objective for all, as they are univocally defined. Second such methods are strictly spatial-coordinates dependent, as the segmentation based on *e.g.,* geometrical, operational, context etc. characteristics lie outside any spatial location information. Therefore, there is no possibility to directly associate crash event to a specific road segment just based on such features. However, the availability of spatial coordinates is not always guaranteed. Third, these aspects might somehow hinder the practical implications of the RNS itself. Indeed, improvement measures required on the most critical sites should be implemented by those who are responsible for road safety in those sections, namely road authorities and local administration. Such bodies, however, have specific jurisdictional authority. Conversely, the jurisdictional definition of the road network may collide with the fixed-length or homogeneous segmentation of the network itself. As a result, problems may arise when it comes to propose corrective measures and allocate resources for them, if the same *e.g.,* fixed length or homogeneous segment belongs to different jurisdictions. In this perspective, the segmentation method proposed may support practitioners' task in that it also considers the jurisdictional partition of the area interested by the road network. Indeed, if the road network is divided into sub-sections based on the census block (e.g., LAU) at the different level, the resulting segments are consequently generated with respect to the related administrative boundaries. In addition, it does not rely on spatial coordinates (which may be unavailable) but rather on those location attribute that are always recorded, namely administrative location and road name/code. In doing so, the association of crashes to the network is completely coordinates-independent, and so the segmentation process.

Step A.2 – Spatial unit characterisation

Once the whole road network has been partitioned into paths according to the hierarchy of territorial units, each path needs to be enriched with the related information related to *e.g.,* road crashes occurred, road infrastructure design, environmental context features, etc. To do so, it is necessary to develop an integration process that allows to distinctively relate each path with the related information from the several data sources in a *one-to-one* or a *one-to-many* relationship, depending on the type of data considered. In other words, a relational database must be developed in which each observation is made by each path. A univocal field should be created then, which serves as the *primary key* for the integration process. The road network partition based on the path criterion helps in this task. Indeed, if each path is identified by a univocal code, then the process can be automatically performed by the mean of such a common field. The code can be derived from the definition of path itself. More precisely, the univocal code can be created by merging the name/code of the road where the path belongs, and the nomenclature/code of the territorial unit considered. For instance, referring to the scheme of Figure 12, the path *p* can be attributed to the code "road A_t3", being part of the "road A" within the territorial unit "t3". As the definition of path was built on the identification of the common location information to all the data sources, then the *primary key code* can be retrieved/created in each data source included in the analysis. Figure 14 schematically shows the road path characterisation process.

As mentioned, depending on the type of data considered, a different relationship may exist. When road infrastructure and context features are concerned, a *one-to-one relationship* is defined. Indeed, such data represent unique features that are directly and univocally related to the single path, describing *e.g.,* the context surrounding the paths (*e.g.,* type of terrain, the land use, population size, etc.) or the road infrastructure design of (*e.g.,* road's cross-section, number of lanes, etc.). Conversely, in case more elements are to be related to the same path, a *one-to-many relationship* is defined. Indeed, if *e.g.,* more than one road crash has occurred over a given path, all those elements should be distinctively associated to the same spatial unit.

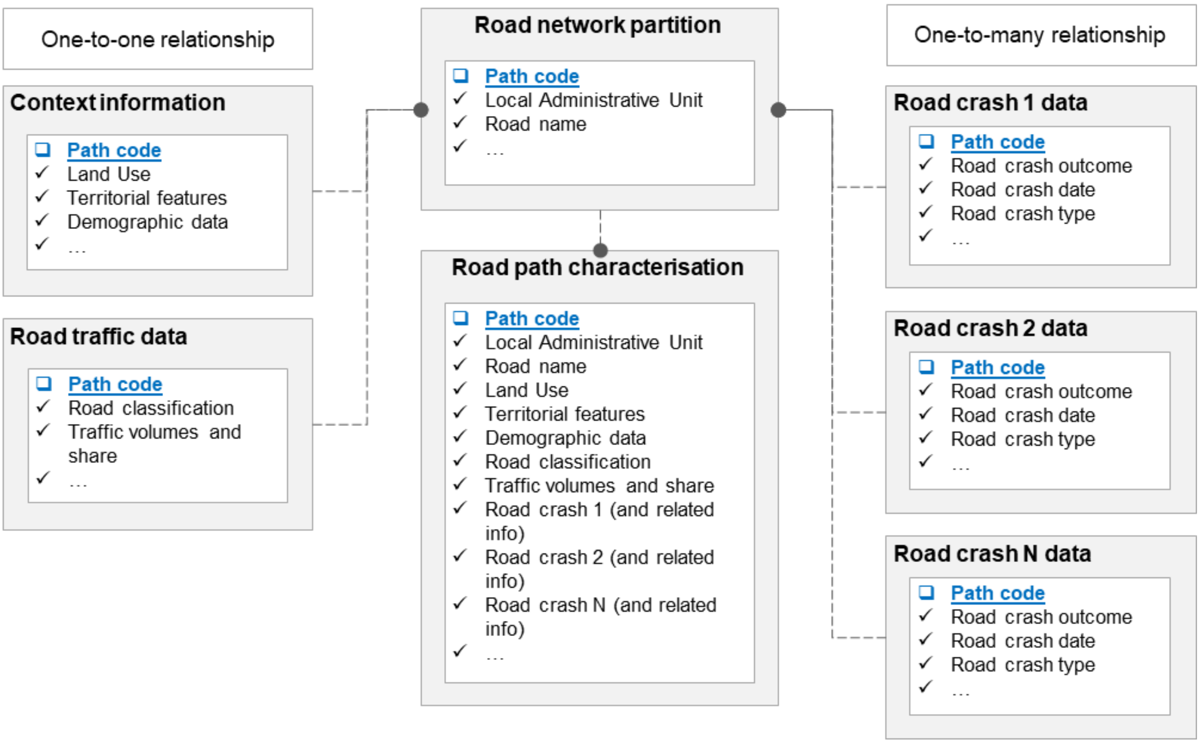

Figure 14 - Road path characterisation process with one-to-one and one-to-many relationships

Please note that such characterisation process for each spatial unit should be better performed over the minimum path. Indeed, being the lowest spatial unit to be reached, more precise results will return.

For what concerns map and graphical information (*e.g.,* basemap sources, context information sources), the integration can be easily performed also in a GIS environment by overlapping the related layers and applying specific geoprocessing function (*e.g.,* intersect, summary attributes by location, etc.). In addition, as also suggested by Hosseinpour et al. (2014) if a specific (univocal) variable happens to present several possible values or categories over the same path, then the category with the largest proportion (*e.g.,* the most extended) or the average of the values can be assumed as the representative characteristic for that variable over the considered path. For instance, if the land use is considered for the characterisation of a path and different are the land use types surrounding the same path (*e.g.,* residential areas, rural areas, commercial areas, etc.) the largest in terms of extension should be considered as the definitive feature.

For what concerns metadata (*e.g.,* traffic volumes, road crash information), the association can be still performed in GIS environment by mean of join function. To do so, the univocal code of the path is required, given that a common input field is mandatory to transfer data which are related to the same element. More precisely, referring to the path length and traffic volume, some intermediate computation must be performed to return a correct result of such information for each path. Each segment of the road is associated with its length and the traffic volume (*e.g.,* Average Annual Daily Traffic - AADT). Let:

- l_s be the length of a generic segment s.
- v_s be the traffic volume of a generic segment s.

Then, the length $l_{r,i}$ of each "minimum" path $p_{r,i,}$ of $r \in R(i),\ i \in I \subset K \subset T$ is computed as:

$$l_{r,i} = \sum_{I} l_s \qquad \forall\, r \in R, \forall\, i \in I \tag{3.4}$$

The traffic volume $v_{r,t}$ of each "minimum" path $p_{r,i,}$ of $r \in R(i),\ i \in I \subset K \subset T$ is computed as a weighted average of the single traffic volumes over the total length of the path, thus:

$$v_{r,i} = \frac{\sum_I l_s \cdot v_s}{l_{r,i}} \qquad \forall\, r \in R, \forall\, i \in I \tag{3.5}$$

B. Evaluation criteria

Step B is aimed at defining the metric that will be used as the assessment parameter for the safety performance of road network. The literature is quite rich in valuable indicators and methods that can be employed to evaluate the road network safety performance. However, to embrace the European directives, the network-wide road safety assessment should be firstly based on a road crash risk metric. Moreover, to account for the recommendations about the employment of proactive approaches, here a crash risk prediction model is proposed, to return a quantitative (but also qualitative) estimation of the expected road crash risk over the network. Further details about the formalisation of such metrics are explained in what follows.

Road crash risk modelling

The road crash risk metric applied in this research relies on the widely agreed formulation of risk, which was discussed in chapter 2.3. More precisely, road crash risk is conceived as the combination of three components, namely crash occurrence likelihood, crash consequences (*i.e.,* the resulted severity), and crash exposure. The mathematical formulation of risk here proposed expands the ones adopted by Fine (1971) and Barabino et al. (2021). Unlike the previous studies, the three components will be estimated and treated separately, by developing three separated prediction models.

As a result, to formally define the risk metric (which, again, must be computed with respect to the lowest level possible of the network partition), let:

- $E_{r,i}$ be the estimation of the exposure factor at the generic $p_{r,i}$ path.
- $H_{r,i}$ be the estimation of the road crash occurrence likelihood at the generic $p_{r,i}$ path.
- $S_{r,i}$ be the estimation of the probability of a severe outcome at the generic $p_{r,i}$ path.

The *road crash risk score* $R_{r,i}$ for the single $p_{r,i}$ minumum path is computed according to the following trivariate equation:

$$R_{r,i} = H_{r,i} \cdot E_{r,i} \cdot S_{r,i} \qquad \forall\, p_{r,i} \in I \tag{3.6}$$

As indicated, Eqn. 3.6 must be applied to the minimum paths first. However, if the risk evaluation is to be returned at a different scale (*e.g.,* the risk score at the county or regional level for a given road), then and aggregation of the single crash risk score $R_{r,i}$ obtained for the minimum paths must be performed.

For sake of clarity, the reader may refer back to Figure 12. Indeed, if the evaluation of the safety performance of the entire road A within the whole study area want to be returned, then the related overall crash risk evaluation must be returned, instead of a single risk score for each of the paths comprising the road A (*i.e.,* $p_{A,t1}$, $p_{A,t3}$, $p_{A,t5}$, and $p_{A,t6}$).

This crash risk score aggregation can be carried out according to two possible values, namely the (i) *total crash risk score* and the (ii) *average crash risk score* for the road.

The **total crash risk score** can be defined as the sum of the single crash risk scores of the minimum paths comprising the k-level territorial unit of a road. Physically, it represents the road crash risk that one can experience when driving a road r within the k territorial units, from the beginning till the end. It is computed as follows:

$$R_{r,k} = \sum_{i \in I} R_{r,i} = \sum_{i \in I} H_{r,i} \cdot E_{r,i} \cdot S_{r,i} \qquad \forall\, k \in K \tag{3.7}$$

The **average crash risk score** can be defined as the average of the single crash risk scores related to the minimum paths comprising the k-level territorial unit of a road. Physically, it represents the average crash risk that one can experience when driving any track of a road r within the k territorial. It is computed as follows:

$$\hat{R}_{r,k} = \frac{1}{|I|} \sum_{i \in I} R_{r,i} = \frac{1}{|I|} \sum_{i \in I} H_{r,i} \cdot E_{r,i} \cdot S_{r,i} \qquad \forall\, k \in K \tag{3.8}$$

The average crash risk score is more intuitive and representative of the physical meaning of the aggregation of the single crash risk score of each minimum path of a entire road, thus “the average risk one may experience while driving a given road”. Therefore, in what follows, the average crash risk will be considered as prior over the total crash risk.

Mathematical formulation of the road crash risk components

Once the general formulation of the risk metric is set according to Eqn. 3.6, which is quite simple to compute, it is necessary to define how the three risk components should be estimated. In this research, three separated prediction econometric models will be applied for the estimation of $H_{r,i}$, $S_{r,i}$, and $E_{r,i}$.

As already discussed in chapter 2.3, according to the way the risk components are conceived, their estimation technique may vary. More precisely, while consequence and exposure have been treated according to a widely agreed definition[22], the likelihood of road crash occurrence may be more controversial to asses. Indeed, road crash likelihood (H) may be interpreted following the stricter statistical meaning of occurrence probability (P) (*i.e.,* the probability of a road crash to occur), or according to the wider sense of the frequency of the event (F) (*i.e.,* how many times crashes occur over a defined time-span).

In this research, the former definition of road crash occurrence is adopted, for two main reasons: first, it is believed that it is better to reflect the meaning of the related risk component and the risk definition itself (*i.e., the* probability to occur); second, regardless the number of potential road crashes over a specific road network sections, the foremost goal is to assess to what extent that site has a potential to generate even a single crash, owing to its *e.g.,* infrastructural, context characteristics. Indeed, the lower the probability of crash occurrence, the lower should be the potential number of crashes that can be registered.

However, to compare the results that can be obtained by considering the two different definitions of crash occurrence likelihood (*i.e.,* probability and frequency), both the cases will be modelled by employing different mathematical structures. In addition, a comparison will be made by also considering the exposure factor either included in or exclude from the frequency model (which, instead, is quite common in the literature). In this way, it will be possible to assess the proper impact of the exposure factor more carefully over the risk results.

Hence, starting from the general formulation of risk given by Eqn. 3.6, let:

- $E_{r,i}$ be the estimation of the exposure to road crashes related to the generic $p_{r,i}$ path.

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[22] Road crash severity can be intended as a surrogate measure of road crash conseuquences, thus the amount of damage or loss (in general, the expected road crash outcome) that can be generated by the road crash. Exposure is the measure of how much an object can be exposed to a defined risk or to a set of risk factors, which jointly interact and may lead to a crash (*i.e.,* the potential hazardous event)

- $S_{r,i}$ be the estimation of the number of consequences of a crash related to the generic $p_{r,i}$ path.
- $F(E)_{r,i}$ be the estimation of the frequency of crash occurrence related to the generic $p_{r,i}$ path, by including the exposure factor into the set of explanatory variables.
- $F_{r,i}$ be the estimation of the frequency of crash occurrence related to the generic $p_{r,i}$ path, by excluding the exposure factor from the set of explanatory variables.
- $P_{r,i}$ be the estimation of the probability of crash occurrence related to the generic $p_{r,i}$ path.

The three adjusted risk formulations can be obtained by substituting these risk components to the one of the general Eqn. 3.6 are the following :

R1) $$R_{r,i} = F(E)_{r,i} \cdot S_{r,i} \tag{3.9}$$

R2) $$R_{r,i} = F_{r,i} \cdot E_{r,i} \cdot S_{r,i} \tag{3.10}$$

R3) $$R_{r,i} = P_{r,i} \cdot E_{r,i} \cdot S_{r,i} \tag{3.11}$$

Figure 15 graphically represents the different formulation alternatives for the crash risk general formula of Eqn. 3.6, namely R1, R2, and R3 of Eqn. 3.9 – 3.11. Moreover, it shows the risk components are included in the three formulations, depending on the way they are conceived. In what follows, specifications about the three model structures is provided. Overall, in order to foster the transferability and applicability of the proposed framework, the most easy-to-develop and intuitive modelling specifications retrieved from the literature are chosen for this research.

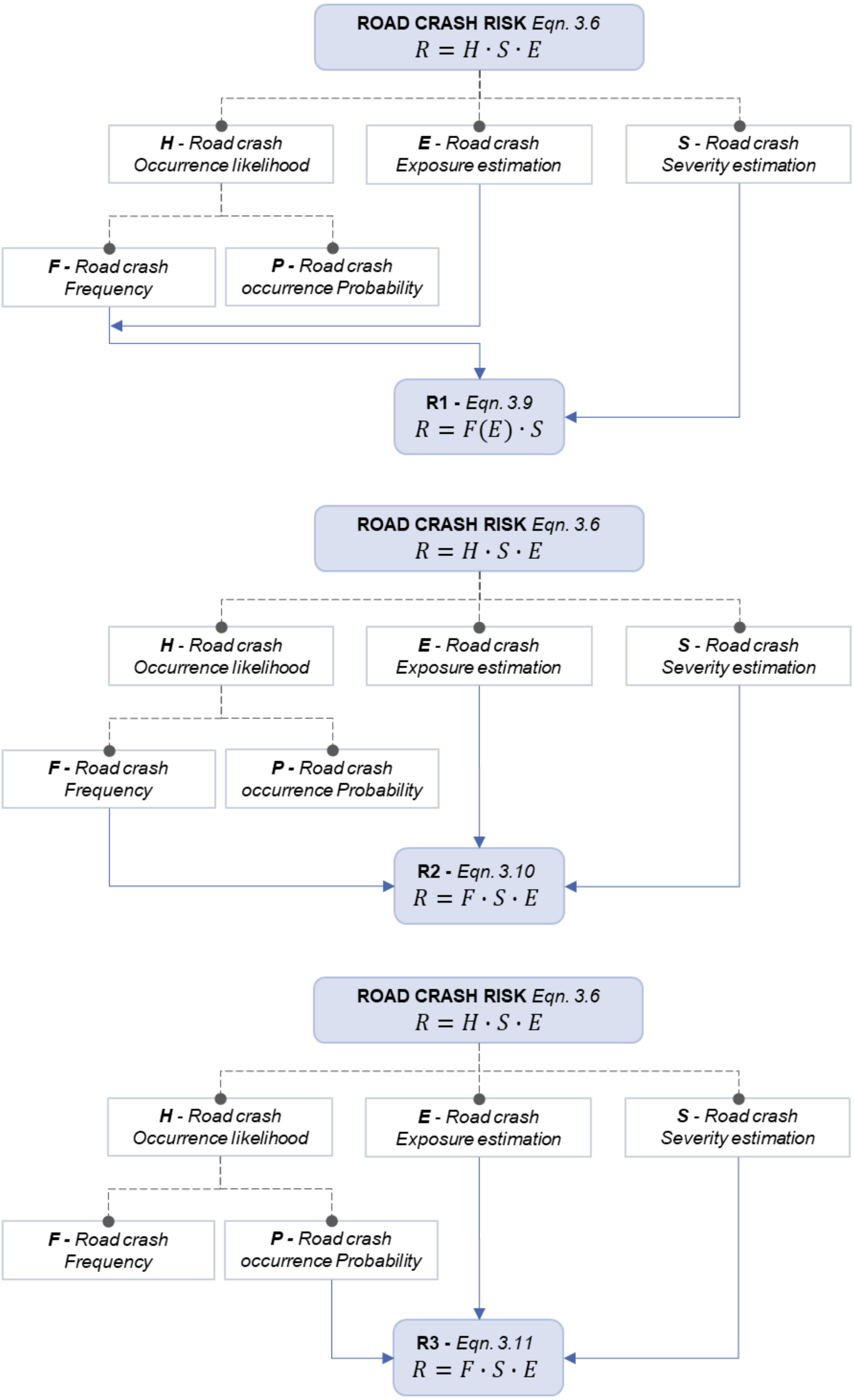

Figure 15 - Road crash risk alternative formulations: differences in road crash risk components assumptions.

Road crash occurrence as a frequency model: $F(E)_{r,i}$ and $F_{r,i}$

Road crash frequency may be defined as the expected total number of crashes in a predefined time interval (*e.g.*, a year) at a site. In this case, the response variable is represented by non-negative discrete values. According to the literature, the most widespread count modelling techniques to be used with such data are Negative Binomial (NB, or Poisson Gamma) models. Besides being the dominant modelling formulation in this field due to their capability to account for overdispersion (*i.e.,* when the variance greatly differs from the mean of the distribution, which is quite common when dealing with road crash data), they are easy to perform and to interpret. Therefore, a Generalised Linear Model (GLM) structure with a NB error distribution is used.

Let:

- J be the set of intermediate outcome factors and $j \in J$ a single factor.
- $x_{j,ri}$ be a generic explanatory variable associated with each intermediate outcome factor j, and n be the number of intermediate outcome factors.
- α, β, γ_j be the coefficients to be estimated in the model.

Then, the expected crash frequency on the $p_{r,i}$ minimum path can be computed as follows:

$$F(E)_{r,i} = \alpha E_{r,i}^{\beta} \cdot \exp\left(\sum_{j \in J} \gamma_j x_{j,ri}\right), \quad \forall\, p_{r,i} \in I \tag{3.12}$$

According to Hauer (2004), the specific modelling structure proposed in Eqn. (3.12) best account for the functional forms that link the several explanatory variables included. To do so, a mixed multiplicative and exponential additive form is chosen. More precisely, it was necessary to account for the non-linear relationship that exists between the road crash frequency and the exposure factor, which refers to a variable that when equal to zero, also the response variable must be null.

Then, if the logarithm function is used as the link function in the models, the equation can be further manipulated and expressed as follows:

$$ln\left(F(E)_{r,i}\right) = ln\left[\alpha E_{r,i}^{\beta} \cdot \exp\left(\sum\nolimits_{j \in J} \gamma_j x_{j,ri}\right)\right] = \ln(\alpha) + \ln\left(E_{r,i}^{\beta}\right) + \ln\left(\exp\left(\sum\nolimits_{j \in J} \gamma_j x_{j,ri}\right)\right) = \ln(\alpha) + \beta \ln\left(E_{r,i}\right) + \sum\nolimits_{j \in J} \gamma_j x_{j,ri}, \quad \forall\, p_{r,i} \in I \tag{3.13}$$

Therefore, depending on the output formulation of the model estimates, exponential or logarithm forms of the coefficients should be considered.

If the exposure factor is not included in the estimation of crash frequency (*i.e.,* to comply with the risk formulation represented by Eqn. 3.10), then Eqn. 3.12 must be modified. Specifically, the multiplicative part related to the exposure factor should be removed, as shown in Eqn. 3.14:

$$F_{r,i} = \alpha \cdot \exp\left(\sum_{j \in J} \gamma_j x_{j,ri}\right), \quad \forall\, p_{r,i} \in I \tag{3.14}$$

Before applying such model structure (*i.e.,* GLM with NB error distribution), it is necessary to check whether crash data are over-dispersed. To do so, the *dispersion parameter D* can be computed as the ratio between the variance and the mean of the distribution of crash data. Let:

- σ^2 be the variance of the distribution of crash count.
- μ be the mean of the distribution of crash count.

The dispersion parameter is computed as follows:

$$D = \frac{\sigma^2}{\mu} \tag{3.15}$$

If the ratio returns a value equal to 1, that means that the set of data is Poisson distributed; if the ratio returns a value higher than 1, that means that the set of data is over dispersed, thus follows a negative binomial distribution; if the ratio returns a value lower than 1, that means that the set of data is under dispersed, thus follows a binomial distribution.

The crash frequency estimation should be interpreted as a count model. Indeed, the aim is to return the expected number (*i.e.,* counts) of road crash. Hence, the input data should be structured in a manner that, for each road paths the number of crashes occurred is computed. To do so, data should be processed in an aggregated form. More precisely, individual road crashes need to merge according to common characteristics of the relative paths, thus same *e.g.,* context, infrastructure, land use, etc. characteristics (*i.e.,* common intermediate factors).

To check the Goodness of Fit (GoF) of the model, the ratio between the regression deviance and the degree of freedom (*i.e.,* the deviance ratio, *d.r.*) was considered in this study, along with the overall statistical significance of the model shown by the χ^2. In addition, the Root Mean Squared Error (RMSE) and the percentage ratio of predicted over observed crashes were computed to further assess the prediction capabilities of the model. More precisely, the RMSE is defined as the difference between the expected and predicted response values. The closer the RMSE to zero the better the result of the model.

More formally, let Y_i be the observed crash frequency for each path $p_{r,i}$ of the network. Then, the RMSE is computed as follows:

$$RMSE = \frac{1}{|I|}\sqrt{\sum_{i \in I}(Y_{r,i} - F_{r,i})^2} \tag{3.16}$$

Then, the magnitude and signs (*i.e.,* the model coefficients) of each intermediate factor and the related significance will be evaluated, to assess the impact of each variable over crash frequency.

Road crash occurrence as a probability model: $P_{r,t}$

Road crash occurrence probability refers to the possibility for a crash to occur, given specific condition. Hence, instead of considering the response variable in terms of counts (*i.e.,* as in the frequency model), crash occurrence can be interpreted as a binary response variable (*e.g.,* "1;0", "yes/no", "passed/fail") that assumes only two different values, depending on the occurrence or non-occurrence of the road crash. Therefore, owing to the binary nature of this type of response variable, a binomial logistic regression (logit) model structure can be adopted for this aim. Specifically, the logit model returns an estimate for the response variable which is defined over the (0;1) interval, so that it is suitable to compute probability of an event to occur, based on certain conditions. Specifically, such formulation models the logit-transformed probability according to a linear relationship with the independent variables (intermediate outcome factors).

More formally let:

- J be the set of intermediate outcome factors and $j \in J$ a single factor.
- $x_{j,ri}$ be a generic explanatory variable associated with each intermediate outcome factor j, and n be the number of intermediate outcome factors.
- θ_0, θ_j be the set of coefficients to be estimated in the model, with respect to the each $x_{j,ri}$ variable.

Then, the crash occurrence probability for a generic minimum path can be computed as:

$$P(x_{j,ri}) = \frac{\exp\left(\theta_0 + \sum_{j \in J} \theta_j x_{j,ri}\right)}{1 + \exp\left(\theta_0 + \sum_{j \in J} \theta_j x_{j,ri}\right)}, \quad \forall\, p_{r,i} \in I \tag{3.17}$$

Then, by manipulating Eqn. 3.17, the logistic function (logit) can be obtained, which expresses the linear combination of the dependent variable with the independent variables and the related coefficients. The model is estimated according to the maximum likelihood procedure:

$$logit\left(P_{r,i}\right) = \ln(odds) = ln\left(P_{r,i}\right) - ln\left(1 - P_{r,i}\right) = ln\left(\frac{P_{r,i}}{1-P_{r,i}}\right) = \theta_0 + \theta_1 x_{1,ri} + \ldots + \theta_n x_{n,ri}, \quad \forall\, p_{r,i} \in I \tag{3.18}$$

If the exponential formulation of Eqn. 3.17 is considered, the probability of the dependent variable y to register a crash occurrence can be interpreted by mean of the Odds Ratio (OR), which represents the odds of a crash to occur, given specific conditions, compared to the odds of the crash to occur, without those conditions. The OR is computed according to the following formula:

$$OR(x_j) = \frac{\frac{P_{r,i}|x_j}{(1-P_{r,i}|x_j)}}{\frac{P_{r,i}|(x+1)_j}{(1-P_{r,i}|(x+1)_j)}} = \frac{\exp\,(\theta_0+\theta_j x_{j,ri})}{\exp\,(\theta_0+\theta_j (x+1)_{j,ri})} = \exp\,(\theta_j) \tag{3.19}$$

The OR can assume different values:

- $OR > 1$ indicates that the probability of the crash to occur increases, with the presence of the specific condition.
- $OR = 1$ indicates that the specific condition does not affect the probability of the crash to occur or not to occur.
- $OR < 1$ indicates that the probability of the crash to occur decreases, with the presence of the specific condition.

Also, the sign of each parameter is to be considered when interpreting the model results. For instance, a negative sign in the parameter estimate implies a reduction in the probability for the crash to occur for each increase in the considered intermediate outcome factor, and *vice versa*.

Unlike the crash frequency model, to estimate occurrence probability a binomial logit is applied and, therefore, disaggregated data (i.e., thus observation per observation) are required to model such entity. Specifically, the original dataset should be manipulated so that the dependent variable (*i.e.,* the one to be modelled) is recorded as a binary response variable, *e.g.,* “occurred; not-occurred”. . In doing so, given the set of independent variables considered and the related possible responses (*e.g.,* the variable *Day type* can assume responses equal to *Weekday* or *Festive,* etc.), all their possible combination should be recorded to clearly return which one lead to – at least – one road crash and which does not. In other words, one needs to know the combination of circumstances when crashes occurred and when they did not. To do so, two are the viable solutions. First, given a specific study area, the whole road network should be known as well as all the related characteristics (*e.g.,* infrastructural, design, operational, context, land use, environment, etc.), so that the network can be completely described. Then, each road crash is related to a location on the road network, where it happened. As a result, a database can be retrieved, where each road segment of the network is listed with its own characteristics and the related number of road crashes (and crash type, and severity, etc.) there occurred. Roads – and the related infrastructure, environmental, operational etc. circumstances – which did not register crashes directly appear. However, if such possibility cannot be pursued for some reasons (*e.g.,* the road network is too broad to know all the required characteristics or there is no information available for some data), then it is not possible to fully describe the whole network in a way that all the single roads are listed and described. Therefore, an alternative solution should be found.

The solution here conceived was to expand and integrate the road crash database (for which all the infrastructural/operational/environmental/context etc. information is known and reported), by identifying all those missing circumstances when/where a crash did not occur. To do so, starting from the original road crash database, a simple pivot table was built[23], which returned for each row a possible combination of variables – and related values – for which road crashes occurred. Indeed, being the original dataset related to "occurred crash" only, all the combinations obtained were associated to a response equal to "occurred". For sake of clarity, an example is reported in Table 9. Let the independent variables be Var 1 = [1,2,3]; Var 2 = [black, white]; Var 3 = [a, b, c]; Var 4 = [yes, no]. The original database can be manipulated to return all those combinations of circumstances that lead to a crash.

Table 9 - Example of manipulated dataset to model the binary response variable for crash occurrence probability

Obs.	**Var 1**	**Var 2**	**Var 3**	**Var 4**	**Response**
1	1	Black	A	Yes	Occurred
2	1	White	B	No	Occurred
3	1	Black	C	Yes	Occurred
4	2	White	A	No	Occurred
5	2	Black	B	Yes	Occurred
6	2	White	C	No	Occurred

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[23] The same procedure was used to implement the crash frequency model, where the total absolute number of road crashes on each segment was required to model the frequency.

7	3	Black	A	Yes	Occurred
8	3	White	B	No	Occurred
9	3	Black	C	Yes	Occurred
10	1	White	A	No	Occurred

However, looking thoroughly to all the possible combinations of the independent variables' response (in this case, 36 combinations were expected), some are missing. In other words, those missing combinations are not associated with a crash having occurred. Therefore, once the missing combinations are identified, they can be added manually to the database and associated to a response equal to "not occurred", as reported in Table 10 and Table 11.

Table 10 - Example of missing combinations of independent variables and related response

Obs.	**Var 1**	**Var 2**	**Var 3**	**Var 4**	**Response**
11	1	Black	A	No	Not Occurred
12	1	Black	B	Yes	Not Occurred
13	1	Black	C	No	Not Occurred
…	…	…	…	…	Not Occurred

Table 11 - Expanded database to model road crash occurrence probability

Combos	**Var 1**	**Var 2**	**Var 3**	**Var 4**	**Response**
1	1	Black	A	Yes	Occurred
11	1	Black	A	No	Not Occurred
2	1	White	B	No	Occurred
12	1	Black	B	Yes	Not Occurred
3	1	Black	C	Yes	Occurred
13	1	Black	C	No	Not Occurred
4	2	White	A	No	Occurred
5	2	Black	B	Yes	Occurred
6	2	White	C	No	Occurred
7	3	Black	A	Yes	Occurred
8	3	White	B	No	Occurred
9	3	Black	C	Yes	Occurred
10	1	White	A	No	Occurred
…	…	…	…	…	Not Occurred

To check the Goodness of Fit (GoF) of the occurrence probability model, the ratio between the regression deviance and the degree of freedom (*i.e.,* the deviance ratio, *d.r.*) was considered in this study, along with the overall statistical significance of the model shown by the χ^2. In addition, the percentage of rights was also considered, which represents – in terms of percentage – the number of consistent responses between the observed and predicted values. Then, the signs of the coefficients, the significance of each explanatory variable, and the OR will be evaluated. In addition, also the percentage of rights will be considered.

Road crash severity model ($S_{r,t}$)

In this research, road crash severity is defined as the highest degree of seriousness experienced among all the people involved in a crash. More precisely, crash severity should be evaluated according to an ordered level, from the most severe outcome (*i.e.,* fatal crashes), to the lightest one (*e.g.,* no injury). However, according to the definition of road crash in force in Italy and due to the related data collection process, crash severity is collected by just assuming a fatal[24] or non-fatal result. Therefore, as happened for crash occurrence probability, also the crash severity can be modelled as a binary variable that assumes 0 if the crash results in injury-only and 1 in case of fatal crash. As a result, a binomial logistic regression can be adopted as well to model crash severity, which follows the same model structure explained for crash occurrence probability.
Therefore, by reproducing the same formulation of Eqn. 3.17, let:

- J be the set of intermediate outcome factors and $j \in J$ a single factor.
- $y_{j,ri}$ be a generic explanatory variable associated with each intermediate outcome factor j, and n be the number of intermediate outcome factors.
- φ_0, φ_n be the set of coefficients to be estimated in the model, with respect to the each $x_{n,ri}$ variable.
- $S_{r,i}$ be the fatal crash probability for a generic minimum path.

$$S(x_{j,ri}) = \frac{\exp\left(\varphi_0 + \sum_{j \in J} \varphi_j y_{j,ri}\right)}{1 + \exp\left(\varphi_0 + \sum_{j \in J} \varphi_j y_{j,ri}\right)}, \quad \forall\, p_{r,i} \in I \qquad (3.20)$$

Alike crash occurrence probability model, the input data should be returned in a disaggregated way, thus observation per observation. In this case, no artificial manipulation of the crash database is required, as the binary nature of the response variable is simply returned by recoding the crash outcome variables as “fatal; non-fatal (injury-only)” crash.

To check the Goodness of Fit (GoF) of the severity model, the ratio between the regression deviance and the degree of freedom (*i.e.,* the deviance ratio, *d.r.*) was considered in this study, along with the

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[24] A road crash in which at least one person got killed at the crash location or by 30 days from the crash date.

overall statistical significance of the model shown by the χ^2. Again, also the percentage of rights was considered to assess the model performances. Then, the signs of the coefficients, the significance of each explanatory variable, and the OR will be evaluated.

Road crash exposure factor model: $E_{r,t}$

Among the many considered in the literature, the most appropriate exposure factor to be considered for the evaluation of the road crash risk can be the traffic volume in terms of AADT. Unless road traffic consists of several categories of road users (*e.g.,* passenger cars, heavy or commercial vehicles, pedestrians, cyclists, etc.), to comply with the scale of the method, a general value of traffic volume is considered, thus a passenger-car equivalent traffic volume.

According to the previous literature, based on road infrastructure and context variables, AADT can be computed as a linear combination of intermediate outcome factors, thus through a linear regression of them. Let:

- J be the set of intermediate outcome factors and $j \in J$ a single factor.
- $z_{j,ri}$ be a generic explanatory variable associated with each intermediate outcome factor j, and m be the number of intermediate outcome factors.
- ρ_0, ρ_j be the estimate coefficients of the linear regression.

The exposure $E_{r,i}$ to road crashes for each road path $p_{r,i}$ can be computed as follows:

$$E_{r,i} = \rho_0 + \sum_{j \in J} \rho_j z_{j,ri}, \quad \forall j = 1, \dots, n \tag{3.21}$$

To model the exposure factor, each minimum path is considered as a single observation, with the related characteristics. The ordinary least squares method was used to estimate the best possible coefficients of the multiple regression model.

To check the Goodness of Fit (GoF) of the severity model, the R^2 and R^2_{adj}[25] were considered in this study, along with the overall statistical significance of the model (*p-value of the F-ratio.*). In addition, some checks on the residuals were also performed. Then, the signs of the coefficients, the significance of each explanatory variable, and the OR will be evaluated.

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[25] The Adjuster R-squared R^2_{adj} is used when estimating the GoF of a MLR model with multiple predictors.

To summarise, starting from Eqn. 3.9 – Eqn. 3.11 and replacing the three risk's components with their related estimation models expressed in Eqn. 3.12, Eqn. 3.14, Eqn. 3.17, Eqn. 3.20, and Eqn. 3.21, respectively, the following severe crash risk prediction models are returned:

$$\text{R1} \quad R_{r,i} = F(E)_{r,i} \cdot S_{r,i} = \alpha E_{r,i}^{\beta} \cdot \exp\left(\sum_{j\in J} \gamma_j x_{j,ri}\right) \cdot \left(\frac{\exp\left(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri}\right)}{1 + \exp\left(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri}\right)}\right) \tag{3.22}$$

$$\text{R2} \quad R_{r,t} = F_{r,t} \cdot E_{r,t} \cdot S_{r,t} = \alpha \cdot \exp\left(\sum_{j\in J} \gamma_j x_{j,ri}\right)\left(\rho_0 + \sum_{j\in J} \rho_j z_{j,ri}\right) \cdot \left(\frac{\exp\left(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri}\right)}{1 + \exp\left(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri}\right)}\right) \tag{3.23}$$

$$\text{R3} \quad R_{r,t} = P_{r,t} \cdot E_{r,t} \cdot S_{r,t} =\cdot \left(\frac{\exp\left(\theta_0 + \sum_{j\in J} \theta_j x_{j,ri}\right)}{1 + \exp\left(\theta_0 + \sum_{j\in J} \theta_j x_{j,ri}\right)}\right) \cdot \left(\rho_0 + \sum_{j\in J} \rho_j z_{j,ri}\right) \cdot \left(\frac{\exp\left(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri}\right)}{1 + \exp\left(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri}\right)}\right) \tag{3.24}$$

Eqn. 3.24 represents the mathematical formalization of the fatal road crash risk estimation, which is adopted by this research as the more appropriate risk formulation, according widely agreed definition of risk. Hence, Eqn. 3.24 will be used in the framework as the final evaluation metric for the network-wide safety assessment.

One may argue whether the proposed three-stages road crash risk prediction model is preferable compared to the models explored in the literature, as it requires the specification of three models instead of *e.g.,* one or two. However, it differentiates itself from the other ones for several reasons. First, simultaneity-based approach such as multivariate or joint models do not return a measure of crash risk but rather the frequency of crashes at different level of severity, which is not the goal of this research. Indeed, when estimating the crash occurrence likelihood component, none of the existing models used a probability model. Second, as previously mentioned in chapter 2.7, the opportunity to have separated models for each crash risk component (exposure measure included) helps in better control the effect of each component over the overall risk result and in implementing more targeted measures. Third, from a practical point of view, multivariate and joint model are characterised by a more complex structure which requires higher computation burden. Conversely, the model structures selected for the crash risk prediction model (*i.e.,* binomial logit and multiple linear regression, which will be explained further in what follows) are recognized to be quite simple and easy to implement and interpret, and among the most widely used and known.

C. Road network ranking

Once the values of the road crash risk are computed for all the paths, they must be ranked to identify the *High Crash Risk Site*. To the best of our knowledge, there are many methods to develop a ranking scale, and in this study a five-level scale is adopted, based on the road crash risk values distribution.

First, once the risk scores have been computed for each path, they are ordered from the lowest to the highest value. Then, thresholds are set based on the main indicators of the distribution of the values, namely the: the minimum and maximum values of the distribution; the lower, the middle and the upper quartiles (*i.e.,* Q1 = 25th percentile, Q2= 50th percentile and Q3 = 75th percentile, respectively); and the interquartile range (IQR) of the distribution, which is defined as the difference between the values of the third and first quartiles. The choice of including the IRQ was made to enable the identification of the most critical paths. Usually, the IQR is employed to identify and remove anomalous values (*i.e.,* outliers) from distribution, as they may affect the overall outcome. To do so, the first and the third quartile are extended by a quantity equal to 1,5*IQR respectively, so that a lower and upper threshold can be defined, beyond which the values of a distribution are considered as outliers. Conversely, in this research, the IQR is used to better detail the ranking scale, and emphasize those ‘anomalous’ values, rather than remove them from the distribution. More precisely, the extension of the third quartile above by 1,5*IQR defines a further threshold, which enables to enlarge the ranking scale to a five-level scale and identify the highest values of the distribution, which – according to a practical perspective - are those paths recording the highest road crash risk score. Therefore, a new level is defined, with a lower limit equal to (Q3 + 1,5 IQR) and the upper limit equal to the maximum value of the distribution. As for the extension of the first quartile by 1,5*IQR below Q1, it does not properly contribute to the definition of a new level of the ranking scale. Indeed, given that $R_{r,i}$ is a non-negative quantity, (Q1-1,5*IQR) must be higher or at least equal to zero.

This risk scale makes it possible to classify all paths according to their risk score (*e.g.,* unlike stetting a fixed threshold) and help to identify paths that require the greatest safety attention. However, although this scale depends on how to define acceptable ranges, one has not to obey the previous indications to use the method, because these ranges can be derived in some other manners.

Table 12 shows how the five-level ranking scale is set and reports the lower and upper limits for each level, which define the range values. The ranking scale should be read as an *unsafety scale*, thus the lower the road crash risk score, the safer the path. Therefore, when defining strategies to improve road safety, roads that get a road crash risk belonging to the 5th level should be considered as a priority for road safety interventions.

Table 12 – Definition of the ranking scale for the crash cost rate distribution.

Level	Ranges values	
	Lower limit	Higher limit
1	(Q1-1,5 IQR)	Q1
2	Q1	Q2
3	Q2	Q3
4	Q3	(Q3 + 1,5 IQR)
5	(Q3 + 1,5 IQR)	MAX

The expected outcome of the road crash risk ranking the provision of road crash risk maps, where each path is represented with a colour corresponding the related safety ranking level. Maps can be produced in a GIS environment, following the path construction rationale, and uploaded on a territorial information system to be consulted by each administrative and road authority.

As mentioned above, the flexibility of the road network partition here proposed (*i.e.,* path of each road within a specific territorial unit) enables to produce road network screening at different detail. More precisely, depending on which level of the hierarchical administrative boundaries are considered, the overall computation procedure can adapt itself with respect to scale chosen.

As the final step of the whole procedure, some recommendations about potential measures and interventions to mitigate crash risk can be provided. More precisely, prevention measures aim at reducing the number of crashes occurred, thus they act on the *H* risk components; protection measures aim at reducing the amount of damage that can be experienced by the people involved, thus they act on the *S* risk component. In addition, both prevention and protection measures can also positively affect the other risk components, exposure included. As a result, measures that can impact on all the three risk components to overall reduce the risk score are to be intended as those with the highest priority.

4. Real case experiment

4.1. Case study description

To test the proposed risk-based network-wide road safety assessment methodology, the main road network of the Province of Brescia has been assumed as case study.

The Province of Brescia represents the largest province of the Lombardy Region (northern Italy), covering a surface of more than 4,500 km² at East. It comprises 205 municipalities and has a population of about 1.250 million people (the second in the Region and the fifth in Italy, per inhabitants). In addition, it covers a strategic position at both the national and European level. It is well connected to three of the main TEN-T corridors and it is directly crossed by the Mediterranean corridor, thus the one with the greatest road traffic volumes. As a result, Brescia represents one of the most important industrial, commercial, and residential areas in Italy, so that it originates/attracts major traffic flows daily (Regione Lombardia, 2016). Moreover, over the latest years, also touristic flow grew, especially in the areas of the well-known Garda and Iseo Lakes, Franciacorta, and the Mountain ski places, besides the city of Brescia itself.

The road network of the Province of Brescia comprises 340+ km of highways, 1.700+ km of provincial roads (*i.e.,* managed by the Province of Brescia Road Department), and about 170 km of state roads (*i.e.,* managed by ANAS), besides 200+ km of local roads (*i.e.,* managed directly by the Municipalities in their jurisdiction) (Faccin et al., 2011). However, its county road network is undersized if compared to the traffic volumes and the territorial extension, so that the accessibility to the whole province is critical and traffic congestions frequently occur on these major roads (Faccin et al., 2011). The Province of Brescia is characterised by a variety of landscapes and morphological areas. The southern area consists mainly of plain ground, being part of the “Pianura Padana”. Moving to north rolling terrain increases until reaching the Alpes.

For what concerns road safety data, a relevant number of road crashes occurred on the province’s road network over the last years, with an average of 3.000+ crashes, 4.000+ injuries and around 80 deaths each year (Polis Lombardia, 2020). Most of road crashes occurred on urban roads (almost 74%), however, the greatest share of fatal crashes occurs on the main road network, being this mostly non-urban and, therefore, characterised by high speeds.

As a result, given the geographical position of the Province, this experiment provides an emblematic case study for road network screening, as it is representatives of different road infrastructure environments (*i.e.,* mountain, rolling and flat terrain), and therefore of many similar areas, especially in northern Italy. The Province of Brescia could be taken as a reference for other similar European and Italian area, apart from being very large in terms of implementation scale and representativeness, this experiment provides a good case study of road network screening from which lessons can be learnt.

As required by the RISM European Directive, besides highways, this study considered primary road, thus the ones belonging to the highest functional class below Highways, according to the classification in force in Italy (MIT, 2001). Moreover, by receiving the further suggestions of the Directive, also other roads were included in the analysis, such as the main State roads, and Provincial roads, which are classified at least as F1 (non-urban high-traffic volume roads).

A total of 482 road segments and a total extent of almost 2.200+ km of road network. A total of 6.123 road crashes occurred on the main road network of the Province of Brescia over the five-year period 2014-2018 were included in the study.

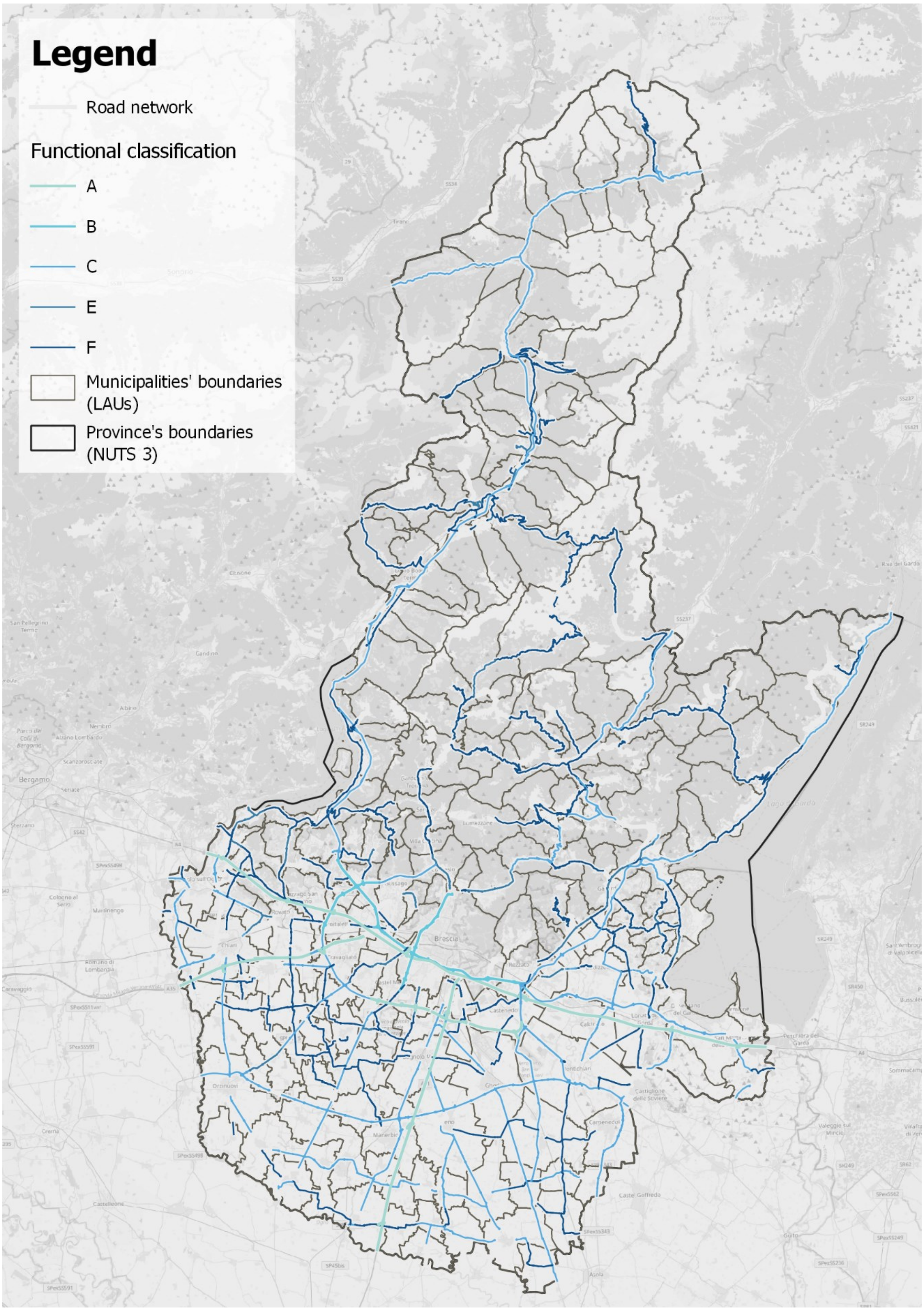

Figure 16 - Main Road network of the Province of Brescia considered in the study

4.2. Data collection and preparation

According to Part I of the framework, once the main road network of the Province of Brescia was set as the case study area, data collection was performed. For this research, data were gathered from three main sources.

Basemap data were retrieved from the Download Geographic Data webpage of the *Geoportale Regione Lomabrdia*[26], which allows to access open-source and information and databases either in raster format or in vector format. More precisely, vector files related to the administrative boundaries of the several NUTS, were gathered from the *Topographic Database* (DBT).
Context information were collected from different sources. Geographical and morphological information (*e.g.,* terrain type) were retrieved by overlapping the *Google Terrain* and *Open Street Maps* standard background map. Vector data for the land use information were, again, downloaded from the Download Geographic Data webpage of the *Geoportale Regione Lomabrdia*, and specifically the DUSAF 6.0 database. Socio-economic (*e.g.,* population size) data were retrieved from the ISTAT database[27].

The road network basemap was retrieved from the Download Geographic Data webpage of the *Geoportale Regione Lomabrdia*, while the functional classification of the road network was directly provided by the Road and Transport Office of Provincia di Brescia Authority. Other information related to road infrastructure design (*e.g.,* number of lanes) were retrieved by other available digital cartography or by overlapping *Google Satellite* standard background map.
Traffic data were provided by the Regional Directorate General (DG) for Road Safety. More precisely, over the year 2016-2018 the Lombardy Region launched a major project aimed at the development of the regional O/D matrix and the estimation of the overall traffic volume of the whole regional road network. The datasets were all provided in a vector-format.

Road crash data were provided by Polis-Lombardia[28], the Regional Institute for Policy Support. Data were provided in a spreadsheet format and reported all the main variables collected by the ISTAT road crashes template, such as crash location (*e.g.,* province and municipality NUTS codes, route name or code), road type, location attributes (*e.g.,* segment and/or intersection type, pavement type),

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[26] Database accessible at the following link: https://www.geoportale.regione.lombardia.it/download-dati
[27] Database accessible at the following link: http://dati.istat.it/Index.aspx
[28] Polis-Lombardia webpage available at: https://www.polis.lombardia.it/wps/portal/site/polis

number of people involved. As for crashes location, almost 33% of the road crash observations lacked spatial coordinates or reported them inaccurately. This aspect is of paramount attention. Indeed, if the analysis had relied on spatial coordinates, a large quota of road crashes would not have been included in the assessment, hence greatly affecting the overall results.

Before proceeding with the following steps, some data cleaning and mis-recording correction were performed, both in the crash and traffic data, to make information consistent in the content and homogeneous in the format among the several data sources (*e.g.*, fixed road names or code, which were differently recorded in the datasets and no connection was possible). This task was crucial for the framework to run properly. Moreover, by simply manipulating data and computing some functions, further information was retrieved from the available database such as seasons and time of the day (by aggregating road crash time information), road network and population density (by dividing respectively the total length of road network and number of inhabitants for each municipality by the relative surface). For modelling purposes, all variables were coded as binary (*e.g.,* urban/non-urban, day/night) or in some cases categorical (*i.e.,* more than two categories within the same variable). In this preliminary stage, data were managed and processed by mean of spreadsheet software (*i.e.,* Microsoft Excel) and a geographical information system (GIS) software (*i.e.,* QGis).

Then, according to Part II of the framework, all the data were associated with the three main risk factor categories, by simply adding an identification code into their name-field. For instance, Table 13 reports the descriptive statistics related to the road crash dataset, which is organized into the several risk factors, according to the ISO 39001 guidance.

Table 13 – Road crash database descriptive statistics

Risk factor/ Category	**Independent variable**	**Description**	**% Value**
Final safety outcome			
	Crash outcome	Fatal	3,61
		Injury only	*96,39*
Intermediate safety outcome factors			
Road Crash dynamic	Crash Type	Hit with obstacle	5,54
		Head-on or sideswipe	41,04
		Single vehicle collision	17,26
		Pedestrian collision	*3,74*
		Rear-end crash	32,42
	Violation	Violation by user A	68,89
		No violation by user A	*31,11*
		Violation by user B	52,83

		No violation by user B	*47,17*
Users involved	Pedestrian	Pedestrian involved	4,00
	Cyclist	Cyclist involved	6,21
	Heavy vehicle	Heavy vehicle involved	23,80
	Powered Two-Wheeler	PTW involved	19,29
	Car	*Car involved*	*87,05*
Road infrastructure design	Road type	*Urban*	*33,24*
		Non-urban	66,76
	Road class	*Primary*	*25,09*
		Non primary	74,91
	N. of lanes per direction	One lane	74,54
		Two or three lanes	*25,46*
	Median presence	*Divided carriageway*	*20,46*
		Undivided carriageway	79,54
	Site type	Segment	65,80
		Intersection	*34,20*
	Pavement condition	Paved	99,61
		Ruined	*0,39*
	Road signs type	Horizontal	7,59
		Vertical	3,97
		Horizontal and Vertical	86,13
		Absent	*2,30*
Operational features	% Heavy Good Vehicle	< 15%	32,03
		15% - 30%	34,59
		>30%	*33,38*
Environmental factors	Type of terrain	Flat	70,98
		Rolling	24,30
		Mountain	*4,72*
	Land Use	Built up areas	31,36
		Rural areas	51,66
		Forests and woods	13,70
		Wet areas	*3,28*
Context conditions	Season	*Spring - Summer*	*45,06*
		Winter-Fall	54,94
	Day type	Weekday	67,79
		Festive	*32,21*
	Daytime	Day	68,58
		Night	*31,42*
	Surface conditions	Dry	80,53
		Not dry	*19,47*

Entries in italics are the reference category

4.3. Risk-based network-wide screening implementation

Once data were collected and prepared, Part III of the framework was implemented following the steps A, B, and C.

4.3.1. Network segmentation and path definition

First, according to step A.1, the segmentation of the road network was performed, by applying the definition of path. More precisely, the road names and territorial units' codes (NUTs and LAUs) were considered as the reference road crash location data, common to all the databases. Then, according to Eqn. 3.1, paths were built by aggregating the s-segments of each road of the road network with respect to the two territorial level considered, thus the municipality level and the whole Province level, being path at the municipality level the minimum paths. A total of 482 minimum paths was obtained for the main road network of the Province of Brescia.

Also, a univocal identification code was created for each path, to be used as the *primary key* for the relational association among all the information from the different datasets. The **path code** was built by simply merging the variable "Road code" and "NUTS code" in each dataset.
Although not exhaustive, Table 14 provides an example of the paths' definition in the specific case study. The A04 Highway (named after "Turin-Venice" Highway) was reported here as an example. Two territorial levels were considered, with their own related codification. More precisely, according to ISTAT, Province's territorial (and administrative) units are identified by a 2-digit code (*e.g.,* "17"), while Municipalities' units by a 5-digit code by ISTAT (*e.g.,* "17029", the first 2-digit refer to the province and the three latter to the specific municipality). Then, according to the definition of path, each segment *s* of the A04 Highway (according to a link-node structure) was aggregated first based on the municipality level, to define the whole set of minimum paths of the A04 road related to each municipality unit. Then, they were further aggregated to return the path of the A04 road at the province level, which is a single path in this case (*i.e.,* the entire A04 road within the Province boundaries).

Table 14 - Path definition for the A04 Highway for the two jurisdiction levels (i.e., Province and Municipalitites)

Provincial path	**Municipality path**	***s*-segment**
A04_17	A04_17029	41681
		43981
		…
	A04_17127	40249
		41641
		…
	A04_17…	…

The dots ("…") stand for the other segments (and path codes) which belong to the same path but are not reported here due to space limitation.

For sake of clarity, in the case study area, the A04 highway is composed by a set of segments (*e.g.,* "41681", "43981", "40249", etc. To define the path of the A04 Highway into the municipality coded as *17029*, such segments were aggregated so that all the s-segments belonging to the limits of the 17029 municipality were included in the A04_17029 path. Likewise, to define the path of the A04 Highway into the Province of Brescia coded as *17*, the single minimum path just found were aggregated so that all the minimum paths (and the related s-segments) belonging to the limits of the 17 Province were included in the A04_17 path.

Next, according to step A.2, by mean of the path code, which served as the primary key for structuring the relational association among all the data sources, each minimum path was also associated with all the other attributes from the different datasets retrieved in Part I, such as *e.g.,* traffic volumes and road infrastructure characteristics, land use, etc.

For what concerns path lengths and traffic volumes, Eqn. 3.4 and Eqn. 3.5 were applied respectively. For what concerns land use characteristics of the surrounding areas to each path of the road network, a buffer was created to define the area into which the land use characteristics were to be analysed. The buffer width was set based on the road class, following the procedure suggested in the previous literature (*e.g.,* Zhao and Chung, 2001; Sfyridis and Agnolucci, 2020; Pulugurtha and Mathew, 2021) and according to the road functional classification provided by MIT (2001). Table 15 provides the buffers' width selected for each road class.

Table 15 - Buffer area to compute land use characteristics of the road network surroundings

Road hierarchy	Road class	Buffer width (radius) [m]
Primary	A	2.000 (1.000) m
	B	2.000 (1.000) m
	D	1.000 (500) m
Non-primary	C	1.500 (750) m
	E	500 (250) m
	F	500 (250) m

Hence, the function "buffer" in QGis was used to automatically create a layer of those buffers. Next, such layer was overlapped to the one related to the land use (DUSAF 6). By mean of the "*join attribute by location (summary)*" function, the most relevant land use category within each buffer, in terms of surface extension, was computed and associated to the related road path. Please note that the DUSAF 6.0 database provides land use information structured onto five levels, from a more general (Level 1) to a detailed classification (Level 5) of land use categories. To be consistent with the scale of the analysis, in this study just Level 1 and some Level 2 of the DUSAF classification were considered only. Table 16 shows the structure of the DUSAF 6.0 information.

Table 16 - Three levels categories for the land use analysis (Source: DUSAF 6.0, Regione Lombardia)

DUSAF LEVEL 1		DUSAF LEVEL 2	
1	Build-up areas	11	Residential areas
		12	Production facilities, large plants and communication networks
		13	Mining areas, landfills, construction sites, artifact and abandoned land
		14	Non-agricultural green areas
2	Agricultural areas	21	Arable land - crops
		22	Permanent crops
		23	Permanent meadows
3	Forest and woods	31	Wooded areas
		32	Shrubby vegetation areas
		33	Sparse and/or absent vegetation areas
4	Wetlands	41	Inland wetlands
5	Lakes and waterways	51	Inland waterways

For what concerns socio-demographic characteristics of each municipality of the Province of Brescia, a simple Pivot table was performed among the road network database and the municipality database, by relying on the path-code (alternatively, a join function in GIS-environment could have been used). Specifically, population size, municipality and urban areas, total and network length density were included as further information.

Table 17 provides a descriptive statistic of the minimum paths for the road network of the Province of Brescia, after being enriched with all the features form the several databases. Alike previous studies (*e.g.,* Hosseinpour et al., 2014), paths showed a length ranging from 1 to 30 km, but most of them (97%) with a length up to 7km.

Table 17 - Road network segments descriptive statistics

Category	Independent variable	Description	Frequency [%]
Road Infrastructure	Road type	*Urban*	*18,05*
		Non-urban	81,95
	Road class	*Primary*	*9,80*
		A	*7,14*
		B	*2,66*
		Non primary	90,20
		C	36,54
		E	5,48
		F	48,17
	N. of lanes per direction	One lane	90,37
		Two or three lanes	*9,63*
Environmental factors	Type of terrain	Flat	66,94
		Rolling	18,60
		Mountain	*14,45*
	Land Use	Built up areas	18,11
		Agricultural zone	60,63
		Forests and woods	19,93
		Wet areas	*1,33*

Category	Independent variable	U.o.M	Mean	Min	Max	Std
Road segments	Segment length	[km]	3,67	0,10	33,33	3,61
Operational factors	Average Annual Daily Traffic (AADT)	[veic]	3.642.209	24.338	25.860.250	3.836.075
	Average km travelled	[veic*km]	17.076.954	32.273	507.587.490	44.131.945
	% of Heavy Vehicles	[%]	23	1	100	17
	< 15%	[%]	42,19			
	15 – 30 %	[%]	32,06			
	> 30 %	[%]	25,75			
Demographic context	Urban area density	[km2/km2]	0,14	0,01	0,60	0,11
	Population density	[ab/km2]	404	4,86	2.154	327,95
Road Network provision	Network density	[km/km2]	4,10	0,16	11,84	2,53
Road crashes		[n crash]	3	1	38	3

U.o.M = Unit of Measure

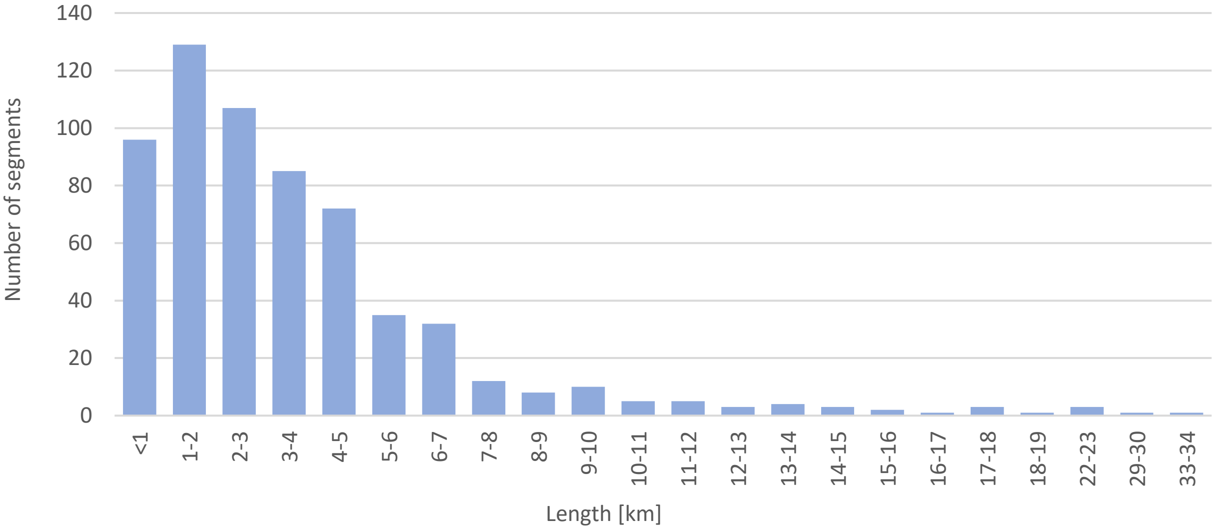

Figure 17 - Distribution of the minimum paths by length

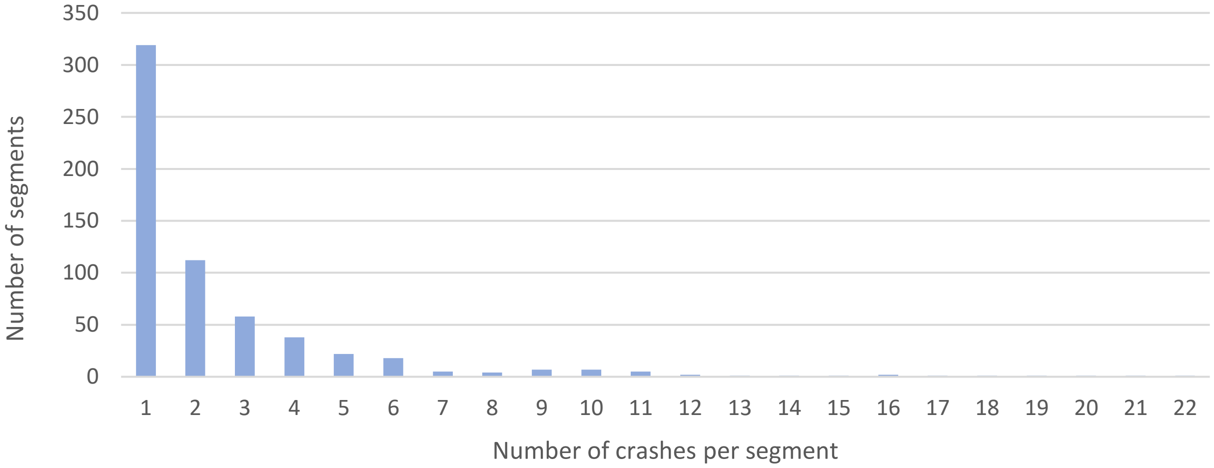

Figure 18 - Distribution of crashes over the road network segments

4.3.2. Computing road crash risk and its components

According to sub-step B of Part III, the risk-based network-wide screening was performed. Assumed Eqn. 3.6 as the general risk formulation structure, evaluation metrics were computed for all the three specific formulation alternatives according to Eqn. 3.22, Eqn. 3.23, and Eqn. 3.24 (*i.e.,* R1, R2, and R3). To do so, first models were developed to estimate all the risk components, by implementing Eqn. 3.12, Eqn. 3.14, Eqn. 3.17, Eqn. 3.20, and Eqn. 3.21. Then, such models were combined to return a risk crash score for R1, R2 and R3. Here below, the final equations are reported to make the read more fluent for the reader.

$$\text{R1}\quad R_{r,i} = F(E)_{r,i} \cdot S_{r,i} = \alpha E_{r,i}^{\beta} \cdot \exp\left(\sum_{j\in J} \gamma_j x_{j,ri}\right) \cdot \left(\frac{\exp\,(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri})}{1 + \exp\,(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri})}\right) \tag{3.22}$$

$$\text{R2}\quad R_{r,t} = F_{r,t} \cdot E_{r,t} \cdot S_{r,t} = \alpha \cdot \exp\left(\sum_{j\in J} \gamma_j x_{j,ri}\right)\left(\rho_0 + \sum_{j\in J} \rho_j z_{j,ri}\right) \cdot \left(\frac{\exp\,(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri})}{1 + \exp\,(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri})}\right) \tag{3.23}$$

$$\text{R3}\quad R_{r,t} = P_{r,t} \cdot E_{r,t} \cdot S_{r,t} = \cdot \left(\frac{\exp\,(\theta_0 + \sum_{j\in J} \theta_j x_{j,ri})}{1 + \exp\,(\theta_0 + \sum_{j\in J} \theta_j x_{j,ri})}\right) \cdot \left(\rho_0 + \sum_{j\in J} \rho_j z_{j,ri}\right) \cdot \left(\frac{\exp\,(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri})}{1 + \exp\,(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri})}\right) \tag{3.24}$$

The results obtained from the estimation of each risk component are reported separately in what follows. For the development of the crash frequency, occurrence probability, and severity models, the integrated road crash dataset was used as input. Indeed, all the response variables were associated to crashes, *i.e.,* number of crashes, occurred/not-occurred crash, and crash damage outcome (severity), respectively. Conversely, for the development of the crash exposure model, being the response variable related to a measure of the traffic volumes over each path, the dataset of road the road network was used instead. All the models were developed by mean of the statistical GenStat Software[29].

For each component estimation, two models were performed by applying the related modelling formulations. More precisely, a first model was performed by including all the intermediate outcome safety factors available within the set of explanatory variables. Such models were defined *baseline model*, as they represented the starting point. Then, for sake of parsimony, specific automatic

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[29] Genstat is a general statistics software package for education and research, developed by VSN International (https://www.vsni.co.uk/software/genstat).

procedures of variable-selection were applied, to obtain an improved model in terms of statistical fit yet reduced in terms of explanatory variables. Such models were defined *best-fit model*.

As a preliminary step, correlation matrices should be produced for each of the models' database, to highlight potentially high correlation among independent variables. In doing so, some pairs of variables were found to be highly correlated (*i.e.,* with a correlation coefficient $|\rho| > 0{,}7$) and therefore they have been removed from the dataset to avoid inaccuracies with the result. However, such variables were also removed by the stepwise regression procedure applied to the model to (i) select and eliminate redundant variables and (ii) obtain an improved model in terms of statistical fit yet parsimonious in terms of explanatory variables. Such models are defined here as *best-fit* models. Different procedures are available in the literature, being forward selection, backward elimination, and stepwise regression the most widely used. In this research, the stepwise regression was selected, which combines both the other procedures. Indeed, stepwise regression sequentially removes existing predictors if a statistically worse model is not produced or add new predictors if a statistically better model is produced (O'Neill, 2010). The opportunity to obtain parsimonious models is extremely beneficial, especially from a practical perspective (*i.e.,* the more the factors considered the more complex the model to be run). If more performing models can be returned with less explanatory variables, then this will gain in simpler interpretability of the results, higher replicability, and updateability of the process over time and over other context.

In what follows, the results of both the baseline and best-fit models are presented for each risk's components estimations and a brief comment is provided. Each table reports the prediction coefficient (*i.e.,* estimates) and the p-value (significance level) of each factor included in the prediction of the response variable. In addition, the *summary statistics* section is reported at bottom of each table, to show the parameter used to evaluate the GoF.

Crash frequency estimation

Before applying the model structure of Eqn. 3.12, the overdispersion of crash data was controlled, to confirm the possibility to apply a GLM with a NB error distribution to the road crash database of this case study. Hence, according to Eqn. 3.15 the dispersion parameter was computed referring to the distribution of crashes occurred over the road network over 2014-2018.

$$D = \frac{\sigma^2}{\mu} \tag{3.15}$$

With a mean of 2,63 crashes per path and a variance of 11,69, the overdispersion parameter returned a value of 4,45, thus confirming the overdispersed nature of the crash data.

The expected number of crashes over a year for each path was computed as the response variable to model crash frequency. Single crash observations were aggregated, based on the combination of similar features among the intermediate outcome safety factors of each crash. Next, for each combination obtained, the total number of crashes was returned as the result of the aggregation. Then, by applying Eqn. 3.12 the crash frequency model was performed.

$$F(E)_{r,i} = \alpha E_{r,i}^{\beta} \cdot \exp\left(\sum_{j \in J} \gamma_j x_{j,ri}\right), \quad \forall\, p_{r,i} \in I \tag{3.12}$$

Table 18 shows the results for the baseline crash frequency model, while Table 17 report the results for the best-fit crash frequency model.

Table 18 - Crash frequency model results (baseline model)

Category	Independent variable	Description	Estimate Coeff.	P-value
Model constant		Natural log of constant (*i.e., α)*	-6,894	
Exposure	Traffic volume	Natural log of km travelled	0,271	****
Road Infrastructure	Road type	Non-urban	0,185	***
	Road class	Non primary	-0,232	-
	N. of lanes per direction	One lane	0,816	****
	Median presence	Undivided carriageway	0,283	***
	Site type	Segment	0,303	****
	Pavement condition	Paved	0,935	***
	Road signs type	Horizontal	0,106	-
		Vertical	-0,009	-
		Horizontal and Vertical	1,177	****
Operational	% Heavy Good Vehicle	< 15%	0,080	-
		15% - 30%	-0,136	*
Environment	Type of terrain	Flat	0,150	*
		Rolling	0,001	-
	Land Use	Built up areas	0,081	-
		Agricultural zone	0,503	***
		Forests and woods	-0,208	-
Context conditions	Surface conditions	Dry	0,608	****
	Season	Winter-Fall	-0,106	*
	Day type	Weekday	0,373	****
	Daytime	Day	0,313	****
	Network provision	Roads per km2	0,282	****
	Population density	Inhabitants per km2	-0,142	*

Summary Statistics of the Model Fit

	Degree of freedom	Deviance	Mean deviance	Deviance Ratio (d.r.)	$\chi2$
Regression	23	768,3	334,045	33.40	<.001
Residual	1680	811,2	0,4828		
Total	1703	1579,5	0,9275		
RMSE	7,136				
% pred./obs.	-6%				

*P-value legend: ****: <0.001; ***: <0.005; **<0.010; *<0.1; -:>0.1*

Overall, the baseline crash frequency model fits the data well, as the statistical test ($\chi2$) on *d.r.* returns a small p-value for goodness-of-fit (<0.001), and a large *d.r.* is returned. Therefore, there is evidence for a regression effect here, so that the null hypothesis can be rejected (*i.e.,* that at least one regression coefficient is not zero). Moreover, according to Eqn. 3.16 the RMSE was computed. It shows a quite low value, pinpointing a small difference between predicted vs observed crash.

$$RMSE = \frac{1}{|I|}\sqrt{\sum_{i\in I}(Y_{r,i}-F_{r,i})^2} \tag{3.16}$$

However, the percentage of predicted over observed crashes returned a negative value, thus indicating an underestimation of the model response with respect to the real occurred crashes. For what concerns the explanatory variables included in the model, it is worth noting that many of them were found to be very significant (*i.e.,* up to the 0.001), and just few resulted not significant.

Table 19 - Crash frequency model results (best-fit model)

Category	**Independent variable**	**Description**		**Estimate Coeff.**	**P-value**
Model constant		Natural log of constant (*i.e., α)*		-7,051	
Exposure	Traffic volume	Natural log of km travelled		0,2826	****
Road Infrastructure	Road type	Non-urban		0,1873	***
	N. of lanes per direction	One lane		0,6220	****
	Median presence	Undivided carriageway		0,2663	***
	Site type	Segment		0,3103	****
	Pavement condition	Paved		0,9350	***
	Road signs type	Horizontal and Vertical		1,1817	****
Operational	% Heavy Good Vehicle	15% - 30%		-0,1332	*
Environment	Land Use	Agricultural zone		0,4348	****
		Forests and woods		-0,2650	**
Context conditions	Surface conditions	Dry		0,6042	****
	Season	Winter-Fall		-0,1052	*
	Day type	Weekday		0,3746	****
	Daytime	Day		0,3111	****
	Network provision	Roads per km2		0,2803	****
	Population density	Inhabitants per km2		-0,1322	*
Summary Statistics of the Model Fit					
	Degree of freedom	Deviance	Mean deviance	Deviance Ratio (d.r.)	χ2
Regression	18	764,1	424,521	42,45	<.001
Residual	1683	812,5	0,4827		
Total	1701	1576,6	0,9269		
RMSE	10,033				
% pred./obs.	+20%				
*P-value legend: ****: <0.001; ***: <0.005; **<0.010; *<0.1; -:>0.1*					

Overall, also the best-fit crash frequency model fits the data well, as the statistical test (χ2) on *d.r.* returns a small p-value for goodness-of-fit (<0.001). Therefore, there is evidence for a regression effect here, so that the null hypothesis can be rejected (*i.e.,* that at least one regression coefficient is not zero). Moreover, a greater *d.r.* factor indicates improvements in the prediction performances compared to the baseline model (*i.e.,* 42,45 vs 33.40). The RMSE, which was computed according to Eqn.

3.16, still shows a quite low value (which is a little bit higher than the one of the baselines models), pinpointing a small difference between predicted vs observed crash. The percentage of predicted over observed crashes returned a positive value, which indicate an overestimation of the model response with respect to the real occurred crashes. This may be intended as a plus of the model. Indeed, according to cautious approach, if a slightly higher number of crashes is returned with respect to the one expected, this may generate a sort of "safety margin" when applying improving measures. In addition, as road crashes are usually translated in economic terms, higher number of expected crashes means greater costs. This may induce those responsible for road safety to pay greater attention.
For what concerns the explanatory variables included in the model, thanks to the stepwise regression, five not significant variables were excluded from the set of explanatory variables, and this helped in improving the prediction performances and make the model even more parsimonious. As a result, all the variables included were found to be significant at least up to the 0.1.

In addition to the full crash frequency models (*i.e.,* including exposure variable among the set of explanatory variables), an attempt was made to develop the crash frequency model as a function of intermediate safety factor-only (*i.e.,* without including the exposure factor in the count model structure). Therefore, by applying Eqn. 3.14 the crash frequency model was performed.

$$F_{r,i} = \alpha \cdot \exp\left(\sum_{j \in J} \gamma_j x_{j,ri}\right), \quad \forall\, p_{r,i} \in I \tag{3.14}$$

For sake of synthesis, Table 20 reports just the result of the best-fit model.

Table 20 - Crash frequency model results without exposure factor (best-fit model)

Category	Independent variable	Description	Estimate Coeff.	P-value
Model constant		Natural log of constant (*i.e., α*)	-2,621	
Road Infrastructure	Road type	Non-urban	0,2025	***
	Road class	Non-Primary	-0,710	****
	N. of lanes per direction	One lane	0,662	***
	Median presence	Undivided carriageway	0,2029	*
	Site type	Segment	0,3015	****
	Pavement condition	Paved	1,047	****
	Road signs type	Horizontal and Vertical	1,3077	****
Operational	% Heavy Good Vehicle	15% - 30%	-0,1125	*
Environment	Type of terrain	Flat	0,568	****
	Land Use	Agricultural zone	0,3346	****
		Forests and woods	-0,1075	**
Context conditions	Surface conditions	Dry	0,6381	****

	Season	Winter-Fall		-0,0971	*
	Day type	Weekday		0,33690	****
	Daytime	Day		0,3129	****
Summary Statistics of the Model Fit					
	Degree of freedom	Deviance	Mean deviance	Deviance Ratio (d.r.)	χ2
Regression	17	705,0	414,699	41.47	<.001
Residual	1684	871,6	0,5176		
Total	1701	1576,6	0,9269		
RMSE	15,261				
% pred./obs.	+57%				
*P-value legend: ****: <0.001; ***: <0.005; **<0.010; *<0.1; -:>0.1*					

Overall, the model fits the data well, as the statistical test ($\chi 2$) on *d.r.* returns a small p-value for goodness-of-fit (<0.001), and a large *d.r.* is obtained. Therefore, the null hypothesis can be rejected (*i.e.,* that at least one regression coefficient is not zero). However, the RMSE, which was computed according to Eqn. 3.16, shows a higher value compared to the previous frequency model and the percentage of predicted over observed crashes returned in a great overestimation of the model response, with respect to the real occurred crashes. Hence, the crash frequency model without the exposure factor did not provide fully satisfactory results in terms of prediction performances.

For what concerns the explanatory variables included in the model, most of them were found to be significant at least up to 0.1. Compared to the full crash frequency model at the best-fit, beside the variable related the road class (*i.e.,* non-primary road) which did not result as significant in Table 20 was not. all the coefficient estimates are consistent with the previous model.

Crash occurrence probability estimation

Before implementing the model, road crash data were manipulated, to enrich the dataset with the set of observation for which the response variable returned "not-occurred". To do so, the crash frequency database was used as a starting point. Indeed, in that case, crash data were input in an aggregate format and the dataset showed all the combination of intermediate factors on which several crashes occurred. However, not all the possible combination of intermediate factors were included in the dataset, meaning that for such missing combination no crash was registered. Hence, those observations were *artificially* built and added to the original dataset. Then, instead of a count-base response variable, for the crash occurrence the response variable was replaced by a simple binary variable. More precisely, for each combination of intermediate factors, the response variable assumed value equal to 1 if at least a crash was registered, 0 otherwise.

From a dataset of 1704 combinations only related to the "occurred crash" observation, a dataset of 147.456 combination was obtained. For sake of clarity, Table 21 shows an excerpt of the wide dataset built to model crash occurrence. Each row represents an observation, while each column represents an intermediate factor. Hence, each observation *e.g.,* 1, 2, etc., represents a combination of intermediate factors that where present when at least a crash occurred. Starting from the original aggregated crash database (the one used for modelling crash frequency), and specifically by referring to the recorded combinations (grey cells) the missing combination of intermediate factors were artificially created and integrated in the dataset (light blue cells), based on the set of potential values assumed by each factor. For instance, referring to obs. 1-4, the related combinations corresponded in all the factors but for the last one, thus "land use". Obs. 1-2 were already registered in the dataset, as 1 crash occurred at those conditions. Whereas, obs. 3-4 were added later to expand the dataset with all those combination for which no crash occurred.

Table 21 – Excerpt of crash occurrence observations artificially integrated

Obs.	…	Surface	Signs	Lane per dir	Hierarchy	…	Terrain	Land Use	N Crash	Occurred
1	…	…	…	…	Primary	…	Flat	1	1	Yes
2					Primary	…	Flat	2	1	Yes
3					Primary	…	Flat	3	0	No
4					Primary	…	Flat	5	0	No
…					…	…	…	…	…	
100					Primary	…	Flat	1	1	Yes
101					Primary	…	Flat	2	1	Yes
102					Primary	…	Flat	3	0	No
103					Primary	…	Flat	5	0	No

… … … … … … … … … …

Once the crash occurrence probability dataset was ready, crash occurrence probability was estimated according to Eqn. 3.17, so by applying a logit model.

$$P(x_{j,ri}) = \frac{\exp\,(\theta_0 + \sum_{j\in J} \theta_j x_{j,ri})}{1+\exp\,(\theta_0 + \sum_{j\in J} \theta_j x_{j,ri})}, \quad \forall\, p_{r,i} \in I \tag{3.17}$$

Table 22 reports the results of the model.

Table 22 - Crash occurrence probability model results (baseline model and best fit)

Category	Independent variable	Description	Estimate Coeff.	OR	P-value	P-value
Model constant			-18,207		<.001	****
Road Infrastructure	Road type	Non-urban	0,5100	1,665	<.001	****
	Road class	Non primary	1,7585	5,804	<.001	****
	Lanes per direction	One lane	1.7087	5,522	<.001	****
	Median presence	Undivided carriageway	1,9248	6,853	<.001	****
	Site type	Segment	0,6240	1,866	<.001	****
	Pavement condition	Paved	4,652	104,7	<.001	****
	Road signs type	Horizontal	0,959	2,610	<.001	****
		Vertical	0,529	1,697	<.001	****
		Horizontal and Vertical	2,695	14,80	<.001	****
Operational	% Heavy Vehicle	< 15%	0,3813	1,464	<.001	****
		15% - 30%	0,3813	1,464	<.001	****
Environment	Type of terrain	Flat	2,1653	8,717	<.001	****
		Rolling	1,4454	4,244	<.001	****
	Land Use	Built up areas	2,480	11,94	<.001	****
		Agricultural zone	2,546	12,76	<.001	****
		Forests and woods	1,849	6,354	<.001	****
Context conditions	Surface conditions	Wet	-0,9249	0,3966	<.001	****
	Season	Winter-Fall	0,0120	1,012	0,827	-
	Day type	Weekday	0,4366	1,548	<.001	****
	Daytime	Day	0,5838	1,793	<.001	****

Summary Statistics of the Model Fit

	Degree of freedom	Deviance	Mean deviance	Deviance Ratio (d.r.)	χ2
Regression	20	8.024	401,19452	401,19	<.001
Residual	147.435	10.566	0,07166		
Total	147.455	18.590	0,12607		

	Observed	Fitted	Rights	Rights [%]
Total	147.456	147.456	145.943	98,97%
Occurred	1.704	341	266	15,61%
Not occurred	145.752	147.115	145.677	99,95%

*P-value legend: ****: <0.001; ***: <0.005; **<0.010; *<0.1; -:>0.1*

Overall, this model fits the data well, as the statistical test ($\chi 2$) on *d.r.* returns a small p-value for goodness-of-fit (<0.001), and the *d.r.* factor registered a very high value. Therefore, strong evidence exists for a regression effect, so that the null hypothesis can be rejected (*i.e.,* that at least one regression coefficient is not zero). Indeed, having available a huge database helped in improving model performances. In addition, looking at the results related to the percentage of rights, almost the 99% of the predicted response was consistent to the related observed result. More precisely, all the observation related to a non-occurred crash were correctly estimated, while the ones of occurred crashes were estimated correctly at almost the 16%. For what concerns the explanatory variables included in the model, all of them resulted to be strongly significant, thus with a p-value at the 0.001. Indeed, it was not deemed necessary to apply stepwise regression to further improve the model performances (a very slight improvement of the *d.r.* was registered doing so).

Crash severity computation

For crash severity estimation, individual crash observations were considered to build the input dataset. The response variable was recorded as a binary outcome, assuming value equal to 1 if the combination of intermediate factors produced a fatal crash, 0 otherwise. Them, again a logit model was employed for this model, according to Eqn. 3.20.

$$S(x_{j,ri}) = \frac{\exp\,(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri})}{1+\exp\,(\varphi_0 + \sum_{j\in J} \varphi_j y_{j,ri})}, \quad \forall\, p_{r,i} \in I \tag{3.20}$$

Table 23 - Crash severity model results (baseline model)

Category	Independent variable	Description	Estimate Coeff.	OR	P-value
Model constant			-5,54		
Users involved		Pedestrian	2,332	10,29	****
		Cyclist	0,851	2,341	**
		Heavy Good Vehicle	1,389	4,010	****
		Powered Two-Wheeler	0,951	2,589	****
Crash Type		Hit with obstacles	0,689	1,991	-
		Head-on or sideswipe	0,933	2,542	-
		Single vehicle collision	1,293	3,643	*
		Rear-end crash	0,112	1,118	-
Violation	Violation by user A	Yes	0,130	1,139	-
	Violation by user B	Yes	-0,084	0,9192	-
Road Infrastructure	Road type	Non-urban	0,761	2,140	****
	Road class	Non primary	0,087	1,091	-
	Lanes per direction	One lane	0,267	1,306	-
	Median presence	Undivided carriageway	0,031	1,032	-
	Site type	Segment	-0,194	0,8237	-
	Pavement condition	Paved	-0,32	0,7236	-
	Road signs type	Horizontal	2,21	9,093	*
		Vertical	1,47	4,356	-
		Horizontal and Vertical	1,980	7,242	*
Operational	% Heavy Vehicle	< 15%	-0,169	0,8441	-
		15% - 30%	-0,026	0,9740	-
Environment	Type of terrain	Flat	-0,052	0,9497	-
		Rolling	-0,088	0,9161	-
	Land Use	Built up areas	-0,262	0,7692	-
		Agricultural zone	-0,658	0,5181	*
		Forests and woods	-0,339	0,7123	-
Socio-demographic	Population density	Inhabitants per km2	-0,00111	0,9989	****
	Network density	Roads per km2	-0,106	0,8998	-
Context conditions	Surface conditions	Dry	-0,118	0,8885	-
	Season	Winter-Fall	-0,024	0,9763	-
	Day type	Weekday	-0,390	0,6770	**

	Daytime	Day	-0,770	0,4628	****
Summary Statistics of the Model Fit					
	Degree of freedom	Deviance	Mean deviance	Deviance Ratio (d.r.)	$\chi 2$
Regression	33	217	65,899	6,59	<.001
Residual	6089	1685	0,2767		
Total	6122	1902	0,3107		
	Observed	Fitted	Rights	Rights [%]	
Total	6.123	6.123	5.902	96,39%	
Fatal	221	0	0	0%	
Non- fatal	5.902	6.123	5.902	96,39%	
*P-value legend: ****: <0.001; ***: <0.005; **<0.010; *<0.1; -:>0.1*					

Overall, the model fits the data well, as the statistical test ($\chi 2$) on *d.r.* returns a small p-value for goodness-of-fit (<0.001). Therefore, there is evidence for a regression effect, so that the null hypothesis can be rejected (*i.e.,* that at least one regression coefficient is not zero). The *d.r.* value registered, however, was not very large. Moreover, looking at the results related to the percentage of rights, almost the 96% of the predicted response was consistent to the related observed result. However, according to the results obtained, the model responded better to the estimation of non-fatal crashes than that of fatal crashes. This may be due to the limited number of fatal crashes included in the dataset, which – fortunately – may be considered as rare events among rare events. For what concerns the explanatory variables included in the model, just few were found to be significant (*i.e.,* up to at least 0.1).

Table 24 - Crash severity model results (best-fit model)

Category	Independent variable	Description	Estimate Coeff.	OR	P-value
Model constant			-5,45		
Users involved		Pedestrian	2,103	8,187	****
		Cyclist	0,651	1,917	*
		Heavy Good Vehicle	1,240	3.455	****
		Powered Two-Wheeler	0,746	2.109	****
Crash dynamic		Hit with other obstacles	0,464	1,591	-
		Head-on or sideswipe	0,856	2,353	****
		Single Vehicle crash	0,997	2,710	****
	Violation by user A	Yes	0,183	1,201	-
Road Infrastructure	Road type	Non-urban	0,744	2,105	****
	Lanes per direction	One lane per direction	0,252	1,287	****
	Site type	Segment	-0,210	0,8107	-
	Road signs type	Horizontal	2,20	9,012	*
		Vertical	1,45	4,275	-
		Horizontal and Vertical	1,980	7,243	*
Environment	Land Use	Agricultural zone	-0,378	0,6855	*
Context conditions	Day type	Weekday	-0,388	0,6782	**
	Daytime	Day	-0,772	0,4623	****
Summary Statistics of the Model Fit					
	Degree of freedom	Deviance	Mean deviance	Deviance Ratio (d.r.)	χ2
Regression	17	185	10,9073	10,91	<.001
Residual	6105	1717	0,2812		
Total	6122	1902	0,3107		
	Observed	Fitted	Rights	Rights [%]	
Total	6.123	6.123	5.902	96,39%	
Fatal crash	221	0	0	0,00%	
Non-fatal crash	5.902	6.123	5.902	96,39%	
*P-value legend: ****: <0.001; ***: <0.005; **<0.010; *<0.1; -:>0.1*					

Overall, the best-fit model fitted the data better than the baseline model. Indeed, the statistical test ($\chi 2$) on *d.r.* still returned a small p-value for goodness-of-fit (<0.001), while the *d.r.* value increased by almost 62%. Therefore, again, evidence for a regression effect was found, so that the null hypothesis can be rejected (*i.e.,* that at least one regression coefficient is not zero). Looking at the results related to the percentage of rights, the same percentages were obtained compared to the baseline model. Likewise, for what concerns the explanatory variables included in the model, similar results were obtained in term of significant variables and their coefficient estimate.

Crash exposure evaluation

In this study, crash exposure was computed in terms of km travelled. More precisely, such value was obtained by multiplying the number of vehicles passing each road path by the path length. Hence, given that path length is an easy-to-collect and always available variable, the sole AADT was included in the model estimation. Then According to Eqn. 3.21, the AADT was estimated by mean of a multiple linear regression (MLR) model.

$$E_{r,i} = \rho_0 + \sum_{j \in J} \rho_j z_{j,ri}, \quad \forall\, j = 1, \dots, n \tag{3.21}$$

It is worth to note that the development of this model aimed at providing proof of a modelling technique able to return a good estimation of traffic volumes in case of missing data. Indeed, for this specific case study, AADT data were already available so there would have been no need to estimate them.

Table 25 - Exposure estimation model results (baseline model)

Category	**Independent variable**	**Description**	**Estimate Co-eff.**	**P-value**
Model constant			7371069	
Road Infrastructure	Road class	Non primary	-3757712	***
	N. of lanes per direction	One lane	-2969238	*
Context conditions	Type of terrain	Flat	1732327	***
		Rolling	2004802	****
	Land Use	Built-up areas	-753519	-
		Agricultural zone	-1618142	-
		Forest and woods	-714537	-
Network density		Roads kms per km2	-142397	*
Population density		Inhabitants per km2	2972	****
% of HGV		% of heavy good vehicles / total AADT	6696786	****

Summary Statistics of the Model Fit

	Degree of freedom	Sum of Squares	Mean Squares	F-ratio	P-value
Regression	11	4,56E+18	4,15E+17	57,75	<.001
Residual	470	3,38E+18	7,18E+15		
Total	481	7,94E+18	1,65E+16		
R^2	0.58				
R^2_{adj}	0.57				

*P-value legend: ****: <0.001; ***: <0.005; **<0.010; *<0.1; -:>0.1*

Overall, the model fitted the data well, as the statistical F-test returned a small p-value (<0.001), and a quite large F-ratio. In addition, the R^2_{adj} returned a quite satisfactory result, as the model was able to explain at least the 57% of AADT's variance by the selected predictors. For what concerns the explanatory variables included in the model, most of them were found to be very significant (*i.e.,* up to the 0.001).

Table 26 - Exposure estimation model results (best fit model)

Category	**Independent variable**	**Description**	**Estimate Co-eff.**	**P-value**
Model constant			4511957	
Road Infrastructure	Road class	Non primary	-2659782	****
	N. of lanes per direction	One lane	-1831778	****
Context conditions	Type of terrain	Flat	1097157	****
		Rolling	1802150	****
	Land Use	Agricultural zone	–297838	*
Network density		Road kms per km2	-31550	-
Population density		Inhabitants per km2	2046	****
% of HGV		% of heavy good vehicles / total AADT	3524487	****

Summary Statistics of the Model Fit

	Degree of freedom	Sum of Squares	Mean Squares	F-ratio.	P-value
Regression	8	1,21E+18	1,34E+17	101.08	<.001
Residual	406	5,38E+17	1,33E+15		
Total	415	1,74E+18	4,20E+15		
R^2	0.69				
R^2_{adj}	0.68				

*P-value legend: ****: <0.001; ***: <0.005; **<0.010; *<0.1; -:>0.1*

Overall, the model fitted the data better than the baseline model. Indeed, the statistical F-test returned a small p-value (<0.001), but a larger F-ratio was obtained. Moreover, also the R^2_{adj} increased, so that the best-fit model was able to explain at least the 68% of AADT's variance by the selected predictors. For what concerns the explanatory variables included in the model, most of them were found to be very significant (*i.e.,* up to the 0.001), thus quite similar results compared to the baseline model.

In addition, some evaluations were also performed with respect to the regression residuals, to further evaluate the performance of the estimated model. More precisely the observed vs predicted AADT values were plotted, as reported in Figure 19. The scattered plot shows that predicted AADT values were uniformly distributed along the expected values of AADT, so that they were close to the ideal situation. For AADT values up to 6 million, the model showed to fit data well. Conversely, some interferences were identified for highest AADT values (*i.e.,* which were generally representative of the most important roads, such as highways).

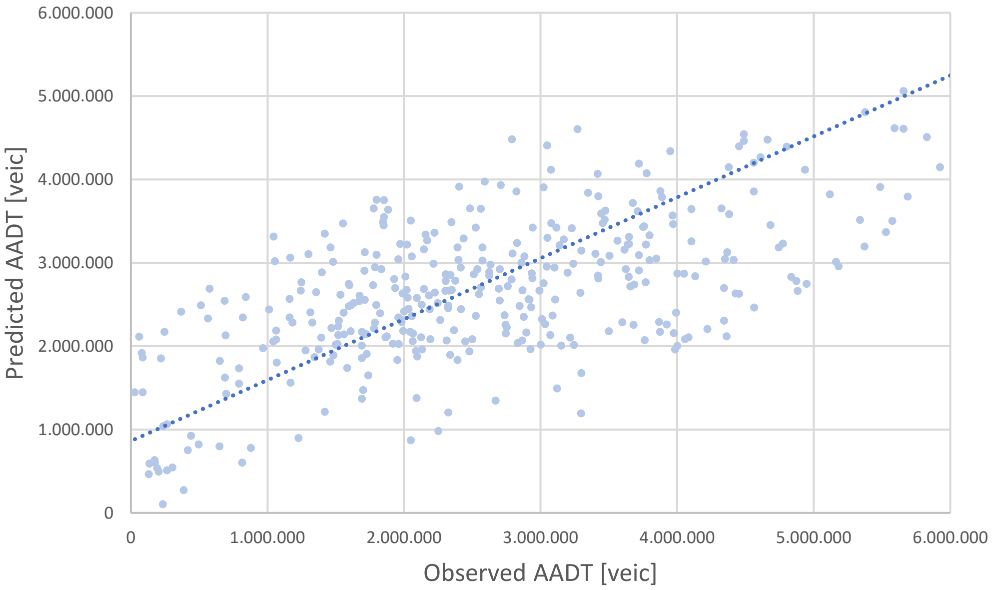


Figure 19 - Observed vs Predicted AADT values for the crash estimate best-fit model

Then, also the residuals distribution was plotted, as reported in Figure 20. The scattered residuals' cloud was not characterized by a well-defined pattern, but residuals were randomly distributed between $\pm 2\sigma$ (which are identified by the two grey lines in the plot), instead.

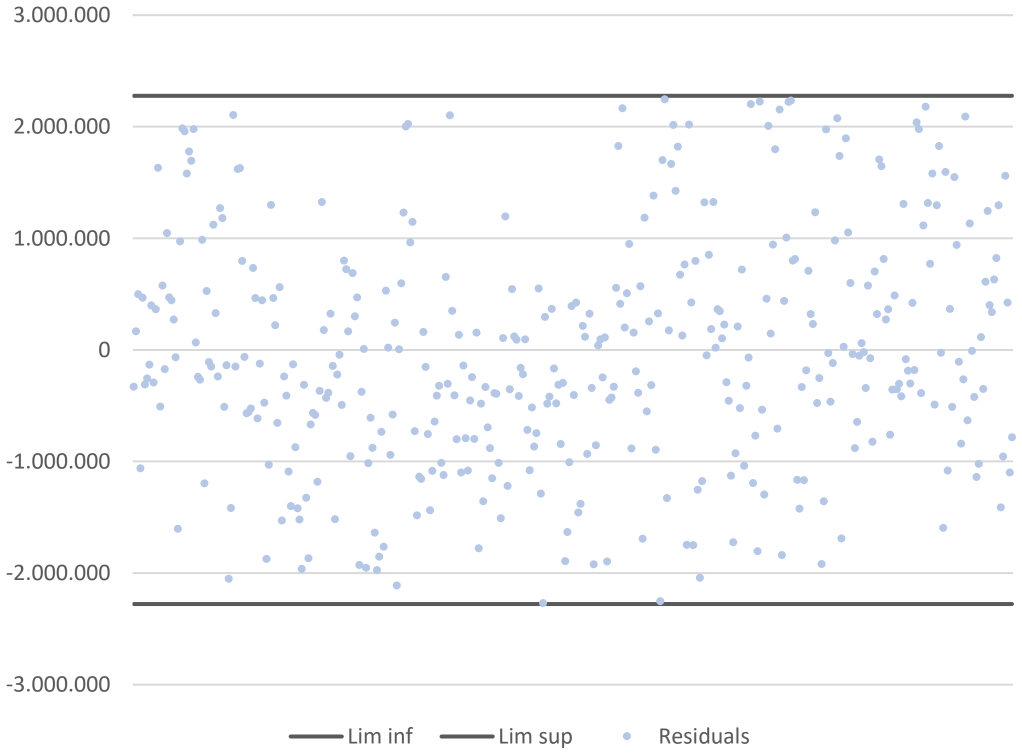


Figure 20 - Residuals distribution of the predicted AADT value by the crash estimate best-fit model

Then, residuals were plotted vs the predicted AADT values, to verify their randomly distributed form against the predicted values, as reported in Figure 21. Again, for AADT volumes lower than 6 million, good results were obtained.

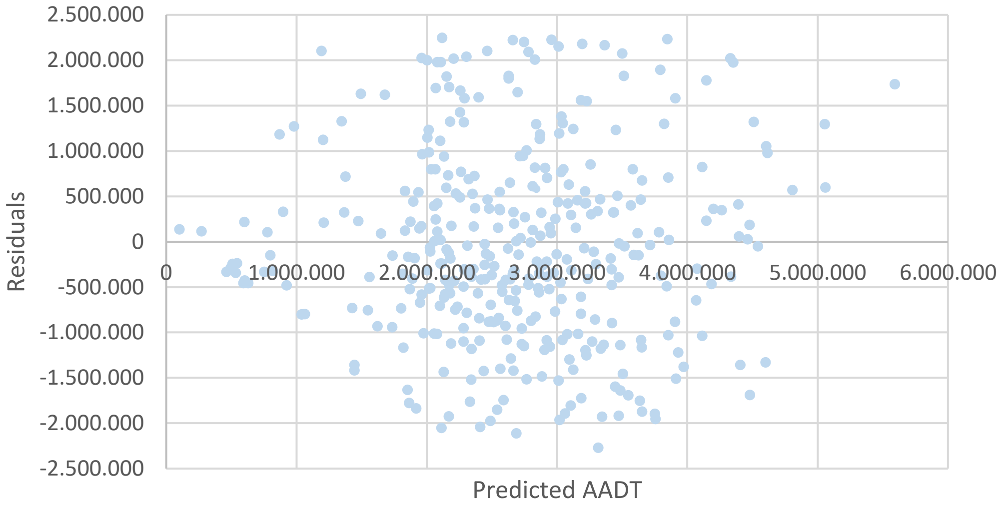


Figure 21 - Residuals vs Predicted AADT values for the crash exposure best-fit model

The results obtained highlighted that for AADT estimates lower than 6 million, the model fitted the data well. Conversely, it was not completely able to model greater AADT volumes. However, this may not be considered a limitation. Indeed, on the one hand, much busier roads (*i.e.,* road that records higher traffic volumes) are generally the ones belonging to the highest hierarchy level of the road network, such as highways or major roads (*e.g.,* A road class, according to MIT (2001)). Such roads are regularly and widely monitored in terms of traffic data (*e.g.*, by mean of automatic traffic detection systems), so that traffic data may be largely available and complete for such roads.

On the other hand, this can also help in optimizing resources when it comes to deciding where to install traffic monitoring devices to have complete information about road network traffic data. Indeed, AADT volumes < 6mil are typical of minor intermediate road classes (*e.g.,* F and C roads, according to MIT (2001)). Then, if traffic volumes can be well estimated by the model up to such AADT levels, then traffic monitoring devices may be primarily assigned to mid-high road classes (*e.g.,* B and some C roads, according to MIT (2001), which are generally not constantly monitored). In addition, as mentioned previously, traffic volume data were retrieved for this study from the traffic simulation performed by Regione Lombardia over the entire network, and not by mean of *e.g.,* on-field traffic survey campaign (vehicles counting devices). As a result, the prediction performance – and so the results – may be affected by this fact. However, the aim of this last model was to provide professionals with an alternative and cost-effective tool to predict traffic volumes for those roads that may lack of such information.

4.3.3. Network ranking based on the road crash risk

According to the last step of the framework, *i.e.,* part C), the crash risk score was computed for each "minimum" path over the entire road network. Specifically, based on the *e.g.,* infrastructural, operational, and context characteristics of each minimum path, as explained in chapter 4.3.2, the risk components were computed for each segment. In doing so, just the most significant variables (*i.e.,* significant at least up to 0.01) for each component were included in the prediction. Then, according to Eqn. 3.22 – 3.24, the estimated values were combined to return the overall crash risk scores of the alternative formulations of risk, *i.e.,* R1, R2 and R3.
Finally, "minimum" paths were ranked based on their risk score and assigned with a range, as shown in Table 12. In addition, separated ranking can be also provided based on the managing road authorities, as this would help in effectively identifying the most critical roads and/or road segments in their own network. In doing so, ranking should be adjusted by considering the specific sub-set of roads.

In what follows, the results of R3 crash risk formulation are reported only, as the related formulation is considered as prior in this research. Specifically, the two screening levels are reported, thus the one at the provincial level (*i.e.,* considering path as the entire road section within the Province's boundaries), and that at the municipality level (*i.e.,* based on the "minimum" path). The results related to R1 and R2 formulations are included in the Appendix.

Table 27 shows the ranges of the crash risk score computed according to R3 for the provincial and municipality level, respectively. Table 28 and Table 29 report the paths at the provincial level (*i.e.,* the entire road within the provincial boundaries) ranked according to a decreasing scale of the risk score, from the highest values (*i.e.,* those belonging to range 5) to the lowest (*i.e.,* those belonging to range 1). More precisely, to obtain the risk score for each road at the provincial level, the single risk scores of the "minimum" paths were aggregated to return the *average crash risk score* (*i.e.,* computed according to Eqn. 3.8), In this way, the most critical road of the network of the Province of Brescia could be identified.

Table 27 - Ranges of the ranking scale for the provincial level and the municipality level

Level	R3 - Ranges values					
	Provincial level			Municipality level		
1	0,00000	-	0,00203	0,0000000	-	0,0000001
2	0,00203	-	0,01632	0,0000001	-	0,00085
3	0,01632	-	0,06792	0,00085	-	0,02594
4	0,06792	-	0,16676	0,02594	-	0,06485
5	0,16676	-	0,54076	0,06485	-	0,81691

Table 28 - Road crash risk score and road ranking at the provincial level (part 1)

Road path (Provincial level)	Crash risk level	R3 Average crash risk	Road path (Provincial level)	Crash risk level	R3 Average crash risk
BSSPVIID1	5	0,54076	BSSP002	3	0,06677
BSSP034V1	5	0,31887	BSSP033	3	0,06375
BSSP060	5	0,31257	BSSP017	3	0,06279
BSSP036	5	0,28987	BSSP049	3	0,05814
BSSP018D1	5	0,28305	BSSPEXSS42	3	0,05642
BSSP018	5	0,27178	BSSPEXSS510T	3	0,05278
BSSPEXSS235D1	5	0,21990	BSSP070	3	0,04670
BSSP034	5	0,18436	BSSP011	3	0,04654
BSSP067	5	0,18096	BSSP111	3	0,04260
BSSP047B	5	0,18072	BSSPEXSS236V2	3	0,04186
BSSP047	4	0,16535	BSSP090	3	0,04086
BSSP075	4	0,15652	BSSP029	3	0,03819
BSSP077	4	0,14631	BSSP008	3	0,03542
BSSP068	4	0,14002	BSSP020	3	0,03476
BSSP061	4	0,13252	BSSPEXSS668	3	0,03410
BSSPEXSS236B	4	0,09856	BSSP016	3	0,03406
BSSP065	4	0,09607	BSSP089	3	0,03262
BSSP062	4	0,09585	BSSPEXSS11V1	3	0,02894
BSSP021	4	0,09368	BSSP037	3	0,02725
BSSPEXSS469D1	4	0,09333	BSSP069	3	0,02722
BSSPEXSS236	4	0,09216	BSSP088	3	0,02562
BSSP028	4	0,08275	BSSP019	3	0,02386
BSSP024	4	0,08238	BSSPVIII	3	0,02226
BSSPIV	4	0,08145	BSSP051B	3	0,02188
BSSP087	4	0,08073	BSSP013	3	0,02035
BSSPEXSS669	4	0,07825	BSSP022	3	0,02015
BSSPEXSS237D1	4	0,07797	SS42	3	0,01879
BSSPVII	4	0,07370	BSSP025	3	0,01844
BSSP066	4	0,07216	BSSP064	3	0,01746
BSSP004	4	0,07195	BSSPEXSS343	3	0,01720
BSSPEXSS236D1	4	0,06843	BSSP072	3	0,01649
BSSPIX	4	0,06831			

As reported in Table 28, the riskiest roads are the ten roads belonging to the 5th level of the ranking scale (*i.e.,* dark red coloured, from BSSPVIID1 to BSSP047B). They are all provincial roads (*i.e.,* managed directly by the Province of Brescia), mostly F or C class (lowest classes for non-urban roads, according to MIT, 2001). They present an undivided carriageway with a one-lane two-way cross section. Also, they are all paved segments with road signs. They are all surrounded by mainly rural contexts (*e.g.,* agricultural land use) and they run over flat terrain. All these features have overall positive effects on crash occurrence and severity thus they increase the odds of greater crash occurrence and severe outcomes. Conversely, the same characteristics are the one that has a negative impact on exposure, thus they limit traffic volumes. Indeed, such roads are characterised by medium-low level of AADT (ranging from 144.686 to 3.186.830) with a quite limited quota of HGV (mostly 0-15% of the total AADT), and a quite short length (ranging from almost 2 km to 5 km, except for BSSP018 which is 10 km long).

Table 29 - Road crash risk score and road ranking at the provincial level (part 2)

Road path (Provincial level)	Crash risk level	R3 Average crash risk
BSSP100	2	0,01616
BSSP027	2	0,01522
BSSP046	2	0,01508
BSSPEXSS235	2	0,01364
A4racc	2	0,01355
BSSP096	2	0,01340
BSSPEXSS237	2	0,01309
BSSP052	2	0,01233
BSSP031	2	0,01098
BSSP086	2	0,00953
BSSP026	2	0,00935
BSSPEXSS45B	2	0,00931
A35	2	0,00762
BSSP073	2	0,00758
BSSP047T	2	0,00752
BSSP051	2	0,00663
TANGOVEST	2	0,00641
BSSP058	2	0,00627
BSSP079	2	0,00583
A35racc	2	0,00580
BSSPEXSS294	2	0,00450
BSSP023	2	0,00419
BSSPEXSS510	2	0,00402
BSSP009	2	0,00389
BSSP041	2	0,00348
BSSP057	1	0,00202
BSSP059	1	0,00198
BSSPI	1	0,00190
BSSPIII	1	0,00189
BSSPXII	1	0,00178
BSSP078	1	0,00132
BSSPEXSS469	1	0,00118
BSSP050	1	0,00117
BSSP116	1	0,00095
BSSP071	1	0,00068
A21racc	1	0,00040
BSSP112	1	0,00037
BSSP006	1	0,00033
BSSPEXSS345	1	0,00029
BSSPEXSS11	1	0,00024
BSSPV	1	0,00023
BSSP106	1	0,00023
BSSP099	1	0,00014
BSSP012	1	0,00003
A21	1	0,00000…
BSSP115	1	0,00000…
BSSPEXSS573	1	0,00000…
BSSPEXSS510V1	1	0,00000…
BSSP005	1	0,00000…
BSSPEXSS567	1	0,00000…

🟨	BSSP076	2	0,00338
🟨	BSSPXI	2	0,00334
🟨	BSSP032	2	0,00249
🟨	BSSPEXSS510B	2	0,00233
🟨	BSSP055	2	0,00209
🟨	BSSP010	2	0,00208
🟨	BSSP100	2	0,01616
🟩	BSSP048	1	0,00000…
🟩	BSSP084	1	0,00000…
🟩	BSSPEXSS572	1	0,00000…
🟩	SS39	1	0,00000…
🟩	A4	1	0,00000…
🟩	BSSPEXSS300	1	0,00000…
🟩	BSSPEXSS510D1	1	0,00000…

Conversely, looking at the result of Table 29, the least critical roads are those belonging to the 1st level of the ranking scale (*i.e.,* light green coloured, from BSSP057 to BSSP057). Focusing on the last 13 safer roads (*i.e.,* the ones showing a risk score lower than 0,00003), some interesting considerations can be made. First, it is noteworthy that all those roads are quite heterogeneous. Indeed, among them, there are two of the main highways (*i.e.,* A4 and A21), and a class B road (*i.e.,* BSSPPEXSS510V1), while all the others are C or F class provincial roads.

For what concerns the formers, which can be accounted as of primary roads, they are characterised by undivided carriageways with at least two lanes per direction and are interested in a quite high share of HGV over the total AADT. However, they record the highest traffic volumes being major roads connecting key commercial and industrial hubs and runs over flat terrain, surrounded by agricultural or industrial land use. For what concerns the latter, which can be accounted as non-primary roads, they are all one-lane two-ways undivided roads. However, they mostly run over mountain areas, which are characterised by forest and wood land use and by a low population density. They are also interested in lower volumes of traffic so that the exposure factor is smaller.

To summarise, Figure 22 and Figure 23 show the box plots of the distribution of the R3 road crash risk values at the provincial level for each crash risk range and for each road functional class, respectively. Such graphs help understanding how crash risk score are distributed.

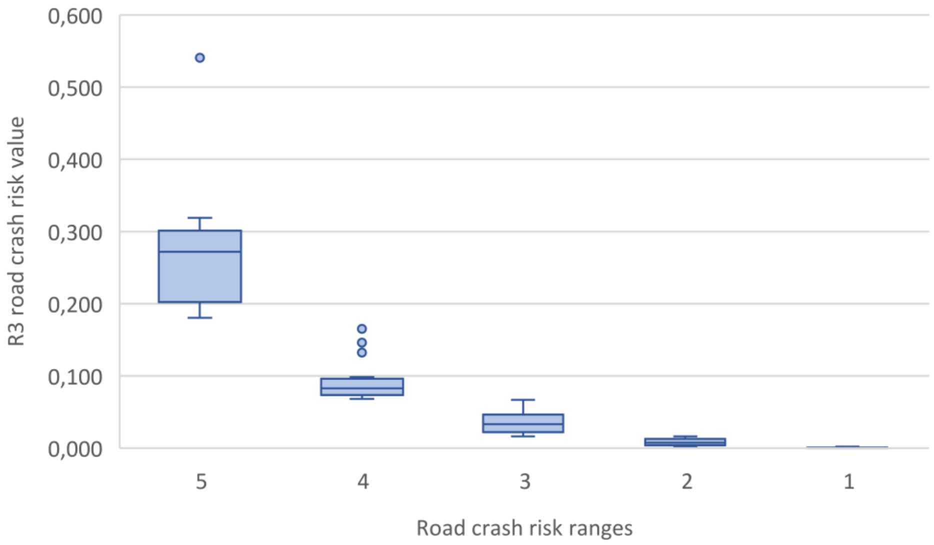


Figure 22 - Box plots related to the distribution of R3 road crash risk value for each range at the provincial level

Figure 22 is quite self-explicative, as it graphically transposes by mean of *box and whisker plots* the distribution of the road crash risk values (computed according to R3) for each road crash risk range. First, it is possible to note that the values are respectful of the numerical ranges of Table 27. In addition, it shows how, within each range, the values obtained for the several paths vary. For instance, in ranges 5, R3 values show higher variability compared to others, as the *box* of former are wider than the ones of the latter.

Conversely, Figure 23 shows for each road functional class (A highways, B primary roads, C secondary roads, and F local non-urban roads) the distribution of the road crash risk values obtained by the several paths included in such categories, by mean of *box and whiskers plot*. As previously mentioned, Figure 23 clearly shows that for highways and primary roads the road crash risk values are substantially lower than the ones of class C and F roads. Indeed, *boxes* of such road class are flattened around zero and shows contained variability.

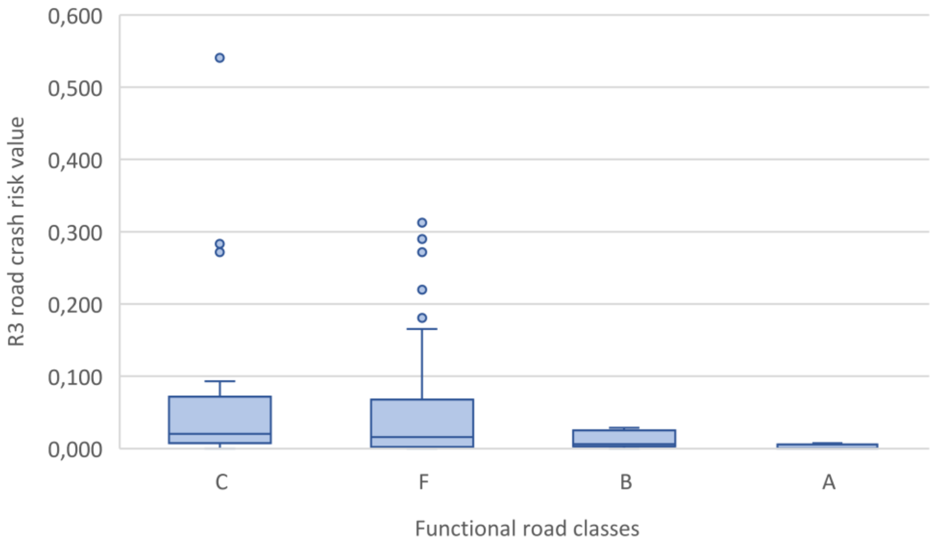


Figure 23 - Box plots related to the distribution of R3 road crash risk value for each road class at the provincial level

Then, looking thoroughly at the municipality level, for each provincial road path, the related minimum paths (*i.e.,* the single road segments within the municipality boundaries that compose the entire path) can be analysed, so that the most critical segment(s) of each road can be identified. This level of safety screening allows to further investigate the entire road and find *e.g.,* among the most critical ones the most critical segment(s). As an example, Table 30 shows an excerpt of the complete list of minimum paths (which is reported in the Appendix). Specifically, for each road (path), the related minimum paths are reported along with their single crash risk score (both as a range level and the numerical value). Then, for sake of completeness, also the estimated values for each risk component are reported, namely: crash severity *S*, crash occurrence probability *P*, and crash exposure *E*.

Table 30 - Ranking of level 5 paths and the related minimum paths

R3	**Path**	**Minimum path**	**R3 (Municipality level)**		**S**	**P**	**E**
🟥	BSSPVIID1	BSSPVIID1_17088	5	0,54076	0,05091	0,70239	15,12256
	BSSP034V1	BSSP034V1_17099	5	0,31887	0,03723	0,54050	15,84662
	BSSP060	BSSP060_17052	5	0,31257	0,03049	0,67735	15,13369
	BSSP036	BSSP036_17200	5	0,28987	0,02371	0,85346	14,32625
	BSSP018D1	BSSP018D1_17188	5	0,28305	0,03280	0,55307	15,60477
	BSSP018	BSSP018_17015	5	0,08074	0,01278	0,40902	15,44953
		BSSP018_17041	5	0,07809	0,13010	0,03697	16,23488
		BSSP018_17045	4	0,04060	0,02127	0,13160	14,50673
		BSSP018_17052	5	0,34254	0,02933	0,75510	15,46549
		BSSP018_17166	5	0,81691	0,10378	0,55011	14,30952

🟥	BSSPEXSS235D1	BSSPEXSS235D1_17186	5	0,21990	0,03028	0,45133	16,08920
	BSSP034	BSSP034_17064	5	0,08904	0,00891	0,69070	14,47006
		BSSP034_17093	5	0,27968	0,02130	0,85195	15,41069
	BSSP067	BSSP067_17043	5	0,18215	0,02932	0,40837	15,21414
		BSSP067_17161	5	0,17977	0,01947	0,57935	15,94025
	BSSP047B	BSSP047B_17112	5	0,20473	0,02283	0,57813	15,51379
		BSSP047B_17123	5	0,15671	0,02283	0,47976	14,31025

E (exposure value) is expressed as the Ln(VTM) for scaling purposes

As shown by Table 30, also the minimum paths of the most critical roads have confirmed the high level of risk of such road network sections. Indeed, the single minimum paths reflect the characteristics of the roads they belong to, so that also the impact of such factors over crash probability, severity and exposure is quite similar and consistent.

In Figure 24 *box and whiskers* plots are reported, representing the distribution of road crash risk values for each “minimum” path with respect to the risk range of the related path considered at the provincial level. For sake of clarity, one may refer to Table 30. Road BSSP018 considered at the provincial level belongs to level 5 of the crash risk scale. However, it consists of several “minimum” paths (*i.e.,* from BSSP018_17015 to BSSP018_17166) which, at the municipality level, may show different risk level compared to the average of the overall road. Indeed, BSSP018_17045 belongs to level 4 of the crash risk scale.

As a result, Figure 24 clearly shows how the distribution of the risk values of the several “minimum paths” may be differently distributed into the five crash risk ranges considered at the provincial level. Some highlights may be retrieved. For instance, level 5 risk scale paths at the provincial level generally consist of “minimum” paths which shows higher level of the risk score (greater than 0,05) thus belonging to higher level of risks (5 or 4), in accordance with Table 27 and Table 30. Conversely, paths of the other risk ranges at the provincial level may show greater variability in the score obtained for the related “minimum” paths (they range from 0 to 0,4 risk score). However, the risk score of the entire path is computed as the average of the scores of the single “minimum” paths, and so the overall result may return a mid-low risk score. As a result, it may happen that a path which show a quite low risk score may present segments with higher-than-average risk score and that require further attention. In this lays the power and potential of the flexibility of the model proposed, as it enable a multi-scale check of the road safety performances of the road network.

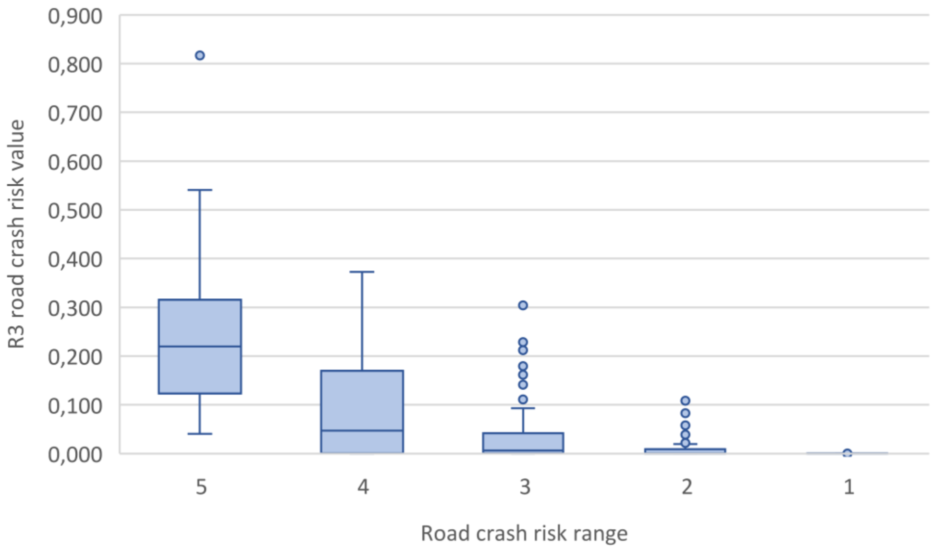


Figure 24 - Box plots of the distribution of R3 road crash risk value for each "minimum" path in each road crash risk range at the provincial level.

In addition to the previous tables and figures, which briefly report the numerical results of the network-wide road safety screening, also crash risk maps were produced. They represent directly on the network basemap the ranking of different paths of the network, according to their crash risk score. Such output represents an extremely useful tool for decision-making process, as it immediately returns and visualizes (*i.e.,* by mean of colours) the most critical roads and segments of the network. Moreover, they were uploaded and integrated into a GIS system, as they can be easily implemented into the Territorial Information System (SIT) to be consulted when needed. Figure 25 provides an example of risk map. It reports the risk mapping of the road network of the Province of Brescia computed according to R3 formulation at the provincial level (*i.e.,* results of Table 28 and Table 29). All the maps are included as attachments to the present research.

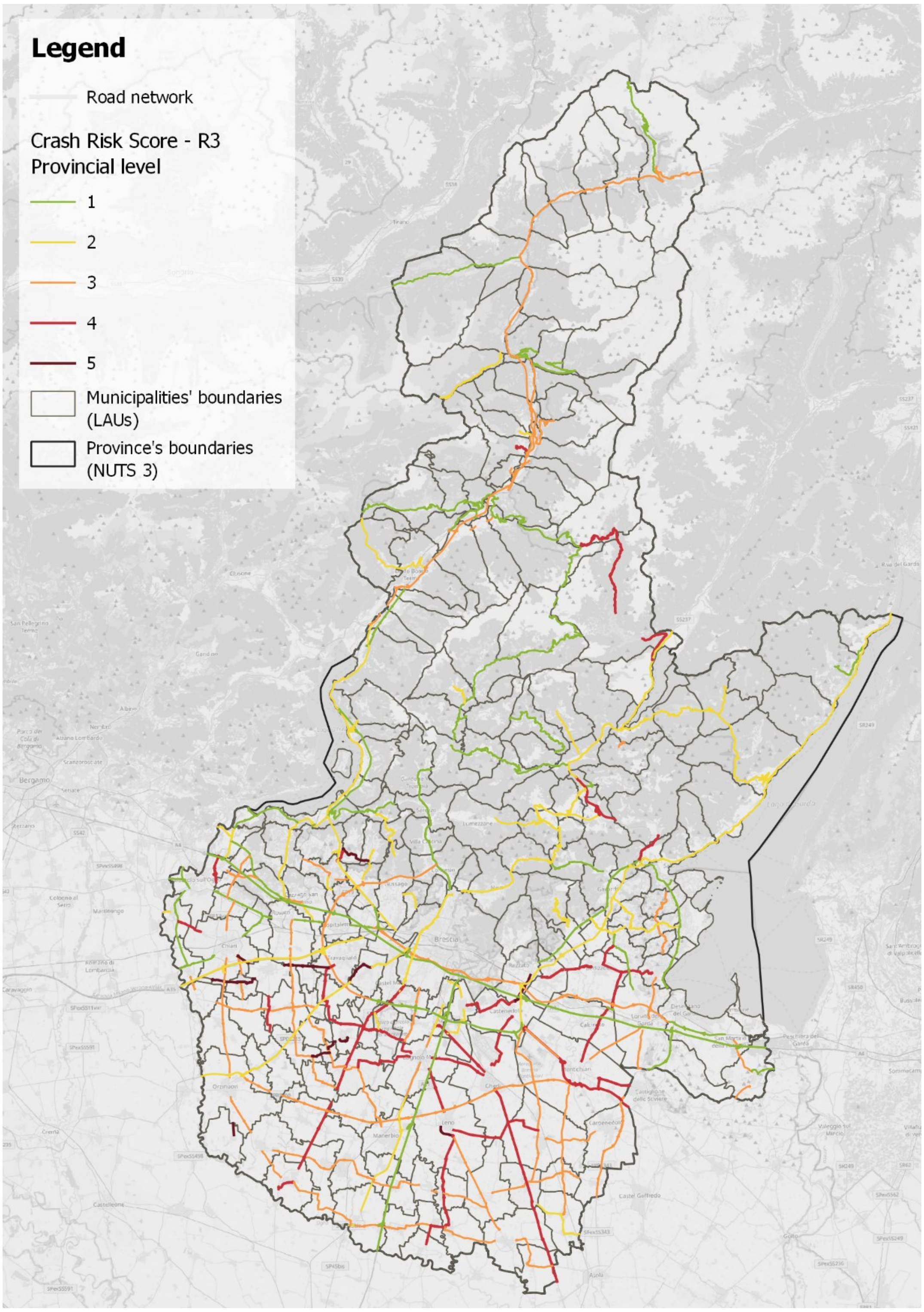


Figure 25 - Example of risk map (Crash risk score computed according to R3 at the provincial level)

5. Discussion

In this chapter, the results obtained from the application of the new methodological proposal for an RB-NWRS will be discussed. Specifically, the discussion will focus on two main points: (i) the comparison among the results obtained by applying the different formulations of risk, *i.e.,* R1, R2, and R3, to understand how the different formulations of risk and the related components' estimation techniques can influence the ranking results. Then, (ii) the impact of the several intermediate safety factors over the risk components will be analysed and compared to the findings of previous research. In addition, recommendations will be provided about potential measures to be implemented to mitigate road crash risk, as the follow-up that is required by the RISM procedure after the network-wide assessment.

5.1. Comparing rankings among different risk formulation alternatives (R1, R2, and R3)

For what concerns the comparison among the crash risk alternative formulations, some interesting findings are highlighted in what follows. Specifically, the discussion will focus on the ranking differences for road paths considered at the provincial level. Here below the three related equations are reported as a reminder.

R1) $$R_{r,i} = F(E)_{r,i} \cdot S_{r,i} \tag{3.9}$$

R2) $$R_{r,i} = F_{r,i} \cdot E_{r,i} \cdot S_{r,i} \tag{3.10}$$

R3) $$R_{r,i} = P_{r,i} \cdot E_{r,i} \cdot S_{r,i} \tag{3.11}$$

Before starting, it is necessary to underline that the differences in crash risk computation by mean of Eqn. 3.7 – 3.9 may be generated primarily by the frequency/probability and exposure component. Indeed, crash severity was estimated by mean of the same modelling structure (*i.e.,* logit model) in all the three alternative formulations, so that results for the severity component are the same for R1, R2 and R3. Therefore, when discussing differences among such risk formulations, specific attention is paid to the other risk components.

Given such premises, a first comparison was made among R1 and R2. Such formulations are quite similar (see Eqn. 3.9 and Eqn. 3.10), in that both estimated crash occurrence in terms of frequency, thus by returning the expected number of crashes over a given period and given specific conditions. However, they differ in that R1 modelled crash frequency as a function of intermediate safety outcome and exposure factors, whereas R2 modelled crash frequency as a function of intermediate safety outcome factors only. Indeed, in R2 the exposure factor is introduced independently. As previously mentioned, the opportunity to model crash frequency excluding the exposure factor from the set of explanatory variables leads to an estimation of the extent to which the road can register a given number of crashes just owing to the *e.g.,* infrastructural, context, etc. characteristics. In other words, independently of how many road users can be exposed to such hazards, it measures to what extent the specific asset of a road can lead to a given number of crashes. Then the exposure factor is introduced to amplify those results, based on how many subjects (*i.e.,* road users) may be exposed. The same rationale, of course, is also effective when severity is concerned.

Regardless of this, looking at Table 31, it appears that the road crash risk scores obtained with R1 and R2 are quite similar. Indeed, more than 72% of the road path at the provincial level was assigned to the same crash risk range according to both formulations. For the remaining road paths, different levels among R1 and R2 were obtained, which, however, reported adjacent levels (*e.g.,* A21racc was ranked in the 4th level as for R1, while it was ranked 5th as for R2).

These differences, of course, are due to the diverse way used to compute crash frequency. Specifically, besides the inclusion of the exposure variable in the frequency function (which was found to be a very significant variable when modelling F in R1), the impact of the other explanatory variables gained major relevance. More precisely, although most of the variables showed in Table 19 and Table 20 were consistent both in terms of magnitude and sign of the estimates coefficient, and significance power (*i.e.,* p-value), some discrepancies were found among the two estimates. For instance, non-primary roads were found to be strongly significant in modelling $F_{r,t}$ and to have a negative impact on crash frequency, which was not found for $F(E)_{r,i}$ instead. Similarly, flat terrain registered high p-value and a positive effect on crash frequency in modelling $F_{r,t}$, compared to $F(E)_{r,i}$. Conversely, population density was slightly significant for $F(E)_{r,i}$, whereas it was not even included in the best-fit model of Table 20.

Table 31 – Road crash risk ranking at the provincial level: comparison among R1, R2, and R3 computation (Part 1)

Path	Average R1	Average R2	Average R3
A21	5	5	1
A21racc	4	5	1
A35	4	4	2
A35racc	2	2	2
A4	5	5	1
A4racc	4	4	2
BSSP002	3	3	3
BSSP004	4	4	4
BSSP005	3	2	1
BSSP006	1	1	1
BSSP008	2	2	3
BSSP009	1	1	2
BSSP010	2	1	2
BSSP011	3	3	3
BSSP012	3	4	1
BSSP013	4	4	3
BSSP016	3	3	3
BSSP017	3	4	3
BSSP018	2	2	5
BSSP018D1	1	1	5
BSSP019	4	4	3
BSSP020	3	3	3
BSSP021	2	2	4
BSSP022	3	3	3
BSSP023	2	2	2
BSSP024	4	4	4
BSSP025	4	3	3
BSSP026	3	2	2
BSSP027	3	3	2
BSSP028	3	3	4
BSSP029	3	4	3
BSSP031	1	1	2
BSSP032	2	1	2
BSSP033	3	3	3
BSSP034	1	1	5
BSSP034V1	2	3	5
BSSP036	1	1	5
BSSP037	3	3	3
BSSP041	1	1	2
BSSP046	2	3	2
BSSP047	2	2	4
BSSP047B	1	1	5
BSSP047T	1	1	2
BSSP048	4	3	1
BSSP049	2	1	3
BSSP050	1	1	1
BSSP051	2	2	2
BSSP051B	2	1	3
BSSP052	2	1	2
BSSP055	1	1	2
BSSP057	2	1	1
BSSP058	1	1	2
BSSP059	1	1	1
BSSP060	1	1	5
BSSP061	2	1	4
BSSP062	3	3	4
BSSP064	3	3	3
BSSP065	3	3	4
BSSP066	4	4	4
BSSP067	1	1	5
BSSP068	2	2	4
BSSP069	2	3	3
BSSP070	2	3	3
BSSP071	1	1	1
BSSP072	4	4	3
BSSP073	2	2	2
BSSP075	1	1	4
BSSP076	2	2	2
BSSP077	1	1	4
BSSP078	3	4	1
BSSP079	3	2	2
BSSP084	2	1	1
BSSP086	1	1	2
BSSP087	1	1	4
BSSP088	1	1	3
BSSP089	1	1	3
BSSP090	1	1	3
BSSP096	2	2	2
BSSP099	3	3	1
BSSP100	1	1	2

BSSP106	2	1	1
BSSP111	1	1	3
BSSP112	2	1	1
BSSP115	1	1	1
BSSP116	3	3	1
BSSPEXSS11	4	4	1
BSSPEXSS11V1	5	5	3
BSSPEXSS235	4	4	2
BSSPEXSS235D1	1	1	5
BSSPEXSS236	5	5	4
BSSPEXSS236B	4	4	4
BSSPEXSS236D1	1	1	4
BSSPEXSS236V2	1	1	3
BSSPEXSS237	4	3	2
BSSPEXSS237D1	1	1	4
BSSPEXSS294	2	2	2
BSSPEXSS300	3	3	1
BSSPEXSS343	3	4	3
BSSPEXSS345	4	3	1
BSSPEXSS42	3	2	3
BSSPEXSS45B	4	4	2
BSSPEXSS469	4	4	1
BSSPEXSS469D1	1	1	4
BSSPEXSS510	4	4	2
BSSPEXSS510B	3	3	2
BSSPEXSS510D1	4	4	1
BSSPEXSS510T	1	1	3
BSSPEXSS510V1	4	4	1
BSSPEXSS567	4	4	1
BSSPEXSS572	4	3	1
BSSPEXSS573	5	5	1
BSSPEXSS668	4	4	3
BSSPEXSS669	2	1	4
BSSPI	2	2	1
BSSPIII	2	1	1
BSSPIV	2	2	4
BSSPIX	3	4	4
BSSPV	4	3	1
BSSPVII	3	3	4
BSSPVIID1	3	2	5
BSSPVIII	3	3	3
BSSPXI	4	4	2
BSSPXII	3	3	1
SS39	2	3	1
SS42	3	3	3
TANGOVEST	5	5	2

Conversely, when comparing R1 and R2 with R3, major differences arise. Indeed, looking at Table 31 and, less than 30% of the total road paths at the provincial level got the same risk level across R1 (or R2) and R3. In this case, of course, the modelling approach made the difference. R3 adopted a probability model structure (*i.e.,* logit model) to estimate the occurrence of a road crash, instead of considering a measure of frequency, as in R1 or R2. In doing so, the response variable represented the first – and foremost – dissimilarity, which strongly affected the overall road crash risk outcome. Based on a set of explanatory variables which may help explain the phenomenon, R3 estimated the probability of "even a single" crash, and no importance is given to the number of crashes that may result. Hence, *e.g.,* infrastructural, context, environmental conditions for which one or more than one crash can be registered are treated at the same level. Conversely, when considering crash frequency, conditions that may lead to one, two, or more expected crashes are considered at different levels. As a result, according to the R3 approach, the identification of roads that can register even a single crash should be accounted for and treated evenly to roads that, according to a frequency approach, can register a higher number of crashes. Indeed, if just a single crash can be avoided by reducing the probability of the crash to occur, then the analysis achieved its objective: it may be reasonable to think that, given specific conditions, the greater the probability of crash occurrence, also the greater the number of crashes that can be registered.

In that sense, the results for the crash risk score obtained for R1 (or R2) and R3 strongly differed, as they considered completely different entities in the risk estimation. Indeed, looking at R1 (or R2) ranking, the roads ranked as the most critical (*i.e.,* 5th level of the ranking, or dark red coloured) are the ones that registered the highest number of observed crashes over the 5 years. However, they represented the major roads of the network which experienced a great number of crashes also due to the highest level of AADT (*e.g,* A4, A21 highways, B class roads such as the BSSPEXSS11V1 or TANG-OVEST). Conversely, the roads ranked among the most critical for R3 are non-primary roads that registered lower numbers of crashes yet are interested in lower traffic volumes. As a result, the bearing of road crashes compared to the traffic volumes is comparable or even greater for the latter. Therefore, it may occur that a greater exposure factor (*e.g.,* an increase in traffic volumes) can strongly amplify an already high crash probability occurrence due to the inherent characteristics of the road and the road environment.

5.2. Impact of the intermediate outcome safety factors over crash risk components

Focusing on the effect of the several intermediate safety outcome factors included in the estimation of the crash risk components, interesting considerations emerged. Specifically, the discussion will focus on those factors that resulted significant for at least one of the risk components.
Table 32 summarises the significant factors, which are retrieved from Table 19, Table 20, Table 22, Table 24, and Table 26, thus from the best-fit models. More precisely, for each category of intermediate outcome factor, the significant sub-factors (*i.e.,* the one with a p-value lower or equal to 0.1) are reported in the column that refers to the "direction" of the effect they showed over each risk component (*i.e.,* increasing or decreasing factor).

Overall, it emerges that the same factors had different effects on crash risk components. For instance, as for land-use factors, the agricultural zone may boost crash occurrence (and frequency) while reducing either the consequences in terms of severity or even the extent of the exposure factor. Likewise, as for context conditions, travelling during weekdays and daytime increase the probability (and frequency) of a crash while reducing the severity outcome. Therefore, depending on the characteristics of each road (*i.e.,* the presence/absence of a safety factor), the extent to which each factor defines the road (*e.g.,* for which length extent it is registered), and the magnitude of the relative coefficient estimate, different values of crash occurrence probability (or frequency), severity, and exposure can be returned.

This fact is witnessed by the brief description of the routes given regarding Table 28 and Table 29: it pinpointed that differences for what concerns *e.g.,* road infrastructural, context, land use feature and exposure factors (*i.e.,* traffic volumes) persist among the wide set of roads, even in the same risk range. Therefore, as also argued by Barabino et al., 2021, at this stage of the analysis, it is not possible to define crash risk ranges based on a specific set of intermediate factors. In this perspective, the concept of *iso-risk curves* (see chapter 2.3) plays a core role: a different combination of risk components (which, in turn, depends on the coefficient estimates for each intermediate factor included in the prediction model) may result in the same risk score.

Table 32 - Comparison of the effects of significant intermediate safety factors over the crash risk components

Intermediate safety factors	**Crash Frequency**		**Crash Probability**		**Crash Severity**		**Crash Exposure**	
	↑	↓	↑	↓	↑	↓	↑	↓
Road infrastructure								
Non-urban road	x		x		x			
Non-primary road		(x)	x					x
One-lane per direction	x		x		x			x
Undivided carriageway	x		x					
Segment	x		x					
Paved surface	x		x					
Wet surface	x			x				
Horizontal and vertical signs	x		x		x			
Road network provision	x							
Operational								
< 15% HGV			x					
15% - 30% HGV	x		x				x	
> 30%							x	
Environment								
Flat terrain	(x)		x				x	
Rolling terrain			x				x	
Land Use								
Built-up areas			x					
Agricultural zones	x		x			x		x
Forest and woods		x	x					
Context conditions								
Winter-Fall season		x	x					
Weekdays	x		x			x		
Daytime	x		x			x		
Socio-demographic								
Population density		x					x	
Users involved								
Pedestrian					x			
Cyclist					x			
HGV					x			
PTW					x			
Crash dynamics								
Single Vehicle crash					x			
Head-on or sideswipe					x			

↑ *indicates factors that increase the extent of the risk component;* ↓ *indicates factors that decrease the extent of the risk component.*

Entries in brackets (x) are referred to as crash frequency estimated with intermediate factors only

5.2.1. Road crash frequency and occurrence probability

Before discussing in depth each category of the intermediate-risk factors, it is worth underlining that, as expected, the risk exposure factor resulted strongly significant in the estimation of the road crash frequency of Table 19, as confirmed by previous research (*e.g.*, Wang et al., 2011; Pei et al., 2011; Anarkooli et al., 2019; Papadimitriou et al., 2019; Afghari et al., 2020). In addition, looking at the modelling results of crash frequency and crash occurrence probability, (see Table 19 and Table 22), for most of the intermediate factors consistent results were obtained. However, besides the number of additional significant factors for the crash occurrence, some differences were found, which will be discussed here below.

As for the intermediate road infrastructure outcome factors, according to Ma and Kockelman (2006), non-urban roads were found to increase the frequency (and occurrence probability) of crashes. Conversely, this result differs from the one of Afghari et al. (2020), where urban roads were found to positively affect road crashes. Indeed, urban roads are characterised by a high level of interference among the several road users' categories, especially vulnerable road users (Bonera and Maternini, 2020). However, this can be justified by the higher speeds that generally characterised non-urban roads, which may contribute to a greater number of crashes. Moreover, as shown in Table 13 and Table 17, most of the road network considered in this study is made by non-urban roads.

Unlike Ma and Kockelman (2006), one-lane roads were found to increase crash frequency (and occurrence probability), which was confirmed by *e.g.,* Wang et al (2011) and Afghari et al. (2020) instead. Similarly, undivided carriageways were associated with a higher number of crashes. Indeed, road without median is usually characterised by a one-lane two-way cross section. As a result, this may contribute to a greater share of head-on or sideswipe crashes, as no separation is provided among the two travel directions (Gomes et al., 2012b; Papadimitriou et al., 2019).

Segment were found to be prone crash-sites, compared to intersections. This represents a novel result as no previous study assessed the effect that segments have on crash frequency, with respect to intersections. Indeed, all previous studies just focused on one of the two types of road location, and specifically analysed the effect of the related design characteristics instead. The positive effect that road segments have on an increase of crash frequency may be explained, in this case, by a higher degree of safety that intersection may have in this road network. More precisely, according to MIT (2001), intersections over non-urban roads are generally are not at-grade, so that different flows are kept separated and their merging is better controlled. Moreover, over the last years, many roundabouts were built over the main road network of Brescia, so decreasing the number of conflict points that may lead to a higher share of crashes.

Another interesting yet counterintuitive result was the one related to the effect of paved surface on crash frequency (and occurrence probability). Indeed, this may be intended as unpaved roads are safer than paved roads. Conversely, as most of the roads are actually paved, this may be interpreted as a sign of lacking maintenance of road pavement conditions that may lead to unsafe conditions (Papadimitriou et al., 2019).

Likewise, the presence of both vertical and horizontal signs increased the number of crashes (and their occurrence probability). This may be intended as a counterintuitive finding. However, again, scares maintenance (*e.g.,* ruined of colour-faded signs) may prevent drivers from adequately seeing road signs; or even an abuse of road signs may lead drivers to pay less attention to the warnings that they are meant to give, and maintain less safe driving behaviour while travelling. This was also confirmed by Yasmin and Eluru (2019), who found that higher road sign density increased the crash frequency.

Surprisingly, road functional class resulted to have a controversial effect over crash frequency and occurrence probability. However, similar findings were also obtained by previous studies, where the same road class were found to oppositely affect crash frequency (*e.g.,* Yasmin and Eluru, 2018; Anarkooli et al., 2019; Papadimitriou et al., 2019; Stipancic et al., 2019).

Specifically, the road class was found to be a non-significant variable in the estimation of the crash frequency as a function of the exposure variable too. Conversely, road class was among the most significant variables in the estimation of crash frequency as an intermediate factor-only function. When estimating road crash occurrence probability, non-primary roads (*i.e.,* those classified as F or C according to MIT, 2001) were found to have almost 6 times higher probability to register crashes, which was also confirmed by *e.g.,* Yasmin and Eluru (2018) and Anarkooli et al. (2019). Indeed, compared to primary roads, non-primary roads may be affected by lacking design properties or low maintenance that can lead to higher likelihood for crash to occur.

Such conflicting results may be related to the fact that most Italian roads were built before the road technical regulation was released in 2001 (MIT, 2001). Consequently, most of the roads were classified according to road classes that did not fully comply with the expected infrastructural and functional features required. As a result, road assigned with a specific class may show characteristics that are not completely appropriate. However, when dealing with crash frequency (*i.e.,* crash counts over a period) it may be the case that a greater share of crash events are likely to be registered with greater traffic volumes (*i.e.,* primary roads), as the exposure factor increase. In addition, non-primary roads are generally managed by local authorities (*e.g.,* Province), which may not have sufficient resources to adjust infrastructural and functional features to the required standard for the road classes. Conversely, primary roads are generally managed by State authority and are subjected to ordinary maintenance to comply with the highest standard requirements (being also part of major TEN-T network).

As for the intermediate operational outcome factors, a quota of heavy good vehicles in the traffic flows ranging 15-30% over the total traffic volume contributed to higher number of crashes (and crash occurrence probability). This is a controversial result. Indeed, similar results were found in Pei et al. (2011) and Hosseinpour et al. (2014), where higher HGV traffic led to an increase in number of crashes. Conversely, Afghari et al. (2020) registered an opposite result. However, it may be possible that with a quite limited number of circulating HGV leads to less carefulness when driving as HGV generally represent a critical element to deal with.

As for the intermediate environment outcome factors, agricultural zones were found to positively affect crash frequency, while wood areas were found to negatively affect crash frequency. As for the former case, agricultural zones are generally related to wide and flat terrain, which may induce drivers to travel at higher speed. Conversely, as for the latter case, wood areas may be more appropriate in mountainous and rolling environment, which may induce drivers to pay more attention. Conversely, a land used characterised by forest and woods seemed to still increase the occurrence of crashes. However, compared to flat terrain, the odds were lower (8,7 and 4,2, respectively). In addition, also built-up areas were found to positively affect crash occurrence probability. Build-up areas are, indeed, characterised by greater traffic volumes and denser zone, which may contribute to the occurrence of interferences among road users.

As for the intermediate context outcome factors, dry road surface positively impacted crash frequency, by increasing the number of crashes. Indeed, a dry surface (which may be related to good weather condition, *e.g.,* no rain, or snow), may contribute to making drivers more confident and drive at higher speeds, as they perceive *e.g.,* no slip is possible.
Travelling by day and during weekdays increased the frequency (and occurrence probability) of crashes. It can be justified by considering that greater exposure (*i.e.,* traffic volumes) are generally registered in daytime and during weekdays, when systematic traffic flows represent the greater share on the main road network. Conversely, travelling during winter and/or fall season, seemed to reduce the frequency of crash occurred, while increasing the probability of a crash occurring.

As for the intermediate socio-economic outcome factors, the population density increased (*i.e.,* inhabitants per over km2 of area) the number of crashes decreased. This may be related to the fact that less densely populated areas are generally associated with rural areas, where speed limits are higher. This result contrasts the one of Yasmin and Eluru (2018), who found that higher household density led to higher crash frequency.

5.2.2. Road crash severity

As for the intermediate outcome factors related to the users involved, the model showed that when the most vulnerable road users (*i.e.,* pedestrians, cyclists, and powered two-wheelers) were involved in a road crash, more severe consequences were registered (the severity odds increased by 8.187, 1.917, and 4.230 times). Indeed, being such users' categories the ones with less protection at their disposal, they suffer more from road crash. In addition, also when HGV were involved in a crash, the severity odds increased by 3.455 times.

As for the intermediate crash dynamic outcome factors, head-on and single vehicle crash increased severity outcome. As for head-on crashes, that may be due to a hazardous manoeuvre that leads two vehicles one against the other, greater damage can result from the stronger hit between the two vehicles involved. As found by Wang et al. (2011), single vehicle crashes can result in more severe consequences as this specific type of crash dynamic may be due to the health condition of drivers, also according to.

As for the intermediate road infrastructure outcome factors, non-urban roads were found to increase the odds of severe outcomes, which confirmed the results in Afghari et al. (2020). Indeed, non-urban roads are characterised by higher speeds which may lead to greater damage and consequences in case of crash. The presence of both vertical and horizontal signs increased the severity of crashes. Again, this may be due to bad maintained road sings, which cannot be perceived anymore by road users. Indeed, as road signs are mainly aimed at alerting road users about road hazards and aware them towards careful driving behaviour, if no advice can be seen less protection is provided. In addition, two-lane two-way (*i.e.,* one way per direction) roads have higher odd to record more severe road crash, as also found by Hosseinpour et al (2014).

As for the intermediate context outcome factors, travelling by day and during weekdays reduced the odds of severe road crashes compared to night-time and festive days, respectively. Travelling by day may secure higher lighting and visibility, so that drivers can have greater control over the surrounding road environment. However, this contrasted with the result of Wang et al. (2011), who found that driving in darkness decrease the odds of severe crashes. This may be justified by the fact that, lower visibility at night (*i.e.,* dark), may reduce travel speed. Hence, lower speed means lower hit energy and so less damage. For what concerns safer driving at weekdays, this may still be related to time with greater traffic congestions (weekdays are working days) and lower speeds. Indeed, this was also confirmed by Wang et al. (2011) and Yasmin and Eluru (2018), who found that traffic peak and greater congestion reduced crash severity.

5.2.3. Road crash exposure

For what concerns road infrastructural factors, non-primary and one-lane roads showed a negative impact on the traffic volume estimation. Indeed, non-primary roads are generally characterised by lower traffic volumes compared to primary roads, due to their functional role (*e.g.,* primary roads have higher speed limits and generally connect major hub, so they may attract greater traffic volume for those long-distance trips). In addition, according to MIT (2001), road sections characterised by one-lane per direction are generally applied to minor roads. As this also affect road capacity, the lower the road lanes the lower the traffic that can circulate on that route. This was also confirmed by previous study that showed that the more the number of lanes, the greater the traffic volumes (Zhao and Chung, 2001; Yang et al., 2014; Shojaeshafiei et al., 2017).

As for the intermediate context outcome factors, further variables resulted significant. A novel and interesting result were the one of the impacts of flat and rolling terrain. More precisely, they both increased the traffic volumes. Presumably, flat and rolling terrain are associated with more regular vertical (but also horizontal) alignment, so that roads on such terrain type may be preferred by drivers. In addition, in the specific case of the network of Province of Brescia, most of major roads (*i.e.,* highways and B-class roads) are in the plain area of the Province, where the surrounding is mainly characterised by flat or slight rolling terrain. Agricultural areas were found to decrease traffic volumes, instead. This may be intuitively related to the low attractiveness of such areas, and the lack of major hub which may generate greater traffic volumes.

As for the intermediate socio-economic outcome factors, according to Zhao and Chung (2001) and Das and Tsapakis (2020), population density increased the AADT estimation. Again, this result may be quite intuitive as, the greater the population density, the more traffic attractive/generating the area is.

Finally, greater percentages of HGV over the total traffic volume increased the traffic itself. Higher presence of heavy vehicles on roads may be associated to great industrial or commercial areas. Hence, as also found by Pulughurtha and Mathew (2021), this may be related to the presence of traffic generating hubs so that greater AADT volume can be registered.

5.2.4. Definition of measures and interventions to mitigate road crash risk

The visualization of the significant variables in Table 32 may help in the definition of the most cost-effective interventions for the follow-up phase which is required after implementing the network-wide road safety assessment. Specifically, oriented to the most critical roads, here below some technical and operational measures are proposed, that may help in reaching a trade-off toward the overall road crash risk reduction. Please note that such measures are intended to provide proactive remedial according to R3 road crash risk formulation (*i.e.,* accounting for crash occurrence probability, severity, and exposure).

As for *road Infrastructure* features, ordinary and extra-ordinary maintenance may be suggested for non-urban roads. As for ordinary maintenance, yet paved, road with uneven or battered road surface may lead to a loss of control by the driver or still dangerous manoeuvres. Hence, keeping the road surface in good condition is key. In addition, a revision of the road signs, both vertical and horizontal, will help enhance the readability of the road. Less but clearer and more effective road signs should be installed only, while avoiding the abuse of too many indications, that may be also ignored by drivers. As for extra-ordinary maintenance, more invasive interventions can be proposed. For instance, if divided carriageway can help keeping separated the two travel directions and so the share of head-on or sideswipe crashes, median barriers can be introduced especially where higher level of traffic is registered, and the cross-section provides enough space. Indeed, as highlighted previously, most of the roads do not fully comply with the road technical regulation in force (MIT, 2001). Hence, for those most critical roads, it would be advisable to renovate the road cross-section according to the actual road class of those road so that greater safety standards can be guaranteed. In doing so, an increase in traffic volumes may be registered. Hence, keeping the travel direction separate is core.
For what concerns the interaction between different road users, it would be advisable to provide separated facilities on the roadside for the most vulnerable road users – VRUs (*e.g.,* cyclists). In this way, beside avoiding conflicts among motorised and non-motorised road users' categories, it would also help in preventing more severe crashes (*e.g.,* when a VRUs is involved).

Furthermore, to prevent single vehicle crashes, that may occur due to a hazardous manoeuvres or loss of control while driving, to reduce the severity of consequences, lower speed limits can be set, and speed control devices can be installed.
Overall, non-urban roads should be set according to the concept of the *forgiving road and roadside* and *self-explaining* road. In this way, road should be designed in a way that drivers immediately can understand which the most appropriate driving behaviour is to be held on the. However, in case of errors while driving, the road is set in a way it compensates for it.

As for *operational* features, the presence of heavy good vehicles turned to be a critical aspect. In that sense, it may be reasonable to first, equip roads with specific road signs to alert other road users about the presence of HGV. Otherwise, when possible, it may be advisable to impose HGV specific itinerary that may follow safer and more adapted routes.

As for *environment* and *land use* features, both flat and rolling terrain may contribute to a higher probability of crashes and higher traffic volumes. Indeed, flat surface (along with straight segments) may be related to higher speed and to preferable itineraries by road users, due to the ease of driving. Rolling surface may be related to an uneven vertical (but also horizontal) alignment of the road that may contribute to driving difficulties. Hence, greater traffic control measures should be adopted to limit the driving speed but also some modification in the road alignment (*e.g.,* traffic calming measures) may help in mitigating those effect.

As for *context conditions,* weekday and daytime travelling was found to positively increase crash probability, while reducing crash severity. However, over these time spans also greater traffic volumes may circulate on the road network. Hence, once again measures and intervention that can limit traffic conflicts, driving speeds and enhance road readability may help mitigate the road crash risk.

6. Conclusion

Although European roads are among the safest in the World, still the burden of road crashes remains too high. Hence, further efforts are required to achieve the road safety targets that have been set for the new decade. Heading to this goal, in 2018, the European Commission delivered the latest EU Strategic Action Plan for Road Safety, in which key strategies have been drawn to improve road safety according to a *Safe System* approach. Specifically focusing on road infrastructure, which contributes to a large part into road *unsafety,* the European Commission has recently updated the Road Infrastructure Safety Management (RISM) Directive, to provide the Member States with new tools to assess and manage road safety performances in a more effective way. Specifically, the new Directive introduced a risk-based network-wide mapping and safety ratings, which should replace the traditional (and reactive) *high accident concentration sites* identification in favour of a risk-based and proactive approach. However, no technical specification has been included in the updated RISM Directive, so that no definitive guidance is available for the implementation of such procedure which is required to the Member States by 2024.

Road network screening is the first step of the RISM process and represents the baseline for the upgrade required by the 1936/2019 Directive. However, looking thoroughly at the past literature on RNS, despite the many contributions provided valuable insights, they do not fully respond to the new RISM characteristics. Among the most relevant ones, one can include the following: the available road network segmentation methods are strongly dependent on accurate spatial road crash location (*e.g.,* spatial coordinates), which, however, are not always available. In addition, they may be not completely appropriate for a network-wide (*i.e.,* large scale) assessment. A well-structured and definitive formulation of *road crash risk* still misses from the literature. Indeed, just a handful of studies tried to formalise a risk-based analysis, which however did not account for all the three risk components (*i.e.,* crash occurrence, crash severity, crash exposure) as intended by the definition of risk. Finally, most used ranking methods rely on a fixed threshold, instead of a multi-level ranking scale.

This research aimed at covering the previous gaps, by proposing a new methodological approach for the implementation of a risk-based road network-wide safety screening, which returns an evaluation of an entire road network by means of a road crash risk prediction model and identifies the most critical site. More precisely, it expanded the state of the art by:

- Providing a replicable and flexible road segmentation to integrate raw crash-related data, without relying on spatial coordinates.
- Proposing a road crash risk prediction model able to return a quantitative and qualitative evaluation of all the three risk's components in a separate manner. Specifically, according to the original definition of risk, the crash occurrence has been addressed in terms of probability as opposed to frequency. Crash exposure was also estimated through a prediction model, to provide an effective and viable solution in case of traffic data unavailability.
- Introducing a five-level ranking scale based on the quartiles of the crash risk scores distribution, where the interquartile range (IQR) is unconventionally used to identify the most critical site of the network.
- Enabling a flexible and multi-scale network screening (e.g., regional, county, and local scale), based on the segmentation rationale.

To assess its applicability and effectiveness, the proposed methodology was tested over the main road network of the Province of Brescia (Lombardy Region - Italy), and it was compared to the alternative risk formulations retrieved in previous studies (*e.g.,* Barabino et al. 2020). Results highlighted the potential of the proposed methodology, as they allow the identification of critical segments (and roads) of the network that would have not been emphasized otherwise.

Indeed, considering occurrence probability helped in attributing higher relevance to those conditions that represent major hazard, regardless the number of crashes that may be registred. Conversely, when considering crash frequency, conditions that may lead to one, two, or more expected crashes are considered at different levels. As a result, roads that can register "even a single crash" are treated evenly to roads that, according to a frequency approach, can register a higher number of crashes. However, it may be reasonable to think that, given specific conditions, the greater the probability of crash occurrence, also the greater the number of crashes that can be registered.
Furthermore, recommendations were given about targeted interventions to mitigate both crash occurrence probability, severity, and control exposure.

Despite the interesting results, this study has some limitations. For what concerns modelling techniques, specifically referring to crash probability and severity models, different prediction structures such as rare-events logit structures (Theofilatos et al., 2016) may be tested compared to the ones of the most common logit models, to obtain more powerful prediction capabilities. In addition, it would be interesting to consider the different levels of the response variable in the probability computation, *i.e.,* to return the probability that *n number* of crashes will occur (*e.g.,* by mean of multivariate logit models). The same may be suggested also for severity estimation. However, for the specific case study, this was prevented by the road crash data collection method in force in Italy, which enables identifying just a binary outcome (*i.e.,* fatal or injured). To do so, it would be necessary to proceed with further integration of datasets to associate each crash with a precise level of severity (*e.g.,* in agreement with the MAIS 3+ classification).

Moreover, to further test the predictive capabilities, the application of the methodology over time or to other contexts may be useful. Indeed, this could help in strengthening the results obtained and specifically confirm the effect of the explanatory variables over the several response variables. In this case, to have a wide-enough dataset to develop and calibrate the model, all the data for the five-year period 2014-2018 were used. In addition, at the time this research was carried out, disaggregated road crash data for 2019 were still not available.

For what concerns explanatory variables it would be interesting to test additional risk factors to further improve the modelling prediction capabilities and assess their effects on crash risk components. The overall goal is – indeed – to provide high-performance predictive models that require a limited set of explanatory variables to be performed.
Finally, further research can be developed to identify potential clusters of *e.g.,* infrastructural, environmental, context conditions that distinctively identify a specific road crash risk level.

6.1. Summary of practical implications

Beside contributing to the state of the art of the road safety scientific field, the present research has a strong orientation towards the practical application. Indeed, the scope of the research was also to providing road safety authorities and practitioners with an effective decision support tool, which could help them in (i) identifying most critical roads, (ii) prioritising interventions, and (iii) defining the most appropriate measure to mitigate the effect of the road infrastructure unsafety. Therefore, this section aims at pinpointing the major practical opportunities and strengths of the work, to foster its application and replication among road safety professionals and practitioners.

First and foremost, it provides a valuable and operational response to the new requirements of the 1936/2019 EU RISM Directive and specifically to the new road network assessment and risk mapping procedures. Indeed, the Directive does not provide any technical specification on how to implement such new task, which are however mandatory for MS and are expected to be performed by 2024.

In doing so, the new methodological framework specifically responds to the need of a proactive approach and a risk-based analysis, as it provides a road infrastructure safety screening tool which is based on a *road crash risk prediction model.*

Specifically, the key drivers for the implementation of proposed risk-based network-wide road safety assessment framework are listed below.

- It provides a flexible, adaptable, and standardised network screening procedure that can easily be applied at all levels (*e.g.,* national, regional, local, etc.), to foster the replicability of the whole methodology to other context and make it less data intensive. More precisely, multiple scales of analysis can be returned, so that both the most critical roads of the entire network (macro-scale) and the most critical segments of such roads (mid-scale) can be identified.
- It relies on the most widespread data retrieved from official sources (*e.g.,* official statistics bodies, Governments, etc.). Indeed, the data required for the analysis purpose must be consistent and standardized for all the roads considered: too detailed information may not be available for all roads, nor their recognition may be feasible or possible. In doing so, the variables included in the model are a restrained yet significant set of information.
- It proposes an alternative segmentation process free of crash coordinates, which enables the association of road crash with the related road network site by mean of census and road name information (which are always available). Indeed*,* spatial coordinates are not always available or correctly recorded. As a result, if the process adopts crash coordinates as a driver for the association, it may lead to a loss in crash information.
- The crash risk prediction model is a combination of three prediction models, one for each of the risk components. Specifically, they estimate the probability of a crash to occur, its severity level and the exposure factor for each road section, based on the previously mentioned set of few yet significant variables. Thanks to its structure, the model enables to compute and control each risk component separately and independently from the other, so that targeted measures

can be better identified. In addition, the model structure selected (*i.e.,* binomial logit and multiple linear regression) are among the easiest to implement and interpret.

- In addition, this also makes it possible to assess crash risk in the road infrastructure planning stage, in other words, to assess the expected impact that a new (or restored) road may show, based on its characteristics.
- The ranking of the road network is based on a flexible and dynamic five-levels scale, that can be easily adapted to each context and allows the association of each road section with a specific level of road safety performance, based on the related road crash risk value.

List of references

1. American Association of State Highway and Transportation Officials - AASHTO, (2010). Highway Safety Manual, First Ediction. Washington DC.
2. American Association of State Highway and Transportation Officials - AASHTO, (2014). Highway Safety Manual, Second Ediction. Washington DC.
3. Afghari, A.P., Haque, M.M., Washington, S., (2020). Applying a joint model of crash count and crash severity to identify road segments with high risk of fatal and serious injury crashes. Accident Analysis & Prevention, 144, 105615. doi:10.1016/j.aap.2020.105615
4. Aguero-Valverde, J., Jovanis, P.P., (2009). Bayesian multivariate Poisson lognormal models for crash severity modeling and site ranking. Transportation Research Record, 2136, pp. 82–91. doi:10.3141/2136-10
5. Alonso, B., Moura, J.L., Ibeas, A., Romero, J.P., (2015). Estimation of annual average daily traffic with optimal adjustment factors. Proceedings of the Institution of Civil Engineers-Transport, 168(5), pp. 406-414. doi:10.1680/TRAN.12.00074
6. Ambros, J., Jurewicz, C., Turner, S., Kieć, M., (2018). An international review of challenges and opportunities in development and use of crash prediction models. European Transport Research Review, 10(2), pp. 1-10. doi:10.1186/s12544-018-0307-7
7. Ambros, J., Sedoník, J., (2017). How to simplify road network safety screening: Two case studies. Advances in Transportation Studies, 44
8. Anarkooli, A.J., Persaud, B., Hosseinpour, M., Saleem, T., (2019). Comparison of univariate and two-stage approaches for estimating crash frequency by severity—Case study for horizontal curves on two-lane rural roads. Accident Analysis & Prevention, 129, pp. 382–389. doi:10.1016/j.aap.2018.08.015
9. Anastasopoulos, P.C., Mannering, F.L., (2011). An empirical assessment of fixed and random parameter logit models using crash- and non-crash-specific injury data. Accident Analysis & Prevention. 43(3), pp. 1140–1147. doi:10.1016/j.aap.2010.12.024
10. Apronti, D., Ksaibati, K., Gerow, K., Hepner, J.J., (2016). Estimating traffic volume on Wyoming low volume roads using linear and logistic regression methods. Journal of traffic and transportation engineering (English Ed.), 3(6), pp. 493-506. doi:10.1016/j.jtte.2016.02.004

11. Aven, T. (2010). On how to define, understand and describe risk. Reliability Engineering & System Safety, 95 (6), pp. 623–631. doi:10.1016/j.ress.2010.01.011
12. Aven, T. (2012). The risk concept-historical and recent development trends. Reliability Engineering & System Safety, 99, pp. 33-44. doi:10.1016/j.ress.2011.11.006
13. Barabino, B., Bonera, M., Maternini, G., Olivo, A., Porcu, F., (2021). Bus crash risk evaluation: An adjusted framework and its application in a real network. Accident Analysis & Prevention, 159, 106258. doi:10.1016/j.aap.2021.106258
14. Bhowmik, T., Yasmin, S., Eluru, N., (2018). A joint econometric approach for modelling crash counts by collision type. Analytic Methods in Accident Research, 19, pp. 16-32. doi:10.1016/j.amar.2018.06.001
15. Bonera, M., Barabino, B., Maternini, G., (in press). Road network safety screening of county-wide road network. The case of the Province of Brescia (Northern – Italy). Advances in Road Infrastructure and Mobility Proceedings of the 18th International Road Federation World Meeting & Exhibition, Dubai 2021. Springer.
16. Bonera, M., Maternini, G., (2020). Methodology for the application of predictive method for road safety analysis in urban areas. the case study of Brescia. Transportation Research Procedia, pp. 659–667. doi:10.1016/j.trpro.2020.03.044
17. Borghetti, F., 2019. Rischio e sicurezza nei sistemi di trasporto, in: Malavasi, G. (a cura di), Sicurezza Dei Trasporti. Teoria e Gestione. EGAF Srl, Forlì, pp. 23–66.
18. Borghetti, F., Marchionni, G., De Bianchi, M., Barabino, B., Bonera, M., Caballini, C., (2021). A new methodology for accidents analysis: The case of the state road 36 in Italy. International journal of transport development and integration, 5(3), pp. 278-290. doi:10.2495/TDI-V5-N3-278-290
19. Boroujerdian, A.M., Saffarzadeh, M., Yousefi, H., Ghassemian, H., (2014). A model to identify high crash road segments with the dynamic segmentation method. Accident Analysis & Prevention. 73, 274–287. doi:10.1016/j.aap.2014.09.014
20. Castro-Neto, M., Jeong, Y., Jeong, M.K., Han, L.D., (2009). AADT prediction using support vector regression with data-dependent parameters. Expert Systems with Applications, 36(2), pp. 2979-2986. doi:10.1016/j.eswa.2008.01.073
21. Crichton, D., 1999. The risk triangle. Natural Disaster Management. Tudor Rose, London. pp. 102–103.
22. Danish Road Traffic Accident Investigation Board - AIB, (2014). Why do road traffic accidents happen?

23. Das, S., Tsapakis, I., (2020). Interpretable machine learning approach in estimating traffic volume on low-volume roadways. International journal of transportation science and technology, 9(1), 76-88.. doi:10.1016/j.ijtst.2019.09.004
24. Dell'Acqua, G., De Luca, M., Mauro, R., (2011). Road safety knowledge-based decision support system, in: Procedia - Social and Behavioural Sciences. pp. 973–983. doi:10.1016/j.sbspro.2011.08.106
25. Leur, P. D., & Sayed, T. (2002). Development of a road safety risk index. Transportation Research Record, 1784(1), 33-42.
26. El-Basyouny, K., Sayed, T., (2009). Collision prediction models using multivariate Poisson-lognormal regression. Accident Analysis & Prevention, 41(4), pp. 820–828. doi:10.1016/j.aap.2009.04.005
27. Elvik, R., (2007). State-of-the-art approaches to road accident black spot management and safety analysis of road networks. Transport Økonomisk Institutt (TØI) Report.
28. Elvik, R., (2010). Assessment and applicability of road safety management evaluation tools: Current practice and state-of-the-art in Europe. Transport Økonomisk Institutt (TØI) Report.
29. Elvik, R., (2011). Assessing causality in multivariate accident models. Accident Analysis & Prevention, 43(1), pp. 253–264. doi:10.1016/j.aap.2010.08.018
30. Elvik, R., Vaa, T., Hoye, A., Sorensen, M., (2009). The handbook of Road Safety Measures, Elsevier Science. Emerald Group Publishing, Burlington, MA.
31. Elyasi, M.R., Saffarzade, M., Boroujerdian, A.M., (2016). A novel dynamic segmentation model for identification and prioritization of black spots based on the pattern of potential for safety improvement. Transportation Research Part A: Policy and Practice, 91, pp. 346-357, doi:10.1016/j.tra.2016.06.020
32. European Commission, (1992). Treaty of Maastricht. Official Journal of the European Union and Commission.
33. European Commission, (2003). EC Regulation 1059/2003 of the European Parliament and of the Council on the establishment of a common classification of territorial units for statistics (NUTS).
34. European Commission, (2008). Directive 2008/96/EC of the European Parliament and of the Council on Road Infrastructure Safety Management.
35. European Commission, (2019). EU Road Safety Policy Framework 2021-2030 - Next steps towards "Vision Zero,"
36. European Commission, (2019). Directive 2019/1936 of the European Parliament and of the Council amending Directive 2008/96/EC on Road Infrastructure Safety Management.

37. European Commission, (2021). Road safety press release. 20 April 2021, European commission website.
38. European Road Assessment Program - EuroRAP, (2020). Crash Risk Mapping: Technical Specification.
39. European Transport Safety Council - ETSC, (2018a). Joint Statement on Revision of the Road Infrastructure Safety Management Directive 2008/96
40. European Transport Safety Council - ETSC, (2018b). Briefing EU Strategic Action Plan on Road Safety.
41. European Transport Safety Council - ETSC, (2020). PIN briefing. The impact of covid-19 lockdowns on road deaths in April 2020.
42. European Union (2017). Valletta Declaration on Road Safety.
43. Faccin, C., Zavanella, L., Savoldi, E., Boroni, A., Rossini, P., (2011). Piano del traffico della viabilitá extraurbana (PTVE).
44. Fan, Z., Liu, C., Cai, D., Yue, S., (2019). Research on black spot identification of safety in urban traffic accidents based on machine learning method. Safety Science, 118, pp. 607–616. doi:10.1016/j.ssci.2019.05.039
45. Fancello, G., Carta, M., Fadda, P., (2015). A decision support system for road safety analysis. Transportation Research Procedia., pp. 201–210. doi:10.1016/j.trpro.2015.01.009
46. Fancello, G., Carta, M., Serra, P., (2020). Data Envelopment Analysis for the assessment of road safety in urban road networks: A comparative study using CCR and BCC models. Case Studies on Transport Policy, 8(3), pp. 736-744. doi:10.1016/j.cstp.2020.07.007
47. Fawcett, L., Thorpe, N., Matthews, J., Kremer, K., (2017). A novel Bayesian hierarchical model for road safety hotspot prediction. Accident Analysis & Prevention, 99, pp. 262–271. doi:10.1016/j.aap.2016.11.021
48. Fine, W.T. (1971). Mathematical evaluation for controlling hazards. Journal of Safety Research. 3 (4), pp. 157–166.
49. Fu, M., Kelly, J.A., Clinch, J.P., (2017). Estimating annual average daily traffic and transport emissions for a national road network: A bottom-up methodology for both nationally-aggregated and spatially-disaggregated results. Journal of Transport Geography, 58, pp. 186-195. doi:10.1016/j.jtrangeo.2016.12.002
50. Geedipally, S.R., Patil, S., Lord, D., (2010). Examination of Methods to Estimate Crash Counts by Collision Type. Transportation Research Record, 2165(1), pp. 12-20. doi:10.3141/2165-02

51. Ghadi, M., Török, Á., (2019). A comparative analysis of black spot identification methods and road accident segmentation methods. Accident Analysis & Prevention, 128, 1–7. doi:10.1016/j.aap.2019.03.002
52. Gomes, S. V., Geedipally, S. R., Lord, D. (2012a). Estimating the safety performance of urban intersections in Lisbon, Portugal. Safety science, 50(9), pp. 1732-1739
53. Gomes, S. V., Cardoso, J. L. (2012b). Safety effects of low-cost engineering measures. An observational study in a Portuguese multilane road. Accident Analysis & Prevention, 48, pp. 346-352.
54. Gomes, S.V., Cardoso, J.L., Azevedo, C.L., (2018). Portuguese mainland road network safety performance indicator. Case Studies in Transport Policy, 6(3), pp. 416–422. doi:10.1016/j.cstp.2017.10.006
55. Greibe, P., (2003). Accident prediction models for urban roads. Accident Analysis & Prevention, 35(2), pp. 273–285, doi:10.1016/S0001-4575(02)00005-2
56. Guarascio, M., Lombardi, M., Rossi, G., (2019). Metodi di analisi del rischio, in: Malavasi, G. (a cura di), *Sicurezza Dei Trasporti. Teoria e Gestione*. EGAF Srl, Forlì, pp. 73–88.
57. Gupta, A., Bansal, A., (2018). Integrating Traffic Datasets for Evaluating Road Networks, in: Proceedings - 12th IEEE International Conference on Semantic Computing, ICSC 2018. Institute of Electrical and Electronics Engineers Inc., pp. 411–416. doi:10.1109/ICSC.2018.00081
58. Hakkert, S., Braimaister, L. (2002). The uses of exposure and risk in road safety studies. SWOV Institute for Road Safety, Vol. 12/2002.
59. Harwood, D.W., Bauer, K.M., Potts, I.B., Torbic, D.J., Richard, K.R., Rabbani, E.R., Hauer, E., Elefteriadou, L., (2002). Safety effectiveness of intersection left- and right-turn lanes. (No. FHWA-RD-02-089). United States. Federal Highway Administration. Office of Safety Research and Development. Washington DC.
60. Hauer, E. (1982). Traffic conflict and exposure. Accident Analysis & Prevention, 14(5), pp. 359-364.
61. Hauer, E., (2004). Statistical road safety modeling. Transportation Research Records. 1897, pp. 81–87. doi:10.3141/1897-11
62. Hauer, E., Kononov, J., Allery, B., Griffith, M.S., 2002. Screening the road network for sites with promise, in: Transportation Research Record. National Research Council, pp. 27–32. doi:10.3141/1784-04
63. Hosseinpour, M., Sahebi, S., Zamzuri, Z.H., Yahaya, A.S., Ismail, N., (2018). Predicting crash frequency for multi-vehicle collision types using multivariate Poisson-lognormal spatial model:

A comparative analysis. Accident Analysis & Prevention, 118, pp. 277–288. doi:10.1016/j.aap.2018.05.003

64. Hosseinpour, M., Yahaya, A.S., Sadullah, A.F., (2014). Exploring the effects of roadway characteristics on the frequency and severity of head-on crashes: Case studies from Malaysian Federal Roads. Accid. Accident Analysis & Prevention, 62, pp. 209–222. doi:10.1016/j.aap.2013.10.001
65. Imprialou, M., Quddus, M., (2019). Crash data quality for road safety research: Current state and future directions. Accident Analysis & Prevention. 130, pp. 84–90. doi:10.1016/j.aap.2017.02.022
66. International Organization for Standardization – ISO (2018). ISO 31000:2018 - Risk Management Guidelines.
67. International Organization for Standardization – ISO (2012). ISO 39001:2012 - Road traffic safety (RST) management system. Requirements with guidance for use.
68. ISTAT, (2021). Rilevazione degli incidenti stradali con lesioni a persone – Anno 2021.
69. Jiang, X., Abdel-Aty, M., Alamili, S., (2014). Application of Poisson random effect models for highway network screening. Accident Analysis & Prevention, 63, pp. 74–82. doi:10.1016/j.aap.2013.10.029
70. Jovanis, P.P., Chang, H.L., (1986). Modeling the Relationship of Accidents To Miles Traveled. Transportation Research Record, 42–51.
71. Khan, S.M., Islam, S., Khan, M.Z., Dey, K., Chowdhury, M., Huynh, N., Torkjazi, M., (2018). Development of Statewide Annual Average Daily Traffic Estimation Model from Short-Term Counts: A Comparative Study for South Carolina. Transportation Research Record 2672(43), pp. 55–64. doi:10.1177/0361198118798979
72. King, G., Zeng, L., (2003). Logistic regression in rare events data. Journal of Statistical Software, 8, pp. 137–163. doi:10.18637/jss.v008.i02
73. Kwon, O.H., Park, M.J., Yeo, H., Chung, K., (2013). Evaluating the performance of network screening methods for detecting high collision concentration locations on highways. Accident Analysis & Prevention, 51, pp. 141–149. doi:10.1016/j.aap.2012.10.019
74. La Torre, F., Domenichini, L., Meocci, M., Graham, D., Karathodorou, N., Richter, T., Ruhl, S., Yannis, G., Dragomanovits, A., Laiou, A., (2016). Development of a Transnational Accident Prediction Model. Transportation Research Procedia, pp. 1772–1781. doi:10.1016/j.trpro.2016.05.143

75. La Torre, F., Tanzi, N., Yannis, G., Dragomanovits, A., Richter, T., Ruhl, S., ... & Graham, D. (2018). Accident prediction in European countries–development of a practical evaluation tool. 7th Transport Research Arena, Vienna.
76. Larsson, P., and Tingvall, C. (2013). The safe system approach–A road safety strategy based on human factors Principles. In International Conference on Engineering Psychology and Cognitive Ergonomics (pp. 19-28).
77. Lord, D. (2002). Application of accident prediction models for computation of accident risk on transportation networks. Transportation Research Record, 1784(1), 17-26.
78. Lord, D., Mannering, F., (2010). The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. Transportation research part A: policy and practice, 44(5), pp.291-305. doi:10.1016/j.tra.2010.02.001
79. Ma, J., Kockelman, K.M., (2006). Poisson Regression for Models of Injury Count, by Severity. Transportation Research Record. Journal of the Transportation Research Board, 1950, pp. 24–34.
80. Ma, J., Kockelman, K.M., Damien, P., (2008). A multivariate Poisson-lognormal regression model for prediction of crash counts by severity, using Bayesian methods. Accident Analysis & Prevention, 40(3), pp. 964–975. doi:10.1016/j.aap.2007.11.002
81. Mamčic, S., Sivilevičius, H. (2013). The analysis of traffic accidents on Lithuanian regional gravel roads. Transport, 28(1), pp. 108-115.
82. Mannering, F., Bhat, C.R., Shankar, V., Abdel-Aty, M., (2020). Big data, traditional data and the tradeoffs between prediction and causality in highway-safety analysis. Analytic methods in accident research, 25, 100113. doi:10.1016/j.amar.2020.100113
83. Mannering, F.L., Bhat, C.R., (2014). Analytic methods in accident research: Methodological frontier and future directions. Analytic methods in accident research, 1, pp. 1-22. doi:10.1016/j.amar.2013.09.001
84. Milton, J.C., Shankar, V.N., Mannering, F.L., (2008). Highway accident severities and the mixed logit model: An exploratory empirical analysis. Accident Analysis & Prevention, 40(1), pp. 260–266. doi:10.1016/j.aap.2007.06.006
85. Miranda-Moreno, L.F., Fu, L., Ukkusuri, S., Lord, D., (2009). How to incorporate accident severity and vehicle occupancy into the hot spot identification process? Transportation Research Record. Journal of the Transportation Research Board, 2102, pp. 53–60. doi:10.3141/2102-07
86. Ministero delle Infrastrutture e dei Trasporti - MIT, (2001). DM 5 novembre 2001. Norme Funzionali E Geometriche Per La Costruzione Delle Strade.

87. Ministero delle Infrastrutture e dei Trasporti - MIT, (2012). Linee guida per la gestione della sicurezza del- le infrastrutture stradali ai sensi dell'articolo 8 del decreto legislativo 15 marzo 2011, n. 35.
88. Montella, A., (2010). A comparative analysis of hotspot identification methods. Accident Analysis & Prevention, 42(2), pp. 571–581. doi:10.1016/j.aap.2009.09.025
89. Montella, A., Chiaradonna, S., Criscuolo, G., De Martino, S., (2019). Development and evaluation of a web-based software for crash data collection, processing and analysis. Accident Analysis & Prevention. 130, pp. 108–116. doi:10.1016/j.aap.2017.01.013
90. O'Neill, M., (2010). Regression & Generalized Linear (Mixed) Models.
91. Papadimitriou, E., Filtness, A., Theofilatos, A., Ziakopoulos, A., Quigley, C., & Yannis, G. (2019). Review and ranking of crash risk factors related to the road infrastructure. Accident Analysis & Prevention, 125, pp. 85-97.
92. Park, E.S., Lord, D., (2007). Multivariate Poisson-lognormal models for jointly modelling crash frequency by severity. Transportation Research Record. Journal of the Transportation Research Board, 2019, pp. 1–6. doi:10.3141/2019-01
93. Park, P.Y., Sahaji, R., 2013. Safety network screening for municipalities with incomplete traffic volume data. Accident Analysis & Prevention, 50, pp. 1062–1072. doi:10.1016/j.aap.2012.08.012
94. Pei, X., Wong, S.C., Sze, N.N., 2011. A joint-probability approach to crash prediction models. Accident Analysis & Prevention, 43(3), pp. 1160–1166. doi:10.1016/j.aap.2010.12.026
95. Persaud, B., Lan, B., Lyon, C., Bhim, R., (2010). Comparison of empirical Bayes and full Bayes approaches for before-after road safety evaluations. Accident Analysis & Prevention, 42(1), pp. 38–43. doi:10.1016/j.aap.2009.06.028
96. Persia, L., Usami, D.S., De Simone, F., Beaumelle, V.F.D. La, Yannis, G., Laiou, A., Han, S., Machata, K., Pennisi, L., Marchesini, P., Salathè, M., (2016). Management of Road Infrastructure Safety. Transportation Research Procedia 14, pp. 3436–3445. doi:10.1016/j.trpro.2016.05.303
97. Persia, L., Gigli, R., Azarko, A., & Usami, D. S. (2020). Accident data analysis and on-field inspections: do they lead to similar conclusions?. Transportation research procedia, 45, pp. 266-274.
98. Polis-Lombardia, (2020). L'incidentalità sulle strade della Lombardia nel 2019.
99. Pulugurtha, S.S., Mathew, S., (2021). Modeling AADT on local functionally classified roads using land use, road density, and nearest nonlocal road data. Journal of Transport Geography, 93. doi:10.1016/j.jtrangeo.2021.103071

100. Pun, L., Zhao, P., Liu, X., (2019). A Multiple Regression Approach for Traffic Flow Estimation. IEEE Access, 7, 35998–36009. doi:10.1109/ACCESS.2019.2904645
101. Regev, S., Rolison, J.J., Moutari, S., (2018). Crash risk by driver age, gender, and time of day using a new exposure methodology. Journal of Safety Research, 66, pp. 131–140. doi:10.1016/j.jsr.2018.07.002
102. Regione Lombardia, (2016). Programma Regionale Mobilità e Trasporti.
103. Rumar, K. (1999). Road safety and benchmarking. Proceedings of the Paris Conference on Transport Benchmarking. November 1999, Paris, France.
104. Savolainen, P.T., Mannering, F.L., Lord, D., Quddus, M.A., (2011). The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives. Accident Analysis & Prevention. 43(5), pp. 1666–1676. doi:10.1016/j.aap.2011.03.025
105. Schlögl, M., Stütz, R., (2019). Methodological considerations with data uncertainty in road safety analysis. Accident Analysis & Prevention, 130, pp. 136–150. doi:10.1016/j.aap.2017.02.001
106. SETRA. (2006). Démarche SURE - Étude d'enjeux de sécurité routière pour la hiérarchisation des itinéraires
107. Sfyridis, A., Agnolucci, P., (2020). Annual average daily traffic estimation in England and Wales: An application of clustering and regression modelling. Journal of Transport Geography, 83. doi:10.1016/j.jtrangeo.2020.102658
108. Shojaeshafiei, M., Doustmohammadi, M., Subedi, S., Anderson, M., (2017). Comparison of Estimation Methodologies for Daily Traffic Count Prediction in Small and Medium Sized Communities. International Journal of Traffic and Transportation Engineering, 6(4), pp. 71-75 doi:10.5923/j.ijtte.20170604.01
109. Stipancic, J., Miranda-Moreno, L., Saunier, N., Labbe, A., (2018). Surrogate safety and network screening: Modelling crash frequency using GPS travel data and latent Gaussian Spatial Models. Accident Analysis & Prevention, 120, pp. 174–187. doi:10.1016/j.aap.2018.07.013
110. Stipancic, J., Miranda-Moreno, L., Saunier, N., Labbe, A., (2019). Network screening for large urban road networks: Using GPS data and surrogate measures to model crash frequency and severity. Accident Analysis & Prevention, 125, pp. 290–301. doi:10.1016/j.aap.2019.02.016
111. Tarko, A.P., Azam, S., (2009). Safety screening of road networks with limited exposure data. Transportation Research Record, 2102, pp. 18–26. doi:10.3141/2102-03

112. Thakali, L., Kwon, T.J., Fu, L., (2015). Identification of crash hotspots using kernel density estimation and kriging methods: a comparison. Journal of Modern Transportation, 23(2), pp. 93-106. doi:10.1007/s40534-015-0068-0

113. Theofilatos, A., Yannis, G., Kopelias, P., Papadimitriou, F., (2016). Predicting Road Accidents: A Rare-events Modeling Approach. Transportation Research Procedia, 14 April , 3399–3405. doi:10.1016/j.trpro.2016.05.293

114. United Nations Office for Disaster Risk Reduction – UNDRR (1999). Available at: https://www.undrr.org/terminology

115. Vieira Gomes, S., Cardoso, J. L., and Azevedo, C. L. (2018). Portuguese mainland road network safety performance indicator. Case Studies on Transport Policy, 6(3), pp. 416-422.

116. Vieira Gomes, S., Geedipally, S.R., Lord, D., 2012. Estimating the safety performance of urban intersections in Lisbon, Portugal. Safety Science, 50(9), pp. 1732–1739. doi:10.1016/j.ssci.2012.03.022

117. Wang, C., Quddus, M.A., Ison, S.G., (2011). Predicting accident frequency at their severity levels and its application in site ranking using a two-stage mixed multivariate model. Accident Analysis & Prevention, 43(6), pp. 1979–1990. doi:10.1016/j.aap.2011.05.016

118. Wang, K., Bhowmik, T., Zhao, S., Eluru, N., Jackson, E., (2021). Highway safety assessment and improvement through crash prediction by injury severity and vehicle damage using Multivariate Poisson-Lognormal model and Joint Negative Binomial-Generalized Ordered Probit Fractional Split model. Journal of Safety Research, 76, pp. 44–55. doi:10.1016/j.jsr.2020.11.005

119. Wang, K., Ivan, J.N., Ravishanker, N., Jackson, E., (2017). Multivariate poisson lognormal modeling of crashes by type and severity on rural two lane highways. Accident Analysis & Prevention, 99, pp. 6–19. doi:10.1016/j.aap.2016.11.006

120. Wegman, F. C., & Aarts, L. T. (2006). Advancing sustainable safety: National Road Safety Outlook for 2005-2020.

121. World Health Organization – WHO (2018). Global status report on road safety 2018. Available at: https://www.who.int/publications/i/item/9789241565684

122. Wijnen, W., Weijermars, W., Schoeters, A., van den Berghe, W., Bauer, R., Carnis, L., Elvik, R., Martensen, H., (2019). An analysis of official road crash cost estimates in European countries. Safety Science, 113, pp. 318–327. doi:10.1016/j.ssci.2018.12.004

123. Xie, K., Ozbay, K., Yang, H., (2019). A multivariate spatial approach to model crash counts by injury severity. Accident Analysis & Prevention, 122, pp. 189–198. doi:10.1016/j.aap.2018.10.009

124. Yang, B., Wang, S.G., Bao, Y., (2014). New efficient regression method for local AADT estimation via SCAD variable selection. IEEE Transactions on Intelligent Transportation Systems, 15(6), pp. 2726-2731. doi:10.1109/TITS.2014.2318039

125. Yannis, G., Papadimitriou, E., Lejeune, P., Bijleveld, F., & Cardoso, J. L. (2008). Risk exposure data availability, collection methodologies and use in the EU. In Proceedings of the Transport Research Arena Conference, Ljubljana.

126. Yannis, G., Dragomanovits, A., Laiou, A., Richter, T., Ruhl, S., La Torre, F., Domenichini, L., Graham, D., Karathodorou, N., Li, H., (2016). Use of Accident Prediction Models in Road Safety Management - An International Inquiry. Transportation Research Procedia. doi:10.1016/j.trpro.2016.05.397

127. Yannis, G., Weijermars, W., Gitelman, V., Vis, M., Chaziris, A., Papadimitriou, E., Azevedo, C.L., (2013). Road safety performance indicators for the interurban road network. Accident Analysis & Prevention, 60, pp. 384–395. doi:10.1016/j.aap.2012.11.012

128. Yasmin, S., Eluru, N., (2018). A joint econometric framework for modelling crash counts by severity. Transportmetrica A: transport science, 14(3), pp. 230-255. doi:10.1080/23249935.2017.1369469

129. Ye, X., Pendyala, R.M., Washington, S.P., Konduri, K., Oh, J., (2009). A simultaneous equations model of crash frequency by collision type for rural intersections. Safety Science, 47(3), pp. 443–452. doi:10.1016/J.SSCI.2008.06.007

130. Zeng, Q., Wen, H., Huang, H., Pei, X., Wong, S.C., (2017). A multivariate random-parameters Tobit model for analyzing highway crash rates by injury severity. Accident Analysis & Prevention, 99, pp. 184–191. doi:10.1016/j.aap.2016.11.018

131. Zhao, F., Chung, S., (2001). Contributing Factors of Annual Average Daily Traffic in a Florida County. Transportation Research Record. Journal of the Transportation Research Board, 1769 01, pp. 113–122.

List of Figures

List of Tables

7.Appendix

7.1. Ranking of the main road network of the Province of Brescia – R1

R1	**Path** *(Provincial level)*	**Minimum path** *(Municipality level)*	**R1** *(Municipality level)*		**F**	**S**
5	BSSPEXSS11V1	BSSPEXSS11V1_17014	4	0,62546	19,80402	0,03158
5	BSSPEXSS11V1	BSSPEXSS11V1_17029	5	1,67763	187,55397	0,00894
5	BSSPEXSS11V1	BSSPEXSS11V1_17032	3	0,22409	18,23331	0,01229
5	BSSPEXSS11V1	BSSPEXSS11V1_17040	2	0,12759	6,72625	0,01897
5	BSSPEXSS11V1	BSSPEXSS11V1_17067	2	0,12245	2,52291	0,04854
5	BSSPEXSS11V1	BSSPEXSS11V1_17092	4	0,97429	22,27664	0,04374
5	BSSPEXSS11V1	BSSPEXSS11V1_17107	4	0,54544	27,69604	0,01969
5	BSSPEXSS11V1	BSSPEXSS11V1_17161	5	2,33056	103,95870	0,02242
5	BSSPEXSS11V1	BSSPEXSS11V1_17165	5	1,34953	86,22545	0,01565
5	BSSPEXSS573	BSSPEXSS573_17056	3	0,33968	20,04630	0,01694
5	BSSPEXSS573	BSSPEXSS573_17059	4	0,90071	45,75211	0,01969
5	BSSPEXSS573	BSSPEXSS573_17133	5	1,18022	38,81064	0,03041
5	BSSPEXSS236	BSSPEXSS236_17039	1	0,03776	1,17584	0,03211
5	BSSPEXSS236	BSSPEXSS236_17043	5	1,14519	42,20441	0,02713
5	BSSPEXSS236	BSSPEXSS236_17113	5	3,98551	104,72354	0,03806
5	A4	A4_17002	4	0,75726	28,70959	0,02638
5	A4	A4_17029	4	0,60145	80,33811	0,00749
5	A4	A4_17032	5	1,66194	64,34541	0,02583
5	A4	A4_17040	4	0,63718	34,77038	0,01833
5	A4	A4_17043	5	2,46760	52,84794	0,04669
5	A4	A4_17046	5	2,21126	66,82448	0,03309
5	A4	A4_17067	5	2,47635	105,80925	0,02340
5	A4	A4_17069	5	2,42826	74,55627	0,03257
5	A4	A4_17092	5	2,55104	63,98598	0,03987
5	A4	A4_17107	3	0,33504	25,29356	0,01325
5	A4	A4_17127	3	0,21423	29,70813	0,00721
5	A4	A4_17133	5	1,56784	76,80157	0,02041
5	A4	A4_17136	5	1,21486	43,02837	0,02823
5	A4	A4_17151	3	0,33245	15,58802	0,02133
5	A4	A4_17161	5	1,23684	51,13510	0,02419
5	A4	A4_17165	4	0,72024	45,27171	0,01591
5	A4	A4_17166	4	0,49181	27,93176	0,01761
5	TANGOVEST	TANGOVEST_17029	5	4,15035	261,93787	0,01584
5	TANGOVEST	TANGOVEST_17042	2	0,04502	5,39877	0,01668
5	A21	A21_17004	2	0,18346	4,87665	0,03762
5	A21	A21_17009	5	1,84762	59,60154	0,03100
5	A21	A21_17013	2	0,15558	14,55094	0,01069
5	A21	A21_17021	3	0,43303	17,62071	0,02457
5	A21	A21_17029	2	0,19380	25,56170	0,00758
5	A21	A21_17088	4	0,69424	23,49841	0,02954
5	A21	A21_17103	5	1,76818	64,82569	0,02728
5	A21	A21_17114	3	0,41810	17,70149	0,02362
5	A21	A21_17147	4	0,58268	14,11992	0,04127

5	A21	A21_17149	5	1,52917	41,98356	0,03642
5	A21	A21_17172	4	0,84754	30,30315	0,02797
5	A21	A21_17173	4	0,76953	31,16439	0,02469
4	BSSPEXSS237	BSSPEXSS237_17005	4	0,54609	12,34093	0,04425
4	BSSPEXSS237	BSSPEXSS237_17010	1	0,00949	0,87700	0,01082
4	BSSPEXSS237	BSSPEXSS237_17012	4	0,68625	18,09347	0,03793
4	BSSPEXSS237	BSSPEXSS237_17025	2	0,13697	8,78794	0,01559
4	BSSPEXSS237	BSSPEXSS237_17031	3	0,31775	14,13983	0,02247
4	BSSPEXSS237	BSSPEXSS237_17082	3	0,42560	12,02910	0,03538
4	BSSPEXSS237	BSSPEXSS237_17087	3	0,23159	8,50796	0,02722
4	BSSPEXSS237	BSSPEXSS237_17117	4	0,53770	34,66685	0,01551
4	BSSPEXSS237	BSSPEXSS237_17121	2	0,16397	5,61195	0,02922
4	BSSPEXSS237	BSSPEXSS237_17153	1	0,04668	0,99125	0,04710
4	BSSPEXSS237	BSSPEXSS237_17193	3	0,26939	7,66942	0,03513
4	BSSPEXSS237	BSSPEXSS237_17197	4	0,51967	24,68367	0,02105
4	BSSPEXSS572	BSSPEXSS572_17102	3	0,23141	15,78328	0,01466
4	BSSPEXSS572	BSSPEXSS572_17109	3	0,41102	31,14364	0,01320
4	BSSPEXSS572	BSSPEXSS572_17129	3	0,46749	34,82070	0,01343
4	BSSPEXSS572	BSSPEXSS572_17158	3	0,45581	22,67926	0,02010
4	BSSPEXSS572	BSSPEXSS572_17170	4	0,47983	23,16167	0,02072
4	BSSPEXSS510	BSSPEXSS510_17081	3	0,22614	12,23945	0,01848
4	BSSPEXSS510	BSSPEXSS510_17085	2	0,10171	9,94472	0,01023
4	BSSPEXSS510	BSSPEXSS510_17106	2	0,13370	9,37914	0,01426
4	BSSPEXSS510	BSSPEXSS510_17136	4	0,46901	12,47733	0,03759
4	BSSPEXSS510	BSSPEXSS510_17142	1	0,02735	2,40640	0,01137
4	BSSPEXSS510	BSSPEXSS510_17143	4	0,91521	25,00021	0,03661
4	BSSPEXSS510	BSSPEXSS510_17156	4	0,63541	24,34522	0,02610
4	BSSPEXSS510	BSSPEXSS510_17163	5	1,77909	67,60753	0,02631
4	BSSPEXSS510	BSSPEXSS510_17169	2	0,06591	7,35305	0,00896
4	BSSPEXSS510	BSSPEXSS510_17182	2	0,08669	3,38293	0,02563
4	BSSP013	BSSP013_17067	2	0,08415	7,16775	0,01174
4	BSSP013	BSSP013_17151	4	0,65513	22,07224	0,02968
4	A4racc	A4racc_17043	4	1,01431	43,54165	0,02330
4	A4racc	A4racc_17161	3	0,35938	12,64355	0,02842
4	BSSP019	BSSP019_17008	2	0,08770	2,76791	0,03169
4	BSSP019	BSSP019_17046	4	0,67983	25,37299	0,02679
4	BSSP019	BSSP019_17061	4	0,47973	32,80550	0,01462
4	BSSP019	BSSP019_17081	4	1,04937	48,26373	0,02174
4	BSSP019	BSSP019_17091	3	0,30575	8,45175	0,03618
4	BSSP019	BSSP019_17127	3	0,43333	32,67217	0,01326
4	BSSP019	BSSP019_17130	4	0,64612	34,08612	0,01896
4	BSSP019	BSSP019_17136	2	0,18798	9,18560	0,02047
4	BSSP019	BSSP019_17163	5	1,40301	52,85131	0,02655
4	BSSP019	BSSP019_17186	1	0,01383	1,92929	0,00717
4	BSSP019	BSSP019_17188	4	0,89791	37,38255	0,02402
4	BSSPEXSS45B	BSSPEXSS45B_17013	4	1,03776	21,23542	0,04887
4	BSSPEXSS45B	BSSPEXSS45B_17074	3	0,36982	23,91130	0,01547

4	BSSPEXSS45B	BSSPEXSS45B_17076	4	0,51944	16,45200	0,03157
4	BSSPEXSS45B	BSSPEXSS45B_17077	5	1,28995	48,80323	0,02643
4	BSSPEXSS45B	BSSPEXSS45B_17089	2	0,10449	5,48556	0,01905
4	BSSPEXSS45B	BSSPEXSS45B_17103	4	0,66015	26,93513	0,02451
4	BSSPEXSS45B	BSSPEXSS45B_17107	3	0,40940	27,12311	0,01509
4	BSSPEXSS45B	BSSPEXSS45B_17119	3	0,32092	11,54174	0,02780
4	BSSPEXSS45B	BSSPEXSS45B_17120	4	0,97423	29,69009	0,03281
4	BSSPEXSS45B	BSSPEXSS45B_17122	2	0,15804	4,28058	0,03692
4	BSSPEXSS45B	BSSPEXSS45B_17147	5	1,10276	29,89696	0,03689
4	BSSPEXSS45B	BSSPEXSS45B_17149	4	0,74035	31,48236	0,02352
4	BSSPEXSS45B	BSSPEXSS45B_17155	5	1,14583	54,31453	0,02110
4	BSSPEXSS45B	BSSPEXSS45B_17161	4	0,77583	48,20807	0,01609
4	BSSPEXSS45B	BSSPEXSS45B_17164	4	0,55795	30,65549	0,01820
4	BSSPEXSS45B	BSSPEXSS45B_17170	4	1,06780	41,33495	0,02583
4	BSSPEXSS45B	BSSPEXSS45B_17173	3	0,40687	15,35529	0,02650
4	BSSPEXSS45B	BSSPEXSS45B_17185	2	0,16952	4,70863	0,03600
4	BSSPEXSS45B	BSSPEXSS45B_17187	4	0,74974	42,87212	0,01749
4	BSSPEXSS45B	BSSPEXSS45B_17189	2	0,19657	5,45729	0,03602
4	BSSPEXSS45B	BSSPEXSS45B_17195	1	0,02248	1,03290	0,02177
4	BSSPEXSS45B	BSSPEXSS45B_17201	3	0,45897	21,58053	0,02127
4	BSSPEXSS45B	BSSPEXSS469_17038	4	0,52820	30,77599	0,01716
4	BSSP024	BSSP024_17071	1	0,03436	0,72950	0,04711
4	BSSP024	BSSP024_17073	4	0,51844	11,27188	0,04599
4	BSSP024	BSSP024_17078	4	0,92845	34,61747	0,02682
4	BSSP024	BSSP024_17086	3	0,31387	9,22531	0,03402
4	BSSP024	BSSP024_17114	3	0,44562	23,64947	0,01884
4	BSSP024	BSSP024_17147	2	0,06026	2,70718	0,02226
4	BSSPEXSS510V1	BSSPEXSS510V1_17085	4	1,02469	34,43848	0,02975
4	BSSPEXSS510V1	BSSPEXSS510V1_17106	4	0,83195	26,68269	0,03118
4	BSSPEXSS510V1	BSSPEXSS510V1_17169	3	0,31067	16,57135	0,01875
4	BSSPEXSS510V1	BSSPEXSS510V1_17182	4	0,70432	22,28801	0,03160
4	BSSP025	BSSP025_17092	5	1,39871	33,88227	0,04128
4	BSSP025	BSSP025_17129	2	0,11406	8,85879	0,01287
4	BSSP025	BSSP025_17145	1	0,03879	3,19284	0,01215
4	BSSP025	BSSP025_17158	3	0,21523	8,98150	0,02396
4	BSSP025	BSSP025_17180	3	0,22090	7,58093	0,02914
4	BSSPV	BSSPV_17164	2	0,20970	8,56733	0,02448
4	BSSPV	BSSPV_17170	4	0,51329	29,47287	0,01742
4	BSSP048	BSSP048_17085	3	0,30191	9,47970	0,03185
4	BSSP048	BSSP048_17144	3	0,39079	14,26186	0,02740
4	BSSPEXSS236B	BSSPEXSS236B_17113	3	0,36132	10,14600	0,03561
4	BSSP066	BSSP066_17043	2	0,06488	4,21594	0,01539
4	BSSP066	BSSP066_17078	4	0,75204	23,62787	0,03183
4	BSSPEXSS345	BSSPEXSS345_17018	2	0,19608	4,52232	0,04336
4	BSSPEXSS345	BSSPEXSS345_17024	1	0,03674	1,75164	0,02097
4	BSSPEXSS345	BSSPEXSS345_17028	3	0,37144	12,82654	0,02896
4	BSSPEXSS345	BSSPEXSS345_17055	1	0,04873	8,14993	0,00598

4	BSSPEXSS345	BSSPEXSS345_17058	3	0,34517	8,24022	0,04189
4	BSSPEXSS345	BSSPEXSS345_17061	5	1,93797	86,12437	0,02250
4	BSSPEXSS345	BSSPEXSS345_17075	4	0,70308	31,99369	0,02198
4	BSSPEXSS345	BSSPEXSS345_17100	4	0,50096	13,70751	0,03655
4	BSSPEXSS345	BSSPEXSS345_17141	2	0,09261	3,38564	0,02735
4	BSSPEXSS345	BSSPEXSS345_17174	4	0,79333	52,47251	0,01512
4	BSSPEXSS345	BSSPEXSS345_17183	2	0,13724	5,08216	0,02700
4	BSSPEXSS345	BSSPEXSS345_17199	3	0,43573	36,06343	0,01208
4	BSSPEXSS345	BSSPEXSS42_17016	3	0,21570	8,05941	0,02676
4	A35	A35_17045	2	0,08060	5,06688	0,01591
4	A35	A35_17046	3	0,26926	10,51165	0,02562
4	A35	A35_17052	5	1,19315	36,36565	0,03281
4	A35	A35_17127	1	0,00424	2,76639	0,00153
4	A35	A35_17166	5	1,22122	43,86877	0,02784
4	A35	A35_17188	3	0,27423	19,56324	0,01402
4	A35	A35_17192	1	0,03239	1,39984	0,02314
4	BSSPEXSS469	BSSPEXSS469_17133	3	0,40297	28,10320	0,01434
4	BSSPEXSS469	BSSPEXSS469_17134	3	0,31709	23,14854	0,01370
4	BSSPEXSS469	BSSPEXSS469_17150	2	0,11367	8,20641	0,01385
4	BSSPEXSS469	BSSPEXSS469_17192	4	0,51949	6,27981	0,08272
4	BSSP072	BSSP072_17052	3	0,43058	17,17365	0,02507
4	BSSP072	BSSP072_17162	3	0,46718	10,35853	0,04510
4	BSSPEXSS510D1	BSSPEXSS510D1_17040	4	0,47960	50,63251	0,00947
4	BSSPXI	BSSPXI_17002	3	0,21539	11,32349	0,01902
4	BSSPXI	BSSPXI_17046	1	0,02223	1,47097	0,01511
4	BSSPXI	BSSPXI_17062	4	0,56665	24,73617	0,02291
4	BSSPXI	BSSPXI_17069	4	0,95592	43,07596	0,02219
4	BSSPXI	BSSPXI_17085	5	1,29760	43,95509	0,02952
4	BSSPEXSS567	BSSPEXSS567_17067	3	0,35160	24,52974	0,01433
4	BSSPEXSS567	BSSPEXSS567_17092	4	0,94418	29,31301	0,03221
4	BSSPEXSS11	BSSPEXSS11_17032	3	0,33508	12,61080	0,02657
4	BSSPEXSS11	BSSPEXSS11_17040	4	0,77926	34,94404	0,02230
4	BSSPEXSS11	BSSPEXSS11_17046	3	0,46764	17,96307	0,02603
4	BSSPEXSS11	BSSPEXSS11_17052	4	0,60292	25,79986	0,02337
4	BSSPEXSS11	BSSPEXSS11_17056	3	0,41930	21,81789	0,01922
4	BSSPEXSS11	BSSPEXSS11_17067	5	1,73666	83,70009	0,02075
4	BSSPEXSS11	BSSPEXSS11_17092	3	0,30633	9,72861	0,03149
4	BSSPEXSS11	BSSPEXSS11_17127	2	0,11640	8,88766	0,01310
4	BSSPEXSS11	BSSPEXSS11_17165	1	0,05859	4,89024	0,01198
4	BSSPEXSS11	BSSPEXSS11_17166	4	0,52891	31,06317	0,01703
4	BSSPEXSS11	BSSPEXSS11_17192	3	0,21942	13,25722	0,01655
4	BSSPEXSS668	BSSPEXSS668_17032	3	0,26741	11,68320	0,02289
4	BSSPEXSS668	BSSPEXSS668_17078	5	1,50657	46,16006	0,03264
4	BSSPEXSS668	BSSPEXSS668_17088	3	0,26978	12,54556	0,02150
4	BSSPEXSS668	BSSPEXSS668_17092	3	0,32360	8,97383	0,03606
4	BSSPEXSS668	BSSPEXSS668_17103	5	1,14113	19,85807	0,05746
4	BSSPEXSS668	BSSPEXSS668_17113	5	1,34390	43,71506	0,03074

4	BSSPEXSS668	BSSPEXSS668_17122	4	0,56840	11,35018	0,05008
4	BSSPEXSS668	BSSPEXSS668_17125	3	0,23319	7,92175	0,02944
4	BSSPEXSS668	BSSPEXSS668_17126	2	0,16836	9,03646	0,01863
4	BSSPEXSS668	BSSPEXSS668_17138	4	0,49815	11,19014	0,04452
4	A21racc	A21racc_17008	4	0,60736	15,52977	0,03911
4	A21racc	A21racc_17037	2	0,12210	6,64264	0,01838
4	A21racc	A21racc_17042	1	0,03229	2,72457	0,01185
4	A21racc	A21racc_17043	5	1,45018	52,34003	0,02771
4	A21racc	A21racc_17072	4	0,85797	50,48660	0,01699
4	A21racc	A21racc_17114	4	0,79597	19,89211	0,04001
4	A21racc	A21racc_17147	4	0,53487	21,06438	0,02539
4	BSSPEXSS235	BSSPEXSS235_17026	3	0,25292	4,42301	0,05718
4	BSSPEXSS235	BSSPEXSS235_17042	2	0,12071	8,74484	0,01380
4	BSSPEXSS235	BSSPEXSS235_17064	1	0,04503	1,83748	0,02450
4	BSSPEXSS235	BSSPEXSS235_17091	4	1,01147	29,82772	0,03391
4	BSSPEXSS235	BSSPEXSS235_17097	2	0,07456	5,43353	0,01372
4	BSSPEXSS235	BSSPEXSS235_17125	5	1,24283	28,86083	0,04306
4	BSSPEXSS235	BSSPEXSS235_17126	2	0,17535	12,72917	0,01378
4	BSSPEXSS235	BSSPEXSS235_17146	2	0,14818	9,81790	0,01509
4	BSSPEXSS235	BSSPEXSS235_17165	4	0,57228	44,78606	0,01278
4	BSSPEXSS235	BSSPEXSS235_17186	3	0,38680	15,42749	0,02507
4	BSSPEXSS235	BSSPEXSS235_17188	1	0,03725	2,27269	0,01639
4	BSSP004	BSSP004_17014	4	0,71819	24,12217	0,02977
4	BSSP004	BSSP004_17092	2	0,07537	1,81846	0,04145
4	BSSP004	BSSP004_17107	3	0,27545	22,16767	0,01243
4	BSSP004	BSSP004_17120	2	0,07414	3,20094	0,02316
4	BSSP004	BSSP004_17129	4	0,70782	29,23169	0,02421
3	BSSP016	BSSP016_17011	1	0,04907	3,45945	0,01418
3	BSSP016	BSSP016_17045	1	0,02742	1,69956	0,01613
3	BSSP016	BSSP016_17064	3	0,21877	7,03914	0,03108
3	BSSP016	BSSP016_17166	4	0,58691	27,17330	0,02160
3	BSSP016	BSSP016_17190	3	0,29390	14,37072	0,02045
3	BSSPXII	BSSPXII_17002	3	0,36759	16,34962	0,02248
3	BSSPXII	BSSPXII_17038	1	0,03442	3,55125	0,00969
3	BSSPXII	BSSPXII_17069	4	0,48040	23,28568	0,02063
3	BSSP065	BSSP065_17009	3	0,22336	9,04367	0,02470
3	BSSP065	BSSP065_17078	3	0,27366	10,98152	0,02492
3	BSSP022	BSSP022_17072	2	0,16456	15,55422	0,01058
3	BSSP022	BSSP022_17147	3	0,25043	15,29738	0,01637
3	BSSPVIID1	BSSPVIID1_17088	2	0,17316	3,40140	0,05091
3	BSSP099	BSSP099_17133	3	0,29538	13,74623	0,02149
3	BSSPEXSS510B	BSSPEXSS510B_17085	3	0,22015	7,76737	0,02834
3	BSSP116	BSSP116_17077	3	0,27157	18,37779	0,01478
3	BSSP116	BSSP116_17107	2	0,10849	10,80636	0,01004
3	BSSP116	BSSP116_17119	3	0,30902	11,72035	0,02637
3	BSSP116	BSSP116_17120	3	0,30594	11,26818	0,02715
3	BSSP116	BSSP116_17132	2	0,08058	3,62729	0,02221

3	BSSP116	BSSP116_17155	3	0,40904	18,17920	0,02250
3	BSSP116	BSSP116_17164	2	0,20037	10,00180	0,02003
3	BSSP116	BSSP116_17201	3	0,41432	22,27856	0,01860
3	BSSP011	BSSP011_17013	1	0,02510	0,61761	0,04064
3	BSSP011	BSSP011_17020	4	0,50761	13,06961	0,03884
3	BSSP011	BSSP011_17053	1	0,03112	1,05973	0,02936
3	BSSP011	BSSP011_17080	2	0,11784	6,01592	0,01959
3	BSSP011	BSSP011_17086	3	0,29168	13,95608	0,02090
3	BSSP011	BSSP011_17125	2	0,17000	6,97107	0,02439
3	BSSP011	BSSP011_17137	1	0,03101	5,67062	0,00547
3	BSSP011	BSSP011_17172	1	0,03613	1,89322	0,01908
3	BSSP011	BSSP011_17195	3	0,44728	22,91746	0,01952
3	BSSP011	BSSP011_17196	3	0,38893	8,24565	0,04717
3	BSSP011	BSSP011_17203	3	0,25477	9,63614	0,02644
3	BSSP012	BSSP012_17085	3	0,46670	24,64279	0,01894
3	BSSP012	BSSP012_17134	2	0,08404	5,34348	0,01573
3	BSSP020	BSSP020_17060	4	0,52894	11,13025	0,04752
3	BSSP020	BSSP020_17097	1	0,05415	1,48431	0,03648
3	BSSP020	BSSP020_17162	1	0,02568	3,07321	0,00836
3	BSSP020	BSSP020_17190	2	0,13719	6,82294	0,02011
3	BSSP005	BSSP005_17022	2	0,16444	8,53839	0,01926
3	BSSP005	BSSP005_17100	2	0,12572	4,52300	0,02780
3	BSSP005	BSSP005_17128	3	0,32846	8,09216	0,04059
3	BSSP078	BSSP078_17033	3	0,36027	15,87276	0,02270
3	BSSP078	BSSP078_17092	2	0,09273	3,37740	0,02745
3	BSSP026	BSSP026_17077	2	0,10072	4,49283	0,02242
3	BSSP026	BSSP026_17102	1	0,00878	1,01871	0,00861
3	BSSP026	BSSP026_17116	3	0,38715	19,35242	0,02001
3	BSSP026	BSSP026_17145	3	0,27371	18,76411	0,01459
3	BSSP062	BSSP062_17190	3	0,21743	4,35025	0,04998
3	BSSP027	BSSP027_17033	2	0,21332	9,36251	0,02278
3	BSSP027	BSSP027_17155	2	0,15966	8,44170	0,01891
3	BSSP064	BSSP064_17004	4	0,57078	18,40608	0,03101
3	BSSP064	BSSP064_17020	2	0,09749	3,39059	0,02875
3	BSSP064	BSSP064_17073	1	0,00232	0,24537	0,00945
3	BSSP064	BSSP064_17108	3	0,29168	1,52300	0,19152
3	BSSP064	BSSP064_17149	4	0,66925	27,69730	0,02416
3	BSSP064	BSSP064_17152	2	0,12817	6,90603	0,01856
3	BSSP064	BSSP064_17159	1	0,05821	2,49313	0,02335
3	BSSP064	BSSP064_17196	3	0,22583	6,35353	0,03554
3	BSSP028	BSSP028_17014	3	0,34595	13,59136	0,02545
3	BSSP028	BSSP028_17032	3	0,35862	12,72117	0,02819
3	BSSP028	BSSP028_17033	1	0,03524	0,93686	0,03762
3	BSSP028	BSSP028_17092	1	0,00185	0,10521	0,01756
3	BSSP028	BSSP028_17113	4	0,47102	13,89059	0,03391
3	BSSP017	BSSP017_17002	2	0,09529	6,74707	0,01412
3	BSSP017	BSSP017_17041	1	0,03013	2,82675	0,01066

3	BSSP017	BSSP017_17052	3	0,24509	9,27694	0,02642
3	BSSP017	BSSP017_17059	4	0,61108	24,63267	0,02481
3	BSSP017	BSSP017_17069	4	0,47564	6,03942	0,07876
3	BSSP029	BSSP029_17034	3	0,40510	5,88135	0,06888
3	BSSP029	BSSP029_17113	3	0,40176	14,96656	0,02684
3	BSSP029	BSSP029_17160	1	0,03669	1,14983	0,03191
3	BSSP029	BSSP029_17203	3	0,42609	9,22457	0,04619
3	BSSP002	BSSP002_17125	3	0,34932	14,44630	0,02418
3	BSSP002	BSSP002_17162	3	0,26215	9,04786	0,02897
3	BSSP002	BSSP002_17167	2	0,17493	3,47777	0,05030
3	BSSP002	BSSP002_17192	1	0,04323	2,83098	0,01527
3	BSSPEXSS300	BSSPEXSS300_17148	3	0,21584	6,44215	0,03350
3	BSSPIX	BSSPIX_17008	4	0,77744	33,62228	0,02312
3	BSSPIX	BSSPIX_17020	2	0,08490	3,18944	0,02662
3	BSSPIX	BSSPIX_17037	4	0,50548	20,72392	0,02439
3	BSSPIX	BSSPIX_17042	2	0,16873	11,33829	0,01488
3	BSSPIX	BSSPIX_17066	4	0,46780	15,78747	0,02963
3	BSSPIX	BSSPIX_17072	3	0,32501	17,97124	0,01808
3	BSSPIX	BSSPIX_17099	1	0,03934	1,58936	0,02475
3	BSSPIX	BSSPIX_17138	4	0,60815	12,95059	0,04696
3	BSSPIX	BSSPIX_17159	3	0,30133	11,72634	0,02570
3	BSSPIX	BSSPIX_17195	1	0,01600	0,28787	0,05558
3	BSSPIX	BSSPIX_17196	2	0,15434	3,34960	0,04608
3	BSSPEXSS343	BSSPEXSS343_17001	3	0,36704	9,36821	0,03918
3	BSSPEXSS343	BSSPEXSS343_17039	4	0,47566	15,10528	0,03149
3	BSSPEXSS343	BSSPEXSS343_17113	1	0,03372	2,70311	0,01248
3	BSSPVII	BSSPVII_17009	2	0,14143	4,46457	0,03168
3	BSSPVII	BSSPVII_17088	3	0,37331	18,01973	0,02072
3	BSSPVII	BSSPVII_17108	2	0,12260	3,83037	0,03201
3	BSSPVII	BSSPVII_17137	4	0,55609	15,85766	0,03507
3	BSSPVII	BSSPVII_17152	2	0,13456	3,40854	0,03948
3	BSSPVII	BSSPVII_17177	1	0,03099	1,28597	0,02410
3	BSSP033	BSSP033_17026	2	0,16430	7,63849	0,02151
3	BSSP033	BSSP033_17066	3	0,24172	8,17271	0,02958
3	BSSP033	BSSP033_17093	2	0,09617	5,47194	0,01758
3	BSSP033	BSSP033_17103	2	0,11558	5,14325	0,02247
3	BSSP033	BSSP033_17122	3	0,27790	7,70050	0,03609
3	BSSPVIII	BSSPVIII_17071	1	0,04071	2,59457	0,01569
3	BSSPVIII	BSSPVIII_17073	2	0,12298	5,68849	0,02162
3	BSSPVIII	BSSPVIII_17080	3	0,24321	10,54037	0,02307
3	BSSPVIII	BSSPVIII_17088	3	0,28259	9,14864	0,03089
3	BSSPEXSS42	BSSPEXSS42_17028	1	0,00708	1,00215	0,00707
3	BSSPEXSS42	BSSPEXSS42_17035	1	0,01351	1,68367	0,00802
3	BSSPEXSS42	BSSPEXSS42_17047	1	0,01813	0,53763	0,03372
3	BSSPEXSS42	BSSPEXSS42_17050	1	0,00304	0,29417	0,01033
3	BSSPEXSS42	BSSPEXSS42_17118	1	0,01038	0,21100	0,04921
3	BSSPEXSS42	BSSPEXSS42_17176	2	0,10502	2,99940	0,03501

3	BSSPEXSS42	BSSPEXSS45B_17009	5	1,11350	58,24066	0,01912
3	BSSP037	BSSP037_17034	3	0,22721	8,87934	0,02559
3	BSSP037	BSSP037_17043	2	0,11496	5,39584	0,02131
3	BSSP037	BSSP037_17086	2	0,08816	4,40127	0,02003
3	BSSP037	BSSP037_17113	4	0,52462	15,52128	0,03380
3	BSSP079	BSSP079_17003	2	0,20404	4,77606	0,04272
3	BSSP079	BSSP079_17019	1	0,01999	0,35192	0,05679
3	BSSP079	BSSP079_17096	2	0,10316	5,32926	0,01936
3	BSSP079	BSSP079_17153	3	0,30377	9,58295	0,03170
3	BSSP079	BSSP079_17168	3	0,38848	9,00478	0,04314
3	SS42	SS42_17007	3	0,21653	5,64593	0,03835
3	SS42	SS42_17016	2	0,11372	7,16467	0,01587
3	SS42	SS42_17027	1	0,01329	0,53864	0,02467
3	SS42	SS42_17028	3	0,32347	10,03530	0,03223
3	SS42	SS42_17035	2	0,20813	5,99172	0,03474
3	SS42	SS42_17050	3	0,23849	4,37928	0,05446
3	SS42	SS42_17055	3	0,21727	16,19198	0,01342
3	SS42	SS42_17065	4	0,76225	33,96755	0,02244
3	SS42	SS42_17068	2	0,17534	7,94706	0,02206
3	SS42	SS42_17070	5	1,20357	27,67613	0,04349
3	SS42	SS42_17079	3	0,22813	4,99011	0,04572
3	SS42	SS42_17083	3	0,25117	4,57808	0,05486
3	SS42	SS42_17101	2	0,20593	11,26706	0,01828
3	SS42	SS42_17110	2	0,11699	2,92072	0,04006
3	SS42	SS42_17118	2	0,06014	2,71118	0,02218
3	SS42	SS42_17142	2	0,19047	7,27667	0,02618
3	SS42	SS42_17148	3	0,42282	8,33148	0,05075
3	SS42	SS42_17176	2	0,10214	2,88656	0,03539
3	SS42	SS42_17181	4	0,47310	13,22546	0,03577
3	SS42	SS42_17184	3	0,28871	10,53895	0,02739
3	SS42	SS42_17198	2	0,13754	5,20911	0,02640
3	SS42	SS42_17202	2	0,16509	6,39528	0,02581
2	BSSP096	BSSP096_17038	2	0,11393	4,45935	0,02555
2	BSSP049	BSSP049_17136	2	0,19359	13,58514	0,01425
2	BSSP049	BSSP049_17163	1	0,00898	0,42756	0,02100
2	BSSPIII	BSSPIII_17044	3	0,33360	11,94446	0,02793
2	BSSPIII	BSSPIII_17090	2	0,13685	4,08267	0,03352
2	BSSPIII	BSSPIII_17104	1	0,00115	0,37987	0,00302
2	BSSPIII	BSSPIII_17115	2	0,07966	2,40540	0,03312
2	BSSPIII	BSSPIII_17197	1	0,00275	0,58015	0,00473
2	BSSP021	BSSP021_17008	1	0,04184	1,49275	0,02803
2	BSSP021	BSSP021_17009	1	0,02324	1,00727	0,02307
2	BSSP021	BSSP021_17037	2	0,06866	4,04433	0,01698
2	BSSP021	BSSP021_17091	3	0,40391	11,16123	0,03619
2	BSSP021	BSSP021_17099	2	0,17865	7,46254	0,02394
2	BSSP021	BSSP021_17147	1	0,02318	2,50657	0,00925
2	BSSP021	BSSP021_17188	1	0,04077	4,36899	0,00933

2	BSSP057	BSSP057_17077	1	0,00462	1,20466	0,00384
2	BSSP057	BSSP057_17193	3	0,25634	11,57500	0,02215
2	BSSPEXSS294	BSSPEXSS294_17006	2	0,13904	5,52488	0,02517
2	BSSPEXSS294	BSSPEXSS294_17065	2	0,12571	6,56030	0,01916
2	BSSPEXSS294	BSSPEXSS294_17131	1	0,00420	0,23888	0,01756
2	BSSPEXSS669	BSSPEXSS669_17005	1	0,02559	0,47450	0,05392
2	BSSPEXSS669	BSSPEXSS669_17010	3	0,32480	6,54410	0,04963
2	BSSPEXSS669	BSSPEXSS669_17028	1	0,03257	1,47287	0,02211
2	BSSP008	BSSP008_17017	1	0,05265	2,02476	0,02600
2	BSSP008	BSSP008_17018	1	0,00971	0,85580	0,01134
2	BSSP008	BSSP008_17070	2	0,17945	5,55686	0,03229
2	BSSP008	BSSP008_17206	1	0,01793	1,04640	0,01713
2	BSSP106	BSSP106_17151	1	0,05270	1,72454	0,03056
2	BSSP023	BSSP023_17021	2	0,12522	13,78040	0,00909
2	BSSP023	BSSP023_17114	2	0,11241	5,30268	0,02120
2	BSSP023	BSSP023_17173	2	0,08325	6,01972	0,01383
2	BSSP051B	BSSP051B_17046	2	0,06618	4,04989	0,01634
2	BSSP051B	BSSP051B_17069	1	0,02387	1,80210	0,01324
2	BSSP032	BSSP032_17106	2	0,08805	1,35363	0,06505
2	BSSP084	BSSP084_17016	2	0,06033	3,22101	0,01873
2	SS39	SS39_17063	3	0,26033	8,06269	0,03229
2	SS39	SS39_17068	2	0,08212	4,40709	0,01863
2	A35racc	A35racc_17040	2	0,16293	5,40645	0,03014
2	A35racc	A35racc_17165	2	0,06671	6,13386	0,01088
2	BSSP018	BSSP018_17015	1	0,00942	0,73742	0,01278
2	BSSP018	BSSP018_17041	3	0,35720	2,74553	0,13010
2	BSSP018	BSSP018_17045	2	0,06727	3,16337	0,02127
2	BSSP018	BSSP018_17052	1	0,04648	1,58459	0,02933
2	BSSP018	BSSP018_17166	2	0,06746	0,65007	0,10378
2	BSSPI	BSSPI_17007	2	0,18615	5,68436	0,03275
2	BSSPI	BSSPI_17079	2	0,11788	3,08628	0,03819
2	BSSPI	BSSPI_17142	2	0,08573	5,95342	0,01440
2	BSSPI	BSSPI_17143	2	0,12353	3,81793	0,03235
2	BSSP034V1	BSSP034V1_17099	2	0,06568	1,76419	0,03723
2	BSSPIV	BSSPIV_17164	3	0,26800	11,60317	0,02310
2	BSSPIV	BSSPIV_17168	1	0,04537	0,36116	0,12561
2	BSSPIV	BSSPIV_17204	2	0,18960	7,68285	0,02468
2	BSSP010	BSSP010_17030	1	0,00222	0,74408	0,00299
2	BSSP010	BSSP010_17048	3	0,34510	23,60565	0,01462
2	BSSP010	BSSP010_17081	1	0,01256	0,49980	0,02512
2	BSSP010	BSSP010_17144	1	0,00361	0,66180	0,00545
2	BSSP112	BSSP112_17055	1	0,04409	8,88095	0,00496
2	BSSP112	BSSP112_17206	2	0,11665	7,26323	0,01606
2	BSSP073	BSSP073_17037	2	0,09736	5,68740	0,01712
2	BSSP051	BSSP051_17046	2	0,17630	10,88287	0,01620
2	BSSP051	BSSP051_17136	1	0,01083	1,67000	0,00649
2	BSSP076	BSSP076_17160	2	0,10546	2,80399	0,03761

2	BSSP052	BSSP052_17141	2	0,06187	0,80336	0,07701
2	BSSP046	BSSP046_17123	1	0,01571	2,05519	0,00764
2	BSSP046	BSSP046_17163	3	0,31726	14,69650	0,02159
2	BSSP061	BSSP061_17052	2	0,06307	6,24920	0,01009
2	BSSP061	BSSP061_17150	1	0,02392	0,90909	0,02632
2	BSSP047	BSSP047_17112	3	0,24805	6,69835	0,03703
2	BSSP047	BSSP047_17136	1	0,05361	1,52907	0,03506
2	BSSP047	BSSP047_17156	1	0,02476	1,21173	0,02044
2	BSSP068	BSSP068_17034	2	0,10777	1,40464	0,07672
2	BSSP068	BSSP068_17078	2	0,12650	5,05271	0,02504
2	BSSP068	BSSP068_17080	1	0,00704	0,77565	0,00907
2	BSSP068	BSSP068_17088	2	0,06916	2,03477	0,03399
2	BSSP069	BSSP069_17034	2	0,11631	4,78192	0,02432
2	BSSP069	BSSP069_17039	2	0,19776	14,07115	0,01405
2	BSSP070	BSSP070_17069	3	0,28363	8,34939	0,03397
2	BSSP070	BSSP070_17133	1	0,00394	0,23588	0,01672
1	BSSP041	BSSP041_17119	1	0,02785	1,57249	0,01771
1	BSSP041	BSSP041_17178	1	0,00747	0,35091	0,02129
1	BSSP067	BSSP067_17043	1	0,02297	0,78349	0,02932
1	BSSP067	BSSP067_17161	1	0,03436	1,76492	0,01947
1	BSSP111	BSSP111_17191	1	0,00967	0,41701	0,02319
1	BSSP055	BSSP055_17140	1	0,00361	0,06429	0,05622
1	BSSP055	BSSP055_17197	1	0,00296	0,77441	0,00382
1	BSSP031	BSSP031_17003	1	0,01021	1,05718	0,00966
1	BSSP075	BSSP075_17009	1	0,01838	0,70397	0,02610
1	BSSP075	BSSP075_17037	1	0,03617	0,66643	0,05428
1	BSSP075	BSSP075_17066	1	0,04948	2,70225	0,01831
1	BSSP100	BSSP100_17150	1	0,00181	1,05370	0,00172
1	BSSP018D1	BSSP018D1_17188	1	0,04023	1,22666	0,03280
1	BSSP115	BSSP115_17089	1	0,00712	0,51875	0,01373
1	BSSP115	BSSP115_17189	2	0,06361	2,40235	0,02648
1	BSSP077	BSSP077_17021	1	0,00046	1,34853	0,00034
1	BSSP077	BSSP077_17043	1	0,05482	1,72377	0,03180
1	BSSP036	BSSP036_17200	1	0,03031	1,27862	0,02371
1	BSSP058	BSSP058_17036	2	0,06038	1,42609	0,04234
1	BSSP058	BSSP058_17082	1	0,00438	0,90974	0,00482
1	BSSP058	BSSP058_17194	1	0,03965	0,48150	0,08235
1	BSSPEXSS236D1	BSSPEXSS236D1_17113	1	0,00940	1,25775	0,00748
1	BSSP059	BSSP059_17012	1	0,03237	0,97828	0,03308
1	BSSP047B	BSSP047B_17112	1	0,02846	1,24673	0,02283
1	BSSP047B	BSSP047B_17123	1	0,01788	0,78330	0,02283
1	BSSP060	BSSP060_17052	1	0,03707	1,21572	0,03049
1	BSSP047T	BSSP047T_17136	1	0,00105	1,59000	0,00066
1	BSSPEXSS469D1	BSSPEXSS469D1_17133	1	0,00849	0,63348	0,01341
1	BSSP034	BSSP034_17064	1	0,01179	1,32343	0,00891
1	BSSP034	BSSP034_17093	2	0,06049	2,83938	0,02130
1	BSSP086	BSSP086_17124	1	0,02954	1,43567	0,02058

1	BSSP006	BSSP006_17051	1	0,02142	1,75135	0,01223
1	BSSP087	BSSP087_17049	1	0,02094	0,76643	0,02732
1	BSSP050	BSSP050_17139	1	0,03971	1,15997	0,03423
1	BSSP050	BSSP050_17183	1	0,00199	0,13910	0,01432
1	BSSP088	BSSP088_17050	1	0,01188	1,51307	0,00785
1	BSSP088	BSSP088_17054	1	0,00786	0,35513	0,02213
1	BSSPEXSS235D1	BSSPEXSS235D1_17186	1	0,01929	0,63693	0,03028
1	BSSPEXSS510T	BSSPEXSS510T_17085	1	0,01870	1,34224	0,01393
1	BSSP071	BSSP071_17085	1	0,03910	2,40788	0,01624
1	BSSP089	BSSP089_17027	1	0,00212	0,61162	0,00347
1	BSSPEXSS236V2	BSSPEXSS236V2_17113	1	0,03130	4,18589	0,00748
1	BSSP090	BSSP090_17094	1	0,00356	0,11286	0,03152
1	BSSPEXSS237D1	BSSPEXSS237D1_17012	1	0,02480	2,88198	0,00861
1	BSSPEXSS237D1	BSSPEXSS237D1_17168	1	0,03716	1,70697	0,02177
1	BSSP009	BSSP009_17076	2	0,06694	1,34221	0,04988
1	BSSP009	BSSP009_17194	1	0,00464	0,09572	0,04847

7.2. Ranking of the main road network of the Province of Brescia – R1

R2	Path *(Provincial level)*	Minimum path *(Municipality level)*	R2 *(Municipality level)*		F	S	E
5	BSSPEXSS11V1	BSSPEXSS11V1_17014	4	11,78598	22,20318	0,03158	16,80762
5	BSSPEXSS11V1	BSSPEXSS11V1_17029	5	32,16189	182,66485	0,00894	19,68411
5	BSSPEXSS11V1	BSSPEXSS11V1_17032	2	4,37907	22,01201	0,01229	16,18683
5	BSSPEXSS11V1	BSSPEXSS11V1_17040	3	6,26576	21,10233	0,01897	15,65279
5	BSSPEXSS11V1	BSSPEXSS11V1_17067	2	3,25321	4,36782	0,04854	15,34583
5	BSSPEXSS11V1	BSSPEXSS11V1_17092	4	17,04344	22,71318	0,04374	17,15698
5	BSSPEXSS11V1	BSSPEXSS11V1_17107	3	9,81623	30,54851	0,01969	16,31649
5	BSSPEXSS11V1	BSSPEXSS11V1_17161	5	70,66990	175,73430	0,02242	17,93817
5	BSSPEXSS11V1	BSSPEXSS11V1_17165	5	33,95961	118,94685	0,01565	18,24165
5	A4	A4_17002	4	20,03052	44,15484	0,02638	17,19879
5	A4	A4_17029	3	10,39443	71,55007	0,00749	19,40495
5	A4	A4_17032	5	31,63189	65,74337	0,02583	18,62843
5	A4	A4_17040	4	14,36764	43,64265	0,01833	17,96482
5	A4	A4_17043	5	54,82496	65,86356	0,04669	17,82736
5	A4	A4_17046	5	48,45295	81,08254	0,03309	18,05877
5	A4	A4_17067	5	41,33290	92,22260	0,02340	19,15005
5	A4	A4_17069	5	49,33283	82,98594	0,03257	18,25243
5	A4	A4_17092	5	53,68653	73,49478	0,03987	18,32218
5	A4	A4_17107	3	8,58814	37,36146	0,01325	17,35381
5	A4	A4_17127	3	5,05072	40,14948	0,00721	17,44510
5	A4	A4_17133	5	35,15712	96,33577	0,02041	17,87700
5	A4	A4_17136	5	35,01613	73,01125	0,02823	16,98663
5	A4	A4_17151	4	14,71362	40,29704	0,02133	17,12008
5	A4	A4_17161	5	26,75771	62,25166	0,02419	17,77061
5	A4	A4_17165	4	15,86912	55,29407	0,01591	18,03954
5	A4	A4_17166	4	14,33234	47,14888	0,01761	17,26409
5	A21	A21_17004	3	7,76499	12,11639	0,03762	17,03543
5	A21	A21_17009	5	54,59822	95,78912	0,03100	18,38685
5	A21	A21_17013	3	5,44170	29,77782	0,01069	17,09161
5	A21	A21_17021	4	14,96227	35,58504	0,02457	17,10948
5	A21	A21_17029	4	10,95346	97,29143	0,00758	14,84966
5	A21	A21_17088	5	25,65595	49,22652	0,02954	17,64091
5	A21	A21_17103	5	45,12772	88,49096	0,02728	18,69670
5	A21	A21_17114	4	12,68839	30,15932	0,02362	17,81216
5	A21	A21_17147	4	13,69553	22,33072	0,04127	14,86199
5	A21	A21_17149	5	46,48960	69,88373	0,03642	18,26428
5	A21	A21_17172	5	28,69222	57,41656	0,02797	17,86716
5	A21	A21_17173	4	21,88020	50,22993	0,02469	17,64088
5	BSSPEXSS573	BSSPEXSS573_17056	3	8,69323	33,33868	0,01694	15,38857
5	BSSPEXSS573	BSSPEXSS573_17059	4	19,03039	58,65087	0,01969	16,48160
5	BSSPEXSS573	BSSPEXSS573_17133	5	27,02916	55,57966	0,03041	15,99204
5	A21racc	A21racc_17008	5	24,63178	37,01397	0,03911	17,01571
5	A21racc	A21racc_17037	3	5,72353	19,23221	0,01838	16,19011

5	A21racc	A21racc_17042	1	1,33827	6,99293	0,01185	16,14586
5	A21racc	A21racc_17043	5	39,77115	76,93706	0,02771	18,65709
5	A21racc	A21racc_17072	4	21,67621	69,25933	0,01699	18,41664
5	A21racc	A21racc_17114	5	25,76958	36,80426	0,04001	17,49827
5	A21racc	A21racc_17147	4	17,53182	39,72135	0,02539	17,38199
5	BSSPEXSS236	BSSPEXSS236_17039	1	1,12116	2,37714	0,03211	14,68864
5	BSSPEXSS236	BSSPEXSS236_17043	4	22,07511	51,31498	0,02713	15,85402
5	BSSPEXSS236	BSSPEXSS236_17113	5	50,62473	73,56786	0,03806	18,08151
5	TANGOVEST	TANGOVEST_17029	5	75,09625	249,70882	0,01584	18,98008
5	TANGOVEST	TANGOVEST_17042	2	1,11583	8,47530	0,01668	15,78831
4	A35	A35_17045	2	2,84353	10,30576	0,01591	17,34639
4	A35	A35_17046	2	4,34814	10,34031	0,02562	16,41603
4	A35	A35_17052	5	27,80142	45,48829	0,03281	18,62793
4	A35	A35_17127	1	0,21650	9,56203	0,00153	14,78322
4	A35	A35_17166	5	31,04387	61,01349	0,02784	18,27730
4	A35	A35_17188	3	7,07574	27,30379	0,01402	18,48715
4	A35	A35_17192	1	1,03469	2,58597	0,02314	17,29354
4	BSSP004	BSSP004_17014	4	17,85875	38,04616	0,02977	15,76590
4	BSSP004	BSSP004_17092	2	2,63779	4,69387	0,04145	13,55904
4	BSSP004	BSSP004_17107	3	6,78581	33,95979	0,01243	16,08117
4	BSSP004	BSSP004_17120	2	2,42595	7,24426	0,02316	14,45778
4	BSSP004	BSSP004_17129	3	8,71420	22,78296	0,02421	15,79614
4	BSSP019	BSSP019_17008	2	1,89909	4,12161	0,03169	14,54152
4	BSSP019	BSSP019_17046	4	13,42482	32,27503	0,02679	15,52422
4	BSSP019	BSSP019_17061	3	8,96185	37,76995	0,01462	16,22574
4	BSSP019	BSSP019_17081	4	15,14770	42,08376	0,02174	16,55477
4	BSSP019	BSSP019_17091	3	5,91340	10,41766	0,03618	15,69073
4	BSSP019	BSSP019_17127	4	13,89747	59,01070	0,01326	17,75660
4	BSSP019	BSSP019_17130	4	20,82557	62,49982	0,01896	17,57844
4	BSSP019	BSSP019_17136	3	8,14009	23,81100	0,02047	16,70473
4	BSSP019	BSSP019_17163	5	41,60159	87,65954	0,02655	17,87749
4	BSSP019	BSSP019_17186	1	0,35011	3,47745	0,00717	14,04610
4	BSSP019	BSSP019_17188	4	12,79608	31,45201	0,02402	16,93810
4	BSSPIX	BSSPIX_17008	4	16,04655	43,85281	0,02312	15,82504
4	BSSPIX	BSSPIX_17020	2	2,30448	5,80357	0,02662	14,91672
4	BSSPIX	BSSPIX_17037	4	12,03456	32,21687	0,02439	15,31496
4	BSSPIX	BSSPIX_17042	2	4,11894	18,83686	0,01488	14,69338
4	BSSPIX	BSSPIX_17066	4	10,93209	21,67052	0,02963	17,02502
4	BSSPIX	BSSPIX_17072	3	7,57541	28,20488	0,01808	14,85146
4	BSSPIX	BSSPIX_17099	1	0,84768	2,40440	0,02475	14,24503
4	BSSPIX	BSSPIX_17138	4	14,37526	19,32829	0,04696	15,83793
4	BSSPIX	BSSPIX_17159	3	8,31507	20,43076	0,02570	15,83813
4	BSSPIX	BSSPIX_17195	1	0,54068	0,64288	0,05558	15,13208
4	BSSPIX	BSSPIX_17196	2	3,13765	4,83221	0,04608	14,09164
4	BSSP078	BSSP078_17033	4	15,48672	42,60540	0,02270	16,01464
4	BSSP078	BSSP078_17092	2	2,98785	7,15635	0,02745	15,20716
4	BSSPEXSS668	BSSPEXSS668_17032	3	6,26494	17,51479	0,02289	15,62754

4	BSSPEXSS668	BSSPEXSS668_17078	5	29,64191	53,14198	0,03264	17,09011
4	BSSPEXSS668	BSSPEXSS668_17088	3	5,22898	14,17184	0,02150	17,15792
4	BSSPEXSS668	BSSPEXSS668_17092	3	6,35429	11,19280	0,03606	15,74358
4	BSSPEXSS668	BSSPEXSS668_17103	4	20,63976	21,53938	0,05746	16,67528
4	BSSPEXSS668	BSSPEXSS668_17113	5	25,20972	48,36408	0,03074	16,95539
4	BSSPEXSS668	BSSPEXSS668_17122	4	13,99653	17,00797	0,05008	16,43300
4	BSSPEXSS668	BSSPEXSS668_17125	3	6,04050	12,71587	0,02944	16,13735
4	BSSPEXSS668	BSSPEXSS668_17126	2	4,16362	14,10335	0,01863	15,84573
4	BSSPEXSS668	BSSPEXSS668_17138	4	10,89801	14,70027	0,04452	16,65322
4	BSSP029	BSSP029_17034	4	17,55513	15,71582	0,06888	16,21759
4	BSSP029	BSSP029_17113	4	13,31876	30,51689	0,02684	16,25836
4	BSSP029	BSSP029_17160	1	1,51198	3,10192	0,03191	15,27721
4	BSSP029	BSSP029_17203	4	11,98331	16,30971	0,04619	15,90644
4	BSSPEXSS567	BSSPEXSS567_17067	3	7,98134	34,59285	0,01433	16,09638
4	BSSPEXSS567	BSSPEXSS567_17092	4	17,76963	31,98831	0,03221	17,24620
4	BSSP013	BSSP013_17067	2	1,74574	9,35930	0,01174	15,88831
4	BSSP013	BSSP013_17151	4	20,66517	41,94163	0,02968	16,60021
4	BSSPEXSS510V1	BSSPEXSS510V1_17085	4	12,00819	24,24046	0,02975	16,64892
4	BSSPEXSS510V1	BSSPEXSS510V1_17106	3	9,32199	17,52875	0,03118	17,05652
4	BSSPEXSS510V1	BSSPEXSS510V1_17169	2	3,75840	12,09264	0,01875	16,57846
4	BSSPEXSS510V1	BSSPEXSS510V1_17182	4	14,03506	26,70504	0,03160	16,63125
4	BSSPEXSS11	BSSPEXSS11_17032	3	10,14337	26,29615	0,02657	14,51722
4	BSSPEXSS11	BSSPEXSS11_17040	4	15,20194	41,90210	0,02230	16,26882
4	BSSPEXSS11	BSSPEXSS11_17046	4	10,96707	27,54160	0,02603	15,29587
4	BSSPEXSS11	BSSPEXSS11_17052	4	16,52411	45,45522	0,02337	15,55580
4	BSSPEXSS11	BSSPEXSS11_17056	3	9,39676	30,16461	0,01922	16,20963
4	BSSPEXSS11	BSSPEXSS11_17067	5	29,16241	81,81728	0,02075	17,17870
4	BSSPEXSS11	BSSPEXSS11_17092	4	15,52823	39,29706	0,03149	12,54927
4	BSSPEXSS11	BSSPEXSS11_17127	2	3,42981	18,31099	0,01310	14,30155
4	BSSPEXSS11	BSSPEXSS11_17165	2	2,21491	13,03282	0,01198	14,18564
4	BSSPEXSS11	BSSPEXSS11_17166	4	11,28995	42,78658	0,01703	15,49691
4	BSSPEXSS11	BSSPEXSS11_17192	3	5,74685	21,76518	0,01655	15,95282
4	BSSPEXSS510D1	BSSPEXSS510D1_17040	4	14,17232	86,08790	0,00947	17,37990
4	BSSP072	BSSP072_17052	3	9,18814	22,31396	0,02507	16,42334
4	BSSP072	BSSP072_17162	4	12,71739	17,53786	0,04510	16,07823
4	BSSPEXSS510	BSSPEXSS510_17081	2	4,66305	15,66921	0,01848	16,10690
4	BSSPEXSS510	BSSPEXSS510_17085	1	1,10722	6,59114	0,01023	16,42452
4	BSSPEXSS510	BSSPEXSS510_17106	2	2,24272	9,16563	0,01426	17,16485
4	BSSPEXSS510	BSSPEXSS510_17136	4	17,73113	27,95695	0,03759	16,87287
4	BSSPEXSS510	BSSPEXSS510_17142	1	0,42361	2,38517	0,01137	15,62408
4	BSSPEXSS510	BSSPEXSS510_17143	3	9,91436	15,54666	0,03661	17,42009
4	BSSPEXSS510	BSSPEXSS510_17156	4	11,14301	25,64445	0,02610	16,64814
4	BSSPEXSS510	BSSPEXSS510_17163	5	47,74171	99,54352	0,02631	18,22565
4	BSSPEXSS510	BSSPEXSS510_17169	1	0,78819	5,29867	0,00896	16,59453
4	BSSPEXSS510	BSSPEXSS510_17182	1	1,12215	2,72827	0,02563	16,04951
4	BSSP066	BSSP066_17043	2	1,62395	6,72792	0,01539	15,68415
4	BSSP066	BSSP066_17078	4	18,67872	36,16525	0,03183	16,22695

4	BSSPEXSS469	BSSPEXSS469_17133	3	9,04335	41,51289	0,01434	15,19239
4	BSSPEXSS469	BSSPEXSS469_17134	3	6,05907	26,62105	0,01370	16,61598
4	BSSPEXSS469	BSSPEXSS469_17150	2	2,36521	10,31154	0,01385	16,55902
4	BSSPEXSS469	BSSPEXSS469_17192	4	12,32007	9,18702	0,08272	16,21081
4	BSSP024	BSSP024_17071	1	1,00493	1,34353	0,04711	15,87872
4	BSSP024	BSSP024_17073	4	14,87460	19,99907	0,04599	16,17074
4	BSSP024	BSSP024_17078	4	17,31191	38,11843	0,02682	16,93359
4	BSSP024	BSSP024_17086	3	6,90566	12,45000	0,03402	16,30324
4	BSSP024	BSSP024_17114	3	9,34311	30,67116	0,01884	16,16650
4	BSSP024	BSSP024_17147	2	1,99750	5,98118	0,02226	15,00239
4	BSSPEXSS45B	BSSPEXSS45B_17013	4	19,67930	24,93326	0,04887	16,15084
4	BSSPEXSS45B	BSSPEXSS45B_17074	3	5,58111	23,06996	0,01547	15,64165
4	BSSPEXSS45B	BSSPEXSS45B_17076	4	10,89938	20,81724	0,03157	16,58305
4	BSSPEXSS45B	BSSPEXSS45B_17077	4	22,79500	53,56414	0,02643	16,10053
4	BSSPEXSS45B	BSSPEXSS45B_17089	3	5,58733	17,64298	0,01905	16,62523
4	BSSPEXSS45B	BSSPEXSS45B_17103	4	11,15145	27,39657	0,02451	16,60780
4	BSSPEXSS45B	BSSPEXSS45B_17107	3	7,30039	30,96332	0,01509	15,62015
4	BSSPEXSS45B	BSSPEXSS45B_17119	3	6,75460	15,86660	0,02780	15,31064
4	BSSPEXSS45B	BSSPEXSS45B_17120	4	19,04264	36,11419	0,03281	16,06938
4	BSSPEXSS45B	BSSPEXSS45B_17122	2	3,84954	7,07826	0,03692	14,73097
4	BSSPEXSS45B	BSSPEXSS45B_17147	4	21,54668	36,69637	0,03689	15,91857
4	BSSPEXSS45B	BSSPEXSS45B_17149	4	15,13763	39,85559	0,02352	16,15095
4	BSSPEXSS45B	BSSPEXSS45B_17155	4	17,38742	50,71382	0,02110	16,25185
4	BSSPEXSS45B	BSSPEXSS45B_17161	4	12,75503	48,40807	0,01609	16,37259
4	BSSPEXSS45B	BSSPEXSS45B_17164	3	5,62683	18,69690	0,01820	16,53517
4	BSSPEXSS45B	BSSPEXSS45B_17170	4	13,14191	30,70189	0,02583	16,56997
4	BSSPEXSS45B	BSSPEXSS45B_17173	4	12,50170	33,21683	0,02650	14,20409
4	BSSPEXSS45B	BSSPEXSS45B_17185	2	4,53345	7,50832	0,03600	16,77084
4	BSSPEXSS45B	BSSPEXSS45B_17187	3	10,61404	36,70871	0,01749	16,53390
4	BSSPEXSS45B	BSSPEXSS45B_17189	3	5,86651	9,79558	0,03602	16,62704
4	BSSPEXSS45B	BSSPEXSS45B_17195	1	0,19140	0,71305	0,02177	12,33128
4	BSSPEXSS45B	BSSPEXSS45B_17201	3	5,42766	15,48964	0,02127	16,47582
4	BSSPEXSS45B	BSSPEXSS469_17038	4	11,53079	40,75826	0,01716	16,48380
4	BSSP017	BSSP017_17002	2	2,38854	10,88159	0,01412	15,54209
4	BSSP017	BSSP017_17041	1	0,98834	5,86632	0,01066	15,80625
4	BSSP017	BSSP017_17052	3	6,40076	15,16674	0,02642	15,97428
4	BSSP017	BSSP017_17059	4	17,41661	43,81411	0,02481	16,02374
4	BSSP017	BSSP017_17069	4	12,01925	9,97627	0,07876	15,29778
4	BSSPEXSS343	BSSPEXSS343_17001	4	11,05245	17,62861	0,03918	16,00248
4	BSSPEXSS343	BSSPEXSS343_17039	3	10,35614	18,74372	0,03149	17,54595
4	BSSPEXSS343	BSSPEXSS343_17113	1	1,26602	6,95491	0,01248	14,59178
4	BSSP012	BSSP012_17085	4	12,37351	39,65391	0,01894	16,47631
4	BSSP012	BSSP012_17134	2	2,42609	10,10674	0,01573	15,26251
4	BSSPEXSS236B	BSSPEXSS236B_17113	3	7,68794	13,12611	0,03561	16,44656
4	A4racc	A4racc_17043	4	16,99280	43,54187	0,02330	16,75300
4	A4racc	A4racc_17161	3	6,38490	13,77005	0,02842	16,31297
4	BSSPEXSS235	BSSPEXSS235_17026	3	7,16337	8,42980	0,05718	14,86060

4	BSSPEXSS235	BSSPEXSS235_17042	2	3,00643	13,62263	0,01380	15,98772
4	BSSPEXSS235	BSSPEXSS235_17064	1	1,37623	3,61629	0,02450	15,53057
4	BSSPEXSS235	BSSPEXSS235_17091	4	23,15910	43,12193	0,03391	15,83757
4	BSSPEXSS235	BSSPEXSS235_17097	2	1,73055	8,27790	0,01372	15,23532
4	BSSPEXSS235	BSSPEXSS235_17125	4	22,07160	30,31102	0,04306	16,90947
4	BSSPEXSS235	BSSPEXSS235_17126	2	3,98507	18,63452	0,01378	15,52438
4	BSSPEXSS235	BSSPEXSS235_17146	2	3,70418	15,93433	0,01509	15,40277
4	BSSPEXSS235	BSSPEXSS235_17165	4	11,96184	59,68069	0,01278	15,68551
4	BSSPEXSS235	BSSPEXSS235_17186	4	10,96997	28,24093	0,02507	15,49307
4	BSSPEXSS235	BSSPEXSS235_17188	1	1,06353	4,52070	0,01639	14,35296
4	BSSPXI	BSSPXI_17002	3	5,49456	18,86816	0,01902	15,30907
4	BSSPXI	BSSPXI_17046	1	0,59357	2,82321	0,01511	13,91161
4	BSSPXI	BSSPXI_17062	4	12,69632	33,94890	0,02291	16,32566
4	BSSPXI	BSSPXI_17069	4	19,33175	54,99468	0,02219	15,84025
4	BSSPXI	BSSPXI_17085	5	28,92696	60,92777	0,02952	16,08262
3	BSSP027	BSSP027_17033	3	5,92252	16,51733	0,02278	15,73751
3	BSSP027	BSSP027_17155	2	4,38467	14,47069	0,01891	16,02095
3	BSSPEXSS572	BSSPEXSS572_17102	3	6,02283	24,97725	0,01466	16,44608
3	BSSPEXSS572	BSSPEXSS572_17109	3	7,58130	35,14268	0,01320	16,34602
3	BSSPEXSS572	BSSPEXSS572_17129	3	5,03720	22,46382	0,01343	16,70199
3	BSSPEXSS572	BSSPEXSS572_17158	3	6,74016	20,64668	0,02010	16,24293
3	BSSPEXSS572	BSSPEXSS572_17170	3	8,25945	25,70806	0,02072	15,50843
3	BSSP020	BSSP020_17060	4	13,95180	18,39698	0,04752	15,95811
3	BSSP020	BSSP020_17097	2	2,01667	3,74690	0,03648	14,75228
3	BSSP020	BSSP020_17162	1	1,00044	8,17857	0,00836	14,63634
3	BSSP020	BSSP020_17190	2	4,43116	13,72409	0,02011	16,05730
3	BSSPVIII	BSSPVIII_17071	1	1,00142	3,81337	0,01569	16,73793
3	BSSPVIII	BSSPVIII_17073	2	3,86217	11,05851	0,02162	16,15467
3	BSSPVIII	BSSPVIII_17080	3	9,21423	24,37255	0,02307	16,38434
3	BSSPVIII	BSSPVIII_17088	3	7,90774	16,11779	0,03089	15,88364
3	BSSP002	BSSP002_17125	3	8,44609	22,65121	0,02418	15,42027
3	BSSP002	BSSP002_17162	3	6,48838	14,59083	0,02897	15,34819
3	BSSP002	BSSP002_17167	3	5,69208	7,67272	0,05030	14,74850
3	BSSP002	BSSP002_17192	1	1,55457	7,11381	0,01527	14,31169
3	BSSPEXSS300	BSSPEXSS300_17148	3	5,69577	11,21698	0,03350	15,15548
3	SS39	SS39_17063	3	7,72219	13,94978	0,03229	17,14454
3	SS39	SS39_17068	2	2,59002	8,69162	0,01863	15,99208
3	BSSPVII	BSSPVII_17009	2	3,85698	8,30796	0,03168	14,65471
3	BSSPVII	BSSPVII_17088	3	9,02242	25,90554	0,02072	16,81149
3	BSSPVII	BSSPVII_17108	2	3,12249	6,12507	0,03201	15,92764
3	BSSPVII	BSSPVII_17137	4	13,94632	24,35111	0,03507	16,33178
3	BSSPVII	BSSPVII_17152	3	4,89442	7,75678	0,03948	15,98307
3	BSSPVII	BSSPVII_17177	1	1,22911	3,47745	0,02410	14,66859
3	BSSPXII	BSSPXII_17002	3	9,69756	27,13325	0,02248	15,89660
3	BSSPXII	BSSPXII_17038	1	0,93741	6,42901	0,00969	15,04471
3	BSSPXII	BSSPXII_17069	4	11,09317	32,34348	0,02063	16,62490
3	BSSPEXSS237	BSSPEXSS237_17005	3	8,26074	11,10897	0,04425	16,80455

3	BSSPEXSS237	BSSPEXSS237_17010	1	0,32050	1,90637	0,01082	15,53213
3	BSSPEXSS237	BSSPEXSS237_17012	3	9,94366	15,89218	0,03793	16,49689
3	BSSPEXSS237	BSSPEXSS237_17025	2	3,34408	13,84104	0,01559	15,50171
3	BSSPEXSS237	BSSPEXSS237_17031	2	4,44945	12,15208	0,02247	16,29360
3	BSSPEXSS237	BSSPEXSS237_17082	3	6,45708	11,18834	0,03538	16,31179
3	BSSPEXSS237	BSSPEXSS237_17087	2	4,24783	9,67103	0,02722	16,13621
3	BSSPEXSS237	BSSPEXSS237_17117	3	9,79256	37,63501	0,01551	16,77571
3	BSSPEXSS237	BSSPEXSS237_17121	2	2,45449	5,20662	0,02922	16,13406
3	BSSPEXSS237	BSSPEXSS237_17153	1	0,47587	0,63163	0,04710	15,99741
3	BSSPEXSS237	BSSPEXSS237_17193	2	3,45497	6,20099	0,03513	15,86222
3	BSSPEXSS237	BSSPEXSS237_17197	3	7,09844	20,20170	0,02105	16,68998
3	BSSP011	BSSP011_17013	1	0,56502	0,92979	0,04064	14,95435
3	BSSP011	BSSP011_17020	4	14,71056	24,04743	0,03884	15,75053
3	BSSP011	BSSP011_17053	1	1,13619	2,61491	0,02936	14,79767
3	BSSP011	BSSP011_17080	2	4,69391	14,72383	0,01959	16,27559
3	BSSP011	BSSP011_17086	3	7,58561	22,42753	0,02090	16,18339
3	BSSP011	BSSP011_17125	2	3,76945	9,58596	0,02439	16,12451
3	BSSP011	BSSP011_17137	1	0,77028	8,93114	0,00547	15,77000
3	BSSP011	BSSP011_17172	1	1,05376	3,47745	0,01908	15,88022
3	BSSP011	BSSP011_17195	3	10,24543	32,04926	0,01952	16,37935
3	BSSP011	BSSP011_17196	3	9,45708	12,56001	0,04717	15,96317
3	BSSP011	BSSP011_17203	3	6,25736	14,44163	0,02644	16,38823
3	BSSP065	BSSP065_17009	3	6,30679	16,32848	0,02470	15,63892
3	BSSP065	BSSP065_17078	3	7,86121	20,06438	0,02492	15,72220
3	BSSPEXSS510B	BSSPEXSS510B_17085	2	4,32457	9,17102	0,02834	16,63705
3	BSSP064	BSSP064_17004	4	13,76678	26,96337	0,03101	16,46449
3	BSSP064	BSSP064_17020	2	4,00163	9,30668	0,02875	14,95325
3	BSSP064	BSSP064_17073	1	0,07243	0,49683	0,00945	15,42105
3	BSSP064	BSSP064_17108	3	8,23588	2,76691	0,19152	15,54193
3	BSSP064	BSSP064_17149	4	12,93725	31,98114	0,02416	16,74172
3	BSSP064	BSSP064_17152	2	3,74967	12,06524	0,01856	16,74489
3	BSSP064	BSSP064_17159	2	1,61588	4,29243	0,02335	16,12390
3	BSSP064	BSSP064_17196	3	5,54433	9,82435	0,03554	15,87768
3	BSSP025	BSSP025_17092	5	24,90345	36,03005	0,04128	16,74324
3	BSSP025	BSSP025_17129	2	3,09155	16,09038	0,01287	14,92348
3	BSSP025	BSSP025_17145	1	0,48151	2,49740	0,01215	15,87165
3	BSSP025	BSSP025_17158	2	3,32501	8,45608	0,02396	16,40881
3	BSSP025	BSSP025_17180	2	3,03284	6,44896	0,02914	16,13958
3	BSSP062	BSSP062_17190	3	6,49900	8,17404	0,04998	15,90739
3	BSSP022	BSSP022_17072	2	3,59703	20,99064	0,01058	16,19712
3	BSSP022	BSSP022_17147	2	4,84445	18,72212	0,01637	15,80573
3	BSSP048	BSSP048_17085	2	3,46164	6,43427	0,03185	16,89285
3	BSSP048	BSSP048_17144	3	5,24515	11,79153	0,02740	16,23400
3	SS42	SS42_17007	3	5,26107	9,04368	0,03835	15,16874
3	SS42	SS42_17016	2	1,71253	6,53600	0,01587	16,50725
3	SS42	SS42_17027	1	0,19206	0,50926	0,02467	15,28898
3	SS42	SS42_17028	3	5,16519	9,79125	0,03223	16,36596

3	SS42	SS42_17035	2	3,39241	6,00267	0,03474	16,26948
3	SS42	SS42_17050	2	3,27243	3,60687	0,05446	16,66009
3	SS42	SS42_17055	2	2,14242	9,87609	0,01342	16,16646
3	SS42	SS42_17065	4	11,23478	28,63040	0,02244	17,48654
3	SS42	SS42_17068	3	5,30134	14,70277	0,02206	16,34230
3	SS42	SS42_17070	4	19,76603	27,42602	0,04349	16,57266
3	SS42	SS42_17079	3	5,82343	8,57582	0,04572	14,85338
3	SS42	SS42_17083	3	5,04712	5,90843	0,05486	15,57006
3	SS42	SS42_17101	2	3,39611	11,53108	0,01828	16,11412
3	SS42	SS42_17110	2	2,47785	3,98203	0,04006	15,53504
3	SS42	SS42_17118	1	1,18106	3,47241	0,02218	15,33365
3	SS42	SS42_17142	2	4,18954	10,45881	0,02618	15,30357
3	SS42	SS42_17148	4	11,82610	14,32164	0,05075	16,27086
3	SS42	SS42_17176	1	1,50225	2,60272	0,03539	16,31145
3	SS42	SS42_17181	3	9,14849	15,54614	0,03577	16,45085
3	SS42	SS42_17184	3	6,41195	14,83411	0,02739	15,77858
3	SS42	SS42_17198	2	3,07005	7,32099	0,02640	15,88188
3	SS42	SS42_17202	2	3,20378	8,06406	0,02581	15,39062
3	BSSP046	BSSP046_17123	1	0,67446	5,85278	0,00764	15,07808
3	BSSP046	BSSP046_17163	3	8,99599	26,86049	0,02159	15,51426
3	BSSP016	BSSP016_17011	1	1,32625	5,88185	0,01418	15,89704
3	BSSP016	BSSP016_17045	1	0,97433	4,16522	0,01613	14,50122
3	BSSP016	BSSP016_17064	3	5,79052	11,69334	0,03108	15,93379
3	BSSP016	BSSP016_17166	4	13,34803	37,28550	0,02160	16,57480
3	BSSP016	BSSP016_17190	3	6,90337	20,45086	0,02045	16,50530
3	BSSP037	BSSP037_17034	3	9,67686	22,32006	0,02559	16,94314
3	BSSP037	BSSP037_17043	2	3,21420	9,57271	0,02131	15,75942
3	BSSP037	BSSP037_17086	2	3,10692	10,16596	0,02003	15,25702
3	BSSP037	BSSP037_17113	3	10,57603	18,69418	0,03380	16,73781
3	BSSP116	BSSP116_17077	3	6,14610	25,50791	0,01478	16,30533
3	BSSP116	BSSP116_17107	2	2,19168	13,82138	0,01004	15,79490
3	BSSP116	BSSP116_17119	3	6,85435	16,45325	0,02637	15,80052
3	BSSP116	BSSP116_17120	3	7,21731	16,99094	0,02715	15,64509
3	BSSP116	BSSP116_17132	2	1,84680	5,38124	0,02221	15,44889
3	BSSP116	BSSP116_17155	3	8,84011	25,16173	0,02250	15,61437
3	BSSP116	BSSP116_17164	2	2,38194	7,50068	0,02003	15,85206
3	BSSP116	BSSP116_17201	3	8,41824	28,11976	0,01860	16,09758
3	BSSP034V1	BSSP034V1_17099	2	4,82504	8,17857	0,03723	15,84662
3	BSSP099	BSSP099_17133	3	7,07204	21,41775	0,02149	15,36622
3	BSSP033	BSSP033_17026	2	4,51053	13,19736	0,02151	15,88935
3	BSSP033	BSSP033_17066	3	5,67231	11,77621	0,02958	16,28607
3	BSSP033	BSSP033_17093	2	2,48745	9,23165	0,01758	15,33128
3	BSSP033	BSSP033_17103	2	2,57729	7,49491	0,02247	15,30260
3	BSSP033	BSSP033_17122	3	6,34242	11,07651	0,03609	15,86656
3	BSSPEXSS345	BSSPEXSS345_17018	2	4,12848	5,80318	0,04336	16,40789
3	BSSPEXSS345	BSSPEXSS345_17024	2	2,39859	7,21747	0,02097	15,84504
3	BSSPEXSS345	BSSPEXSS345_17028	3	5,23194	11,02048	0,02896	16,39408

3	BSSPEXSS345	BSSPEXSS345_17055	1	0,61976	6,48291	0,00598	15,98694
3	BSSPEXSS345	BSSPEXSS345_17058	3	6,56470	9,75021	0,04189	16,07336
3	BSSPEXSS345	BSSPEXSS345_17061	5	33,57345	88,67523	0,02250	16,82567
3	BSSPEXSS345	BSSPEXSS345_17075	3	9,93359	27,54621	0,02198	16,40972
3	BSSPEXSS345	BSSPEXSS345_17100	3	8,11719	14,23894	0,03655	15,59867
3	BSSPEXSS345	BSSPEXSS345_17141	2	1,65867	3,91656	0,02735	15,48238
3	BSSPEXSS345	BSSPEXSS345_17174	3	9,66971	39,37628	0,01512	16,24268
3	BSSPEXSS345	BSSPEXSS345_17183	2	2,49012	5,63915	0,02700	16,35266
3	BSSPEXSS345	BSSPEXSS345_17199	3	5,40632	27,85873	0,01208	16,06172
3	BSSPEXSS345	BSSPEXSS42_17016	2	4,47504	10,53789	0,02676	15,86683
3	BSSPV	BSSPV_17164	2	2,35098	6,15346	0,02448	15,60894
3	BSSPV	BSSPV_17170	3	6,76129	23,38772	0,01742	16,59987
3	BSSP028	BSSP028_17014	4	10,96238	26,04074	0,02545	16,53850
3	BSSP028	BSSP028_17032	4	10,80431	23,51840	0,02819	16,29611
3	BSSP028	BSSP028_17033	1	1,30806	2,37714	0,03762	14,62761
3	BSSP028	BSSP028_17092	1	0,06688	0,25123	0,01756	15,15843
3	BSSP028	BSSP028_17113	4	12,22472	23,43492	0,03391	15,38355
3	BSSP070	BSSP070_17069	3	7,92256	14,64228	0,03397	15,92788
3	BSSP070	BSSP070_17133	1	0,21469	0,96146	0,01672	13,35788
3	BSSP069	BSSP069_17034	3	5,43317	13,85880	0,02432	16,11753
3	BSSP069	BSSP069_17039	3	5,69403	26,53478	0,01405	15,26879
2	BSSP051	BSSP051_17046	3	4,86320	18,92158	0,01620	15,86536
2	BSSP051	BSSP051_17136	1	0,25309	2,52721	0,00649	15,43658
2	BSSP005	BSSP005_17022	2	3,15040	10,33925	0,01926	15,82154
2	BSSP005	BSSP005_17100	2	1,70779	4,07213	0,02780	15,08820
2	BSSP005	BSSP005_17128	3	5,98991	10,06446	0,04059	14,66247
2	BSSPIV	BSSPIV_17164	2	4,05346	10,74666	0,02310	16,33055
2	BSSPIV	BSSPIV_17168	1	1,31655	0,69635	0,12561	15,05119
2	BSSPIV	BSSPIV_17204	3	5,40521	14,65394	0,02468	14,94697
2	BSSP021	BSSP021_17008	1	1,42733	3,36423	0,02803	15,13841
2	BSSP021	BSSP021_17009	1	0,44597	1,27138	0,02307	15,20314
2	BSSP021	BSSP021_17037	1	1,56815	5,85007	0,01698	15,79008
2	BSSP021	BSSP021_17091	3	9,35766	15,78004	0,03619	16,38641
2	BSSP021	BSSP021_17099	3	4,93859	13,07556	0,02394	15,77729
2	BSSP021	BSSP021_17147	1	0,61630	4,70112	0,00925	14,17362
2	BSSP021	BSSP021_17188	1	1,00146	6,93106	0,00933	15,48249
2	BSSP026	BSSP026_17077	2	3,25512	10,03004	0,02242	14,47666
2	BSSP026	BSSP026_17102	1	0,41438	3,30054	0,00861	14,57471
2	BSSP026	BSSP026_17116	2	4,56558	13,64077	0,02001	16,73067
2	BSSP026	BSSP026_17145	2	3,35001	13,98432	0,01459	16,42255
2	BSSP047	BSSP047_17112	3	8,14429	14,77641	0,03703	14,88404
2	BSSP047	BSSP047_17136	2	2,35989	5,06538	0,03506	13,28808
2	BSSP047	BSSP047_17156	1	0,98472	3,47745	0,02044	13,85579
2	BSSP023	BSSP023_17021	2	2,63527	18,02369	0,00909	16,09033
2	BSSP023	BSSP023_17114	2	3,48084	10,37050	0,02120	15,83378
2	BSSP023	BSSP023_17173	2	1,92413	8,99534	0,01383	15,46642
2	BSSPEXSS42	BSSPEXSS42_17028	1	0,13906	1,31811	0,00707	14,92796

2	BSSPEXSS42	BSSPEXSS42_17035	1	0,28473	2,26284	0,00802	15,68175
2	BSSPEXSS42	BSSPEXSS42_17047	1	0,25853	0,51556	0,03372	14,87297
2	BSSPEXSS42	BSSPEXSS42_17050	1	0,06318	0,37704	0,01033	16,22577
2	BSSPEXSS42	BSSPEXSS42_17118	1	0,14451	0,19284	0,04921	15,22849
2	BSSPEXSS42	BSSPEXSS42_17176	2	1,77235	3,17660	0,03501	15,93430
2	BSSPEXSS42	BSSPEXSS45B_17009	4	20,34659	65,87978	0,01912	16,15379
2	BSSP008	BSSP008_17017	2	2,82114	8,56535	0,02600	12,66594
2	BSSP008	BSSP008_17018	1	0,33346	2,28773	0,01134	12,85254
2	BSSP008	BSSP008_17070	3	6,55579	13,63186	0,03229	14,89224
2	BSSP008	BSSP008_17206	1	0,46185	1,90637	0,01713	14,13998
2	BSSP018	BSSP018_17015	1	0,25096	1,27138	0,01278	15,44953
2	BSSP018	BSSP018_17041	4	10,70454	5,06803	0,13010	16,23488
2	BSSP018	BSSP018_17045	2	2,74168	8,88731	0,02127	14,50673
2	BSSP018	BSSP018_17052	1	1,57749	3,47745	0,02933	15,46549
2	BSSP018	BSSP018_17166	2	2,72815	1,83712	0,10378	14,30952
2	BSSP076	BSSP076_17160	2	2,77379	4,43518	0,03761	16,62861
2	BSSPEXSS294	BSSPEXSS294_17006	2	4,35979	11,69017	0,02517	14,81921
2	BSSPEXSS294	BSSPEXSS294_17065	2	3,16023	10,56853	0,01916	15,60442
2	BSSPEXSS294	BSSPEXSS294_17131	1	0,12288	0,51556	0,01756	13,57137
2	BSSP073	BSSP073_17037	2	2,94367	11,26538	0,01712	15,26439
2	BSSPVIID1	BSSPVIID1_17088	2	3,61932	4,70112	0,05091	15,12256
2	A35racc	A35racc_17040	3	5,02707	9,97542	0,03014	16,72213
2	A35racc	A35racc_17165	2	2,18438	12,11639	0,01088	16,57740
2	BSSP096	BSSP096_17038	2	3,21981	8,08224	0,02555	15,59338
2	BSSPI	BSSPI_17007	3	5,28980	10,58258	0,03275	15,26399
2	BSSPI	BSSPI_17079	2	3,68048	6,44619	0,03819	14,94854
2	BSSPI	BSSPI_17142	2	1,82191	8,08745	0,01440	15,64442
2	BSSPI	BSSPI_17143	2	1,68295	3,24565	0,03235	16,02649
2	BSSP079	BSSP079_17003	2	2,52876	3,64589	0,04272	16,23507
2	BSSP079	BSSP079_17019	1	0,43147	0,49813	0,05679	15,25256
2	BSSP079	BSSP079_17096	1	1,56633	5,11379	0,01936	15,82251
2	BSSP079	BSSP079_17153	3	5,23381	10,52797	0,03170	15,68270
2	BSSP079	BSSP079_17168	3	7,68460	11,31130	0,04314	15,74741
2	BSSP068	BSSP068_17034	3	5,30469	4,36699	0,07672	15,83282
2	BSSP068	BSSP068_17078	2	3,78480	9,44880	0,02504	15,99966
2	BSSP068	BSSP068_17080	1	0,57714	4,70112	0,00907	13,53060
2	BSSP068	BSSP068_17088	2	2,03693	3,74730	0,03399	15,99218
1	BSSP010	BSSP010_17030	1	0,03224	0,71294	0,00299	15,12786
1	BSSP010	BSSP010_17048	2	4,13279	17,39352	0,01462	16,25263
1	BSSP010	BSSP010_17081	1	0,14562	0,37704	0,02512	15,37377
1	BSSP010	BSSP010_17144	1	0,05955	0,73653	0,00545	14,82870
1	BSSP067	BSSP067_17043	1	0,59926	1,34353	0,02932	15,21414
1	BSSP067	BSSP067_17161	1	0,74609	2,40440	0,01947	15,94025
1	BSSP051B	BSSP051B_17046	2	1,63138	6,37705	0,01634	15,65476
1	BSSP051B	BSSP051B_17069	1	0,82731	4,28027	0,01324	14,59455
1	BSSP047T	BSSP047T_17136	1	0,03100	3,25047	0,00066	14,39978
1	BSSPEXSS236D1	BSSPEXSS236D1_17113	1	0,28546	2,40440	0,00748	15,87899

1	BSSP047B	BSSP047B_17112	1	0,87950	2,48358	0,02283	15,51379
1	BSSP047B	BSSP047B_17123	1	0,81289	2,48855	0,02283	14,31025
1	BSSP058	BSSP058_17036	2	2,22817	3,22448	0,04234	16,32164
1	BSSP058	BSSP058_17082	1	0,06704	0,92593	0,00482	15,03391
1	BSSP058	BSSP058_17194	2	2,13240	1,67458	0,08235	15,46368
1	BSSP088	BSSP088_17050	1	0,24694	2,09052	0,00785	15,04687
1	BSSP088	BSSP088_17054	1	0,38109	1,31811	0,02213	13,06386
1	BSSP089	BSSP089_17027	1	0,09327	1,84190	0,00347	14,59354
1	BSSP087	BSSP087_17049	1	0,75387	1,90637	0,02732	14,47297
1	BSSP106	BSSP106_17151	2	1,77589	3,60104	0,03056	16,13931
1	BSSP041	BSSP041_17119	1	0,45679	1,71525	0,01771	15,03802
1	BSSP041	BSSP041_17178	1	0,12796	0,38136	0,02129	15,75789
1	BSSP061	BSSP061_17052	2	2,06443	13,80618	0,01009	14,81680
1	BSSP061	BSSP061_17150	1	0,73125	1,81630	0,02632	15,29935
1	BSSP086	BSSP086_17124	1	0,86860	3,37786	0,02058	12,49755
1	BSSP059	BSSP059_17012	1	0,76797	1,67458	0,03308	13,86199
1	BSSP036	BSSP036_17200	2	1,59667	4,70112	0,02371	14,32625
1	BSSP055	BSSP055_17140	1	0,09999	0,13772	0,05622	12,91258
1	BSSP055	BSSP055_17197	1	0,03562	0,66911	0,00382	13,94054
1	BSSP084	BSSP084_17016	1	0,57759	2,13173	0,01873	14,46652
1	BSSP050	BSSP050_17139	1	1,00682	1,84705	0,03423	15,92238
1	BSSP050	BSSP050_17183	1	0,06658	0,37704	0,01432	12,32731
1	BSSP034	BSSP034_17064	1	0,41901	3,25047	0,00891	14,47006
1	BSSP034	BSSP034_17093	1	1,54331	4,70112	0,02130	15,41069
1	BSSP111	BSSP111_17191	1	0,38325	1,39417	0,02319	11,85270
1	BSSPIII	BSSPIII_17044	3	5,07535	10,89727	0,02793	16,67584
1	BSSPIII	BSSPIII_17090	2	2,76566	5,02140	0,03352	16,43141
1	BSSPIII	BSSPIII_17104	1	0,02296	0,50926	0,00302	14,91072
1	BSSPIII	BSSPIII_17115	2	1,64587	3,28920	0,03312	15,10903
1	BSSPIII	BSSPIII_17197	1	0,03603	0,51510	0,00473	14,78080
1	BSSP018D1	BSSP018D1_17188	1	0,94021	1,83712	0,03280	15,60477
1	BSSP032	BSSP032_17106	2	1,98536	1,90439	0,06505	16,02671
1	BSSP100	BSSP100_17150	1	0,06152	2,46034	0,00172	14,54221
1	BSSP031	BSSP031_17003	1	0,14844	0,97502	0,00966	15,75981
1	BSSPEXSS669	BSSPEXSS669_17005	1	0,29176	0,35647	0,05392	15,17956
1	BSSPEXSS669	BSSPEXSS669_17010	2	4,66011	5,48488	0,04963	17,11821
1	BSSPEXSS669	BSSPEXSS669_17028	1	0,98404	2,66392	0,02211	16,70577
1	BSSPEXSS235D1	BSSPEXSS235D1_17186	1	0,61188	1,25583	0,03028	16,08920
1	BSSP060	BSSP060_17052	1	1,09697	2,37714	0,03049	15,13369
1	BSSP077	BSSP077_17021	1	0,01285	2,48855	0,00034	15,24304
1	BSSP077	BSSP077_17043	1	1,35489	2,54314	0,03180	16,75118
1	BSSP009	BSSP009_17076	2	2,64733	3,08409	0,04988	17,21061
1	BSSP009	BSSP009_17194	1	0,27601	0,35647	0,04847	15,97416
1	BSSPEXSS510T	BSSPEXSS510T_17085	1	0,20556	0,97502	0,01393	15,13288
1	BSSP006	BSSP006_17051	1	0,50385	2,87033	0,01223	14,35426
1	BSSP075	BSSP075_17009	1	0,51020	1,27138	0,02610	15,37257
1	BSSP075	BSSP075_17037	1	1,04539	1,27138	0,05428	15,14960

1	BSSP075	BSSP075_17066	1	1,48837	5,19795	0,01831	15,63757
1	BSSP057	BSSP057_17077	1	0,08043	1,39417	0,00384	15,03943
1	BSSP057	BSSP057_17193	2	2,96115	8,25550	0,02215	16,19669
1	BSSPEXSS237D1	BSSPEXSS237D1_17012	1	0,32597	2,32524	0,00861	16,28887
1	BSSPEXSS237D1	BSSPEXSS237D1_17168	1	0,48821	1,31811	0,02177	17,01537
1	BSSP052	BSSP052_17141	2	2,20624	2,10651	0,07701	13,59970
1	BSSPEXSS469D1	BSSPEXSS469D1_17133	1	0,19816	0,90901	0,01341	16,26150
1	BSSP090	BSSP090_17094	1	0,17099	0,38136	0,03152	14,22507
1	BSSPEXSS236V2	BSSPEXSS236V2_17113	1	0,63910	5,19466	0,00748	16,45489
1	BSSP049	BSSP049_17136	2	3,81530	16,38082	0,01425	16,34456
1	BSSP049	BSSP049_17163	1	0,36529	1,34353	0,02100	12,94448
1	BSSP115	BSSP115_17089	1	0,37938	2,23399	0,01373	12,37191
1	BSSP115	BSSP115_17189	2	2,00223	5,82208	0,02648	12,98887
1	BSSP112	BSSP112_17055	1	0,63545	8,01588	0,00496	15,96819
1	BSSP112	BSSP112_17206	2	2,33023	9,42300	0,01606	15,39777
1	BSSP071	BSSP071_17085	1	1,19008	5,30274	0,01624	13,82053

7.3. Ranking of the main road network of the Province of Brescia – R3

R3	Path *(Provincial level)*	Minimum path *(Municipality level)*	R3 *(Municipality level)*		P	S	E
5	BSSPVIID1	BSSPVIID1_17088	5	0,70239	0,54076	0,05091	15,12256
5	BSSP034V1	BSSP034V1_17099	5	0,54050	0,31887	0,03723	15,84662
5	BSSP060	BSSP060_17052	5	0,67735	0,31257	0,03049	15,13369
5	BSSP036	BSSP036_17200	5	0,85346	0,28987	0,02371	14,32625
5	BSSP018D1	BSSP018D1_17188	5	0,55307	0,28305	0,03280	15,60477
5	BSSP018	BSSP018_17015	5	0,40902	0,08074	0,01278	15,44953
5	BSSP018	BSSP018_17041	5	0,03697	0,07809	0,13010	16,23488
5	BSSP018	BSSP018_17045	4	0,13160	0,04060	0,02127	14,50673
5	BSSP018	BSSP018_17052	5	0,75510	0,34254	0,02933	15,46549
5	BSSP018	BSSP018_17166	5	0,55011	0,81691	0,10378	14,30952
5	BSSPEXSS235D1	BSSPEXSS235D1_17186	5	0,45133	0,21990	0,03028	16,08920
5	BSSP034	BSSP034_17064	5	0,69070	0,08904	0,00891	14,47006
5	BSSP034	BSSP034_17093	5	0,85195	0,27968	0,02130	15,41069
5	BSSP067	BSSP067_17043	5	0,40837	0,18215	0,02932	15,21414
5	BSSP067	BSSP067_17161	5	0,57935	0,17977	0,01947	15,94025
5	BSSP047B	BSSP047B_17112	5	0,57813	0,20473	0,02283	15,51379
5	BSSP047B	BSSP047B_17123	5	0,47976	0,15671	0,02283	14,31025
4	BSSP047	BSSP047_17112	5	0,16336	0,09004	0,03703	14,88404
4	BSSP047	BSSP047_17136	5	0,41121	0,19158	0,03506	13,28808
4	BSSP047	BSSP047_17156	5	0,75731	0,21445	0,02044	13,85579
4	BSSP075	BSSP075_17009	5	0,51550	0,20687	0,02610	15,37257
4	BSSP075	BSSP075_17037	5	0,28720	0,23616	0,05428	15,14960
4	BSSP075	BSSP075_17066	4	0,09270	0,02654	0,01831	15,63757
4	BSSP077	BSSP077_17021	3	0,63414	0,00327	0,00034	15,24304
4	BSSP077	BSSP077_17043	5	0,54312	0,28935	0,03180	16,75118
4	BSSP068	BSSP068_17034	5	0,23586	0,28651	0,07672	15,83282
4	BSSP068	BSSP068_17078	5	0,28446	0,11394	0,02504	15,99966
4	BSSP068	BSSP068_17080	5	0,85195	0,10459	0,00907	13,53060
4	BSSP068	BSSP068_17088	4	0,10129	0,05506	0,03399	15,99218
4	BSSP061	BSSP061_17052	4	0,25668	0,03838	0,01009	14,81680
4	BSSP061	BSSP061_17150	5	0,56299	0,22666	0,02632	15,29935
4	BSSPEXSS236B	BSSPEXSS236B_17113	5	0,16828	0,09856	0,03561	16,44656
4	BSSP065	BSSP065_17009	5	0,19632	0,07583	0,02470	15,63892
4	BSSP065	BSSP065_17078	5	0,29687	0,11631	0,02492	15,72220
4	BSSP062	BSSP062_17190	5	0,12055	0,09585	0,04998	15,90739
4	BSSP021	BSSP021_17008	5	0,76387	0,32408	0,02803	15,13841
4	BSSP021	BSSP021_17009	5	0,51550	0,18083	0,02307	15,20314
4	BSSP021	BSSP021_17037	4	0,11259	0,03018	0,01698	15,79008
4	BSSP021	BSSP021_17091	3	0,02262	0,01341	0,03619	16,38641
4	BSSP021	BSSP021_17099	2	0,00002	0,00001	0,02394	15,77729

4	BSSP021	BSSP021_17147	5	0,77556	0,10167	0,00925	14,17362
4	BSSP021	BSSP021_17188	3	0,03853	0,00557	0,00933	15,48249
4	BSSPEXSS469D1	BSSPEXSS469D1_17133	5	0,42813	0,09333	0,01341	16,26150
4	BSSPEXSS236	BSSPEXSS236_17039	5	0,58621	0,27648	0,03211	14,68864
4	BSSPEXSS236	BSSPEXSS236_17043	1	0,00000	0,00000	0,02713	15,85402
4	BSSPEXSS236	BSSPEXSS236_17113	1	0,00000	0,00000	0,03806	18,08151
4	BSSP028	BSSP028_17014	2	0,00050	0,00021	0,02545	16,53850
4	BSSP028	BSSP028_17032	2	0,00005	0,00002	0,02819	16,29611
4	BSSP028	BSSP028_17033	5	0,67735	0,37272	0,03762	14,62761
4	BSSP028	BSSP028_17092	3	0,07535	0,02006	0,01756	15,15843
4	BSSP028	BSSP028_17113	3	0,03979	0,02076	0,03391	15,38355
4	BSSP024	BSSP024_17071	5	0,40837	0,30545	0,04711	15,87872
4	BSSP024	BSSP024_17073	3	0,02440	0,01815	0,04599	16,17074
4	BSSP024	BSSP024_17078	2	0,00001	0,00001	0,02682	16,93359
4	BSSP024	BSSP024_17086	3	0,01561	0,00866	0,03402	16,30324
4	BSSP024	BSSP024_17114	2	0,00091	0,00028	0,01884	16,16650
4	BSSP024	BSSP024_17147	5	0,48424	0,16172	0,02226	15,00239
4	BSSPIV	BSSPIV_17164	1	0,00000	0,00000	0,02310	16,33055
4	BSSPIV	BSSPIV_17168	5	0,12924	0,24434	0,12561	15,05119
4	BSSPIV	BSSPIV_17204	1	0,00000	0,00000	0,02468	14,94697
4	BSSP087	BSSP087_17049	5	0,20414	0,08073	0,02732	14,47297
4	BSSPEXSS669	BSSPEXSS669_17005	3	0,00251	0,00205	0,05392	15,17956
4	BSSPEXSS669	BSSPEXSS669_17010	1	0,00000	0,00000	0,04963	17,11821
4	BSSPEXSS669	BSSPEXSS669_17028	5	0,62997	0,23271	0,02211	16,70577
4	BSSPEXSS237D1	BSSPEXSS237D1_17012	3	0,10544	0,01478	0,00861	16,28887
4	BSSPEXSS237D1	BSSPEXSS237D1_17168	5	0,38112	0,14116	0,02177	17,01537
4	BSSPVII	BSSPVII_17009	3	0,00788	0,00366	0,03168	14,65471
4	BSSPVII	BSSPVII_17088	3	0,00355	0,00124	0,02072	16,81149
4	BSSPVII	BSSPVII_17108	4	0,07092	0,03615	0,03201	15,92764
4	BSSPVII	BSSPVII_17137	3	0,00803	0,00460	0,03507	16,33178
4	BSSPVII	BSSPVII_17152	5	0,20549	0,12966	0,03948	15,98307
4	BSSPVII	BSSPVII_17177	5	0,75510	0,26689	0,02410	14,66859
4	BSSP066	BSSP066_17043	5	0,59682	0,14406	0,01539	15,68415
4	BSSP066	BSSP066_17078	2	0,00050	0,00026	0,03183	16,22695
4	BSSP004	BSSP004_17014	2	0,00005	0,00002	0,02977	15,76590
4	BSSP004	BSSP004_17092	5	0,34639	0,19466	0,04145	13,55904
4	BSSP004	BSSP004_17107	2	0,00053	0,00011	0,01243	16,08117
4	BSSP004	BSSP004_17120	5	0,49257	0,16495	0,02316	14,45778
4	BSSP004	BSSP004_17129	2	0,00004	0,00002	0,02421	15,79614
4	BSSPEXSS236D1	BSSPEXSS236D1_17113	5	0,57642	0,06843	0,00748	15,87899
4	BSSPIX	BSSPIX_17008	2	0,00000	0,00000	0,02312	15,82504
4	BSSPIX	BSSPIX_17020	5	0,51275	0,20360	0,02662	14,91672
4	BSSPIX	BSSPIX_17037	2	0,00000	0,00000	0,02439	15,31496

4	BSSPIX	BSSPIX_17042	2	0,00008	0,00002	0,01488	14,69338
4	BSSPIX	BSSPIX_17066	2	0,00119	0,00060	0,02963	17,02502
4	BSSPIX	BSSPIX_17072	2	0,00002	0,00000	0,01808	14,85146
4	BSSPIX	BSSPIX_17099	5	0,66850	0,23568	0,02475	14,24503
4	BSSPIX	BSSPIX_17138	3	0,00887	0,00660	0,04696	15,83793
4	BSSPIX	BSSPIX_17159	3	0,04349	0,01770	0,02570	15,83813
4	BSSPIX	BSSPIX_17195	5	0,19775	0,16631	0,05558	15,13208
4	BSSPIX	BSSPIX_17196	5	0,18616	0,12088	0,04608	14,09164
3	BSSP002	BSSP002_17125	3	0,00501	0,00187	0,02418	15,42027
3	BSSP002	BSSP002_17162	3	0,01380	0,00614	0,02897	15,34819
3	BSSP002	BSSP002_17167	5	0,30149	0,22366	0,05030	14,74850
3	BSSP002	BSSP002_17192	4	0,16207	0,03542	0,01527	14,31169
3	BSSP033	BSSP033_17026	3	0,02187	0,00747	0,02151	15,88935
3	BSSP033	BSSP033_17066	5	0,19311	0,09302	0,02958	16,28607
3	BSSP033	BSSP033_17093	5	0,33542	0,09038	0,01758	15,33128
3	BSSP033	BSSP033_17103	3	0,04547	0,01564	0,02247	15,30260
3	BSSP033	BSSP033_17122	5	0,19606	0,11226	0,03609	15,86656
3	BSSP017	BSSP017_17002	2	0,00139	0,00031	0,01412	15,54209
3	BSSP017	BSSP017_17041	3	0,05412	0,00912	0,01066	15,80625
3	BSSP017	BSSP017_17052	2	0,00197	0,00083	0,02642	15,97428
3	BSSP017	BSSP017_17059	2	0,00000	0,00000	0,02481	16,02374
3	BSSP017	BSSP017_17069	5	0,25210	0,30372	0,07876	15,29778
3	BSSP049	BSSP049_17136	3	0,02251	0,00524	0,01425	16,34456
3	BSSP049	BSSP049_17163	5	0,40837	0,11103	0,02100	12,94448
3	BSSPEXSS42	BSSPEXSS42_17028	5	0,62890	0,06635	0,00707	14,92796
3	BSSPEXSS42	BSSPEXSS42_17035	3	0,04918	0,00619	0,00802	15,68175
3	BSSPEXSS42	BSSPEXSS42_17047	5	0,22550	0,11308	0,03372	14,87297
3	BSSPEXSS42	BSSPEXSS42_17050	3	0,02473	0,00414	0,01033	16,22577
3	BSSPEXSS42	BSSPEXSS42_17118	3	0,03425	0,02566	0,04921	15,22849
3	BSSPEXSS42	BSSPEXSS42_17176	5	0,32169	0,17948	0,03501	15,93430
3	BSSPEXSS42	BSSPEXSS45B_17009	2	0,00000	0,00000	0,01912	16,15379
3	BSSPEXSS510T	BSSPEXSS510T_17085	4	0,25034	0,05278	0,01393	15,13288
3	BSSP070	BSSP070_17069	3	0,01063	0,00575	0,03397	15,92788
3	BSSP070	BSSP070_17133	5	0,39253	0,08765	0,01672	13,35788
3	BSSP011	BSSP011_17013	5	0,37243	0,22632	0,04064	14,95435
3	BSSP011	BSSP011_17020	3	0,00860	0,00526	0,03884	15,75053
3	BSSP011	BSSP011_17053	4	0,08603	0,03738	0,02936	14,79767
3	BSSP011	BSSP011_17080	2	0,00010	0,00003	0,01959	16,27559
3	BSSP011	BSSP011_17086	2	0,00041	0,00014	0,02090	16,18339
3	BSSP011	BSSP011_17125	3	0,03385	0,01331	0,02439	16,12451
3	BSSP011	BSSP011_17137	2	0,00028	0,00002	0,00547	15,77000
3	BSSP011	BSSP011_17172	5	0,75510	0,22882	0,01908	15,88022
3	BSSP011	BSSP011_17195	2	0,00002	0,00000	0,01952	16,37935

3	BSSP011	BSSP011_17196	2	0,00038	0,00029	0,04717	15,96317
3	BSSP011	BSSP011_17203	2	0,00079	0,00034	0,02644	16,38823
3	BSSP111	BSSP111_17191	4	0,15498	0,04260	0,02319	11,85270
3	BSSPEXSS236V2	BSSPEXSS236V2_17113	4	0,34023	0,04186	0,00748	16,45489
3	BSSP090	BSSP090_17094	4	0,09113	0,04086	0,03152	14,22507
3	BSSP029	BSSP029_17034	5	0,06822	0,07620	0,06888	16,21759
3	BSSP029	BSSP029_17113	2	0,00001	0,00000	0,02684	16,25836
3	BSSP029	BSSP029_17160	5	0,15512	0,07561	0,03191	15,27721
3	BSSP029	BSSP029_17203	3	0,00127	0,00094	0,04619	15,90644
3	BSSP008	BSSP008_17017	2	0,00000	0,00000	0,02600	12,66594
3	BSSP008	BSSP008_17018	2	0,00372	0,00054	0,01134	12,85254
3	BSSP008	BSSP008_17070	2	0,00000	0,00000	0,03229	14,89224
3	BSSP008	BSSP008_17206	5	0,58251	0,14112	0,01713	14,13998
3	BSSP020	BSSP020_17060	3	0,00342	0,00259	0,04752	15,95811
3	BSSP020	BSSP020_17097	4	0,11479	0,06178	0,03648	14,75228
3	BSSP020	BSSP020_17162	5	0,58720	0,07183	0,00836	14,63634
3	BSSP020	BSSP020_17190	3	0,00878	0,00284	0,02011	16,05730
3	BSSPEXSS668	BSSPEXSS668_17032	3	0,01089	0,00390	0,02289	15,62754
3	BSSPEXSS668	BSSPEXSS668_17078	2	0,00003	0,00002	0,03264	17,09011
3	BSSPEXSS668	BSSPEXSS668_17088	3	0,06800	0,02509	0,02150	17,15792
3	BSSPEXSS668	BSSPEXSS668_17092	5	0,12614	0,07161	0,03606	15,74358
3	BSSPEXSS668	BSSPEXSS668_17103	4	0,03522	0,03375	0,05746	16,67528
3	BSSPEXSS668	BSSPEXSS668_17113	1	0,00000	0,00000	0,03074	16,95539
3	BSSPEXSS668	BSSPEXSS668_17122	3	0,02463	0,02027	0,05008	16,43300
3	BSSPEXSS668	BSSPEXSS668_17125	3	0,00665	0,00316	0,02944	16,13735
3	BSSPEXSS668	BSSPEXSS668_17126	5	0,62056	0,18320	0,01863	15,84573
3	BSSPEXSS668	BSSPEXSS668_17138	2	0,00005	0,00004	0,04452	16,65322
3	BSSP016	BSSP016_17011	5	0,35518	0,08009	0,01418	15,89704
3	BSSP016	BSSP016_17045	4	0,12814	0,02997	0,01613	14,50122
3	BSSP016	BSSP016_17064	3	0,04586	0,02271	0,03108	15,93379
3	BSSP016	BSSP016_17166	2	0,00013	0,00005	0,02160	16,57480
3	BSSP016	BSSP016_17190	4	0,11097	0,03746	0,02045	16,50530
3	BSSP089	BSSP089_17027	4	0,64417	0,03262	0,00347	14,59354
3	BSSPEXSS11V1	BSSPEXSS11V1_17014	3	0,03666	0,01946	0,03158	16,80762
3	BSSPEXSS11V1	BSSPEXSS11V1_17029	1	0,00000	0,00000	0,00894	19,68411
3	BSSPEXSS11V1	BSSPEXSS11V1_17032	3	0,10806	0,02150	0,01229	16,18683
3	BSSPEXSS11V1	BSSPEXSS11V1_17040	2	0,00002	0,00001	0,01897	15,65279
3	BSSPEXSS11V1	BSSPEXSS11V1_17067	5	0,28477	0,21210	0,04854	15,34583
3	BSSPEXSS11V1	BSSPEXSS11V1_17092	3	0,00982	0,00737	0,04374	17,15698
3	BSSPEXSS11V1	BSSPEXSS11V1_17107	2	0,00022	0,00007	0,01969	16,31649
3	BSSPEXSS11V1	BSSPEXSS11V1_17161	1	0,00000	0,00000	0,02242	17,93817
3	BSSPEXSS11V1	BSSPEXSS11V1_17165	1	0,00000	0,00000	0,01565	18,24165
3	BSSP037	BSSP037_17034	3	0,00590	0,00256	0,02559	16,94314

3	BSSP037	BSSP037_17043	3	0,02156	0,00724	0,02131	15,75942
3	BSSP037	BSSP037_17086	5	0,22769	0,06959	0,02003	15,25702
3	BSSP037	BSSP037_17113	4	0,05235	0,02962	0,03380	16,73781
3	BSSP069	BSSP069_17034	4	0,11997	0,04703	0,02432	16,11753
3	BSSP069	BSSP069_17039	3	0,03455	0,00741	0,01405	15,26879
3	BSSP088	BSSP088_17050	2	0,00478	0,00056	0,00785	15,04687
3	BSSP088	BSSP088_17054	4	0,17525	0,05067	0,02213	13,06386
3	BSSP019	BSSP019_17008	5	0,39837	0,18356	0,03169	14,54152
3	BSSP019	BSSP019_17046	3	0,00315	0,00131	0,02679	15,52422
3	BSSP019	BSSP019_17061	2	0,00000	0,00000	0,01462	16,22574
3	BSSP019	BSSP019_17081	2	0,00003	0,00001	0,02174	16,55477
3	BSSP019	BSSP019_17091	3	0,00208	0,00118	0,03618	15,69073
3	BSSP019	BSSP019_17127	1	0,00000	0,00000	0,01326	17,75660
3	BSSP019	BSSP019_17130	1	0,00000	0,00000	0,01896	17,57844
3	BSSP019	BSSP019_17136	2	0,00002	0,00001	0,02047	16,70473
3	BSSP019	BSSP019_17163	1	0,00000	0,00000	0,02655	17,87749
3	BSSP019	BSSP019_17186	5	0,75731	0,07625	0,00717	14,04610
3	BSSP019	BSSP019_17188	2	0,00023	0,00010	0,02402	16,93810
3	BSSPVIII	BSSPVIII_17071	4	0,14610	0,03837	0,01569	16,73793
3	BSSPVIII	BSSPVIII_17073	3	0,03740	0,01306	0,02162	16,15467
3	BSSPVIII	BSSPVIII_17080	3	0,00949	0,00359	0,02307	16,38434
3	BSSPVIII	BSSPVIII_17088	4	0,06931	0,03401	0,03089	15,88364
3	BSSP051B	BSSP051B_17046	3	0,00401	0,00103	0,01634	15,65476
3	BSSP051B	BSSP051B_17069	4	0,22113	0,04274	0,01324	14,59455
3	BSSP013	BSSP013_17067	4	0,21824	0,04071	0,01174	15,88831
3	BSSP013	BSSP013_17151	2	0,00000	0,00000	0,02968	16,60021
3	BSSP022	BSSP022_17072	2	0,00083	0,00014	0,01058	16,19712
3	BSSP022	BSSP022_17147	4	0,15519	0,04016	0,01637	15,80573
3	SS42	SS42_17007	3	0,00591	0,00344	0,03835	15,16874
3	SS42	SS42_17016	3	0,00750	0,00196	0,01587	16,50725
3	SS42	SS42_17027	4	0,16795	0,06334	0,02467	15,28898
3	SS42	SS42_17028	2	0,00064	0,00034	0,03223	16,36596
3	SS42	SS42_17035	2	0,00040	0,00023	0,03474	16,26948
3	SS42	SS42_17050	4	0,06779	0,06150	0,05446	16,66009
3	SS42	SS42_17055	2	0,00076	0,00016	0,01342	16,16646
3	SS42	SS42_17065	1	0,00000	0,00000	0,02244	17,48654
3	SS42	SS42_17068	1	0,00000	0,00000	0,02206	16,34230
3	SS42	SS42_17070	1	0,00000	0,00000	0,04349	16,57266
3	SS42	SS42_17079	3	0,03534	0,02399	0,04572	14,85338
3	SS42	SS42_17083	2	0,00000	0,00000	0,05486	15,57006
3	SS42	SS42_17101	2	0,00001	0,00000	0,01828	16,11412
3	SS42	SS42_17110	5	0,25967	0,16158	0,04006	15,53504
3	SS42	SS42_17118	3	0,06442	0,02191	0,02218	15,33365

3	SS42	SS42_17142	2	0,00001	0,00001	0,02618	15,30357
3	SS42	SS42_17148	1	0,00000	0,00000	0,05075	16,27086
3	SS42	SS42_17176	5	0,12966	0,07484	0,03539	16,31145
3	SS42	SS42_17181	1	0,00000	0,00000	0,03577	16,45085
3	SS42	SS42_17184	2	0,00000	0,00000	0,02739	15,77858
3	SS42	SS42_17198	2	0,00016	0,00007	0,02640	15,88188
3	SS42	SS42_17202	1	0,00000	0,00000	0,02581	15,39062
3	BSSP025	BSSP025_17092	1	0,00000	0,00000	0,04128	16,74324
3	BSSP025	BSSP025_17129	3	0,03039	0,00584	0,01287	14,92348
3	BSSP025	BSSP025_17145	3	0,07008	0,01351	0,01215	15,87165
3	BSSP025	BSSP025_17158	3	0,01632	0,00642	0,02396	16,40881
3	BSSP025	BSSP025_17180	5	0,14128	0,06644	0,02914	16,13958
3	BSSP064	BSSP064_17004	3	0,01126	0,00575	0,03101	16,46449
3	BSSP064	BSSP064_17020	3	0,00923	0,00397	0,02875	14,95325
3	BSSP064	BSSP064_17073	3	0,03432	0,00500	0,00945	15,42105
3	BSSP064	BSSP064_17108	4	0,01859	0,05532	0,19152	15,54193
3	BSSP064	BSSP064_17149	2	0,00002	0,00001	0,02416	16,74172
3	BSSP064	BSSP064_17152	3	0,04062	0,01262	0,01856	16,74489
3	BSSP064	BSSP064_17159	3	0,05957	0,02243	0,02335	16,12390
3	BSSP064	BSSP064_17196	4	0,06125	0,03457	0,03554	15,87768
3	BSSPEXSS343	BSSPEXSS343_17001	3	0,01417	0,00888	0,03918	16,00248
3	BSSPEXSS343	BSSPEXSS343_17039	2	0,00010	0,00005	0,03149	17,54595
3	BSSPEXSS343	BSSPEXSS343_17113	4	0,23429	0,04265	0,01248	14,59178
3	BSSP072	BSSP072_17052	3	0,00330	0,00136	0,02507	16,42334
3	BSSP072	BSSP072_17162	4	0,04361	0,03162	0,04510	16,07823
2	BSSP100	BSSP100_17150	3	0,64616	0,01616	0,00172	14,54221
2	BSSP027	BSSP027_17033	3	0,02347	0,00841	0,02278	15,73751
2	BSSP027	BSSP027_17155	3	0,07270	0,02203	0,01891	16,02095
2	BSSP046	BSSP046_17123	4	0,23887	0,02753	0,00764	15,07808
2	BSSP046	BSSP046_17163	3	0,00785	0,00263	0,02159	15,51426
2	BSSPEXSS235	BSSPEXSS235_17026	4	0,04861	0,04131	0,05718	14,86060
2	BSSPEXSS235	BSSPEXSS235_17042	2	0,00068	0,00015	0,01380	15,98772
2	BSSPEXSS235	BSSPEXSS235_17064	3	0,02627	0,01000	0,02450	15,53057
2	BSSPEXSS235	BSSPEXSS235_17091	2	0,00001	0,00000	0,03391	15,83757
2	BSSPEXSS235	BSSPEXSS235_17097	3	0,02282	0,00477	0,01372	15,23532
2	BSSPEXSS235	BSSPEXSS235_17125	3	0,00640	0,00466	0,04306	16,90947
2	BSSPEXSS235	BSSPEXSS235_17126	2	0,00133	0,00028	0,01378	15,52438
2	BSSPEXSS235	BSSPEXSS235_17146	3	0,02684	0,00624	0,01509	15,40277
2	BSSPEXSS235	BSSPEXSS235_17165	1	0,00000	0,00000	0,01278	15,68551
2	BSSPEXSS235	BSSPEXSS235_17186	2	0,00000	0,00000	0,02507	15,49307
2	BSSPEXSS235	BSSPEXSS235_17188	5	0,35108	0,08259	0,01639	14,35296
2	A4racc	A4racc_17043	2	0,00003	0,00001	0,02330	16,75300
2	A4racc	A4racc_17161	4	0,05843	0,02709	0,02842	16,31297

2	BSSP096	BSSP096_17038	3	0,03363	0,01340	0,02555	15,59338
2	BSSPEXSS237	BSSPEXSS237_17005	1	0,00000	0,00000	0,04425	16,80455
2	BSSPEXSS237	BSSPEXSS237_17010	5	0,58251	0,09793	0,01082	15,53213
2	BSSPEXSS237	BSSPEXSS237_17012	1	0,00000	0,00000	0,03793	16,49689
2	BSSPEXSS237	BSSPEXSS237_17025	4	0,22270	0,05381	0,01559	15,50171
2	BSSPEXSS237	BSSPEXSS237_17031	1	0,00000	0,00000	0,02247	16,29360
2	BSSPEXSS237	BSSPEXSS237_17082	2	0,00000	0,00000	0,03538	16,31179
2	BSSPEXSS237	BSSPEXSS237_17087	1	0,00000	0,00000	0,02722	16,13621
2	BSSPEXSS237	BSSPEXSS237_17117	1	0,00000	0,00000	0,01551	16,77571
2	BSSPEXSS237	BSSPEXSS237_17121	3	0,00952	0,00449	0,02922	16,13406
2	BSSPEXSS237	BSSPEXSS237_17153	3	0,00120	0,00091	0,04710	15,99741
2	BSSPEXSS237	BSSPEXSS237_17193	1	0,00000	0,00000	0,03513	15,86222
2	BSSPEXSS237	BSSPEXSS237_17197	1	0,00000	0,00000	0,02105	16,68998
2	TANGOVEST	TANGOVEST_17042	6	0,14607	0,01923	0,01668	31,57662
2	BSSP052	BSSP052_17141	3	0,01177	0,01233	0,07701	13,59970
2	BSSP031	BSSP031_17003	3	0,07214	0,01098	0,00966	15,75981
2	BSSP086	BSSP086_17124	3	0,03706	0,00953	0,02058	12,49755
2	BSSP026	BSSP026_17077	3	0,00462	0,00150	0,02242	14,47666
2	BSSP026	BSSP026_17102	4	0,28600	0,03591	0,00861	14,57471
2	BSSP026	BSSP026_17116	2	0,00000	0,00000	0,02001	16,73067
2	BSSP026	BSSP026_17145	2	0,00000	0,00000	0,01459	16,42255
2	BSSPEXSS45B	BSSPEXSS45B_17013	3	0,03282	0,02591	0,04887	16,15084
2	BSSPEXSS45B	BSSPEXSS45B_17074	1	0,00000	0,00000	0,01547	15,64165
2	BSSPEXSS45B	BSSPEXSS45B_17076	1	0,00000	0,00000	0,03157	16,58305
2	BSSPEXSS45B	BSSPEXSS45B_17077	1	0,00000	0,00000	0,02643	16,10053
2	BSSPEXSS45B	BSSPEXSS45B_17089	1	0,00000	0,00000	0,01905	16,62523
2	BSSPEXSS45B	BSSPEXSS45B_17103	3	0,03624	0,01475	0,02451	16,60780
2	BSSPEXSS45B	BSSPEXSS45B_17107	2	0,00174	0,00041	0,01509	15,62015
2	BSSPEXSS45B	BSSPEXSS45B_17119	3	0,01152	0,00490	0,02780	15,31064
2	BSSPEXSS45B	BSSPEXSS45B_17120	3	0,00311	0,00164	0,03281	16,06938
2	BSSPEXSS45B	BSSPEXSS45B_17122	5	0,19976	0,10864	0,03692	14,73097
2	BSSPEXSS45B	BSSPEXSS45B_17147	2	0,00028	0,00016	0,03689	15,91857
2	BSSPEXSS45B	BSSPEXSS45B_17149	2	0,00061	0,00023	0,02352	16,15095
2	BSSPEXSS45B	BSSPEXSS45B_17155	2	0,00000	0,00000	0,02110	16,25185
2	BSSPEXSS45B	BSSPEXSS45B_17161	1	0,00000	0,00000	0,01609	16,37259
2	BSSPEXSS45B	BSSPEXSS45B_17164	1	0,00000	0,00000	0,01820	16,53517
2	BSSPEXSS45B	BSSPEXSS45B_17170	1	0,00000	0,00000	0,02583	16,56997
2	BSSPEXSS45B	BSSPEXSS45B_17173	2	0,00003	0,00001	0,02650	14,20409
2	BSSPEXSS45B	BSSPEXSS45B_17185	1	0,00000	0,00000	0,03600	16,77084
2	BSSPEXSS45B	BSSPEXSS45B_17187	1	0,00000	0,00000	0,01749	16,53390
2	BSSPEXSS45B	BSSPEXSS45B_17189	1	0,00000	0,00000	0,03602	16,62704
2	BSSPEXSS45B	BSSPEXSS45B_17195	4	0,21428	0,05752	0,02177	12,33128
2	BSSPEXSS45B	BSSPEXSS45B_17201	1	0,00000	0,00000	0,02127	16,47582

2	BSSPEXSS45B	BSSPEXSS469_17038	1	0,00000	0,00000	0,01716	16,48380
2	A35	A35_17045	3	0,00402	0,00111	0,01591	17,34639
2	A35	A35_17046	4	0,09218	0,03876	0,02562	16,41603
2	A35	A35_17052	1	0,00000	0,00000	0,03281	18,62793
2	A35	A35_17127	2	0,02553	0,00058	0,00153	14,78322
2	A35	A35_17166	1	0,00000	0,00000	0,02784	18,27730
2	A35	A35_17188	2	0,00000	0,00000	0,01402	18,48715
2	A35	A35_17192	3	0,03213	0,01286	0,02314	17,29354
2	BSSP073	BSSP073_17037	3	0,02901	0,00758	0,01712	15,26439
2	BSSP047T	BSSP047T_17136	3	0,78808	0,00752	0,00066	14,39978
2	BSSP051	BSSP051_17046	2	0,00132	0,00034	0,01620	15,86536
2	BSSP051	BSSP051_17136	3	0,12898	0,01292	0,00649	15,43658
2	TANGOVEST	TANGOVEST_17029	1	0,00000	0,00000	0,01584	18,98008
2	BSSP058	BSSP058_17036	3	0,02324	0,01606	0,04234	16,32164
2	BSSP058	BSSP058_17082	2	0,00001	0,00000	0,00482	15,03391
2	BSSP058	BSSP058_17194	3	0,00215	0,00274	0,08235	15,46368
2	BSSP079	BSSP079_17003	2	0,00001	0,00001	0,04272	16,23507
2	BSSP079	BSSP079_17019	4	0,03347	0,02899	0,05679	15,25256
2	BSSP079	BSSP079_17096	2	0,00000	0,00000	0,01936	15,82251
2	BSSP079	BSSP079_17153	2	0,00026	0,00013	0,03170	15,68270
2	BSSP079	BSSP079_17168	2	0,00000	0,00000	0,04314	15,74741
2	A35racc	A35racc_17040	2	0,00056	0,00028	0,03014	16,72213
2	A35racc	A35racc_17165	3	0,06283	0,01133	0,01088	16,57740
2	BSSPEXSS294	BSSPEXSS294_17006	1	0,00000	0,00000	0,02517	14,81921
2	BSSPEXSS294	BSSPEXSS294_17065	1	0,00000	0,00000	0,01916	15,60442
2	BSSPEXSS294	BSSPEXSS294_17131	3	0,05666	0,01351	0,01756	13,57137
2	BSSP023	BSSP023_17021	3	0,00807	0,00118	0,00909	16,09033
2	BSSP023	BSSP023_17114	3	0,02181	0,00732	0,02120	15,83378
2	BSSP023	BSSP023_17173	3	0,01902	0,00407	0,01383	15,46642
2	BSSPEXSS510	BSSPEXSS510_17081	3	0,00441	0,00131	0,01848	16,10690
2	BSSPEXSS510	BSSPEXSS510_17085	2	0,00000	0,00000	0,01023	16,42452
2	BSSPEXSS510	BSSPEXSS510_17106	1	0,00000	0,00000	0,01426	17,16485
2	BSSPEXSS510	BSSPEXSS510_17136	2	0,00001	0,00000	0,03759	16,87287
2	BSSPEXSS510	BSSPEXSS510_17142	4	0,14625	0,02597	0,01137	15,62408
2	BSSPEXSS510	BSSPEXSS510_17143	1	0,00000	0,00000	0,03661	17,42009
2	BSSPEXSS510	BSSPEXSS510_17156	1	0,00000	0,00000	0,02610	16,64814
2	BSSPEXSS510	BSSPEXSS510_17163	1	0,00000	0,00000	0,02631	18,22565
2	BSSPEXSS510	BSSPEXSS510_17169	2	0,00001	0,00000	0,00896	16,59453
2	BSSPEXSS510	BSSPEXSS510_17182	3	0,03149	0,01295	0,02563	16,04951
2	BSSP009	BSSP009_17076	1	0,00000	0,00000	0,04988	17,21061
2	BSSP009	BSSP009_17194	3	0,01006	0,00779	0,04847	15,97416
2	BSSP041	BSSP041_17119	1	0,00000	0,00000	0,01771	15,03802
2	BSSP041	BSSP041_17178	3	0,02075	0,00696	0,02129	15,75789

2	BSSP076	BSSP076_17160	3	0,00540	0,00338	0,03761	16,62861
2	BSSPXI	BSSPXI_17002	3	0,01954	0,00569	0,01902	15,30907
2	BSSPXI	BSSPXI_17046	3	0,05231	0,01100	0,01511	13,91161
2	BSSPXI	BSSPXI_17062	2	0,00004	0,00002	0,02291	16,32566
2	BSSPXI	BSSPXI_17069	1	0,00000	0,00000	0,02219	15,84025
2	BSSPXI	BSSPXI_17085	2	0,00000	0,00000	0,02952	16,08262
2	BSSP032	BSSP032_17106	3	0,00238	0,00249	0,06505	16,02671
2	BSSPEXSS510B	BSSPEXSS510B_17085	3	0,00494	0,00233	0,02834	16,63705
2	BSSP055	BSSP055_17140	3	0,00562	0,00408	0,05622	12,91258
2	BSSP055	BSSP055_17197	2	0,00188	0,00010	0,00382	13,94054
2	BSSP010	BSSP010_17030	2	0,00013	0,00001	0,00299	15,12786
2	BSSP010	BSSP010_17048	1	0,00000	0,00000	0,01462	16,25263
2	BSSP010	BSSP010_17081	3	0,01268	0,00490	0,02512	15,37377
2	BSSP010	BSSP010_17144	3	0,04233	0,00342	0,00545	14,82870
1	BSSP057	BSSP057_17077	3	0,06995	0,00404	0,00384	15,03943
1	BSSP057	BSSP057_17193	1	0,00000	0,00000	0,02215	16,19669
1	BSSP059	BSSP059_17012	3	0,00432	0,00198	0,03308	13,86199
1	BSSPI	BSSPI_17007	3	0,01463	0,00731	0,03275	15,26399
1	BSSPI	BSSPI_17079	2	0,00048	0,00028	0,03819	14,94854
1	BSSPI	BSSPI_17142	2	0,00000	0,00000	0,01440	15,64442
1	BSSPI	BSSPI_17143	2	0,00001	0,00001	0,03235	16,02649
1	BSSPIII	BSSPIII_17044	1	0,00000	0,00000	0,02793	16,67584
1	BSSPIII	BSSPIII_17090	2	0,00005	0,00003	0,03352	16,43141
1	BSSPIII	BSSPIII_17104	3	0,01914	0,00086	0,00302	14,91072
1	BSSPIII	BSSPIII_17115	2	0,00078	0,00039	0,03312	15,10903
1	BSSPIII	BSSPIII_17197	3	0,11694	0,00818	0,00473	14,78080
1	BSSPXII	BSSPXII_17002	2	0,00015	0,00005	0,02248	15,89660
1	BSSPXII	BSSPXII_17038	3	0,03622	0,00528	0,00969	15,04471
1	BSSPXII	BSSPXII_17069	1	0,00000	0,00000	0,02063	16,62490
1	BSSP078	BSSP078_17033	2	0,00098	0,00036	0,02270	16,01464
1	BSSP078	BSSP078_17092	3	0,00549	0,00229	0,02745	15,20716
1	BSSPEXSS469	BSSPEXSS469_17133	1	0,00000	0,00000	0,01434	15,19239
1	BSSPEXSS469	BSSPEXSS469_17134	1	0,00000	0,00000	0,01370	16,61598
1	BSSPEXSS469	BSSPEXSS469_17150	2	0,00001	0,00000	0,01385	16,55902
1	BSSPEXSS469	BSSPEXSS469_17192	3	0,00353	0,00473	0,08272	16,21081
1	BSSP050	BSSP050_17139	2	0,00009	0,00005	0,03423	15,92238
1	BSSP050	BSSP050_17183	3	0,01292	0,00228	0,01432	12,32731
1	BSSP116	BSSP116_17077	1	0,00000	0,00000	0,01478	16,30533
1	BSSP116	BSSP116_17107	3	0,00640	0,00101	0,01004	15,79490
1	BSSP116	BSSP116_17119	3	0,00399	0,00166	0,02637	15,80052
1	BSSP116	BSSP116_17120	3	0,00326	0,00138	0,02715	15,64509
1	BSSP116	BSSP116_17132	3	0,00892	0,00306	0,02221	15,44889
1	BSSP116	BSSP116_17155	2	0,00013	0,00005	0,02250	15,61437

1	BSSP116	BSSP116_17164	2	0,00135	0,00043	0,02003	15,85206
1	BSSP116	BSSP116_17201	2	0,00002	0,00000	0,01860	16,09758
1	BSSP071	BSSP071_17085	2	0,00303	0,00068	0,01624	13,82053
1	A21racc	A21racc_17008	2	0,00000	0,00000	0,03911	17,01571
1	A21racc	A21racc_17037	2	0,00000	0,00000	0,01838	16,19011
1	A21racc	A21racc_17042	3	0,01457	0,00279	0,01185	16,14586
1	A21racc	A21racc_17043	1	0,00000	0,00000	0,02771	18,65709
1	A21racc	A21racc_17072	1	0,00000	0,00000	0,01699	18,41664
1	A21racc	A21racc_17114	1	0,00000	0,00000	0,04001	17,49827
1	A21racc	A21racc_17147	1	0,00000	0,00000	0,02539	17,38199
1	BSSP112	BSSP112_17055	2	0,00922	0,00073	0,00496	15,96819
1	BSSP112	BSSP112_17206	1	0,00000	0,00000	0,01606	15,39777
1	BSSP006	BSSP006_17051	2	0,00188	0,00033	0,01223	14,35426
1	BSSPEXSS345	BSSPEXSS345_17018	2	0,00001	0,00000	0,04336	16,40789
1	BSSPEXSS345	BSSPEXSS345_17024	2	0,00257	0,00085	0,02097	15,84504
1	BSSPEXSS345	BSSPEXSS345_17028	1	0,00000	0,00000	0,02896	16,39408
1	BSSPEXSS345	BSSPEXSS345_17055	2	0,00756	0,00072	0,00598	15,98694
1	BSSPEXSS345	BSSPEXSS345_17058	1	0,00000	0,00000	0,04189	16,07336
1	BSSPEXSS345	BSSPEXSS345_17061	1	0,00000	0,00000	0,02250	16,82567
1	BSSPEXSS345	BSSPEXSS345_17075	1	0,00000	0,00000	0,02198	16,40972
1	BSSPEXSS345	BSSPEXSS345_17100	2	0,00005	0,00003	0,03655	15,59867
1	BSSPEXSS345	BSSPEXSS345_17141	2	0,00002	0,00001	0,02735	15,48238
1	BSSPEXSS345	BSSPEXSS345_17174	1	0,00000	0,00000	0,01512	16,24268
1	BSSPEXSS345	BSSPEXSS345_17183	3	0,00322	0,00142	0,02700	16,35266
1	BSSPEXSS345	BSSPEXSS345_17199	1	0,00000	0,00000	0,01208	16,06172
1	BSSPEXSS345	BSSPEXSS42_17016	2	0,00176	0,00075	0,02676	15,86683
1	BSSPEXSS11	BSSPEXSS11_17032	3	0,00616	0,00238	0,02657	14,51722
1	BSSPEXSS11	BSSPEXSS11_17040	1	0,00000	0,00000	0,02230	16,26882
1	BSSPEXSS11	BSSPEXSS11_17046	2	0,00044	0,00017	0,02603	15,29587
1	BSSPEXSS11	BSSPEXSS11_17052	1	0,00000	0,00000	0,02337	15,55580
1	BSSPEXSS11	BSSPEXSS11_17056	2	0,00007	0,00002	0,01922	16,20963
1	BSSPEXSS11	BSSPEXSS11_17067	1	0,00000	0,00000	0,02075	17,17870
1	BSSPEXSS11	BSSPEXSS11_17092	2	0,00001	0,00000	0,03149	12,54927
1	BSSPEXSS11	BSSPEXSS11_17127	2	0,00001	0,00000	0,01310	14,30155
1	BSSPEXSS11	BSSPEXSS11_17165	2	0,00054	0,00009	0,01198	14,18564
1	BSSPEXSS11	BSSPEXSS11_17166	2	0,00000	0,00000	0,01703	15,49691
1	BSSPEXSS11	BSSPEXSS11_17192	2	0,00002	0,00001	0,01655	15,95282
1	BSSPV	BSSPV_17164	2	0,00123	0,00047	0,02448	15,60894
1	BSSPV	BSSPV_17170	1	0,00000	0,00000	0,01742	16,59987
1	BSSP106	BSSP106_17151	2	0,00046	0,00023	0,03056	16,13931
1	BSSP099	BSSP099_17133	2	0,00042	0,00014	0,02149	15,36622
1	BSSP012	BSSP012_17085	1	0,00000	0,00000	0,01894	16,47631
1	BSSP012	BSSP012_17134	2	0,00021	0,00005	0,01573	15,26251

1	A21	A21_17004	2	0,00005	0,00003	0,03762	17,03543
1	A21	A21_17009	1	0,00000	0,00000	0,03100	18,38685
1	A21	A21_17013	1	0,00000	0,00000	0,01069	17,09161
1	A21	A21_17021	1	0,00000	0,00000	0,02457	17,10948
1	A21	A21_17029	1	0,00000	0,00000	0,00758	14,84966
1	A21	A21_17088	1	0,00000	0,00000	0,02954	17,64091
1	A21	A21_17103	1	0,00000	0,00000	0,02728	18,69670
1	A21	A21_17114	1	0,00000	0,00000	0,02362	17,81216
1	A21	A21_17147	2	0,00003	0,00002	0,04127	14,86199
1	A21	A21_17149	1	0,00000	0,00000	0,03642	18,26428
1	A21	A21_17172	1	0,00000	0,00000	0,02797	17,86716
1	A21	A21_17173	1	0,00000	0,00000	0,02469	17,64088
1	BSSP115	BSSP115_17089	2	0,00003	0,00000	0,01373	12,37191
1	BSSP115	BSSP115_17189	2	0,00000	0,00000	0,02648	12,98887
1	BSSPEXSS573	BSSPEXSS573_17056	2	0,00003	0,00001	0,01694	15,38857
1	BSSPEXSS573	BSSPEXSS573_17059	1	0,00000	0,00000	0,01969	16,48160
1	BSSPEXSS573	BSSPEXSS573_17133	2	0,00000	0,00000	0,03041	15,99204
1	BSSPEXSS510V1	BSSPEXSS510V1_17085	1	0,00000	0,00000	0,02975	16,64892
1	BSSPEXSS510V1	BSSPEXSS510V1_17106	1	0,00000	0,00000	0,03118	17,05652
1	BSSPEXSS510V1	BSSPEXSS510V1_17169	2	0,00001	0,00000	0,01875	16,57846
1	BSSPEXSS510V1	BSSPEXSS510V1_17182	1	0,00000	0,00000	0,03160	16,63125
1	BSSP005	BSSP005_17022	2	0,00000	0,00000	0,01926	15,82154
1	BSSP005	BSSP005_17100	1	0,00000	0,00000	0,02780	15,08820
1	BSSP005	BSSP005_17128	1	0,00000	0,00000	0,04059	14,66247
1	BSSPEXSS567	BSSPEXSS567_17067	1	0,00000	0,00000	0,01433	16,09638
1	BSSPEXSS567	BSSPEXSS567_17092	1	0,00000	0,00000	0,03221	17,24620
1	BSSP048	BSSP048_17085	1	0,00000	0,00000	0,03185	16,89285
1	BSSP048	BSSP048_17144	1	0,00000	0,00000	0,02740	16,23400
1	BSSP084	BSSP084_17016	1	0,00000	0,00000	0,01873	14,46652
1	BSSPEXSS572	BSSPEXSS572_17102	1	0,00000	0,00000	0,01466	16,44608
1	BSSPEXSS572	BSSPEXSS572_17109	1	0,00000	0,00000	0,01320	16,34602
1	BSSPEXSS572	BSSPEXSS572_17129	1	0,00000	0,00000	0,01343	16,70199
1	BSSPEXSS572	BSSPEXSS572_17158	1	0,00000	0,00000	0,02010	16,24293
1	BSSPEXSS572	BSSPEXSS572_17170	1	0,00000	0,00000	0,02072	15,50843
1	SS39	SS39_17063	1	0,00000	0,00000	0,03229	17,14454
1	SS39	SS39_17068	1	0,00000	0,00000	0,01863	15,99208
1	A4	A4_17002	1	0,00000	0,00000	0,02638	17,19879
1	A4	A4_17029	1	0,00000	0,00000	0,00749	19,40495
1	A4	A4_17032	1	0,00000	0,00000	0,02583	18,62843
1	A4	A4_17040	1	0,00000	0,00000	0,01833	17,96482
1	A4	A4_17043	1	0,00000	0,00000	0,04669	17,82736
1	A4	A4_17046	1	0,00000	0,00000	0,03309	18,05877
1	A4	A4_17067	1	0,00000	0,00000	0,02340	19,15005

1	A4	A4_17069	1	0,00000	0,00000	0,03257	18,25243
1	A4	A4_17092	1	0,00000	0,00000	0,03987	18,32218
1	A4	A4_17107	1	0,00000	0,00000	0,01325	17,35381
1	A4	A4_17127	1	0,00000	0,00000	0,00721	17,44510
1	A4	A4_17133	1	0,00000	0,00000	0,02041	17,87700
1	A4	A4_17136	1	0,00000	0,00000	0,02823	16,98663
1	A4	A4_17151	1	0,00000	0,00000	0,02133	17,12008
1	A4	A4_17161	1	0,00000	0,00000	0,02419	17,77061
1	A4	A4_17165	1	0,00000	0,00000	0,01591	18,03954
1	A4	A4_17166	1	0,00000	0,00000	0,01761	17,26409
1	BSSPEXSS300	BSSPEXSS300_17148	1	0,00000	0,00000	0,03350	15,15548
1	BSSPEXSS510D1	BSSPEXSS510D1_17040	1	0,00000	0,00000	0,00947	17,37990

7.4. EU 2019/1936 – Annex III - ISO 39001:2012 - CPM components

CPM Components	**ISO 39001and Risk Components**	**EU 1936/2019 Annex III List of factors**	
	Risk factor	**Level 1**	**Level 2**
Response variable/Explanatory variable	Risk exposure factors	Traffic volumes	*Traffic volumes;* *Observed motorcycle/bicycle/heavy vehicle/pedestrian volumes; on both sides, noting "along" or "crossing"* *Estimated pedestrian flows determined from adjacent land use attributes;* *Estimated bicycle flows determined from adjacent land use attributes.*
Response variable	Final Safety Outcome factors	Accident data	*Number or road crashes;* *Number of fatalities and/or people killed;* *Number of injuries and/or serious injuries.*
Explanatory variables	Intermediate Safety Outcome Factors	General	*Type of road in relation to the type and size of regions/cities it connects;* *Length of road section;* *Area type (rural, urban);* *Land use (educational, commercial, industrial and manufacturing, residential, farming and agricultural, undeveloped areas);* *Property access points density;* *Presence of service road (e.g., for shops);* *Presence of road works;* *Presence of parking.*
		Operational characteristics	*Speed limit (general, for motorcycles; for trucks);* *Operating speed (85th percentile);* *Speed management and/or traffic calming;* *Presence of its devices: queue alerts, variable message signs;* *School zone warning;* *Presence of school crossing supervisor at prescribed periods.*
		Geometric characteristics	*Cross section characteristics (number, type and width of lanes, central median shoulders layout and material, cycle tracks, foot paths, etc.), including their variability;* *Horizontal curvature;* *Grade and vertical alignment;* *Visibility and sight distances.*
		Objects, clear zones and road restraint systems	*Roadside environment and clear zones;* *Fixed obstacles at the roadside (e.g. Lighting poles, trees, etc.);* *Distance of obstacles from roadside;* *Density of obstacles;* *Rumble strips;* *Road restraint systems.*
		Bridges and tunnels	*Presence and number of bridges, as well as relevant information concerning them;*

	Presence and number of tunnels, as well as relevant information concerning them; *Visual elements representing hazards for the safety of the infrastructure.*
Intersections	*Intersection type and number of arms (noting the type of control and the presence of protected turns);* *Presence of channelisation;* *Intersection quality;* *Intersecting road volume;* *Presence of level crossings (noting, in particular, the type of crossing and whether they are manned, unmanned, manual or automated).*
Maintenance	*Pavement defects;* *Pavement skid resistance;* *Shoulder condition (including vegetation);* *Condition of signs, markings and delineation;* *Condition of road restraint systems.*
Vulnerable road users' facilities	*Pedestrian and cycling crossings (surface crossings and grade separation);* *Cycling crossings (surface crossings and grade separation);* *Pedestrian fencing;* *Existence of sidewalk or separated facility;* *Bicycle facilities and their type (cycle paths, cycle lanes, other);* *Quality of pedestrian crossings with regard to the conspicuity and signposting of each facility;* *Pedestrian and cycling crossing facilities on entry arm of minor road joining network;* *Existence of alternative routes for pedestrians and cyclists where there are no separated facilities.*
Pre-crash systems and Post-crash response	*Network operational centres and other patrolling facilities;* *Mechanisms to inform road users of driving conditions in order to prevent accidents or incidents;* *Aid (automatic incident detection) systems: sensors and cameras;* *Incident management systems;* *Systems for communicating with emergency services.*

7.5. List of significant intermediate safety outcome and exposure factors

A list of factors, sub-factors and sub-sub factors affecting road safety outcome factors (*i.e.,* crash occurrence and severity) and the related references. Although not comprehensive, the list of references is quite representative.

More precisely, in the following tables both the factors included in the model and the ones resulted significant are reported. For the significant variables only, red references identify variables that increase the value of the response variable, while blue references identify variables that decrease the value of the response variable.

Table 33 - List of intermediate safety outcome factors for crash frequency and severity estimation

Intermediate factor	Level 1	Level 2	Included	Sig. Frequency	Sig. Severity	Sig. Joint model
Segment design		Segment length	Caliendo et al. (2007); Hosseinpour et al. (2018); Han et al. (2018); Hosseinpour et al. (2014); Ma et al. (2008); Aguero-Valverde et Jovanis (2009); Wang et al. (2011); Afghari et al. (2020); Stipancic et al. (2019); Ma et al. (2008); Xie et al. (2021);	Stipancic et al. (2019); Afghari et al. (2020); Wang et al (2011);		Afghari et al. (2020); Aguero-Valverde et Jovanis (2009); Xie et al. (2021);
	Cross-section	Lane width	Anarkooli et al. (2019); Ma et al. (2008); Aguero-Valverde et Jovanis (2009); Wang et al. (2017); Zeng et al. (2017); Pei et al. (2011);		Anarkooli et al. (2019); Pei et al. (2011);	Ma et al. (2008); Ma et al. (2008); Aguero-Valverde et Jovanis (2009); Wang et al. (2017); Zeng et al. (2017);
		Number of lanes	Hosseinpour et al. (2018); Hosseinpour et al. (2014); Park et Lord (2007); Wang et al. (2011); Afghari et al. (2020); Ma and Kockelman (2006)	Ma and Kockelman (2006); Afghari et al. (2020); Wang et al (2011);		Afghari et al. (2020);
	Shoulder	Shoulder presence	Afghari et al. (2020)	Afghari et al. (2020);		Afghari et al. (2020);
		Shoulder width	Anarkooli et al. (2019); Ma et al. (2008); Aguero-Valverde et Jovanis (2009); Afghari et al. (2020); Ma and Kockelman (2006); Wang et al. (2017);	Ma and Kockelman (2006); Anarkooli et al. (2019);		Ma et al. (2008); Aguero-Valverde et Jovanis (2009); Wang et al. (2017);
		Paved shoulder width	Hosseinpour et al. (2018); Hosseinpour et al. (2014); Anarkooli et al. (2019)	Hosseinpour et al. (2014)	Hosseinpour et al. (2014)	
		Unpaved shoulder width	Hosseinpour et al. (2018); Hosseinpour et al. (2014); Anarkooli et al. (2019)	Hosseinpour et al. (2014); Anarkooli et al. (2019);		
	Horizontal alignment	Curve length	Anarkooli et al. (2019); Michalaki et al. (2015); Ma et al. (2008); Ma and Kockelman (2006)	Anarkooli et al. (2019);		Ma et al. (2008); Ma et al. (2008);
		Curve radius/minimum radius	Anarkooli et al. (2019); Wang et al. (2011); Afghari et al. (2020)	Anarkooli et al. (2019);	Wang et al (2011); Anarkooli et al. (2019);	Ma et al. (2008);
		Curvature	Caliendo et al. (2007); Hosseinpour et al. (2018); Hosseinpour et al. (2014); Ma et al. (2008); Afghari et al. (2020); Hosseinpour et al. (2014); Ma and Kockelman (2006); Zeng et al. (2017);	Hosseinpour et al. (2014); Ma and Kockelman (2006); Afghari et al. (2020);	Hosseinpour et al. (2014)	Afghari et al. (2020); Ma et al. (2008); Ma et al. (2008); Zeng et al. (2017);
	Vertical alignment	Grade	Anarkooli et al. (2019); Ma et al. (2008); Wang et al. (2011)*; Caliendo et al. (2007); Ma and Kockelman (2006); Zeng et al. (2017);		Wang et al (2011); Anarkooli et al. (2019);	
		Vertical curve length	Anarkooli et al. (2019); Ma et al. (2008); Ma and Kockelman (2006)	Ma and Kockelman (2006); Anarkooli et al. (2019);		Ma et al. (2008); Ma et al. (2008);

	Median	Median presence	Hosseinpour et al. (2018); Han et al. (2018); Afghari et al. (2020); Hosseinpour et al. (2014); Ma and Kockelman (2006); Zeng et al. (2017); Wang et al. (2021);	Ma and Kockelman (2006)	Hosseinpour et al. (2014)	
		Median type	Hosseinpour et al. (2018); Han et al. (2018); Afghari et al. (2020); Hosseinpour et al. (2014)		Hosseinpour et al. (2014)	
		Media width	Afghari et al. (2020);	Afghari et al. (2020);		Afghari et al. (2020);
		Lane Changing Opportunity	Zeng et al. (2017);			Zeng et al. (2017);
		Traffic signal density	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);		
Intersection design	Right/left turn		Wang et al. (2017); Wang et al. (2021); Pei et al. (2011);			Wang et al. (2021);
	Merging ramps		Zeng et al. (2017);			Zeng et al. (2017);
	Diverging ramps		Zeng et al. (2017);			Zeng et al. (2017);
		4-leg	Wang et al. (2021);			Wang et al. (2021);
		All-way signed	Wang et al. (2021);			Wang et al. (2021);
Surface/pavement		Sealed	Afghari et al. (2020)	Afghari et al. (2020);		Afghari et al. (2020);
		Roughness	Afghari et al. (2020)			Afghari et al. (2020);
Side friction (interaction between raod side activities and flow)		Low	Hosseinpour et al. (2018); Hosseinpour et al. (2014)		Hosseinpour et al. (2014)	
		High	Hosseinpour et al. (2018); Hosseinpour et al. (2014)			
Access point	Access density/presence		Hosseinpour et al. (2018); Hosseinpour et al. (2014); Wang et al. (2021);	Hosseinpour et al. (2014);	Hosseinpour et al. (2014);	Wang et al. (2021);
	Access control		Ma and Kockelman (2006);	Ma and Kockelman (2006);		
	Intersection density/number		Yasmin and Eluru (2018); Zeng et al. (2017); Xie et al. (2021);	Yasmin and Eluru (2018);		Zeng et al. (2017); Xie et al. (2021);
Road furniture	Lighting	Presence	Park et Lord (2007); Wang et al. (2017); Wang et al. (2021);			Wang et al. (2017); Wang et al. (2017);
	Tram and LRT stops		Pei et al. (2011);	Pei et al. (2011);		

Speed limit	Posted speed limit (mph)		Hosseinpour et al. (2018); Hosseinpour et al. (2014); Anarkooli et al. (2019); Michalaki et al. (2015); Ma et al. (2008); Aguero-Valverde et Jovanis (2009); Wang et al. (2011); Afghari et al. (2020); Ma and Kockelman (2006); Yasmin and Eluru (2018); Wang et al. (2017); Zeng et al. (2017);	Hosseinpour et al. (2014); Ma and Kockelman (2006); Wang et al (2011); Anarkooli et al. (2019) severe;	Yasmin and Eluru (2018); Anarkooli et al. (2019);	Ma et al. (2008); Ma et al. (2008); Aguero-Valverde et Jovanis (2009); Wang et al. (2017) slight at segm; Zeng et al. (2017);
		> 50 km/k and < 100 km/h	Afghari et al. (2020);	Afghari et al. (2020);		Afghari et al. (2020)
		> 100 km/h	Afghari et al. (2020);		Afghari et al. (2020);	
Functional class		Major/Primary	Anarkooli et al. (2019); Ma et al. (2008); Wang et al. (2011); Ma and Kockelman (2006); Yasmin and Eluru (2018);	Ma and Kockelman (2006); Yasmin and Eluru (2018); Anarkooli et al. (2019);	Anarkooli et al. (2019);	
		Motorway	Stipancic et al. (2019)	Stipancic et al. (2019)	Stipancic et al. (2019) inters; Wang et al (2011);	
		Arterial/collector	Stipancic et al. (2019); Anarkooli et al. (2019)	Stipancic et al. (2019)	Stipancic et al. (2019) fatal at inters;	
		Minor/local	Yasmin and Eluru (2018); Anarkooli et al. (2019)	Anarkooli et al. (2019);	Yasmin and Eluru (2018);	
Urban/rural		Urban	Ma and Kockelman (2006); Pei et al. (2011);	Pei et al. (2011);		
		Rural	Ma and Kockelman (2006); Afghari et al. (2020);	Ma and Kockelman (2006); Afghari et al. (2020);	Afghari et al. (2020);	Afghari et al. (2020)
Level of Service		Low	Afghari et al. (2020)	Afghari et al. (2020);		Afghari et al. (2020);
Congestion index			Stipancic et al. (2019)	Stipancic et al. (2019)		
Traffic peak/density			Michalaki et al. (2015); Wang et al. (2011); Yasmin and Eluru (2018);		Wang et al (2011); Yasmin and Eluru (2018);	
Congestion	Vehicle delay		Wang et al. (2011)	Wang et al (2011);	Wang et al (2011);	
Terrain type	Mountain		Ma and Kockelman (2006); Afghari et al. (2020); Park et Lord (2007); Ma et al. (2008)			Afghari et al. (2020);
	Rolling		Ma and Kockelman (2006); Afghari et al. (2020); Park et Lord (2007); Ma et al. (2008)	Ma and Kockelman (2006);		Afghari et al. (2020);
	Undulating		Hosseinpour et al. (2018); Hosseinpour et al. (2014); Park et Lord (2007); Ma et al. (2008); Afghari et al. (2020)	Hosseinpour et al. (2014)	Hosseinpour et al. (2014)	

Appendix

Area type	Roadside development	Urban	Hosseinpour et al. (2018); Afghari et al. (2020); Hosseinpour et al. (2014); Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	
Land use	Level of activity along roadway	Low	Michalaki et al. (2015); Hosseinpour et al. (2014)		Hosseinpour et al. (2014);	
		High	Michalaki et al. (2015); Hosseinpour et al. (2014)		Hosseinpour et al. (2014)	
	Type	Mix	Yasmin and Eluru (2018); Xie et al. (2021);	Yasmin and Eluru (2018);		Xie et al. (2021);
		Retail and office	Yasmin and Eluru (2018); Xie et al. (2021);	Yasmin and Eluru (2018);		Xie et al. (2021);
		Residential	Xie et al. (2021);			Xie et al. (2021);
		Green/park	Xie et al. (2021);			Xie et al. (2021);
Weather	Bad (rain, fog, etc.)		Wang et al. (2011); Zeng et al. (2017);		Wang et al (2011);	Zeng et al. (2017);
Lighting/Visibility	Daylight		Michalaki et al. (2015); Park et Lord (2007);			
	Darkness		Wang et al. (2011);		Wang et al (2011);	
Hubs	Law enforcement offices		Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	
	Restaurants		Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	
	Parks and leisure hub		Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	
	Transportation hub		Yasmin and Eluru (2018);	Yasmin and Eluru (2018);		
	Shopping centers		Yasmin and Eluru (2018);		Yasmin and Eluru (2018);	
Road network density		Road net density	Xie et al. (2021);			Xie et al. (2021);
Hard brake events (HBE)			Stipancic et al. (2019)	Stipancic et al. (2019);	Stipancic et al. (2019);	
Coefficient of variation of speed (CVS)			Stipancic et al. (2019)	Stipancic et al. (2019);	Stipancic et al. (2019);	
Average speed			Stipancic et al. (2019)	Stipancic et al. (2019);	Stipancic et al. (2019);	
Single vehicle			Wang et al. (2011);		Wang et al (2011);	
No. Of casualties per accident			Wang et al. (2011);		Wang et al (2011);	
Population	Total		Xie et al. (2021);			Xie et al. (2021);

Household	HH density	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	
	Poor population	Yasmin and Eluru (2018);		Yasmin and Eluru (2018);	
Age	under 14	Xie et al. (2021);			Xie et al. (2021) severe;
Population share	Female	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);		
	Caucasian	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	
	Asian	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);		
	Hispanic	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	
	African American	Yasmin and Eluru (2018);		Yasmin and Eluru (2018);	
Work	Soft mobility commuters	Yasmin and Eluru (2018); Xie et al. (2021)	Yasmin and Eluru (2018);		Xie et al. (2021);
	Car commuters	Yasmin and Eluru (2018); Xie et al. (2021)		Yasmin and Eluru (2018);	
	Transit commuters	Yasmin and Eluru (2018); Xie et al. (2021)		Yasmin and Eluru (2018);	Xie et al. (2021);
	Employment density	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	Yasmin and Eluru (2018);	
	Smart workers	Yasmin and Eluru (2018);		Yasmin and Eluru (2018);	
	Non working pop/working pop	Yasmin and Eluru (2018); Xie et al. (2021)	Yasmin and Eluru (2018);		
Age	under 14	Xie et al. (2021);			Xie et al. (2021);

Red entries have increasing effect; blue entries have reducing effect; black entries have opposite effects on frequency and severity

Table 34 - List of risk exposure factors

Exposure factor	Level 1	Level 2	Included	Sig. Frequency	Sig. Severity	Sig. Joint model
Traffic volume or flow		AADT or Ln (AADT)	Caliendo et al. (2007); Anarkooli et al. (2019); Park et Lord (2007); Ma et al. (2008); El Basyouny et al. (2009); Wang et al. (2011); Afghari et al. (2020); Han et al. (2018); Aguero-Valverde et Jovanis (2009); Wang et al (2017); Zeng et al. (2017); Wang et al. (2021); Pei et al. (2011);	Wang et al (2011); Afghari et al. (2020); Anarkooli et al. (2019); Pei et al. (2011);	Wang et al (2011); Anarkooli et al. (2019) severe; Pei et al. (2011);	El Basyouny et al. (2009); Afghari et al. (2020); Ma et al. (2008); Aguero-Valverde et Jovanis (2009); Wang et al (2017); Zeng et al. (2017); Wang et al. (2021);
		MVT or Ln(VMT)	Ma et al. (2008); Ma and Kockelman (2006); Yasmin and Eluru (2018); Xie et al. (2021)	Ma and Kockelman (2006)	Yasmin and Eluru (2018);	Xie et al. (2021)
	Number of trips	Ln(trips)	Stipancic et al. (2019)	Stipancic et al. (2019)		

Traffic categories/portion		Heavy vehicle	Hosseinpour et al. (2014); Hosseinpour et al. (2018); Afghari et al. (2020); Yasmin and Eluru (2018); Xie et al. (2021); Pei et al. (2011);	Hosseinpour et al. (2014); Afghari et al. (2020); Pei et al. (2011);	Yasmin and Eluru (2018);	Afghari et al. (2020) hv; Xie et al. (2021);

Red entries have increasing effect; blue entries have reducing effect; black entries have opposite effects on frequency and severity

Table 35 - List of intermediate safety outcome factors for traffic volumes estimation

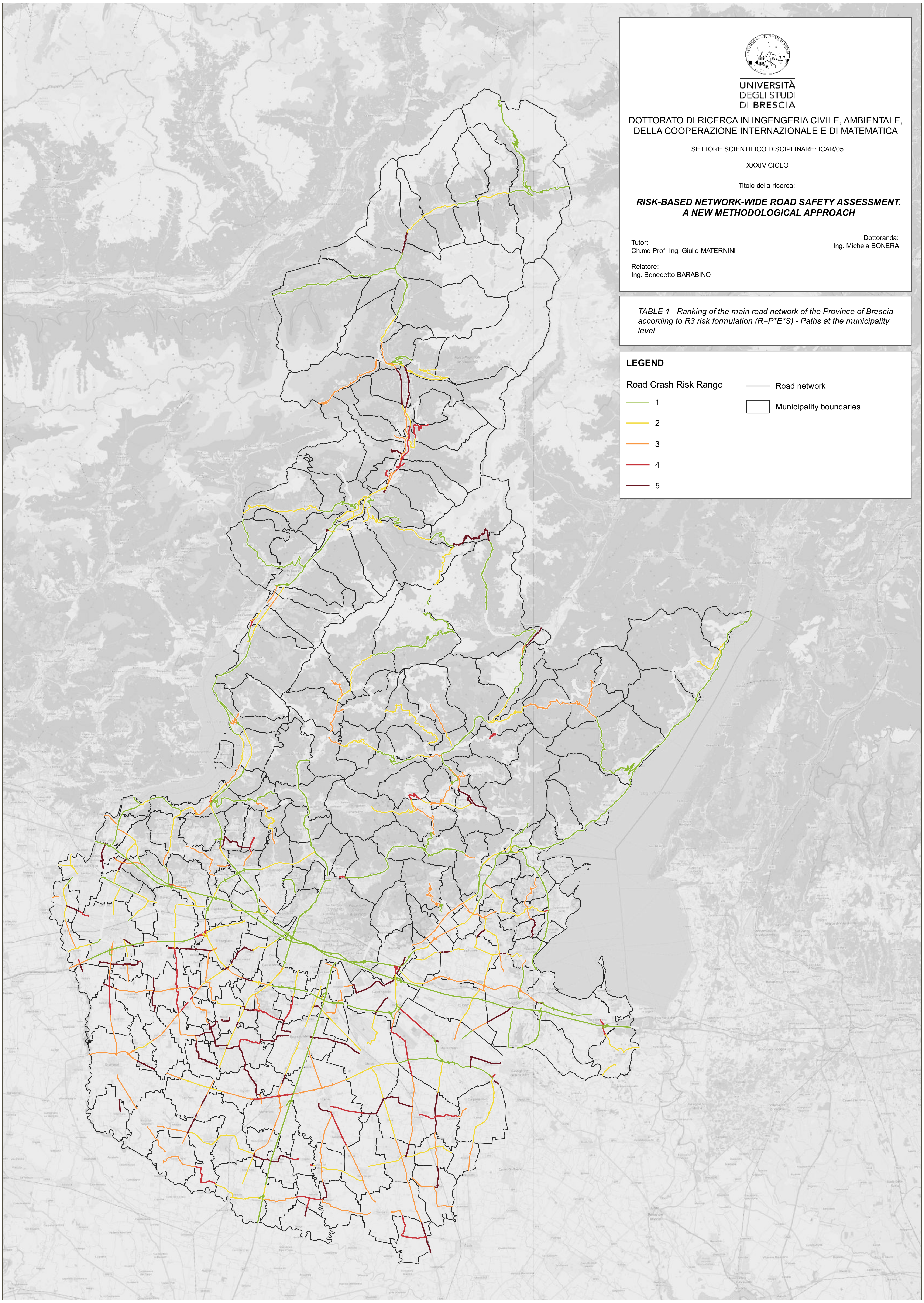
Variable context	**Level 1**	**Level 2**	**Level 3**	**Included**	**Positively affecting**	**Negatively affecting**
Road characteristics		Functional class / Road category	Urban/rural	Pulugurtha and Mathew (2021); Sfyridis and Agnolucci (2020); Zhao and Chung (2001); Shojaeshafiei et al., 2017; Yang et al. (2014)	Zhao and Chung (2001); Shojaeshafiei et al., 2017	
		Road density		Pulugurtha and Mathew (2021)	Pulugurtha and Mathew (2021)	
		Distance from non-local roads		Pulugurtha and Mathew (2021)	Pulugurtha and Mathew (2021)	
	Road geometry	Road-segment length		Pun et al. (2019); Yang et al. (2014)	Pun et al. (2019)	
			Number of lanes	Zhao and Chung (2001); Shojaeshafiei et al., 2017; Yang et al. (2014)	Zhao and Chung (2001); Shojaeshafiei et al., 2017; Yang et al. (2014);	
Topology		Centrality measure	Degree - connectivity	Pun et al. (2019)	Pun et al. (2019)	
			Betweeness	Pun et al. (2019)	Pun et al. (2019)	
			Closeness	Pun et al. (2019)	Pun et al. (2019)	
			PageRank	Pun et al. (2019)	Pun et al. (2019)	
			Clustering coefficient	Pun et al. (2019)	Pun et al. (2019)	
		Accessibility to expressway	minimum distance	Zhao and Chung (2001); Das and Tsapakis (2020);	Zhao and Chung (2001)	
			Network distance to the regional mean centres of population	Zhao and Chung (2001);		Zhao and Chung (2001)
			Regional accessibility to employment centres	Zhao and Chung (2001);	Zhao and Chung (2001)	
Land-use		Area type		Zhao and Chung (2001); Sfyridis and Agnolucci (2020); Pulugurtha and Mathew (2021)	Pulugurtha and Mathew (2021)	

			single family use	Pulugurtha and Mathew (2021)	Pulugurtha and Mathew (2021)	
			multifamily use	Pulugurtha and Mathew (2021)	Pulugurtha and Mathew (2021)	
			Commercial	Pulugurtha and Mathew (2021)	Pulugurtha and Mathew (2021)	
Socioeconomic and demographic	Population	Population density		Pulugurtha and Mathew (2021); Sfyridis and Agnolucci (2020); Zhao and Chung (2001); Shojaeshafiei et al., 2017*; Das and Tsapakis (2020)	Zhao and Chung (2001); Das and Tsapakis (2020)	Shojaeshafiei et al., 2017;
		Employment density/size		Pulugurtha and Mathew (2021); Sfyridis and Agnolucci (2020); Zhao and Chung (2001);Shojaeshafiei et al., 2017; Das and Tsapakis (2020)	Zhao and Chung (2001); Shojaeshafiei et al., 2017*; Das and Tsapakis (2020)	Shojaeshafiei et al., 2017+;
		Household	hi-industrial	Pulugurtha and Mathew (2021)	Pulugurtha and Mathew (2021)	
		housing units		Yang et al. (2014)	Yang et al. (2014)	
Others		number of cars		Yang et al. (2014)	Yang et al. (2014)	
		car density		Yang et al. (2014)	Yang et al. (2014)	

7.6. Road crash risk maps

Road crash risk maps were produced as a visual decision support tool of the risk-based network-wide road safety assessment. Specifically, the following maps are here attached:

- Table 1 – Ranking of the main road network of the Province of Brescia according to R3 risk formulation (R=P*S*E) – Paths at the municipality level
- Table 2 – Ranking of the main road network of the Province of Brescia according to R3 risk formulation (R=P*S*E) – Paths at the provincial level: Average risk score
- Table 3 – Ranking of the main road network of the Province of Brescia according to R3 risk formulation (R=P*S*E) – Paths at the provincial level: Total risk score
- Table 4 – Ranking of the main road network of the Province of Brescia according to R1 risk formulation (R=F(E)*S) – Paths at the municipality level
- Table 5 – Ranking of the main road network of the Province of Brescia according to R1 risk formulation (R=F(E)*S) – Paths at the provincial level: Average risk score
- Table 6 – Ranking of the main road network of the Province of Brescia according to R1 risk formulation (R=F(E)*S) – Paths at the provincial level: Total risk score
- Table 7 – Ranking of the main road network of the Province of Brescia according to R2 risk formulation (R=F*S*E) – Paths at the municipality level
- Table 8 – Ranking of the main road network of the Province of Brescia according to R2 risk formulation (R=F*S*E) – Paths at the provincial level: Average risk score
- Table 9 – Ranking of the main road network of the Province of Brescia according to R2 risk formulation (R=F*S*E) – Paths at the provincial level: Total risk score



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XXXIV CICLO

Titolo della ricerca:

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Dottoranda:
Ing. Michela BONERA

Relatore:
Ing. Benedetto BARABINO

*TABLE 1 - Ranking of the main road network of the Province of Brescia according to R3 risk formulation (R=P*E*S) - Paths at the municipality level*

LEGEND

Road Crash Risk Range

🟩 1
🟨 2
🟧 3
🟥 4
🟫 5

▭ Road network
☐ Municipality boundaries

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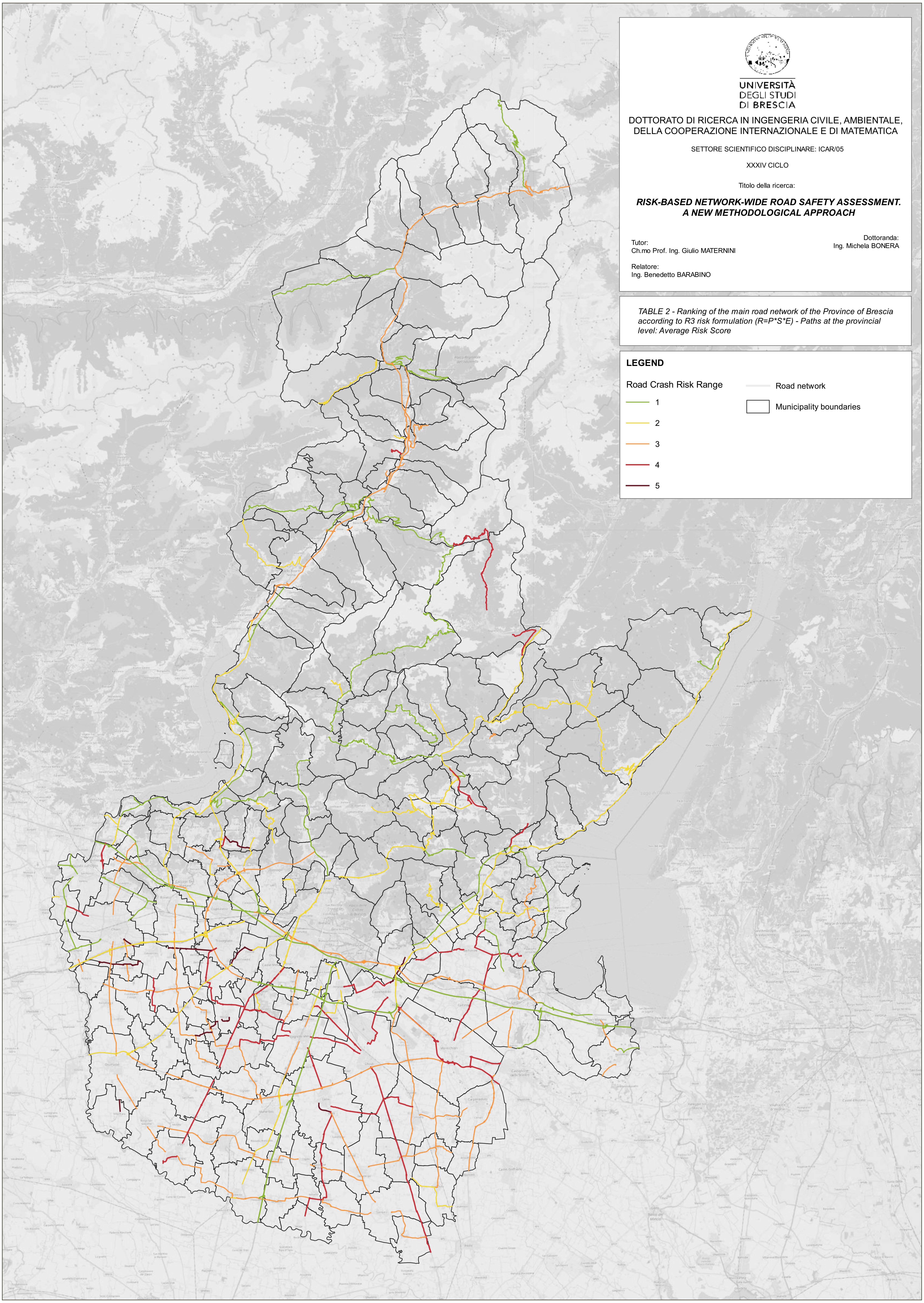

*TABLE 2 - Ranking of the main road network of the Province of Brescia according to R3 risk formulation (R=P*S*E) - Paths at the provincial level: Average Risk Score*

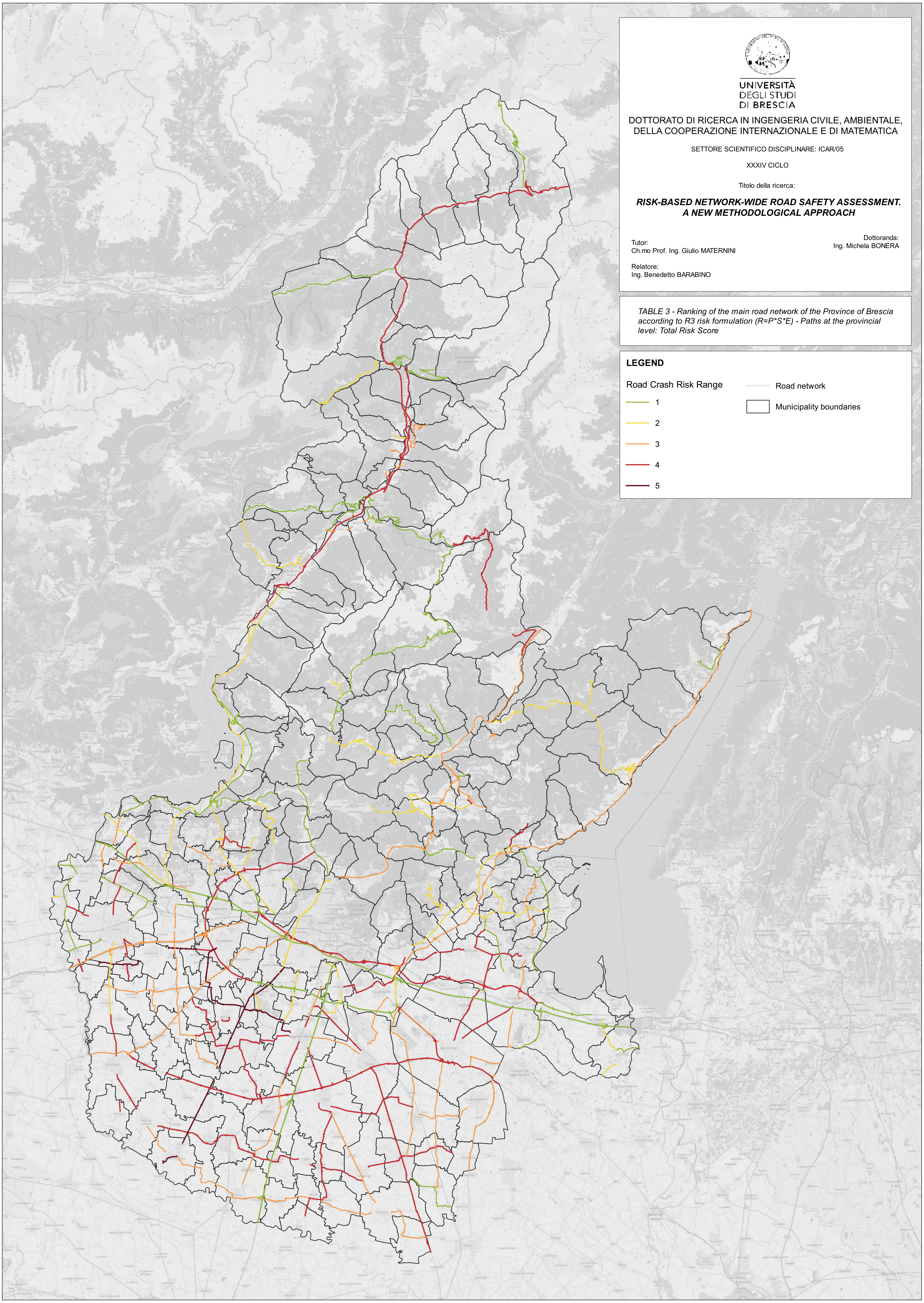

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*TABLE 3 - Ranking of the main road network of the Province of Brescia according to R3 risk formulation (R=P*S*E) - Paths at the provincial level: Total Risk Score*

LEGEND

Road Crash Risk Range
- 1
- 2
- 3
- 4
- 5

Road network

☐ Municipality boundaries

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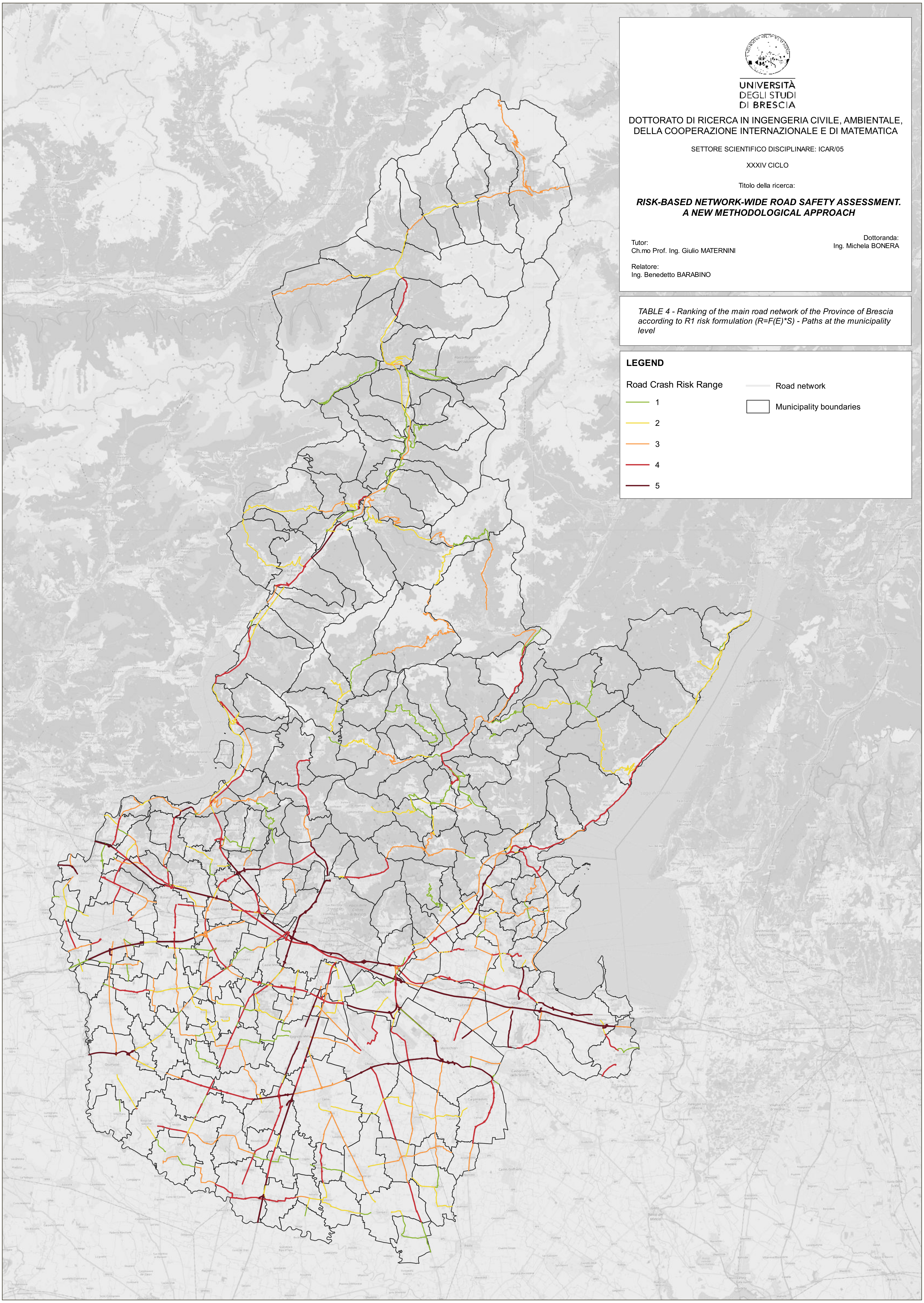
*TABLE 4 - Ranking of the main road network of the Province of Brescia according to R1 risk formulation (R=F(E)*S) - Paths at the municipality level*



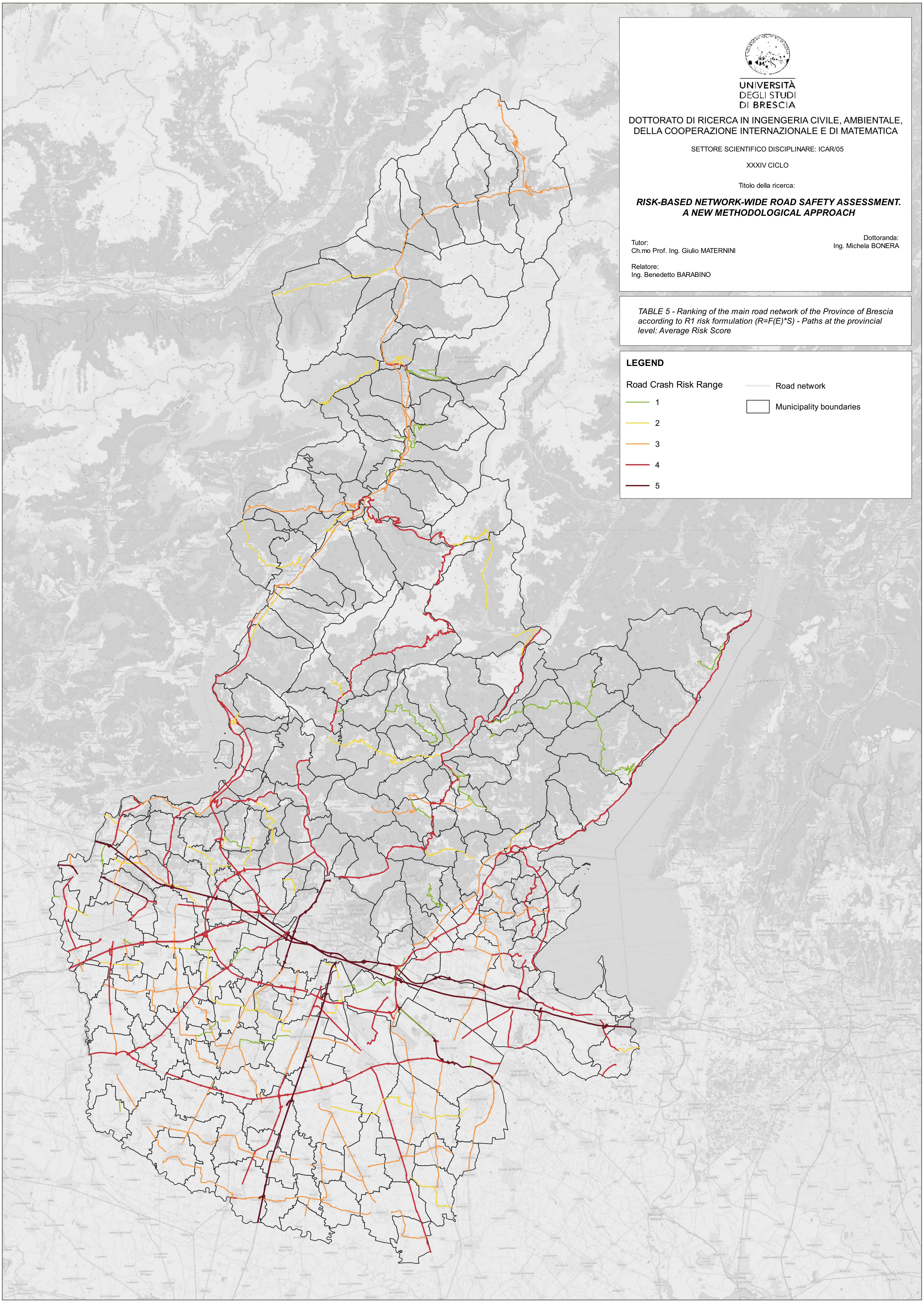


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*TABLE 5 - Ranking of the main road network of the Province of Brescia according to R1 risk formulation (R=F(E)*S) - Paths at the provincial level: Average Risk Score*

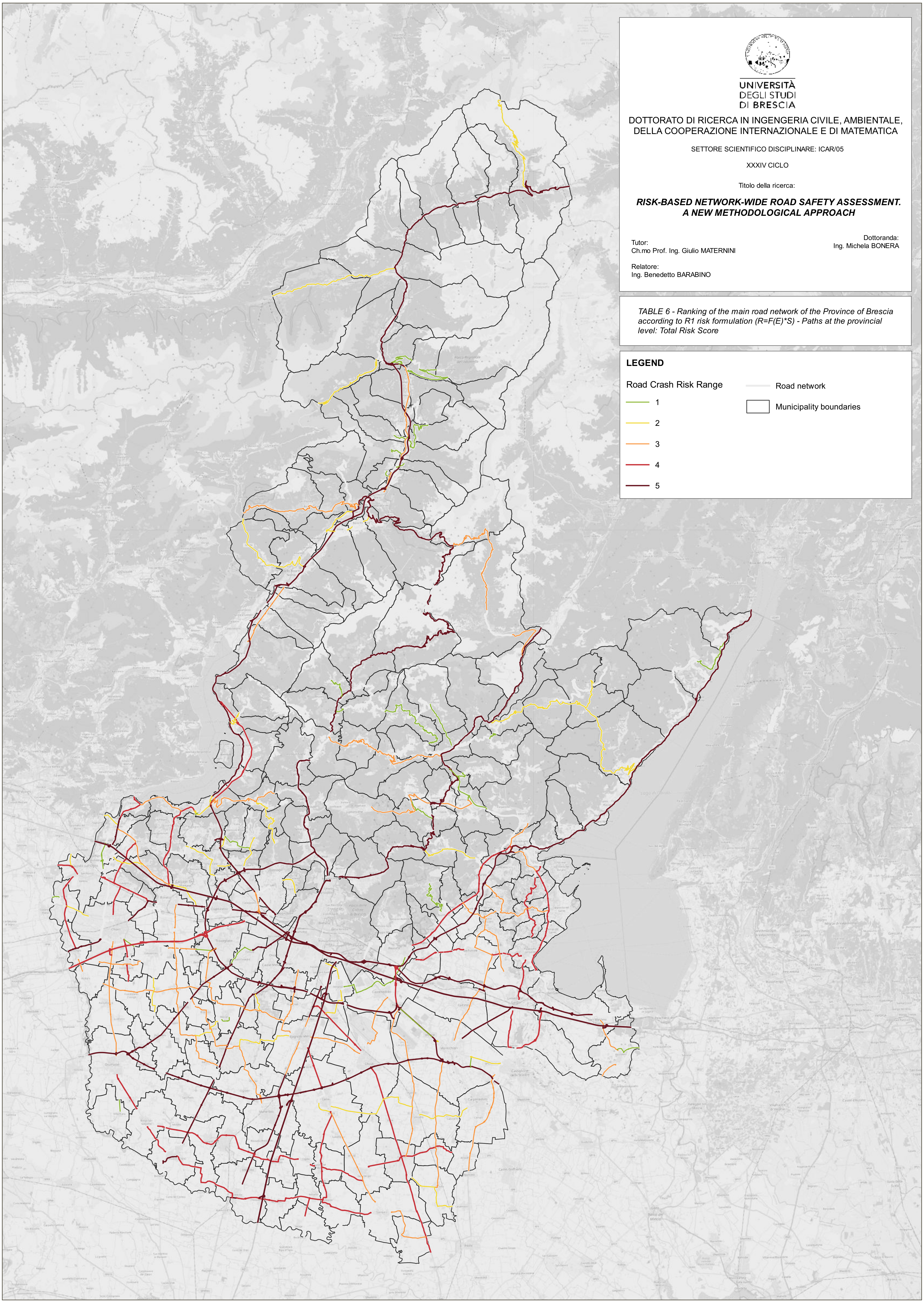

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*TABLE 6 - Ranking of the main road network of the Province of Brescia according to R1 risk formulation (R=F(E)*S) - Paths at the provincial level: Total Risk Score*

LEGEND

Road Crash Risk Range
— 1
— 2
— 3
— 4
— 5

— Road network
☐ Municipality boundaries

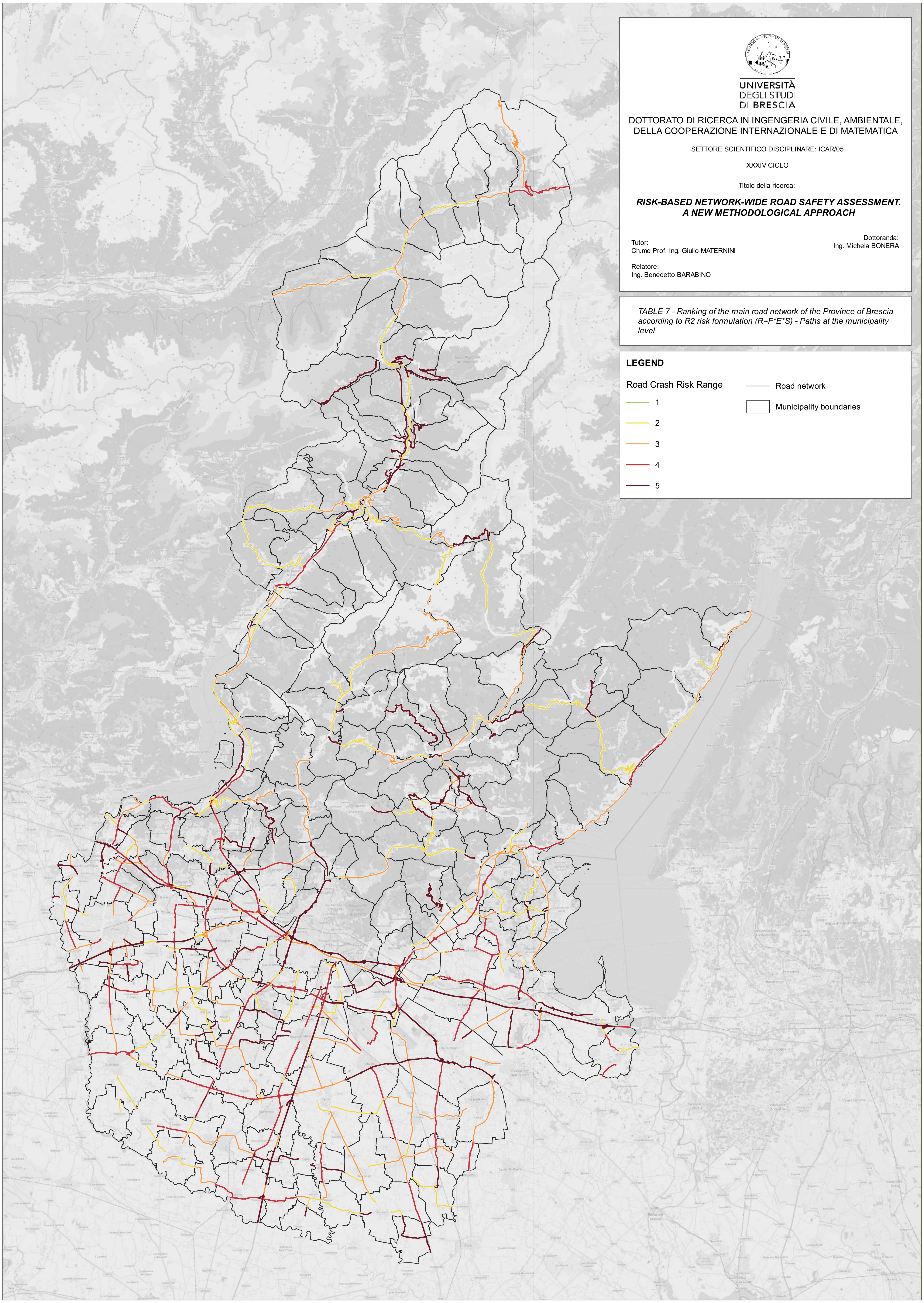

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*TABLE 7 - Ranking of the main road network of the Province of Brescia according to R2 risk formulation (R=F*E*S) - Paths at the municipality level*

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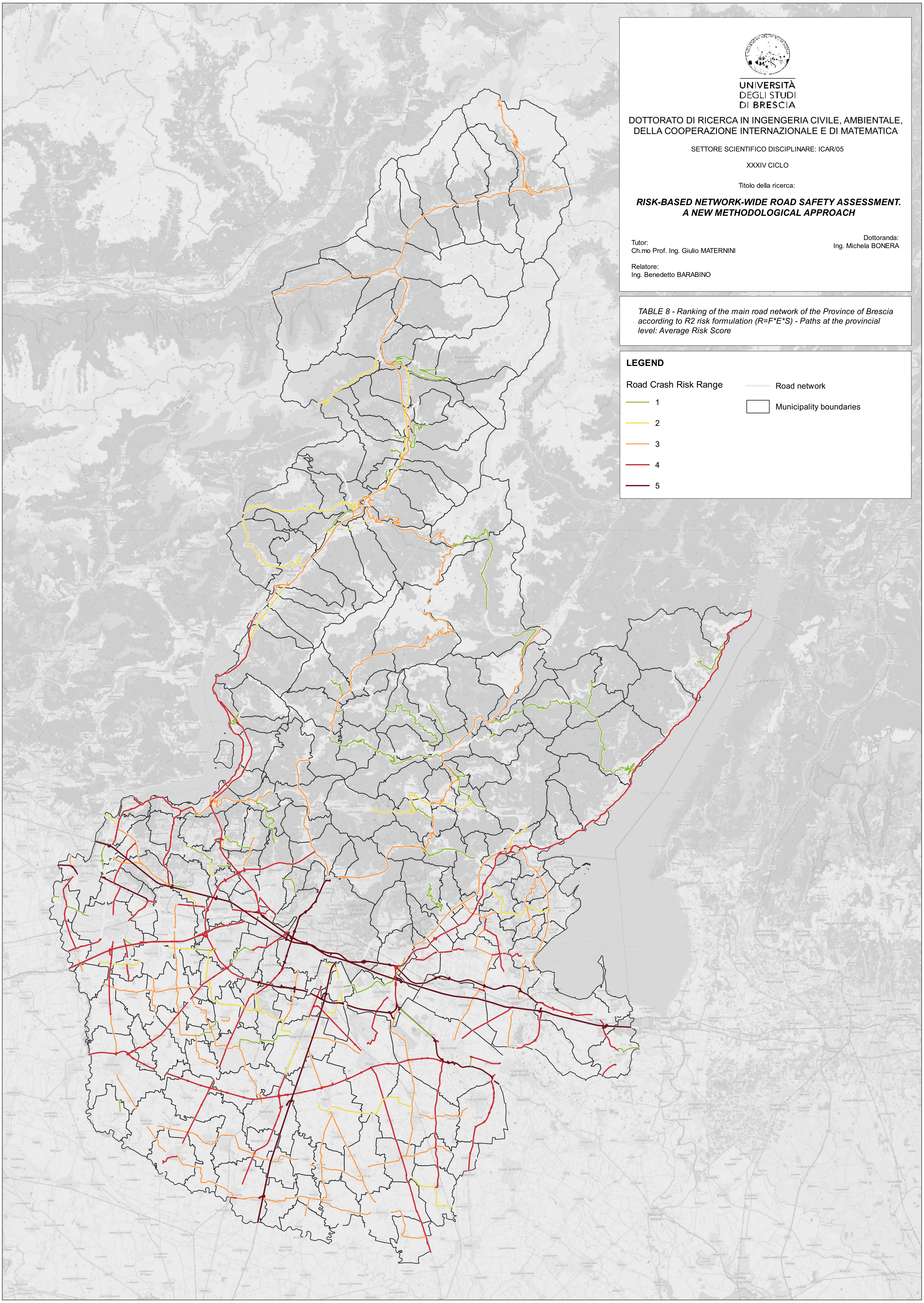

*TABLE 8 - Ranking of the main road network of the Province of Brescia according to R2 risk formulation (R=F*E*S) - Paths at the provincial level: Average Risk Score*

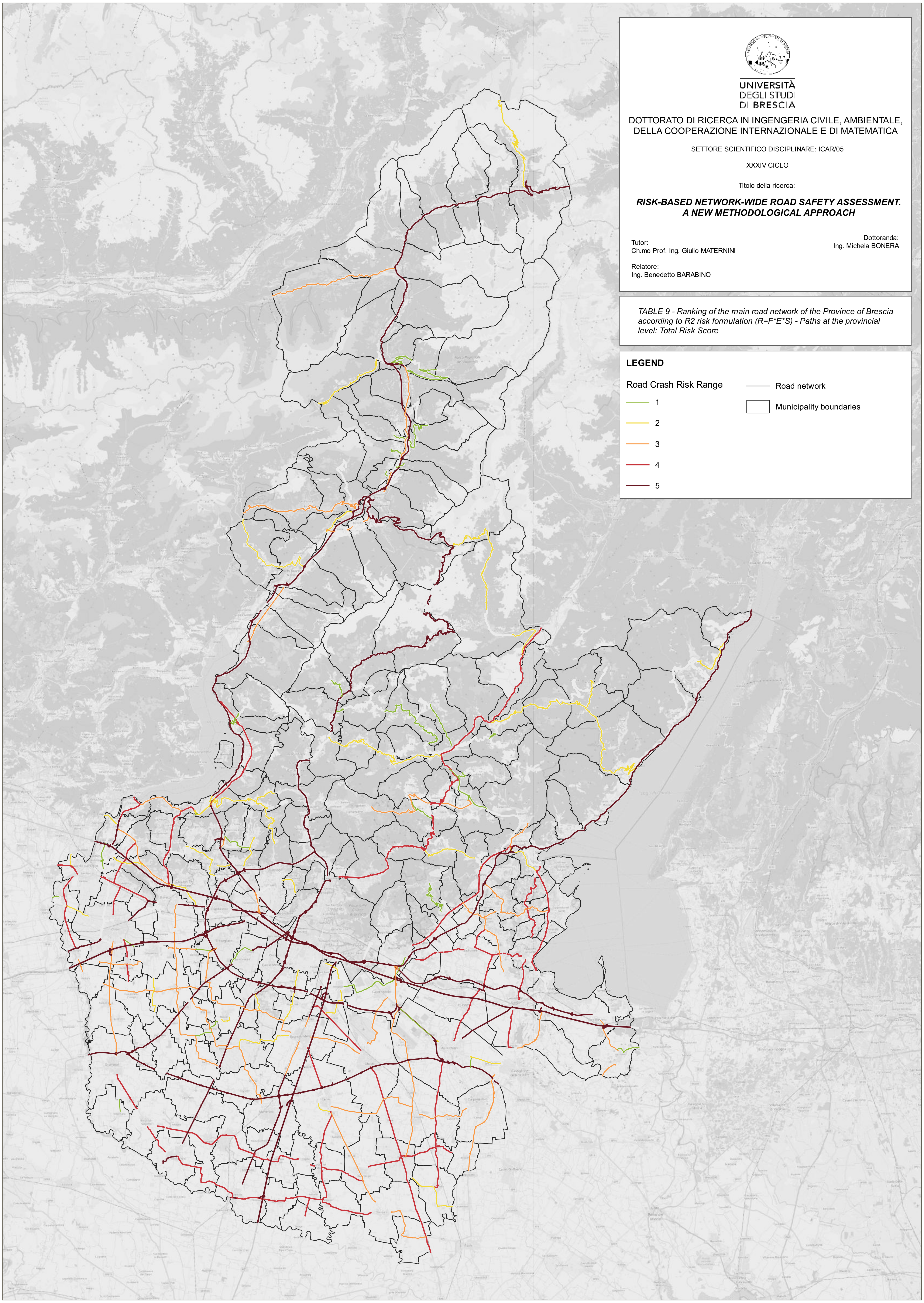

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*TABLE 9 - Ranking of the main road network of the Province of Brescia according to R2 risk formulation (R=F*E*S) - Paths at the provincial level: Total Risk Score*

LEGEND

Road Crash Risk Range
- — 1
- — 2
- — 3
- — 4
- — 5

- — Road network
- ☐ Municipality boundaries