

1 **SPATIAL DIFFERENTIATION OF ROAD SAFETY IN EUROPE**
2 **BASED ON NUTS-2 REGIONS**

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28 *Spatial Differentiation of Road Safety in Europe based on NUTS-2 Regions*

29 **Abstract**

30 Road safety varies significantly across the regions in Europe. To understand the factors behind
31 this differentiation and the effects they have, data covering 263 NUTS-2 (Nomenclature of
32 Territorial Units for Statistics) regions across Europe (European Union and Norway) have been
33 analysed. The assessment was made using Geographically Weighted Regression (GWR). As a
34 dependent variable the Road Fatality Rate (RFR – number of fatalities in a given year per one
35 million population of the region) was used. The GWR was developed from 2014 data and took
36 account of variables that characterise economic, infrastructural and social development. The
37 model was validated using 2016-2018 data. The following factors were found to be statistically
38 significant: gross domestic product per person (GDPPC), number of passenger cars per
39 inhabitant (MRPC), share of passenger vehicles (PPC), life expectancy at birth (LIFE), as well
40 as variables related to the border of the regions, innerborder (IB) and outerborder (OB).

41 Results suggest that the GWR has an advantage over the global linear model which does not
42 address regional proximity. The model allows for identification of the differences in the level
43 of road safety in regions, estimated on the basis of the RFR and the available data in Eurostat
44 databases. This in turn allows for indicating regions in which activities to improve road safety
45 should have the highest priority. The model shows a large spatial diversity of factors affecting
46 the RFR, which indicates the need to take different actions to improve road safety depending
47 on the region. The results suggest that the GWR model can be useful for predicting and more
48 efficient management of road safety at the regional level in Europe.

49

50

51 **Keywords:** Geographically Weighted Regression, GWR, NUTS-2, Road Safety, Road Fatality
52 Rate, Spatial

53

54 **Highlights**

- 55 • The paper compared the NUTS-2 region in Europe in terms of road safety based on the
56 Road Fatality Rate (fatalities per one million population).
- 57 • Applying Geographically Weighted Regression to model the Road Fatality Rate in the
58 EU's NUTS2 regions provides a good tool not only for prediction but also for identifying
59 regional differences.
- 60 • Gross domestic product per person, number of passenger cars per inhabitant, share of
61 passenger vehicles, life expectancy at birth as well as existing inner and outer borders were
62 found to be statistically significant.

63

64 1. Introduction

65 According to the WHO (World Health Organization) report of January 2018, more than
66 1.35 million people are killed annually in road accidents (WHO, 2018). In most countries the
67 costs of road accidents represent 3% of their gross domestic product. Unless sustained and
68 effective efforts are taken, by 2030 road accidents will continue to be one of the seven leading
69 causes of death worldwide. The new Agenda for Sustainable Development sets a target of
70 halving the number of fatalities and injuries from road crashes by 2030 (“WHO Fact Sheet
71 2018; Road traffic injuries,” n.d.). This is to be delivered through the establishment and
72 implementation of road safety programmes, effective accident data collection and more
73 spending on road infrastructure to ensure that all new road projects address safety management
74 during the entire process of design, construction and maintenance.

75 While efforts are taken across the European Union (EU) to improve road safety, fatality
76 reduction targets are not met in all countries in the same way. This suggests the presence of
77 country specific features as well as regional differences within countries. The regional approach
78 to the analysis of the level of safety, which can be found in the literature, enables taking into
79 account the detailed characteristics of each area. (Chen et al., 2017; Erdogan, 2009; Gomes et
80 al., 2017; Jones et al., 2019; Xu and Huang, 2015).

81 Regional analyses are justified, if based on their conclusions, the effective measures are
82 implemented to improve road safety. Some regions feature similar road safety data even though
83 their respective national figures differ from other. This is due to inter-regional influences. What
84 is a major problem in one region may very well be of marginal significance in other regions.
85 As we can see from international as well as Polish experience (*County Donegal Road Safety*
86 *Plan 2007 - 2009*, 2007, *County Wicklow Road Safety Plan 2010-2014*, 2010; Davis and
87 Swenson, 2003; Essex and Safer, 2006; Objectives, 2012; Wachnicka, 2012) regarding regional
88 road safety performance, the main groups of risk and road safety problems differ from one
89 region to the other. By adopting a micro scale approach, it is possible to identify recurring
90 problems in each area.

91 One of the approaches to assess the road safety level in Europe may be the NUTS-2
92 (Nomenclature of Territorial Units for Statistics) regions, i.e. areas that are smaller than
93 countries. NUTS-2 regions are statistical territorial units introduced in Europe to identify areas
94 requiring EU support. Road safety is a social problem that generates high social cost and
95 requires EU support. In order to correctly identify regions due to road safety problems, it is
96 necessary to use the same data, available in each of the NUTS-2 regions in Europe, and reliable



97 predictive tools. Therefore, the same data available for all regions in the Eurostat database and
98 in national databases were used in the development of the model.

99 This prompted the authors to apply the *Geographically Weighted Regression* (GWR)
100 model for predicting fatalities in Europe's NUTS-2 regions (EU and Norway). The GWR model
101 is the right tool for analysing regions for their location in relation to each other. The authors are
102 not aware of any other publication looking into how the GWR can be used to model road safety
103 in the NUTS-2 regions across the EU.

104 The following objectives have been formulated in the paper: (1) develop a model to
105 predict Road Fatality Rate based on social, demographic, economic, and geographical factors
106 (statistically significant) , (2) evaluate the effects of the characteristics of regions and the
107 usefulness of the model as a practical tool for modelling level of safety in NUTS-2 regions. as
108 well as a limited discussion of the inter-regional differences in road safety of the EU.

109

110 **2. Literature review**

111 In the literature so far factors that may have an effect on NUTS-2 regional road safety
112 indicators were divided into several groups of traffic and motorization, demographic,
113 infrastructural, economic and social aspects. Developed in the mid-20th century, the initial
114 models would predict a continuous increase in fatalities in keeping with growing populations
115 and cars (Smeed, 1949). In the years that followed, however (ADAMS, 1987; Andreassen,
116 1985; Broughton, 1988; Oppe, 1991), it became evident that this relationship is more complex
117 and no longer holds true when countries take up legislative and educational measures to
118 improve road safety. The lack of clarity as to how growing motorization affected regions meant
119 that the new fatality models had to include new variables which influenced road safety at the
120 national and regional level. Some of them point to miles travelled as having a big influence on
121 road traffic victims (Berhanu, 2004; Cai et al., 2017; Fernández et al., 2009; Ivan et al., 2004;
122 Ma et al., 2008; Wachnicka et al., 2017). Yet because regional traffic data were difficult to
123 access, other variables were considered to ensure that changes in regional fatality numbers
124 could be explained reliably. One of the characteristics known from the literature is population
125 density. With the decrease in population density, the mortality on the roads increases (Clark,
126 2003; Eksler, 2006; Erdogan, 2009; S. Lassarre and Thomas, 2005). Higher risk levels on roads
127 were indicated in rural areas (Baker and et al., 1987; Eksler et al., 2008; Jones et al., 2019;
128 Najaf et al., 2018; Rothman et al., 2017). Safety was mostly observed to improve as areas
129 became more urbanised. The literature suggests that this may be linked to better access to health
130 care and shorter waiting times for emergency services to arrive at the scene of an accident. As



131 the number of doctors per capita increases, the number of road deaths decreases (Noland R.B.,
132 2003). Shorter time for emergency services to get to the scene reduces the likelihood of death
133 in an accident (Derrig and et al., 2002; Sánchez-Mangas and et al., 2010). While a higher degree
134 of urbanisation usually means a denser road network, the standard of roads and their
135 maintenance are also at a higher level. As the density of the road network increases, the level
136 of safety increases. (Jamroz et al., 2019; Ogden, 2004). The literature points to the effects of
137 economic growth on road safety. Higher gross domestic product (GDP) or income indicates
138 less road fatalities (Bester, 2001; Bhavan, 2019; Elvik, 2015; Jones et al., 2019; Noland R.B.,
139 2003; Sánchez González et al., 2020; Scuffham and Langley, 2002; Thomas L Traynor, 2008).
140 On the contrary the same authors claimed that high growth areas do not always boast top safety
141 on their road networks (Antoniou et al., 2016; Bester, 2001; Bishai et al., 2006; Jamroz et al.,
142 2019; Yannis et al., 2014). Others (Paulozzi et al., 2007) indicated that income increase is
143 associated with a prompt reduction of pedestrian mortality rates only and this reduction is more
144 gradual because of motor vehicles per capita increase. Results from some long-term analysis
145 (Kuznets, 1955; Nghiem et al., 2013) confirmed Kuznets curve in the traffic fatality rate for all
146 OECD countries. For the same reasons economic recession may also affect fatality rates (Law
147 et al., 2009; Wegman et al., 2017). In literature the unemployment rate was included into
148 analyses as an important factor for road fatalities. In his analysis, Eksler pointed out that the
149 unemployment rate increase was positively correlated with the number of road fatalities (Eksler,
150 2006), while (Douglas and Likens, 2000) showed the opposite correlation. National research
151 has shown that the number of fatalities also depends on social development, the Human
152 Development Index (HDI) (Bester, 2001), a rate which is not only determined by economic
153 growth but also by life expectancy and the society's level of education. The factors above were
154 identified based on country level analyses.

155 The problem of modelling fatalities in regions (NUTS2) is only presented in the literature
156 to a limited extent. The work so far has been to analyse the differences in safety levels without
157 dedicated mathematical models. Models, if any, are designed to depict groups of regions in a
158 country or in neighbouring countries and analyse the trends in road safety changes. Neither do
159 they address region-specific features (Eksler, 2010; Eksler et al., 2008; Eksler and Lassare,
160 2008; MacNab, 2004, 2003).

161 The analysis of factors that may influence road safety in NUTS-2 regions was presented
162 in the works by (Wachnicka, 2017, 2013; Wachnicka and Smolarek, 2012). Based on the non-
163 linear regression model, it was presented that population density, rate of motorization and
164 economic development have an effect on the fatality rate in the particular NUTS-2 regions.



165 With the regions' strongly differentiated road safety levels and independent variables, the
166 degree of model determination was low leading to unreliable results for some of the regions.

167 Given the nature of these problems, a better fit can be found with a GWR model. It was
168 successfully applied in other research which included geographic factors (population density,
169 land use, structure of road network) and their effect on road safety (Erdogan, 2009; Gris  et al.,
170 2018; Zhang et al., 2015).

171

172 **3. Data**

173 NUTS-2 regions, which spatial aggregation has been used for basedata for the calibration
174 of the GWR model, belong in one of the three categories of regions featured in the EU. NUTS-
175 1 are major socio-economic regions with a population of 3 to 7 million people. NUTS-2 are
176 basic regions for the application of policies at the regional level with a population from 800,000
177 up to 3 million people. While NUTS-3 are regions with populations between 150,000 and
178 800,000 inhabitants. NUTS-2 are also statistical territorial units from which regions eligible for
179 support from EU cohesion policy are selected. The given classification is not restrictive and
180 sometimes the number of inhabitants in the region differs from the range specified above.

181 For the purpose of the conducted study the NUTS-2 2013 classification was adopted (in
182 2016 there was a change in the selected NUTS-2 boundaries), which listed 323 regions in 36
183 countries.

184 The dependent variable RFR was used to determine the hazard level in NUTS-2. Killed
185 or seriously injured (KSI) rates have not been analysed, due to the different definitions of
186 severely injured casualties in analysed countries. The use of KSI rates would be more
187 advantageous due to the assumptions for reducing these casualty groups in the European road
188 safety improvement programmes, but it requires establishing a uniform definition of seriously
189 injured in all regions.

190 A database containing all the social, economic, demographic, and geographic factors,
191 as well as the dependant variable had to be developed to describe road safety in NUTS-2 regions
192 on the basis of data available from the Eurostat database ("EUROSTAT Base," n.d.) for 2014-
193 2018 period. It was important to collect as many variables as possible that are characteristic of
194 the regions.

195 While developing the database, it was found that exposure factors such as average
196 annual daily traffic or vehicle km travelled (Berhanu, 2004; Cai et al., 2017; Clark DE et al.,
197 2004; Fern ndez et al., 2009; Ivan et al., 2004; Ma et al., 2008; Thomas L. Traynor, 2008;
198 Wachnicka et al., 2017), or other factors such as speeding or average time for emergency



199 services to get to accident victims (Clark and Cushing, 1999; Derrig and et al., 2002) indicated
 200 in the studied literature were not available for specific regions.

201 The developed database contains the following variables: number of road fatalities
 202 (FAT), area of the region (AREA), population size (DEMO), population density (DP), road
 203 network density (ROAD), motorway density (MWAY), density of other roads (RDOTH), gross
 204 domestic product per person (GDPPC), number of vehicles (VAH), number of vehicles per
 205 inhabitant (VAHP), number of passenger cars per inhabitant (MRPC), share of passenger
 206 vehicles (PPC), life expectancy at birth (LIFE), area of the region, percentage of arable land
 207 (ARAL). Since there was no regional continuity for some data during the period analysed, they
 208 could not be used in the modelling process (e.g. the length of highways). Due to the lack of data
 209 in the European Eurostat database, the GWR modelling process used data from 263 NUTS-2 in
 210 28 countries, for the remaining areas there were deficiencies that were not filled in the process
 211 of completing the database (using data from national databases). In the table 1 descriptive
 212 statistics for collected variables are included.

213

214 Table1. List of analysed variables and the descriptive statistics (2014, 263 Europe regions)

Variable	Unit	Average	Min	Max	Standard Deviation	Relative Standard Deviation
RFR	fatalities/1 million population	55.8	11.89	133.68	25.51	45.72%
FAT	numbers	103.32	3.00	518.00	83.35	80.68%
AREA	1,000 km ²	19.29	0.01	227.15	23.47	121.66%
DEMO	1,000 persons	2.01	0.03	14.16	1.72	85.60%
DP	people/km ²	400.93	3.02	10409.83	1109.18	276.65%
GDPPC	1,000 Euro/person	26.85	8.3	74.4	9.71	36.18%
VEH	1,000	1,082.66	28.51	6,606.20	991.07	91.54%
VEHP	cars/100 population	54.29	5.10	140.70	17.62	32.45%
MRPC	cars/100 population	49.7	17.7	114.4	11.07	22.28%
PPC	%	85.32	52	97.1	5.72	6.70%
LIFE	years	80.85	73	84.9	2.47	3.06%
ARAL	1,000 km ²	3.98	0.00	34.21	4.72	118.62%
MWAY	km/1,000 km ²	17.51	0.00	190.93	25.71	146.83%
RDOTH	km/1,000 km ²	1,176.37	22	7,626.58	1,080.57	91.86%
ROAD	km/1,000 km ²	1,198.71	22	7,626.58	1,088.43	90.80%

215

216 In the GWR model, in addition to the variables listed in Table 1, three binary variables
 217 are included: Coast (CO), InnerBorder (IB) and OuterBorder (OB). The first one CO assumes
 218 values 0 (no coast) and 1 (coast). The IB involves the presence of an internal border between
 219 countries and assumes values of 0 in the case of absence and 1 in the case of occurrence. The
 220 OB variable is related to the presence of an external border and assumes a value of 1 when the
 221 region has an external border (i.e. borders with a region or regions omitted in the model), and
 222 a value of 0 if it does not.

223 Based on the developed database, it can be stated that the risk of a road fatality (RFR in
 224 2014) differs in NUTS-2 regions. The RFR was the highest in eastern parts of the EU (Latvia,
 225 Poland, Bulgaria) and the RFR was the lowest in selected regions of the British Isles, Belgium,
 226 the Netherlands and Sweden (table 2 and fig 1).

227 The variability of the observed RFR indicates a large heterogeneity of results in the
 228 analysed regions. Regions that require measures to improve road safety (high RFR) are mainly
 229 Eastern European countries, regions located in Greece and some regions of Italy, Belgium and
 230 France. In Eastern Europe, it could be related to a much lower density of high-standard roads,
 231 a high proportion of pedestrian traffic among traffic participants, less police oversight and a
 232 different culture of traffic behaviour. In the case of Greece and Eastern Europe, a lower GDDPC
 233 level may be significant, as it affects the amount of expenditure allocated to road safety
 234 improvement.

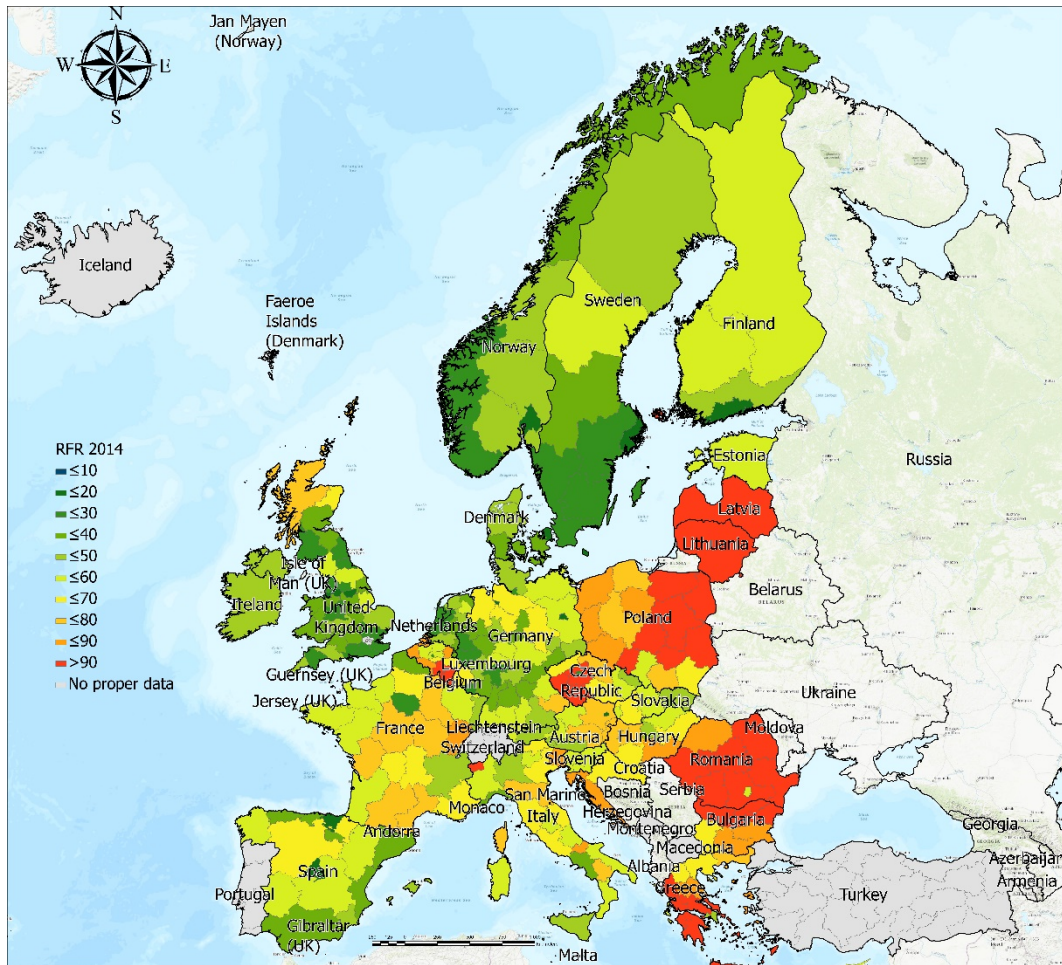
235

236 Table 2. Road Fatality Rate in selected EU regions in 2014

Country	Nuts no.	RFR				Country	Nuts no.	RFR			
		Average	Min	Max	Standard Deviation			Average	Min	Max	Standard Deviation
Austria	9	53.8	11.9	76.5	18.9	Italy	21	61.2	36.4	101.1	15.4
Belgium	11	76.0	23.9	133.7	31.4	Latvia	1	105.9	105.9	105.9	0.0
Bulgaria	6	97.4	68.2	129.6	19.0	Lithuania	1	90.7	90.7	90.7	0.0
Croatia	2	76.8	64.1	89.6	12.8	Luxembourg	1	63.7	63.7	63.7	0.0
Cyprus	1	52.5	52.5	52.5	0.0	Malta	1	23.3	23.3	23.3	0.0
Czechia	8	65.0	20.1	94.5	22.7	Netherlands	12	39.6	21.8	86.7	17.0
Denmark	5	35.6	17.2	49.9	10.7	Norway	7	31.5	16.5	43.1	10.0
Estonia	1	59.3	59.3	59.3	0.0	Poland	16	87.9	54.8	108.3	15.1
Finland	5	55.3	15.8	104.7	28.8	Romania	8	91.7	56.9	112.8	15.0
France	22	60.7	26.1	82.3	14.0	Slovakia	4	53.5	40.3	66.4	9.6
Germany	38	44.8	15.2	79.1	14.8	Slovenija	2	52.5	50.2	54.8	2.3
Greece	13	85.9	47.1	123.9	22.4	Spain	17	40.7	16.6	64.4	13.8
Hungary	7	66.2	49.9	84.4	10.4	Sweden	8	32.5	16.2	51.5	9.9
Ireland	1	41.4	41.4	41.4	0.0	United Kingdom	35	34.1	17.8	70.6	12.8

237





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Fig. 1 Road Fatality Rate in EU regions (2014).

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241

4. Methodology

242

The classic method of regression assumes that a phenomenon is spatially stationary in the sense that each region in the analysis shares the same relationship between independent variables and a dependent variable, expressed with coefficients of a single global model (linear model).

245

246

The GWR model is a linear model defined by 263 sets of coefficients (a set for each region), so it constitutes a set of 263 local linear models. To demonstrate the benefits of using GWR, the article compares the GWR model with the linear model (Global model) developed using one set of coefficients. This single set was determined "globally", i.e. all 263 regions were included.

250

251

Numerous works (Bivand et al., 2008; Brundson et al., 1999; Fotheringham and Charlton, 2016) have demonstrated the limitations of the classic method of regression for modelling socio-economic relationships, a result of the lack of spatial stationarity of the phenomena in question. In the work (Bivand, 2017) it was proved that due to different socio-

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255 economic factors in EU countries, separate models had to be built for developed and developing
256 countries.

257 Factors that may affect road safety in the regions were selected and quantified in a GWR
258 model (Fortheringham et al., 2002; Suchecki, 2010). Geographically weighted regression takes
259 account of the variability of regression factors in each region. The basic GWR model takes this
260 form:

$$261 \quad y_i = \beta_{i0} + \sum_{k=1}^m \beta_{ik} x_{ik} + \epsilon_i \quad (1)$$

262
263
264 where:

265 y_i – dependent variable for region i

266 x_{ik} – independent variable k for region i

267 m – number of independent variables in the model

268 β_{i0} – estimated coefficient (intercept) for region i

269 β_{ik} – regression coefficient that corresponds to variable k for region i

270 ϵ_i – random error for region i

271
272 The GWR method is an extension of the linear regression model which does not always
273 represent the differences between regions (Bivand et al., 2008). The GWR method centres
274 around spatial weights (Fortheringham et al., 2002), a function which defines the spatial
275 relationships between the observed variables. In estimating the parameters of local models of
276 regression is taken account of explanatory variables from neighbouring regions. Influence of
277 regions decays with distance between centroids.

278 The analysis used the package `spgwr` (Bivand, 2017), available in the R environment.
279 Elements of weight matrixes were determined using the Gaussian kernel function:

$$280 \quad w_{ij} = \begin{cases} e^{-0,5\left(\frac{d_{ij}}{b}\right)^2} & \text{for } d_{ij} < b \\ 0 & \text{for } d_{ij} \geq b \end{cases} \quad (2)$$

281
282 where:

283 d_{ij} – distance between region i and j ,

284 b – bandwidth.

285

286 The geographic coordinates of regional centres of gravity were transformed into
287 Cartesian coordinates using the Robinson Projection. The optimal window width $b=365.16$ km
288 was determined using $gwr.sel$ with the cross-validation criterion. For $b \rightarrow \infty$, weights $w_{ij} \rightarrow$
289 1, making GWR consistent with the global model.

290 The GWR model was validated using 2015-2018 data. To that end observed values and
291 model-predicted values were compared. To compare the results of analyses both the global
292 (linear model) and GWR models are presented in the results part.

293

294 **5. Results and discussion**

295 **5.1 GWR model calibration**

296 The process of model development and the selection of independent variables for the model
297 consisted, firstly, of checking the correlation of variables and selecting those that strongly affect
298 the RFR variable and at the same time to a small extent each other. Next, selected independent
299 variables (GDPPC, MRPC, PPC, LIFE and ARAL as well as CO, IB and OB) were introduced
300 into the model taking into account their statistical significance.

301 Eventually, considering statistically significant (p -value <0.05) variables the following
302 data were used: GDPPC, MRPC, PPC, LIFE, IB i OB. The introduction of variables encoding
303 regional boundaries (IB and OB) improved the goodness-of fit of the model. While developing
304 the model, the potential impact of collinearity between variables was considered.

305 Spatial differentiation of GDPPC, MRPC, PPC, LIFE and the limitations of the linear
306 regression model have been confirmed by Moran's I (Li et al., 2007) statistics as shown in Table
307 3. Thus, the null hypothesis of the lack of spatial autocorrelation of the variables is rejected.
308 The values p -value=0.00 for Table 3 variables show that they are statistically significant. The
309 positive Z-score shows that regions with extreme values of variables are in spatial proximity
310 (regions form clusters). To include the geographic location of EU regions, geographic
311 coordinates of their centres of gravity were determined.

312

313 Tab. 3 Moran Indice test for the RFR and input variables

Variable	Moran Indice test	p-value	Z-score
RFR	0.149	0.00	22.63
GDPPC	0.138	0.00	21.16
MRPC	0.115	0.00	17.80
PPC	0.144	0.00	22.21
LIFE	0.215	0.00	32.52



314 The GWR model describes the influence of the region's social, economic and
 315 infrastructural factors which have an effect on road safety and takes account of the spatial
 316 differentiation of the variables within the region. The GWR model (Table 4) was developed
 317 using 2014 data. The model was validated by applying it to predict RFR in 2015-2018.

318

319 Table 4. GWR model statistics RFR ~ GDPPC + MRPC + PPC + LIFE + IB+OB

Variable	GWR model's coefficients					Coefficient of p-value	
	Min.	1 quartile	Median	3 quartile	Max.	the global model	
Intercept	-1,371.68	394.31	529.78	638.12	1,239.70	609.282	< 2e-16
GDPPC	-4.12	-1.04	-0.57	-0.19	1.99	-0.586	8.86e-05
MRPC	-2.42	0.58	0.70	0.98	3.04	0.824	7.24e-10
PPC	-4.05	-2.87	-2.01	-1.64	0.73	-2,124	<2e-16
LIFE	-16.78	-4.89	-3.83	-2.36	16.89	-4.965	5.35e-12
IB	-25.39	-2.72	3.90	13.89	25.27	6.556	0.00543
OB	-18.48	9.73	18.20	31.00	105.22	10.522	0.02259
Bandwidth					365.16 km	∞	
AIC criterion					2,133.82	2,275.63	
Sum of the squares of model's residuals					42,669.35	82,953.98	
Adjusted R ²					0.7498	0.5136	

320 In the global model, 51.36% of RFR's variability is explained with selected diagnostic
 321 variables. The parameters of the global model are statistically significant. MRPC, IB and OB
 322 variables have a positive influence on RFR, the influence of the other variables is negative.

323 GWR's R² coefficient is higher than in the global model and amounts to 0.7498. The
 324 GWR model's Akaike criterion (AIC=2,133.82) is also better than that in the global model
 325 (AIC=2,275.63).

326 A comparison of adjusted R², Akaike criterion (Table 4) and Moran's I statistics for the
 327 residuals of the global model and GWR model (Table 5) shows that the GWR is more reliable.
 328 With p-value = 0.221 and Z-score =1.22, there is no ground to reject the null hypothesis of the
 329 lack of spatial autocorrelation of GWR model residuals. Thus, there is no spatial autocorrelation
 330 of GWR residuals, and their distribution is random (Fig. 2), which confirms the model's
 331 applicability for describing the relationship between RFR and the input factors. Unlike the
 332 GWR residuals, residuals of the global model show spatial autocorrelation (Z-score =8.80) due
 333 to rejection of the null hypothesis of the residuals random distribution (p-value = 0.00).

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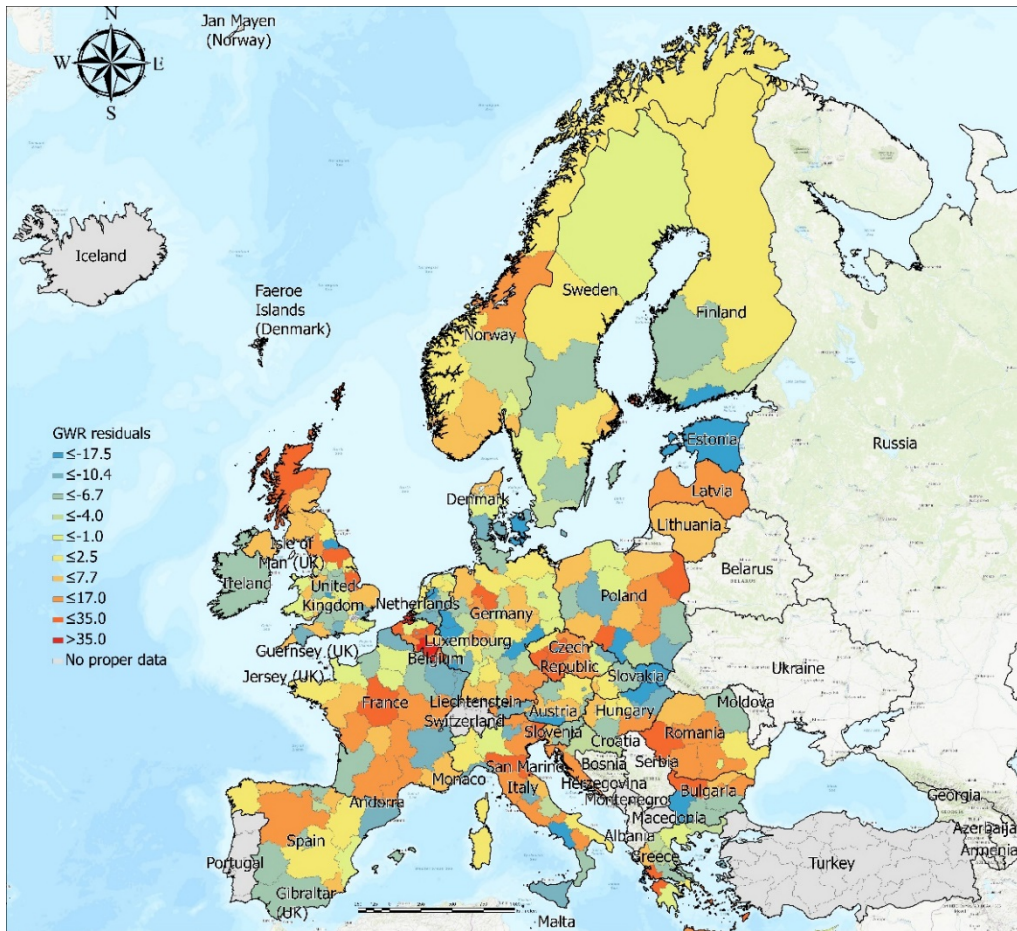


Fig.2 Random spatial distribution of GWR residuals.

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Tab. 5 Moran Indice test for residuals

Residuals	Moran Indice test	p-value	Z-score
Global model	0.055	0	8.80
GWR model	0.004	0.221	1.22

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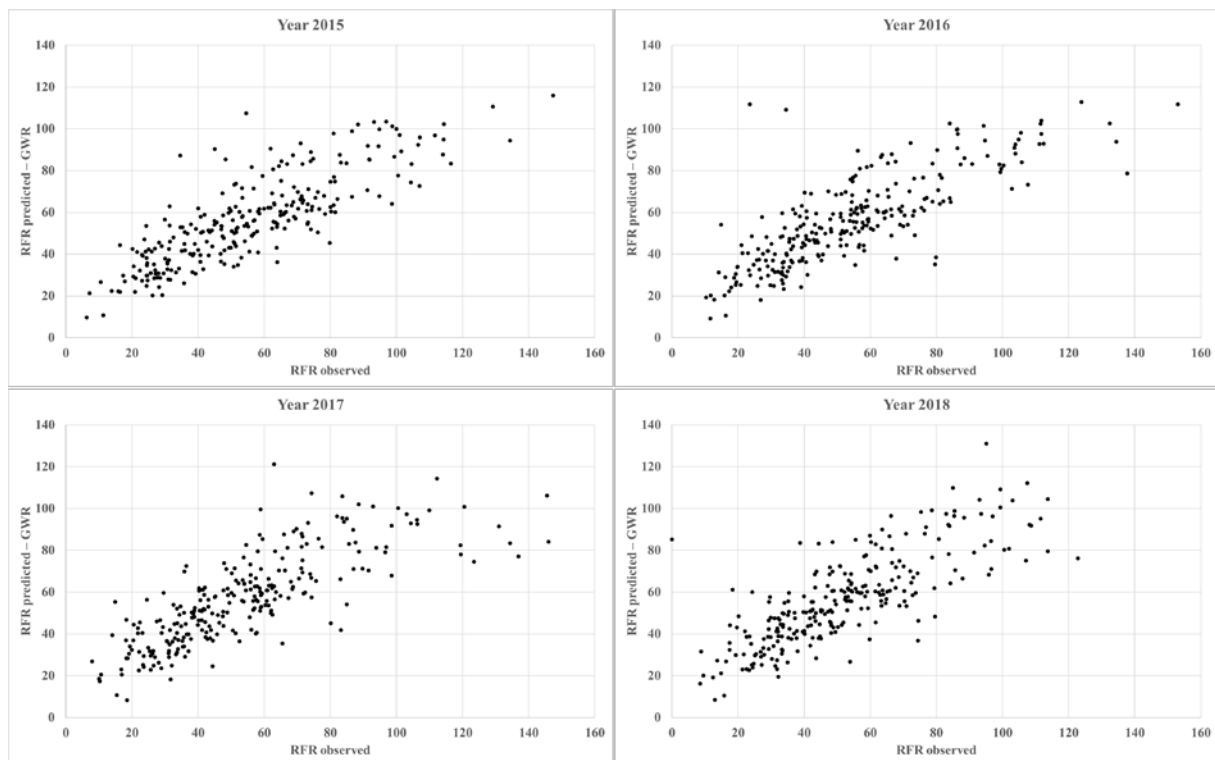
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Tab. 6 Moran Indice test of GWR model coefficients

Coefficient	Moran Indice test	p-value	Z-score
GDPPC	0.263	0.00	39.70
MRPC	0.147	0.00	22.61
PPC	0.254	0.00	38.36
LIFE	0.150	0.00	23.41
IB	0.425	0.00	63.50
OB	0.301	0.00	45.32

345 The GWR model developed from 2014 data, was used to predict RFR in 2015-2018.
 346 The determination coefficient (adjusted R^2) for GWR predicted values is 0.63 (2015, 2016),
 347 0.61 (2017) and 0.57 (2018) (to compare: the adjusted R^2 for the global model's prediction in
 348 2015-2018 was lower than 0.50 (respectively for years 2014-2018: 0.47, 0.48, 0.46 and 0.40).
 349 Comparison of observed and predicted values of RFR based on the developed model for 2015-
 350 2018 is presented in fig. 3.



351
 352 Fig. 3 Comparison of the values observed and obtained from the GWR model for 2015-2018.

353
 354 It is also important to note the limitations of the developed GWR resulting from the
 355 following data limitations:

- 356 • Due to the limited access to conclusive data on accident victims, the developed model
 357 allows for estimating only the number of fatalities, without accounting for the KSI,
 358 which may affect the identification of NUTS-2 regions at risk in terms of road safety.
- 359 • Low dynamics of change in time of independent variables included in the model.
- 360 • Inability to take into account other influences e.g. cultural, legislative, climatic, traffic
 361 in details.
- 362 • Possibility of variability of the number and shape of regions over time (every 3 years),
 363 which means that the model should be recalibrated, or variables converted for the
 364 selected NUTS-2 system.

- 365
- It is not possible to include all regions due to their divergence from the sample (mainly
- 366 regions of large cities that should not be included in the model developing).
- 367

368 **5.2 RFR and factors affecting its value**

369 Description of the variability of the RFR indicator and the GWR model coefficients

370 affecting its value, which are independent variables available in the Eurostat and national

371 databases are presented below.

372 Figures 4-7 present the results of the analysis of the spatially differentiated influence of

373 input variables on RFR in European regions on the basis of GWR coefficient variability. Each

374 figure represents spatial differentiation of the variable (a) as well as coefficients (b) in the GWR

375 model which has positive or negative impact on RFR. The observations are as follows.

376 The impact of **GDPPC** on road safety is not conclusive, as confirmed by previous studies.

377 The equivocal effect of GDPPC in the developed model has also been observed in the studied

378 literature (Antoniou et al., 2016; Bester, 2001; Bhavan, 2019; Elvik, 2015; Kuznets, 1955; Law

379 et al., 2009; Nghiem et al., 2013; Noland R.B., 2003; Paulozzi et al., 2007; Thomas L Traynor,

380 2008; Wegman et al., 2017).

381 From the GWR model one can observe that an increasing gross domestic product per

382 capita in Central and Eastern European countries improves road safety significantly by

383 decreasing the RFR (Fig. 4). While their gross domestic product per capita is low, Central and

384 Eastern European countries follow the example of countries with the best road safety record

385 and their potential for improvement is high. A positive correlation between GDPPC and RFR

386 can be observed in regions with a high level of road safety, i.e. in the north of Scandinavia,

387 north of Great Britain and western Europe. This may indicate a lack of potential to improve

388 road safety as measured by the reduction in the number of fatalities along with the increase in

389 GDPPC, indicating the society's wealth. It should be noted, however, that even within countries

390 with a high GDPPC value there are regions that still have the potential to improve road safety

391 (e.g. South of Sweden, central and eastern Germany). The problem of lack of improvement in

392 road safety described above, despite the increase in the level of society affluence and

393 implementation of remedial programmes, has been recognised in the EU. In the years 2014-

394 2018 the assumed improvement of road safety was not accomplished. There was also no

395 decrease in the number of fatalities in 2018 (European Commission, 2018). This signifies the

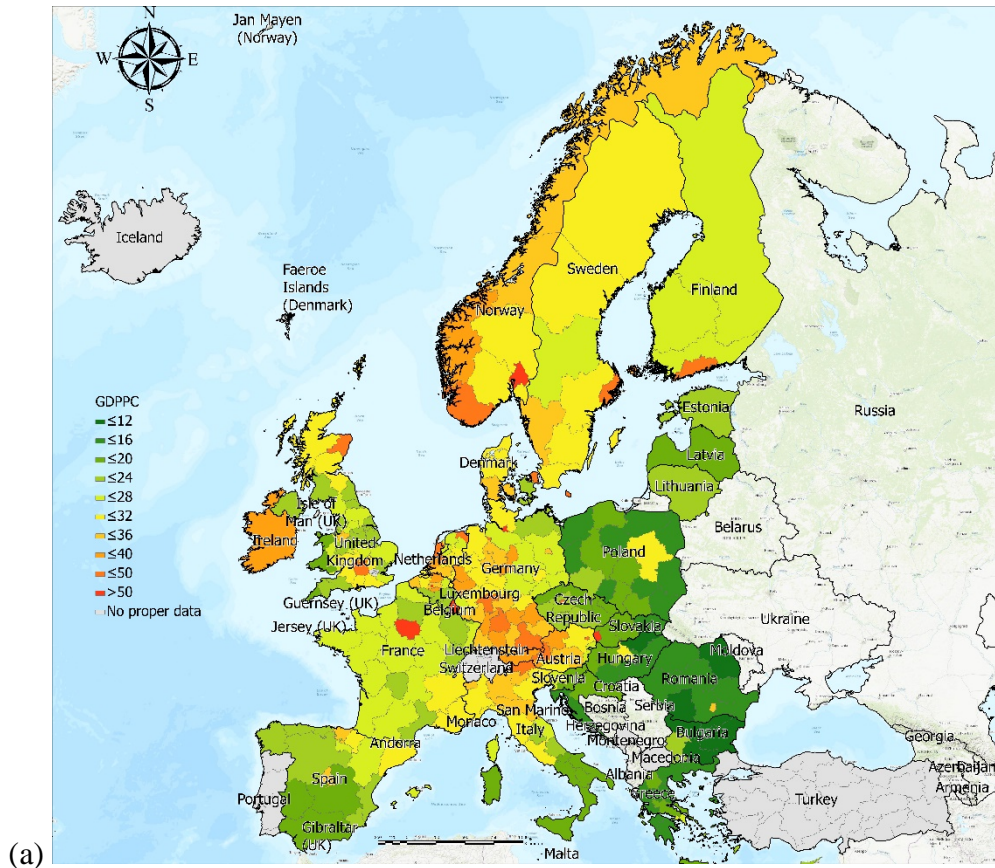
396 need to search for new tools that will reduce the number of road fatalities e.g. by extending the

397 scope of the provisions regarding Directive 2008/EC/96 on road infrastructure safety

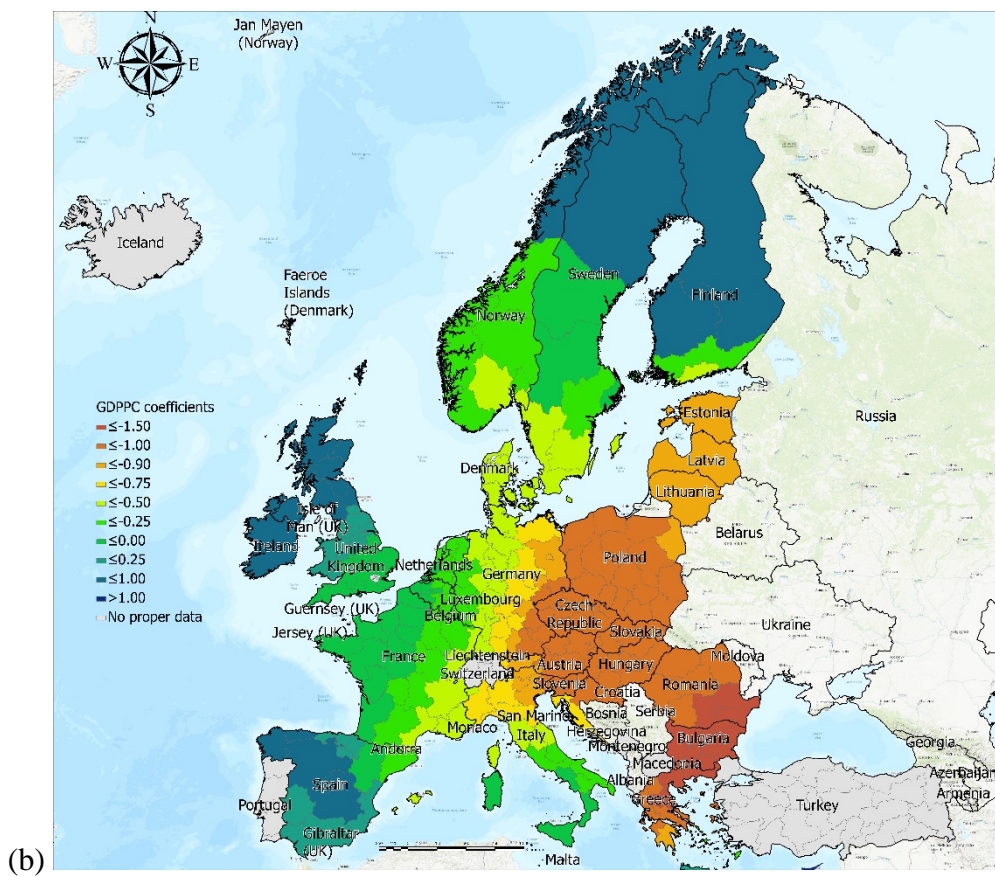
398 management in the new Directive 2019/1936 (European Parliament and the Council, 2018).



399



400



401

Fig. 4 Spatial differentiation of GDPPC (a) in 2014 and GDPPC coefficients (b) in the GWR model.

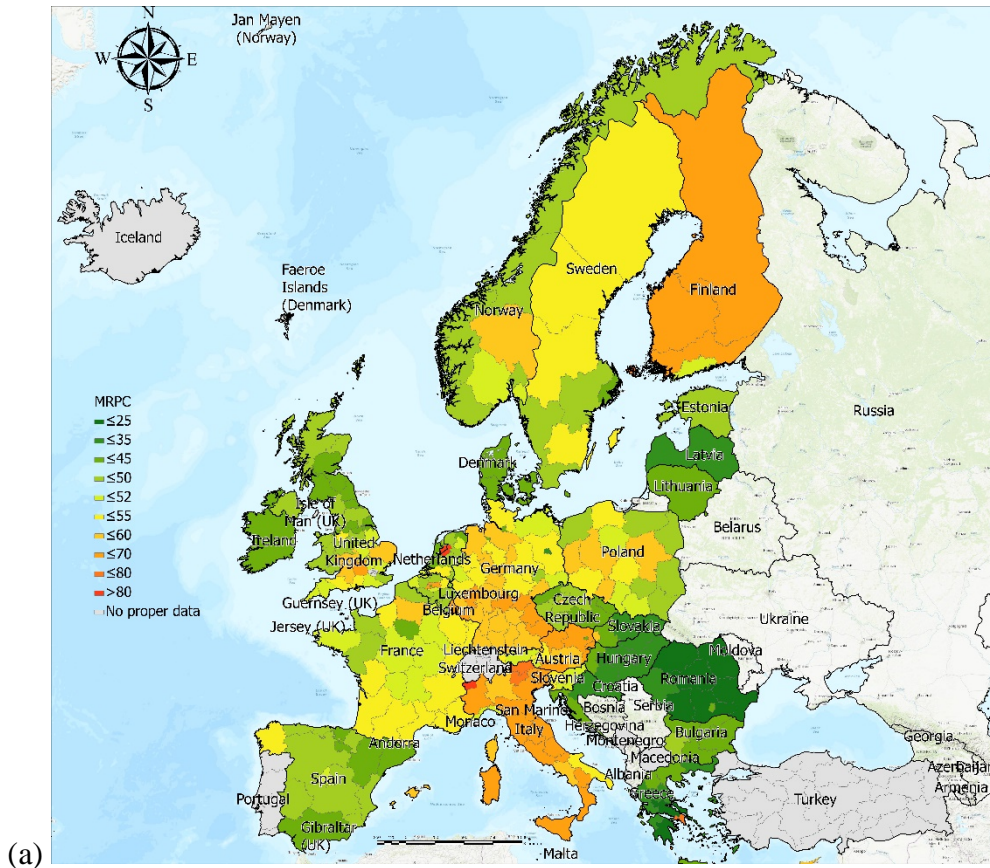
402 There is concern over the upward trend in RFR in some regions which are developing
403 dynamically from a poor economic baseline. This may suggest that as societies increase their
404 wealth and are likely to buy better cars and build better roads, their road user behaviour does
405 not improve. This may be the case in Spain, which is also a country with a relatively low
406 GDPPC, but according to the forecast, the country's economic development, according to the
407 model, will not significantly improve road safety.

408 Also other economic development variables turned out to be statistically significant for
409 RFR as already highlighted in many publications (Douglas and Likens, 2000; Jones et al., 2019;
410 Scuffham, 2003; Thomas L. Traynor, 2008).

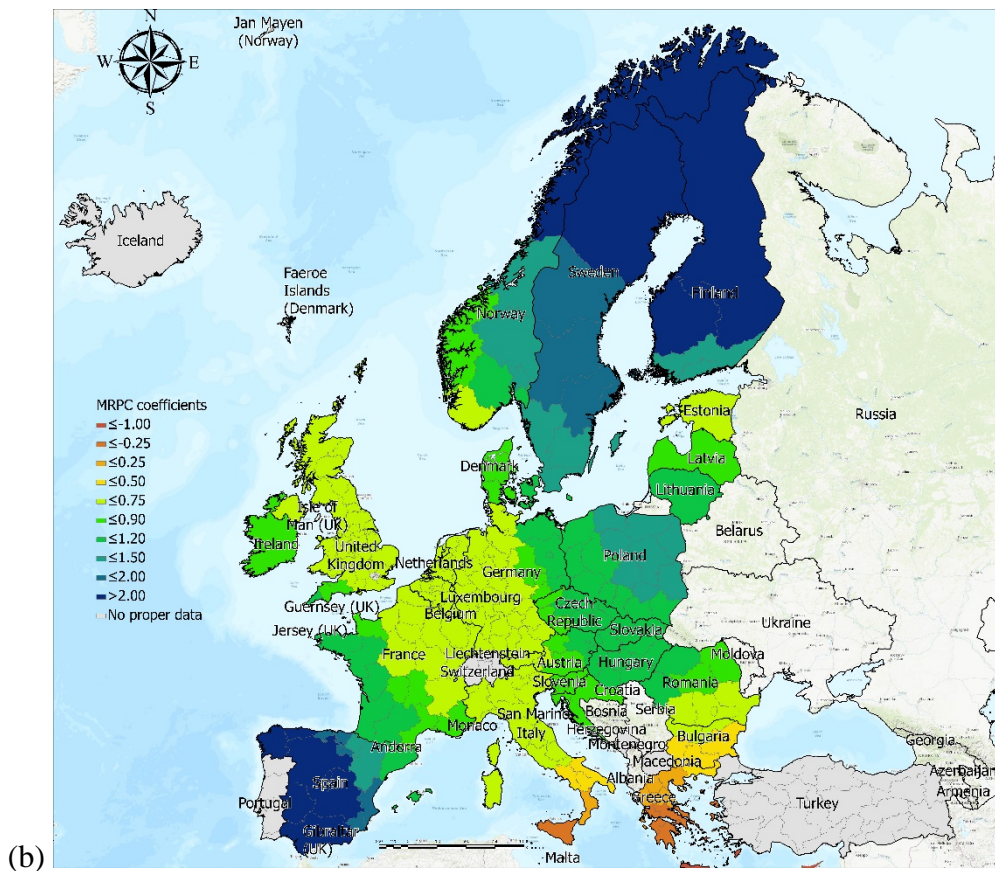
411 In the developed model, the impact of a growing motorisation rate **MRPC** has an
412 equivocal effect on RFR, depending on the region, which is consistent with previous research
413 (ADAMS, 1987; Andreassen, 1985; Broughton, 1988; Oppe, 1991). MRPC varies greatly from
414 region to region, regardless of the country, with the highest values in 2014 in the regions of
415 Italy and Finland, and the lowest in Romania and southern Greece. An analysis of model
416 coefficients shows that apart from the southern parts of the Apennine and Balkan Peninsulas a
417 further increase in motorisation rate increases the risk of being fatality in an accident. The
418 largest negative impact of automotive growth is predicted for the Scandinavian regions, the
419 Iberian Peninsula and eastern regions of Poland. The MRPC variable can constitute an easily
420 accessible indirect risk exposure measure within the regions. Inconclusive results also indicate
421 a need to collect additional data, for example on mobility (e.g. vehicle km travelled) or the use
422 of BIG data (e.g. Probe Vehicle Data). In the studies where the increase in MRPC affected the
423 deterioration of the level of road safety, the factors of law and corruption index were also
424 considered (Law et al., 2009). MRPC describes the number of vehicles registered in a given
425 region but not the traffic volume they generate, neither does it provide any information about
426 user behaviour. In addition, some regions may have high through traffic with a low number of
427 high standard roads, and such data would probably be a better risk indicator than MRPC.
428 Unfortunately, they are not collected in the Eurostat database which limited the possibilities
429 developing of the model.



430



431



432

Fig. 5 Spatial differentiation of the MRPC variable (a) in 2014 and MRPC coefficients (b) in the GWR model.



433 In general, a reduction in **PPC** has a negative effect on safety level, hence a negative
434 coefficient in the model. Regions within a country may differ. If the coefficient for a given
435 region is -3.3, then if the share of passenger cars in the entire fleet increases, the decrease in
436 RFR will be greater than for a region with RFR of -1.0. Some of the UK's regions feature a
437 strong differentiation in PPC just as different regions in Germany (Fig. 6). It is interesting that
438 the effect this variable on RFR is not proportional to the real values of PPC. While these results
439 may be difficult to interpret, the reason behind them is that vehicle data are incomplete. What
440 is not known, for example, is the average vehicle age in a region. While heavy goods vehicles
441 usually represent a small percentage of the entire vehicle fleet, their technical condition or
442 driver fatigue (Jamroz and Smolarek, 2013; Wilde, 2000) (with drivers spending long hours in
443 their trucks) may have a more significant influence on road safety.

444 An increase in the **LIFE** variable in the majority of regions decreases RFR (Fig. 7) and
445 the effect is the strongest in countries that have a high LIFE rate. Life expectancy differs from
446 region to region even within one country. Life expectancy is highest in the regions of Spain,
447 France and Italy. At the same time, the potential for RFR reduction with increased life
448 expectancy is greatest in some regions of Spain and France, as well as in Sweden, Finland, the
449 northern regions of Norway, Lithuania, Latvia and Estonia. Longer life is likely to reduce the
450 RFR. Life expectancy reflects the standards of living in a region, the quality of health care and
451 a healthy lifestyle which may translate into more careful driving and less risk on the roads. The
452 results confirm the research from the literature (Clark DE et al., 2004; Derrig and et al., 2002).
453 LIFE data easily is available, the idea to use it in place of the regionally unavailable *spgwr*
454 (Bester, 2001) (is not available in the EU databases) proved successful because of its
455 statistically significant effect in the model on RFR.

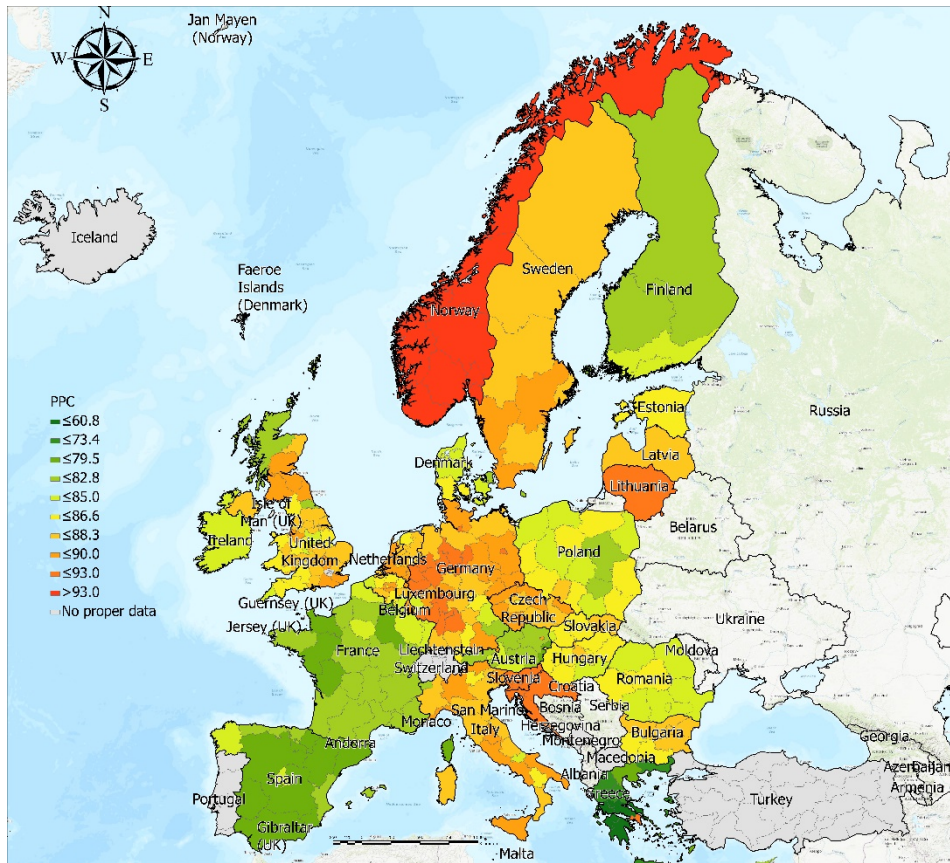
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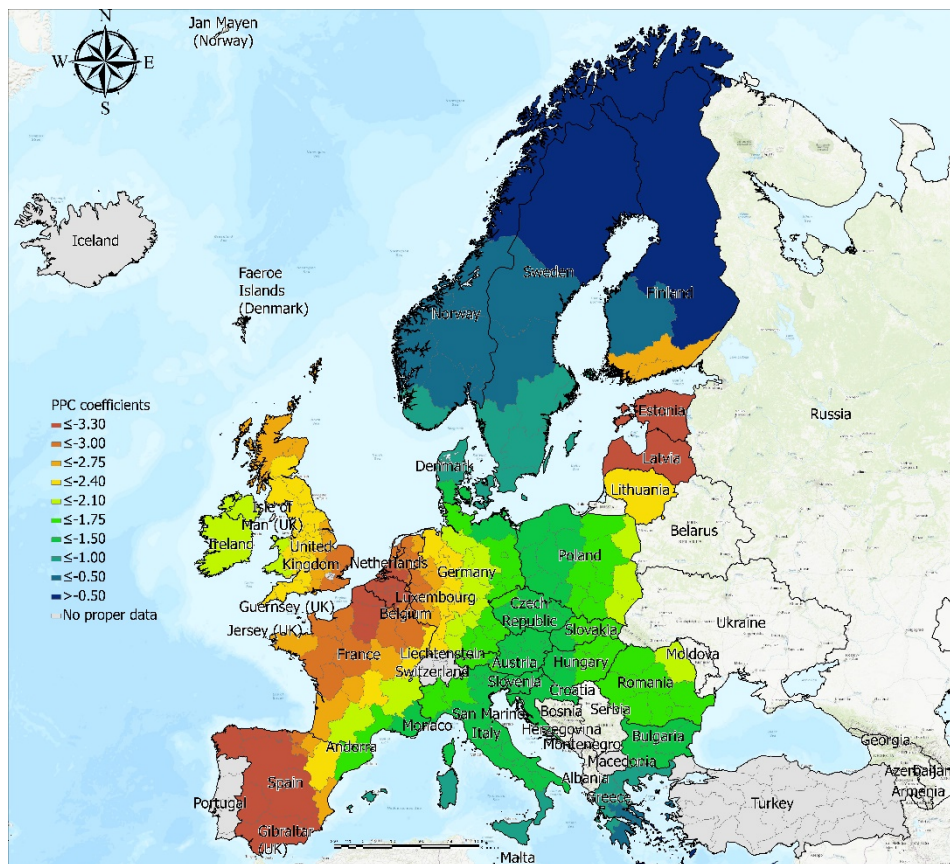
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(a)



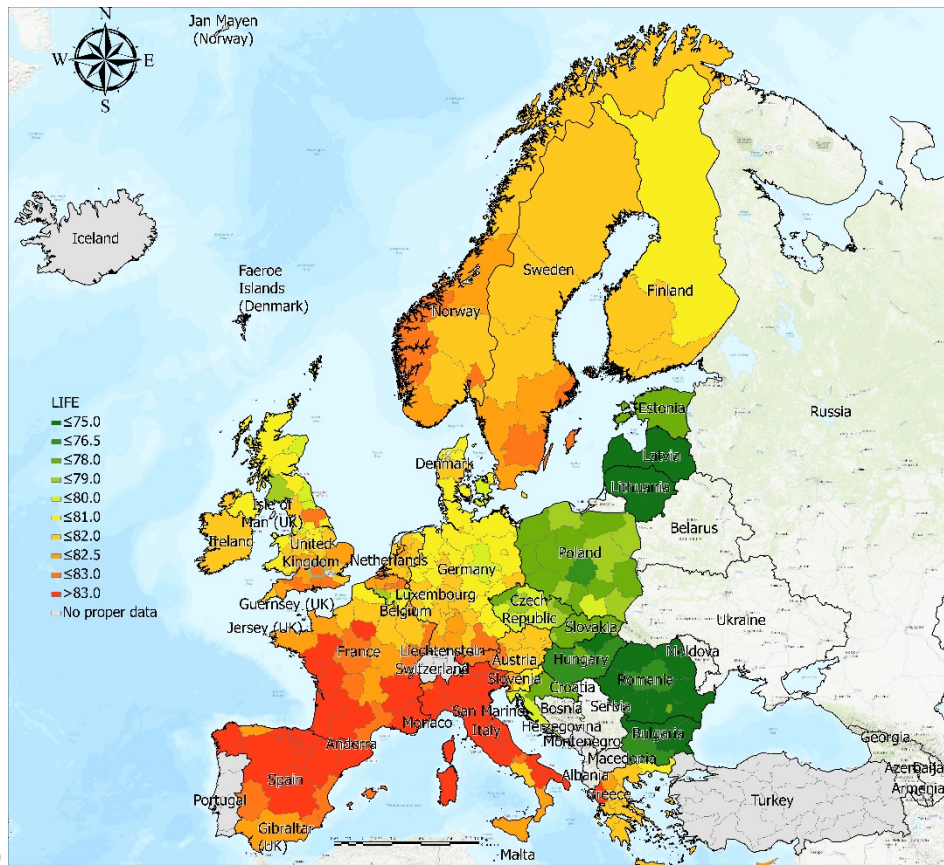
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(b)



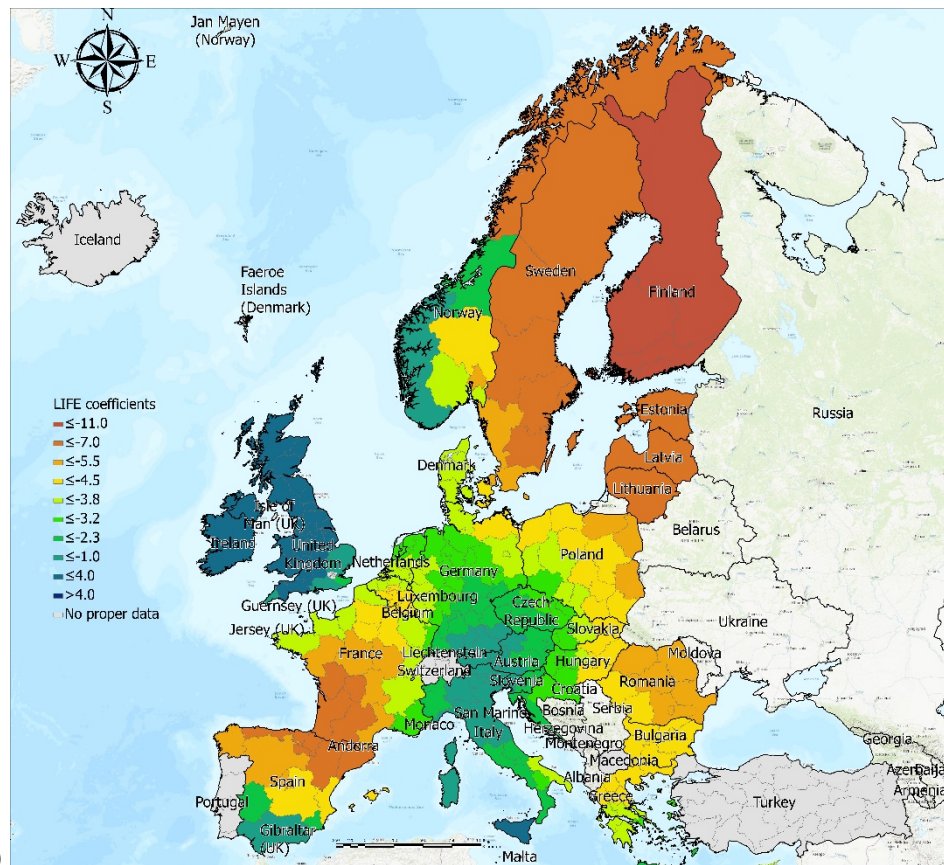
461

Fig. 6 Spatial differentiation of the PPC variable (a) in 2014 and PPC coefficients (b) in the GWR model.



463

(a)



464

(b)

Fig. 7 Spatial differentiation of the LIFE variable (a) in 2014 and LIFE coefficients (b) in the GWR model.



466 Based on the literature review which indicated that the higher the **DP**, the higher the
467 safety level is observed (Clark, 2003; Eksler, 2006; Eksler et al., 2008), DP was taken into
468 account in the model for regions. However, preliminary analyses identified MRPC as a variable
469 that described RFR variability better and at the same time with strong correlation with the DP
470 variable, which led to the elimination of this variable from the model.

471 The level of urbanisation, although suggested by some researchers as significant (Clark,
472 2003; Sylvain Lassarre and Thomas, 2005; Wegman F, Eksler V, Hayes S, Lynam D, Morsink
473 P, 2005) was not available in EU databases. Obtaining urbanisation data should perhaps be
474 included in further work. This, however, requires closer international cooperation to help with
475 data exchange if data are stored at local centres of statistical analyses. Therefore, the percentage
476 of arable land (**ARAL**) had been included in the model, but it turned out to be statistically
477 insignificant.

478 The density of the road network, identified in the literature as affecting road safety
479 (Ogden, 2004), in these analyses was found to be insignificant perhaps due to the stability of
480 this variable over time. Information on motorway density, which affects the reduction of the
481 fatality number (Wachnicka et al., 2017) and has been changing rapidly in the developing world
482 in recent years, was in many cases unavailable at regional level and could not be included in
483 the developed GWR model.

484

485 **6. Conclusion**

486 The use of data available in Eurostat databases and national databases for NUTS-2 regions
487 in spatial analyses can enable better targeting of actions to prevent the negative impact of road
488 traffic in Europe. This macroscale approach can help in the identification of
489 structural/substantial and endemic safety problems and can actively contribute to the aimed
490 50% reduction of road casualties by 2030 in line with the objectives set in the EU White Paper
491 (UN Road Safety Collaboration, 2020). The use of spatial data in the GWR model can provide
492 useful information on the risk of fatalities due to road accidents per million habitants in NUTS-
493 2 regions in selected European countries (EU and Norway) in relation to social, demographic,
494 economic, and geographical factors.

495 The GWR model can be a useful tool for road safety estimation and identifying regions
496 with a high RFR, that require road safety activities as well as identifying regional spatial
497 differences, by using parameters other than traffic accidents. An extension of the proposed
498 method to accident of different severities can be of great importance in regions or areas where
499 the underreporting or road accidents is particularly high, and the RFR can be much easily



500 computed with data that are already available and with higher reliability. The combination of
501 GWR and NUTS-2 data provide information at macroscale and it can be a perfect tool for a
502 first screening to identify road safety problems at macro level. However, due to the complexity
503 of accident occurrence, this tool has limited application in reducing the number of fatalities.

504 The use of the GWR model allowed the analysis of spatially non-linear variables, by
505 considering the linear relationship only within a macro-area, which the traditional (linear) regression
506 models do not allow. The global linear model looks at this relationship in the entire database
507 assuming a linear correlation between dependant in independent variables and discounting
508 possible different relationships in the NUTS-2 regions. In analyses of the relationship between
509 fatality rate and socioeconomic factors in NUTS-2 regions, it was found that the GWR model
510 is significantly better than the global model of linear regression. The model's adjusted R^2 is
511 higher than that of the global model of linear regression. In addition, its stability and validation
512 were tested in subsequent years and it was found that the model's goodness-of-fit level only
513 decreases to a small extent and so can be successfully used to predict years ahead. Predicted
514 changes in the model's other variables will help to predict changes in the relative RFR with
515 great accuracy. Should undesirable changes occur, additional road safety management efforts
516 can be undertaken to prevent the consequences. The main limitations of the proposed method
517 consist in the fact that it does not allow any control of possible confounding factors related to
518 socioeconomical variables. In the same way the GWR model cannot control possible
519 fluctuations of the RFR due to the implementation of effective safety treatment related to
520 policies or possible upgrading of key infrastructures. The variation of the adjusted R^2 , although
521 positive, demonstrated that the extension of validity in time for the model can be limited. At
522 the same time the validation does not show which factors have reduced their influence in the
523 prediction of the RFR in the calibrated model. For these reasons the GWR models should be
524 used with care considering not only the actual conditions but also the history/trend of variation
525 of the selected covariates.

526

527

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