Postprint of: Wachnicka J., Palikowska K., Kustra W., Mariusz K., Spatial differentiation of road safety in Europe based on NUTS-2 regions, ACCIDENT ANALYSIS AND PREVENTION, Vol. 150 (2021), 105849, DOI: 10.1016/j.aap.2020.105849

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

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

Abstract

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

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

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

Highlights

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

1. Introduction

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

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

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

One of the approaches to assess the road safety level in Europe may be the NUTS-2 (Nomenclature of Territorial Units for Statistics) regions, i.e. areas that are smaller than countries. NUTS-2 regions are statistical territorial units introduced in Europe to identify areas requiring EU support. Road safety is a social problem that generates high social cost and requires EU support. In order to correctly identify regions due to road safety problems, it is necessary to use the same data, available in each of the NUTS-2 regions in Europe, and reliable predictive tools. Therefore, the same data available for all regions in the Eurostat database and in national databases were used in the development of the model.

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

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

2. Literature review

In the literature so far factors that may have an effect on NUTS-2 regional road safety indicators were divided into several groups of traffic and motorization, demographic, infrastructural, economic and social aspects. Developed in the mid-20th century, the initial models would predict a continuous increase in fatalities in keeping with growing populations and cars (Smeed, 1949). In the years that followed, however (ADAMS, 1987; Andreassen, 1985; Broughton, 1988; Oppe, 1991), it became evident that this relationship is more complex and no longer holds true when countries take up legislative and educational measures to improve road safety. The lack of clarity as to how growing motorization affected regions meant that the new fatality models had to include new variables which influenced road safety at the national and regional level. Some of them point to miles travelled as having a big influence on road traffic victims (Berhanu, 2004; Cai et al., 2017; Fernández et al., 2009; Ivan et al., 2004; Ma et al., 2008; Wachnicka et al., 2017). Yet because regional traffic data were difficult to access, other variables were considered to ensure that changes in regional fatality numbers could be explained reliably. One of the characteristics known from the literature is population density. With the decrease in population density, the mortality on the roads increases (Clark, 2003; Eksler, 2006; Erdogan, 2009; S. Lassarre and Thomas, 2005). Higher risk levels on roads were indicated in rural areas (Baker and et al., 1987; Eksler et al., 2008; Jones et al., 2019; Najaf et al., 2018; Rothman et al., 2017). Safety was mostly observed to improve as areas became more urbanised. The literature suggests that this may be linked to better access to health care and shorter waiting times for emergency services to arrive at the scene of an accident. As the number of doctors per capita increases, the number of road deaths decreases (Noland R.B., 2003). Shorter time for emergency services to get to the scene reduces the likelihood of death in an accident (Derrig and et al., 2002; Sánchez-Mangas and et al., 2010). While a higher degree of urbanisation usually means a denser road network, the standard of roads and their maintenance are also at a higher level. As the density of the road network increases, the level of safety increases. (Jamroz et al., 2019; Ogden, 2004). The literature points to the effects of economic growth on road safety. Higher gross domestic product (GDP) or income indicates less road fatalities (Bester, 2001; Bhavan, 2019; Elvik, 2015; Jones et al., 2019; Noland R.B., 2003; Sánchez González et al., 2020; Scuffham and Langley, 2002; Thomas L Traynor, 2008). On the contrary the same authors claimed that high growth areas do not always boast top safety on their road networks (Antoniou et al., 2016; Bester, 2001; Bishai et al., 2006; Jamroz et al., 2019; Yannis et al., 2014). Others (Paulozzi et al., 2007) indicated that income increase is associated with a prompt reduction of pedestrian mortality rates only and this reduction is more gradual because of motor vehicles per capita increase. Results from some long-term analysis (Kuznets, 1955; Nghiem et al., 2013) confirmed Kuznets curve in the traffic fatality rate for all OECD countries. For the same reasons economic recession may also affect fatality rates (Law et al., 2009; Wegman et al., 2017). In literature the unemployment rate was included into analyses as an important factor for road fatalities. In his analysis, Eksler pointed out that the unemployment rate increase was positively correlated with the number of road fatalities (Eksler, 2006), while (Douglas and Likens, 2000) showed the opposite correlation. National research has shown that the number of fatalities also depends on social development, the Human Development Index (HDI) (Bester, 2001), a rate which is not only determined by economic growth but also by life expectancy and the society's level of education. The factors above were identified based on country level analyses.

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

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

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

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

3. Data

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

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

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

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

While developing the database, it was found that exposure factors such as average annual daily traffic or vehicle km travelled (Berhanu, 2004; Cai et al., 2017; Clark DE et al., 2004; Fernández et al., 2009; Ivan et al., 2004; Ma et al., 2008; Thomas L. Traynor, 2008; Wachnicka et al., 2017), or other factors such as speeding or average time for emergency services to get to accident victims (Clark and Cushing, 1999; Derrig and et al., 2002) indicated in the studied literature were not available for specific regions.

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

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%

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

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

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

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

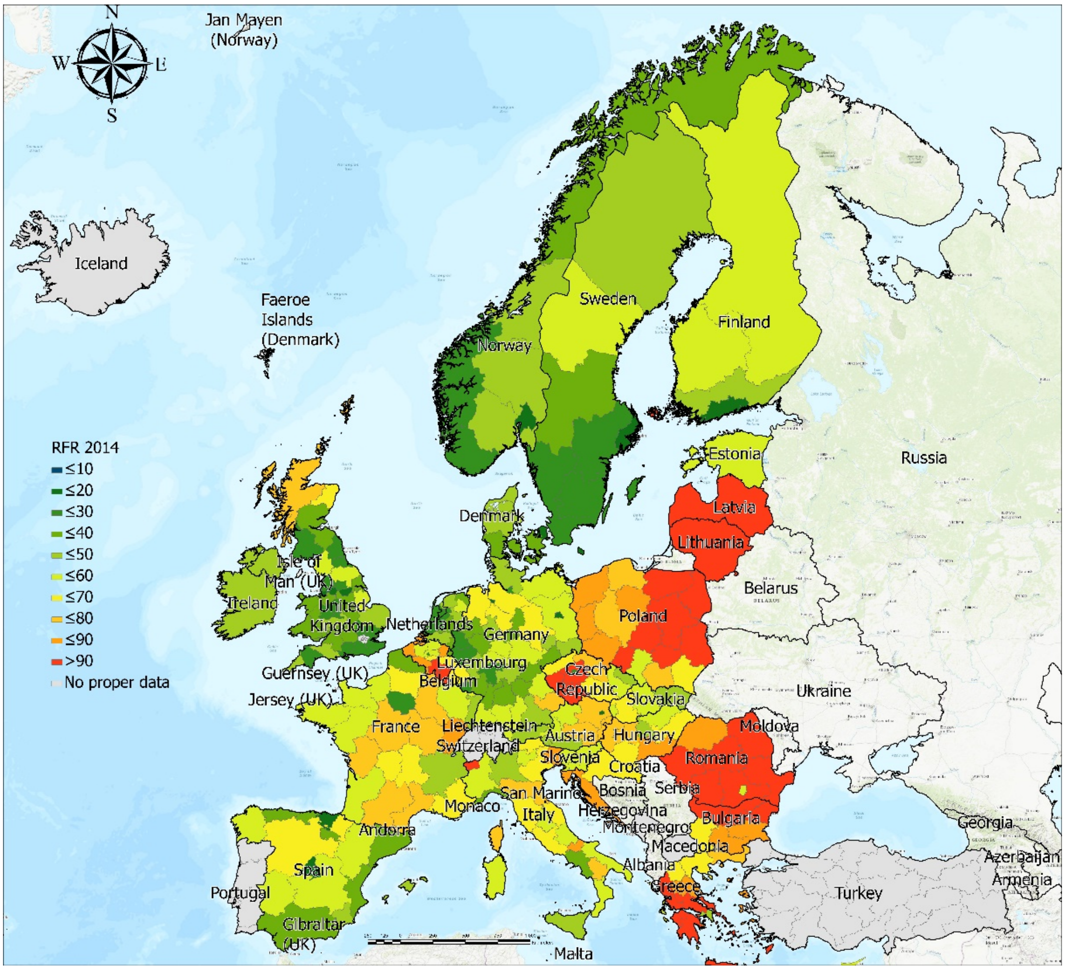


Fig. 1 Road Fatality Rate in EU regions (2014).

4. Methodology

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).

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.

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

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

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

where:

y_i – dependent variable for region *i*

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

m – number of independent variables in the model

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

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

ϵ_i – random error for region *i*

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

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

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

where:

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

b – bandwidth.

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

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

5. Results and discussion

5.1 GWR model calibration

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

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

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

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

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

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

Variable	GWR model's coefficients					Coefficient of the global model	p-value
	Min.	1 quartile	Median	3 quartile	Max.		
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	

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

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

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

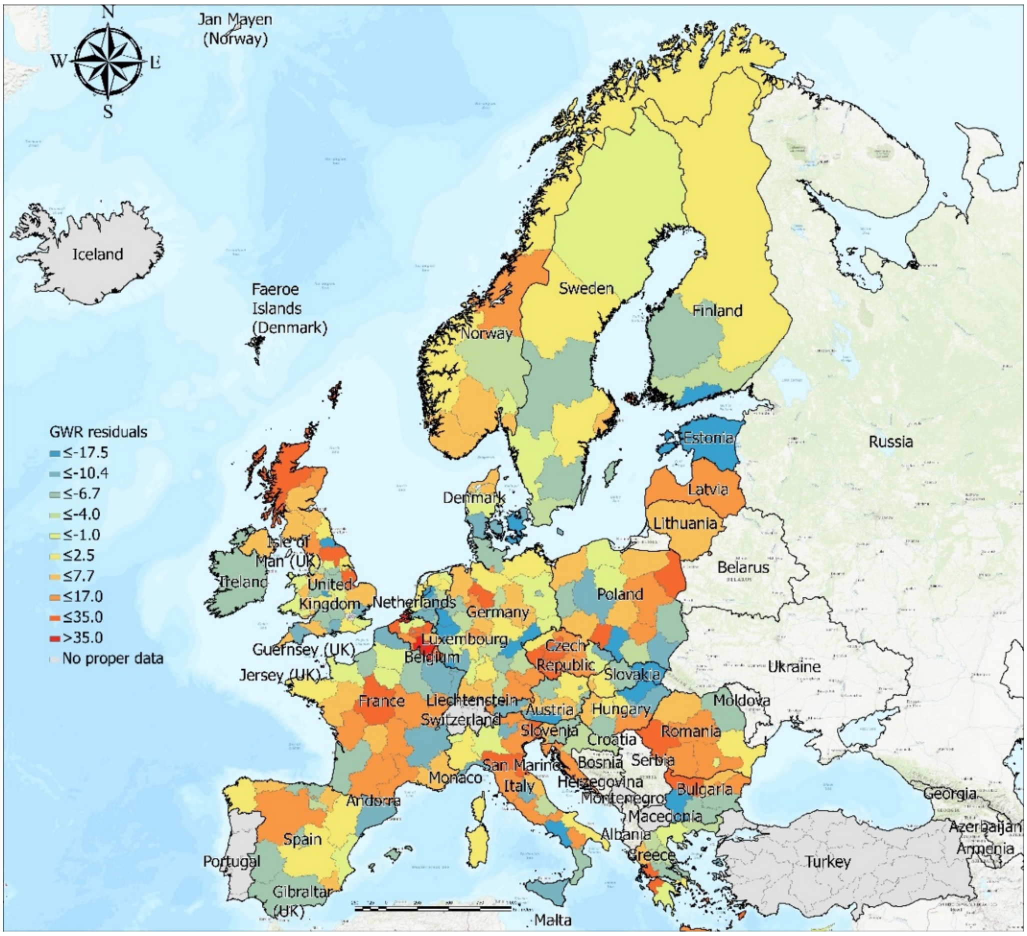


Fig.2 Random spatial distribution of GWR residuals.

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

There is a strong spatial autocorrelation in GWR coefficients (Table 6) which shows that the input variables have a spatially differentiated effect on road safety in the particular analysed regions of the EU and Norway.

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

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

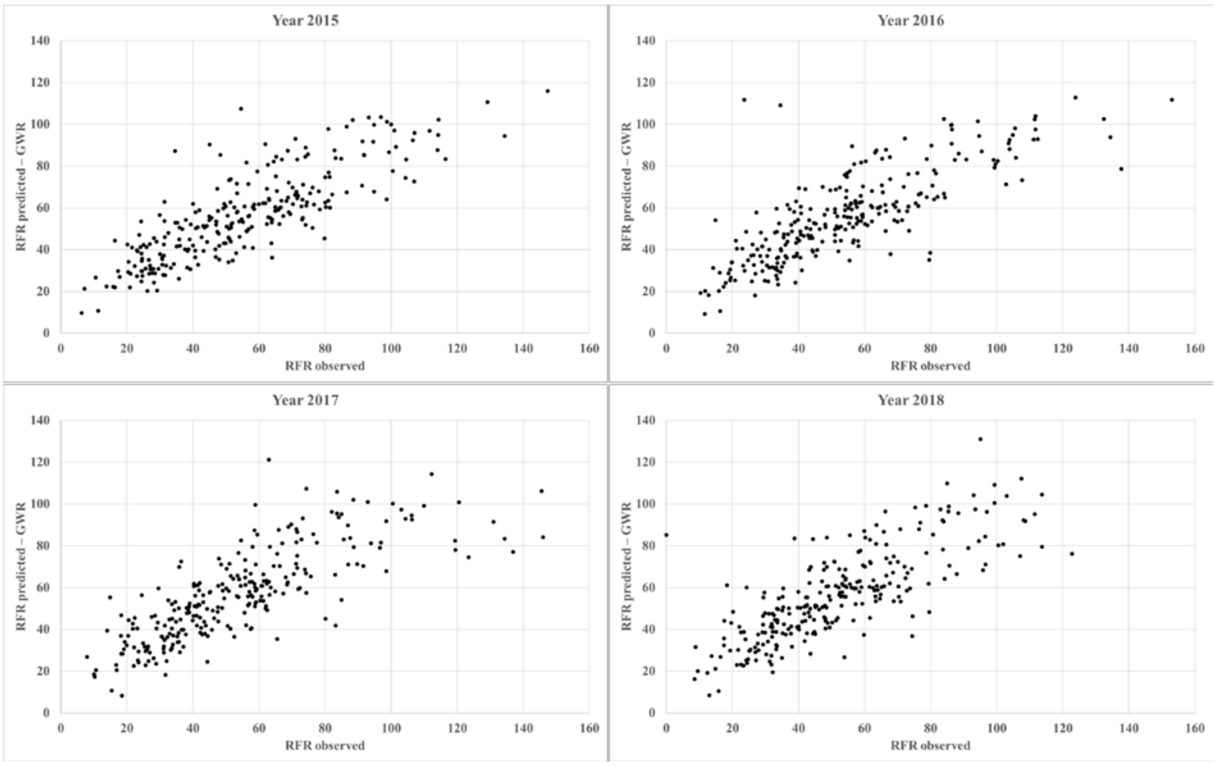


Fig. 3 Comparison of the values observed and obtained from the GWR model for 2015-2018.

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

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

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

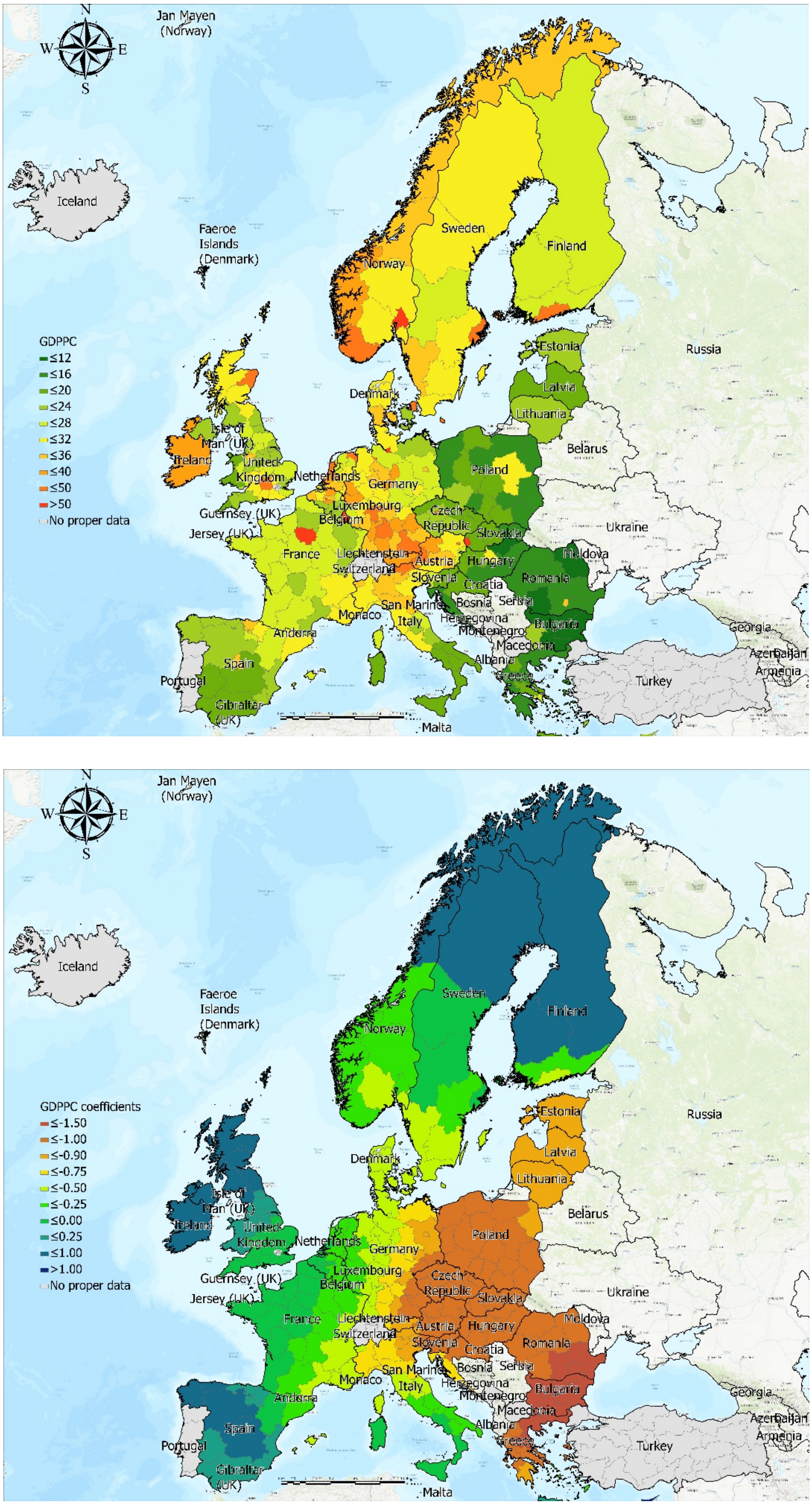
5.2 RFR and factors affecting its value

Description of the variability of the RFR indicator and the GWR model coefficients affecting its value, which are independent variables available in the Eurostat and national databases are presented below.

Figures 4-7 present the results of the analysis of the spatially differentiated influence of input variables on RFR in European regions on the basis of GWR coefficient variability. Each figure represents spatial differentiation of the variable (a) as well as coefficients (b) in the GWR model which has positive or negative impact on RFR. The observations are as follows.

The impact of **GDPPC** on road safety is not conclusive, as confirmed by previous studies. The equivocal effect of GDPPC in the developed model has also been observed in the studied literature (Antoniou et al., 2016; Bester, 2001; Bhavan, 2019; Elvik, 2015; Kuznets, 1955; Law et al., 2009; Nghiem et al., 2013; Noland R.B., 2003; Paulozzi et al., 2007; Thomas L Traynor, 2008; Wegman et al., 2017).

From the GWR model one can observe that an increasing gross domestic product per capita in Central and Eastern European countries improves road safety significantly by decreasing the RFR (Fig. 4). While their gross domestic product per capita is low, Central and Eastern European countries follow the example of countries with the best road safety record and their potential for improvement is high. A positive correlation between GDPPC and RFR can be observed in regions with a high level of road safety, i.e. in the north of Scandinavia, north of Great Britain and western Europe. This may indicate a lack of potential to improve road safety as measured by the reduction in the number of fatalities along with the increase in GDPPC, indicating the society's wealth. It should be noted, however, that even within countries with a high GDPPC value there are regions that still have the potential to improve road safety (e.g. South of Sweden, central and eastern Germany). The problem of lack of improvement in road safety described above, despite the increase in the level of society affluence and implementation of remedial programmes, has been recognised in the EU. In the years 2014-2018 the assumed improvement of road safety was not accomplished. There was also no decrease in the number of fatalities in 2018 (European Commission, 2018). This signifies the need to search for new tools that will reduce the number of road fatalities e.g. by extending the scope of the provisions regarding Directive 2008/EC/96 on road infrastructure safety management in the new Directive 2019/1936 (European Parliament and the Council, 2018).



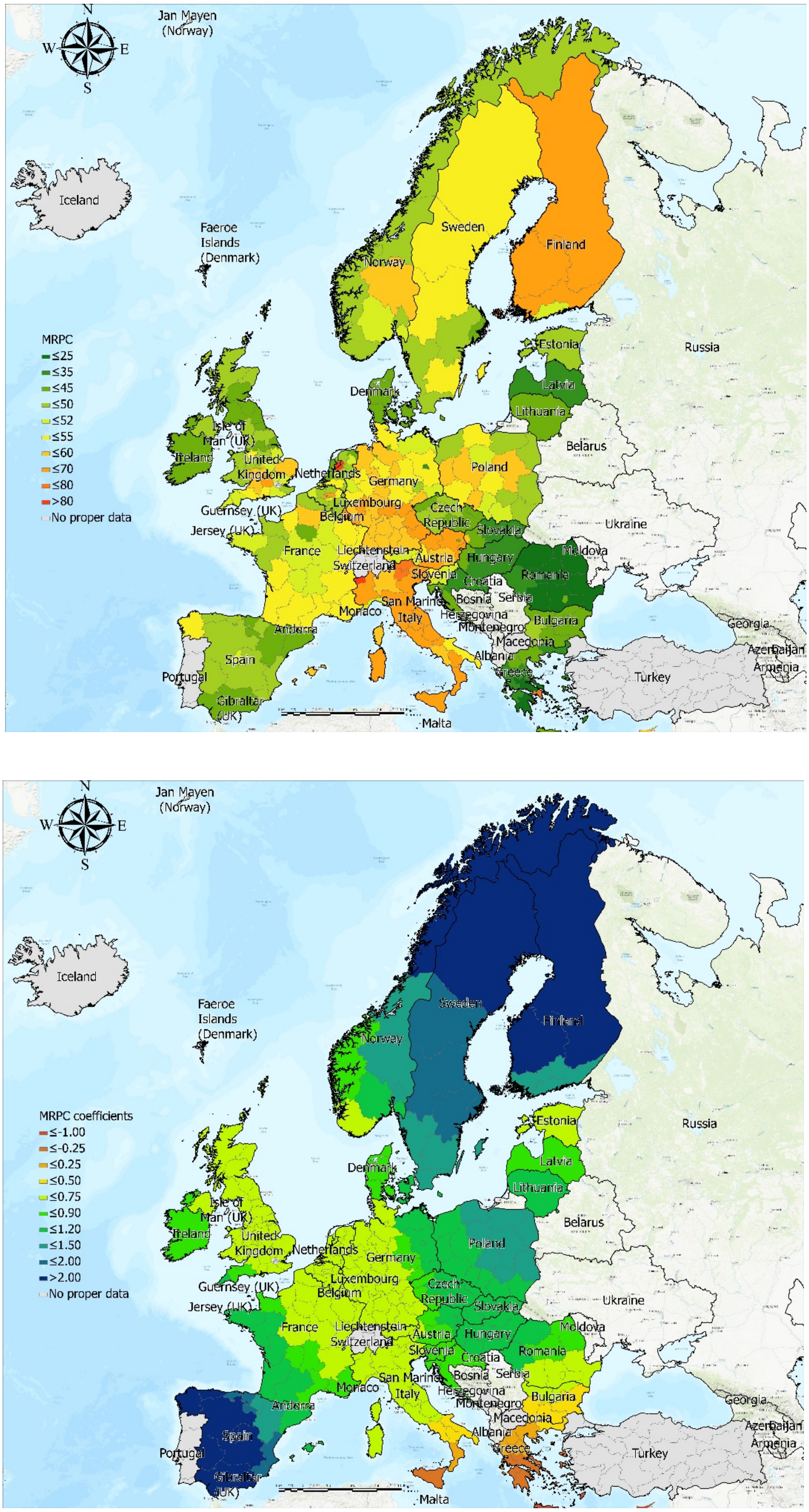
(a)
(b)

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

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

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

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



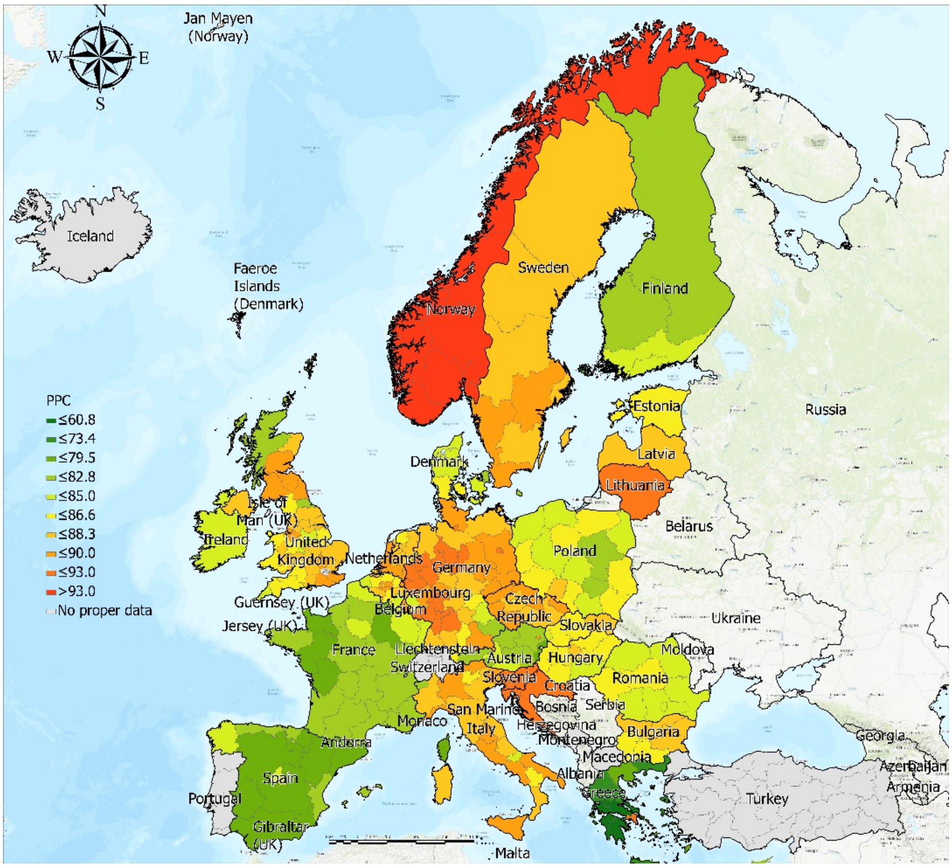
(a)

(b)

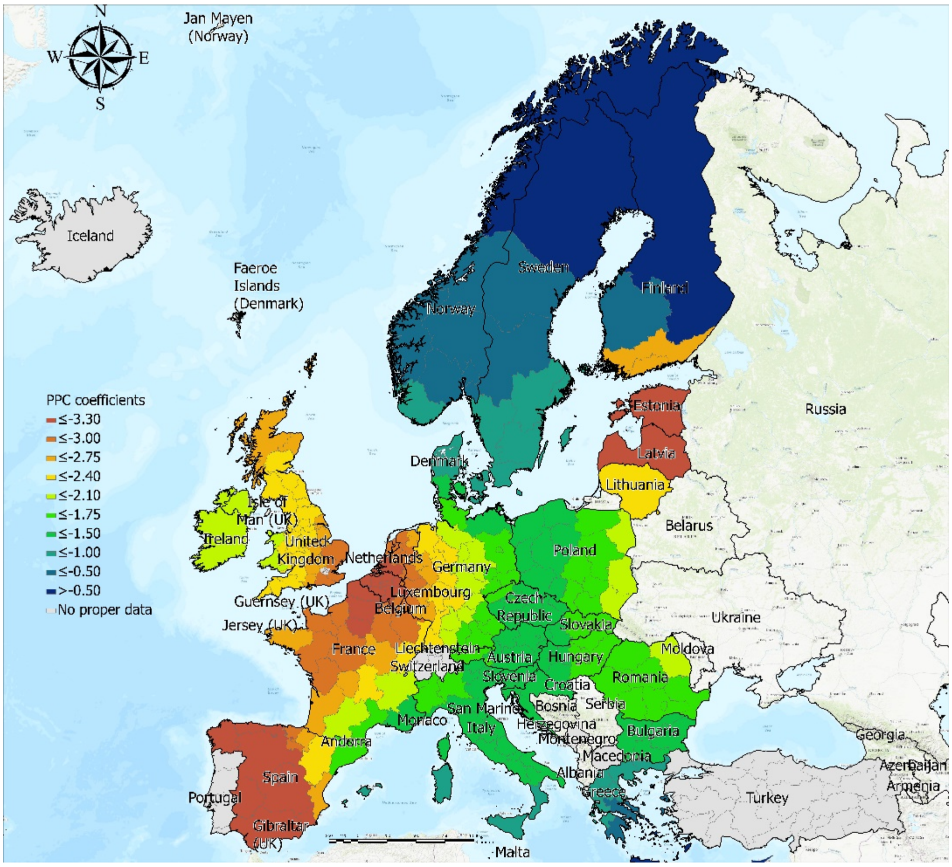
Fig. 5 Spatial differentiation of the MRPC variable (a) in 2014 and MRPC coefficients (b) in the GWR model.

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

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

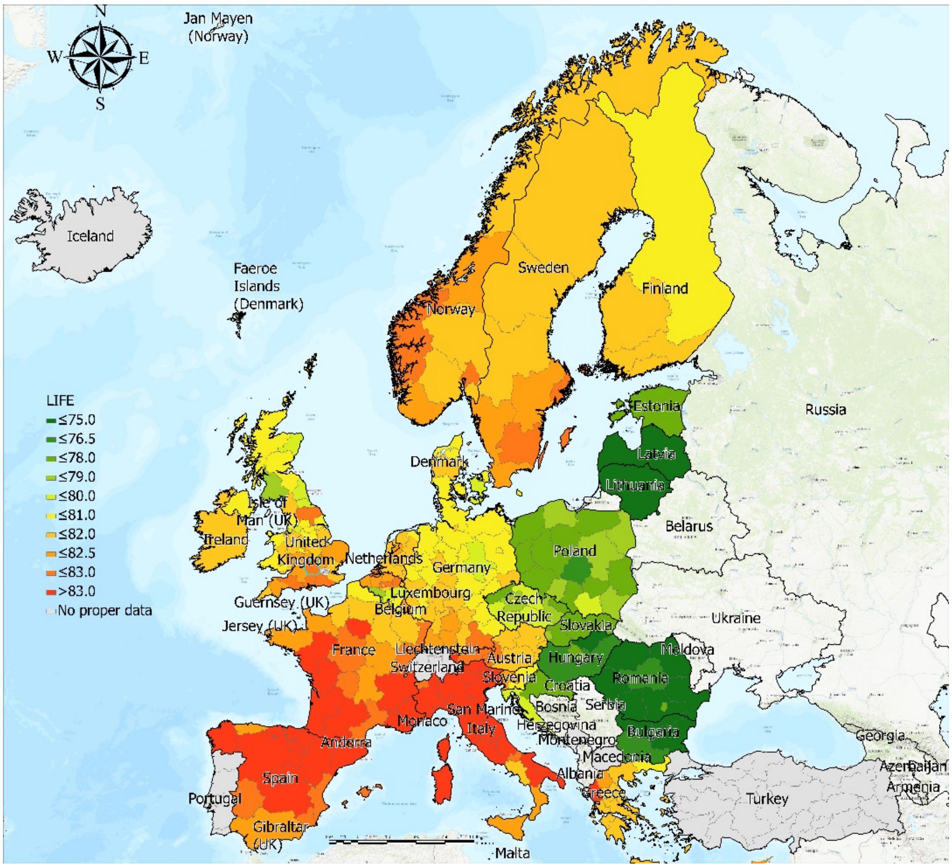


(a)



(b)

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

(a) 

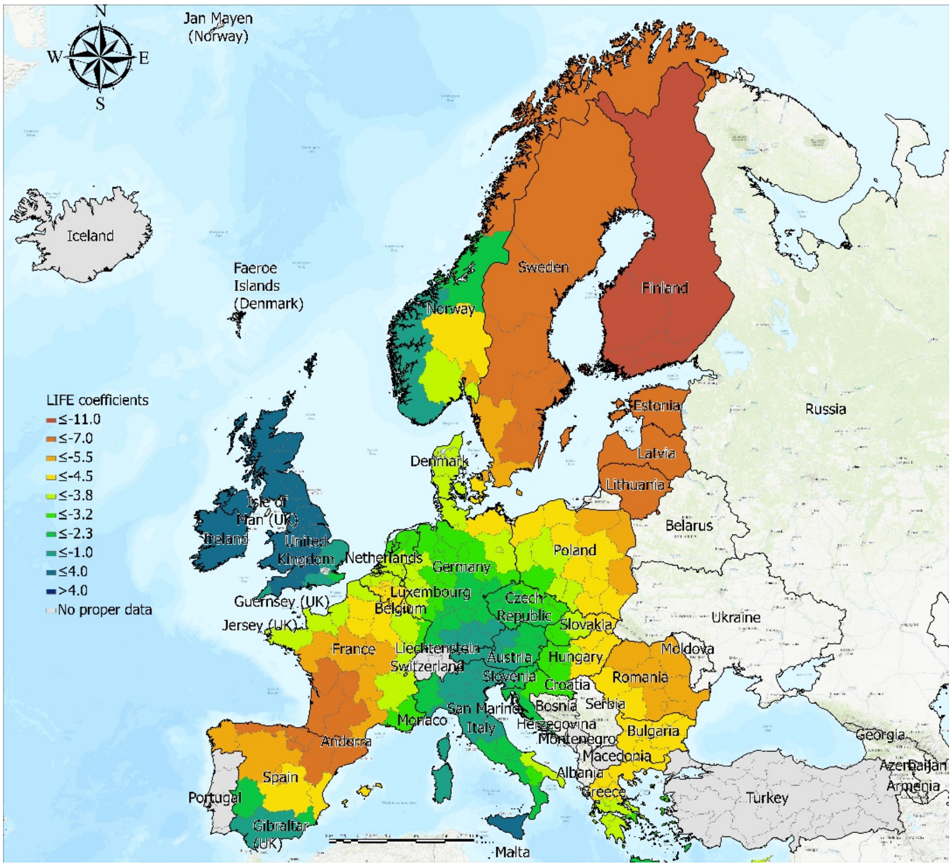
(b) 

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

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

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

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

6. Conclusion

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

The GWR model can be a useful tool for road safety estimation and identifying regions with a high RFR, that require road safety activities as well as identifying regional spatial differences, by using parameters other than traffic accidents. An extension of the proposed method to accident of different severities can be of great importance in regions or areas where the underreporting or road accidents is particularly high, and the RFR can be much easily computed with data that are already available and with higher reliability. The combination of GWR and NUTS-2 data provide information at macroscale and it can be a perfect tool for a first screening to identify road safety problems at macro level. However, due to the complexity of accident occurrence, this tool has limited application in reducing the number of fatalities.

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

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