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Predictive Choropleth Maps Using ARIMA Time Series Forecasting for Crime Rates in Visegrád Group Countries

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Abstract: Geographical mapping has revolutionized data analysis with the help of analytical tools in the fields of social and economic studies, whereby representing statistical research variables of interest as geographic characteristics presents visual insights. This study employed the QGIS mapping tool to create predicted choropleth maps of Visegrád Group countries based on crime rate. The forecast of the crime rate was generated by time series analysis using the ARIMA (autoregressive integrated moving averages) model in SPSS. The literature suggests that many variables influence crime rates, including unemployment. There is always a need for the integration of widespread data insights into unified analyses and/or platforms. For that reason, we have taken the unemployment rate as a predictor series to predict the future rates of crime in a comparative setting. This study can be extended to several other predictors, broadening the scope of the findings. Predictive data-based choropleth maps contribute to informed decision making and proactive resource allocation in public safety and security administration, including police patrol operations. This study addresses how effectively we can utilize raw crime rate statistics in time series forecasting. Moreover, a visual assessment of safety and security situations using ARIMA models in SPSS based on predictor time-series data was performed, resulting in predictive crime mapping.

Keywords: public safety and security; predictive analysis; crime rates mapping; resource planning; decision making; Visegrád countries

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1. Introduction

The fact that the world is now a global village that is extensively interconnected can be credited to digitalization, which has been a major instigator of transformations in many areas of life. Smart data analytics and informatics (artificial intelligence in specialty applications) are primary tools supporting digitalization and are taught in academia and discussed in research across multiple fields of study. Countries have evolved, incorporating digital innovation and tools in industries, healthcare, public governance, entertainment, education, travel, logistics, agriculture, banking, safety, and security, and are passionate about being smart in business as well as in public administration. Urban safety and security are pressing societal problems. Nowadays, we can see the integration of many data-driven insights into planning, forecasting, and managing urban safety and security. For instance, the authors of [1,2] point out several aspects involved in solving urban safety problems, e.g., social, technological, administrative, urban, and societal.

We have a keen interest in the integration of data analysis and smart analytics into public safety administration. Such findings can be deployed to enhance the presentation, promotional analysis, planning, forecasting, and management of urban safety and security problems [3]. As such, a vital exercise would be focusing on the geographical distribution of crime intensity in particular countries using crime statistics. Moreover, this can be extended into predictive crime analysis and mapping, taking social statistics (where unemployment is in the analysis scope of this study) into account as an influencing factor in geographical safety and security assessment. Unemployment arises from social disorganization in the community. This is elaborated on in later sections to justify the broader scope of the subject; here, we are focusing on the urban nexus of crime in the community and unemployment [4,5]. Many studies indicate the importance of crime rates in security decision making and planning. There is always a need for the integration of widespread data insights into unified analyses and/or platforms for administrative assessments. Furthermore, the quest to apply such data analysis and modelling techniques to planning will help with future visualizations.

The results of this study would not only be easy to apply to planning, but would help make future predictions and geo-characteristic models based on selected variables using QGIS. This study addresses how effectively we can utilize crime rates and time-series forecasting using autoregressive integrated moving average (ARIMA) models in SPSS based on a predictor time series, which in this study is the unemployment rate.

As part of the literature review, we review predictive analyses regarding crime data statistics and methods. This study contributes towards filling the gap in the geographical and data heat map representation of predicted crime rates in V4 countries. The tools to be used are QGIS, taking advantage of secondary data from official police portals, crime statistical resources, and World Bank indicators regarding unemployment. We have found a strong relationship between the crime rate and the unemployment rate in the V4 countries Hungary, Czech Republic, Slovakia, and Poland.

ARIMA models are specialized regression models with two parts: AR (autoregressive) and MA (moving averages); independent variables (unemployment rate) or terms are used as lags to the dependent time series (crime rate). Autocorrelations within the time series based on the past values of the dependent series as a transfer function of the independent series are used to predict future values. However, SPSS needs the predictor values in the period of the forecast for the predicted variable. The authors of [6] discussed a specialized crime mapping program based on GIS spatial mapping. "Spatial statistics in itself is an emerging field" (p. 53), combining a visual and creative analysis with spatial data exploration.

1.1. *Brief Methodological Review of the Literature*

This study is a part of the research investigating complex problems such as the identification of hotspots via isolation based on the predicted values in a certain area (county, city, country, or region). For example, the authors of [7] have identified some computational methods for crime hotspot identification. The main algorithms used in the literature are time-series prediction methods—SPSS, R, and other modelling software. Another method is K-means clustering, which provides clusters within a range of values to segregate high- and low-risk areas based on the crime rate (or, for instance, to predict sales, consumer demand, and high/low sales areas). That is a helpful method when many areas of analysis are under observation.

Visualization also plays an important role. We have adopted QGIS software for the professional mapping of crime in the four countries being analysed, i.e., the Czech Republic, Hungary, Poland, and Slovakia in 2020. We have taken the data for yearly crime rates from cited sources for 2013–2019. The unemployment rates are for 2013–2020 (SPSS needs the predictor variable values to predict the dependent variable at the prediction phase of the time series, i.e., 2020 crime rates). This can help not only with security administration in a particular area; with more in-depth data, more insights could be obtained to improve law and order in a particular area [7]. It is worth mentioning the limitations of statistical objectivity in terms of crime categorization in a certain region. The willingness of the public to report crimes leads to the further categorization of crime statistics into reported, recorded, cleared, and prosecuted and convicted crimes. The police and community dynamics play a vital role in all steps of criminal procedures and prosecution. Moreover, there are subjective factors when dealing with crimes that include public perception, police effectiveness, fear among the public, law and order, public awareness, and more [8].

The authors of [9] applied ARIMA models along with other contemporary time series prediction and/or forecasting methods in case-based scenarios for security applications, indicating the need for such forecasting in the security administration to deliver the best public services with limited resources. For that, we need efficient and needful resource allocation where there is a need. As the authors of [10] also mention, such insights are very beneficial for police and military units. The authors of [11] analysed the differences between multi- and univariate ARIMA models, indicating the wide usage of such forecasting models and how these functions work. The authors of [12] extended the use of time series forecasting in advanced algorithms of machine learning as ARIMA and seasonal ARIMA into traffic forecasting, combining the models to discuss seasonality.

The authors of [13] discussed the constraints when carrying out studies where crime statistics are involved. The phrase “reported crime” or “crimes known to the police” is used instead of overall crime in police statistics as a good basis for a crime index (sometimes along with statistics on the whole process of penalization, depending on the nature of the study). Methodological considerations are of concern in this regard, which have been supported by many contemporary data analysis methods [14] in recent studies, but still with some limitations—for instance, when conventional crime indexes per 100,000 population normal values for crimes ((total recorded/pop) $\times$ 100,000) are constructed. However, we have to question the significance of scaling and the use of such conventions in less populated urban areas [6,15]. There are also many studies that emphasize time series analysis by data computing methods, which can be practiced on various secondary data sources such as crime and public safety surveys [16]. The authors of [17] explain some geospatial insights using open-access data visualization tools. The authors of [18] discussed the importance of underlying crime rate analysis since increased figures in a city hinder economic activity and immigration. The crime rate also has emotional implications for locals and newcomers. The authors of [6,19,20] also highlight such implications from crime, emphasizing the promotion of analysis and the need for the standardization of both data and survey-based indicators of crime indexes to cater to the interests of stakeholders in public safety and security. Furthermore, it is important to compare the seasonality and non-seasonality-based forecasting methods ARIMA and GPF-ARIMA (Geographic probability method: a new geographic/spatial time series method introduced by [21] as the most suitable forecasting method with the lowest scaling error) [9]. However, more sophisticated data and spatial probability models using kernel density functions are needed, which could be a novel extension to the findings of this article.

The data-based situational assessment of public safety and security using forecasting models leads to the re-organization and modernization of old-fashioned administrative systems and platforms. In this era of visual communication, it is not practical for the general public (as informed users of information) or the decision makers (advanced users of information) to dig into large data sheets to identify areas of concern [22–24]. Instead, data models should use socioeconomic factors (unemployment rate) and stack them onto the raw data (crime and population statistics). However, we have identified challenges and limitations in public data integration. The cleansing of the data and the standardization of the units of analysis need special attention prior to data input into the forecasting and mapping tools.

This study concerns future innovations in urban safety and security administration and monitoring systems. It concludes by creating a system for the development and diffusion of new technology in ongoing project operations and processes. The authors of [23,25] emphasized advancement-driven monitoring, control, and strategic resource allocation planning based on scenario change analysis [26]. This study proposes that such findings be added to industrial and governmental system modifications and rollouts as part of a security policy for crime prevention, thereby aiding problem solving in regions of concern [1,8,27,28]. In any country, these safety and security reforms and data insights are important, as is addressing other socioeconomic problems. However, the nature of the other variables may vary considering regional, cultural, legal, political, and institutional mores and capabilities [29,30].

In addition, the technological advancement and upgrading of pre-existing public safety and security structures are useful. Statements of support from UN organizations and agencies for these initiatives can be translated into urban security advancements, unified crime, and analysis. As the authors of [31,32] discussed, fighting crime is important to ensure public safety.

The focus of this study is on the data aspect of predictive public safety and security assessment using a predictive time series analysis and choropleth mapping. The research objectives are summarized as follows, in line with the research questions.

1.2. Research Objectives

(1) To review contemporary data forecasting models to collate predictive insights from the segregated crime rate data using the unemployment rate as a socioeconomic factor.

(2) To propose ARIMA-based crime forecasting models and geographical mapping integration to achieve urban administrative forecasting, decision support, and proactive assessment in terms of public safety and security.

1.3. Research Questions

(1) What are the most practical contemporary data forecasting models for collating predictive insights from the segregated crime rate data, using dependency on the unemployment rate as a socioeconomic factor?

(2) How can we practically use publicly available raw data statistics for decision support and monitoring? Moreover, this study addresses public data limitations and emphasizes the need for practical integration into urban safety and security monitoring platforms.

2. Materials and Methods

2.1. Purpose of Simulation

This study proposes that a critical foresight tool be used for emergency and resource management. This analysis helps extract predictive crime patterns, aiding in decision making for crime control and in resource management for urban safety and security. It can be suitable in time series of any sort, predicted based on past values and future values of predictors as a transfer function, as discussed in the problem statement.

2.2. Necessary Inputs

1. Crime rate data (Table 1);
2. Unemployment rate data (Table 2);
3. Shape files for EU NUTS 0-1 for V4 countries [18,33];
4. Excel files for SPSS in percentages for the unemployment rate, and recalculated per 100,000 of population crime rates [28,34,35].

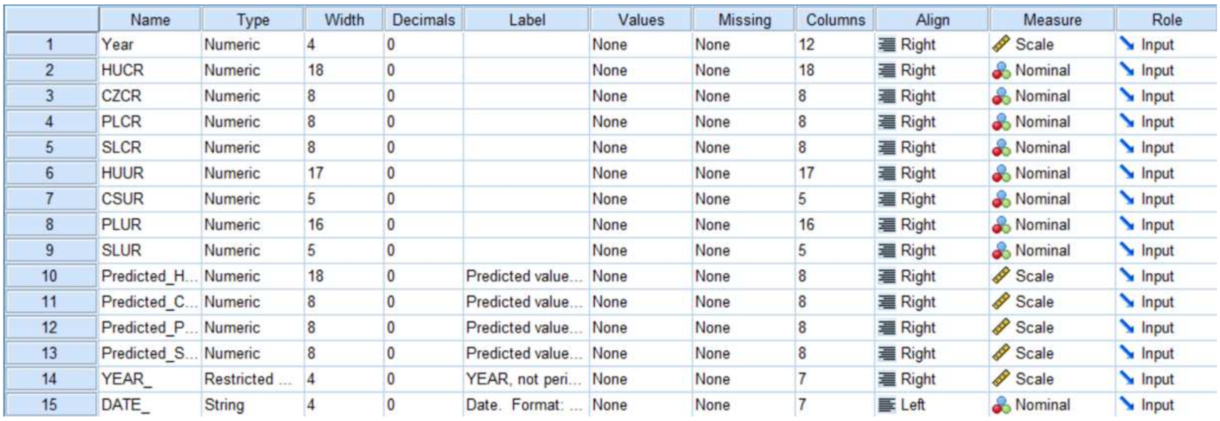
Table 1. Crime rate data [18].

Crime Rate	2013	2014	2015	2016	2017	2018	2019
Czech Republic	741.6205	691.901	621.739	581.3086	525.7948	512.2142	520.9396
Hungary	3819.123	3340.35	2845.8	2962.893	1411.928	2044.179	1695.278
Poland	1912.976	1549.79	1375.49	1291.28	1221.599	1294.808	1335.951
Slovak Republic	826.7089	737.047	641.248	622.7814	575.1915	506.1347	460.622

Table 2. Unemployment rate data [34,35].

Unemployment Rate	2013	2014	2015	2016	2017	2018	2019	2020	2021
Hungary	10.18	7.73	6.81	5.11	4.16	3.71	3.42	4.25	4.05
Slovak Republic	14.22	13.18	11.48	9.67	8.13	6.54	5.75	6.69	6.83
Czechia	6.95	6.11	5.05	3.95	2.89	2.24	2.01	2.55	2.81
Poland	10.33	8.99	7.5	6.16	4.89	3.85	3.28	3.16	3.36

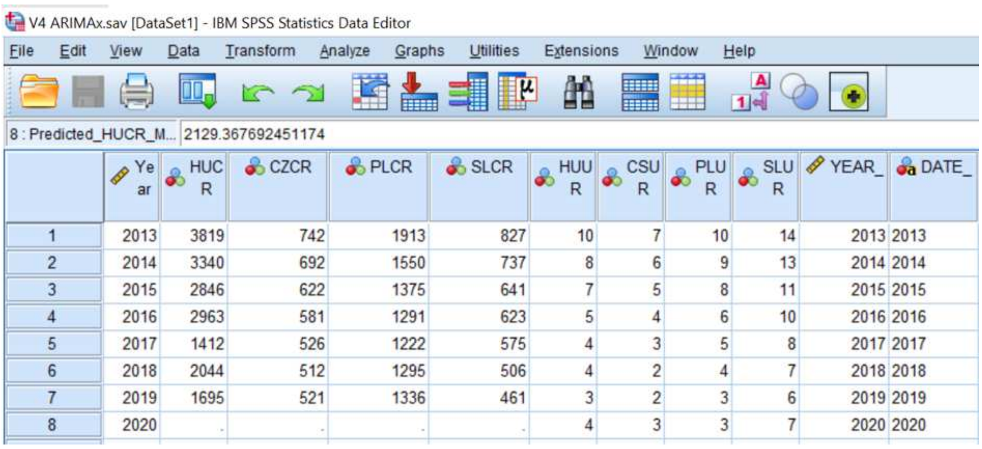
Based on the transfer function established for the independent series (unemployment rate), we can obtain a corresponding predicted value for the dependent series for each estimated model. Figure 1 shows the list of variables and the data table for all the V4 (Visegrád Group) countries, hereinafter called V4, i.e., PL: Poland, HU: Hungary, SL: Slovakia, and CZ: Czech Republic). The CR abbreviation is used for crime rates. UR is the abbreviation for the unemployment rate.



	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	Year	Numeric	4	0		None	None	12	Right	Scale	Input
2	HUCR	Numeric	18	0		None	None	18	Right	Nominal	Input
3	CZCR	Numeric	8	0		None	None	8	Right	Nominal	Input
4	PLCR	Numeric	8	0		None	None	8	Right	Nominal	Input
5	SLCR	Numeric	8	0		None	None	8	Right	Nominal	Input
6	HUUR	Numeric	17	0		None	None	17	Right	Nominal	Input
7	CSUR	Numeric	5	0		None	None	5	Right	Nominal	Input
8	PLUR	Numeric	16	0		None	None	16	Right	Nominal	Input
9	SLUR	Numeric	5	0		None	None	5	Right	Nominal	Input
10	Predicted_H...	Numeric	18	0	Predicted value...	None	None	8	Right	Scale	Input
11	Predicted_C...	Numeric	8	0	Predicted value...	None	None	8	Right	Scale	Input
12	Predicted_P...	Numeric	8	0	Predicted value...	None	None	8	Right	Scale	Input
13	Predicted_S...	Numeric	8	0	Predicted value...	None	None	8	Right	Scale	Input
14	YEAR_	Restricted ...	4	0	YEAR, not peri...	None	None	7	Right	Scale	Input
15	DATE_	String	4	0	Date. Format: ...	None	None	7	Left	Nominal	Input

Figure 1. Variable view in SPSS time series forecasting ARIMA model variables; crime rate as the dependent variable and unemployment rate as an independent variable for V4 countries (Hungary (HU), the Czech Republic (CZ), Poland (PL), and Slovakia (SL)).

In the second step (Figure 2), we set up dates for the time series data from 2013 to 2019, and the yearly data variable is declared against each entry.



	Year	HUCR	CZCR	PLCR	SLCR	HUUR	CSUR	PLUR	SLUR	YEAR_	DATE_
1	2013	3819	742	1913	827	10	7	10	14	2013	2013
2	2014	3340	692	1550	737	8	6	9	13	2014	2014
3	2015	2846	622	1375	641	7	5	8	11	2015	2015
4	2016	2963	581	1291	623	5	4	6	10	2016	2016
5	2017	1412	526	1222	575	4	3	5	8	2017	2017
6	2018	2044	512	1295	506	4	2	4	7	2018	2018
7	2019	1695	521	1336	461	3	2	3	6	2019	2019
8	2020	.	.	.	.	4	3	3	7	2020	2020

Figure 2. Data table view in SPSS time series forecasting ARIMA model variables; crime rates as the dependent variable and unemployment rate as an independent variable.

Here, Visegrád group countries are analysed to predict the crime rates in 2020 based on past crime rates and unemployment rates. Below, we present the correlation and regression analyses for the crime rate and unemployment rate datasets to present evidence for the relationship between variables in Tables 3 and 4.

Table 3. Correlation analysis.

			Correlation Analysis		
		HUUR	**CSUR**	**PLUR**	**SLUR**
HUCR	Pearson Correlation	0.906 **	0.922 **	0.915 **	0.903 **
	Sig. (2-tailed)	0.005	0.003	0.004	0.005
	N	7	7	7	7
CZCR	Pearson Correlation	0.986 **	0.987 **	0.983 **	0.968 **
	Sig. (2-tailed)	0	0	0	0
	N	7	7	7	7
PLCR	Pearson Correlation	0.909 **	0.830 *	0.830 *	0.782 *
	Sig. (2-tailed)	0.005	0.021	0.021	0.038
	N	7	7	7	7
SLCR	Pearson Correlation	0.970 **	0.978 **	0.987 **	0.980 **
	Sig. (2-tailed)	0	0	0	0
	N	7	7	7	7

** Correlation is significant at the 0.01 level (two-tailed). * Correlation is significant at the 0.05 level (two-tailed).

Collinearity statistics are presented for the correlation analysis in Table 3. We merged the tables for four separate linear correlations (Pearson's correlation), in which each country's crime rate is correlated with the unemployment rate. Therefore, in a single model for each country, we deal with only one independent variable. That eliminates multicollinearity as VIF = 1 for each model in the analysis. However, for ease of representation, we merged the four models into one table (Tables 3–8, including ARIMA modelling).

Table 4. Collinearity analysis.

		Coefficients [a]	
Model		**Collinearity Statistics**	
		Tolerance	**VIF**
1	HUUR	1.000	1.000
	a. Dependent Variable: HUCR		
		Coefficients [a]	
Model		**Collinearity Statistics**	
		Tolerance	**VIF**
1	CSUR	1.000	1.000
	a. Dependent Variable: CZCR		
		Coefficients [a]	
Model		**Collinearity Statistics**	
		Tolerance	**VIF**
1	SLUR	1.000	1.000
	a. Dependent Variable: SLCR		
		Coefficients [a]	
Model		**Collinearity Statistics**	
		Tolerance	**VIF**
1	PLUR	1.000	1.000

[a]. Dependent variable: PLCR.

Table 5. Regression analysis.

Model Summary				
Model	R	R-Squared	Adjusted R-Squared	Std. Error of the Estimate
1	0.906 [a]	0.821	0.785	412.774
a. Predictors: (Constant), HUUR, Dependent HUCR, β = 0.906				
2	0.987 [a]	0.974	0.969	15.904
a. Predictors: (Constant), CSUR, Dependent CZCR, β = 0.987				
3	0.980 [a]	0.96	0.951	28.037
a. Predictors: (Constant), SLUR, Dependent SLR, β = 0.98				
4	0.830 [a]	0.689	0.627	145.488

[a]. Predictors: (Constant), PLUR, Dependent PLCR, β = 0.830.

Table 6. Arima prediction model for Hungary, the Czech Republic, Poland, and Slovakia.

Model	Number of Predictors	Model Fit Statistics Stationary R-Squared
HUCR-Model_1	1	0.022
CZCR-Model_1	1	0.374
PLCR-Model_1	1	0.934
SLCR-Model_1	1	0.020

Table 7. Arima prediction model for Hungary, the Czech Republic, Poland, and Slovakia: forecast count.

Forecast		
Model		2020
HUCR-Model_1	Forecast	2129
	UCL	5976
	LCL	646
CZCR-Model_1	Forecast	498
	UCL	559
	LCL	444
PLCR-Model_1	Forecast	1410
	UCL	1524
	LCL	1303
SLCR-Model_1	Forecast	420
	UCL	475
	LCL	371

Table 8. Arima prediction model forecast value of crime rate in 2020 for the V4 countries highlighted in the SPSS data table (ARIMA forecast generated for 2020).

Serial	Country	Predicted Crime Rate in 2020
1	Hungary	2129
2	Czech Republic	498
3	Poland	1410
4	Slovakia	420

2.3. Definition and Rationale of the Simulation Tools

2.3.1. IBM SPSS V26

IBM SPSS V26 is best for in-program time series modelling, as the user interface directs easy specifications for the parameters required in the basic modelling of ARIMA and other time series models. We can easily import Excel datasets into the program, change the variable specifications, and save the output in graphs, tables, and figures.

2.3.2. QGIS Desktop 3.22.3

QGIS Desktop 3.22.3 is open-source and easy to use, with basic functions and a basic user interface. Many tutorials and source files are available due to the open-source design of the shape files. Easy import and linking functions allow one to input the data into maps, generating heat or choropleth maps for data visualization. Layers can be segregated into NUTS 0, NUTS 1, NUTS 2, and NUTS 3 levels as per the levelling of organization of geographical boundaries. (Regions, countries, counties, and cities, respectively).

3. Results

The ARIMA/Expert Modeler option is used to specify a custom ARIMA model in SPSS. This involves explicitly specifying autoregressive and moving average orders and the degree of differencing. One can include independent (predictor) variables and define transfer functions for any or all of them. One can also specify the automatic detection of outliers or an explicit set of outliers. Estimation and forecast periods are important in analyses. For a given dependent variable, the true estimation period is the period remaining after eliminating any contiguous missing values of the variable occurring at the beginning or end of the specified estimation period.

ARIMA models are run on errors in the autocorrelations as in ACF/PACF residual graphs. Lags in the regressor time series are used to adjust errors in autocorrelations [11]. We used ARIMA (0,1,0), with a difference of 1 in the autocorrelation of the dependent time series and a lag of 1 for the independent time series using square root transformation, as specified in SPSS.

$$\hat{Y}t - \phi 1Yt - 1 = \mu - \theta 1et - 1 + \beta\ (Xt - \phi 1Xt - 1) \tag{1}$$

Thus, the AR part of the model (and also the differencing transformation, if any) is applied to the X variable in exactly the same way as it is applied to the Y variable before X is multiplied by the regression coefficient. This effectively means that the ARIMA model is fitted to the errors of the regression for Y on X (i.e., the series “Y minus beta X”). We adopted a (0, 1, 0) model due to the predicted values based on predictor time series values based on the transfer function in the ARIMA (0,1,0) model; also, with the series being nonstationary, it is recommended to not define P and Q terms. In addition, we have not discussed seasonality due to the short time series samples and yearly data. So, the equation would be as below, where μ is the slope of the transfer function:

$$\hat{Y}t = \mu + Yt - 1 + \beta\ (Xt - (Xt - 1))), \tag{2}$$

with dependent Y and independent X time series.

Based on the transfer function declared for the independent series (unemployment rate), we obtained a corresponding predicted value for the dependent series for each estimated model. Table 3 shows the list of variables and the data table for all the V4 (Visegrád Group) countries.

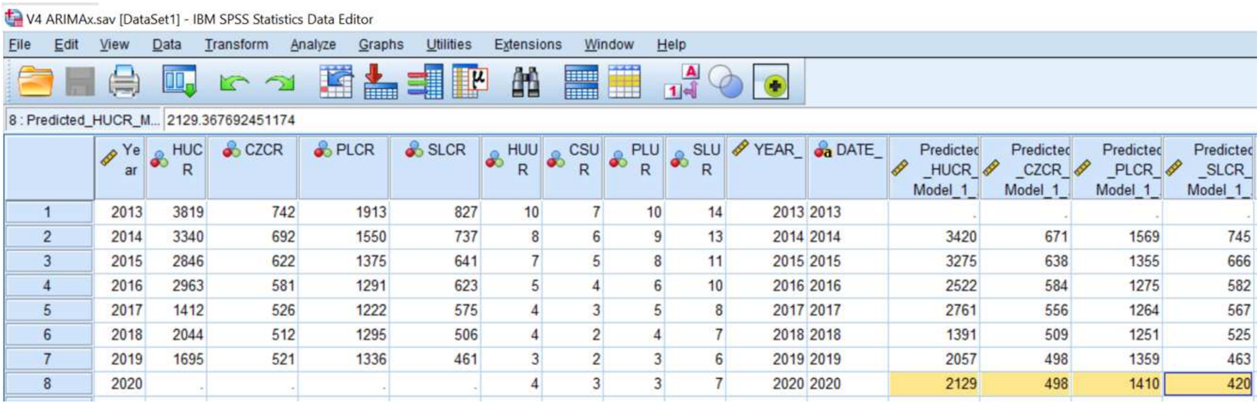
In the second step, we set up the dates for the time series data from 2013 to 2019 and a yearly data variable against each entry in the dataset in SPSS. Crime rate is the dependent variable, and the unemployment rate is an independent variable. Visegrád group countries were analysed to predict the values of crime rates in 2020 based on past crime rates and unemployment rates.

Then we selected the “Analyse” option in the SPSS toolbar to generate the specific time series model. Analyse > Forecasting > Create Traditional Model > Expert Modeler > ARIMA (0,1,0). We obtained the predicted values for each set of variables for all four countries one by one and saved them in the data table. We repeated these steps for all four countries using the respective CR (crime rates) and UR (unemployment rate) values.

We obtained separate forecasting models for all four countries, as seen in Tables 6 and 7. For each model, forecasts started after the last available value in the range of the requested estimation period and ended at the last period for which values for all the predictors were available or the end date of the requested forecast period, whichever was earlier. In the ARIMA model, we had R-squared values that were different from the linear regression due to the specified transfer function (Equations (1) and (2)) in the forecasting model. We obtained forecast values as shown below.

Predicted values are the model-predicted values. One can save model predictions, confidence intervals, and residuals as new variables in the active dataset. Each dependent series gives rise to its own set of new variables, and each new variable contains values for both the estimation and forecast periods. New cases are added if the forecast period extends beyond the length of the dependent variable series. One can choose to save new variables by selecting the associated save tick box for each. By default, no new variables are saved (Figure 3).

- Hungary, HU; R-squared value, 0.22; the predicted crime rate for the year 2020: 2129;
- The Czech Republic, CZ; R-squared value: 0.374; the predicted crime rate for the year 2020: 498;
- Slovakia, SL; R-squared: 0.020; the predicted crime rate for the year 2020: 420;
- Poland, PL; R-squared: 0.934; the predicted crime rate for the year 2020: 1410.


V4 ARIMAx.sav [DataSet1] - IBM SPSS Statistics Data Editor

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8 : Predicted_HUCR_M... 2129.367692451174

	Year	HUCR	CZCR	PLCR	SLCR	HUUR	CSUR	PLUR	SLUR	YEAR_	DATE_	Predicted_HUCR_Model_1_	Predicted_CZCR_Model_1_	Predicted_PLCR_Model_1_	Predicted_SLCR_Model_1_
1	2013	3819	742	1913	827	10	7	10	14	2013	2013	.	.	.	.
2	2014	3340	692	1550	737	8	6	9	13	2014	2014	3420	671	1569	745
3	2015	2846	622	1375	641	7	5	8	11	2015	2015	3275	638	1355	666
4	2016	2963	581	1291	623	5	4	6	10	2016	2016	2522	584	1275	582
5	2017	1412	526	1222	575	4	3	5	8	2017	2017	2761	556	1264	567
6	2018	2044	512	1295	506	4	2	4	7	2018	2018	1391	509	1251	525
7	2019	1695	521	1336	461	3	2	3	6	2019	2019	2057	498	1359	463
8	2020	.	.	.	.	4	3	3	7	2020	2020	2129	498	1410	420

Figure 3. ARIMA prediction model forecast value of crime rate in 2020 for V4 countries highlighted in SPSS data table (ARIMA forecast generated for 2020).

The authors of [36] emphasized the role of crime prediction using ARIMA in determining seasonality based on monthly or weekly data from the past as part of their prescriptive analyses. There is greater accuracy with better computational tools, algorithms, and learning. It depends on how in-depth the data are [37]. The authors of [38] adopted survival analyses based on spatiotemporal (continuous time model) crime data. Based on this prediction, the model has been used to deploy forces to patrol areas, efficiently reducing the incident response time. However, survival analyses are aided by high-end programming support.

The authors of [39] presented ARIMA-based modelling as a quantitative technique to predict types of crimes as well as incident time and location. The data provided by local police departments could be more detailed to help with analyses. The authors of [40] stated that time series analysis is the best tool for analysing quantitative data predictions over time, employing the autoregressive integrated moving average (ARIMA) [41]. It has been used for several forecasting tasks in production, economics, and marketing. In this study, it is emphasized as a critical foresight tool to be used in emergency and resource management. The authors of [33,37,42] employed data mining and exponential smoothing ARIMA to extract different usage patterns and improve forecasts, thereby aiding decision making in crime control. ARIMA [43,44] with the model specifications given above ensures accuracy based on the moving average-based model after processing for categorical attributes [45].

For professional use, one needs map shape file packages with the exact territories. In the EU, we use the NUTS system to compare and draw territorial boundaries (Figures 4–6).

	NUTS_ID	LEVL_CODE	CNTR_CODE	NAME_LATN	NUTS_NAME	MOUNT_TYPE	URBN_TYPE	COAST_TYPE	FID
1	FR	0	FR	France	France	0	NULL	0	FR
2	HR	0	HR	Hrvatska	Hrvatska	0	NULL	0	HR
3	HU	0	HU	Magyarország	Magyarország	0	NULL	0	HU
4	AL	0	AL	Shqipëria	Shqipëria	0	NULL	0	AL
5	AT	0	AT	Österreich	Österreich	0	NULL	0	AT
6	BE	0	BE	Belgique/België	Belgique/België	0	NULL	0	BE
7	BG	0	BG	Bulgaria	България	0	NULL	0	BG
8	CH	0	CH	Schweiz/Suisse/...	Schweiz/Suisse/...	0	NULL	0	CH
9	CY	0	CY	Kýpros	Κύπρος	0	NULL	0	CY
10	CZ	0	CZ	Česko	Česko	0	NULL	0	CZ
11	DE	0	DE	Deutschland	Deutschland	0	NULL	0	DE
12	DK	0	DK	Danmark	Danmark	0	NULL	0	DK
13	EE	0	EE	Eesti	Eesti	0	NULL	0	EE

Figure 4. QGIS data table: NUTS 0 data file loaded in QGIS for mapping predicted values of crime rates in 2020. Indicated selection of V4 countries from NUTS geographical dataset.

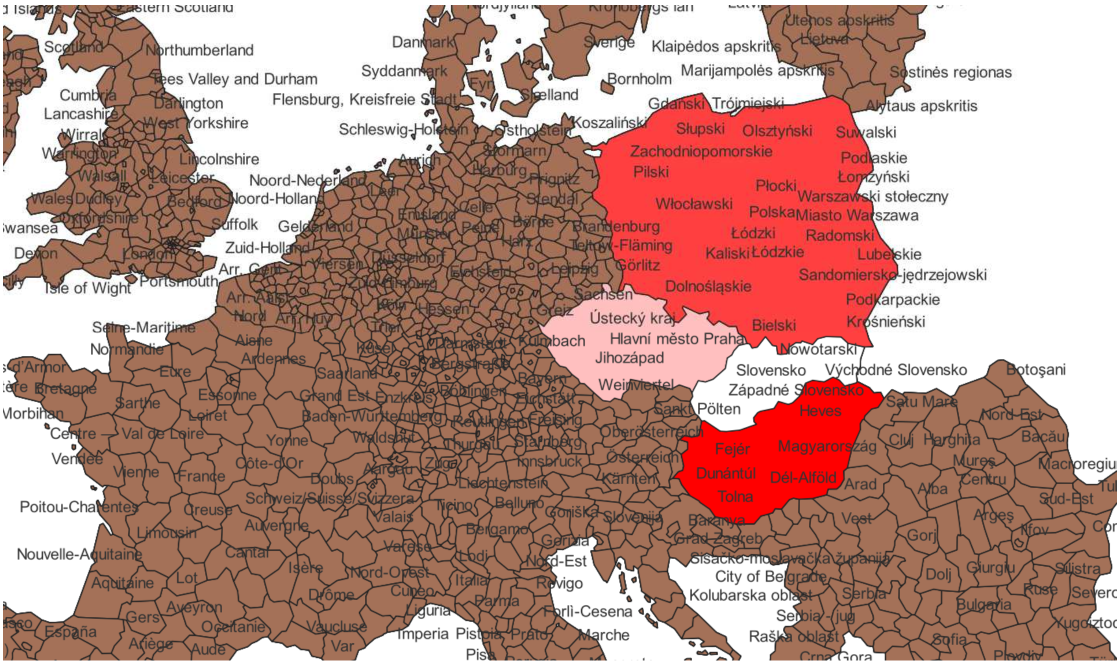

Figure 5. QGIS data table output: NUTS 0 data file loaded in QGIS for mapping predicted values of crime rates in 2020.

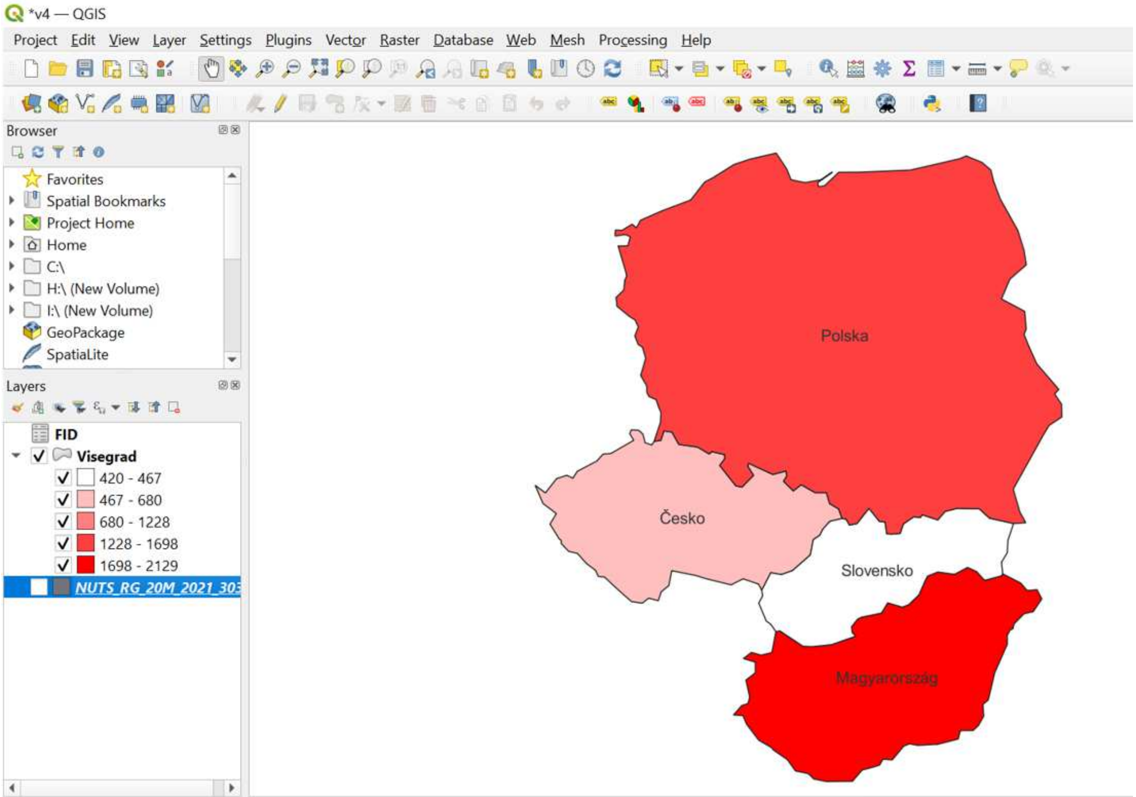

Figure 6. QGIS data table output visualization for 2020 crime rates in V4 countries.

4. Discussion

Safety and security are generally defined as being free from risks and hazards about which a community might feel fear. The administrative challenge is to address such factors and facilitate redress while understanding the social criminological reasons behind crime. For instance, the deprivation of a certain social class and inequity in the justice system make some people feel powerless [46,47]. These conditions generate bias and disruptive forces such as unemployment. As the authors of [48,49] elaborate, the spread of bad behaviour in neighbourhoods can lead to a chain of criminal activities, as stated by "the broken window theory." This article, however, discusses how such social factors relate to crime rates. Moreover, the data generate insights that can help us address societal problems—for instance, algorithm-based dashboards and visualizations of data.

Perception is central to the discussion of cultural narratives, understanding of the self, mental states, etc. In this research context, perception is what a community feels and understands regarding practical measures in terms of technology and policy making by stakeholders to improve safety and security. Public policy determines an intervention in response to a social need, and innovation helps with the development of responsive measures using social and technological tools. Predictive data-based analyses and visualizations aid in addressing complex social problems [50,51].

Keeping the scope of this research article in mind, we attempted to include a diverse set of concepts directly or indirectly related to crime statistics or the broader field of criminology. Social dilemmas of such a scale present challenges and limitations as well as opportunities in research; it is important to break problems down into smaller possible chunks to reduce the complexity [52]. This article fills a research gap in terms of predictive analysis and the conceptual alignment of crime rate statistics with social reasons. We applied this problem-solving approach to highlight the importance of crime data in technological advancement and the upgrading of existing public security structures, administration, informed decision making, and understanding crime data analytics. As the authors of [53] argue, data platforms and systems play a role in the holistic framework of public safety and security.

The limitations of this study include a lack of information systems that make use of abundant data with composite characteristic variables; for that, complex analytics is crucial. The cognitive, cultural, behavioural, and regional attributes of community and crime face representational challenges in terms of dark data (the unprocessed and nonuniform abundance of data). Open-access, comprehensive geospatial criminal data and access are rare.

This study should motivate researchers in the subject domain to incorporate more data analyses in case-based studies rather than simple descriptive statistics. This practice makes the research more innovative, insightful, interpretable, and wide-ranging for audiences and stakeholders. An extension of the research might be assessing the contribution of data-based insights and considering their integration into smart security and governance. Data depth is a challenge, as more detailed time series data can produce more insights and smoother results for predicted periods (for instance, monthly and weekly records and rates). Depending on the type of data (e.g., sales, customer visits), one could even acquire daily data. However, for macroeconomic indicators, as in this study, yearly values are most used and publicly available, and we opted for the economic indicator of unemployment as a predictor of the crime rate. Of course, there were many factors that could have been used as crime predictors, and we look forward to including those factors in future studies. For instance, we plan to include some of the survey variables in criminal analyses as part of understanding community perceptions of public safety in V4 countries.

5. Conclusions

Crime is a reason for social conflict and unrest; it mainly constitutes nonconformity of behaviour in a certain society and causing harm to others. Criminology is a discipline in the social sciences that characterizes crimes and facilitates the formulation of a framework to see patterns in crimes. It includes the study of criminal characteristics and behaviours, the nature of the crime, and categories. The most contemporary objectivist approach in criminology is to identify the criminal patterns, considering unforeseeable patterns to anticipate these events and identify seasonality and hotspots [6,54]. The complexity of dealing with the enormous amount of information delivered each day has made it imperative to apply information mining strategies. The ARIMA model is one such technique to identify patterns in crime rates by depending on past values.

This article elaborates on the utility of crime data analysis, indicating the predictive capability of raw statistical analysis and social variables associated with urban safety and security. This article makes use of crime rates and unemployment rates and demonstrates a relationship between social, demographic, and criminal data records using a model in SPSS. The model shows promising results in relation to crime rates and unemployment, as mentioned in Section 3, using correlation and regression analysis. The predicted values retrieved from the ARIMA model are then loaded into QGIS along with the shape files of the Visegrád group countries. Further processing of data for geographic mapping is performed in QGIS based on the predictive values from the SPSS model. The results show predictive visualization in terms of choropleth maps. We recommend an extension of this study in the future. For instance, yearly, monthly, and daily regular patterns can be distinguished and forecasted depending on the depth and details of the data and an in-depth understanding of the model. Additionally, some predictors, such as the unemployment rate, inequality in education, the number of police officers per 100,000 people, and others are related to crime, safety, and security.

Moreover, this study contributes to geographical situational and forecasting assessments for public safety and security. Visuals based on statistics deliver information in a more comprehensible way to the public as well as to law enforcement agencies. However, maintaining data integrity and transparency are some associated challenges when reporting data based on facts. This study elaborates on data forecasting and choropleth mapping using EU regional datasets from official resources as secondary data sources. Furthermore, we have identified challenges and limitations in public data integration, whereby data cleansing standardization into the units of analysis needs special attention prior to the data being inputted into the forecasting and mapping tools. These challenges might be more complex for multidimensional data and platform integration practices. We recommend extensions to this study in the abovementioned cases because the upgrading of pre-existing public safety and security structures is essential due to rapid technological advancements. Moreover, we must ensure the use of technologically enhanced surveillance practices (TESPs) in maintaining law and order.

This study encourages innovation in urban safety and security administration and monitoring systems. We emphasize advancement-driven monitoring, control, and strategic resource allocation planning based on scenario change analysis. We propose that the findings be taken into account in regional government system modifications when formulating security policies for crime prevention. Such practices could aid problem solving in regions of concern. These safety and security reforms and data insights can address a wide variety of socioeconomic problems and their interactions at the domestic and regional levels of administration. However, the magnitude and nature of the variables may vary due to regional, cultural, legal, political, and institutional preferences, as well as policies and capabilities.

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