INTERNATIONAL SCIENTIFIC JOURNAL

GEOGRAPHICA PANNONICA

Volume 27, Issue 1 (March 2023)

UNIVERSITY OF NOVI SAD, FACULTY OF SCIENCES
DEPARTMENT OF GEOGRAPHY, TOURISM AND HOTEL MANAGEMENT

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INTERNATIONAL SCIENTIFIC JOURNAL

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Volume 27, Issue 1, March 2023

ISSN 0354-8724 (hard copy) | ISSN 1820-7138 (online) | UDC 05:91(497.1)=20

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ISSN 0354-8724 (hard copy) | ISSN 1820-7138 (online)

Excess Mortality and COVID-19 Deaths: Preliminary Data from Serbia and Comparison with European Experience

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Received: October 12, 2022 | Revised: February 11, 2023 | Accepted: February 27, 2023
doi: 10.5937/gp27-40621

Abstract

Mortality statistics is underlay for public health measures and action and consequently it is one of the major indicator in measures of Covid-19 impact on population. This study aim to explore excess mortality during the Covid-19 pandemic in Serbia. Excess mortality compares expected and observed number of deaths during the given period. Analysis in this paper was based on excess deaths and excess mortality rate. Data was downloaded from the national COVID-19 database and obtained from a relevant source from the Statistical Office of the Republic of Serbia. In order to provide better understanding of excess death, the excess mortality rate was calculated for the period January 2015-June 2022. For the period January 2015-February 2020, 38 months were observed without excess deaths, while in months with excess deaths, almost in all months excess mortality rate was below 12%. Since March 2020, the excess mortality rate has increased significantly, with highest values in December 2020 (91.4%), October (84.3) and November (67.8) 2021.

Keywords: excess mortality rate; excess deaths; Covid-19; pandemic; Serbia

Introduction

The first Covid-19 cases in China were reported in December 2019, spreading quickly to neighbouring countries and then across other regions including Europe (Michelozzi et al., 2020). The Covid-19 pandemic has been declared on March 11 2020 by the World Health Organization and continuously world population stands up to new health, economic and societal issues and challenges. Over 560 million confirmed Covid-19 cases, including more than 6 million deaths have been reported globally[1]. According to the data from Ministry of Health and Institute for Public Health of Serbia „Dr Milan Jovanović Batut" in Serbia, more than 2 milion persons have been diagnosed with virus and more than 16 thousand deaths were related to the Covid-19 (on July 21 2022). The Covid-19 has brought various concerns regarding the demographic and epidemiological consequences. Therefore, since January 2020, many studies and research papers have been published, addressing of Covid-19 disease, risk and prevention (Arsenović, 2020), as well as demographic, economic and social consequences. According to Hulikova Tesarkova (2020), first studies were oriented on biological, medical, epidemiological and medical issues. In a short time they were followed with demographic approaches. Population age structure was highlighted as one of the main determinants in Covid-19 pandemic (Balbo et al., 2020; Dowd et al., 2020). According to the Dowd et al. (2020) countries with higher proportion of

[1] Source: WHO, July 20 2022 (www.covid19.who.int)

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older population are at higher risk under the coronavirus and age structure could explain differences in fatality rate as well as transmission pathways. The role of age structure play important role, but population diversity is important too, since the young population in metropolitan areas, certain ethnic groups, male population and those with chronic diseases, have also been affected by the virus (Balbo et al., 2020). Role and impact of demographic determinants varies across regions. Research conducted in Wuhan (China) shows that small places with weak gravitational forces are more likely to contribute to quickier spreading across the country (Kustudic et al., 2021). Investigation across 23 European countries found that social and economic factors are strongly associated with Covid-19, while the impact of population density and cultural factors was low (Mogi & Spijker, 2021). Findings for Slovakia, analysis of lethality shows that areas with very high lethality but also with very low lethality, are located as isolated regions in country (Michalek, 2022).

The impact of Covid-19 on a population of given country is usually assessed using the two indicators: number of cases and number of deaths (Karlinsky & Kobak, 2021). These two metrics have been reported on daily level by each country and merged into international database such as the ones maintained by World Health Organization or by the Johns Hopkins University (Dong et al., 2020; Karlinsky & Kobak, 2021). Usage of this datasets is limited due to diverse methodological aprroaches in how Covid-19 deaths are reported. The World Health Organization defines a Covid-19 death as one where Covid-19 is the underlying cause of death, including both confirmed and suspected cases (Beaney, 2020). However, in Russia, confirmation of Covid-19 death relies on results from autopsy. In Spain only hospital Covid-19 deaths are included in the death count, while in Belgium, all suspected cases are included in Covid-19 mortality (Beaney et al., 2020; Marinković & Galjak, 2021a). Divergency between countries may also vary with respect to different demographic, medical, economic and social drivers of spreading Covid-19.

Additionally, available mortality data about Covid-19 could be underestimated for several reasons. Absence of testing and low rates of diagnoses at the beginning of pandemic, and less known complication of Covid-19 related to the coagulopathy, myocarditis, inflammatory processes and arrhythmias could lead that some Covid-19 deaths were assigned to other causes (Boukhris et al. 2020; Driggin et al., 2020; Del Pinto et al., 2020; Gill & DeJoseph, 2020; Stokes et al., 2021). Also, Covid-19 deaths do not counts cases linked with indirect impact of pandemic-limited access to the medical services, psychological stress, economical issues etc. (Stokes et al., 2021).

Regarding to the Covid-19 deaths, lockdown and other restrictions have increased deaths from chronic and acute diseases due to limited access to the medical services (Wang et al., 2022) and death from self-harms due to crisis of psychological well-being (Sierra et al., 2020). Recent study (Sher, 2020) confirmed that increases stress and depression related to the pandemic could result with suicides and overdose deaths too. Furthermore, economic circumstances, such as housing and food insecurity, could increase death, particularly among population with some pre-existing chronic conditions (Stokes et al., 2021). Simultaneously, pandemic decrease deaths from specific external causes linked to road accidents (Wang et al., 2022), sports, nightlife and work accidents (Sierra et al. 2020).

As a effective way to quantify the direct and indirect impact of Covid-19 on all-cause mortality, many studies as metric used excess mortality (Arsenović, 2020; Arsenović, 2021; Blangiardo et al., 2020; Wang et al., 2022; Konstantinoudis et al., 2022; Islam et al., 2021; Vandoros 2020). This measure was used for regional estimation, country level and specific location, counting excess death in various stages of pandemic. This paper aims to analyse and to give insights into the number of all-cause excess mortality (January 2015-June 2022) and COVID-19 death (March 2020-June 2022) in Serbia. Since the COVID-19 pandemic is still in progress, data and results presented in this research are preliminary.

Data and methods

In the analysis was used data from the national COVID-19 database[2], where data about confirmed cases and reported deaths are available. COVID-19 data was downloaded for the period from 6th March to 30th June 2022. As the available data from the national Covid-19 database provide information daily, the data was aggregated on a monthly level. Research was constrained only to the total number of Covid-19 deaths, due to the lack of data in Covid-19 database (i.e data by gender and age was not available for the observed period).

In order to assess excess mortality total number of deaths by month was obtained from the Statistical Office of the Republic of Serbia (SORS), for the

[2] https://covid19.data.gov.rs

period since 2010, while excess mortality was calculated from January 2015 until June 2022. Mortality data for January 2010 until December 2014 was provided from the following reference: SORS 2015. Data for January 2015 until December 2021 was extracted from SORS online database[3], while for the period January-June 2022 data was extracted from SORS Population Statistics Report (RZS, 2022). Data from these two sources (SORS online database and Population Statistics Report) may vary and since 2022 is still in progress, final mortality statistics at the end of the year could count different numbers of deaths. Excess mortality can be measured in different ways. In this paper the excess mortality defined as the observed minus the expected number (average number of death in the baseline period) of deaths in month M_i was estimated as:

$$ED\ (M_i^{t+n}) = OD\ (M_i^{t+n}) - AND\ (M_i^{t,t+n})$$

were:

- ED - Excess deaths
- OD - Observed deaths
- M_i^{t+n} - observed month
- AND - Average number of deaths
- $M_i^{t,t+n}$ – historical baseline from previous years

The excess mortality rate was calculated as the percentage difference between the number of deaths in M_i^{t+n} and the average number of deaths in the same month ($M_i^{t,t+n}$) over the historical baseline period.

$$EMR = \frac{OD\ (M_i^{t+n}) - AND\ (M_i^{t,t+n})}{AND\ (M_i^{t,t+n})} \cdot 100$$

were:

- EMR - Excess mortality rate

In this paper, the historical baseline consists of the average number of deaths that occured in each month in the five year period before observed year. Excess mortality for the 2020, 2021 and first half of 2022 was calculated using historical baseline from previous years in a period which was not affected by the Covid-19, considering the number of deaths that occurred in each month during the period 2015-2019.

Results and discussion

Serbia reported the first case of Covid-19 on the 6th March 2020. Nine days later (March 15th), a state of emergency was declared in the country and in order to reduce transmission, the whole population was lockdown. All public sectors were redirected to telecommuting, while other places of services and for public gathering were closed. Regardless of all country-wide measures during March 2020, transmission of Covid-19 was very fast and intense. Fast transmission in this period could be related to the fact that about 300,000 of Serbian residents arrived from abroad (Arsenović, 2020). After two months, on May 7th 2020, the government ended the state of emergency, with recommendation and not very restrictive social distancing. Since second half of June 2020, large-scale testing was conducted and the number of new confirmed cases and number of deaths due to Covid-19 has started to increase (Arsenović, 2020). During the second half of 2020 and the whole 2021 government applied different restrictions regarding the reduced or limited working time in public administration and services (e.g. restaurants, bars and markets), but without lockdown. Since the beginning of 2022 these restrictions have been withdrawn.

With exception in February, the average number of monthly deaths during the Covid-19 pandemic years 2020-21 was higher in all other months compared to the average number of monthly deaths in two preceding years 2018-19 (Figure 1). Divergence in average number of monthly deaths has ranged from 665 (in August) to 5 665 (in December) when it was recorded the highest number of deaths and excess deaths too.

From March 2020 until June 2022, 16 136 Covid-19 deaths and 2 029 403 confirmed cases were registered in Serbia. Since the first case of Covid-19 was reported in Serbia, all months registered Covid-19 mortality. The highest numbers of Covid-19 deaths were registered in October and November 2021, while the lowest Covid-19 deaths were in March, June and September 2020. Analysis of excess deaths shows slightly different monthly pattern, respectively highest excess death was recorded in December 2020 and October and November 2021 (Table 1). Also, data for March and May 2020, as well as for June 2022 didn t show excess death.

Observing excess death during the pandemic period only, can not provide complete perception of excess mortality. In order to achieve better understanding, excess mortality rate was calculated from the 2015. Figure 2 shows estimated excess mortality rate on monthly level, while with red line was marked period before and after Covid-19 pandemic has started. From January 2015 until the March 2020, excess

[3] https://data.stat.gov.rs/Home/Result/18030306?languageCode=sr-Cyrl

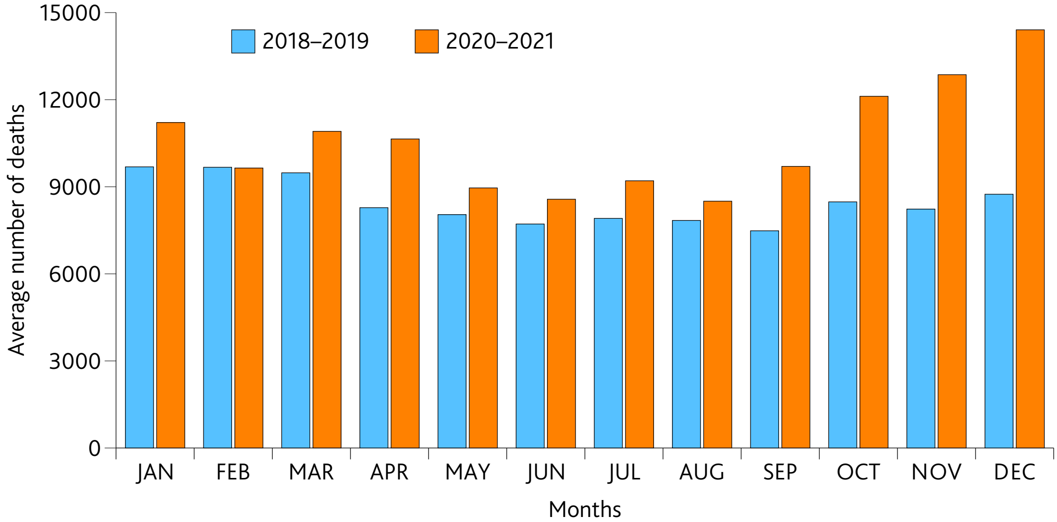

Figure 1. Average number of death per month in 2018-19 and 2020-21
Note: Author calculation based on data from RZS and Covid-19 database

Table 1. Estimated excess mortality and number of confirmed deaths from Covid-19, March 2020-June 2022

Month	Observed number of deaths	Excess deaths	Number of confirmed deaths from Covid-19
March 2020	9050	-184.0*	23
April 2020	8710	245.0	154
May 2020	7943	-255.8*	64
June 2020	8222	449.8	34
July 2020	9959	1980.8	296
August 2020	8626	807.8	140
September 2020	7646	198.6	36
October 2020	8580	88.2	71
November 2020	11914	3685.8	784
December 2020	17109	8172.0	1607
January 2021	12538	2056.8	818
February 2021	10085	867.6	429
March 2021	12767	3533	845
April 2021	12584	4119	1067
May 2021	9977	1778.2	517
June 2021	8918	1145.8	182
July 2021	8452	473.8	67
August 2021	8379	560.8	178
September 2021	11756	4308.6	932
October 2021	15653	7161.2	1721
November 2021	13808	5579.8	1736
December 2021	11705	2768	1023
January 2022	11392	910.8	915
February 2022	13094	3876.6	1612
March 2022	11250	2016	558
April 2022	8479	14	192
May 2022	8387	188.2	90
June 2022	7744	-28.2*	45

Note: Author calculation based on data from RZS .

** Negative value means that fewer deaths occured in given month compared with baseline period*

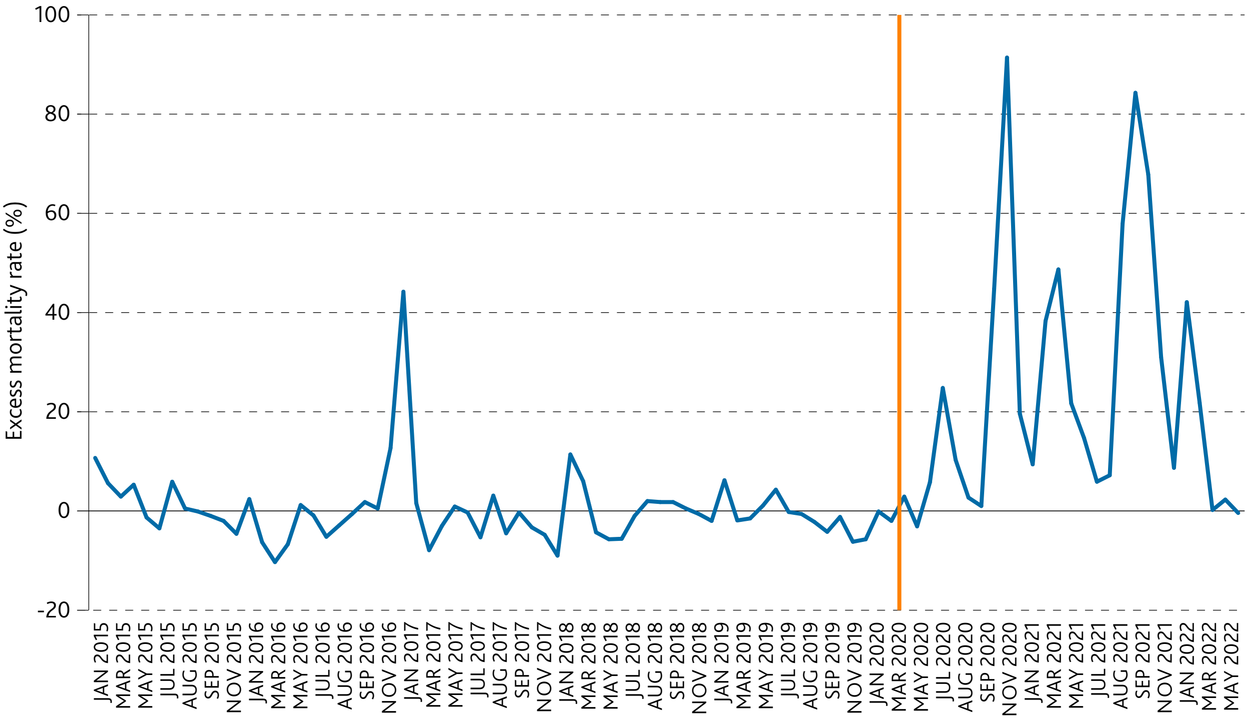

Figure 2. Estimated excess mortality rate in Serbia, from January 2015 to June 2022

mortality was observed in some months, but there were also months where excess deaths were not registered (Figure 2). In this period, 38 months were observed without excess deaths, and in months with excess deaths-almost in all months excess mortality rate was below 12%. Only outlier were December 2016 with excess mortality rate of 12.7% and January 2017, with excess mortality rate of 44.2%. Namely, in January 2017, observed number of death was 44% higher than expected, when the seasonal flu in the winter 2016/17 was spread all over Europe. Mortality is not uniform during the year and seasonal changes are well known with higher mortality rate during the winter (Arsenović, 2018; Healy, 2003; Marti-Soler et al., 2014). Seasonal pattern of mortality is related with different drivers, and one of them is flu (Iuliano et al. 2018; Portugal 2021). Winter season 2016/17 in Europe was characterized with influenza-associated mortality (Josipovič, 2021; Nielsen et al., 2018) and increase in excess deaths particularly among elderly (Rosano et al. ,2019).

Since the March 2020, excess mortality rate has significant increase, with highest values in December 2020 (91.4%), October (84.3) and November (67.8) 2021. High value of excess mortality rate were estimated also in November 2020 (44.8), April 2021 (48.7), September 2021 (57.9) and February 2022 (42.1). Excess mortality rate above 20% was also registered in July 2020, March, May and December 2021 and March 2022 (Figure 2).

Since the beginning of COVID-19 pandemic, all countries in Europe experienced higher excess mortality compared to the period before 2020, with apparent regional differences. Regardless to the fact that first wave of pandemic has most harvesting impact for population in countries located in Western and South Europe, study for 2020-21, conducted by Wang et al. (2022), shows that highest reported Covid-19 mortality rate and estimated excess mortality rate were observed in countries of Central and Eastern Europe.

According to Eurostat, between March 2020 and June 2022, the EU recorded four peaks of excess mortality[4]: April 2020 (25.2%), November 2020 (40%), April 2021 (20.9%) and November 2021 (26.5%). At the beginning, in March-April 2020 the highest peak of excess mortality was in Italy, Spain, then France, Belgium and Netherlands, and according to some authors (Kontis et al., 2020; Konstantinoudis et al., 2022) in England and Wales too. In Spain, during the first wave, MoMo estimated 44 583 excess deaths (Leon. Gomez et al., 2021). While for the same period, in Italy, Dorrucci et al. (2021) estimated 52 437 excess deaths. In Portugal, between March 16 and April 14 in 2020, observed mortality was 14% higher than expected, respectively excess of 1 255 all-cause deaths (Vieira et al., 2020). Analysis for Belgium, conducted by Bus-

[4] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Excess_mortality_-_statistics&oldid=565539#Excess_mortality_in_the_EU_between_January_2020_and_June_2022

tos Sierra et al, (2020), indicated that during the first wave in 2020, 96% of the excess mortality were likely attributable to Covid-19. Results for England and Wales show that in the first half of 2020, apart from the official Covid-19 death, there were an additional 968 weekly deaths (Vandoros, 2020). Until the end of 2020, geographical prevalence was in Eastern Europe, with highest peaks in Poland, Bulgaria and Slovenia4. During this second wave, Serbia also recorded a high excess mortality rate witha peak in December 2020 (91.4%). Third peak EU reached in April 2021 (20.9%)4, the same month as in Serbia with a 48.7% excess mortality rate. In following summer period 2021 all countries in Europe, including Serbia, had decreasing trend in excess mortality, while the autumn period recorded new increase for EU in September (12.9%) and for Serbia in October (84.3%). This was fourth wave which as extended to the first months of 2022 when excess mortality weakened in most of EU countries4. In Serbia, fourth wave has peak in February 2022 (42.1%).

Excess mortality was also reported in studies focusing on the regional level, but with large intra-country divergency (Blangiardo et al. 2020; Konstatinoudis et al., 2022). In Italy and Greece northern regions were more affected with highest excess mortality compared to the other parts of country. In Spain, regions Madrid, Castile-la Mancha and Castile-Leon, in England regions Outer London and West Midlands and in Switzerland region Ticino were most affected (Konstantinoudis et al., 2022). Regional variations of case-fatality rates in Germany shows considerably higher risk in eastern federal states (Morwinsky et al., 2021). Regional analysis of Covid-19 deaths, in 2020, in Serbia confirmed highest fatality effects in south region of country, but also in area of large cities such as Belgrade, Kragujevac and Nis (Marinković, 2021b).

Study, like one conducted for Belgium population founded that monthly mortality during the Covid-19 was higher than the number of monthly deaths during the influenza pandemic in late 1970s. According to the same study, compared to the April 2020, higher number of deaths in Belgium was recorded in World War II and during the Spanish influenza (Sierra et al. 2020). As the Covid-19 is one of the greatest pandemic since the beginning of 20st century, various studies follow impact and patterns between Covid-19 and Spanish fly pandemic. First Covid-19 wave was quite equal with major wave of the 1918-19 influenza in context of similar magnitude and length (He et al., 2020). While estimation of mortality shows that Spanish fly had higher number of death relative to population size and caused more significant loss of remaining life expectancy due to the fact that 1918 pandemic were killed many of middle-aged population (Goldstein & Lee, 2020).

Conclusion

Seasonal variation in mortality followed by excess mortality are well recognized and established, following U or V shape mostly, with higher mortality during the colder period of the year. Simultaneously, excess mortality could be found during the both-cold and hot weather, forming seasonal patterns. Different socio-demographic (age, gender, marital status, education, occupation) and medical (seasonal flu, pre-existing chronic diseases etc) factors shape excess mortality too. In order to assess the Covid-19 impact on mortality, analysis in this paper was based on excess mortality. Relative to the Covid-19 death, excess mortality is more convenient measure of total impact of the pandemic, considering that excess mortality could captures Covid-19 deaths that are „covered“ or unestimated due to not correctly diagnoses, and other causes that can be attributed to the overall crisis.

Results in this paper shows that Covid-19 has an impact on excess mortality, and since the beginning of March 2020 monthly excess mortality rate has a higher value compared to the historical baseline period. Analysis in this paper does not observe other anomalies that could be related with excess mortality, which imply that not all excess deaths could be referred to Covid-19.

Nevertheless, severity of Covid-19 pandemic imply continously accurate measurement of death including excess mortality, for better understanding of variations in excess mortality, giving strong evidence for public health threaths.

Acknowledgement

This research has been contributed by the Ministry of Education, Science and Technological Development of the Republic of Serbia through the Project No. 451-03-68/2022-14/200125.

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ISSN 0354-8724 (hard copy) | ISSN 1820-7138 (online)

Networks, Agriculture and Geography: How business connections of agricultural enterprises shape the connection of settlements in Western Hungary

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Received: August 29, 2022 | Revised: December 11, 2022 | Accepted: December 19, 2022
doi: 10.5937/gp27-39849

Abstract

Networks and network science are not new: since the middle of the 20th century, networked structures are analyzed in geography. In recent years, however, with the emergence of network science, with the availability of big data, with improved computational capabilities and new software, the knowledge and analysis of networks have improved substantially.

Present paper uses network science in economical geography: it analyzes the connections between settlements in western Hungary based on the business connections of agribusinesses. For the research, we used a questionnaire asking for purchase and sales connections of the selected agribusinesses and analyzed the results from the perspective of network science.

Results show that in an agribusiness network the purchase network is more complex than the selling network and that in spatial networks connected to agribusinesses not large cities, but small towns and villages play a central role.

Keywords: agribusinesses; networks; business relationships

Introduction

Networks

Networks are systems consisting of nodes connected by edges. Networks exist all around us: for example in our social life, where connections between people can be described as networks (cf. Barabási, 2016); in the interaction of constituents in cells (cf. Albert, 2005); or in the physical space, where roads between settlements represent connections (cf. Xie & Levinson, 2009). Networks and networked structures are described in mathematics since the seminal paper of Euler from 1736 analyzing the problem of the *Seven bridges of Königsberg* as graphs (Barabási, 2016).

Networks are thus systems with nodes, connected by edges. In the simplest form networks are not directed and weighted: only the existence of a connection between nodes is important. Think for example of roads between two cities: traffic can flow from City A to City B and from City B to City A.

Connections however can be seen as weighted: weighted connections mean that information or

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goods flow in one direction in larger quantity, and into the opposite direction in a smaller quantity or not at all. Think for example of a mine mining iron ore and transporting the ore via railways to a nearby harbor. In this case, the movement of the trains will be in both directions: from the mine to the harbor trains will be laden with thousands of tons of ore while in the other direction (harbor to mine) they will move empty.

In directed networks, the direction between nodes is important: it exists just in one direction. For example, a lot of papers – like this paper – cite the book of Peter Haggett (Haggett, 1965), the works of Peter Haggett cite however not every one of the papers citing him. Thus the citation exists in one direction, it does not exist however in the opposite direction.

In the past, networks were discovered and used in different disciplines (most prominently in sociology) to explain how systems of nodes function (cf. e.g. Granovetter, 1973; Milgram, 1967). The results of analyses of networks were however examined just inside the given field; no general characteristics of networks themselves were analyzed.

The field of network science is experiencing a renaissance since the end of the 20th century: Barabási et al. (1999) explored and described general characteristics of networks, Watts (1999) analyzed small worlds extensively and Castells (1996) described his idea of a networked society, just to mention a few.

In the 21st century new data collection methods and the increasing computational power enabled us to analyze networks that contain not just a few, but millions of nodes with millions of connections (cf. e.g. Onnela et al., 2007). Today methods rooting in network analysis are used in almost all scientific fields, from economy (e.g. Easley & Kleinberg, 2010), to sociology (Light & Moody, 2021), to medicine (Loscalzo et al., 2017) and several journals (e.g. *Networks, Journal of Complex Networks, Applied Network Science, Network Science*) are published on the field.

Networked geography

Networked structures are not new to geography: such structures are assumed and analyzed since the mid-20th century (cf. e.g. Barthélemy, 2022; Uitermark & van Meeteren, 2021). In the 1950s and 1960s a turn in geography was taken which aimed at the spatial definition of geography (Uitermark & van Meeteren, 2021). Geographers of that period focused more on interaction and dynamics (Uitermark & van Meeteren, 2021). In this era, an approximation to mathematical methods like graphs was observable, as shown for example in the works of Haggett (1965), and Haggett and Chorley (1969). It was possible to use graphs as an abstraction of spatial networks; and by using graphs for different entities, the similarities in the network structures could be analyzed (for an overview see e.g. Tinkler, 1979; Uitermark & van Meeteren, 2021).

As a critique of these first attempts to analyze networked structures was formulated by several scholars in the early 1970s, mainly pointing out that 1) in these analyses the method is the constant, which is a weak connection when comparing for example river networks with street networks; and that 2) networks and the function of different networks needs to be explained in light of specific geographical knowledge; meaning that the simplification of real-world geographical data to networks and the conclusion deriving from the analysis of these networks needs to be done very carefully (Uitermark & van Meeteren, 2021). It was also noted, that geographical space changes over time, and it is also paramount to incorporate the changes and flows into geographical analysis (Uitermark & van Meeteren, 2021). Barthélemy (2022) points also out, that analyzing networks in geography must consider also space since the length of edges is important: thus, the network structure and network connections are influenced by spatial proximity.

Network analysis in geography is experiencing a new boom in the 21st century, when data (later big data) is available in digital format; and also several software for network analysis are available (cf. e.g. Barthélemy, 2022; Bosco, 2006; Glückler & Panitz, 2021; Uitermark & van Meeteren, 2021). It must be noted, however, that geographical network analysis must take into account, that 1) in human geography networks are formed around collective goals, 2) in human acting social reality is considered and 3) humans interact while constituting networks (Uitermark & van Meeteren, 2021). Uitermark and van Meeteren (2021) also point out, that network analysis in geography 1) needs to consider the actual geographical space; 2) it has to be holistic; both abstract and incorporating actual contexts; 3) needs to understand that networks in geography are not abstract, but depict real connections; 4) that connections must be carefully considered since not all connections can be seen as equal; and 5) network analysis is best used together with other methods. Völker (2021) points out, however, that geographic network research does not need its own methods: it can well build on the existing methods of (general) network analysis.

Today network analysis is used to analyze a wide area of geographical data from broad overviews such as Barthélemy (2011, 2022), Daraganova et al. (2012), Glückler (2010) or Uitermark and van Meeteren (2021) to human geography in general (Glückler & Panitz, 2021) to urban networks and geography (Derudder & Neal, 2018; Lewinson & Krizek, 2008; Neal 2012) to transportation geography (see e.g. Derudder et al., 2008; and papers in *Geojournal* 71/1) and to medical geography (Smyth, 2005) (see e.g. also the issue *Tijdschrift voor Economische en Sociale Geografie* 2021/4).

Geography and economy or business-related research also uses network approaches from the seminal paper of Glückler (2007) e.g. to the longitudinal analysis of the function of ports (Ducruet & Itoh, 2022; Rousset & Ducruet, 2020) or maritime networks (Álvarez et al., 2021), to the connectedness of rural and urban business activity (Mahmud, 2021), to the location of services in cities (Zhao et al., 2020) to knowledge flow and innovation (Broekel et al., 2014., Bell & Zaheer, 2007; Maggioni et al., 2007; Maggioni & Uberti, 2011), to industrial geography (Sorenson, 2005) to public transportation (Ding et al., 2019; Hajdu et al., 2020) or to migration (Connor, 2019), just to mention a few.

Connected to agriculture, however, less research analyzes networked structures. One of the more researched topics in the triangulation of geography, agriculture, and networks is connected to food networks) where the interactions of food, food production, food consumption and networks are described (e.g. Niles & Roff, 2008), and to Actor-Network Theory, which analyzes the interconnectedness of human and non-human actors in an agricultural system (c.f. Watts & Scales, 2015).

Research lacks, however, papers and analyses which use the methods of network research to the functions of agricultural businesses. The goal of current paper is to fill in this research gap: it aims to show on the example of Hungarian agricultural businesses, how business relations are distributed in geographical space and how these relations can be analyzed from the network point of view.

Based on the literature, we assume that tools and methods of network science are appropriate to analyze the central role of settlements in networks: we set the goal to show on the example of small-scale data, that network analysis can provide a deeper inside into the business-related connections between settlements.

Since agricultural businesses are situated where arable land is (mostly further away from larger cities), and since some of the businesses providing equipment for agribusinesses needs large areas to store goods, we hypothesize that in the agribusiness network smaller settlements can play a central role.

Based on this hypothesis, we search for answers to the following research questions:

- RQ1) Are large cities automatically centers in the agribusiness network?
- RQ2) Which factors influence whether a settlement has a more or less central role in an agribusiness network?

To achieve this goal, in the next part we summarize the geographical and agricultural characteristics of the analyzed area.

Agricultural geography of the area – an overview

Hungary's agriculture is significant due to its natural geography and economic geography, as 79% of Hungary's land is arable land and 57% is agricultural land (KSH, 2021). The share of agriculture in GDP was 13.7% in 1989-1990 in Hungary (Berényi, 2011), by 2020 this share decreased to 4.1% (KSH, 2020).

The paper analyzes business connections and spatial relations of agribusinesses in the Hungarian counties Vas and Zala. Both counties are situated in western Hungary: Vas county has an area of 3,336 km², while Zala has an area of 3,784 km². The cities

Table 1. Cities and towns of Vas and Zala county, by population

Vas county		Zala county	
City / Town	**Population (2019.01.01)**	**City / Town**	**Population (2019.01.01)**
Szombathely	78 407	Zalaegerszeg	57 403
Sárvár	15 226	Nagykanizsa	46 649
Kőszeg	11 865	Keszthely	19 289
Körmend	11 179	Lenti	7 348
Celldömölk	10 555	Zalaszentgrót	6 172
Szentgotthárd	8 819	Hévíz	4 523
Vasvár	4 130	Letenye	3 937
Bük	3 624	Zalalövő	2 857
Vép	3 293	Zalakaros	1 988
Csepreg	3 277	Pacsa	1 576
Répcelak	2 630		
Jánosháza	2 430		
Őriszentpéter	1 141		

Source: own editing, based on Vas megye (2022) and Zala megye (2022).

Table 2. Production of the main arable crops in Vas county in 2015

Crop	Yield		Yield average	
	tons	country = 100,0%	tons/ha	country = 100,0%
wheat	247 214	4,7	5,240	102,0
maize	179 941	2,8	6,110	107,4
sunflower	16 977	1,1	2,420	96,4
rapeseed	37 188	6,1	2,300	87,5

Source: KSH, 2016.

and towns of both counties are summarized in Table 1.

The agricultural land of the counties is 260 and 274 thousand hectares, respectively. The agricultural land of Vas is characterized by a fragmented structure. In Vas county wheat, maize sunflower and rapeseed are the main crops (Table 2); sugar beet and spring barley are also cultivated in the county (Grosz, 2007).

It is important to note that Vas County has a larger wheat area than Zala County, with 74% more wheat harvested in 2020 than in Zala County. In the case of maize, the opposite is true, with Zala county having a larger area due to better natural conditions, which is why 58% more maize was harvested in Zala.

Table 3. Production of the main arable crops in Zala county in 2015

Crop	Yield		Yield average	
	tons	country = 100,0%	tons/ha	country = 100,0%
maize	284 408	4,4	6,330	111,2
wheat	141 997	2,7	5,250	102,1
sunflower	16 050	1,0	2,380	94,8
rapeseed	18 039	3,1	2,320	88,2

Source: KSH, 2016.

In Zala county wheat and maize are the most produced crops (Table 3). The agricultural land in Zala is characterized by a fragmented structure, the average agricultural area of individual farms is one of the lowest in Hungary. 72% of individual farms produce exclusively for their own consumption.

Among arable crops, rapeseed cultivation shows also a difference between the two counties: in 2020, the harvest in Vas County was twice as high as in Zala County.

Data and methods

Data collection

Data was collected via a questionnaire in western Hungary, in the counties Vas and Zala (in detail see Szőke, 2022). The initial goal was to ask 100 agribusinesses using snowball sampling. The goal was not achieved, however: more than 50% of the contacted businesses refused to answer the questionnaire, although all data was collected and analyzed anonymously. The agribusinesses refusing an answer argued that their businesses are easily identifiable even anonymously, since in a given settlement just a few agribusinesses exist.

The questionnaires consisted of 14 questions. Data collection was between late 2019 and early 2021, on digitally distributed (email) questionnaires. Initially, also on-site data collection was planned for 2020; the coronavirus pandemic made this however an exception.

The questions were partly business-related – for example number of employees, machines used on the farm – and partly they were connected to the networks created via business connections, e.g. asking from where (which settlement or foreign country) the agribusiness regularly bought products or raw material and where (which settlement or foreign country) the agricultural products were sold. The questionnaire also asked for the used services and settlements where these services were used.

In current paper, we analyze only the connections between settlements based on purchasing and selling activities of agribusinesses.

Data analysis

The received questionnaires were analyzed: from the received 46 questionnaires we could use at the end only 30: 10 questionnaires were from other counties, while 6 questionnaires had serious data gaps; therefore we had to omit them from the analysis. The questionnaires with data gaps could not be used since exactly the needed information (settlement names) was missing. Since network analysis can only work with data where nodes also have edges, these answers were not used.

The data was first entered into MS Excel for data processing. For secondary data – agribusinesses and agricultural performance in general – the data of the Hungarian Central Statistical Office (Központi Statisztikai Hivatal) was used.

For analyzing, grouping and cleaning data Microsoft Excel, for network analysis Gephi 0.9.7 on Windows was used. Gephi is a free software designed for network analysis and visualization (Gephi, 2022). In order to implement data for Gephi, the input data needs to be arranged according to the input criteria of the software. In our case, for every context (purchase, selling, purchase and selling superimposed) two .csv input files were created. In one of the files the nodes were defined (id, name (label), settlement type, county); in the other, the existence of a connection was marked, together with the direction and weight of the connection. For the best visualization, we chose the layouts "Label adjust" and "Yifan Hu", because after testing, these algorithms provided the best results.

Results

General characteristics of the agribusinesses

The focus of the activity of the analyzed businesses according to county is presented in Table 4.

Table 4. Activity of agribusinesses who completed the questionnaire by county and by activity

Scope of activity of agricultural enterprises	Vas county	Zala county	Total
crop production	15	2	17
animal husbandry	2	4	6
crop and animal production	4	3	7
total	21	9	30

Source: own editing.

The agribusinesses engaged in crop production (including enterprises engaged both in crop and animal husbandry) farm an average of 259.58 ha. The enterprises in Vas county are more involved in arable crops, with an average area of 305.26 ha, while in Zala county the enterprises are more involved in apple, pine, thuja, and fir tree cultivation, which means that the average area cultivated is smaller, 86.00 ha.

Networks of agribusinesses

Purchasing networks

In the following, we analyze the connection between settlements based on the business connections of the analyzed agribusinesses, based on Szőke (2022). We analyze the agribusinesses of both counties together. The network of purchases is a directed network, characterized by the following indices (Table 5):

A value of modularity indicates that clear communities are formed – in our case 10 – and a value of 0.4 < indicates that these communities are well separated. As for the purchases from abroad, cities were just in some cases indicated by the respondents, therefore we used the country names to indicate a connection to the given country. The weighted network (weight = number of connections) is complex, the weighted centers are Rádóckölked and Körmend (Figure 1).

Table 5. Network indicators of the supply chain network of crop production enterprises. * = calculated by Gephi 0.9.7 on Windows. Settlements with a smaller degree as 3 are not named.

Number of nodes:	N = 54
Number of connections:	E = 84
Outdegree (k_i^{out}):	Hegyfalu $k_i^{out} = 9$ Sárvár, Szombathely $k_i^{out} = 7$ Vasvár, Zalaegerszeg $k_i^{oui} = 5$ Bak, Körmend $k_i^{out} = 4$ Egyházasrádóc, Austria $k_i^{out} = 3$
Indegree (k_{iin}):	Rádóckölked $k_i^{in} = 15$ Körmend, Nagyrákos $k_i^{in} = 7$ Bük, Szeleste, Egyházasrádóc $k_i^{in} = 6$ Csönge $k_i^{in} = 5$ Egervár, Pethőhenye $k_i^{in} = 4$ Cák, Hegyfalu, Őrimagyarósd, Vép $k_i^{in} = 3$
Total degree of nodes ($k_i = k_i^{in} + k_i^{out}$)	Rádóckölked $k_i = 15$ Hegyfalu $k_i = 12$ Körmend $k_i = 11$ Egyházasrádóc $k_i = 9$ Bük $k_i = 8$ Nagyrákos, Sárvár, Szombathely $k_i = 7$ Szeleste $k_i = 6$ Csönge, Vasvár, Zalaegerszeg $k_i = 5$ Bak, Egervár, Pethőhenye, Vép $k_i = 4$ *Austria*, Cák, Nagykanizsa, Őrimagyarósd $k_i = 3$
Average Degree	1,5556
Avg. Weighted Degree*	2,611
Network Diameter*	3
Graph Density*	0,029
Modularity*	0,468
Avg. Clustering Coefficient*	0,064
Number of Communities*	10
Avg. Path Lenght	1,39

Source: own editing.

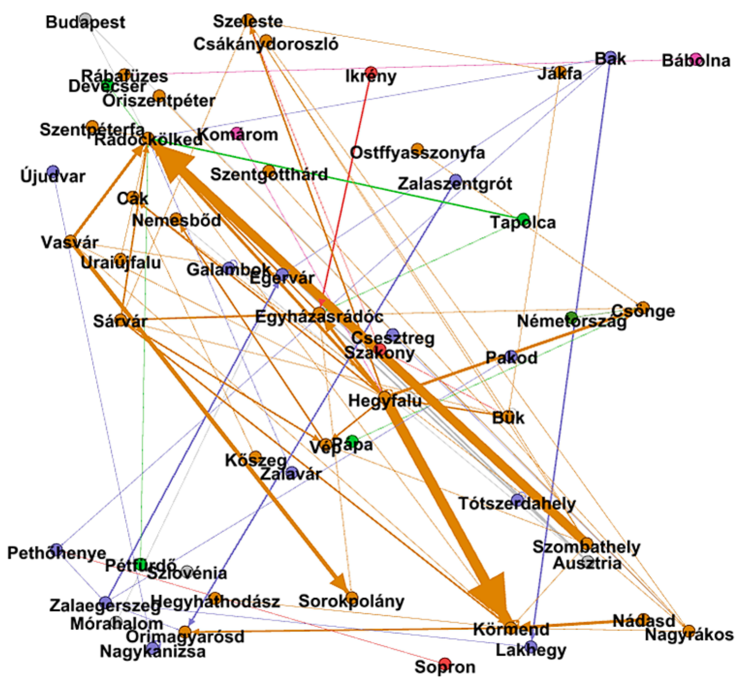

Figure 1. The network representing the purchasing relationships, weighted by the number of relationships. Brown indicates Vas county, blue Zala county. Ausztria = Austria, Németország = Germany, Szlovénia = Slovenia.
Source: Szőke 2022, using Gephi version 0.9.7.

Sales networks

The network of sales is a directed network, characterized by the following indices (Table 6).

As for the selling abroad, cities were just in some cases indicated by the respondents, we used the country names to indicate a connection to the giv-

Table 6. Network indicators of the sales network of crop production enterprises. Settlements with a smaller degree as 3 are not named.

Number of nodes:	N = 28
Number of connections:	**E = 37**
Outdegree (k_i^{out}):	Bük és Szeleste $k_i^{out} = 6$ Csönge, Rádóckölked $k_i^{out} = 5$ Körmend $k_i^{out} = 4$ Egyházasrádóc, Hegyfalu $k_i^{out} = 3$
Indegree (k_i^{in}):	*Austria* $k_i^{ine} = 7$ *Italy* $k_i^{in} = 5$ Egyházasrádóc $k_i^{in} = 3$
Total degree of nodes ($k_i = k_i^{in} + k_i^{out}$)	*Austria* $k_i = 7$ Egyházasrádóc, Körmend $k_i = 6$ Csönge, Hegyfalu, *Italy* $k_i = 5$ Szeleste $k_i = 4$ Bük, Vép $k_i = 3$
Average Degree	1,3214
Avg. Weighted Degree*	1,536
Network Diameter*	4
Graph Density*	0,049
Modularity*	0,484
Avg. Clustering Coefficient*	0,051
Number of Communities*	7
Avg. Path Lenght	1,617

** = calculated by Gephi 0.9.7 on Windows.*

Source: own editing.

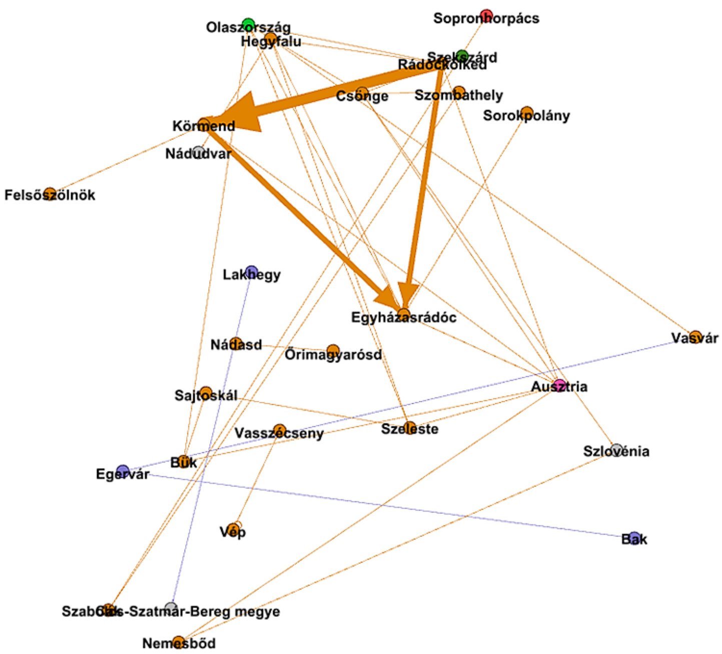

Figure 2. A network representing the selling relationships, weighted by the number of relationships. Brown: Vas county, blue: Zala county. Ausztria = Austria, Olaszország = Italy, Szlovénia = Slovenia.

Source: Szőke 2022, using Gephi version 0.9.7.

en country. The weighted network (weight = number of connections) is complex, the weighted centers are Rádóckölked and Körmend (Figure 2). In the network 7 communities are formed – and a value of 0.4 < indicates that these communities are well separated.

Austria is the node in the network with the most connections (high number of indegree), followed by Egyházasrádóc and Körmend, where there are enterprises with large areas of land that sell their products. These large farmers also buy crops from other farmers. The weight by the number of connections is however not the best visualization describing selling; therefore Figure 3 shows the network of selling relationships, weighted by the weight of the sold products (tons).

The complex network of selling and purchasing

The network of purchasing and sales contacts was superimposed and the number of connections was examined. The node with the highest degree is Rádóckölked: the reason is, that in the village a large area farmer and several small area farmers filled in the questionnaire.

In the complex network, 62 nodes exist, with 121 connections. The complex network is depicted in Figure 4. As we can see the largest part of the network is connected, only some settlements in Zala county are not part of the network. The agricultural businesses in these settlements are small, mostly producing for their own consumption.

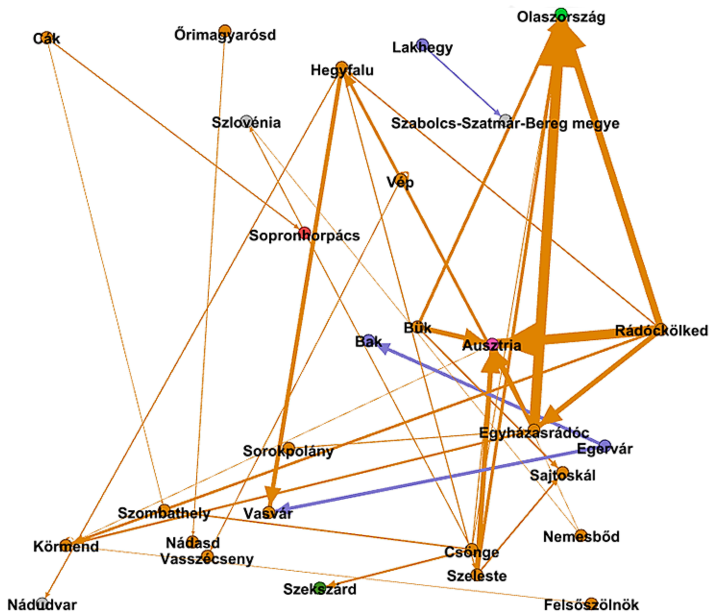

Figure 3. The network representing the selling relationships, weighted by the weight of the sold products (tons). Quantities calculated according to yield data of the Hungarian Central Statistical Office. Brown: Vas county, blue: Zala county. Ausztria = Austria, Olaszország = Italy, Szlovénia = Slovenia.

Source: own editing, using Gephi version 0.9.7.

As we can see, the structure is the same but weighed with the sold quantity of crops it is clear that the most important nodes are not settlements in Hungary, but the countries where the crop is sold: Austria and Italy. The village Egyházasrádóc is an important node, too: a farmer in the village buys crop from smaller farmers, stores them for a longer time, and sells it. Weighed by tons Körmend is less important.

Since the network drawn by Gephi is not drawn according to the geographical location and distribution, Figure 5 shows how the settlements are distributed in the geographical space. It can be seen that the densest network is inside Vas and Zala counties and that – although geographical proximity influences connections – there are well business connections outside this smaller area.

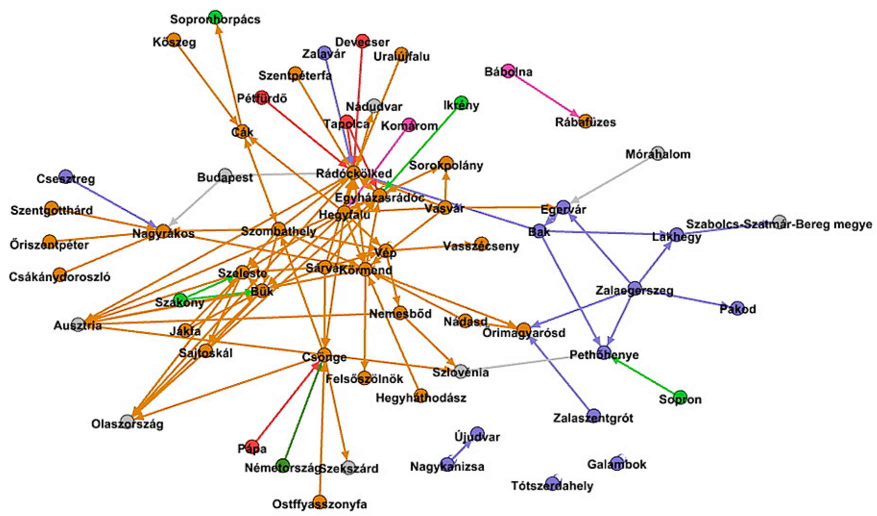

Figure 4. Purchasing and sales network. Brown: Vas county, blue: Zala county, green: Győr-Moson-Sopron county, purple: Veszprém and Komárom-Esztergom counties, grey: cities from other parts of Hungary and other countries. In the case of Galambok and Tótszerdahely purchasing happens at the same settlement. Ausztria = Austria, Olaszország = Italy, Szlovénia = Slovenia.

Source: own editing, using Gephi version 0.9.7.

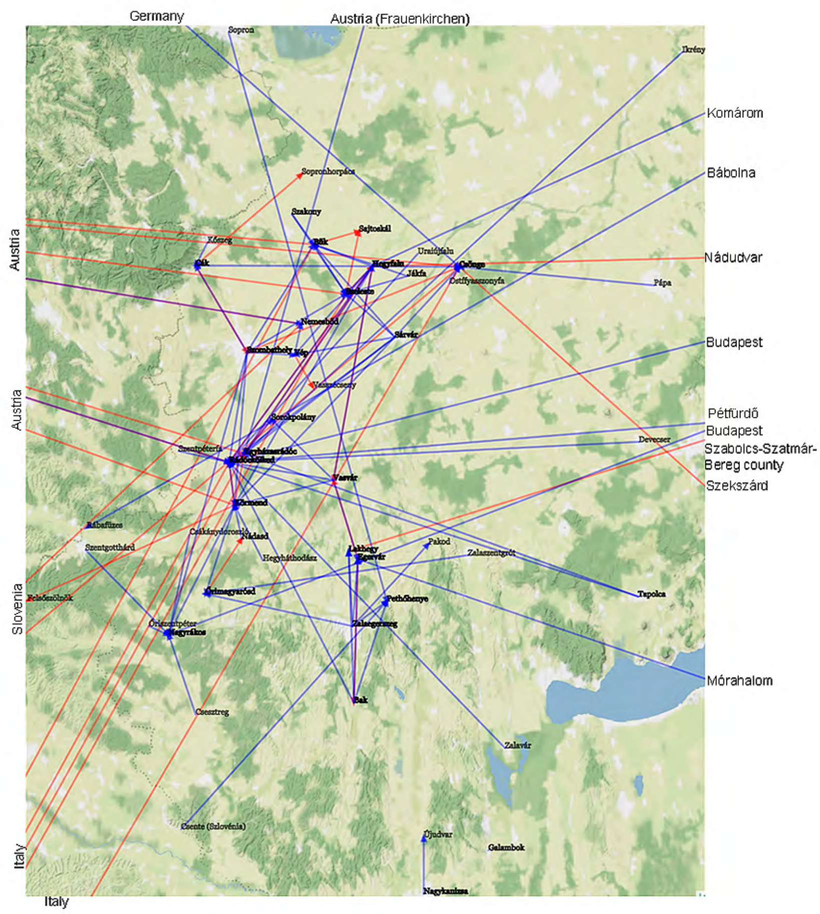

Figure 5. Map of the network of purchasing and sales connections. Blue: purchasing, Red: selling.

Source: Szőke 2022, source of the background map: https://leafletjs.com.

Discussion

Main characteristics of the networks

The main characteristics of the purchasing, selling and complex network are compared in Table 7.

The above indices all describe the complexness of a network (for an overview see Barabási, 2016; Kansky, 1963; or Szőke, 2022). The alpha index (α-index) is an indicator of the complexness of networks, the less connected networks are tree-shaped and the more complex ones contain several circuits or multiple edges (Dusek & Kotosz, 2016). If the α-index is close to 0, the network is tree-shaped, while if it is 1, it is fully connected (Erdősi, 2000).

Table 7. Main characteristics of the networks

	Purchase networks	Sales networks	The complex network of sales and purchasing
Number of nodes (N)	54	28	62
Number of connections	84	37	121
Beta Index (β) (Average Degree)	1,5556	1,3214	1,9516
Gamma Index (γ)	0,5385	0,4744	0,6722
Alpha Index (α)	0,3010	0,1961	0,5042
Pi Index (π)	28	9,25	12,1
Network Diameter*	3	4	10
Avg. Path Lenght	1,39	1,62	3,48

** = calculated by Gephi 0.9.7 on Windows*

Source: own calculations

The beta index (β-index) is another quantity measuring the complexity of networks: a larger β value denotes a more complex network structure, similar to the gamma index (γ-index) which describes the density of the network (Barabási, 2016). With the pi index (π) again the complexity of the network can be described: a larger value indicates a more complex network.

Purchase network

- α-index: a value of 0.3010 indicates a less complex network. The number of directed cycles in the network is 30% of the maximum number of possible directed cycles.
- β = 1.5556: since the value is greater than 1, it means that the network has more than one directed cycle or multiple edges. The value of the index is higher for purchase than for the sales network, which means the purchase network is the more complex of the two.
- γ = 0.5385, indicating a less complex network
- π index: the π index of the purchasing network is 3 times higher than that of the sales network. The network of purchasing relationships is more complex than that of sales relationships.

Sales network

- α-index: a value of 0.1961 indicates a not connected network. The number of directed cycles in the network is 20% of the maximum number of possible directed cycles.
- β = 1.3214 since the value is greater than 1, it means that the network has more than one directed cycle or multiple edges.
- γ = 0.4744, which indicates a partly connected network

Purchase and sales network

- α-index: a value of 0.5042 indicates a moderately complex network. The number of directed cycles in the network is 50% of the maximum number of possible directed cycles.
- β = 1.9516: the β index of the purchasing + sales network is higher than that of the purchasing and sales network separately, indicating that the two networks together are more complex.
- γ = 0.6722, indicates a complex network.
- π index: the π index of the purchase and sales network is lower than that of the purchase network and higher than that of sales network. This seemingly contradictory result can be explained by the structure of the separate networks: the purchase network has a high number of nodes and a high number of edges, while the sales network has fewer nodes and fewer edges. If the two networks are superimposed, we will have slightly more nodes, but the number of links will increase at a higher rate; hence the π value will be lower.

Central settlements

The first research question seeked to answer the question, whether large cities are automatically centers in the agribusiness network (RQ1).

Our results show that agricultural enterprises with large arable lands have a more extensive and complex network of connections. This is the reason why in the network of purchase contacts (Figure 1) a village – Radóckölked – has the most contacts: it is due to the high number of respondents at the settlement and the extensive network of contacts of large agribusinesses. The next node is Hegyfalu, which is ranked 2nd due to its high out-degree. The settlement is one of the sites of KITE Zrt. from which many farmers in Vas County purchase fertilizers, pesticides, and machinery parts. Egyházasrádóc, Bük, Szeleste, and Csönge have a high indegree, because they are home to large-scale farmers with many connections, and are therefore considered to be important nodes in the network. Sárvár, Szombathely, Vasvár, and Zalaegerszeg, as well as Bak will have a high outdegree, as farmers buy various products from these settlements, e.g. fertilizers, pesticides, or spare parts for machines.

In the sales network, the indegree of settlements is large when farmers at the settlement have agribusinesses that purchase crops from neighboring (smaller) farmers. Similarly, purchasing countries – Austria and Italy – have a high indegree. It is important to note that the crop sold to Austria and Italy also has two possible uses:

a) bought from Hungary and resold by Austrian or Italian companies specialized in the trade of crops,
b) bought for processing, e.g. for pasta production.

The outdegree of a settlement in the sales network is depending on the number of farmers filling out the questionnaire from the given settlement since most farmers sell their products to only one or two buyers. This is the reason, why the sales network is less complex than the purchase network (see above). The small number of partners can be explained by the fact that in agribusiness trust, correctness, and long-lasting relationships are paramount (cf. Sadovska et al., 2020; Zander & Beske, 2014). This is, why existing partnerships are highly valued and why established selling partner networks just seldom change.

In the complex network (purchase and selling) the degree of Hegyfalu will be high due to the high number of purchasing out-degrees (fertilizers, pesticides, etc.), while the degree of Körmend will be high due to the high purchasing indegrees. In Egyházasrádóc, Bük, and Szeleste, larger farmers cultivate areas with significant purchases and sales, and therefore these settlements have a higher degree and a more important node function in the network. Szombathely, Sárvár, and Vasvár have high out-degrees in the purchasing network (=purchasing from the perspective of the agribusinesses) and also high indegrees in the sales network, which is because some of the agribusiness enterprises in these towns are involved in both product sales and partly (in a smaller degree) in buying crops or other products. In the case of agribusinesses, we see that according to the complex network of purchase and selling the most central nodes in the network are not large towns or cities: they are smaller towns or villages, where enterprises buy agricultural products (crops) from other agribusinesses.

We can conclude, that small towns and villages can also have a central role in an agribusiness network, thus the answer to RQ1 (Are large cities automatically centers in the agribusiness network?) is no, since smaller towns or even villages can play a central role in agribusiness networks.

Factors influencing central roles of settlements in business networks

As seen from the results and the discussion of the first research, smaller towns and villages can also function as centers in agribusiness networks. This leads us to the second research question – RQ2: Which factors influence, whether a settlement has a more or less central role in an agribusiness network? In the following, we summarize the factors responsible for the central role of a settlement in an agribusiness network.

As we see from the results, central nodes of agribusiness networks can be smaller towns or villages. These central roles can be shaped by three contexts:

1. the size of the agribusiness in the given settlement,
2. the activities of the agribusinesses in the given settlement and
3. the existence and scope of businesses important for agricultural production at the given settlement.

Since the production site of agribusinesses cannot be changed (they have to produce on the given land), therefore on one side the place of production is given. On the other side, it is inefficient storing large quantities of agricultural products in large cities: it is much more effective to collect them in smaller settlements, where

a) a business selling and storing agricultural products already has large storage space, or
b) a large farmer producing crops has facilities to store additional agricultural products.

These two kinds of companies shape the network as local collectors of agricultural products.

In the case of purchasing networks, important nodes with large outdegrees will be settlements where

a) agricultural input (e.g. seeds, fertilizers, insecticides, pesticides), and/or
b) for daily business necessary parts, tools and products (e.g. machine parts, screws, belts) can be bought.

Businesses selling these products are not exclusively supplying agribusinesses; e.g. screws or tools are needed also by a wide range of industrial companies. These businesses and specialized agricultural businesses often are situated outside of cities (cf. Szőke & Kovács, 2019), but also in smaller towns or villages, nearer to local agribusinesses, where purchasing land for business activities is much cheaper.

Thus, the agribusiness network has four main actors: 1) producers, 2) resellers 3) companies processing crops and reselling new products 4) companies providing input material and machine parts and tools for agribusinesses. None of these actors needs necessarily to be located in large cities.

From the above, RQ2 (Which factors influence, whether a settlement has a more or less central role in an agribusiness network?) can be answered. It can be concluded that in agribusiness purchasing and sales networks three kinds of settlements can have a central role:

1. large cities supplying agribusinesses with specialized equipment
2. smaller towns or larger villages having specialized businesses for agribusinesses and/or having businesses re-selling agricultural products,
3. villages where larger agricultural businesses are situated that both buy and sell crops.

Practical implications and future research

First results show that the network analysis approach applied to business connections can be used to identify connections between settlements. Since results show the existing business connections, this knowledge can be used by new businesses connected to the agribusiness sector, but also by local authorities for settlement development.

First, results could provide information for future businesses selling products for or buying crops from agricultural businesses. Based on the data it can be calculated and suggested where to place and open new businesses: placing businesses near producers, crop buyers or near usual traffic routes may increase the chance of success for future businesses.

Second, results clearly show (local) governments where targeted road development may be necessary. An agribusiness purchasing crops from smaller farms necessarily creates heavy traffic, which affects the condition of roads and the traffic situation on that road. Note that just one typical agribusiness producing crop on 1000 ha can generate a traffic of 3-400 truckloads of transport in the vicinity of the given agribusiness (cf. Szőke & Kovács, 2019).

Third, the results can provide input for local decision-makers, where infrastructure in a given settlement needs to be developed or tax reliefs provided in order to attract new businesses, which provide services according to the needs of nearby agribusinesses.

The results open up the possibilities of several new research directions. One possibility is to verify and refine the first results on a larger dataset by analyzing the connections of more agribusinesses in the same geographical area. A second possibility is to analyze the connections of agribusinesses in other counties, thus verifying the results in other geographical areas. It would also be interesting to compare the business connections of other economic sectors with those of agribusinesses, including e.g., production companies, touristic companies, service companies, etc., or even include the connections of local governmental organizations into the analysis. Thus, a more detailed and diversified network structure between settlements could be uncovered, where the peculiarities and the characteristic network structure of the given sector could be captured and analyzed.

There is another research direction that is worth taking in the future. One interesting outcome of the analysis is – when we compare the connections to other data obtained through the questionnaire –, that results suggest that the language knowledge of the farmers influences the business connections they form and maintain. The farmers who speak foreign languages – in several cases, the farmers were born abroad and settled in Hungary – tend to create business connections outside Hungary both for purchasing (e.g., buying equipment from Austrian vendors) and for selling (selling crops to Austria or Italy) purposes. This result is not surprising per se, shows, however, that sometimes neglected (not analyzed) soft factors such as spoken languages may explain spatial connections between businesses and between settlements. The result implies that when analyzing spatial structures, it is necessary to collect data that seems – at first glance – not to be connected to the given research goal since, as we see, in our case, such a factor provides the explanation for some spatial structures. Thus, a future research direction could be to identify all the factors – including human-related soft factors – which can influence and explain the spatial connection between businesses and, therefore, connections between settlements.

Conclusion

The paper sought to show the potential of the use of network research methods to analyze the connections between settlements. We pointed out that the analysis of networked structures in geography can describe complex relations between the actors of the network and can help to understand the complex interaction of these actors.

In the paper, we analyzed the purchase and sales networks around agribusinesses: with a questionnaire, we mapped out connections of agribusinesses in the Hungarian counties Vas and Zala, and we analyzed the resulting networks with Gephi.

Results showed that the network structures are different when we analyze the purchasing and the selling network: settlements that are central in one network do not necessarily play a central role in the other network. This is due to the different roles of settlements: while some settlements have more vendors selling input material, parts and goods for agribusinesses, others rather host businesses which collect crops.

After analyzing the network structure, and the role – and businesses – on the given settlement, we concluded that from the agribusinesses network's point of view, central nodes are not necessarily larger cities: small towns and villages can also have a central role, depending on the agri- or agriculture-related businesses situated in the given settlement.

Results implicate that network science has potential in geographical space research: with data obtained either from questionnaires or from databases, networked structures can be identified and analyzed. The tools and results of network analysis must be, however, connected to geographical knowledge – in our case, to knowledge of economic geography – to be able to give explanations for the results and to map out the practical use of the results.

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ISSN 0354-8724 (hard copy) | ISSN 1820-7138 (online)

Confessional Pluralism in Central and Eastern Europe – a GIS approach

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Received: January 27, 2023 | Revised: March 10, 2023 | Accepted: March 15, 2023
doi: 10.5937/gp27-42461

Abstract

In this recent study, we analyse the religious diversity of Central and Eastern Europe, from the Balkans up to the Baltic region. This region has many religious confessions, without claiming completeness, Roman Catholic, Reformed, Lutheran, Orthodox, Islam, Hussite and many people without any religion. The recent spatial distribution of the religious confessions has been shaped by different drivers across Central and Eastern Europe. We chose a quantitative method to visually interpret the pluralism of the religious confessions and we selected diversity indices. We calculated the diversity of the religious confessions and ethnicities in a very detailed resolution, at municipality level of each country, based on population census data of 2011. We found statistically significant relationship between the diversity of religious confessions and the diversity of ethnicities. We have also shown that near the national borders, the religious pluralism is higher than in another areas. There is statistically significant connection between the former national borders (1900s and 1930s) and the religiously plural areas. The results of this study provide the evidence of the spatial distribution of borderline syndrome and serves as a good basis for further research (theoretical and statistical) of the religion pluralism in Central-Eastern Europe.

Keywords: religious pluralism; religious diversity; GIS; borderline; region; statistical analysis

Introduction

Globalisation and technological progress influencing the spatial distribution of religions and their diversity continuously changing. The measuring of religious diversity is getting more important world-wide (Pew Research Center, 2022; Warf & Vincent, 2007), like in USA (Eck, 2001; Warf & Winsberg, 2008), Asia and Australia (Bouma, Ling, & Pratt, 2010) and also in Europe (Dövényi & Németh, 2014; Ferrari & Pastorelli, 2012; Monnot & Stolz, 2014; Pollack, 2008; Vertovec, 2007). The religious diversity of Central and Eastern Europe, from the Balkans to the Baltic region were examined. Central and Eastern Europe is a geographical subunit of the continent between three seas the Nordic, the Adriatic, and the Black Sea. Gerard Dalanty is a well-known historian on the field of Europe (Delanty, 2015, 2018). He developed six subregions across the continent using two main criteria. The first is cultural, which refers to historical roots, and the second is modernity's unique features. The entire region is one big borderland, culturally influenced by West and East Christianism. Europe is a borderland in the sense that it consists of multiple spatiality in terms of state formation, markets, social and cultural institutions, and identities (Balibar, 2004). According to this viewpoint, any reference to a geopolitical or historical region must acknowledge its connections with other regions. Europe's regions should thus be viewed as hyphenated spatiality rather than separate territories (Delanty, 2018). There are several religious confessions in this region, including Roman Catholic, Reformed, Lutheran, Orthodox, Islam, Hussite, and many others who do not identify with any religion (Cipriani, 2011). Var-

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ious drivers have impacted the recent spatial distribution of religious confessions across Central and Eastern Europe. First and second world wars have the biggest impact on the spatial distribution change of religions in this area. Communism also had a strong effect on the religious denominations, but in a different way (not in the spatial distribution), was influenced by the number of believers.

When it comes to concerns of diversity and pluralism, post-communist states are frequently viewed as a special case. Post-communist Europe is usually defined as an area in which religion has been revitalised in the post-1989 period, and a place in which debates concerning church and state are particularly significant, despite a general understanding of considerable diversity in terms of basic religious landscape. This is mostly due to established Churches' attempts to reclaim its pre-communist public dominance, attempts that contradict the positions and rights of other (minority and new) religions and clash with competing perspectives on secularity in modern Europe. Another, more complex scenario involves countries that have recently had violent conflicts (such as those in post-Yugoslav countries) in which religions, as essential symbols of separate ethnic identities, played a significant social role (Zrinščak, 2014). All of the previously stated historical and recent traumas are not outliers. They represent and demonstrate the enormous significance of collective wounds in CEE societies. Politicians and citizens see their fate through the lens of a wounded collective identity, and they are captivated by natural and phantom pains. For a proper understanding of the region, as well as the presence, distribution and functions of religion in CEE, it is necessary to centre the interpretation on the factor of wounded collective identity (Máté-Tóth, 2019; Szilárdi & Kakuszi, 2022).

The present study attempts to observe the link between the borderline syndrome phenomenon and wounded collective identity effect and religious diversity. Religious diversity is a normal occurrence in Central and Eastern European countries, as the region includes countries with a wide range of confessional traditions (Catholic, Orthodox, Protestant, Muslim, and so on) that have long existed in the region (Sealy, Magazzini, Modood, & Triandafyllidou, 2021). On the other side, there are countries that are extremely monolithic, with more than 90% of their people belonging to a single confession ('Catholic' Poland and 'Orthodox' Romania), as well as countries with many confessions or a substantial percentage of atheists (Hungary, Czech Republic and Estonia). The crucial thing to remember is that diversity is a historical fact that has not changed over the twentieth century, despite the presence of atheist regimes (Zrinščak, 2014).

To analyse the spatial trends of the religious pluralism in Central-Easter Europe, it must be visualised spatially. Population census datasets from 2011 for 13 countries at municipality level (LAU1) were collected. To measure the spatial distribution of the religious confessions two diversity indices were chosen: the Richness Index and the Simpson Diversity Index. Both of these indices evaluate diversity and were created by Simpson in 1949 (Simpson, 1949). Other disciplines have adopted this indicator, such as economics' Herfindahl–Hirschman-index (Rhoades, 1993) or the Pew Research Center's Global Religious Diversity Index (Pew Research Center, 2022). Three countries, 'Catholic' Poland, 'Orthodox' Romania and Hungary with many confessions have been selected for further analysis related to present and historical national borders (ANOVA test).

The main goals of this study are the following: (i) to make a unique and unified religion dataset for Central-Easter Europe and visualise spatially the religious pluralism, (ii) analyse the relationship between religious confessions and ethnicities, (iii) prove the borderline syndrome phenomenon based on the religious diversity and historical national borders. This study also serves as a good basis for further research (theoretical and statistical) of the religion pluralism in Central and Eastern Europe.

Databases and methods

Study area

Regional scale study area covers Central and Eastern Europe from Balkans up to Baltic area (13 countries). This region was the western border of the former Soviet Union and it had a very eventful history in the last century. The national borders changed several times as the population and the religious confessions too. Country scale analysis contains Hungary, Poland and Romania (Figure 1). These countries were chosen because Hungary is very diverse in religious denominations and ethnicities, inhabitants of Poland are mostly Roman catholic, while Romania is mostly orthodox. All of the three countries' national borders changed according to the years of 1900.

Datasets

The Population and Householding Censuses 2011 give the basis of our research. Every country conducted this census in many topics, the religion and ethnicity related datasheets were selected. All of the

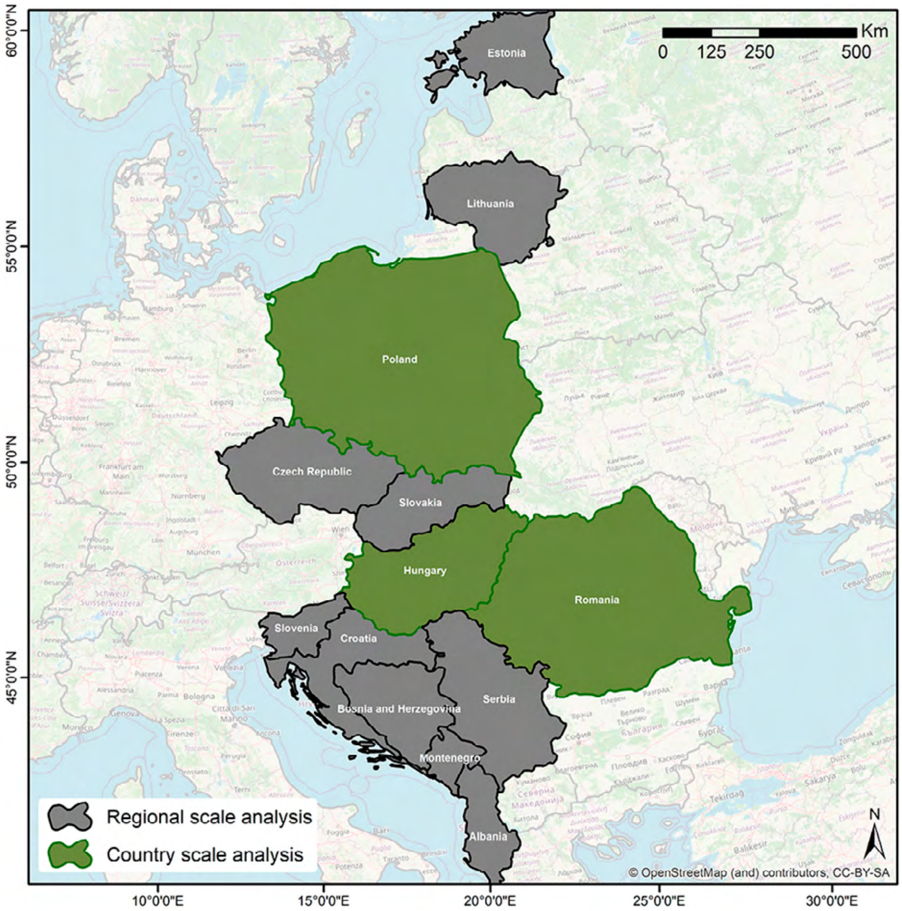

Figure 1. Study area of the analysis, countries highlighted with grey: regional scale analysis, green: country scale analysis

dataset by municipalities is freely available on the census 2011 website of all countries (Table 1). On these websites the methodology of all survey is available. The answered data was used; values of no responses have been excluded. Latvia was not analysed as no public data on religion at the municipal level was available.

The following countries' data have been collected in order from north to south (Table 1).

The GIS dataset of countries' municipality polygons are available on the Eurostat website (Eurostat, 2022). All of datasheets were merged, edited and restructured to make a unified database, which contains more than 7000 units.

Table 1. List of the analysed countries and link to the population and householding census of each country from 2011

Country name	Link to the dataset webpage
Estonia	https://www.stat.ee/en/statistics-estonia/population-census-2021
Lithuania	https://osp.stat.gov.lt/2011m.-visuotinis-gyventoju-ir-bustu-surasymas
Poland	https://stat.gov.pl/en/databases/
Czech Republic	https://vdb.czso.cz/vdbvo2/faces/en/index.jsf?page=statistiky#katalog=33476
Slovakia	https://slovak.statistics.sk/wps/portal/ext/themes/demography/census/indicators/
Hungary	https://www.ksh.hu/nepszamlalas/detailed_tables
Romania	https://www.recensamantromania.ro/
Slovenia	https://www.stat.si/Popis2011/eng/Popul.aspx?lang=eng
Croatia	https://web.dzs.hr/arhiva_e.htm
Serbia	https://data.stat.gov.rs/?caller=3102&languageCode=en-US
Bosnia and Herzegovina	https://popis.gov.ba/
Montenegro	http://monstat.org/eng/page.php?id=1708&pageid=1708
Albania	http://databaza.instat.gov.al/pxweb/en/DST/

Historical national boundaries from 1900 were created by Max Planck Institute for Demographic Research and Chair for Geodesy and Geoinformatics of University of Rostock (MPIDR & CGG, 2013). The year 1900 was chosen as a reference point because it was before the two world wars, which significantly changed the national borders and the demographic composition of Poland and Romania. We wanted to capture the historical diversity of these regions before they were affected by the major political and social upheavals of the 20th century.

GIS and statistical analysis

The unified census dataset has been joined to the municipality polygons to visualise the spatial distribution of religious confessions and ethnicities and conduct spatial analysis. A webmap was created to make our regional scale results available to everyone. The webmap was created in the ArcGis Online application and it contains switchable layers, legends, data charts, export option and pop-up windows with detailed attributes. The webmap can be accessed via the following link: https://www.convivence.eu/research/projects.

We chose two diversity indices, Richness Index and Simpson Diversity Index. The measurement of the diversity is coming from the ecology, in 1949, Simpson made this index (Simpson, 1949). Other disciplines have also adopted this index, like in economics, the Herfindahl–Hirschman-index (Rhoades, 1993) or the Global Religious Diversity Index of the Pew Research Center (Pew Research Center, 2022). Richness Index (RI) shows the number of different religious confessions or nationalities in a unit. Simpson Diversity Index (SDI) represents the probability that two individuals randomly selected from a sample will belong to different categories (religion, ethnicity, etc.), the value of this index ranges between 0 and 1, the greater the value, the greater the sample diversity. The calculation was done in Microsoft Excel software for every municipality polygon.

$$SDI = 1 - \left(\frac{\sum n(n-1)}{N(N-1)} \right)$$

- where n=the total number of members in a confession, N= the total number of members in all confessions.

Central and Eastern European diversity calculations at regional scale have been done based on the five most frequent religious denominations at municipality level (Roman catholic, Lutheran, Reformed, Orthodox, Muslim). The statistical analysis of the relationship between religious confessions and ethnicities in country scale (Hungary, Poland, Romania) has been done at municipality level in the IBM SPSS Statistics 20 software. The normality of our dataset has been checked by the Kolmogorov-Smirnov (Smirnov, 1939) and Shapiro-Wilk (Shapiro & Wilk, 1965) test and they resulted that our dataset is not normally distributed. On our non-normally distributed data the non-parametric Spearman rank correlation was used to analyse the relationship between religion and ethnicity (Kendall, 1994). For non-normal datasets, it is recommended to use Spearman correlation instead of Pearson correlation.

We divided the area of Poland and Romania into two parts based on the national borders of the year 1900. One part contains just the municipalities inside the 1900 borders and the other part contains just the left-over municipalities inside the present-day borders. On our municipality dataset, one-way analysis of variance (ANOVA) test (containing religious and ethnicity diversity) was used. The two parts of countries were declared as groups since this analysis can be performed on a dataset with two or more groups. The ANOVA test uses the F distribution to compare the means of groups, the null hypothesis states that all groups' samples have the same mean values (Kaufmann & Schering, 2014).

Results

In this chapter our result based on regional and country scale analysis will be presented, dominant religious confessions, spatial distribution of confessions' diversity, relationship between confessions and ethnicities and the importance of historical national borders.

Religious and ethnicity diversity in Central and Eastern Europe

As it is described in the introduction section, Central and Eastern Europe is very divers in religious denominations. On the Figure 2A), the dominant religious denominations are nicely outlined, as well as the Roman catholic blocks, like Poland, Lithuania and Croatia. Most of Hungary is Roman catholic, but some regions are dominated by other denominations of Christianity. Orthodox is dominant in Romania (ex-

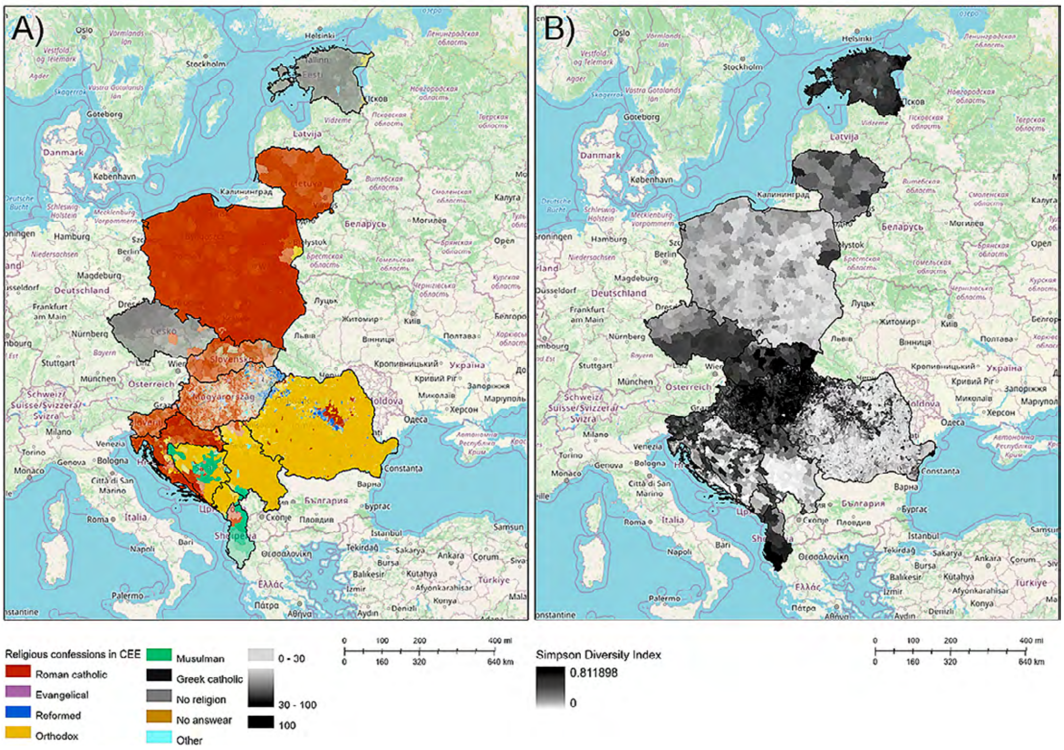

Figure 2. A) Dominant religious confessions at municipality level in Central-Eastern Europe; B) Diversity of main five religious' confessions (Roman catholic, Lutheran, Reformed, Orthodox, Muslim) at municipality level in Central-Eastern Europe

cept the areas inhabited by Hungarians), Serbia and Montenegro. Muslim is dominant in two countries, Albania and Bosnia Herzegovina, but not homogeneous, Roman catholic and orthodox also appear in some regions. The Czech Republic and Estonia were dominated by people without religion in most of the municipalities.

On the Figure 2B), the spatial distribution of the religious pluralism can be observed based on the Simpson diversity index and it gives a more nuanced picture of the religions across Central and Eastern Europe. In the extremely monolithic countries, such as Poland, Romania and southern Serbia, the diversity index is low or close to the zero value, which means that one religious denomination dominates the municipalities. Albania, Estonia, Hungary and Slovakia show quiet high diversity values in most of their regions.

Religious and ethnicity diversity in Hungary

The Simpson diversity index (SDI) of religious confessions in Hungary shows an unequal distribution, eastern and middle part of the country are the most diverse (highest SDI=0.82), the western part is more homogeneous (lowest SDI=0.07) (Figure 3A). The diversity of ethnicities has different spatial distribution, more diverse region take place along the Romanian, Ukrainian and Slovakian borders and in the South-Western part of the country (highest SDI=0.82) (Figure 3B). The lowest SDI of ethnicities is zero, which means that there are settlements inhabited only one ethnicity (most likely Hungarian). Number of religious confessions and the number of ethnicities show very similar spatial distribution in Hungary (Figure 3C, D). The highest numbers of RI (15) can be found in the Hungarian Great Plain and in the capital, Budapest.

We found positive significant correlations between the number of religious confessions and number of ethnicities, see in Table 2 (r=0.74, p=0.01, n=3154). In the Figure 3C, D, it can be clearly observed visually. Correlation between number of ethnicities and Simpson diversity of religious confessions also show positive significant relation (r=0.305, p=0.01, n=3154), but much weaker as in the previous case. The Simpson diversity of ethnicities has no significant correlation with number of religious confessions and neither the Simpson diversity of religious confession, but these are also important result.

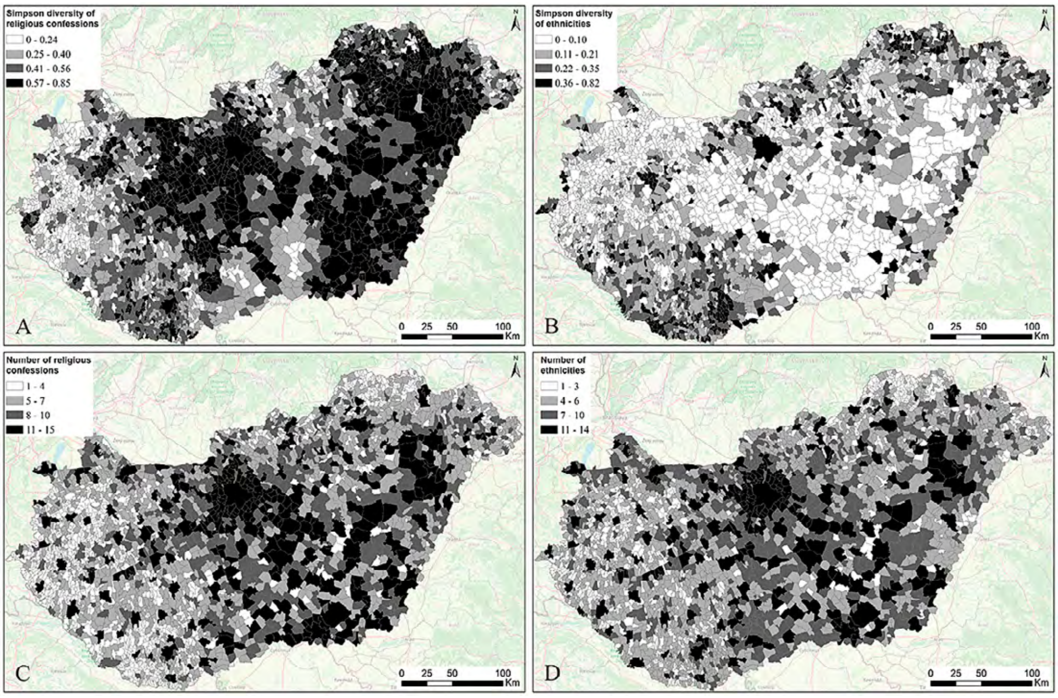

Figure3. A) Simpson Diversity Index of religious confessions at municipality level in Hungary B) Simpson Diversity Index of ethnicities at municipality level in Hungary C) Number of different religious confessions at municipality level in Hungary D) Number of different ethnicities at municipality level in Hungary; Zero = no diversity; A, B, C and D based on Hungarian Population and Householding Census 2011

Table 2. Results of the Spearman correlation analysis between diversity and number of religious confessions and ethnicities in case of Hungary

	Number of ethnicities	Simpson diversity of ethnicities	Number of pairs
Number of religious confessions	0.74**	Not significant	3154
Simpson diversity of religious confessions	0.305**	Not significant	3154
Number of pairs	3154	3154	

*** Significant at 0.01 level*

Religious and ethnicity diversity in Poland

Based on the religious confessions and ethnicities Poland has a homogeneous core area according to Hungary. The spatial distribution of religious confessions' SDI is much higher in the surroundings of the Belarus, Russian, German and Czech Republic borders (Figure 4A). The highest values can be observed in the area of Bielsko-Biała and Białystok (SDI=0.51). In case of the ethnicities SDI, it has a more homogeneous distribution outside of the core area, the most diverse areas are Belarus, Russian, Baltic-See shoreline and Czech Republic borders (Figure 4B). The most diverse hotspots are Białystok, Katowice surroundings (50 km), Suwałki and Gdynia-Gdansk surroundings (50 km) (SDI=0.59). The number of religious confessions is higher in the bigger cities and near the national border, highest number is 12 (Figure 4C). Number of different ethnicities show other spatial distribution, higher numbers appear near Białystok, Katowice surroundings (50 km), Suwałki, Gdynia-Gdansk surroundings (50 km) and Warsaw (highest number=24) (Figure 4D). According to Hungary in Poland there is no totally homogeneous municipality, minimum number of confessions and ethnicities is 3.

In case of Poland, four positive significant correlation were found between ethnicities and religions (Table 3). The highest correlation (r=0.73, p=0.01, n=369) shows up between number of ethnicities and number of religious confessions. Second highest presented between diversity indices of ethnicities and religious confessions (r=0.585, p=0.01, n=369). Results show two quiet high correlation, first between number of ethnicities and SDI of religious confessions (r=0.45, p=0.01, n=369) and between the SDI of ethnicities and number of religious confessions (r=0.452, p=0.01, n=369).

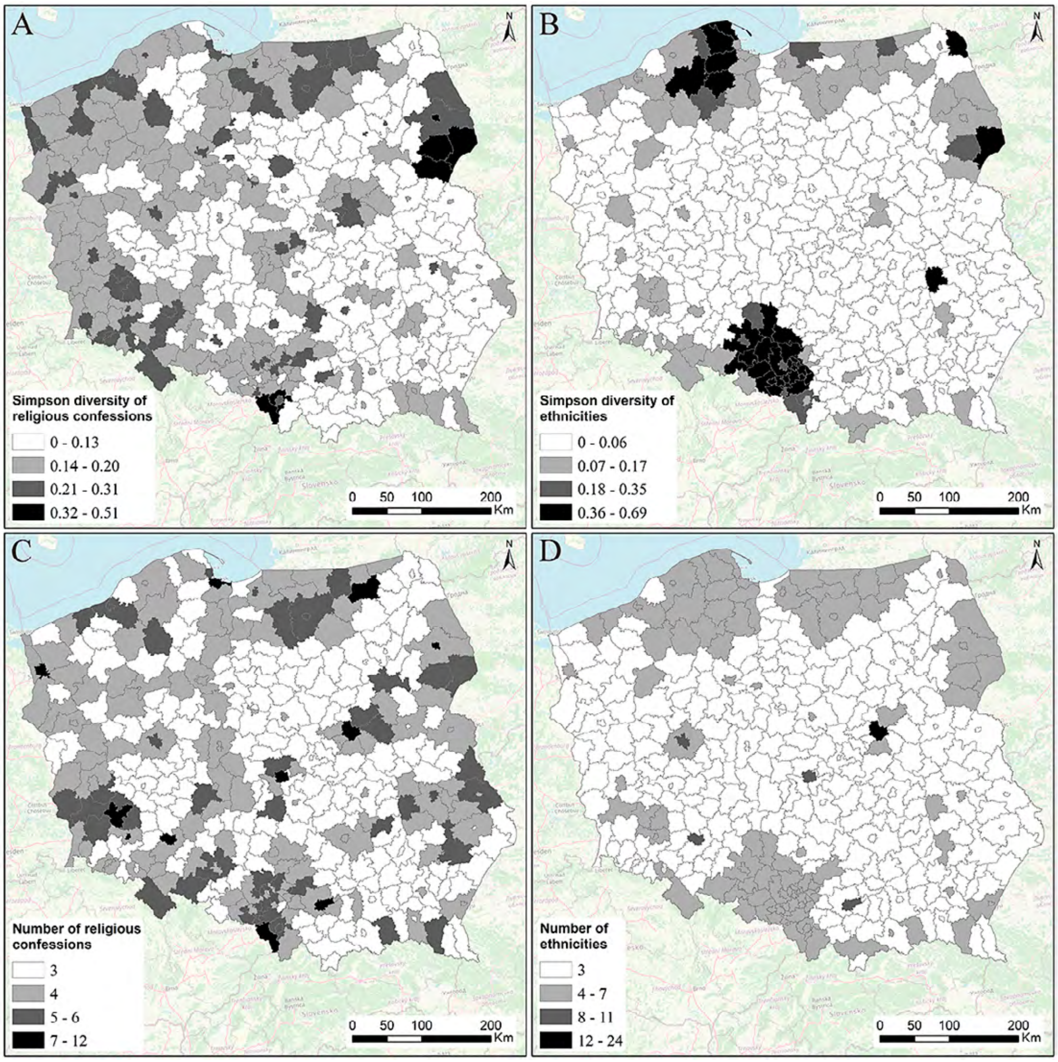

Figure 4. A) Simpson Diversity Index of religious confessions at municipality level in Poland B) Simpson Diversity Index of ethnicities at municipality level in Poland C) Number of different religious confessions at municipality level in Poland D) Number of different ethnicities at municipality level in Poland; Zero = no diversity; A, B, C and D based on Polish Population and Householding Census 2011

Table 3. Results of the Spearman correlation analysis between diversity and number of religious confessions and ethnicities in case of Poland

	Number of ethnicities	Simpson diversity of ethnicities	Number of pairs
Number of religious confessions	0.73**	0.452**	369
Simpson diversity of religious confessions	0.450**	0.585**	369
Number of pairs	369	369	

*** Significant at 0.01 level*

Religious and ethnicity diversity in Romania

According to the Figure 5A, Romania can be divided into two parts, within the Carpathians and outside of the Carpathians. The SDI of religious confessions is the highest near the Hungarian border and where Hungarians are in majority in Transylvania. The highest SDI value is 0.83 and the lowest is zero. SDI of ethnicities show very similar spatial distribution as in the previous figure (Figure 5B). The number of religious confessions is higher near the Hungarian border, Serbian border, at the Black Sea shoreline, around Bucharest, Cluj-Napoca, Timisoara and Brasov (Figure 5C). Highest number is 22 and the lowest is zero. The number of ethnicities highest near the triple border between Hungary, Serbia and Romania and Black Sea shoreline. According to the Figure 5D

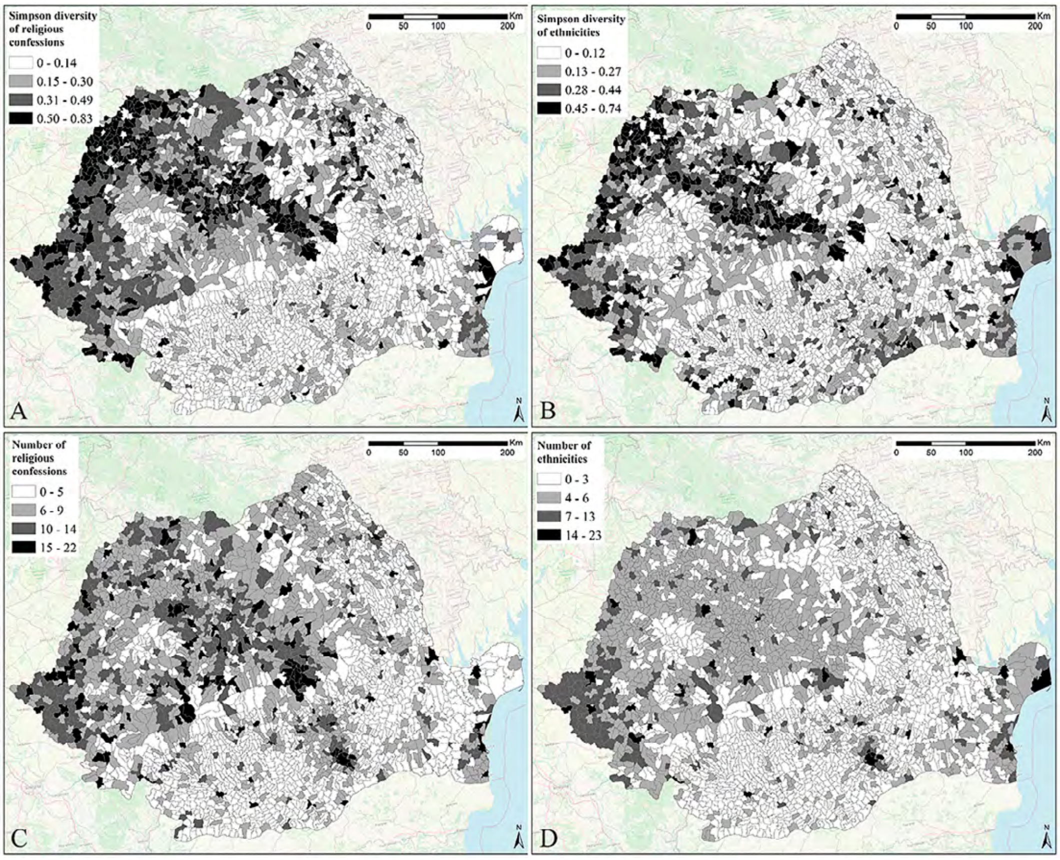

Figure 5. A) Simpson Diversity Index of religious confessions at municipality level in Romania B) Simpson Diversity Index of ethnicities at municipality level in Romania C) Number of different religious confessions at municipality level in Romania D) Number of different ethnicities at municipality level in Romania; Zero = no diversity; A, B, C and D based on Romanian Population and Householding Census 2011

Table 4. Results of the Spearman correlation analysis between diversity and number of religious confessions and ethnicities in case of Romania

Romania	Number of ethnicities	Simpson diversity of ethnicities	Number of pairs
Number of religious confessions	0.687**	0.479**	2939
Simpson diversity of religious confessions	0.558**	0.612**	2939
Number of pairs	2939	2939	

*** Significant at 0.01 level*

the highest number of ethnicities (33) can be found near the Black Sea shoreline, around Bucharest, Brasov and Timisoara.

In case of Romania, four positive significant correlation was found between ethnicities and religions (Table 4). Highest correlation coefficient represents between Number of ethnicities and number of religious confessions (r=0.687, p=0.01, n=2939). Between SDI of religions and ethnicities have also quiet strong correlation (r=0.612, p=0.01. n=2939). Compared to Hungary and Poland, stronger correlations resulted between number of ethnicities and SDI of religious confessions (r=0.558, p=0.01, n=2939) and between SDI of ethnicities and number of religious confessions (r=0.479, p=0.01, n=2939).

Spatial distribution of religious diversity - historical approach

National border of Poland from 1900 enclose an area, which is religiously homogeneous. Areas outside of the border from 1930 even more clearly delineate the religiously more plural part of the country.

According to our result there is a significant difference in religious diversity [F(1,378)=24.4, p<0.0001], ethnic diversity [F(1,378)=8.1, p=0.005] and number of religions [F(1,378)=11.3, p=0.001] between the two part of Poland based on the historical national border from 1900 (Table 5). The biggest difference between the two parts of the country can be found in the religious diversity, then in the number of religions and finally the ethnicity diversity.

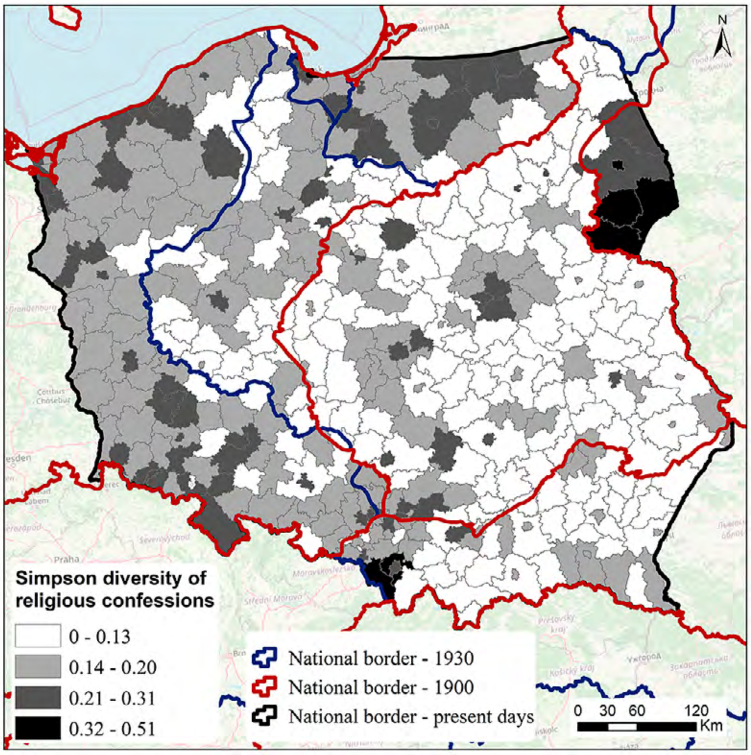

Figure 6. Historical and present-day borders of Poland overlayed on the Simpson Diversity Index map of religious confessions, red line = national border from 1900, blue line = national border from 1930, black line = present-day national border

Table 5. Results of one-way ANOVA test based on the two parts of Poland (inside 1900 border and outside the 1900 border). df means degrees of freedom; F mean F ratio=mean square(between groups)/mean square(within groups).

		Sum of Squares	df	Mean Square	F	Sig.
Religious diversity	Between Groups	0.115	1	0.115	24.403	< 0.0001
	Within Groups	1.774	378	0.005		
	Total	1.888	379			
Ethnic diversity	Between Groups	0.206	1	0.206	8.056	0.005
	Within Groups	9.648	378	0.026		
	Total	9.854	379			
Number of religions	Between Groups	13.306	1	13.306	11.317	0.001
	Within Groups	444.421	378	1.176		
	Total	457.726	379			
Number of ethnicities	Between Groups	6.008	1	6.008	2.670	0.103
	Within Groups	850.463	378	2.250		
	Total	856.471	379			

National border of Romania from 1900 enclose an area, which is religiously homogeneous. Areas outside of the border from 1900 even more clearly delineate the religiously more plural part of the country.

According to our result there is a significant difference in religious diversity [$F(1,2937)=1421.4$, $p<0.0001$], ethnic diversity [$F(1,2937)=701$, $p<0.0001$], number of religions [$F(1,2937)=518.7$, $p<0.0001$] and number of ethnicities $F(1,2937)=290.2$, $p<0.0001$] between the two part of Romania based on the historical national border from 1900 (Table 6). Comparing to the Poland ANOVA test the Romanian show much more significant and biggest differences between the two parts of the country. The biggest difference can be observed in case of the religious diversity, on the second place the ethnic diversity, third is the number of religions and finally the number of ethnicities.

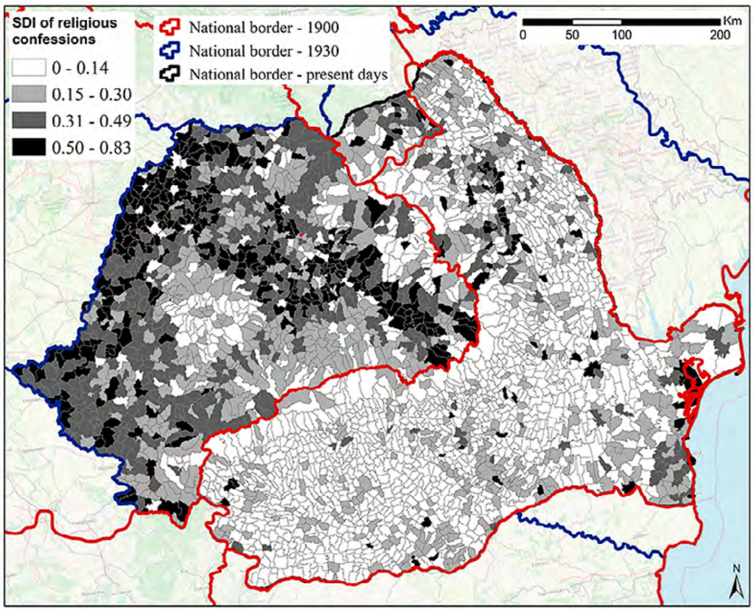

Figure 7. Historical and present-day borders of Romania overlayed on the Simpson Diversity Index map of religious confessions, red line = national border from 1900, blue line = national border from 1930, black line = present-day national border

Table 6. Results of one-way ANOVA test based on the two parts of Romania (inside 1900 border and outside the 1900 border). df means degrees of freedom; F mean F ratio=mean square(between groups)/mean square(within groups).

		Sum of Squares	df	Mean Square	F	Sig.
Religious diversity	Between Groups	30.832	1	30.832	1421.396	<0.0001
	Within Groups	63.708	2937	0.022		
	Total	94.540	2938			
Ethnic diversity	Between Groups	9050.180	1	9050.180	700.897	<0.0001
	Within Groups	37923.348	2937	12.912		
	Total	46973.528	2938			
Number of religions	Between Groups	11.438	1	11.438	518.681	<0.0001
	Within Groups	64.766	2937	0.022		
	Total	76.204	2938			
Number of ethnicities	Between Groups	1571.016	1	1571.016	290.156	<0.0001
	Within Groups	15902.058	2937	5.414		
	Total	17473.074	2938			

Discussion

In this study, the spatial distribution of religious pluralism and ethnic diversity were analysed across Central and Eastern Europe and in more detailed in three selected countries, Hungary, Poland and Romania. We also investigated the importance and effect of the historical and present-day borders and our results also support the borderline syndrome theory. However, we know that the data collection and processing of population censuses are so far not flawless, but at this number of units the error is negligible.

One of the main aims of the research was the creature of a unique dataset of the religious confessions in Central and Eastern Europe. This dataset is ready and free for anyone to use. The built webmap give the opportunity to the non-GIS experts to easily use this dataset. In the pop-up window, percentage of the religious confessions and Simpson Diversity values can be checked by municipalities. The infographic tab gives the chance to check the percentage distribution of religions by country. In the print tab anyone can make and print a professional map (current window extent) in several document type, which also support the non-GIS expert users. This kind of webmap and dataset about Central and Eastern Europe is unique.

Our manuscript provides a comprehensive Central European analysis of dominant religion and religious diversity at the municipality level, compared with other authors who providing similar analyses in just country or state scale (Ahlin et al., 2012; Cnaan & Boddie, 2015; Dövényi & Németh, 2014; Hero, Krech, & Zander, 2008; Pew Research Center, 2022) or only per larger unit at lower resolution (Pew Research Center, 2022; Warf & Vincent, 2007). Diversity of religious confessions researches exist in our country scale study area too, like in Hungary (Bajmócy, n.d.; Bajmócy Péter., 2009; Dövényi & Németh, 2014; Harrach, 2013; Kocsis, 1996), Poland (Sealy et al., 2021) and Romania (Csala, 2015; Pavel, Moldovan, Kourtit, & Nijkamp, 2020; Vințe, Furtună, & Dârdală, 2017).

Sociological theories of modernization (e.g., Berger, 1981; Pollack, 2008; Pollack & Rosta, 2017) have undoubtedly made it possible to analyse changes in the values of various societies, whether on the European continent or globally, using general indicators. These indicators have demonstrated their ability to forecast the strength and direction of change. It is important to note, however, that in the case of Central and Eastern European societies, the cultural indicators included in the variables of theories lack historical relevance. Since 1990, historical trauma-centred memory and memory politics have played a prominent role in the Central and Eastern European region. For centuries, the hegemonic empire power from the West and East defined the borders and national and state belongings. The region's common sense was emphasised by the region's endless needs for autonomy under the various occupations, which had a formative influence on the region's sensibilities and led to temptations of nationalism and xenophobia. Central and Eastern Europe is a border region that exhibits symptoms of collective borderline disorder (Szilárdi & Kakuszi, 2022). Our result (diversity, coefficient of variance) also supports this theory that the former national borders and traumas have significant effect on the today religious pluralism in the Central and Easter European countries and also in more detailed scale, in Hungary, Poland and Romania. Our results can prove that there is a big difference in the religious diversity between the municipalities inside the former borders and inside the present-day borders (Eberhardt & Owsinski, 2015). The borders moved away, but a certain percentage of the population remained in its previous place (Eberhardt & Owsinski, 2015). Kocsis et al. (2015) found similar results in Pannonian area, but our results are supported by significant statistical analysis (ANOVA) (Kocsis et al., 2015). The website of phantomgrenzen.eu also shows differences between current and formal state borders, but more focused on other social processes such as elections. The differences between the parts of the countries can be explained by the ethnicities, as our results show there are positive significant correlations were found between religious confessions (SDI, RI) and ethnicities (SDI, RI), as Dimova & Dimov (2021) in their study also found that different ethnicities have different and stronger religious identity.

Our work applies a quantitative method (diversity indices) to measure and visualize the religious diversity of Central and Eastern Europe (CEE) at a very high resolution (municipality level). To our knowledge, this is the first study that uses this method at this level of analysis for this region. We also explore the relationship between religious diversity and ethnic diversity, as well as historical factors such as former national borders. We believe that our work contributes to a better understanding of how religion shapes national identity and social cohesion in CEE, which is an important topic in light of recent political developments in this region. Our work also serves as a basis for further research on religious pluralism in CEE using other methods or perspectives.

Conclusion

In this study, the spatial distribution of religious pluralism and ethnic diversity was analysed across Central and Eastern Europe and in more detailed in three selected countries, Hungary, Poland and Romania. The importance and effect of the historical and present-day borders was investigated and our results also support the borderline syndrome theory. One of the main aims of the research was the creature of a unique dataset of the religious confessions in Central and Eastern Europe. This dataset is ready and free for anyone to use. The built webmap give the opportunity to the non-GIS experts to easily use this dataset. This kind of webmap and dataset about Central and Eastern Europe is unique. Our manuscript provides a comprehensive Central European analysis of dominant religion and religious diversity at the municipality level. Our results prove that there is a big difference in the religious diversity between the municipalities inside the former borders and inside the present-day borders. Central and Eastern Europe is a border region that exhibits symptoms of collective borderline disorder and our result supports this theory that the former national borders and traumas have significant effect on the today religious pluralism in the Central and Easter European countries. This study and public dataset (webmap) also serve as a good basis for further research (theoretical and statistical) of the religious pluralism in Central and Eastern Europe.

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ISSN 0354-8724 (hard copy) | ISSN 1820-7138 (online)

Geospatial Analysis of Population Ageing in Bosnia and Herzegovina

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Received: December 28, 2022 | Revised: March 09, 2023 | Accepted: March 10, 2023
doi: 10.5937/gp27-41960

Abstract

The aim of this research is to analyze the spatial distribution of the population ageing in Bosnia and Herzegovina and identify areas of the country that are particularly vulnerable to negative demographic trends. To achieve the goal of the study, data on the ageing coefficient and ageing index for the period 2013-2020 were used. The geospatial analysis of these indicators was performed using global (Global Moran's I and Getis-Ord General G) and local (Anselin Local Moran's I and Getis-Ord G*) indexes of spatial autocorrelation. The research results confirmed the clustering of both indicators. Ageing coefficient values are clustered in municipalities in western, northwestern, eastern, and central Bosnia and Herzegovina. Ageing index values are clustered in municipalities in central, western, northwestern, and northeastern Bosnia and Herzegovina. This study provides insight into the research methods of spatial demographic trends and phenomena, and its findings can serve as a basis for future demographic research and development in Bosnia and Herzegovina.

Keywords: spatial analysis; spatial autocorrelation; spatial patterns; population ageing; Bosnia and Herzegovina

Introduction

The age distribution of a population is a vital indicator of its composition, which when analysed, can reveal the demographic development of a particular population. Analysis of age population composition, when applied to five-year age groups, can reveal the population's potential vitality and biodynamics. Demographic process of population ageing is a widespread phenomenon. The increase in the share of people who are 65 or older and the increase in the mean age of the population characterize this adverse demographic process in contemporary society (Wu et al., 2021; Li et al., 2019; d'Albris & Collard, 2013; Kerbler, 2015; Bucher, 2014).

Socio-economic, political, social, biological, and other factors at the beginning of the 21st century influenced Bosnia and Herzegovina's demographic trends, including the population's age structure. The total population of Bosnia and Herzegovina declined because of a considerable decrease in birth rates, a slight increase in mortality rates, and, consequently, low natural population change rates along with a negative migration balance. Bosnia and Herzegovina has recorded negative population change rates since 2007, and the country is still losing its youthful and productive population due to economic emigrations. All of the processes mentioned above have an effect on the population's ageing process, potential bio-dynamics, and population vitality or health (Kadusic & Suljic, 2018; Kadusic et al., 2016).

Spatial analysis is especially important in demographic analysis, and thus in the analysis of popu-

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lation ageing and spatial differences in the level and causes of population ageing in different areas. The spatial autocorrelation method can be used to analyze the spatial distribution of different demographic processes, including population ageing. As a result, numerous studies in the field of spatial analysis of population ageing using spatial autocorrelation methods have been conducted. Wang (2020), for example, examined the spatial patterns and socioeconomic factors of population ageing on a global scale from 1990 to 2010. Káčerová et al. (2022) examined population ageing in Slovakia from 1950 to 2021, with a particular emphasis on spatiotemporal analysis. Guan et al. (2020) investigated the spatial and temporal variations of population ageing in China's Liaoning Province, whereas Chen et al. (2019) used spatial autocorrelation methods to investigate the spatial patterns of population ageing in China from 1998 to 2014. Reynaud et al. (2018) studied spatial distribution and patterns of population ageing in Italy from 2002 to 2014. Nikitović et al. (2016) used spatial autocorrelation indices to determine spatial patterns of demographic trends in Serbia from 1961 to 2010, and Kurek (2003) analyzed the spatial distribution of the ageing process in Poland from 1988 to 2001.

There have not been many studies on the spatial distribution and disparities of the population ageing process in Bosnia and Herzegovina. However, several studies on Bosnia and Herzegovina's demographic trends have been conducted. For example, Gekic et al. (2020) studied depopulation trends in Bosnia and Herzegovina at the end of the 20th and beginning of the 21st centuries, whereas Gekic et al. (2019) researched spatial differentiation of the age structure of the population in Bosnia and Herzegovina. Mijic & Ateljevic (2018) studied the use of contemporary GIS software in demographic research of the Bosnian entity of the Republic of Srpska. Kadusic et al. (2016) researched the causes and consequences of population ageing in Bosnia and Herzegovina. It should be noted that prior studies on population ageing and other demographic variables in Bosnia and Herzegovina did not make extensive use of spatial analysis and spatial autocorrelation methods.

The primary assumption of this research is that certain areas of Bosnia and Herzegovina are particularly at risk due to population ageing. As a result, the primary goals of this study are to investigate trends in population ageing and population change in municipalities of Bosnia and Herzegovina from 2013 to 2020, to analyze the spatial pattern of population ageing in Bosnia and Herzegovina using global and local autocorrelation statistics parameters, and to provide a geovisualization of population ageing spatial distribution.

Methods and data

Spatial analysis of demographic phenomena provides a comprehensive understanding of demographic processes and demonstrates the significance of spatial statistical techniques in the spatial analysis of demographic occurrences (Kurek et al., 2021, Nikitović et al., 2016). In this study, a spatial analysis of population ageing in Bosnia and Herzegovina was conducted using spatial autocorrelation methods in order to identify spatial clusters with high or low population ageing values. Spatial autocorrelation methods enable the analysis of the various variables and demonstrate how similar or different variables are in adjacent locations. Global statistical indices of spatial autocorrelation and local statistical indices can be distinguished. Global statistical indices can be used to analyze spatial autocorrelation through an entire dataset or statistical sequence. Local statistical indices of spatial autocorrelation can be used to identify hot and cold spot areas (Guan et al., 2020; Chen et al., 2019; Anselin, 1995; Ord & Getis 1995; Anselin & Getis, 1992).

Global statistical indices (Global Moran's I and Getis-Ord General G) and local statistical indices (Anselin Local Moran's I and Local Getis-Ord Gi*) were used to determine the spatial distribution of population ageing, that is, whether population ageing is clustered or dispersed in Bosnia and Herzegovina.

The value of the global Moran's I index ranges between -1 and +1. The research begins with the null hypothesis, which states that there is no spatial autocorrelation between variables. The statistical significance of global Moran's I is determined using the p-value and z-score. If the index value is significant and positive, the index value will vary between 0 and +1, indicating positive spatial autocorrelation and spatial clustering of values. If the global Moran's I is statistically significant and negative, its value will be in the range of 0 to -1, indicating a negative spatial correlation between the values and the data dispersion. Therefore, using this index, it can be determined whether the ageing is clustered, dispersed, or random.

The Global Getis-Ord General G Index indicates the clustering of low or high values. The index's results must always be interpreted in the context of the null hypothesis. If the null hypothesis is rejected (statistically significant p-value), a positive z-score value indicates the clustering of high values in the researched area. If the z-score value is negative, the low values are clustered in the study area.

The clustering of low and/or high values can also be determined using the Anselin Local Moran's I index. Positive and statistically significant z-score values reveal where high and low values are concentrated in the research area. Negative and statistically significant z-score values indicate spatial data outliers (low-high, high-low values).

In this study, the Local Getis-Ord Gi* Index of spatial autocorrelation was also utilized. This index identifies spatial clusters of statistically significant high and low values. For each feature in the Input Feature Class, a new Output Feature Class with a *z*-score, *p*-value, and confidence level bin is generated (Gi Bin). This index's high *z*-score and low *p*-value indicate hot spots, while its low negative *z*-score and low *p*-value indicate cold spots. The Gi Bin field reveals statistically significant hot and cold spots with a 99%, 95%, and 90% degree of confidence. Clustering for features in bin 0 is not statistically significant, whereas features in bins +/-3 show statistical significance with a 99% confidence level, features in +/-2 show statistical significance with a 95% confidence level, and features in +/-1 show statistical significance with a 90% confidence level.

As an indicator of population ageing in Bosnia and Herzegovina, the ageing coefficient, or the share of the population aged 65 and over in the overall population, and the ageing index, which compares the population older than 65 and the population 0 to 14 years old, for 142 municipalities, were calculated over the period from 2013 to 2020. The ageing coefficient and ageing index are often used indicators because they provide more detailed information on a population's ageing. These indicators are important for identifying areas where the population is ageing faster, comparing the ageing of populations of various sizes, and determining the degree of population ageing. Since the last population census in Bosnia and Herzegovina was conducted in 2013, age distribution estimates by municipalities in Bosnia and Herzegovina were acquired from the Agency for Statistics of Bosnia and Herzegovina (BHAS), Institute for Statistics of Federation of Bosnia and Herzegovina (FZS), and the Republic of Srpska Institute of Statistics (RZSRS).

In order to determine the main factors in the spatial distribution of the ageing process in Bosnia and Herzegovina, average death rates and other demographic indicators, like average birth rates, natural population change rates, vital indexes, and ageing coefficients, were calculated for 142 municipalities in Bosnia and Herzegovina over the course of eight years (2013–2020). Kolmogorov-Smirnov and Shapiro-Wilk tests were conducted to determine the distribution of the abovementioned datasets (Pallant, 2011). In order to determine the correlation between demographic parameters and indicators of population ageing in Bosnia and Herzegovina, the nonparametric method Spearman's Rank-Order Correlation was used.

Results

A variety of factors can influence population ageing, including demographic, economic, social, health and healthcare, and environmental factors (Wan et al., 2022; Beard & Bloom, 2015; Almedia de Melo et al., 2010). Many different factors influenced the ageing process of Bosnia and Herzegovina's population, but demographic factors and changes were the largest ones. According to Gekic et al. (2019), the demographic development of Bosnia and Herzegovina in the 20th century was significantly influenced by a number of complex social, political, and economic issues. This was most visible at the end of the twentieth century, during the war in 1992-1995, which resulted in significant negative demographic consequences. Bosnia and Herzegovina entered the twenty-first century with two distinct demographic depopulation processes: total depopulation and demographic ageing, both with distinct spatial-regional and with urban-rural population polarization (Gekic et al., 2019).

There is a significant correlation between the natural population rates of Bosnia and Herzegovina and its age structure. The war in Bosnia and Herzegovina from 1992 to 1995 resulted in major population shifts. The total population of Bosnia and Herzegovina has decreased due to war fatalities and forced migration. In addition to the adverse economic, social, political, and other situations, it resulted in a decrease in post-war population growth rates caused by negative population change rates and emigration of the young population (Table 1).

Table 1. Natural population change rates in B&H, 2013-2020

Year	Birth rates in ‰	Death rates in ‰	NPG* rate in ‰
2013	8.7	10.1	-1.4
2014	8.6	10.2	-1.6
2015	8.5	10.8	-2.3
2016	8.6	10.4	-1.8
2017	8.6	10.8	-2.2
2018	8.4	10.8	-2.4
2019	8.1	11.1	-3.0
2020	7.8	12.8	-5.0

** NPG - Natural Population Change*
Source: BHAS, 2022

Bosnia and Herzegovina's birth rates have a decreasing trend, whereas mortality rates have an increasing trend, which indicates that Bosnia and Herzegovina has entered a post-transition stage of demographic development. Negative natural population change rates have been recorded in this country since 2007. In 2013, the natural population change rate was -1.4, and in 2020 reached a value of -5.0‰. The result of a decrease in birth rates and natural population change rates was a decrease in the proportion of young people and an increase in the proportion of older people in Bosnia and Herzegovina's total population. In the period from 2013 to 2020, the median age of the population of Bosnia and Herzegovina increased from 41.3 to 43.3 years, the vital index decreased from 0.869 to 0.618, the ageing coefficient increased from 14.3% to 17.8%, and the ageing index increased from 86.42% to 126.45% (BHAS, FZS, RZSRS, 2022). Table 2. depicts the relationship between fundamental demographic components and population ageing indicators in Bosnia and Herzegovina from 2013 to 2020.

The calculation of Spearman's correlation for Bosnia and Herzegovina's basic demographic components from 2013 to 2020 confirmed that there is a strong relationship between the ageing coefficient, the ageing index, and the components of natural population change and the vital index. Municipalities in Bosnia and Herzegovina with low vitality indexes and negative natural population change rates have higher ageing coefficient and ageing index values (Table 2).

According to *p*-values of 0.000 for Global Moran's I and 0.011 for Getis-Ord General G, which indicate that the null hypothesis is rejected, the spatial distribution of high and/or low values in the observed statistical ageing coefficient dataset in Bosnia and Herzegovina is more clustered than would be expected in random spatial processes. Furthermore, given the z-score of 6.129 for Global Moran's I, the likelihood that the spatial distribution of the ageing coefficient is a product of chance is less than 1.0%. Given the *z*-score of 2.537 for Getis-Ord General G, there is less than a 5% likelihood that the high-clustered pattern of the ageing coefficient could be the result of random chance. The clustering of the ageing coefficient in Bosnia and Herzegovina is therefore confirmed by Global Moran's I of 0.299 (z-score of 6.129; *p*-value of 0.000) and Getis-Ord General G value of 0.007 (*z*-score of 2.537; *p*-value of 0.011) (Figs. 1, 2).

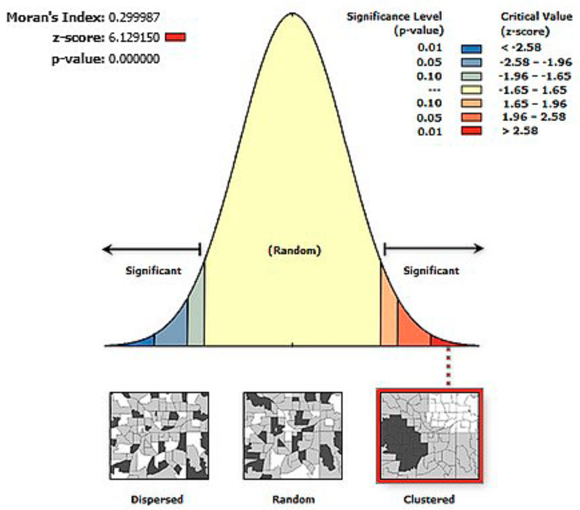
Table 2. Spearman's Rank Order Correlation between ageing indicators and demographic variables in B&H, 2013-2020

Variable	Correlation	Age Coefficient	Ageing Index
Birth rates	Corr. Coefficient	-.467**	-.627**
	Sig. (2-tailed)	.000	.000
Death rates	Corr. Coefficient	.701**	.596**
	Sig. (2-tailed)	.000	.000
NPG*	Corr. Coefficient	-.852**	-.883**
	Sig. (2-tailed)	.000	.000
Vital index	Corr. Coefficient	-.830**	-.912**
	Sig. (2-tailed)	.000	.000

** Natural Population Change*

***. Correlation is significant at the 0.01 level (2-tailed).*

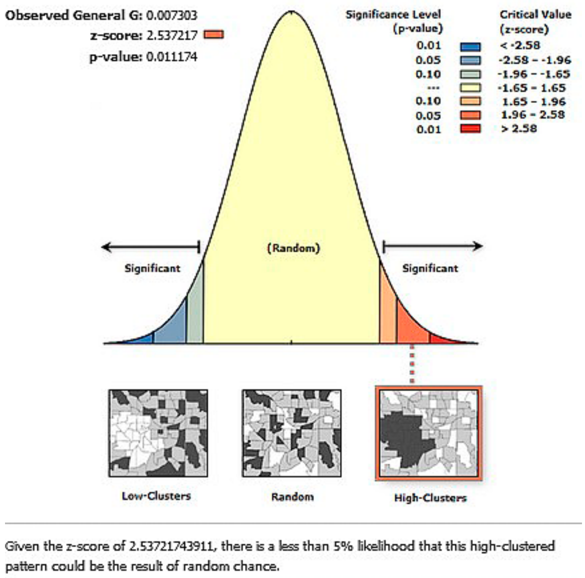
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)



Given the z-score of 6.12915001206, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

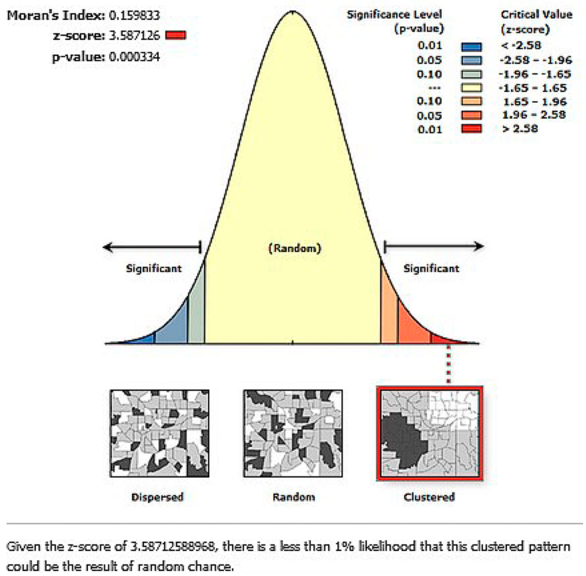
Global Moran's I Summary	
Moran's Index:	0.299987
Expected Index:	-0.007092
Variance:	0.002510
z-score:	6.129150
p-value:	0.000000

Figure 1. Global Moran's I final statistics and diagram for ageing coefficient in B&H, 2013-2020
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)



General G Summary	
Observed General G:	0.007303
Expected General G:	0.007092
Variance:	0.000000
z-score:	2.537217
p-value:	0.011174

Figure 2. Getis Ord General G final statistics and diagram for ageing coefficient in B&H, 2013-2020
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

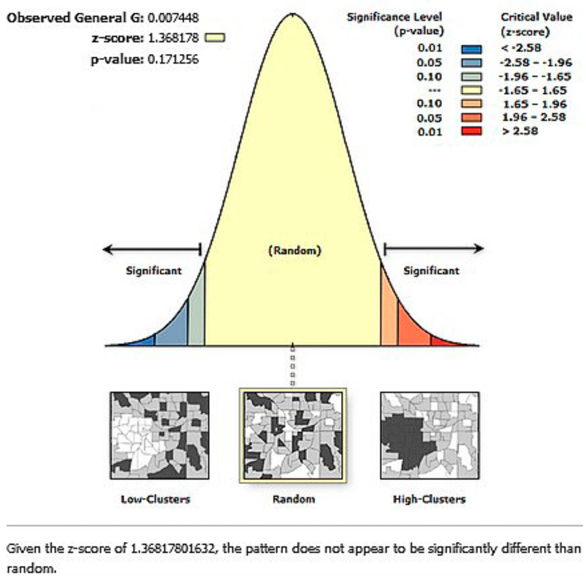


Global Moran's I Summary	
Moran's Index:	0.159833
Expected Index:	-0.007092
Variance:	0.002165
z-score:	3.587126
p-value:	0.000334

Figure 3. Global Moran's I final statistics and diagram for ageing index in B&H, 2013-2020
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

A p-value of 0.000 for Global Moran's I indicate that the null hypothesis is rejected and that the spatial distribution of high and/or low values in the observed statistical ageing index dataset in Bosnia and Herzegovina is more clustered than would be expected in random spatial processes. Given the z-score of 3.587 for Global Moran's I, there is less than a 1.0% probability that this spatial distribution of ageing index values in Bosnia and Herzegovina could be the result of chance (Fig. 3). However, the spatial distribution of ageing index values does not appear to be significantly different from random based on the z-score of 1.368 and p-value of 0.171 for Getis Ord General G (Fig. 4).

Spatial clusters with high or low ageing coefficient and ageing index values in Bosnia and Herzegovina for the period 2013-2020 were identified using the local statistical indices Anselin Local Moran's I and Getis Ord Gi*. The statistical significance of local indices is based on the ratio of the z-score and p-value at the 0.01 significance level. For both datasets, the Anselin Local Moran's I of 0.299 for the age coefficient and 0.159 for the ageing index indicate moderate positive spatial autocorrelation. Positive autocorrelation means that the values in one area are similar to the values in the areas around it, while negative autocorrelation indicates outliers (Figs. 5 and 6, Table 3).



General G Summary	
Observed General G:	0.007448
Expected General G:	0.007092
Variance:	0.000000
z-score:	1.368178
p-value:	0.171256

Figure 4. Getis Ord General G final statistics and diagram for ageing index in B&H, 2013-2020
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

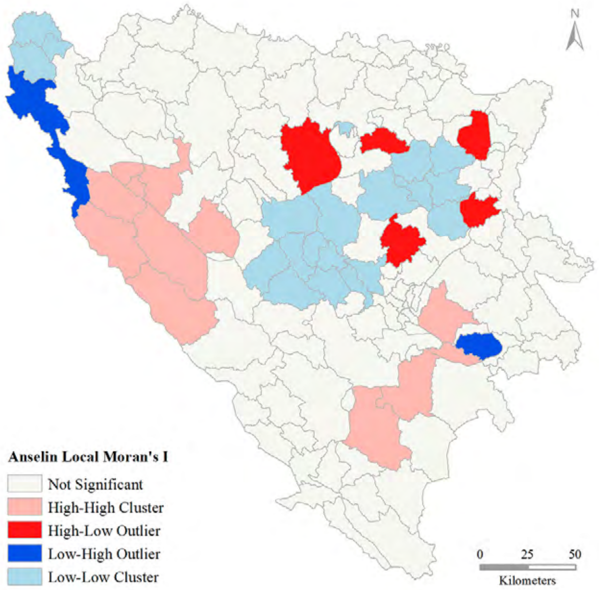


Figure 5. Spatial autocorrelation analysis of ageing coefficient in Bosnia and Herzegovina from 2013 to 2020
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

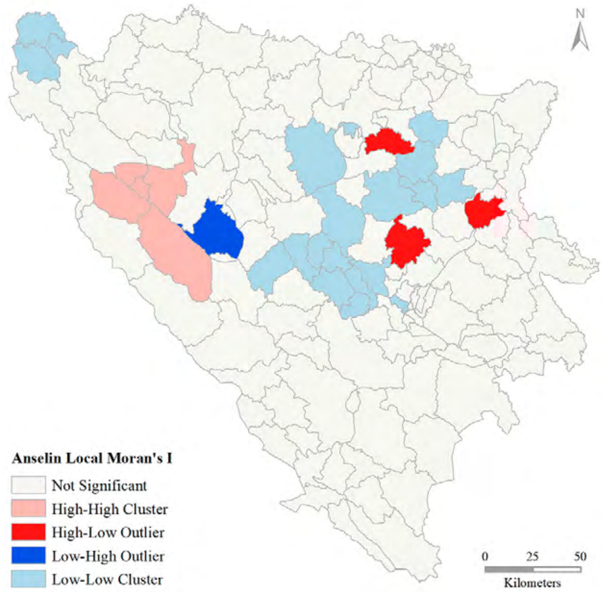


Figure 6. Spatial autocorrelation analysis of ageing index in Bosnia and Herzegovina from 2013 to 2020
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

Table 3. Local Moran's I statistics of ageing coefficient and ageing index in Bosnia and Herzegovina, 2013-2020

Municipality	Ageing Coefficient				Ageing index			
	Moran's I	z-score	p-val.	Type	Moran's I	z-score	p-val.	Type
B. Grahovo	2.601	1.749	0.046	HH	-	-	-	-
Banovići	1.114	2.077	0.006	LL	0.425	1.200	0.016	LL
Bihać	-0.694	-1.995	0.026	LH	-	-	-	-
Bugojno	0.588	1.740	0.032	LL	0.292	1.299	0.016	LL
Busovača	0.980	2.361	0.002	LL	0.469	1.707	0.002	LL
Bužim	2.194	2.208	0.006	LL	0.769	1.300	0.002	LL
Cazin	1.782	2.436	0.002	LL	0.630	1.572	0.002	LL
Drvar	2.634	3.363	0.004	HH	2.387	5.103	0.002	HH
Foča (FBiH)	0.978	2.336	0.018	HH	-	-	-	-
Fojnica	0.527	2.088	0.006	LL	0.315	1.506	0.006	LL
G. Vakuf	0.555	1.452	0.048	LL	-	-	-	-
Glamoč	2.591	4.820	0.002	HH	0.889	6.723	0.002	HH
Goražde	1.438	2.281	0.03	HH	-	-	-	-
Goražde	-0.218	-2.092	0.034	LH	-	-	-	-
Ist. Drvar	0.179	3.283	0.01	HH	4.738	2.160	0.032	HH
Kiseljak	0.487	1.876	0.022	LL	0.317	1.482	0.006	LL
Kladanj	0.668	1.474	0.046	LL	-	-	-	-
Livno	0.065	2.562	0.026	HH	-	-	-	-
Lopare	-0.314	-1.643	0.04	HL	-	-	-	-
Lukavac	0.284	1.900	0.016	LL	0.162	1.443	0.018	LL
N.Travnik	1.035	2.438	0.004	LL	0.462	1.526	0.004	LL
Nevesinje	0.456	2.128	0.018	HH	-	-	-	-
Pale (RS)	0.072	2.755	0.006	HH	-	-	-	-
Petrovac	1.294	1.778	0.05	HH	0.929	3.518	0.014	HH
Petrovo	-0.739	-1.733	0.028	HL	-0.231	-1.397	0.012	HL

Municipality	Ageing Coefficient				Ageing index			
	Moran's I	z-score	p-val.	Type	Moran's I	z-score	p-val.	Type
Ribnik	0.892	2.170	0.032	HH	0.415	2.823	0.016	HH
Šekovići	-0.258	-2.014	0.012	HL	-0.072	-1.404	0.024	HL
Šipovo	0.407	2.289	0.02	HH	-0.006	-2.375	0.046	LH
Teslić	-0.075	-1.995	0.02	HL	0.127	1.557	0.008	LL
Travnik	0.455	1.859	0.022	LL	-	-	-	-
Tuzla	0.011	1.590	0.042	LL	-	-	-	-
Usora	0.360	1.595	0.036	LL	-	-	-	-
V. Kladuša	2.301	2.249	0.002	LL	0.789	1.390	0.002	LL
Vareš	-0.572	-1.990	0.016	HL	-0.216	-1.531	0.004	HL
Visoko	0.536	1.693	0.03	LL	0.314	1.434	0.01	LL
Vitez	0.921	2.096	0.006	LL	0.445	1.451	0.004	LL
Zenica	0.599	2.401	0.002	LL	0.352	1.771	0.002	LL
Živinice	0.82	1.611	0.028	LL	0.328	1.161	0.05	LL

Results significant at the 0.05 level

Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

In certain municipalities in western, northwestern, eastern, northeastern, and central Bosnia and Herzegovina, the clustering of ageing coefficient values is identified. The municipalities of western Bosnia and Herzegovina identified in the high-high quadrant are Ribnik, Petrovac, Istočni Drvar, Drvar, Glamoč, Šipovo, Livno; the municipalities of northwestern Bosnia and Herzegovina located in the high-high quadrant are Velika Kladuša, Bužim and Cazin; in eastern Bosnia and Herzegovina, the municipalities of Pale-RS, Foča-FBiH, Kalinovik and Nevesinje are identified in the high-high quadrant. In the low-low quadrant in the central areas of Bosnia and Herzegovina, municipalities Zenica, Zavidovići, Travnik, Novi Travnik, Bugojno, Vitez, Busovača, Gornji-Vakuf-Uskoplje, Fojnica and Kiseljak are identified; in northeastern Bosnia and Herzegovina, municipalities Tuzla, Lukavac, Živinice, Kladanj and Banovići are identified in the low-low quadrant (Fig. 5, Table 3).

Clustering of ageing index values is identified in western, northwestern, northeastern, and central Bosnia and Herzegovina. The municipalities of western Bosnia and Herzegovina identified in the high-high quadrant are Ribnik, Petrovac, Istočni Drvar, Drvar and Glamoč. In the low-low quadrant in the central areas of Bosnia and Herzegovina, municipalities Zenica, Teslić, Bugojno, Novi Travnik, Vitez, Busovača, Visoko, Kiseljak, Fojnica, Kreševo and Novi Grad Sarajevo are identified; in northeastern Bosnia and Herzegovina, municipalities Zavidovići, Banovići, Živinice, Lukavac and Srebrenik are identified in the low-low quadrant; in the northwest of the country, the municipalities Velika Kladuša, Bužim and Cazin are identified in the low-low quadrant (Fig. 6, Table 3).

The Getis-Ord Gi* Index was used to identify high-risk and low-risk areas of population ageing in Bosnia and Herzegovina using values of the ageing coefficient and ageing index. Hot spots of the ageing coefficient with 99% confidence intervals were identified in western Bosnia and Herzegovina (municipalities of Istočni Drvar, Drvar, Bosansko Grahovo, Glamoč and Kupres-RS), eastern Bosnia and Herzegovina (Pale-RS, Foča-FBiH and Kalinovik) and 95% confidence intervals in western Bosnia and Herzegovina (municipalities of Petrovac, Ribnik, Šipovo and Livno). A cold spot cluster of ageing coefficient with a 99% confidence interval was identified in the northwestern parts of Bosnia and Herzegovina (municipalities Velika Kladuša, Bužim and Cazin), whereas cold spot clusters with a 95% confidence level were identified in central Bosnia and Herzegovina (municipalities Zenica, Travnik, Novi Travnik, Vitez, Bugojno, Fojnica, Kiseljak and Zavidovići), and northeastern Bosnia and Herzegovina (municipalities Lukavac, Živinice and Banovići) (Fig. 7). Hot spots of the ageing index with 99% and 95% confidence intervals were identified in western Bosnia and Herzegovina (municipalities Petrovac, Istočni Drvar, Drvar, Ribnik, Glamoč, Kupres-RS, Bosansko Grahovo and Šipovo) (Fig. 8, Table 4).

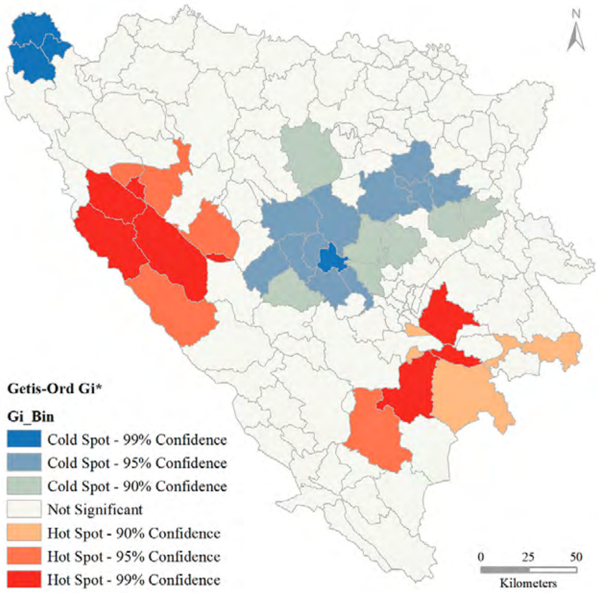


Figure 7. Getis-Ord G* analysis of ageing coefficient in Bosnia and Herzegovina from 2013 to 2020
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

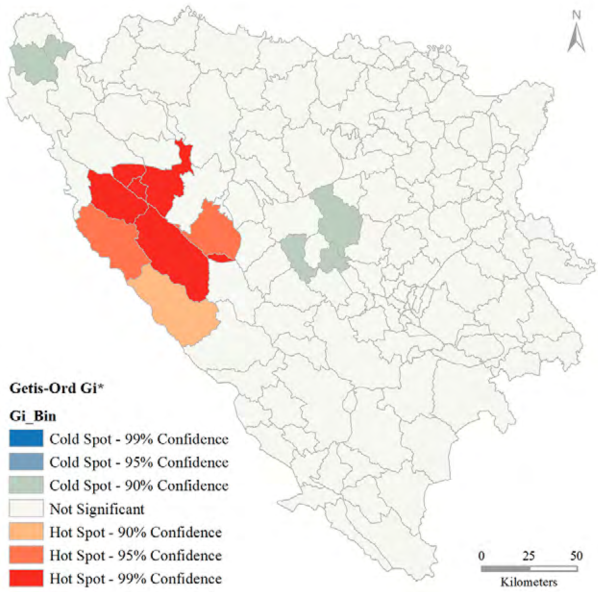


Figure 8. Getis-Ord G* analysis of ageing index in Bosnia and Herzegovina from 2013 to 2020
Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

Table 4. Getis Ord G* statistics for ageing coefficient and ageing index in Bosnia and Herzegovina, 2013-2020

Municipality	Ageing Coefficient			
	z-score	p-value	Gi-Bin	Confidence Level
B. Grahovo	2.923	0.003	Hot Spot	99%
Banovići	-2.324	0.02	Cold Spot	95%
Bugojno	-1.969	0.048	Cold Spot	95%
Busovača	-2.638	0.008	Cold Spot	99%
Bužim	-2.803	0.005	Cold Spot	99%
Cazin	-2.882	0.003	Cold Spot	99%
Drvar	3.842	0.000	Hot Spot	99%
Foča (FBiH)	2.596	0.009	Hot Spot	99%
Fojnica	-2.164	0.03	Cold Spot	95%
Glamoč	4.986	0.000	Hot Spot	99%
Ist. Drvar	3.137	0.001	Hot Spot	99%
Kalinovik	2.653	0.007	Hot Spot	99%
Kiseljak	-2.027	0.04	Cold Spot	95%
Kupres (RS)	2.835	0.004	Hot Spot	99%
Livno	2.243	0.024	Hot Spot	95%
Lukavac	-1.972	0.04	Cold Spot	95%
N. Travnik	-2.559	0.01	Cold Spot	95%
Nevesinje	2.160	0.03	Hot Spot	95%
Pale (RS)	2.832	0.004	Hot Spot	99%
Petrovac	2.349	0.018	Hot Spot	95%
Ribnik	2.513	0.011	Hot Spot	95%
Šipovo	2.410	0.015	Hot Spot	95%
Travnik	-2.024	0.04	Cold Spot	95%
V. Kladuša	-2.725	0.006	Cold Spot	99%

Municipality	Ageing Coefficient			
	z-score	p-value	Gi-Bin	Confidence Level
Vitez	-2.317	0.02	Cold Spot	95%
Zavidovići	-2.169	0.03	Cold Spot	95%
Zenica	-2.468	0.013	Cold Spot	95%
Živinice	-2.040	0.04	Cold Spot	95%
Municipality	Ageing Index			
	z-score	p-value	Gi-Bin	Confidence Level
B. Grahovo	2.338	0.019	Hot Spot	95%
Drvar	4.729	0.000	Hot Spot	99%
Ist. Drvar	4.287	0.000	Hot Spot	99%
Kupres (RS)	2.650	0.008	Hot Spot	99%
Petrovac	3.749	0.000	Hot Spot	99%
Ribnik	2.835	0.004	Hot Spot	99%
Šipovo	2.114	0.034	Hot Spot	95%

Results significant at the 0.05 level

Source: Author's calculation (BHAS, FZS, RZSRS, 2022)

Discussion

Numerous studies have been conducted all over the world on the extent of population ageing and the factors that contribute to it (Káčerová et al., 2022; Wang, 2020; Guan et al., 2020; Bucher, 2014). According to Wang (2020) and Bucher (2014), there are significant regional differences in population ageing. Therefore, studies indicating spatial inequalities and variations in population ageing in various countries and regions of the world have received special attention (Reynaud et al., 2018; Nikitović et al., 2016; Pina et al., 2013).

The spatial autocorrelation method is a particularly effective tool for identifying the spatial distribution, spatial disparities, and clustering of the population ageing process. This method can be used to determine a connection between numerous variables and provides insight into spatial disparities, such as whether or not there is a concentration of data in the area being studied (Kurek et al., 2021; Anselin, 1995; Ord & Getis, 1995). Therefore, the findings of studies based on spatial autocorrelation analysis can contribute to a better understanding of population ageing and the factors that influence this demographic phenomenon (Káčerová et al., 2022; Chen et al., 2019).

This study presents the results of a spatial analysis of population ageing in Bosnia and Herzegovina. The findings of this study confirmed that the spatial autocorrelation method is a particularly effective tool for identifying spatial disparities in Bosnia and Herzegovina's population ageing process. To determine spatial variations of ageing indicators in Bosnia and Herzegovina, the Global Morans I, Getis-Ord General G, and Anselin Local Morans I and Getis-Ord Gi* indexes of spatial autocorrelation were used. Both the ageing coefficient and the ageing index were discovered to cluster together in Bosnia and Herzegovina, as predicted by the Global Statistical Indexes. The clustering of ageing coefficient values was confirmed by local statistical indices in areas in western, northwestern, eastern, northeastern, and central Bosnia and Herzegovina. The clustering of the ageing index value, on the other hand, is identified in western, northwestern, northeastern, and central Bosnia and Herzegovina.

Population ageing is influenced by a variety of factors, including demographic, economic, social, environmental, health, and health care (Wan et al., 2022; Beard & Bloom, 2015; Almedia de Melo et al., 2010). Various studies have shown that numerous variables contribute to population ageing disparities in different areas of Bosnia and Herzegovina, with social, economic, and political factors being the most significant (Gekic et al., 2020; Gekic et al., 2021; Kadusic, Suljic, 2018). These factors have had a considerable impact on the demographic patterns and processes of Bosnia and Herzegovina's population at the beginning of the 21st century. For instance, these factors contributed to negative natural population changes and the emigration of young people (mainly between 20 and 40 years old). Consequently, these processes led to a decrease in the population's potential biodynamics and vitality (Kadusic et al., 2023). Bosnia and Herzegovina's age distribution and natural population change are significantly correlated. The study's findings demonstrated that the vital index and the components of natural population change, as well as the ageing index and the ageing coefficient, are strongly correlated. Higher ageing coefficient and ageing index values are found in Bosnia and Herzegovina municipalities with low vitality index values and negative natural population change rates.

Rural municipalities along the entity boundary line between administrative units of Bosnia and Herzegovina (the Federation of Bosnia and Herzegovina and the Republic of Srpska), and municipalities that were divided by the entity boundary are particularly affected by unfavorable demographic trends. Due to adverse socio-economic and political circumstances, these municipalities are losing some of their population. Economic factors are the primary causes of the continual emigration from Bosnia and Herzegovina. Young, highly educated individuals leaving the country is one issue that is particularly important. Emigration has a direct effect on the ageing of the population, natural changes in the population, and the decrease of population in Bosnia and Herzegovina. Areas with higher levels of economic development and employment opportunities attract younger people, increasing the younger population. Social factors such as cultural norms and values, improved access to healthcare, and higher quality of care all influence population ageing. Areas with higher environmental quality and better availability of natural resources mostly attract a younger population. All of the aforementioned factors are contributing to a decrease in the population's potential biodynamics and vitality, as well as negative natural population changes, an ageing population, and a large number of young people (mostly between the ages of 20 and 40) leaving the country. According to the Ministry of Security of Bosnia and Herzegovina (2019), the estimated number of emigrants who are originally from Bosnia and Herzegovina in foreign countries is at least 2 million, which is 53% of the total population in Bosnia and Herzegovina. According to World Bank estimates, that percentage is slightly lower and amounts to 44.5%, placing Bosnia and Herzegovina in 16th place in the world in terms of emigration rate in relation to the number of inhabitants in the country (out of a total of 214 countries and territories). Bosnia and Herzegovina is faced with a significantly higher rate of population emigration compared to the other countries in the region. With an emigration rate of 44.5%, it is significantly ahead of Serbia (18%), Croatia (20.9%), and Albania (43.6%). Emigration from Bosnia and Herzegovina is a continuous process, and its main causes are economic factors. One especially significant problem is the emigration of young, highly educated people. In Bosnia and Herzegovina, only one in eight young people (aged 16–24) is employed. A large number of young, highly educated people leave this country in search of better living and employment conditions (Ministry of Security, B&H, 2019). According to the laws of Bosnia and Herzegovina, a citizen who permanently settles abroad or who stays abroad for more than three months registers his residence in Bosnia and Herzegovina and the place of residence abroad at the competent diplomatic and consular representation of Bosnia and Herzegovina. However, if a citizen does not plan to stay in the country where he lives permanently, he is not required to register. According to data from the Agency of statistics in Bosnia and Herzegovina (2022), in the period from 2013 to 2020, 31,693 of its citizens emigrated from Bosnia and Herzegovina (an average of about 4,000 citizens emigrated annually). Of course, this does not represent the total number of people who left Bosnia and Herzegovina during the mentioned period, because the majority of people do not register their departure from the country. The population of Bosnia and Herzegovina mostly emigrates to Croatia, Slovenia, Germany, and Austria (Ministry of Security B&H, 2019; ANUBiH, 2019; FZS, 2020).

Ongoing depopulation processes are likely to have an effect on changes in the age structure of Bosnia and Herzegovina's population in the future. This will lead to an unfavorable demographic situation and population development. One of the primary issues facing Bosnia and Herzegovina's contemporary demographic development is a lack of population policy. As a result, this country's economic and social development must be strengthened. Therefore, it is important to define an adequate population policy that will revitalize Bosnia and Herzegovina's demographics.

The results of this study revealed spatial differences in Bosnia and Herzegovina's population ageing. This study's findings are a substantial contribution to demographic studies and a necessary condition for future demographic research, as well as the foundation for the planned demographic development of Bosnia and Herzegovina. Identifying the locations in Bosnia and Herzegovina that are losing population due to population ageing is a major contribution of the study that has been undertaken. The findings can be used to guide future demographic studies in Bosnia and Herzegovina, as well as to identify and further investigate variables that cause regional disparities in population ageing and other demographic variables.

Conclusion

The study emphasizes the use of spatial autocorrelation analysis as an effective method for identifying spatial disparities in population ageing and presents findings on the spatial distribution of ageing coefficient and ageing index values in Bosnia and Herzegovina. Global statistical autocorrelation indices revealed that autocorrelation was moderately positive. Local statistical indices confirmed a clustering of ageing coefficient values in western, northwestern, eastern, northeastern, and central Bosnia and Herzegovina. The ageing index values, on the other hand, are clustered in Bosnia and Herzegovina's central, western, northwestern, and northeastern areas. The study emphasizes that demographic, economic, social, environmental, and healthcare factors have the most significant impact on population ageing disparities in Bosnia and Herzegovina. All of these factors contributed to a decline in the potential biodynamics and vitality of the population, as well as to negative natural population changes and emigration. The ongoing processes of depopulation in Bosnia and Herzegovina are likely to have a negative impact on the population's age structure, leading to negative demographic trends. The results of this study are important for future research on population and are the basis for the planned population development of Bosnia and Herzegovina. Identifying areas with declining populations due to ageing is a significant contribution of the study and can be used to guide future demographic research and identify factors causing spatial demographic disparities.

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ISSN 0354-8724 (hard copy) | ISSN 1820-7138 (online)

Flood Hazard Risk Assessment based on Multi-criteria Spatial Analysis GIS as Input for Spatial Planning Policies in Tegal Regency, Indonesia

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Received: October 31, 2022 | Revised: February 20, 2023 | Accepted:March 08, 2023
doi: 10.5937/gp27-40927

Abstract

Recent discussions on flood disasters concern the risk factors and causes between nature and anthropogenic activities. This disaster requires serious handling, which needs to be analysed, especially in areas affected by flooding with the Tegal Regency, Indonesia case study. The weakness of the existing mitigation efforts still needed comprehensive analyses, requiring a multi-criteria assessment based on GIS spatial analysis. The GIS method used is a raster calculator and weighted superimpose by setting several calculation variables from both physical and non-physical aspects to support the multicriteria spatial analysis. The results show that spatially, more than 30% of areas with a high-risk index are located in the downstream or coastal regions of Tegal Regency. However, the index of capacity and resilience in several flood-affected sub-districts is at an index above 0.5, so they have good strength to disasters such as the four sub-districts of Adiwerna, Bumijawa, Bojong, and Kramat. From the analysis results, land use change is the biggest problem that affects the number of the flood event. With this condition, the appropriate mitigation effort for Tegal Regency is strengthening the spatial planning policy and increasing the capacity, especially in disaster governance in a high-risk area. Thus, the vulnerability and hazard factors will be anticipated with high community participation in strengthening the capacity index.

Keywords: GIS spatial analysis; Flood disaster; Capacity Index; Land Use change

Introduction

Recent discussions on flood disaster are about the risk factors and causes between nature and anthropogenic activities such as land conversion that converts protected areas into agriculture and settlements (Bae & Chang, 2019; Liu & Ran, 2021; Sipos et al., 2022; Vaggela et al., 2022; Villarreal-Rosas et al., 2022; Wisha et al., 2022). Natural physical changes due to anthropogenic factors have occurred in several regions of the world (Kaliraj et al., 2017; Shao et al., 2020; Szilassi et al., 2022). That is as consequence of the large rate of urbanization, as predicted by the WHO that 60% of the world's population will live in urban areas by 2050 (Sejati et al., 2019; WHO, 2014). With this population growth, the need for land for food crops and settlements increases which has an impact on the conversion of land which is now a threat to environmental sustainability (Han et al., 2022; Sejati et al., 2018).

In some areas, land conversion, especially in the highlands, has resulted in flooding, especially due to the loss of conservation areas in the mountains and

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watersheds that have been converted into settlements and agriculture (Bae & Chang, 2019). Flood problems have occured in many countries, especially in fast-growing countries. It happens in several country like in Asia aspects (Ishiwatari & Sasaki, 2021; Venkatappa et al., 2021; Yang et al., 2021), Western Europe (Figueiredo et al., 2020), Africa (Nkeki et al., 2022), and America (Palacio-Aponte et al., 2022) that are growing economically strong but ignore environmental sustainability, Indonesia, one of Asian country, has a similar problem, which is on the north coast of Java (Bott et al., 2020; Irawan et al., 2021).

Meteorological factors, such as extreme weather or high rainfall, are the leading causes of flooding (Faccini et al., 2018; Hartanto & Rachmawati, 2017). In addition, flood risk is exacerbated by massive urbanization and land use change (Handayani et al., 2020; Jodar-Abellan et al., 2019). One part of the north coast of Java that experiences high disaster risk in flood areas is Tegal Regency. Based on data from the Regional Disaster Management Agency of Tegal Regency, there have been 16 flood disasters recorded during November 2021. Land use change and high intensity of rainfall caused this disaster. It resulted in overflowing river water and caused residents' settlements to be flooded.

The increasing number of disaster events must be analyzed like the coverage of disaster affected areas and the level of disaster risk. Furthermore, the analysis must be able to explain disaster events spatially so that geospatial technology-based analysis is necessary. Previous research on the flood with a geospatial approach has focused on several topics (de Vries, 2021). The topic is implementing geospatial technology for flood risk mapping (Dejen & Soni, 2021; Rezaie-Balf et al., 2022). Another topic was also interesting such as identifying and assessing flood vulnerability (Liu et al., 2021; Saur & Rathore, 2022; Singh & Pandey, 2021), factors towards the occurrence of flood disasters (Kieu & Tran, 2021; Psomiadis et al., 2020), the impact of flooding on property prices (Balogun et al., 2020), and predicting spatial flooding (Nguyen et al., 2020).

There is a lack of studies on assessing flood by combining physical and socio-economic factor, as in the research of Monteil et al. (2022), which emphasizes the use of physical and environmental variables to take into account disaster risk in flood-affected areas. An interesting topic also conducted by El-Saoud & Othman (2022), which assessed flood risk with several variables that cause flooding. Based on these studies, the use of physical and environmental vulnerability variables combined with the consideration of the socio-economic vulnerability of the community in mapping flood risk has not been widely carried out. It will increase the level of accuracy that is more detailed and on target in making policy for flood disaster risk management. Based on these conditions, the purpose of this paper is to provide an assessment of flood risk from various variables, both physical and social variables. This research explores disaster risk mapping based on the level of disaster, vulnerability, and the capacity of regions and communities to deal with floods and be the part of efforts to strengthen geospatial community-based disaster risk management policies.

Data and Methods

Study area

The research study area focuses on Tegal Regency (Figure 1). Tegal Regency is one of the regencies located in Central Java Province, Indonesia. Tegal Regency is directly adjacent to the north coast of the Java Sea. It has three main watersheds: the Kaligung, Pemali, and Rambut watersheds and the Cacaban Reservoir as water storage.

Study Methods

The risk assessment based on two aspects of spatial conern; physical and socio-economic aspects. The physical aspect is analyzed from physical and environmental vulnerability as well as disaster hazard. Some spatial data sources are from InaRisk (Indonesian Disaster Geoportal) (The Disaster Mitigation Agency of Indonesia, 2012). At the same time, the socio-economic aspect is analyzed from socio-cultural and economic vulnerability as well as regional resilience and disaster preparedness. The social aspect is obtained by a participatory mapping process so that the community capacity aspect can be appropriately mapped, describing the regional resilience level (Figure 2).

Hazard Assessment

The disaster hazard assessment aims to identify elements at risk of causing harm, especially to the community (Chen et al., 2022). The flood hazard assessment uses InaRISK data from the National Agency for Disaster Management. InaRISK data processing uses GIS software, which is then grouped into 3 (three) hazard classes, namely low class ($H < 0.333$), medium class ($0.333 < H < 0.666$), and high class ($0.666 < H$).

Flood hazard mapping involves hydrological analysis of potential flood inundation (Kocsis et al., 2022). The method of making a disaster hazard map is to identify potential areas of flood inundation and then

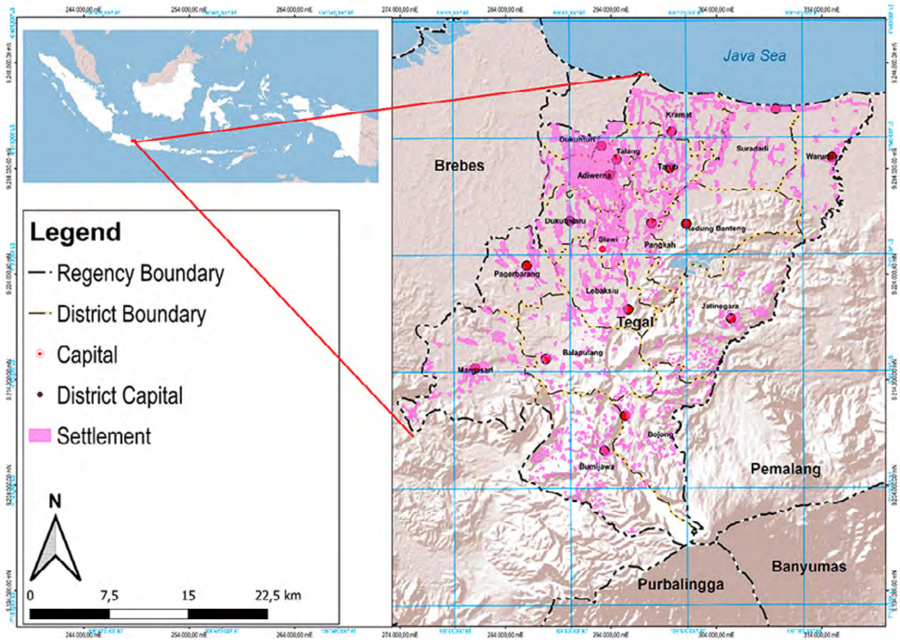

Figure 1. Tegal Regency as Study Area
Source: Authors, 2022

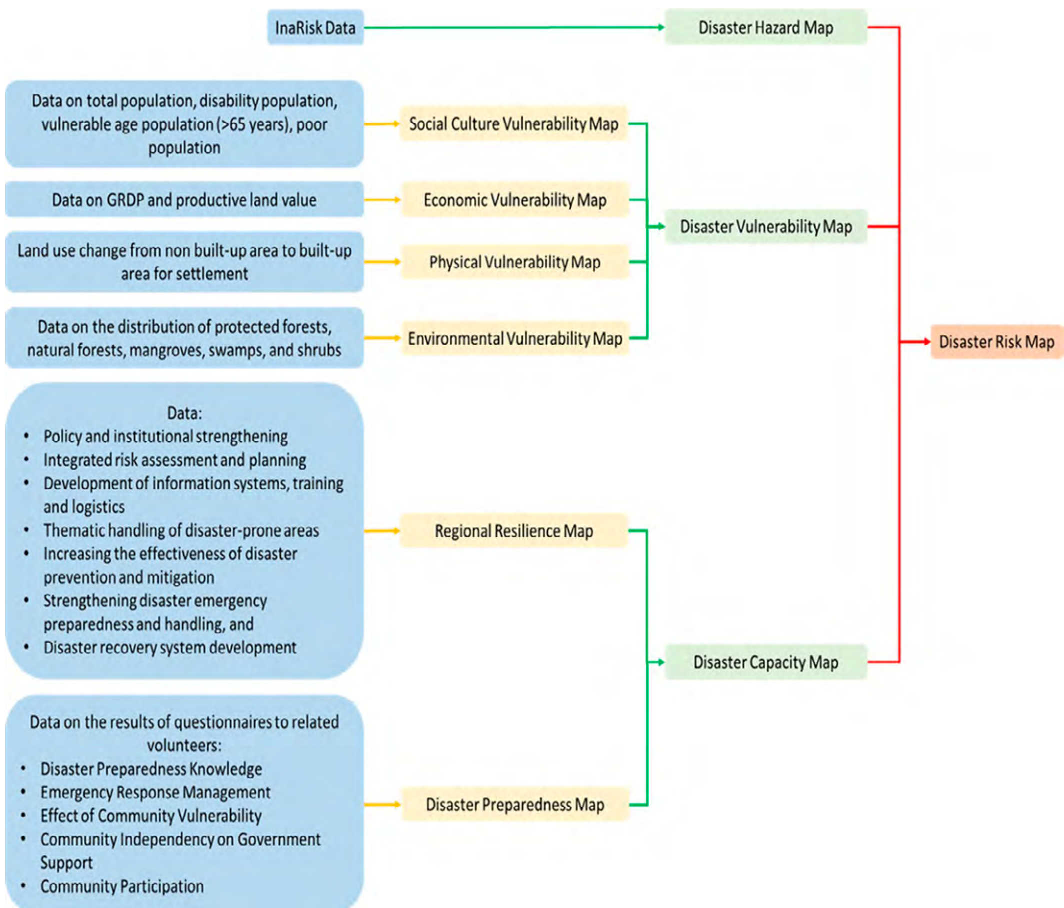

Figure 2. Disaster Risk Analysis Model
Source: Author Identification, 2022

Table 1. List of Data

№	Data Type	Data Form	Data source	Year
	Flood Disaster Data			
1	Administration Boundary	Vector (Polygon)	Geospatial Information Agency of Indonesia	2022
2	National DEM (DEMNAS)	Raster	Geospatial Information Agency of Indonesia	
3	Watershed Boundary Map	Vector (Polygon)	Ministry of Environment and Forest	
4	River Network Map (RBI)	Vector (Polyline)	Geospatial Information Agency of Indonesia	
5.	Landsat Satellite Imagery	Raster	USGS	2012, 2022
	Flash Flood Disaster Data			
1	Main river	River Network	Geospatial Information Agency of Indonesia	2022
2	Main topography	DEMNAS	Geospatial Information Agency of Indonesia	
3	Potential for hazard location	InaRisk	National Agency for Disaster Management	

Source: Author Identification, 2022

estimate the height of the inundation. The preparation of the disaster hazard map uses the data such as administration boundary, DEM, Watershed Boundary, river network, and Satellite imagery (Table 1).

Disaster Vulnerability Assessment

Vulnerability refers to the condition of a community that causes an inability to deal with disasters. This vulnerability assessment is needed to determine the factors that affect the community's ability to deal with disasters. The higher the level of community vulnerability to disasters, the greater the losses obtained by the community. The vulnerability assessment consists of several constituent components: social, physical, economic, and environmental.

The social vulnerability uses several ratio data, namely population density data and vulnerable groups consisting of data on gender, population with disabilities, age group over 65 years, and poor population. This data uses the latest 2021 data sourced from the Central Statistics Agency in the form of the Tegal Regency document in figures and data from the Ministry of Social Affairs in the form of the Social Welfare Integrated Data document. Social vulnerability analysis uses parameters in the form of weighting for each indicator based on the participatory process, shown in Table 2.

The social vulnerability analysis approach is in the form of dasymetric mapping, resulting in a more realistic spatial distribution of the population. The spatial distribution method of population density is carried out through a proportional distribution based on the InaRiskPop (The Disaster Mitigation Agency of Indonesia, 2012) data correction with the following equation.

$$\mathrm{Pij} = \frac{\mathrm{Prij}}{\sum_{i,j=1}^{n} \mathrm{Prij}} \cdot \mathrm{Xdi}$$

Information:

- Pij: Total population in the i-th and j-th grids/cells
- Prij: The population of InariskPop data on the ith residential grid/cell in the jth village administration unit (if Pri = 1 and Prj = 0, then Prij = min (Prij)
- Xdi: Total population in the ith village administration unit

The minimum Prij value is the minimum value on the grid/cell in the village area.

Table 2. Social Vulnerability Parameters

Parameter	Weight (%)	Class		
		Low	Medium	High
Population density	60	<500 people/km²	500-1000 people/km²	>1000 people/km²
Sex ratio (10%)	40	>40	20-40	<20
Poverty ratio (10%)		<20%	20-40%	>40%
Disabled people ratio (10%)				
Age group ratio (10%)				
Social Vulnerability Calculation: $\left(0.6\cdot\frac{\mathrm{Log}\left(\frac{\text{Population density}}{0.01}\right)}{\mathrm{Log}\left(\frac{100}{0.01}\right)}\right)+(0.1\cdot\text{sex ratio})+(0.1\cdot\text{poverty ratio})+(0.1\cdot\text{disabled people ratio})+(0.1\cdot\text{age ratio})$				
Calculation of the value of each parameter is carried out based on: • Low hazard class has 0% influence • Medium hazard class has 50% effect • High hazard class has 100% influence				

Source: National Agency for Disaster Management with modification, 2022

The economic vulnerability uses GRDP data and the value of productive lands such as rice fields, plantations, and ponds. Economic vulnerability analysis uses the latest data from BIG for productive land data and Central Statistics Agency for GRDP data for Tegal Regency. The parameters of the analysis of the economic vulnerability assessment are shown in Table 3. The analytical approach used is the Multi-Criteria Decision Analysis (MCDA) method to obtain the value of the economic vulnerability index using the following equation (The Disaster Mitigation Agency of Indonesia, 2012).

$$Ve = FM\left(0.6v_{pd}\right) + FM\left(0.4v_{ip}\right)$$

Information:

- Ve: economic vulnerability index
- FM: *fuzzy* membership function
- V_{pd}: GDP contribution index
- V_{ip}: index of productive land loss

The physical vulnerability uses settlement data in the form of housing density, both permanent, semi-permanent, and non-permanent houses, and also land use change from non-built-up area to built-up area for settlement. The source of physical vulnerability data is from InaRisk for data on public and critical facilities. At the same time, the number of houses per village is obtained through Village Potential data with an average population value of 5 people/per house. The calculation of house density is the division between the built area or village area by the area (ha) multiplied by the unit of each parameter. The land use change assessment is conducted by spatial analysis using Spatio-temporal data from Landsat in 2012 and 2022 (20 years). The parameters used in the physical vulnerability analysis are shown in Table 4. The equations used for the physical vulnerability analysis are as follows.

$$r_{ij} = \frac{P_{ij}}{5} \text{ and if } P_{ij} < 5, \text{ so } r_{ij} = 1$$

Table 3. Economy Vulnerability Parameters

Parameter	Weight (%)	Class		
		Low	Medium	High
Productive land	60	<50 million IDR	50-100 million IDR	>200 million IDR
GDP	40	<100 million IDR	100-300 million IDR	>300 million IDR
Calculation Economy vulnerability = (0.6 * productive land score) + (0.4 * GDP score)				
Calculation of the value of each parameter is carried out based on: • Low hazard class has 0% influence • Medium hazard class has 50% effect • High hazard class has 100% influence				

Source: National Agency for Disaster Management with modification, 2022

Table 4. Physical Vulnerability Parameters

Parameter	Weight (%)	Class		
		Low	Medium	High
House	40	<400 million IDR	400-800 million IDR	>800 million IDR
Other built-up areas	30	<500 million IDR	500 million – 1 million IDR	>1 million IDR
Calculation of the value of each parameter is carried out based on: • Low hazard class has 0% influence • Medium hazard class has 50% effect • High hazard class has 100% influence				

Source: National Agency for Disaster Management with modification, 2022

Information:

- r_{ij}: the number of houses in the i-th and j-th grids/cells
- P_{ij}: the number of population in the i-th and j-th grids/cells

The environmental vulnerability uses data on the distribution of protected forests, natural forests, mangroves, swamps, and shrubs. The data source was obtained from the Ministry of Public Works and Housing document in 2012. The parameters for assessing environmental vulnerability are shown in Table 5.

$$V = FM(W.v1) + FM(W.v2) \ldots FM(W.vn)$$

Information:

- *V*: Vulnerability index value/ vulnerability component
- *v*: Index of vulnerability components/composition parameters
- *w*: Weight of each vulnerability component/composition parameter
- *FM*: Fuzzy membership function
- *n*: Number of vulnerability components/component parameters

Table 5. Environment Vulnerability Parameters

Parameter	Class		
	Low	Medium	High
Protected forest	<20 ha	20-50 ha	>50 ha
Natural forest	<25 ha	25-75 ha	>75 ha
Mangrove forest	<10 ha	10-30 ha	>30 ha
Shrubs	<10 ha	10-30 ha	>30 ha
Swamp	<5 ha	5-20 ha	>20 ha
Calculation of the value of each parameter is carried out based on: • Low hazard class has 0% influence • Medium hazard class has 50% effect • High hazard class has 100% influence			

Source: National Agency for Disaster Management with modification, 2022

The method used to combine all components of vulnerability is the MCDA spatial method, which is a combination of several criteria spatially based on the value of each criterion (Fernández & Lutz, 2010; Malczewski, 1999). The overlay of criteria is carried out by the spatial process using mathematical operations based on the score and weight of each component. The weighting of the flood hazard vulnerability components is 40% social vulnerability, 25% physical vulnerability, 25% economic vulnerability, and 10% environmental vulnerability. The following is a general equation used:

Capacity Assessment

Capacity is the ability of the region and the people of the Tegal Regency to take action to reduce the level of threat and loss due to flooding. Disaster capacity assessment aims at disaster management by reducing risks arising from disasters. Assessment of disaster capacity uses components of regional resilience and community preparedness for disasters.

Regional resilience data collection uses the focus group discussion (FGD) method and distributes questionnaires that need to be responded to by various parties managing disasters in Tegal Regency. The components of the preparation of regional resilience studies consist of strengthening policies and institutions; risk assessment and integrated planning; development of information systems, education, training, and logistics; thematic handling of disaster-prone areas; increasing the effectiveness of disaster prevention and mitigation; strengthening disaster emergency preparedness and handling; and development of disaster recovery systems.

The community preparedness index is an assessment carried out by survey methods and interviews with government officials or community leaders. The questionnaire data collection technique was stratified by random sampling in several villages that were affected by the disaster. The components of the community preparedness assessment consist of knowledge of disaster preparedness, emergency response management, the influence of community vulnerability, community independence from government support, and community participation. The class division of regional resilience and community preparedness is divided into three groups, namely low level (0 indexes 0.4), medium level (0.4 < index 0.8), and high level (0.8 < index 1). The assessment results of disaster resilience and community preparedness are in the form of index values converted into spatial data (Table 6).

Table 6. Weighting and Index Component Capacity Disaster

Component	Weight (%)	Class		
		Low (0 - 0.333)	Medium (0.334 - 0.666)	High (0.667 – 1.000)
Regional Resilience	40	Value transformation 0 – 0.40	Value transformation 0.41 – 0.80	Value transformation 0.81 – 1
Preparedness Public	60	<0.33	0.34 – 0.66	0.67 – 1.00

Source: National Agency for Disaster Management with modification, 2022

Disaster Risk Assessment

The disaster risk assessment is composed of analyzing disaster hazard, disaster vulnerability, and disaster capacity. The disaster risk is determined in a calculation involving the three components in the following equation:

$$\text{Disaster Risk} = \text{Hazard (H)} \cdot \frac{\text{vulnerability(V)}}{\text{capacity(C)}}$$

This study can be developed for the analysis process using a geographic information system to describe the level of disaster risk in flood-affected areas (Santos et al., 2020; Wiratmaja & Sejati, 2021). The results of the disaster risk assessment are displayed in a disaster risk map, where the calculation uses a geographic information system; disaster risk is determined in the following equation:

$$R = \left(H \cdot V \cdot (1\text{-}C)\right)^{1/3}$$

Results

Potential Vulnerability of Flood Disaster

The flood disaster vulnerability assessment is divided into 4 (four) components, namely social, economic, physical, and environmental vulnerability. The other aspect, like social vulnerability, was identified by the number of people exposed to disasters, which considers the vulnerable age groups, the poor, and the disabled. Economic and physical vulnerabilities were identified in the form of nominal rupiah losses experienced by the Tegal Regency. Meanwhile, an environmental vulnerability was identified as an area damaged by flooding.

Flood disasters can potentially affect the activities of the residents of Tegal Regency. the population of Tegal Regency potentially exposed to flood disasters is included in the medium vulnerability class. The number of people exposed to the disaster was as many as 740,586 people. Kramat Subdistrict, with the highest exposed population in Tegal Regency, reached 100,464 people, followed by Talang and Adiwerna Subdistricts. On the other hand, there is a potential for the lowest exposed population in Jatinegara District, which reaches 4,423 people and Bumijawa District, with 4,285 people exposed (Table 7).

The flood disaster harmed 89,063 people in the vulnerable age group. Furthermore, the poor numbered 6,393 people and 5,064 people with disabilities were also exposed to the flood disaster. The distribution of the population exposed to the class disaster was in the sub-districts of Adiwerna, Dukuhturi, Lebaksiu, Slawi, and Talang. It requires special attention to plan disaster management so as not to disturb and harm

Table 7. Potential Flood Disaster Social Vulnerability (people)

Subdistrict	Population Exposed	Vulnerable Age Population	Poor Resident	Persons with Disabilities	Class
Adiwerna	84,086	10,332	708	481	Medium
Balapulang	5,573	686	130	49	Low
Bojong	9,176	1,033	277	72	Low
Bumijawa	4,285	415	204	19	Low
Dukuhturi	77,766	9,159	375	503	Medium
Dukuhwaru	32,263	4,172	381	219	Low
Jatinegara	4,223	547	125	46	Low
Kedung Banteng	21,761	3,109	274	215	Low
Kramat	100,464	12,380	310	509	Low
Lebaksiu	14,622	2,058	216	137	Medium
Margasari	48.103	5,871	667	381	Low
Pagerbarang	12,936	1,740	155	103	Low
Pangkah	55,569	6,741	430	439	Low
Slawi	41,548	5,315	193	245	Medium
Suradadi	49,305	6,019	294	337	Low
Talang	91,373	8,798	551	461	Medium
Tarub	48,835	6,319	856	498	Low
Warureja	38,698	4.369	247	350	Low
Total	740,586	89,063	6,393	5,064	Medium

Source: Analysis Results, 2022

the community in their daily activities. The distribution of potential social vulnerability in Tegal Regency in 2021 is shown in Figure 5.

Meanwhile, the potential losses caused by floods in each sub-district in Tegal Regency with a nominal loss of 2,162,287 million rupiah. Kramat Subdistrict experienced the most significant physical loss in Tegal Regency, as much as 259,256.80 million rupiahs. It also happened to the Subdistricts of Suradadi, Margasari and Warureja, with physical losses of more than 200,000 million rupiahs (Table 8).

Tegal Regency is not only experiencing physical losses but also has a high potential for economic losses. The total loss received by Tegal Regency due

Table 8. Potential Loss Disaster Floods in the District Tegal

Subdistrict	Million Rupiah				Hectares	
	Physical Loss	Physical Class	Economic Loss	Economy class	Environmental Area	Environmental Class
Adiwerna	164,868,90	High	299.73	Medium	1.02	Low
Balapulang	56,812.50	High	189.89	Medium	18.44	Low
Bojong	54,275.00	High	211.30	High	3.58	Low
Bumijawa	30,422.09	High	103.79	Low	7.86	Low
Dukuhturi	136,441.90	High	340.14	Medium	2.97	Low
Dukuhwaru	80,298.04	High	324.61	Medium	1.30	Low
Jatinegara	93,805.00	High	282.84	Medium	24.96	Medium
Kedung Banteng	166.730.00	High	339.44	Medium	109.22	High
Kramat	259,256,80	High	933.71	High	2.48	Low
Lebaksiu	47,869.58	High	212.22	High	0.07	Low
Margasari	219,212.70	High	897.21	High	1.69	Low
Pagerbarang	32552.67	High	188.15	Low	0.05	Low
Pangkah	102,395,00	High	328,70	Low	4.00	Low
Slawi	63.998.18	High	73.95	Low	4.81	Low

Subdistrict	Million Rupiah				Hectares	
	Physical Loss	Physical Class	Economic Loss	Economy class	Environmental Area	Environmental Class
Suradadi	231,799.20	High	933.31	High	0.89	Low
Talang	129,376.00	High	308.65	Medium	0.44	Low
Tarub	89,098.46	High	378.39	Medium	3.15	Low
Warureja	203.075.00	High	1149.09	High	24.65	Medium
Total	2,162,287.00	High	7,495.13	High	211.56	High

Source: Analysis Results, 2022

to the flood disaster reached 7,495.13 million rupiah. Warureja District obtained the highest loss of 1,149.09 million rupiahs. The same thing happened to the Districts of Kramat, Suradadi, Margasari, Lebaksiu, and Bojong, which experienced high losses in the economic component. Meanwhile, low losses were identified in Bumijawa, Pagerbarang, Pangkah, and Slawi subdistricts.

Furthermore, the results of land use change modelling based on satellite imagery from 2012 and 2022 show significant changes to land-use types in the Tegal Regency. Table 9 shows the most significant change between 2012-2022. On the other hand, there was an increase in rice fields covering an area of 8,571.29 ha. The mapping of land use change in the Tegal Regency can be seen in Figure 3.

Floods hurt the environment in the form of forests, swamps, and other green open spaces. The flood caused a high-grade loss of 211.56 ha of the environment in Tegal Regency. Kedung Banteng District experienced the highest environmental loss, with an affected area of 109.22 ha. Medium-class environmental

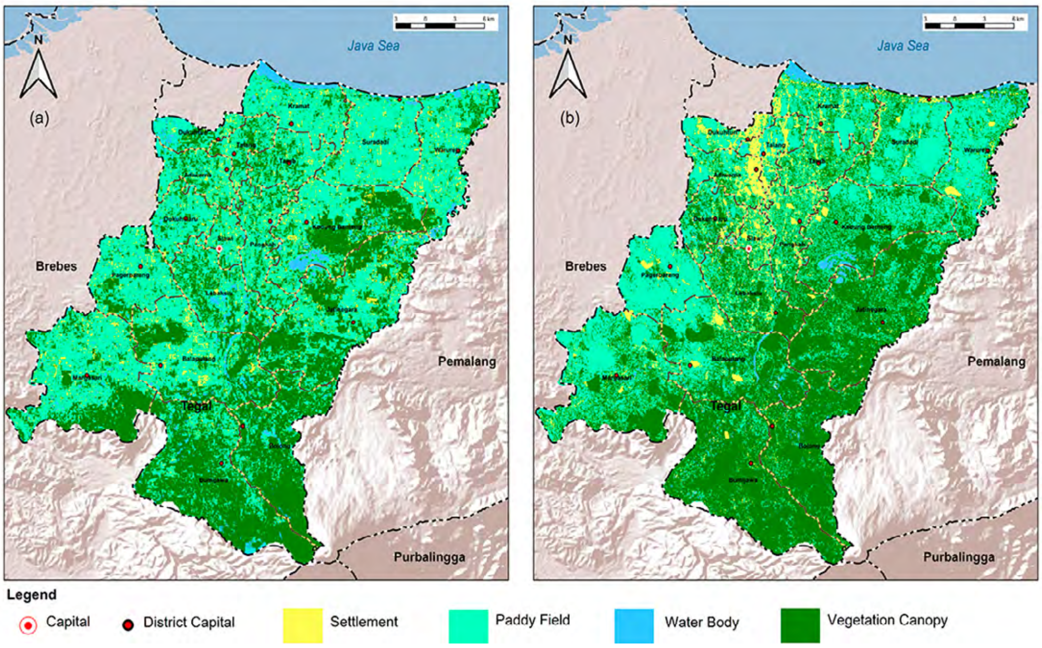

Figure 3. Land Use Change of Tegal Regency in (a) 2012 and (b) 2022
Source: Analysis Results, 2022

Table 9. Changes in Land Use in 2012 and 2022

Types of Land Use	Year (ha)		(ha)
	2012	2022	2012-2022
Settlement	9,424.10	10,701.84	1,277.74
Paddy field	39,003.19	47,574.48	8,571.29
Water Body	2144.70	3,287,77	1,143.06
canopy	47,665.14	36,676.89	- 10,988.26
Total Area	99,457.92	99,457.92	

Source: Analysis Results, 2022

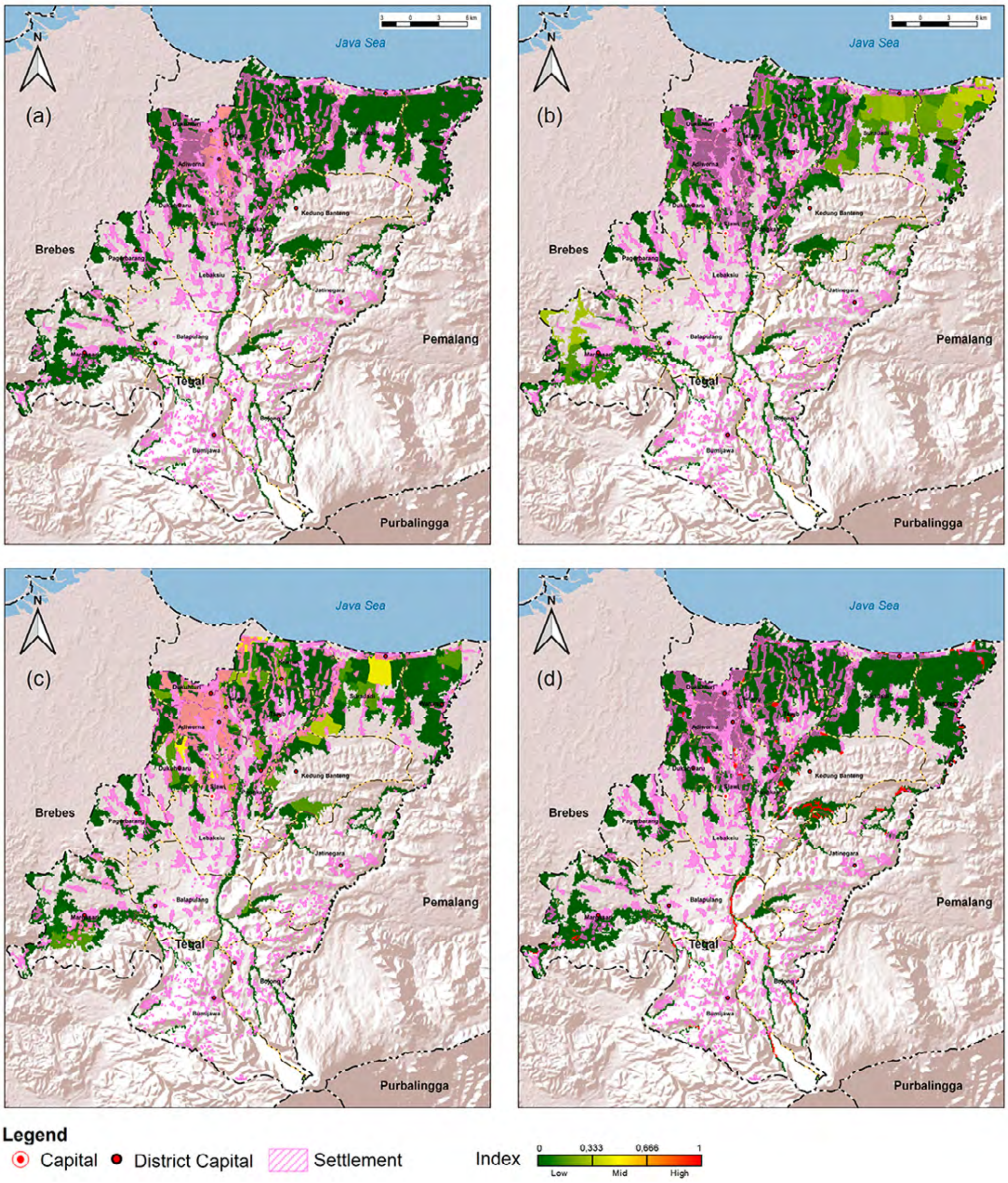

Figure 4. Map of Social (a), Economic (b), Physical (c), and Environmental (d) Vulnerability of Tegal Regency in 2022
Source: Analysis Results, 2022

losses reaching 24.96 ha can occur in the Jatinegara and Warureja sub-districts. In comparison, other sub-districts receive low-class environmental losses, with the smallest impacted environmental area of 0.05 ha in the Pagerbarang District (Figure 4).

Based on the analysis of the components of disaster vulnerability (social, economic, physical, and environmental vulnerabilities), it can be concluded that Tegal Regency is identified as experiencing a high class of vulnerability to flood disasters. Several sub-districts that experienced high vulnerability were in Adiwerna, Dukuhturi, Margasari, and Suradadi sub-districts. Meanwhile, the vulnerability is in the Kramat, Lebaksiu, Slawi, and Talang sub-districts (Figure 6).

Identification of potential flood hazards using InaRisk data analyzed by GIS. The analysis results show that every sub-district in Tegal Regency has the potential to experience flooding. Potential disaster hazard is classified into 3 (three) classes, namely low, medium, and high hazard potential. Based on Table 10, Tegal Regency has a relatively high potential for flood hazards. Warureja sub-district is the sub-district with the largest affected area reaching 4,437.90 ha. The Subdistricts of Margasari, Kramat, and Suradadi are potentially dangerous to flooding with an affected area of more than 3,000 ha. Some areas have moderate potential for flood hazards, namely Pagerbarang District, with an affected area of 804.96 hectares (Figure 5).

Table 10. Potential Area Flood

Subdistrict	Area (Hectares)				
	Low	Medium	High	Total	Class
Adiwerna	63.99	1,427.76	740.61	2232.36	High
Balapulang	58.59	471.51	316.98	847.08	High
Bojong	120.42	429.30	330.48	880,20	High
Bumijawa	81.27	213.21	203.58	498.06	High
Dukuhturi	62.91	897.84	683.01	1,643.76	High
Dukuhwaru	18.72	1,021.32	306.36	1,346.40	High
Jatinegara	42.21	494.19	625.05	1161.45	High
Kedung Banteng	0.00	726.93	1,060.83	1,787.76	High
Kramat	130.77	1983.87	1,584.90	3,699.54	High
Lebaksiu	29.43	678.24	197.64	905.31	High
Margasari	95.13	2,320.65	1,311.57	3,727.35	High
Pagerbarang	38.79	667.08	99.09	804.96	Medium
Pangkah	77.67	960.21	511.74	1,549.62	High
Slawi	17.64	444.15	215.73	677.52	High
Suradadi	17.01	1,843.47	1,275.93	3,136,41	High
Talang	88.02	990.81	479.25	1558.08	High
Tarub	72.99	1,138,05	411.57	1,622.61	High
Warureja	141.57	2,690.19	1,606.14	4.437.90	High

Source: Analysis Results, 2022

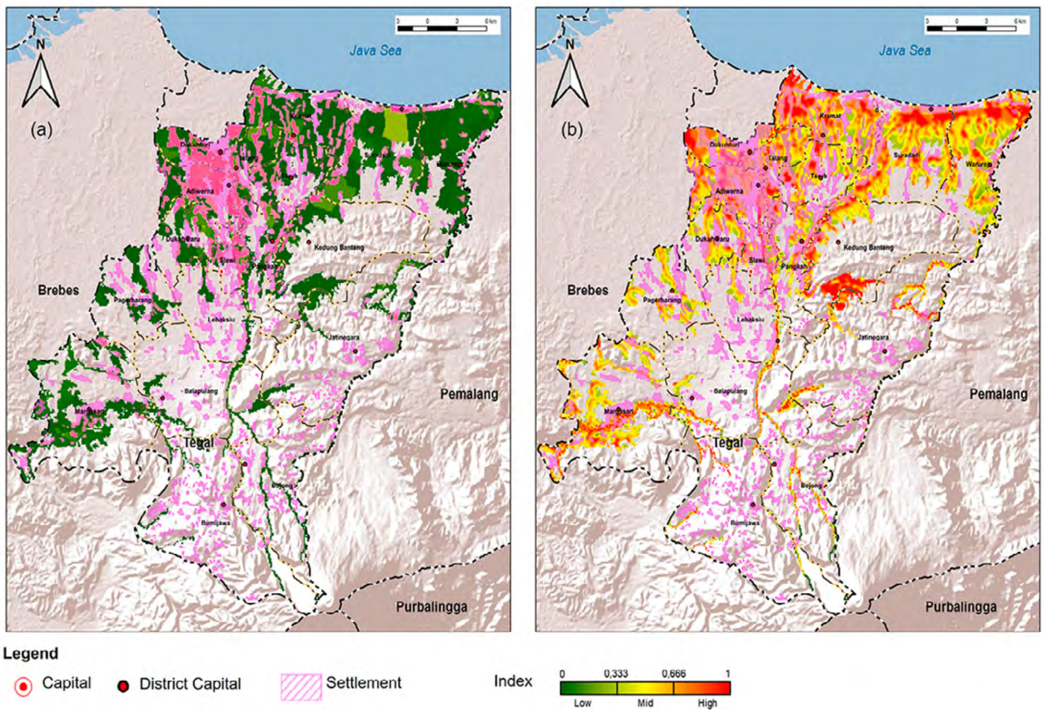

Figure 5. Map of Vulnerability (a) and Hazard (b) Flood Disaster in Tegal Regency in 2022
Source: Analysis Results, 2022

Community Capacity

Resilience and disaster preparedness are the basis for analyzing Tegal Regency's capacity to deal with floods. Table 11 shows that regional resilience in all areas of the Tegal Regency tends to be moderate, which is indicated by the index value reaching 0.66. However, community preparedness for floods is still relatively low, with the index value only reaching 0.32 and 0.43 as the highest index value, which is only in Adiwerna, Bojong, Bumijawa, and Kramat Districts.

Table 11. Community Capacity in the District Tegal

№	Subdistrict	Regional Resilience Index	Preparedness Index	Capacity Index	Capacity Class
1	Adiwerna	0.66	0.43	0.52	High
2	Balapulang	0.66	0.29	0.44	Medium
3	Bojong	0.66	0.43	0.52	High
4	Bumijawa	0.66	0.43	0.52	High
5	Dukuhturi	0.66	0.29	0.44	Medium
6	Dukuhwaru	0.66	0.29	0.44	Medium
7	Jatinegara	0.66	0.35	0.47	Medium
8	Kedung Banteng	0.66	0.29	0.44	Medium
9	Kramat	0.66	0.43	0.52	High
10	Lebaksiu	0.66	0.29	0.44	Medium
11	Margasari	0.66	0.29	0.44	Medium
12	Pagerbarang	0.66	0.29	0.44	Medium
13	Pangkah	0.66	0.29	0.44	Medium
14	Slawi	0.66	0.29	0.44	Medium
15	Suradadi	0.66	0.29	0.44	Medium
16	Talang	0.66	0.29	0.44	Medium
17	Tarub	0.66	0.29	0.44	Medium
18	Warureja	0.66	0.29	0.44	Medium
Tegal Regency	0.66	0.32	0.46	Medium	

Source: Analysis Results, 2022

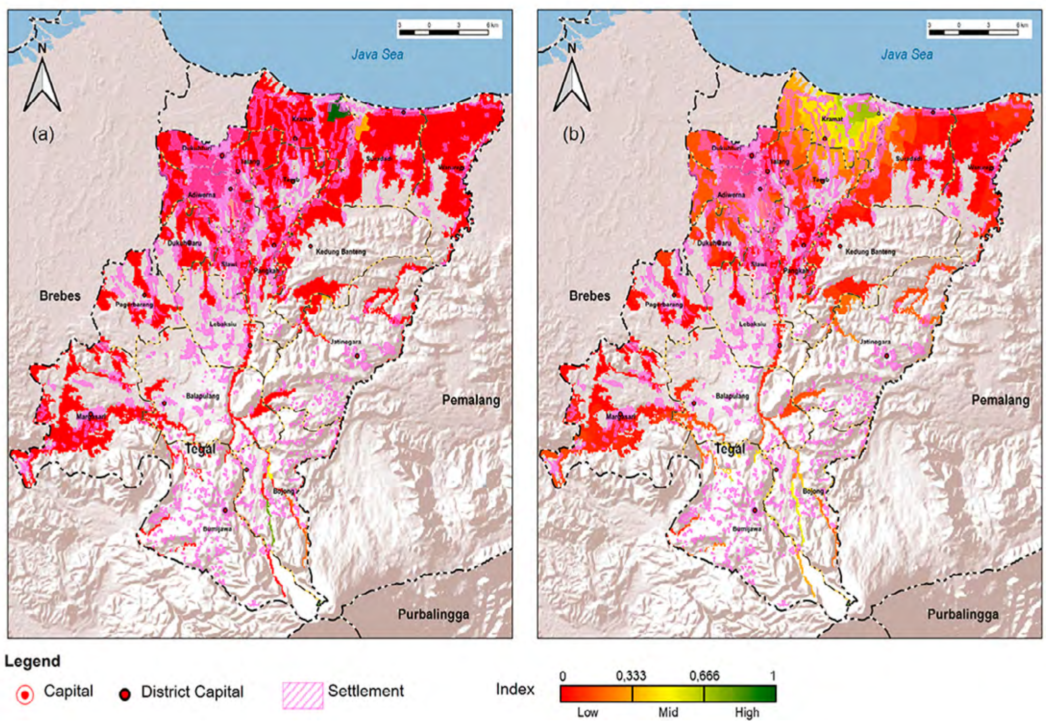

Figure 6. Map of Preparedness (a) and Capacity (b) for Flood Disaster of Tegal Regency in 2022
Source: Analysis Results, 2022

Based on the results of the analysis of regional resilience and community preparedness shows the results of the calculation of the capacity index (Table 11). The average value of the disaster capacity index is 0.46, indicating that Tegal Regency has a medium-class capacity in dealing with floods. There are four area has a high capacity to deal with flood disasters namely adiwerna, Bojong, Bumijawa, and Kramat (capacity index 0.52) (See Figure 6).

Risk Assessment

Based on the calculation of the level of hazard, vulnerability, and capacity, the flood risk level can be obtained and is shown in Table 12. Low risk of disasters occurs in all sub-districts, with the largest affected area being Warureja District (3,790.08 Ha). The moderate risk with the highest affected area is in Kramat District (1,160.64 Ha). Furthermore, the high risk with the largest affected area is in Adiwerna District (394.11 Ha). However, several sub-districts do not potentially risk flooding, namely the Balapulang, Bojong, and Bumijawa sub-districts.

Overall, Tegal Regency is classified as having a high-class flood risk (Table 12). Adiwerna, Dukuhturi, Slawi, and Talang sub-districts are some areas with high risk. The largest area with the potential for moderate risk of flooding is in Warureja District, covering an area of 4,238.55 Ha. Bumijawa sub-district is recorded to be at low risk of disaster, with the affected area reaching 384.21 ha (Figure 7).

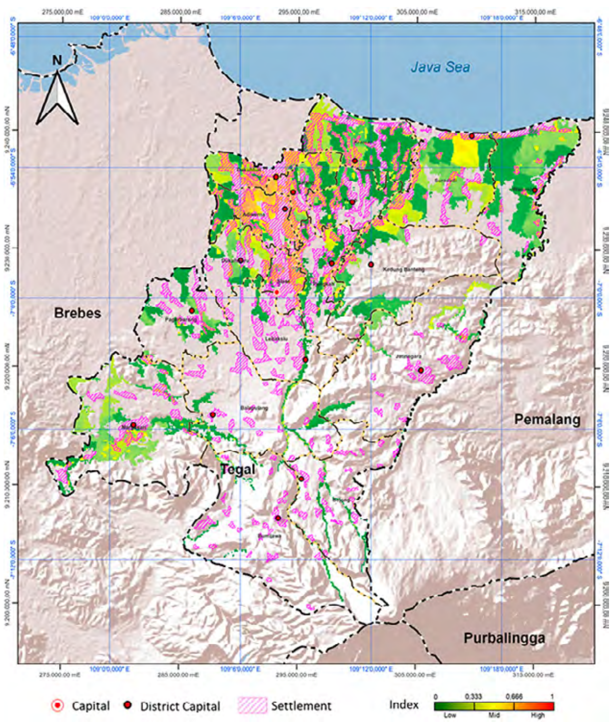

Figure 7. Flood Risk Assessment Result for Tegal Regency in 2022
Source: Analysis Results, 2022

Table 12. Disaster Risk Floods in the Tegal District

Subdistrict	Area (Hectares)				
	Low	Medium	High	Total area	Class
Adiwerna	832.32	917.91	394.11	2144.34	High
Balapulang	721.98	36.27	-	758.25	Low
Bojong	687.78	38.79	-	726.57	Low
Bumijawa	366.12	18.09	-	384.21	Low
Dukuhturi	637.65	756.63	183.51	1,577.79	High
Dukuhwaru	655.29	588.69	16.83	1,260.81	Medium
Jatinegara	818.01	179.19	9.54	1006.74	Low
Kedung Banteng	1,311.39	325.71	72.72	1,709.82	Medium
Kramat	2,411.19	1,160.64	11.07	3,582.90	Medium
Lebaksiu	719.01	102.87	0.09	821.97	Medium
Margasari	2,739.24	594.00	33.75	3,366.99	Medium
Pagerbarang	682.56	80.37	2.61	765.54	Low
Pangkah	892.71	533.70	62.28	1,488.69	Medium
Slawi	183.96	329.58	133.29	646.83	High
Suradadi	1,577.61	1,429.20	71.01	3,077,82	Medium
Talang	649.98	709.65	170.46	1,530.09	High
Tarub	1,140.66	388,98	7.20	1,536.84	Medium
Warureja	3,790.08	426.69	21.78	4,238.55	Low

Source: Analysis Results, 2022

Based on the analysis of flood risk, which is influenced by the components of disaster hazard, vulnerability, and capacity, it can be concluded that the root cause of the disaster occurred. Floods are hazardous to hit the lowlands and coastal areas of Tegal Regency. The occurrence of flooding is relatively caused by high intensity of rainfall, causing sea level rise, which then inundates residential areas. In general, floods occur around the Gung, Kumisik, Cadas, and Kaligung rivers. It causes damage to infrastructure and the environment.

Discussion

Following disaster theory, risk value is strongly influenced by the type of hazard, vulnerability, and capacity index in an area. The hazard and vulnerability model has been analyzed spatially, showing the distribution of hazard and risk areas. The two most essential things in reducing risk are reducing vulnerability and increasing capacity (Etkin, 2016; Wisner et al., 2005). Based on the analysis results, it is obtained that most zones with a high hazard level have high vulnerability. Capacity building in disasters is essential because natural and human disasters can occur anytime and anywhere. When a disaster occurs, a community's ability to respond and cope with an emergency can be vital in minimizing the resulting negative impacts.

The analysis results show that the value of the regional resilience index is 0.66. the regional resilience index is sourced from Indonesia's disaster mitigation agency for Tegal District. The Preparedness Index is an index generated from community preparedness patterns such as ownership of disaster management resources, facilities and the presence of volunteers in disaster management. From these indexes, it can be seen that the value of capacity in each region. The area where the value of the capacity index is above 0.5 has a high capacity for handling the disaster. For example, adiwerna is an area with a high-risk level of physical vulnerability in the form of the type of land use, namely settlements with medium density. Under these conditions, the choice that can be taken to reduce risk is to increase capacity. If look at the calculation results, the most extensive capacity index is in the four sub-districts, namely Adiwerna, Bojong, Bumijawa, and Kramat.

Recognizing that disasters are holistic, not bound by certain disciplinary or political boundaries, delineating risk classes is very helpful in analyzing a condition in the future which is essential in spatial planning (Etkin, 2016; Kaiser et al., 1995; LeGates, 2023). It is in line with spatial planning theory, where future situations can anticipate needing to be included in a more comprehensive spatial planning target. Spatial planning instruments should be the first step in strengthening capacity and reducing physical vulnerability. However, the existing regional spatial planning has little influence in anticipating areas that have a high-risk value (Etkin, 2016; Wisner et al., 2005).

Disaster mitigation and regional spatial planning have a close relationship because regional spatial planning can affect disaster risk and mitigation efforts that can be carried out. Regional spatial planning can affect disaster risk in several ways. In areas near high-risk zones, spatial planning should consider these risks and take mitigation measures to reduce their impact. Likewise, with flood-prone locations, it is necessary to pay attention to land use and utilization of river flows.

In addition, good spatial planning can help minimize disaster risk and accelerate mitigation efforts. An example of mitigation measures that can be taken through spatial planning is Establishing buffer zones: In spatial planning, areas around disaster-prone zones can be designated as buffer zones to reduce risks and minimize disaster impacts (Hervás & Bobrowsky, 2009).

Furthermore, river border areas with a distance of 100 m should be used as river border-protected areas (Loveridge et al., 2017). However, in reality, land conversion in the upstream and riverbank areas of Tegal Regency is used for built-up land, affecting the runoff in the watershed. Some of the most significant risks occur in the downstream area, where the slope is quite gentle and suitable for settlement development. However, matters related to disaster risk should be the primary concern in determining residential areas.

Land use planning should minimize disaster risk. For example, we are avoiding building settlements around rivers prone to flooding. Furthermore, good spatial planning and diaster governance can also improve infrastructure and strengthen buildings and roads to increase the value of resilience in the face of disasters (Handayani et al., 2019). Disaster mitigation and regional spatial planning must complement each other because regional spatial planning can affect disaster risk and affect mitigation efforts that can be carried out (Bae & Chang, 2019). Therefore, good spatial planning can help minimize disaster risk and accelerate mitigation efforts.

The results of this study have confirmed previous studies. For instance studies from Chirisa (2021), Kodag et al. (2022), Ner et al. (2022), Thoyibah & Pamungkas (2021), and Young et al. (2019) that show the several things must be considered such as building resilience and management. The resilience of supporting infrastructure to cope with disasters and post-disaster recovery, fulfilment of sanitation and clean water needs, spatial planning that is resilient to disasters, and protection of ecosystems through the preservation of the availability of green open spaces. Of these criteria, some are not met in residential areas, especially in spatial planning, which should be able to regulate the distribution of population density and the distribution of population settlements.

Several disaster theories also explain that capacity needs to be increased to reduce disaster risk, and vulnerability must be reduced (Monteil et al., 2022; Santos et al., 2020). Based on the distribution of disaster risk in the watershed area, it is necessary to increase the handling capacity of the villages traversed by the watershed, especially in strengthening disaster-resilient villages in each region. The most dominant aspect of vulnerability is the aspect of physical vulnerability, with a loss value of IDR 2,162,287,000,000. A large number of losses in the physical aspect should have been anticipated earlier with spatial planning instruments so that when a disaster occurs, it will not affect the physical condition of the area.

The land use change from 2012-2022 showed a change in the upstream of the river, the majority of which were canopied plants, which changed by 10,988.26 ha. It indicates an indication of land use change which can be fatal in a disaster. Some of the activities carried out in the river's upper reaches are of concern because the protected forest has turned into potato plants. In addition to not having a strong root system, potato plants cannot store much water, which makes runoff from rain unbearable in highlands or upstream rivers.

The facts obtained from this study indicate that spatial planning has not been able to become an instrument for controlling environmental quality. The comparison between the flood risk model and the Tegal Regency spatial plan shows that spaces with high disaster risk are not a priority in the determination as protected areas and are instead planned to remain built and economic growth areas. This comparison is shown in Figure 8, where several areas in the Districts of Adiwerna, Dukuhturi, Slawi, Talang, Margasari, and Suradadi at risk of disaster are still designated to be planned as residential areas. With the results of this study, spatial planning should consider disaster risk aspects in an area so that the growth of settlements is not only based on the strategic location of the location, but also pays attention to natural sustainability factors and the people living in the area.

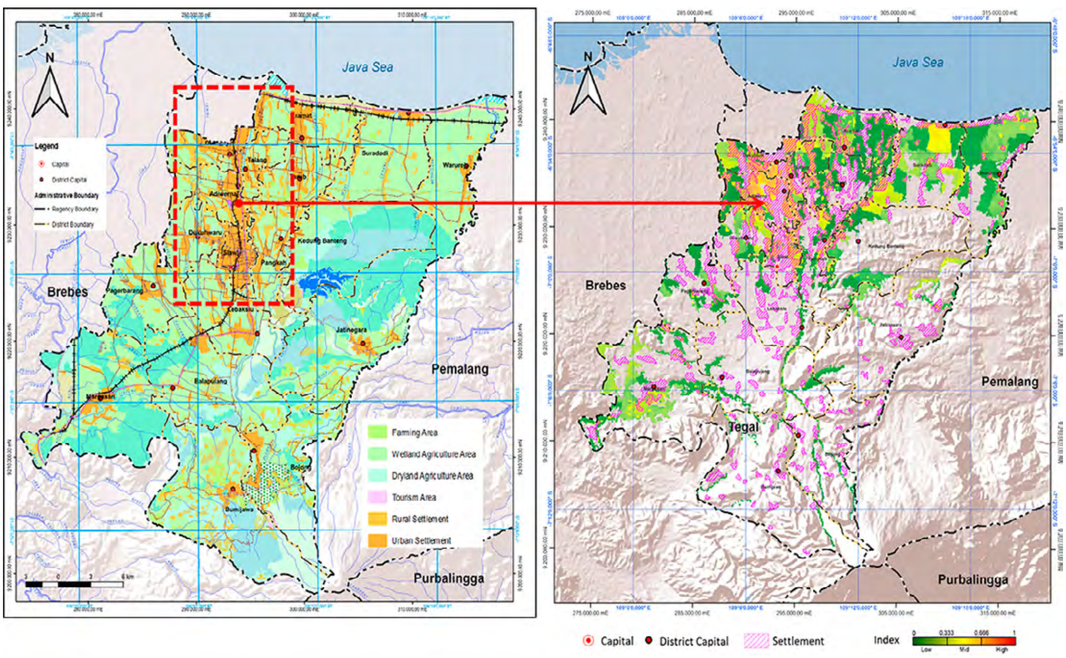

Figure 8. Settlement in spatial Planning (a) is in medium-high risk area (b)
Source: Analysis Result, 2022

Conclusion

This study succeeded in modelling spatial-based disaster risk with multi-criteria regarding the relationship of land use change with flood risk from various criteria. From the analysis results, it can be concluded that high risk is settlements that do not receive attention in controlling the use of space, especially spatial planning. These facts prove that multi-criteria modelling can help in detailing the results of the analysis, especially for evaluating disaster risk areas and spatial planning.

Critical findings in this research are that the highest level of risk is in most areas with residential land use, which has a high vulnerability index above 0.5. Under these conditions, disaster mitigation efforts cannot be carried out by intervening only at the level of vulnerability but also by considering regional capacity and level of preparedness. The four high-risk areas already have a high capacities index like the four sub-districts, namely Adiwerna, Bojong, Bumijawa, and Kramat, with a capacity index of > 0.5. It proves that spatial distribution is essential to see the overall disaster risk model, especially related to spatial planning policies in high-risk locations.

The results of the comparison with the spatial plan show that there is no spatial policy intervention. This evidence is shown by the designation of high-disaster-risk areas as medium-density residential areas. It is dangerous for the sustainability of the community in that location and also shows that weak regulations in minimizing the impact of disasters are a major problem in developing countries like Indonesia. Disaster management and spatial planning should be the main thing in disaster mitigation efforts, especially flood disasters.

Furthermore, several recommendations can be given such as efforts to control land use change especially in controlling the growth of residential areas in high and medium-risk areas. This phenomenon shows that spatial planning has not been able to become an instrument for disaster control and disaster risk reduction at a more detailed level. So, the policies made are also often contrary to the community's real needs and far from disaster risk reduction efforts.

Acknowledgement

"Thank you to the Institute for Research and Community Service (LPPM) Diponegoro University for the 2022 International Publication Research grant with contract number 185-87/UN7.6.1/PP/2022, The Regional Disaster Management Agency in Tegal Regency as a Research Partner, and The anonymous reviewer for the constructive comments"

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ISSN 0354-8724 (hard copy) | ISSN 1820-7138 (online)

Using Landsat Satellite Imagery for Assessment and Monitoring of Long-term Forest Cover Changes in Dak Nong Province, Vietnam

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Received: December 17, 2022 | Revised: February 18, 2023 | Accepted: March 10, 2023
doi: 10.5937/gp27-41813

Abstract

Forests are essential in regulating climate and protecting land resources from natural disasters. In Vietnam's Dak Nong province, forest cover has changed significantly between 1989 and 2021. This study applies remote sensing and geographic information systems (GIS) approaches to detect negative changes in forest cover as well as other land cover types. The maximum likelihood classification tool was used to classify Landsat images for the years 1989, 2001, 2011, and 2021, with post-classification accuracy evaluated through kappa coefficient statistics. The potential to based classification on Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) to detect changes in forest cover compared with supervised classification was also evaluated. The land use and land cover change detection results show that the forest area decreased from 77.54% of the study area in 1989 to 33.97% in 2021, with a total forest loss of 2,953.48 km² and only 117.12 km² of newly planted forest during this period. Broadly, forest cover in the area has been severely reduced, often due to indiscriminate logging and expansion of agricultural land on the forest edge.

Keywords: Forest cover; Forest loss; Landsat; Vegetation Index; Remote sensing; Vietnam

Introduction

Studies of land use and land cover (LULC) change are essential to current strategies for monitoring environmental changes and managing natural resources (Kumari et al., 2014; Han et al., 2015; Meshesha et al., 2016). Performing LULC change detection represents an important tool to determine differences in the state of land cover over time. LULC changes are the conversion of different types of land use and are the result of complex interactions between people and the physical environment (Pielke et al., 2011). LULC changes, especially in developing countries (Hegazy & Kaloop, 2015; Larasati & Hariyanto, 2018), have resulted in decreases in important natural resources, including vegetation, soil, and water (Erb et al., 2018; Hyandye et al., 2018; Azimi Sardari et al., 2019). In addition, changes in LULC are closely related to the sustainable development of society and the economy. Rapidly increasing land use change trends can have significant impacts on local, regional, national, and worldwide environments (Meshesha et al., 2016; Olorunfemi et al., 2020). Therefore, assessing land use patterns and their variations at a regional level is important for resource-specific planning, management, and using resources effectively.

Globally, forest cover has undergone major and unprecedented changes in recent decades due to a range

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of human impacts, including accelerating urbanization, industrialization, agricultural expansion, logging, and mining (Atmiş et al., 2007; Agarwal et al., 2010; Hor et al., 2014; Ahammad et al., 2019; Caballero Espejo et al., 2018). In developing countries located in the tropics, logging activities have become the main cause of forest cover loss. Several drivers affect forest cover in such areas, including logging, unemployment, migration rates, population pressure, infrastructure development, and agriculture (Ranjan, 2019). In addition, the global population is increasing–in the revised 2019 World Population Prospects, the United Nations forecasts that the world population will increase from 7.7 billion in 2019 to 8.5 billion in 2030, 9.7 billion in 2050, and 10.9 billion people in 2100 (United Nations, 2019). In many areas of developing countries, rapid population growth often leads to LULC changes through deforestation and conversion to agricultural land to meet the growing needs of the population, and this transformation will continue in the future (Zeng et al., 2018; Pellikka et al., 2018).

Remote sensing technology and Geographic Information Systems (GIS) have been widely developed and applied globally to research, monitor, and track LULC changes. Remote sensing satellites are the most-used data source to detect, quantify, and map both current land use and LULC changes because of their ability to collect multitemporal spatial data in the form of precisely geolocated, high-resolution images to which a range of processing techniques can be applied (Lu et al., 2004; Yang et al., 2019; Thien et al., 2022a). Many change detection techniques have been developed and used to monitor changes in LULC from remotely sensed data, such as vegetation index differences, image disparity, post-classification comparison, and principal component analysis (Lu et al., 2004; Afify, 2011). The post-classification comparison method is considered to be the most accurate change detection technique, in which land cover changes are detected by comparing post-classification images from different dates (Singh, 1989; Long et al., 2014). In addition, vegetation index analysis has been widely used to increase accuracy when mapping forest cover through indices such as the Enhanced Vegetation Index, Normalized Difference Vegetation Index (NDVI), and Soil Adjusted Vegetation Index (SAVI) (Matsushita et al., 2007; Baloloy et al., 2020; Spadoni et al., 2020).

Vietnam is a country famous for its highly diverse tropical forest ecosystem. Since the 1990s, Vietnam's forests have undergone a transition from pure deforestation to pure reforestation (Meyfroidt & Lambin, 2008). However, in the early years of the 21st century, Vietnam was one of the leading countries in terms of tree cover loss (Hansen et al., 2013). Therefore, this study aims to constrain these changes by: (1) detecting forest land cover in a typical Vietnamese area of Dak Nong province from 1989 to 2021, (2) investigating detailed spatial and temporal variations in forest cover and other major cover types, and (3) linking vegetation indices with changes in forest cover.

Materials and methods

Study area

This study focuses on Dak Nong province, located in the southwest of the Central Highlands of Vietnam between 11°45' to 12°50' N and 107°13' to 108°10' E (Figure 1). Dak Nong covers an area of 6,509.27 km², with a population of 625,822 according to statistics in 2019 (Dak Nong Statistics Office, 2020). The study area shares 130 km of its border with Cambodia's Mondulkiri province. Dak Nong province lies entirely on the M'Nong plateau, with an average altitude of 600 m to 700 m above sea level; its highest altitude of 1,982 m occurs in Ta Dung. In general, the terrain of Dak Nong decreases in elevation from east to west. The terrain is diverse, rich, and strongly dissected, alternating between high mountains, with large plateaus and gently sloping, wavy, fairly flat, low-lying plains.

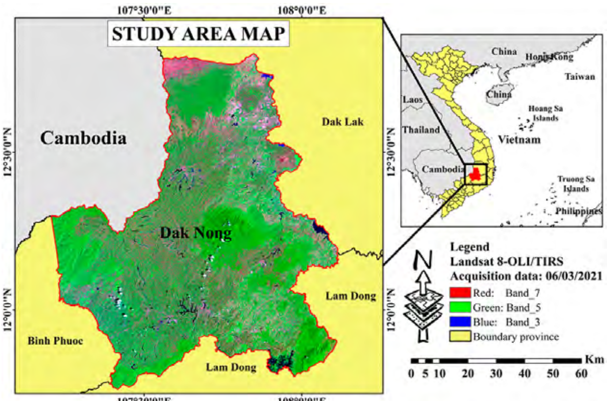

Figure 1. Map showing the study area in Dak Nong province, Vietnam

Dak Nong is a transitional area between the two climatic sub-regions of the Central Highlands and the Southeast. The climate regime has the common characteristics of the sub-equatorial monsoon tropical climate, however, given the elevation of its topography, it has unique characteristics. It is characterized by a humid tropical highland climate and is influenced by the hot and dry southwest monsoon. The climate is divided into two distinct seasons: a rainy season from April to the end of November, during which over 90% of the annual rainfall of 2,513 mm occurs, and a dry season from December to the end of the following March. The average annual temperature is 22 to 23 °C.

Satellite image data acquisition

Satellite images were used to map LULC in Dak Nong province from 1989 to 2021 and assess changes in forest cover. Images without unwanted shade and cloud were set as criteria in the image selection process because their presence can significantly reduce the accuracy of the classification and assessment of vegetation based on vegetation indicators. Remote sensing images acquired during Dak Nong province's dry season (December to March next year) are less affected by clouds and have good quality, thus they were used for the analysis in this work. Landsat 5 TM images were used for the years 1989, 2001, and 2011 and Landsat 8 OLI/TIRS images were used for 2021 in this study. The Landsat image dataset was downloaded from the USGS EarthExplorer (https://earthexplorer.usgs.gov) and USGS GloVis websites (https://glovis.usgs.gov). A detailed data summary is given in Table 1. The ground truth data was collected from January to February 2021 using Global Positioning System (GPS) and used to classify satellite images and accuracy assess post-classification in combination with the historical view of Google Earth images.

Table 1. Detailed data summary of satellite imagery used in the study

Year of acquisition	Satellite	Sensor	Path/row	Resolution (m)	Source
10/02/1989	Landsat 5	TM	124/051	30	USGS GloVis
	Landsat 5	TM	124/052	30	USGS GloVis
10/01/2001	Landsat 5	TM	124/051	30	USGS GloVis
	Landsat 5	TM	124/052	30	USGS GloVis
07/02/2011	Landsat 5	TM	124/051	30	USGS GloVis
	Landsat 5	TM	124/052	30	USGS GloVis
06/03/2021	Landsat 8	OLI/TIRS	124/051	30	USGS EarthExplorer
	Landsat 8	OLI/TIRS	124/052	30	USGS EarthExplorer

Image pre-processing and classification

Image pre-processing was performed to extract meaningful information from satellite data so that they may become easier to interpret (Jensen, 1996). Landsat satellite images were processed, classified and analysed using ArcGIS 10.8. The satellite images listed in Table 1 were geometrically corrected to the Universal Transverse Mercator (UTM) coordinate system 48N on the WGS84 datum. The data were then composited and cropped based on the predefined boundaries of the study area. Although the primary objective of this study was to investigate forest cover changes, we also investigated other major LULC classes in the area to identify detailed variations in forest cover compared to other classes. Based on the field visit to the study area, the modified Anderson LULC scheme level I (Anderson et al., 1976), Vietnam's regulation on LU, the existing condition of the study area and reference to relevant literature, five LULC classes were identified: forest, agriculture, settlements, water, and barren land (Table 2).

For each image classification, a minimum of 300 training samples were selected by drawing polygons around representative classes. The training samples represented the five land-use classes and the number of training samples varied for different classes based on variabilities and ease of identification of each land-use class. Moreover, through false color composites of the satellite images enhances the visualization of the various features when classifying. The pixels enclosed by these polygons were used to record the spectral signatures for the respective classes of the satellite imagery. A satisfactory spectral signature was used to ensure minimum error among the land-uses to be mapped (Gao & Liu, 2010). The study has used the rule-based supervised classification - maximum likelihood classifier (MLC) algorithm for LULC classification for acquired images of 1989, 2001, 2011, and 2021 (Rawat & Kumar,

Table 2. Identified classes by supervised classification

Class	Description
Forest	Forestry, natural forests, individual trees, mangroves
Agriculture	Cultivated outfields, homestead garden fields, aquaculture, salt field and small scattered plots of grazing lands
Settlements	Residential buildings, industrial use, roads, villages, other impervious surfaces
Water	Rivers, canals, lakes, artificial ponds
Barren land	Fallow land, sands, earth dumps

2015; Shivakumar & Rajashekararadhya, 2018; Nguyen et al., 2020a; Thien et al., 2022a). The post-classification refinement was used for the simplicity and effectiveness of the method to improve classification accuracy and reduce misclassifications (Harris & Ventura, 1995).

Classification accuracy assessment

An evaluation of the accuracy of the thematic maps was produced to determine the quality of the information obtained from the data (Owojori & Xie, 2005; Thien et al., 2022b). The error matrix, overall accuracy, producer accuracy, user accuracy, and kappa coefficient metrics were used to evaluate the accuracy of the classified images for the years 1989, 2001, 2011, and 2021. The accuracy validation was performed against 300 random points that were identified and located using stratified randomization in ArcGIS 10.8 software to represent the area's different LULC classes. The comparison of point data and classification results was performed using an error matrix. The equations for kappa coefficient, overall accuracy, user accuracy, and producer accuracy are among the best quantitative measurements for classifying satellite images and are shown in equations (1), (2), (3), and (4) respectively (Chowdhury et al., 2020; Hasan et al., 2020; Thakur et al., 2021):

$$\text{Kappa coefficient} = \frac{\sum_{i=1}^{k} n_{ii} - \sum_{i-1}^{k} n_{ii}(G_i C_i)}{n^2 - \sum_{i=1}^{k} n_{ii}(G_i C_i)} \tag{1}$$

where i is the class number, n is the total number of classified pixels that are being compared to the actual data, nii is the number of pixels belonging to actual data class i that were classified as class i, C_i is the total number of classified pixels belonging to class i, and G_i is the total number of actual data pixels belonging to class i.

Overall accuracy = Total number of corrected classified pixels (diagonal) / Total number of reference pixels · 100 (2)

User accuracy = Number of corectly classified pixels in each category / Total number of reference pixel in each category (row total) · 100 (3)

Producer accuracy = Number of corectly classified pixels in each category / Total number of reference pixel in each category (column total) · 100 (4)

Analysis of vegetation indices to detect forest cover changes

Several vegetation indices can be employed to detect and analyze the existence and extent of vegetation and forest cover. Among the commonest ones are NDVI and SAVI (Huete, 1988; Huete, 2012; Islam et al., 2021). These indices are measures of vegetation and soil surface reflectance. In this research, the viability of these two widely used vegetation indices was therefore investigated to further determine the extent of forest cover and greenness in the ecosystem and its adjourning impact area. In this case, we extracted NDVI and SAVI values from all the forest polygons we detected through supervised classification of Landsat 8 OLI/TIRS imageries, and then we used the maximum and minimum values of NDVI and SAVI to reclassify the classification raster for mapping the area of forest land cover for all other periods. To do so, the NDVI and SAVI values used the raster calculator tool in ArcGIS 10.8 based on the formulas below (Eqs. 5 and 6):

$$\text{NDVI} = \frac{\text{NIR - RED}}{\text{NIR + RED}} \tag{5}$$

where NIR is the reflectance radiated in the near-infrared wave band, and RED is the reflectance radiated in the visible red wave band of the satellite radiometer.

$$SAVI = \frac{\text{NIR - RED}}{\text{NIR + RED + L}} \cdot 1 + \text{L} \tag{6}$$

where L is 0.5, the default value.

Results

Accuracy of classified images

The results of image accuracy assessment after classification for the four studied years are summarized in Table 3. The overall accuracy values for 1989, 2001, 2011, and 2021 are 86.71%, 87.33%, 89.00%, and 92.67%, respectively, with kappa coefficient statistics of 0.82, 0.83, 0.86, and 0.90, respectively. The user accuracy results show that in 1989, the maximum accuracy was for the forest class (93.52%) and the minimum for the barren land class (78.69%). In 2001, the user accuracy ranged from the lowest accuracy of 80.43% (barren land class) to a maximum of 91.43% (water class), while in 2011 it ranged from 82.50% for the barren land class to 95.12% for the water class (Table 3). A high user accuracy was achieved for 2021, with values of at least 90.63% (barren land class). The

Table 3. Land use/land cover classification and accuracy assessment analysis

Year	Producer Accuracy (%)					User Accuracy (%)					Overall Accuracy (%)	Kappa Coefficient
	Forest	Agriculture	Settlements	Water	Barren land	Forest	Agriculture	Settlements	Water	Barren land		
1989	90.99	86.57	77.78	86.84	82.76	93.52	84.06	80.77	89.19	78.69	86.71	0.82
2001	91.09	86.08	86.84	86.49	82.22	89.32	87.18	86.84	91.43	80.43	87.33	0.83
2011	90.53	88.89	90.00	88.64	84.62	92.47	83.12	91.84	95.12	82.50	89.00	0.86
2021	95.52	95.10	91.07	92.50	82.86	94.12	92.38	92.73	92.50	90.63	92.67	0.90

manufacturer's accuracy results show that the forest class was classified relatively accurately year by year at 90.99%, 91.09%, 90.53%, and 95.52% in 1989, 2001, 2011, and 2021, respectively. The corresponding lowest percentages were settlements (77.78%) in 1989 and barren land in 2001, 2011, and 2021, with values of 82.22%, 84.62%, and 82.86%, respectively (Table 3).

Land use/land cover classification of Dak Nong province from 1989 to 2021

The land cover classification images of Dak Nong province for the years 1989, 2001, 2011, and 2021 are shown in Figure 2. We observe that in 1989, most of the study area was covered with forest, accounting for around 77% of the total area. Forests covered 5,047.51 km², followed by barren land covering 1,244.54 km² (around 19%), agricultural land covering 182.74 km² (nearly 3%), settlements with a total area of 22.26 km² (0.34%), and, finally, water, which covered only 12.22 km² (0.19% of the study area) (Table 4). In 2001, the forested area was 4,417.58 km², accounting for 67.87% of the study area; this value decreased sharply to 2,456.62 km² (37.74%) in 2011 and 2,211.15 km² (33.97%) in 2021. The settlement land class in 1989 covered 22.26 km², accounting for 0.34% of the study area. This value increased significantly to 192.88 km², accounting for 2.96% in 2021 (Table 4). This increase in settlements also corresponds to a dramatic increase in agricultural land cover from only 182.74 km² (2.81%) in 1989 to 3,861.68 km² (59.33%) in 2021, at which time it represented the LULC class with the total land area proportion in the region. In addition,

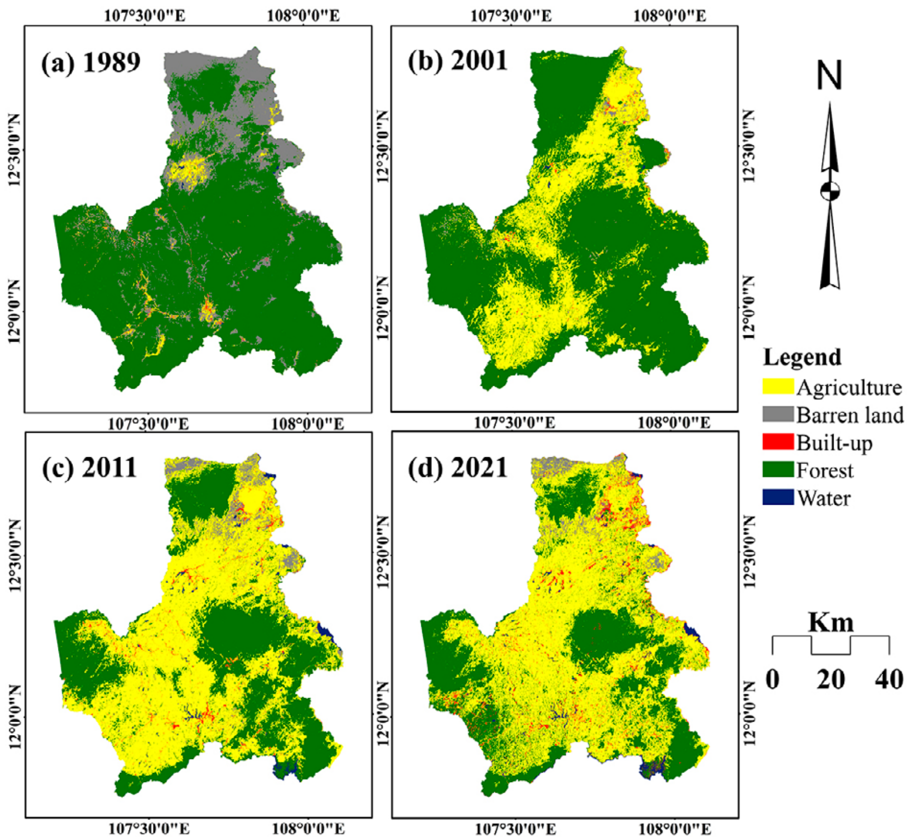

Figure 2. Land use/land cover of Dak Nong province in (a) 1989, (b) 2001, (c) 2011, and (d) 2021

Table 4. Results of land use/land cover classification in Dak Nong province from 1989 to 2021

Class	Land cover in 1989		Land cover in 2001		Land cover in 2011		Land cover in 2021	
	Area (km²)	%	Area (km²)	%	Area (km²)	%	Area (km²)	%
Forest	5047.51	77.54	4417.58	67.87	2456.62	37.74	2211.15	33.97
Agriculture	182.74	2.81	1964.60	30.18	3631.12	55.78	3861.68	59.33
Settlements	22.26	0.34	32.47	0.50	87.20	1.34	192.88	2.96
Water	12.22	0.19	13.72	0.21	89.19	1.37	89.85	1.38
Barren land	1244.54	19.12	80.90	1.24	245.14	3.77	153.71	2.36
Total	6509.27	100.00	6509.27	100.00	6509.27	100.00	6509.27	100.00

the water land class area also increased significantly from 12.22 km² (0.19%) in 1989 to 89.85 km² (1.38%) in 2021. In contrast, the barren land area of 1,244.54 km² (19.12%) in 1989 decreased sharply to 153.71 km² (2.36%) in 2021 (Table 4).

Land use/land cover changes of Dak Nong province from 1989 to 2021

Figure 3 shows the changes in land cover classes during the period 1989–2021. The corresponding area statistics on land cover change in the Dak Nong province are shown in Table 5. During the studied period, agricultural land showed the largest increase (1,781.86 km²), while barren land exhibited the greatest decrease (1,163.64 km²). The forest land class also showed a similar negative trend, with a 9.68% decrease from 5,047.51 km² in 1989 to 4,417.58 km² in 2001. Over the subsequent two decades, the area covered by forest continued to decrease. The largest decrease in forest area of 1,960.96 km² (30.13%) occurred during the period 2001–2011; in the period 2011–2021, this class further decreased but only by 245.47 km² (3.77%). Thus, in the two decades from 2001 to 2021, the agricultural area increased by 1,897.08 km² (29.14%). The residential area class expanded by 170.62 km² (2.62%) in the period 1989–2021, from 22.26 km² (0.34%) in 1989 to

Table 5. Land use/land cover changes assessment of Dak Nong province

Class	Change from 1989 to 2001		Change from 2001 to 2011		Change from 2011 to 2021		Change from 1989 to 2021	
	Area (km²)	%	Area (km²)	%	Area (km²)	%	Area (km²)	%
Forest	-629.93	-9.68	-1960.96	-30.13	-245.47	-3.77	-2836.36	-43.57
Agriculture	1781.86	27.37	1666.52	25.60	230.56	3.54	3678.94	56.52
Settlements	10.21	0.16	54.73	0.84	105.68	1.62	170.62	2.62
Water	1.50	0.02	75.47	1.16	0.66	0.01	77.63	1.19
Barren land	-1163.64	-17.88	164.24	2.52	-91.43	-1.40	-1090.83	-16.76

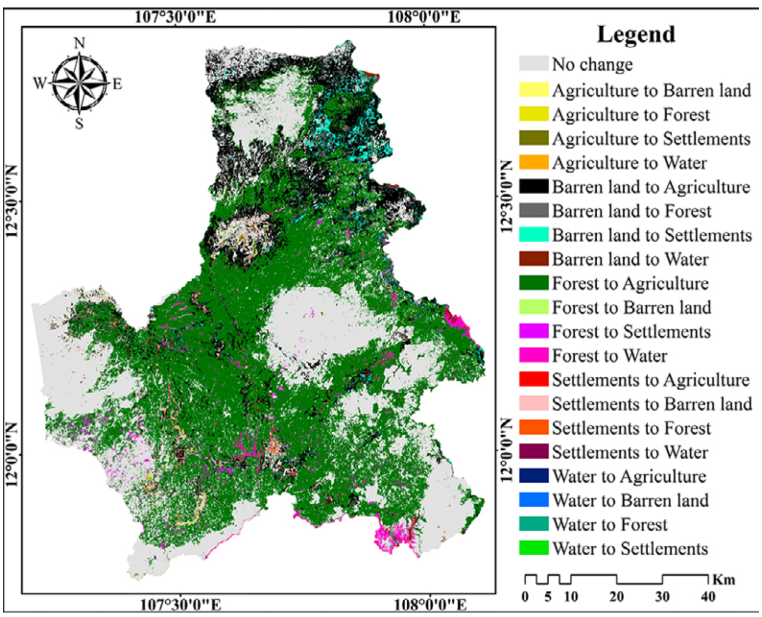

Figure 3. Land use/land cover change map of Dak Nong province from 1989 to 2021

192.88 km² (2.96%) in 2021. The area of barren land increased in the period from 2001 to 2011 by a total of 164.24 km² (2.52%). However, in the following decade (2011–2021), many of these barren land areas were covered by other classes, and the barren land area decreased to 91.43 km² (1.40%). Figures 3 and 4 and Table 5 also highlight that the water area has increased continuously over the past 30 years. However, in the two periods 1989–2001 and 2011–2021, the water class showed the smallest increases of any class, with values of only 1.50 km² (0.02%) and 0.66 km² (0.01%), respectively. From 2001 to 2011, the water class underwent its largest increase in area during the studied period, growing by 75.47 km² (1.16%) (Table 5).

Table 6. Cross-tabulation of land cover classes between 1989 and 2021 (area in km²)

1989 \ 2021	Forest	Agriculture	Settlements	Water	Barren land	Total
Forest	2094.03	2804.50	86.62	55.09	7.27	5047.51
Agriculture	20.51	137.22	18.23	6.10	0.68	182.74
Settlements	1.78	17.26	2.94	0.24	0.04	22.26
Water	1.05	1.26	2.77	7.13	0.01	12.22
Barren land	93.78	901.44	82.32	21.29	145.71	1244.54
Total	2211.15	3861.68	192.88	89.85	153.71	

To perform a detailed assessment of LULC changes, two classified maps were superimposed to create a LULC volatility map for the period 1989–2021 (Figure 3); in addition, a diagonal matrix was also created to illustrate the conversion of LULC classes (Table 6). Of the 5,047.51 km² of forest cover in 1989, a total of 2,094.03 km² was still forested in 2021, however, 2,804.50 km² had been converted to agricultural land and the remainder to settlements, barren land, and water. During this period, the areas of forest class gain from 1989 to 2021 were mainly from the barren land class (93.78 km²). Of the total area of 1,244.54 km² of barren land in 1989, in addition to the losses to the forest class mentioned above, most of the area has been lost to the agricultural land class (901.44 km²), with a total of 145.71 km² retained in 2021. The settlement land class area increased from 22.26 km² in 1989 to 192.88 km² in 2021. This class has retained only 2.94 km² of its original area and has mainly been replaced by agriculture. The main classes replacing settlement areas in 2021 were the forest class (86.62 km²) and the barren land class (82.32 km²) (Table 6). The agricultural class area retained 137.22 km² of its total 182.74 km² from 1989 and had mainly been replaced by forest and settlements by 2021. The water area also increased from 12.22 km² (1989) to 89.85 km² (2021), with 7.13 km² of its original area from 1989 retained (Table 6).

Relationship between vegetation indices and decadal forest cover changes

Maps showing the NDVI and SAVI values in Dak Nong province from 1989 to 2021 are shown in Figures 4 and 5. In this process, we evaluated all NDVI and SAVI pixel values from our graded image in 2021 and classified NDVI values greater than 0.35 and SAVI values greater than 0.58 in a dark green color, which corresponds to the forest polygon areas. Considering these NDVI and SAVI thresholds, we reclassified the classified images for 1989, 2001, and 2011 into forest and non-forest areas.

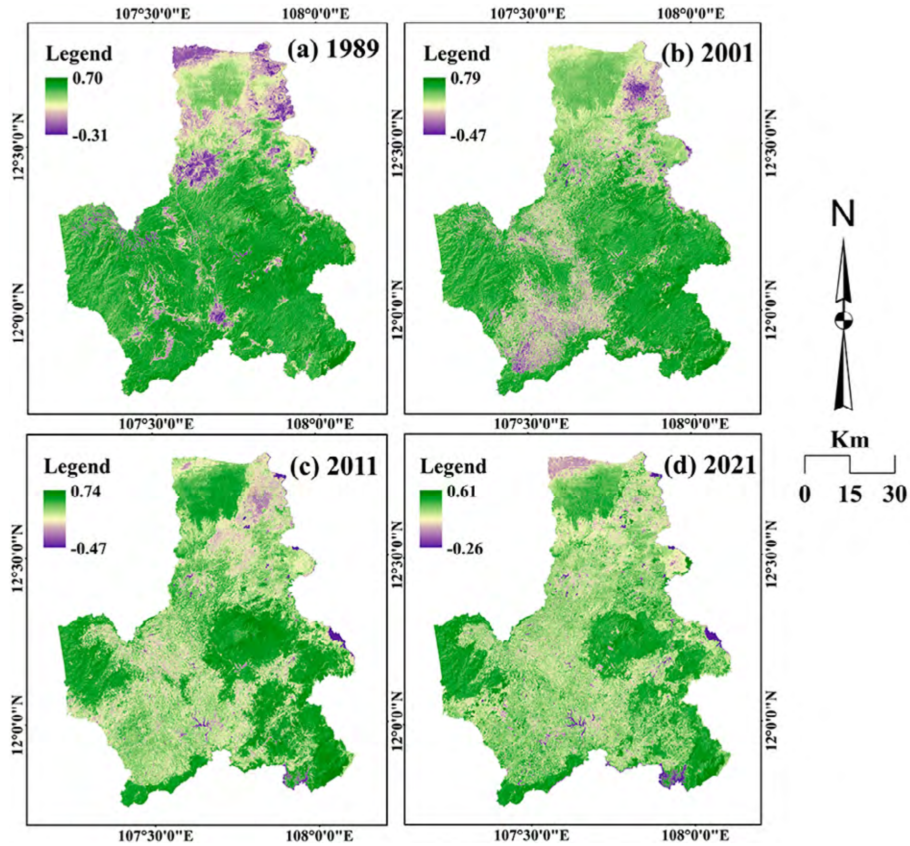

Figure 4. Spatial distribution of NDVI for 1989, 2001, 2011, and 2021

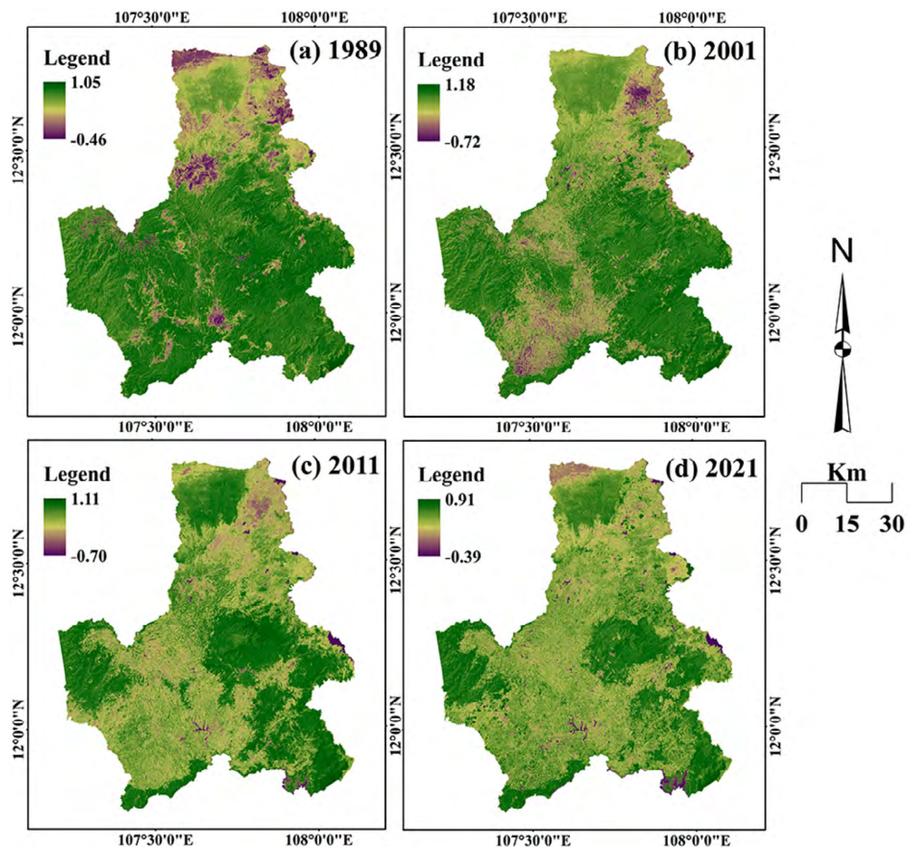

Figure 5. Spatial distribution of SAVI for 1989, 2001, 2011, and 2021

The areas covered by forests from 1989 to 2021 based on these vegetation indices are presented in Table 7. The trend of year-over-year change in the study period was also shown in Figure 6. Analysis results reclassification of forest class based on NDVI index through each year 1989, 2001, 2011 and 2021 are 5452.61 km², 4936.29 km², 3843.98 km² and 2724.91 km² respectively, equivalent to 83.77%, 75.83%, 59.05% and 41.86% (Table 7). In addition, based on the SAVI index the forest class classification results are quite similar to the NDVI index with 5340.68 km² (82.05%) in 1989, 4935.01 km² (75.82%) in 2001, 3540.91 km² (54.40%) in 2011 and 2657.19 km² (40.82%) in 2021 (Table 7).

Table 7. Based forest cover area analyzed by vegetation indices (NDVI and SAVI) from 1989 to 2021

Category		Distribution in 1989		Distribution in 2001		Distribution in 2011		Distribution in 2021	
		Area (km²)	(%)	Area (km²)	(%)	Area (km²)	(%)	Area (km²)	(%)
NDVI	Forest	5452.61	83.77	4936.29	75.83	3843.98	59.05	2724.91	41.86
	Other	1056.66	16.23	1572.98	24.17	2665.29	40.95	3784.36	58.14
	Total	6509.27	100.00	6509.27	100.00	6509.27	100.00	6509.27	100.00
SAVI	Forest	5340.68	82.05	4935.01	75.82	3540.91	54.40	2657.19	40.82
	Other	1168.59	17.95	1574.26	24.18	2968.36	45.60	3852.08	59.18
	Total	6509.27	100.00	6509.27	100.00	6509.27	100.00	6509.27	100.00

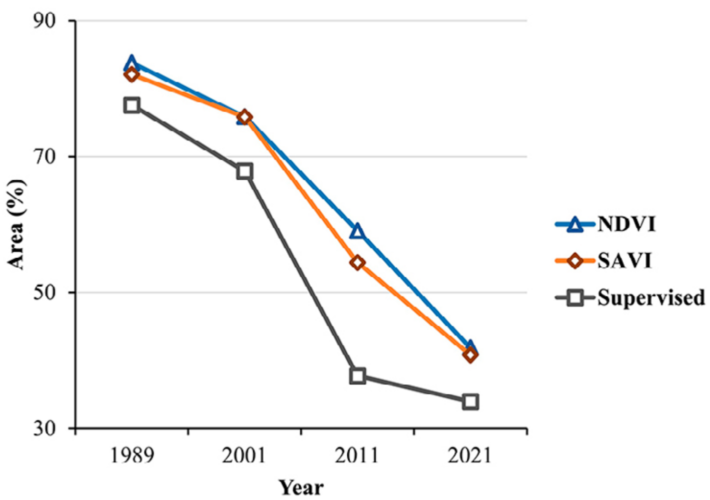

Figure 6. Comparison of forest cover from 1989 to 2021 through NDVI, SAVI, and supervised classification

Discussion

The study adopted contemporary, time and cost-efficient methods to investigate the dynamics to the LULC and forest cover change during the research period from 1989 to 2021 in Dak Nong province, Vietnam. The use of MLC to categorize the Landsat images (TM and OLI/TIRS) has produced maps showing the distribution of the five prevalent LULC classes in the study area for the years 1989, 2001, 2011, and 2021 (Figure 2) and the results of each classes area were also shown in Table 4. Classification results show that in 1989 and 2001 the forest class accounted for the largest area of coverage, but by 2011 and 2021 the forest class area was reduced, instead the area of agricultural land increased to become the cover with the highest area. In addition, evaluating the accuracy and determining the plausibility of the resulting map is an important step after the classification of the soil cover by evaluating the error for each class and in general for the whole classified image. The kappa coefficient values represent a measure of the consistency or precision between the reference data and the classified LULC classes and can take values from -1.00 to +1.00. Kappa coefficients between 0.60 and 0.80 indicate high simulation consistency, while values of 0.80-1.00 indicate near-perfect character (Congalton & Green, 2019, Thien et al., 2022a). In this study, the kappa coefficient values all exceed 0.80 (Table 3), indicating excellent agreement between the classified results and reference data (Manonmani & Suganya, 2010; Lea & Curtis, 2010).

Spatial analysis of the multi-time LULC maps of Dak Nong province shows significant changes in the 32 years from 1989 to 2021. LULC changes have both positive and negative effects and are a continuous process caused by many natural and human factors. Changes in LULC, especially in developing countries, have led to reductions in other important natural resources, including vegetation, soil and water. Therefore, the study of LULC alteration requires a comprehensive understanding and monitoring of all the factors that cause it. In this study, to get an overview of changes in forest class and identify the causes of their change during the 32 years of the study (1989-2021), we compared the forest class group based on the statistics in Tables 5 and 6 and the spatial change in the distribution of the LULC class as in Figure 3.

Forests play an essential role in human life and the environment, providing not only resources such as wood and firewood but also an important part in regulating the climate and protecting the land from natural disasters (Fedler, 2018; Watson et al., 2018). According to the results shown in Table 5, the forest layer area during the study period from 1989 to 2021 has been seriously reduced, while the area of agricultural layers and settlements has continuously increased. Additionally, Figure 3 and Table 6 clearly show that the lost forest area has been largely converted into agricultural land and settlements. This shows that there are many reasons for forest cover degradation in Dak Nong province but most of them are related to human activities such as indiscriminate logging, deforestation, forest fires and conversion to agricultural land (Santos de Lima et al., 2018; Duguma et al., 2019). The population has increased rapidly both naturally and through spontaneous immigration since the reforms took effect in 1990. From 1999 to 2009, Dak Nong province had the highest population growth rate in the country because it has a sub-tropical monsoon climate, so the landscape is highly diverse, with favorable conditions for growing crops such as coffee, pepper, cocoa and strawberries (Central Population and Housing Census Steering Committee, 2010). The expansion of agricultural area has caused the province's natural forest area to decrease sharply, they have destroyed natural forests for agriculture, of which the largest cause of deforestation is to plant industrial trees as mentioned above (Rambo et al., 1995; Nguyen et al., 2020b). Most of the farmland has been converted into farmland and settlements are increasingly causing damage to the natural forests of immigrants. In addition, prioritizing socio-economic development also greatly affects the loss of natural forest area. A large part of the natural forest area of Dak Nong province has been cut down to build hydropower, transport and switch to rubber plantations (MARD, 2019). In addition, there are indirect causes of deforestation and forest degradation such as high agricultural prices and inefficient forest management methods (Dan et al., 2018).

Remotely sensed vegetation indices are a simple and effective method for quantifying and assessing plant cover, vigour, and growth dynamics (Pesaresi et al., 2020; Pasternak & Pawluszek-Filipiak, 2022). The NDVI and SAVI values of the area ranged from -0.47 to 0.79 (Figure 4) and -0.72 to 1.18 (Figure 5) across the years of evaluation, with the higher values indicating forest, low positive values characterizing sparse vegetation and negative values representing water (Huete, 2012; Islam et al., 2021; Pasternak & Pawluszek-Filipiak, 2022). The increased values of the NDVI (0.79 > 0.70) and SAVI (1.18 > 1.05) in 2001 compared to 1989 have partly confirmed earlier evidence of reduced deforestation and increased forest conversion at the end of that period (Table 5). However, further comparative validation of reports of this indicator is necessary to determine deviations in their forest cover assessment, as provided in Figure 6 and Table 7. A comparative review of forest area estimates from both indicators versus supervised classification results showed relatively similar trends but with a relative overestimate in 2011 for both NDVI and SAVI. These estimated deviations may be due to the sensitivity of plant indicators to the effects of soil reflections, soil surface, atmosphere, and cloud shadows, which require calibration of remote sensing (Huete, 1988; Pasternak & Pawluszek-Filipiak, 2022). From these results, we can conclude that NDVI and SAVI are both good indicators that can effectively detect and monitor forest cover in Dak Nong province, especially for quick assessments of forest cover.

Conclusion

In this study, geospatial techniques were used to analyze spatial and temporal forest cover changes in Dak Nong province using Landsat 5 and 8 remote sensing images. The results of this work indicate a significant decrease in forest cover over the studied 32 years. In 1989, forest cover was 77.54%; this value decreased to 67.87% in 2001 and further decreased to 37.74% in 2011, with a final value of only 33.97% in 2021. In contrast, the agricultural land area percentage increased rapidly from 2.81% in 1989 to 30.18%, 55.78%, and 59.33% in the years 2001, 2011, and 2021. This study also illustrates that the NDVI and SAVI indices show notable changes in the characteristics of forest cover from 1989 to 2021. Based on our research results, we encourage policymakers and decision-makers to take more effective measures for conservation and sustainable development in Dak Nong province. In particular, we recommend that the forestry agency needs additional staff to better monitor and protect forests from illegal logging and prevent future forest loss. In addition, the results of this study provide a useful reference for future researchers investigating LULC changes in this area and those examining severe deforestation in future policymaking to ensure forest protection and development.

Acknowledgements

The authors would like to thank the editor and anonymous reviewers for their thoughtful comments and efforts toward improving our manuscript.

Conflict of interest

The authors declare no conflict of interest.

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