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Methods for assessing quality of life: an application to Czech municipalities with extended jurisdiction

Jakub Hanousek

Prague University of Economics and Business, Czech Republic

E-mail: jakubhanousek@seznam.cz

Abstract:

The goal of this article is to measure the objective dimension of quality of life in municipalities with extended jurisdiction in the Czech Republic. Quality of life is measured by four composite indicators. Composite indicators were calculated using two methods based on several socio-economic factors. The methods for calculating composite indicators are the weighted sum approach and the benefit-of-the-doubt method, which is based on linear programming. In the weighted sum method, the target population groups were distinguished by determining different weights for individual socio-economic factors. The article also analyzes the effect of living on the Czech Republic state border on the quality of life, and individual neighboring countries are distinguished. Composite indicators are further analyzed by regression analysis with qualitative variables. The statistically significant results show that municipalities located near the border with Slovakia achieve average higher values of all four composite indicators than other municipalities. The results were further analyzed by spatial analysis. Positive spatial autocorrelation and so-called coldspots and hotspots were found. Hotspots were detected in municipalities with extended coverage bordering Slovakia, with some reaching inland. After including the spatial component in the regression model, the effect of the state border weakened. This is because individual cold spots and hotspots have a significant inland extension from the border.

Keywords: quality of life, spatial dependence, MCDA

JEL classification: C44

Introduction

Assessing quality of life is a very complex and demanding process. Quality of life (QoL) is a concept that aims to capture the well-being of a population or individual regarding both positive and negative elements within the entirety of their existence at a specific point in time (Teoli and Bhardwaj, 2023).

The question of quality of life has been addressed by ancient scholars and philosophers. The desire to live a good life is one of the basic human desires described in ancient times (Murgaš and Kloboučník, 2016). Aristotle's concept of eudaimonia encourages individuals to strive to use all possible means to achieve a good life. Immanuel Kant promoted the idea of achieving a good society through adherence to moral principles (Diener and Suh, 1997). As society has developed, these general philosophical ideas about the quality of life have moved to a more practical level (Macků, 2020). In the early stages of quality of life research (mid-20th century), the topic was mainly associated with economic development. The term quality of life was first used by the English economist Cecil Pigou in the 1920s. (Glatzer, 2007). At that time, the main criterion for a quality and satisfying life was the economic prosperity of society. For this reason, in the past, gross domestic product was often used as a comparative indicator. However, with the development of economic well-being in the post-war years and the satisfaction of the population's basic material needs, other aspects of quality of life opened up that would be appropriate to monitor (Faťunová, 2007). In the United States, quality of life played a major role in the political programs of J. F. Kennedy and L. B. Johnson, for example, who promoted an increase in the quality of life and living standards. Willy Brandt adopted the same goals in his program in West Germany in the 1970s. (Páralová, 2018). Overcoming the pioneering period of the formation of the concept of quality of life (the first comprehensive publications were published by Smith (1973), Campbell et al.(1976), and Andrews (1986)), since approximately the 1980s, scientific research has been trying to define quality of life better and derive methods for its measurement (Macků, 2020). Currently, quality of life has many concepts and represents a complex multidisciplinary topic that is scientifically researched at the academic level, but operated primarily in political and planning practice as a tool of state administration and organizations for planning and decision-making (Macků, 2020).

Before evaluating, we must have the relevant data available. The process of obtaining relevant data is not a trivial matter. The data sources are primarily government census projects, statistical yearbooks, geographic data, and other sources. The results of the studies are likely influenced by two factors at most. The first factor is the selected criteria for evaluation, and the second is the methodology for their evaluation. Both often differ across studies. This article works mainly with data within the Czech Republic, specifically with the measurement of socioeconomic factors in the territory of municipalities with extended jurisdiction in the Czech Republic. It is obvious that each individual person prefers something different in his or her life. Older adults have different needs than young people. Some people love nature and can not live without it, while others prefer city life. In short, every person has different preferences in their life. For the above reasons, it is evident that measuring quality of life is a difficult and complex problem. The dimensions of quality of life include both objective (e.g., income, education, health, environment, safety) and subjective aspects (e.g., personal well-being, satisfaction). This article works only with the objective dimension of quality of life. The quality of life is measured by four composite indicators in this article. A composite indicator is a dimensionless index obtained by aggregating partial factors or criteria. The factors used in this article are criminality, unemployment, kindergartens, primary schools, general practitioners, nature, hospitals, and grocery stores. The above factors are described in more detail in the following chapters. Three composite indicators are calculated using the weighted sum method, and the last composite indicator is calculated using the benefit of the doubt method. The obtained composite indicators are further subjected to spatial analysis using linear regression. The article focuses on municipalities that are immediately adjacent to the state border. It is analyzed whether municipalities on the state borders achieve significantly different results than municipalities in the Czech Republic inland. Linear regressions are estimated parameters of the influence of neighboring states on state border municipalities. Data on individual indicators come from 2018–2019.

The Czech Republic has approximately 10.5 million inhabitants, and the area of the Czech Republic is 78,866 km^2. The Czech Republic is divided into 14 regions, 76 districts, 205 municipalities with extended jurisdiction, and 6,254 municipalities. There are 60 municipalities with extended jurisdiction that are immediately adjacent to the state border. Two million six hundred seventy thousand twenty-one inhabitants live on the territory of these 60 municipalities. The total area of these 60 municipalities is 25,951 km^2. The data used in the article are from 2018 and 2019.

The analysis is made with respect to the different preferences of population groups, but also universally, without regard to the preferences. The article also includes an analysis of border areas, which is sometimes overlooked in similar studies. The article analyzes whether a specific country influences the value of the composite indicator of the municipality with extended jurisdiction that is immediately adjacent to it. This view is unique among studies conducted in the Czech Republic.

This article has 5 sections. The first section is an introduction to the issue and a brief historical development. The second section focuses on current and past projects related to quality of life assessment. The third part defines the methods used in this article. The fourth part is an application to data within the Czech Republic. The last part is the evaluation of the achieved results.

1. Current and past projects

There are various projects and indicators for measuring the quality of life in the Czech Republic. The Czech Statistical Office measures quality of life in regions using 34 indicators. The STEM Institute of Empirical Research and DATLAB have developed a database of quality of life in municipalities, and Vlada.cz has proposed 11 areas for measuring quality of life.

The European Quality of Life Survey (EQLS) is an established instrument designed to capture quality of life in many aspects. Since its launch in 2003, the EQLS has developed into a valuable set of indicators that complement traditional indicators of economic growth and living standards, such as GDP or income levels.

The Organisation for Economic Cooperation and Development (OECD) has its own index: *OECD Better Life Index*. This index is created at the country level and consists of 11 evaluated criteria. Another important initiative in assessing the quality of life is the European Union initiative: *Beyond the GDP – Measuring progress in a changing world*. Defines a theoretical and data framework for quality of life research at the country level.

Table 1 lists publications published in the last 10 years on the topic of quality of life assessment, focusing on evaluation criteria.

Table 1. Overview of quality of life studies over the last 10 years

Authors	Year of publication	Criteria
Lara Fleischer et al. (OECD)	2024	more than 80 indicators
Laura de Dominicis et al.	2023	housing, employment, mobility, environment, public services, safety
Lara Fleischer et al. (OECD)	2020	more than 80 indicators
Noble et al.	2019	income, employment, education, skills and training, health, crime, barriers to housing and services, living environment
Veneri and Murtin	2018	income, health, job
Greyling and Tregenna	2016	housing, social relationships, economic dimension, health, governance, civic engagement, safety, life satisfaction, environmental satisfaction
Murgaš and Klobučník	2016	family, health, education, job, natural environment
Žmuk	2016	health, economic strain, living conditions, working conditions
Lagas et al.	2015	public services, purchasing power and employment, housing, social environment, natural environment, recreation, health, education, governance
Puskorius	2015	health, employment and occupancy rate, environment, lifetime, income, consumption, environment, accommodation, education, spiritual, moral-ethical and cultural values, gender equality, safety, law, order, corruption

Source: Author

Table 1 shows the inconsistent approach to assessing quality of life across different authors. We see that all studies include the health criterion, and most include the education or employment criteria. We could therefore speak of these criteria as essential. In the context of the Czech Republic, several studies have been conducted dealing with the quality of life. Probably the most well-known studies from recent years that have also reached the wider public are the Quality of Life Index study and the Place for Life project. In both of these studies, settlements around large cities such as Prague and Brno showed a high quality of life. A. Sen (1985) introduces a capability approach, which measures quality of life through objectively measurable capabilities and functions of an individual (health, education, living conditions).

Other examples of prominent authors in the field of quality of life research are Sirgy (2021), Diener (1997), Michalos (2017), Martinez and Lyubomirsky (2017), Veenhoven (2000), and others. There are several approaches to assessing quality of life. Some authors deal with only one level of quality of life (objective or subjective), and some with both.

2. Methods

Quality of life evaluation can be defined as a multi-criteria problem. There are many methods for multi-criteria evaluation of alternatives, and choosing the appropriate method may not always be a simple matter. This article works with four methods. The first method is the scoring method, which is used to determine weights based on information from the decision maker. The second method is the weighted sum method. This method belongs to the methods of multi-criteria evaluation of alternatives based on the maximization of the utility function. The third method is the benefit of the doubt method. The benefit of the doubt method is a non-parametric optimization method based on the principle of linear programming. The fourth method is explanatory analysis methods, specifically regression methods and spatial regression. All methods are described in more detail in the following sections.

We will transform our problem into a multi-criteria decision problem, specifically a multi-criteria evaluation of alternatives. In multi-criteria alternatives evaluation models, the task is specified by a list of alternatives $A = \{a_1, a_2, ..., a_p\}$ and a list of criteria $F = \{f_1, f_2, ..., f_k\}$. The criterion matrix has the following form (Fiala *et al.*,1994).

$$\boldsymbol{B} = \begin{array}{c} \\ a_1 \\ a_2 \\ \vdots \\ a_p \end{array} \begin{array}{c} \begin{array}{cccc} f_1 & f_2 & \cdots & f_k \end{array} \\ \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1k} \\ b_{21} & b_{22} & \dots & b_{2k} \\ \dots & \dots & \dots & \dots \\ b_{p1} & b_{p2} & \dots & b_{pk} \end{bmatrix} \end{array} \tag{1}$$

In this article, the alternatives are represented by municipalities with extended jurisdiction. In Matrix **B**, alternatives are ordered by index *i*, $i = 1, 2, \ldots, p$. The criteria are individual socioeconomic factors. In Matrix **B**, criteria are ordered by index *l*, $l = 1, 2, \ldots, k$. The matrix element b_{il} represents the values of the *i-th* municipality according to the *l-th* criterion.

Multi-criteria evaluation of alternatives is a large scientific discipline that includes dozens of methods and algorithms. Choosing the right method or algorithm is not easy these days.

2.1 Scoring method

The scoring method is used to determine the weights for the weighted sum methods in this article. The method assumes that we are able to quantitatively assess the importance of the criteria.

It is assumed that we are able to quantitatively evaluate the importance of the criteria. For the selected scoring scale, we must evaluate the *l-th* criterion with the value p_l of the given scale $p_l \in [0, h]$ h is the maximum possible weight for the criterion.

We get the resulting weights of the criteria after substituting them into formula 2 (Fiala et al.,1994).

$$v_l = \frac{p_l}{\sum_{s=1}^{k} p_s} \qquad l = 1, 2, \ldots, k. \tag{2}$$

2.2 Weighted sum approach

The method is based on the calculation principle of utility maximization. It considers only linear utility functions. Computationally, it is simple.

We will create a matrix **R**, the r_{il} elements of which will be obtained by transformation from the matrix **B** according to the following formula

$$r_{il} = \frac{b_{il} - D_l}{H_l - D_l}, \tag{3}$$

The matrix **R** represents the utility value of the *i-th* alternative according to the *l-th* criterion. The value of D_l represents the minimum value achieved by the evaluated municipality according to the *l-th* criterion. The value of H_l represents the maximum value achieved by the evaluated municipality according to the *l-th* criterion. The benefit from variant a_i is then calculated as:

$$u(a_i) = \sum_{l=1}^{k} v_l r_{il}. \tag{4}$$

The alternative that achieved the highest utility value is selected as the best. We can arrange the other variants according to the values of the utility function (Fiala *et al.*,1994).

2.3 Benefit of the doubt

This approach is based on non-parametric data envelopment analysis methods. The data envelope consists of the best-rated alternatives. The model works with two matrices. The first matrix consists of minimization criteria. We arrange the values of the minimization criteria in the matrix **X** (Cherchye et al.,2007). The matrix element x_{ij} represents the *i-th* unit, $i = 1, 2, ..., p$, according to the *j-th* criterion, $j = 1, 2, …, n$.

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pn} \end{bmatrix} \tag{5}$$

The second matrix consists of maximization criteria. We arrange the values of the maximization criteria into the matrix **Y**. The matrix element y_{ik} represents the *i-th* unit, $i = 1, 2, ..., p$, according to the *k-th* criterion, $k = 1, 2, …, r$.

$$\boldsymbol{Y} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1r} \\ y_{21} & y_{22} & \cdots & y_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ y_{p1} & y_{p2} & \cdots & y_{pr} \end{bmatrix} \tag{6}$$

Now we proceed to the definition of a linear model for calculating the data envelope

$$\begin{aligned} &\text{minimize: } \theta_q, \\ &\text{subject to: } \textstyle\sum_{i=1}^{p} x_{ij}\lambda_i \le \theta_q x_{qj}, && j = 1, 2, \ldots, n, \\ &\textstyle\sum_{i=1}^{p} y_{ik}\lambda_i \ge y_{qk}, && k = 1, 2, \ldots, r, \\ &\lambda_i \ge 0, && i = 1, 2, \ldots, p. \end{aligned} \tag{7}$$

The model works with a vector of weights $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_p), \lambda \ge 0$, which are assigned to individual alternatives. This is a vector of variables of this model. Another model variable is θ_q which is the required reduction rate of the minimization criteria to reach the data envelope boundary. The model tries to find a virtual variant characterized by the minimization criteria **Xλ** and maximization **Yλ** which are a linear combination of the minimization and maximization criteria of the other alternatives and are no worse than the minimization and maximization criteria of the evaluated alternative. Expression x_{qj} represents the value of the evaluation of the unit q according to the *j-th* criterion in the matrix **X**, similarly expression y_{qk} represents the value of the evaluation unit q according to the *k-th* criterion in the matrix **Y.** The evaluated variant lies on the border of the data envelope if a virtual alternative with these properties does not exist or is identical to the evaluated alternative. This situation occurs if the variable θ_q is equal to one. At the same time, all additional variables are equal to zero (Charnes et al.,1978). This method was applied to assess quality of life in the authors' articles González et al. (2011) or Martín and Mendoza (2013).

If there is a situation where more variants lie on the border of the data envelope, these variants can be further organized by applying Model 8.

$$
\begin{aligned}
&\text{minimize: } \theta_q, \\
&\text{subject to: } \textstyle\sum_{i=1,\neq q}^{p} x_{ij}\lambda_i + s_j^- = \theta_q x_{qj}, \qquad j = 1, 2, \ldots, n, \\
&\textstyle\sum_{i=1,\neq q}^{p} y_{ik}\lambda_i - s_k^+ = y_{qk}, \qquad k = 1, 2, \ldots, r, \\
&\lambda_q = 0, \\
&\lambda_i \geq 0, \qquad i = 1, 2, \ldots, p, \; i \neq q \\
&s_j^- \geq 0 \qquad j = 1, 2, \ldots, n, \\
&s_k^+ \geq 0 \qquad k = 1, 2, \ldots, r.
\end{aligned} \tag{8}
$$

The arrangement of the alternatives on the boundary of the data frontier consists of the fact that the weight of the alternative placed on the boundary of the data frontier is equal to zero, so it is removed from the set of alternatives, and thus, the original boundary of the data envelope is changed. Vectors s_j^- s_k^+ are slack variables. They capture how much the *j-th* respectively *k-th* criterion of the evaluated unit q can deteriorate without changing the original data envelope boundary. Model 8 then measures the distance of the evaluated unit from the new boundary of the data envelope (Charnes *et al.*,1994).

2.4 Exploratory analysis

Exploratory factor analysis is a technique that attempts to replace the relationships between a set of interrelated variables with a small number of non-directly observable features, factors. This is also its primary function – data reduction, variable reduction. Once a factor is discovered and named, we can create a new variable from it, which we use in further analysis instead of the original items.

In this article, the data will be subjected to exploratory analysis from the perspective of the state border factor. Linear regression will be used to test whether the resulting indicator is influenced by the proximity of the state border of a specific state. Whether the relevant municipality with extended jurisdiction is adjacent to the relevant state will be expressed in the model. The parameters will be estimated by model 9.

$$\pi = \beta_0 + \beta_1\psi_1 + \cdots + \beta_k\psi_k + \varepsilon_0 \tag{9}$$

Model 9 is a classical linear model, which consists of a vector of dependent variables π, vectors of independent variables ψ_1, ψ_2, ..., ψ_k, residual components ε, and finally parameters β_1, β_2, ..., β_k. Parameter β_0 is the intercept.

The factor of whether the relevant municipality with extended jurisdiction is located at the relevant state border is expressed in the data using a dummy variable. The incidence of a municipality with extended jurisdiction in a given state will be expressed in the data as 1, otherwise 0. The reference variable is municipalities with extended jurisdiction that do not border any state border. The reference variable is the "inland". The inland variable itself is not included in the model. If we included it in the model and left the other variables in the model, we would face the problem of perfect multicollinearity. The random component in the model should satisfy a strong set of assumptions.

Multicollinearity

Violating this assumption would create multicollinearity problems in the model. Multicollinearity causes problems in the calculation of regression coefficients, such as unstable estimates and high variances of the coefficients, making it difficult to reliably determine the influence of individual explanatory variables on the dependent variable.

We will test this by constructing auxiliary regressions.

$$\begin{aligned} \psi_1 &= \alpha_0 + \alpha_2\psi_2 + \cdots + \alpha_k\psi_k + \varepsilon_1 \\ &. \\ &. \\ \psi_k &= \mu_0 + \mu_1\psi_1 + \cdots + \mu_{k-1}\psi_{k-1} + \varepsilon_k \end{aligned} \tag{10}$$

By calculating the coefficient of determination (R^2) of auxiliary regressions, we find the degree of collinearity. From R^2 we can calculate the Variance Inflation Factors according to the following formula.

$$VIF = \frac{1}{(1-R^2)} \tag{11}$$

The evaluation of VIF can be described by the following intervals.

Table 2. Degree of multicollinearity

VIF	Degree of multicollinearity
1	No multicollinearity
(1,5 >⟩	Slight multicollinearity
(5,10 >⟩	High multicollinearity
>10	Extreme multicollinearity

Homoscedasticity of the random component

Heteroskedasticity has several key consequences, the most important of which is that the classical least squares (OLS) method produces inefficient parameter estimates, even if they remain unbiased and consistent. Furthermore, the estimated standard errors of the coefficients are invalid, leading to unreliable t-tests and confidence intervals, and thus incorrect conclusions about the statistical significance of the variables.

The homoscedasticity of the random component will be tested using the White test.

Spatial analysis

Spatial analysis includes some of the formal techniques that study entities using their topological, geometric, or geographical properties. Fotheringham et al. (2002): "Spatial dependency is the extent to which the value of an attribute in one location depends on the values of the attribute in nearby locations." Different definitions of spatial dependency are possible. To discuss spatial dependency, spatial autocorrelation, corresponding tests, and spatial econometric models, we need to formalize the concept of nearby locations – neighbors.

The distance-based approach defines two units as neighbors if their distance does not exceed some ad-hoc predefined threshold: τ. The threshold point can be applied using, for example, (Centroids, Contiguity-based approach or Generalized contiguity approach)

Centroids are used for measuring distances between units with non-zero areas (e.g. regions). Centroids can be purely geographical, "main" city locations, population-weighted, transportation-weighted (highway/railway), etc.

Regardless of the algorithm used for neighbor vs non-neighbor categorization, any spatial structure may be formalized using a connectivity matrix **C**:

$$c_{ij} = \begin{cases} 1 \; if \; i \; and \; j \; are \; neighbors, \\ 0 \; if \; i \; and \; j \; are \; not \; neighbors. \end{cases}$$

Zeros on the diagonal – units are not neighbors to themselves.

Matrix $\boldsymbol{W}$ is a row-standardized matrix $\boldsymbol{C}$

$$w_{ij} = \frac{c_{ij}}{\sum_{j=1}^{N} c_{sj}} \tag{12}$$

In spatial data, we can often encounter the phenomenon of spatial autocorrelation. Spatial autocorrelation is a phenomenon where the values of a phenomenon in a given location are similar to the values in its immediate surroundings.

This article tests spatial autocorrelation using Moran's I.

$$I = z'\boldsymbol{W}z\left(z'z\right)^{-1} \tag{13}$$

z is the centered form of ω: $z_i = \omega_i - \overline{\omega}$, ω_i is the spatial observation (unit).

Moran's I yields only one statistic that summarizes the nature of spatial dependency in the observed variable – it assumes geographical homogenity (stationarity) in the data.

In spatial analysis, we distinguish between positive and negative autocorrelation. Positive autocorrelation can be further analyzed using clustering analyses. A. Getis or J.K. Ord proposed the Getis–Ord statistics (G). The G statistic identifies where features with high or low values are spatially clustered in a statistically significant way, the so-called "cold spots" and "hot spots".

$$G_i^*(\tau) = \frac{\sum_{j=1}^{N} c_{ij}^* \omega_j}{\sum_{j=1}^{N} \omega_j} \tag{14}$$

Where c_{ij}^* come from an amended distance-based (arbitrary τ used) connectivity matrix $\boldsymbol{C}^* = \boldsymbol{C} + \boldsymbol{I_N}$ i.e., ω_i observations enter $G_i^*(\tau)$ calculation. Observations of ω are assumed to have a natural origin and positive support (Ord *et al.*,1995). N is the number of spatial observations (units) of the variable under scrutiny.

The estimated regression model with a spatial component has the form:

$$\omega = \rho \boldsymbol{W} \omega + \boldsymbol{\Psi} \beta + \epsilon \tag{15}$$

where ρ is a spatial autoregressive parameter, $\boldsymbol{W}$ is a spatial weights matrix, ω is a vector of dependent variables, $\boldsymbol{\Psi}$ is a matrix of explanatory variables representing the electoral results of political parties, β is a vector of parameters, and ϵ is a vector of residuals.

3. Application

The main part of this article is the analysis of the quality of life in the municipalities' territory with extended jurisdiction. The territory of the municipality with extended jurisdiction includes the entire territory of the Czech Republic except the capital, Prague (Project OPZ, 2018). Prague is excluded because it is not defined as a municipality with extended jurisdiction (Public administration portal, 2025). Quality of life is assessed based on the socioeconomic factors described below. Part of the description of the factor will also be a justification for why we believe that this particular factor is important and should not be missing from the analysis.

3.1 Socioeconomic factors

The article works with eight socioeconomic factors. Factors were selected that cover the basic needs of an individual for a comfortable living. All values of the indicator are related to the relevant area of the municipality with extended jurisdiction. The selection of appropriate factors is to some extent a subjective matter for the author. The selection of the factor was consulted with experts from the University of Economics in Prague.

General practitioners

The availability of a medical furnace can clearly be classified as an important socio-economic factor. We go to a general practitioner for preventive purposes or in times of acute health problems. This factor indicates the number of general practitioners per 1000 inhabitants. The GP serves as the first point of contact with the healthcare system and provides comprehensive care, including prevention, diagnosis, and treatment of acute and chronic diseases. He is also the key person for administration, referral to specialists, and proper coordination of treatment, including the issuance of sick leave.

Criminality

The crime rate shows the average number of crimes per 1,000 inhabitants on the territory of the municipality with extended jurisdiction. Crime affects the safety of society. The feeling of safety is fundamental.

Unemployment

Unemployment shows the average rate of unemployment measured as the share of job seekers from the total number of economically active residents living in the territory of the municipality with extended jurisdiction. Unemployment is important because it affects the economy, social cohesion, and individual well-being of people (psychological and social impacts). Keeping unemployment low is therefore crucial for stability and prosperity.

Kindergarten

The capacity of kindergartens shows the average number of places in kindergartens in municipalities on the territory of the municipality with extended jurisdiction per thousand persons under the age of 15. There is no data for the population on preschool children. Kindergarten is important for a child's social and emotional development, where they learn to communicate with peers and adults, build self-confidence, independence, and adapt to the team and the new regime. The daily long journey to kindergarten is time- and financially demanding.

Primary school

The capacity of primary schools shows the average number of places in primary schools in municipalities on the territory of the municipality with extended jurisdiction per thousand persons under the age of 15. Primary school provides general education, which is the basis for further studies and future careers. The daily long journey to the primary school is time-consuming and financially demanding.

Nature

The indicator indicates the average driving distance from municipalities to protected landscape areas. Being close to nature is important for physical and mental health.

Grocery store

The availability of a grocery store shows the average walking distance in kilometers in municipalities in the territory of the relevant municipality with extended jurisdiction. Proximity to a grocery store is important mainly for less mobile people (for example, without their own vehicle or any other reason).

Hospital

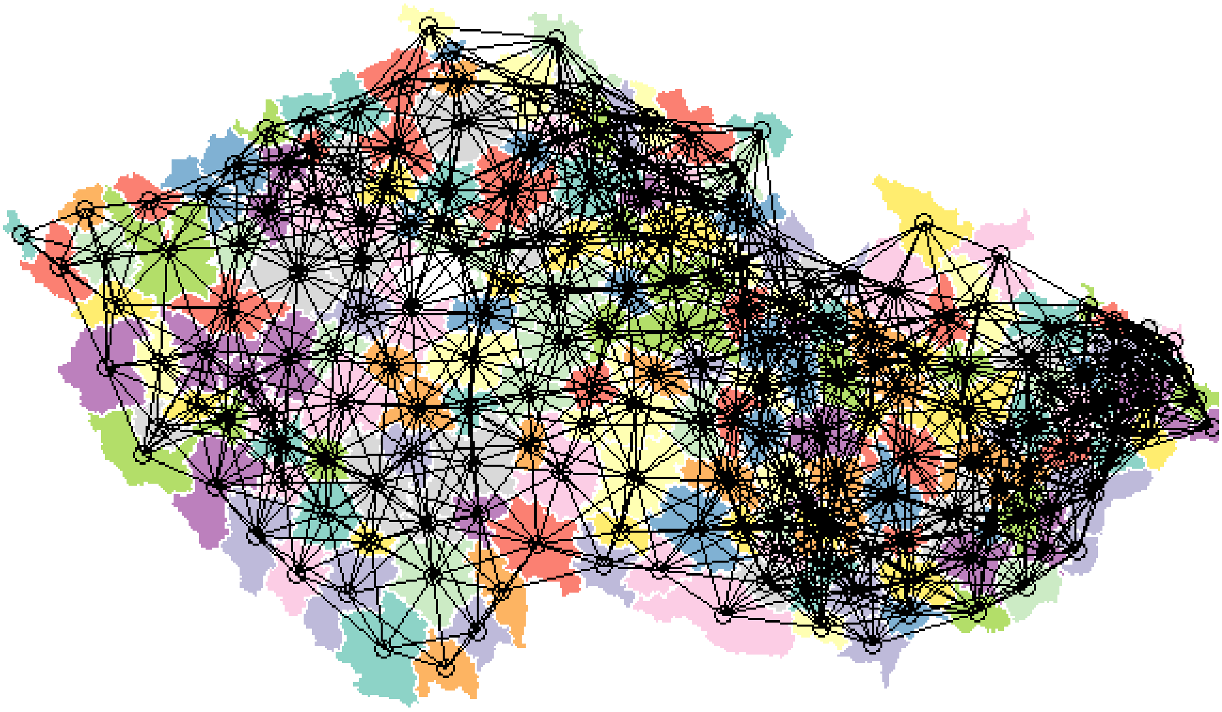
The availability of the nearest hospital indicates the average road distance from the villages to the nearest hospital or polyclinic. Proximity to a hospital is important for quick and timely access to medical care, especially in case of emergencies.

3.2 Composite indicators

This article deals with four composite indicators. The composite indicators 1, 2, and 3 are calculated using the weighted sum method. The weights of individual socio-economic factors, for indicators 1 and 2, were determined based on a survey using the scoring method on a scale [0,20]. 20 is the maximum importance of the criterion 0 is the minimum importance of the criterion. The values of the respective weights were averaged by the arithmetic mean. Composite indicator four is calculated using the benefit of the doubt model. Data collection for determining weights for indicators 1 and 2 was carried out in October 2024 in East Bohemia during sporting events and in restaurants, where people were randomly selected.

For the purposes of spatial analysis, the nearest neighbor is defined by a threshold value τ = 50km from the center of the municipalities with extended jurisdiction. This value was chosen because some municipalities with extended jurisdiction spread a relatively large area, for example, Znojmo 1,243 km^2 or Český Krumlov 1,129 km^2. If the threshold value were set too low, it could happen that some municipalities with extended jurisdiction would not have any closest neighbors. Conversely, if the threshold value is too high, the significance of the nearest neighbor incidence would disappear.

Fig. 1. Distance-based neighbors



Source: Author

Composite indicator 1 – for young families

Composite indicator number 1 is calculated using the weighted sum method. Weights for individual socioeconomic factors are created for people of working age with at least one child. The weight values of individual socio-economic indicators are in Table 3. The criteria weights were obtained based on the questionnaire survey. The questionnaire was done using the PAPI method (Jandourek, 2003) on a sample of 36 people aged 25–45.

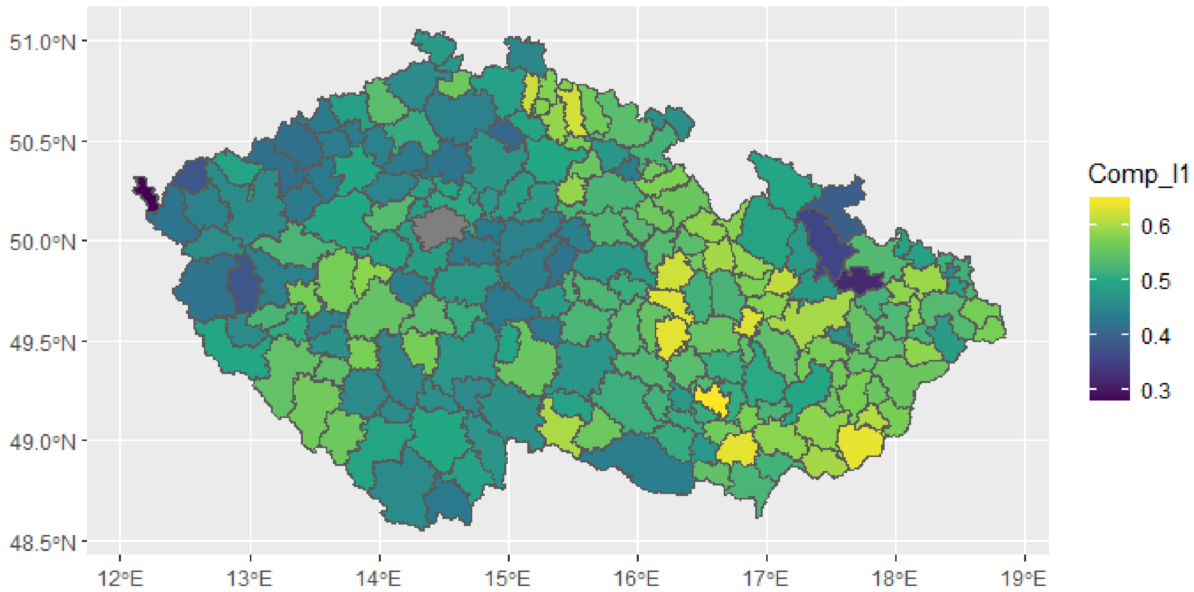
Table 3. Weights for young families

Indicator	Weight
General practitioners	0.122
Criminality	0.163
Unemployment	0.163
Kindergarten	0.163
Primary school	0.114
Nature	0.081
Grocery	0.081
Hospital	0.114

Source: Author

Table 3 shows that this target group attaches the greatest weight to indicators of criminality, unemployment, and kindergarten. The resulting values of the composite indicator 1 for young families are shown in Figure 3.

Fig. 2. Composite indicator for young families



Source: Author

Figure 2 shows the values of Composite Indicator 1 in the territory of the municipality with extended jurisdiction. The lowest values are reached by municipalities Vítkov, Aš, and Bruntál. The highest values are achieved by the municipalities Konice, Uherský Brod, and Bystřice nad Pernštejnem. More municipalities with high scores are located in South Moravia, the Highland region, and further in the foothills of the Krkonoše and Jizera Mountains. Using linear regression, it will be examined whether there is a significant effect between the calculated composite indicator and the geographical location of the municipality with extended jurisdiction near the state borders of a specific state.

Regression model 1

$$Comp\_1_i = \beta_0^{(1)} + \beta_1^{(1)} Germany_i + \beta_2^{(1)} Austria_i + \beta_3^{(1)} Slovakia_i + \beta_4^{(1)} Poland_i + e_i^{(1)} \quad (16)$$

Table 4 shows the resulting estimated parameters of regression model 1.

Table 4. Estimated regression coefficients for Regression model 1

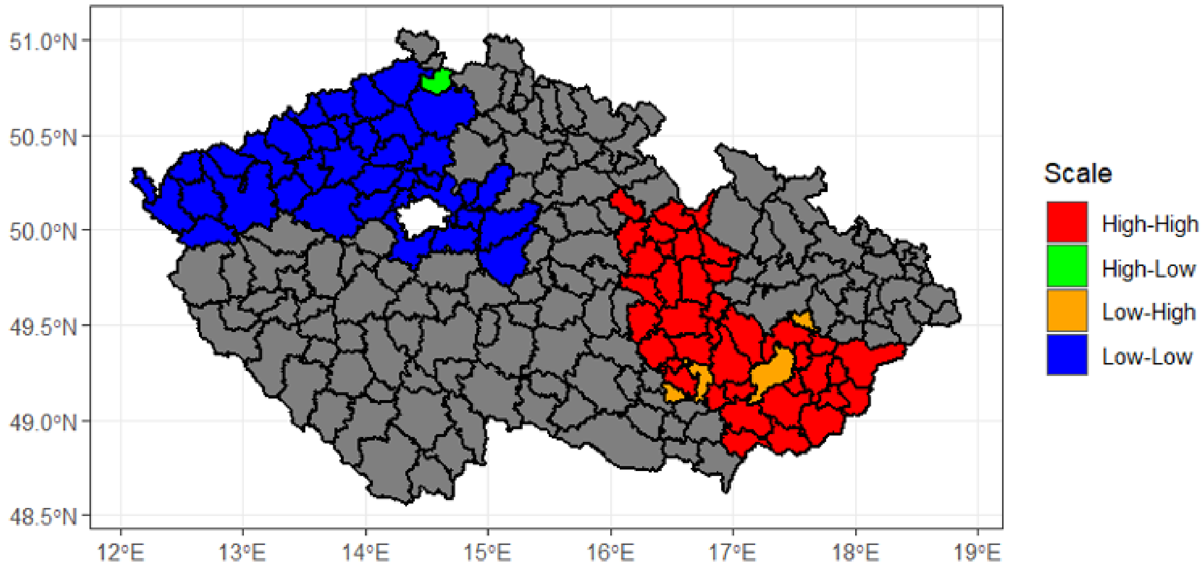
	Coefficient	standard deviation	t-test	p-value	
constant	0.508	0.005	93.480	5.42e–167	***
Poland	0.019	0.014	1.344	0.180	
Slovakia	0.056	0.021	2.609	0.009	***
Austria	–0.008	0.021	–0.388	0.698	
Germany	0.015	0.015	–3.064	0.002	***

Source: Author

Slovakia and Germany were the two estimated parameters that were statistically significant. Municipalities near the border with Slovakia achieve statistically significantly higher values of the composite indicator compared to other municipalities. Municipalities near the border with Germany achieve statistically significantly lower values of the composite indicator compared to other municipalities.

Using Moran's I test, positive spatial autocorrelation was found between municipalities based on the values of composite indicator 1.

Fig. 3. Hot and cold spots Composite indicator 1



Source: Author

Blue areas in Figure 3 are areas where the composite indicator 1 systematically reaches lower values. Red areas are areas where the composite 1 indicator systematically reaches higher values. Orange and green areas are outliers. Areas with significantly better or worse results than surrounding municipalities with an extended scope in the surrounding area. We see that the hotspot stretches from the Slovak border towards the northwest. The cold spot is located from the German border southeast to Prague. The cold spot around Prague is surprising. A significant factor is the limited capacity of kindergartens and primary schools relative to the number of children in the area.

Composite indicator 2 – for older inhabitants

The values of the composite indicator were calculated using the same method as in composite indicator 1.

The criteria weights were obtained based on the questionnaire survey. The questionnaire was done using the PAPI method on a sample of 32 people aged 65+.

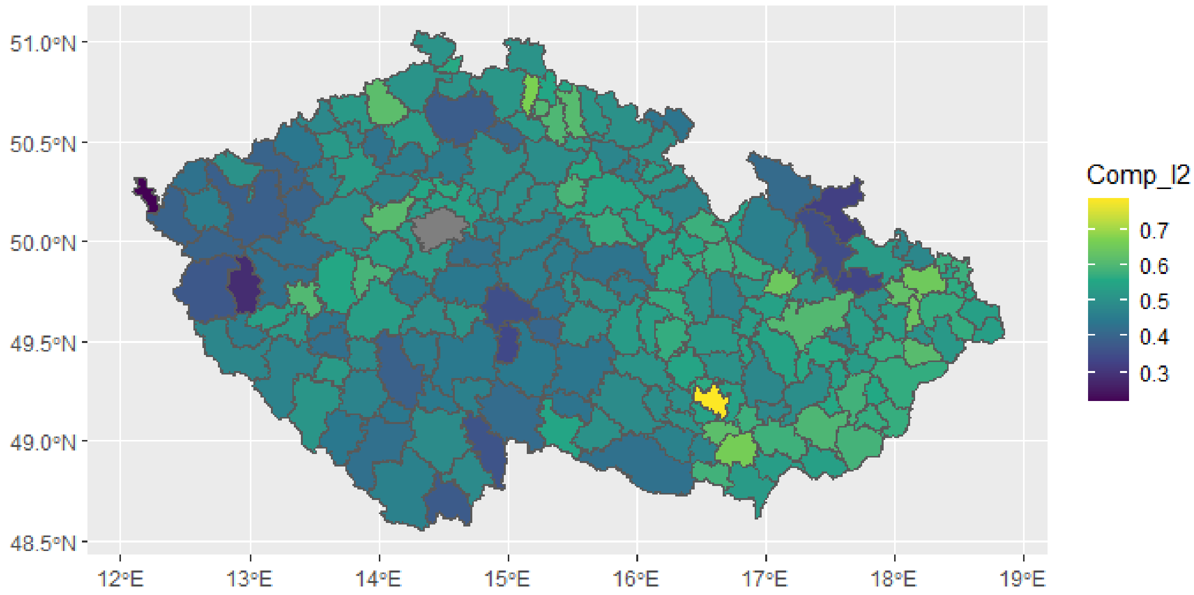
Table 5. Weights for older inhabitants

Indicator	Weight
General practitioners	0.169
Criminality	0.045
Unemployment	0.022
Kindergarten	0.022
Primary school	0.202
Nature	0.135
Grocery	0.202
Hospital	0.202

Source: Author

Table 5 shows that this target group attaches the greatest weight to indicators of primary schools, grocery stores, and hospitals. It is interesting that this group has a relatively high weight value for elementary school, even if it probably does not affect them themselves. The reasoning could be that they already have grandchildren who are in elementary school or will be there soon, and therefore, they perceive the availability of elementary school as important. The resulting values of the composite indicator 2 for older inhabitants are shown in Figure 4.

Fig. 4. Composite indicators for older inhabitants



Source: Author

Figure 4 shows the values of composite indicator 2 in the territory of the municipality with an extended scope. The lowest values are reached by municipalities Aš, Stříbro, and Krnov. The highest values are achieved by the municipalities Brno, Jablonec nad Nisou, and Hustopeče. Several municipalities with higher scores are again located in South Moravia. Brno dominates the entire ranking. This is primarily due to the number of medical facilities that are important for the elderly population and therefore have a high weight in this model. The composite indicator for older inhabitants will be analyzed from the perspective of the state border.

Regression model 2

$$Comp\_2_i = \beta_0^{(2)} + \beta_1^{(2)} Germany_i + \beta_2^{(2)} Austria_i + \beta_3^{(2)} Slovakia_i + \beta_4^{(2)} Poland_i + e_i^{(2)} \quad (17)$$

Table 6 shows the resulting estimated parameters of regression model 2.

Table 6. Estimated regression coefficients for Regression model 2

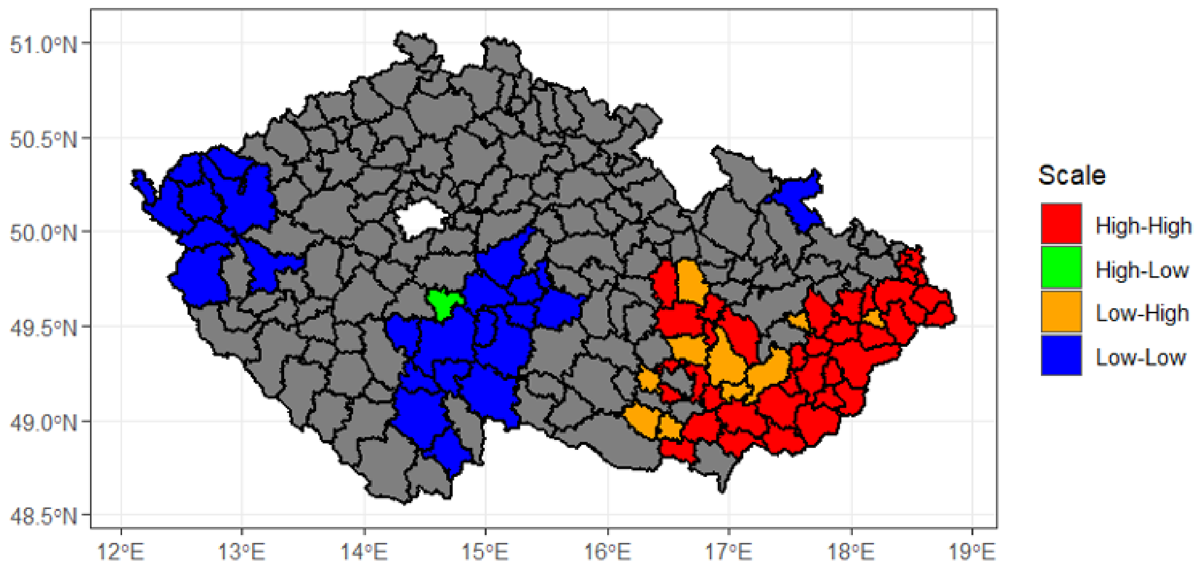
	Coefficient	standard deviation	*t*-test	*p*-value	
Constant	0.508	0.006	86.960	7.28e–161	***
Poland	–0.001	0.016	–0.035	0.9719	
Slovakia	0.046	0.023	2.019	0.044	**
Austria	–0.047	0.023	–2.039	0.042	**
Germany	–0.048	0.016	–2.993	0.003	***

Source: Author

Slovakia, Germany, and Austria were the three estimated parameters that were statistically significant. Municipalities near the border with Slovakia achieve statistically significantly higher values of the composite indicator compared to other municipalities. Municipalities near the border with Germany and Austria achieve statistically significantly lower values of the composite indicator compared to other municipalities. We see that statistically significant border regions have a negative regression parameter. This could again be explained by the poorer availability of healthcare in the border area.

Using Moran's I test, positive spatial autocorrelation was found between municipalities based on the values of composite indicator 2.

Fig. 5. Hot and cold spots Comp 2



Source: Author

Blue areas in Figure 5 are areas where the composite indicator 2 systematically reaches lower values. Red areas are areas where the composite indicator systematically reaches higher values. Orange and green areas are outliers. Areas with significantly better or worse results than surrounding municipalities with an extended scope in the surrounding area. The hotspot area is again located near the border with Slovakia and also affects municipalities with an extended scope more inland. There are two major cold spot areas. The area in the very west of Bohemia and the strip stretching from the Austrian border to the Highlands.

Composite indicator 3 - with the same weights

As it is clear from the name of this indicator, the weights of all criteria used are the same. The calculation of composite indicator 3 does not include any preferences of a particular population group.

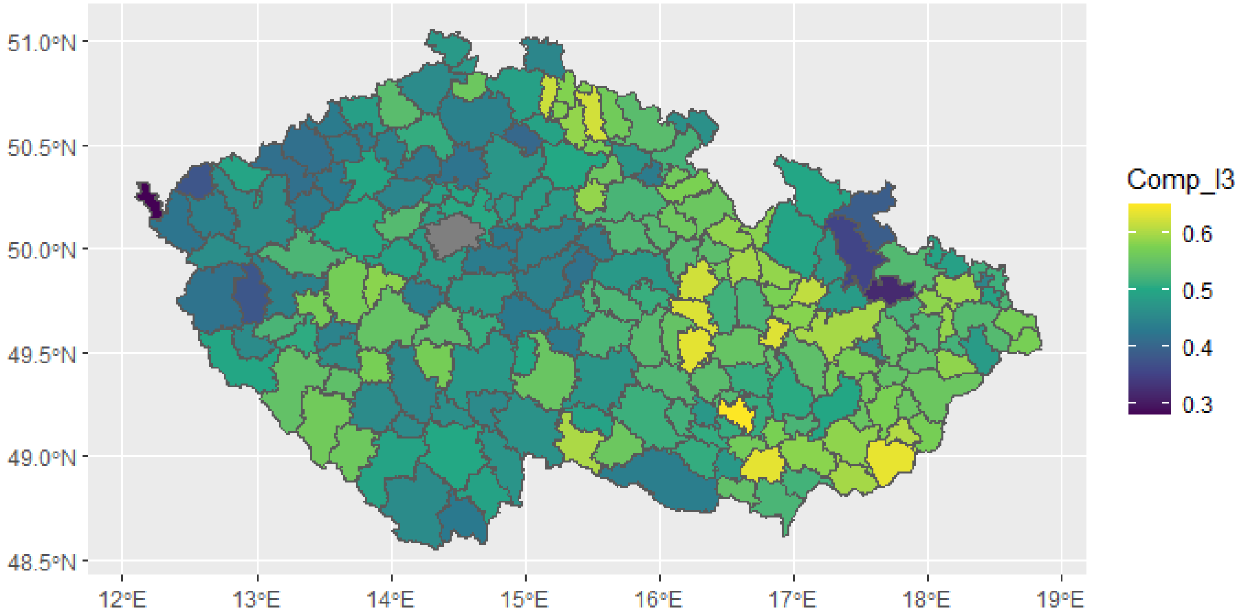
Table 7. Same weights

Indicator	Weight
General practitioners	0.125
Criminality	0.125
Unemployment	0.125
Kindergarten	0.125
Primary school	0.125
Nature	0.125
Grocery	0.125
Hospital	0.125

Source: Author

The resulting values of the composite indicator 3 with the same weights are shown in Figure 6.

Fig. 6. Composite indicators with the same weights.



Source: Author

Figure 6 shows the values of composite indicator 3 in the territory of the municipality with extended jurisdiction. The lowest values are reached by municipalities Aš, Vítkov, and Bruntál. The highest values are achieved by the municipalities Brno, Uherský Brod, and Hustopeče. Here, the indicator values are relatively homogeneous with a slight dominance of regions South Moravia, the Highland region, and further in the foothills of the Krkonoše and Jizera Mountains. The composite indicator with the same weights will be analyzed from the perspective of the state border.

Regression model 3

$$Comp\_3_i = \beta_0^{(3)} + \beta_1^{(3)} Germany_i + \beta_2^{(3)} Austria_i + \beta_3^{(3)} Slovakia_i + \beta_4^{(3)} Poland_i + e_i^{(3)} \quad (18)$$

Table 8 shows the resulting estimated parameters of regression model 3.

Table 8. Estimated regression coefficients for Regression model 3

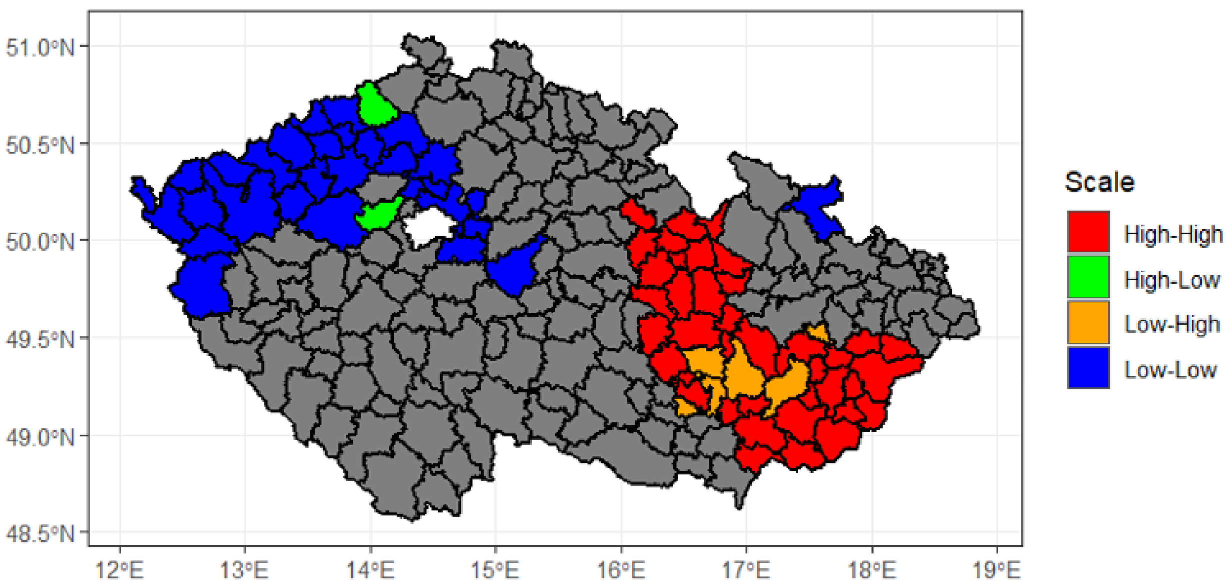
	Coefficient	standard deviation	t-test	*p*-value	
Constant	0.512	0.005	102.500	8.26e–175	***
Poland	0.014	0.013	1.052	0.294	
Slovakia	0.048	0.019	2.423	0.016	**
Austria	−0.021	0.019	−1.083	0.280	
Germany	−0.043	0.014	−3.157	0.001	***

Source: Author

We see in Table 8 that municipalities located near the German border have a statistically significant regression coefficient with a negative value, and municipalities located near the Slovak border have a statistically significant coefficient with a positive value.

Using Moran's I test, positive spatial autocorrelation was found between municipalities based on the values of composite indicator 3.

Fig. 7. Same weights



Source: Author

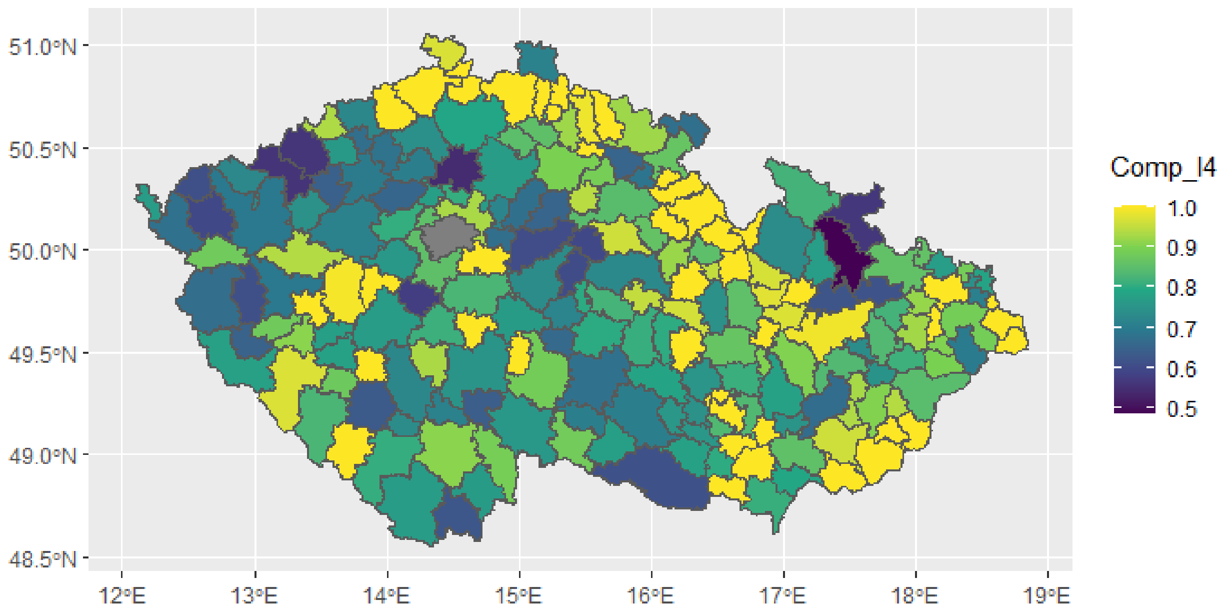
Blue areas in Figure 7 are areas where the composite indicator systematically reaches lower values. Red areas are areas where the composite indicator systematically reaches higher values. Orange and green areas are outliers. Areas with significantly better or worse results than surrounding municipalities with an extended scope in the surrounding area. The coldspot and hotspot areas of indicator 3 are similar to the coldspot and hotspot areas of indicator 1.

Composite indicator 4 – Benefit of the doubt model.

In many cases, obtaining criteria weights can be very complicated or even impossible or otherwise distorted. All of these problems are solved by the Benefit of the Doubt approach, which determines weights through mathematical optimization for each evaluated entity. For relevant results, a certain ratio between criteria and evaluated entities should be maintained. Entities should be at least three times as many as the criteria (Jablonský, et al., 2004).

The resulting values of the composite indicator 4 Benefit of the doubt are shown in Figure 8.

Fig. 8. Composite indicator "Benefit of the doubt"



Source: Author

Figure 8 shows the values of Composite Indicator 4 on the territory of the municipality with an extended scope. We see a relatively large dominance of South Moravia and, further, the foothills of the northern and eastern Bohemian mountains. The composite indicator "Benefit of the doubt" will be analyzed from the perspective of the state border.

Regression model 4

$$Comp\_4_i = \beta_0^{(4)} + \beta_1^{(4)} Germany_i + \beta_2^{(4)} Austria_i + \beta_3^{(4)} Slovakia_i + \beta_4^{(4)} Poland_i + e_i^{(4)} \quad (19)$$

Table 9 shows the resulting estimated parameters of regression model 4.

Table 9. Estimated regression coefficients for model 4.

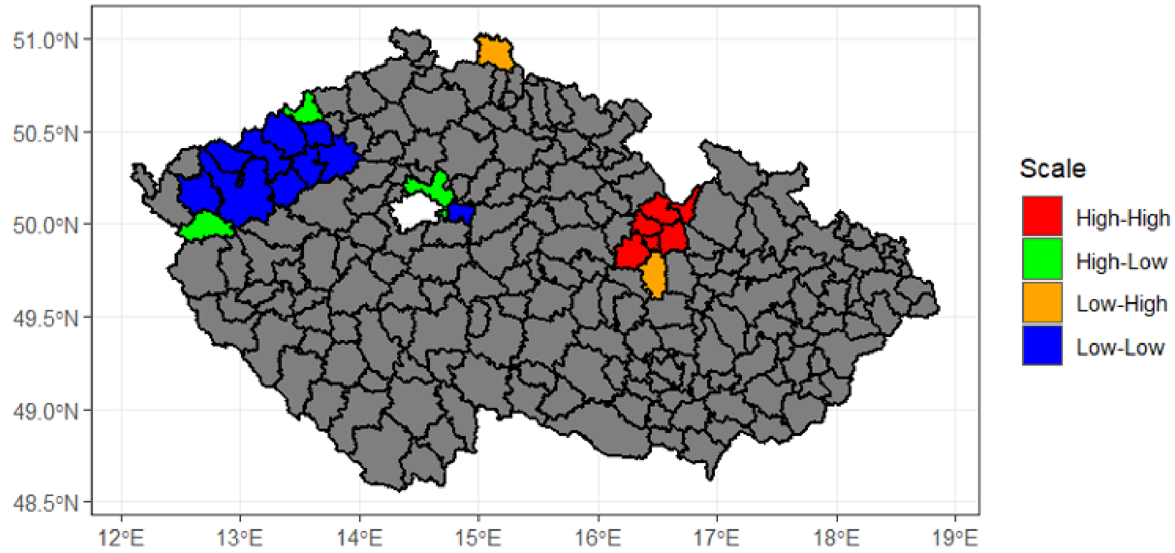
	Coefficient	standard deviation	t-test	p-value	
constant	0.820	0.011	75.63	8.26e–175	***
Poland	0.065	0.029	2.210	0.294	
Slovakia	0.079	0.043	1.866	0.016	**
Austria	–0.036	0.043	–0.855	0.280	
Germany	0.003	0.029	0.113	0.001	***

Source: Author

In regression model 4, the estimated parameters for Germany and Slovakia were statistically significant. Both parameters were positive.

Using Moran's I test, positive spatial autocorrelation was found between municipalities based on the values of composite indicator 4.

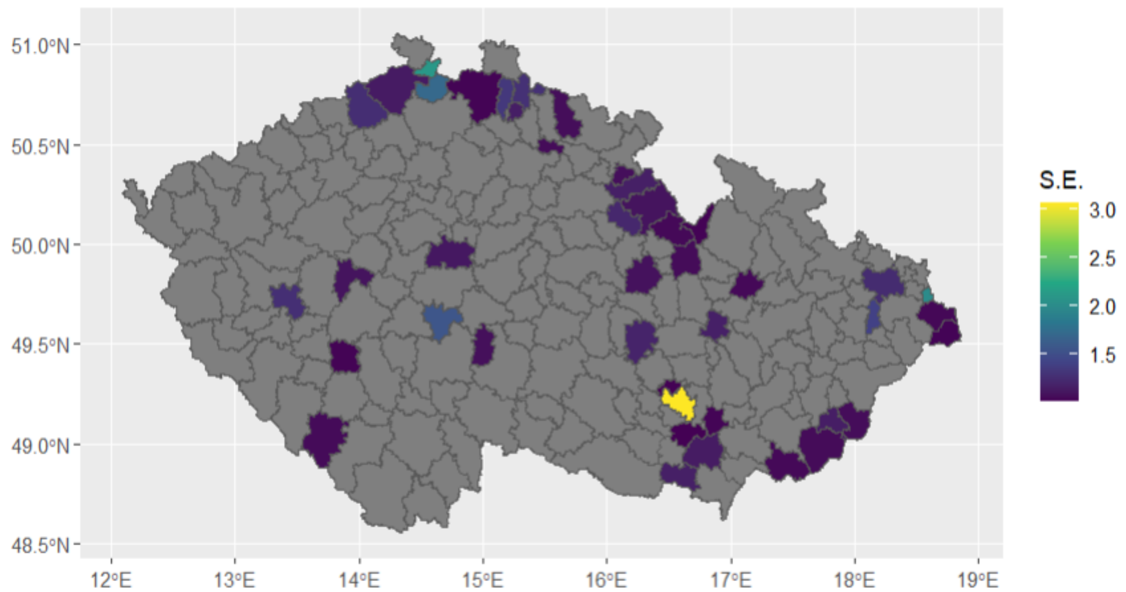
Fig. 9. Benefit of the Doubt



Source: Author

Blue areas are areas where the composite indicator systematically reaches lower values. Red areas are areas where the composite indicator systematically reaches higher values. Orange and green areas are outliers. Areas with significantly better or worse results than surrounding municipalities with an extended scope in the surrounding area.

Fig. 10. Comparison of municipalities located on the border of the data envelope



Source: Author

Figure 10. shows the layout of the municipality with extended jurisdiction, which lies on the boundary of the data envelope. These municipalities with extended jurisdiction were organized based on the results of model 8.

Figure 10. shows the arrangement of the best-rated municipalities that lie on the data envelope. It can be seen from Figure 10 that significantly higher values are achieved by the municipality of Brno with extended jurisdiction. This is because there are many hospitals and medical facilities per thousand inhabitants in Brno.

This factor significantly differs from the rest of the municipalities with extended jurisdiction in favor of Brno.

Table 10. Ranking according to composite indicators

Order	Comp 1	Comp 2	Comp 3	Comp 4
1	Konice	Brno	Brno	Brno
2	Uherský Brod	Jablonec nad Nisou	Uherský Brod	Varnsdorf
3	Bystřice nad Perštejnem	Hustopeče	Hustopeče	Český Těšín
4	Polička	Ostrava	Bystřice nad Perštejnem	Nový Bor
5	Litomyšl	Uničov	Konice	Votice
6	Hustopeče	Kopřivnice	Polička	Kopřivnice
7	Dačice	Bílovec	Jilemnice	Jablonec nad Nisou
8	Veselí nad Moravou	Židlochovice	Litomyšl	Tanvald
9	Jilemnice	Ústí nad Labem	Jablonec nad Nisou	Plzeň
10	Luhačovice	Kladno	Uničov	Ústí nad Labem
…	…	…	…	…
196	Stříbro	Kaplice	Čáslav	Kolín
197	Čáslav	Tachov	Chomutov	Čáslav
198	Chomutov	Třeboň	Kadaň	Sokolov
199	Mělník	Vlašim	Mnichovo Hradiště	Přelouč
200	Most	Bruntál	Krnov	Dobříš
201	Mnichovo Hradiště	Pacov	Stříbro	Krnov
202	Kraslice	Vítkov	Kraslice	Chomutov
203	Bruntál	Krnov	Bruntál	Kadaň
204	Aš	Stříbro	Vítkov	Mělník
205	Vítkov	Aš	Aš	Bruntál

Source: Author

Statistical verification of regression models

Statistical verification is the verification of the validity of a model based on statistical methods and indicates the statistical reality of the estimated parameters and the entire model.

Multicolinearity

Table 11. Variance Inflation Factors results

Variable	VIF	Degree of multicollinearity
Germany	1.0118	Slight multicollinearity
Austria	1.0094	Slight multicollinearity
Slovakia	1.0092	Slight multicollinearity
Poland	1.0121	Slight multicollinearity

Source: Author

The results in Table 9 show that there is negligible multicollinearity in the models. From the point of view of multicollinearity, our regression models are in order.

Homoskedasticity test

Table 12. White's test results

Indicator	p-value	Results
Young families	0.9434	Homoskedasticity
Older Inhabitants	0,8871	Homoskedasticity
Same weights	0,8895	Homoskedasticity
The Benefit of the doubt	0.5847	Homoskedasticity

Source: Author

Using the White test, we verified that the regression models meet the assumption of a homoscedastic random component.

Spatial regresion models

Table 13 with the results of Moran´s I. Positive spatial autocorrelation was found.

Table 13. Moran´s I

	Comp 1	Comp 2	Comp 3	Comp 4
Moran´s I	0.3269	0.3107	0.3320	0.1962
Expectation	−0.0049	−0.0049	−0.0049	−0.0049
Variance	0.0006	0.0006	0.0006	0.0006

Source: Author

In geodata, positive autocorrelation is a relatively common phenomenon. The main reason is that values close to each other tend to be similar.

Conclusion

This article analyzed municipalities with extended jurisdiction in the Czech Republic based on eight selected socioeconomic factors. Based on the values of individual socioeconomic factors, four composite indicators were calculated by aggregation for each municipality with an extended jurisdiction.

Composite indicators one, two, and three were calculated by the weighted sum approach. The calculation differed in the weights of individual socioeconomic indicators. The weights were determined based on the needs of the target group. The first group was people between 25 and 45 years old with at least one child. The second group was the elderly 65+. The third composite indicator was calculated based on weights, which were the same for all socioeconomic factors. Therefore, they did not prioritize the preferences of any population group.

The fourth composite indicator was calculated using the benefit of the doubt model.

All composite indicators were subjected to regression analysis. The aim of the regression analysis was to find out whether municipalities located on state borders show different composite indicator values than other municipalities. The model differentiates which state the municipality is neighbors with.

We obtained different results from each regression model. The results of individual regression models were discussed in the article. Regression models were subjected to basic statistical verification to verify their relevance. The models were tested for heteroskedasticity and multicollinearity was measured using VIF. Both of these phenomena are undesirable in models because they can distort the results. Neither multicollinearity nor heteroscedasticity was confirmed to be significant in the applied models.

Composite indicators were analyzed by spatial analysis. By calculating Moran's I, a positive autocorrelation was found in the models. This positive autocorrelation was further analyzed using the so-called hotspots and coldspots.

Interesting results are achieved by municipalities neighboring Slovakia. The estimated regression parameters for municipalities neighboring Slovakia in all four regression models were positive and statistically significant. However, by adding a spatial component to the regression model, this significance decreased slightly. This is due to the presence of a hotspot and a coldspot. These hotspots and coldspots are not only in municipalities with extended jurisdiction near the borders, but also extend further inland (see figures 3,5,7).

Coldspots and hotspots areas could help in policy decisions because they show that some areas are doing much better than others. Uplifting a region usually requires large investments, great political efforts, and even then, the result is not 100% guaranteed. From this perspective, the "High-Low" areas, which are highlighted in green on the maps in this article, are extremely interesting. These are areas that are doing significantly better within the "coldspot" region. Inspiration from these micro-regions and targeted measures could help improve the situation in the entire region.

Based on these results, it can be concluded that the quality of life near the border with Slovakia achieves better values on average than in other border areas and, to a certain extent, even than in the Czech Republic inland. One of the limitations of this article is the relatively small group of respondents for determining the weights of the criteria. On the other hand, in this article, the "Benefit of the Doubts" method was applied, which does not require knowing the weights of individual criteria for its application, since the weights of the criteria are calculated based on an optimization mathematical model. The application of the benefit of the doubt method is relatively pioneering in the context of assessing quality of life. However, as the article suggests, the application is possible. As a possible continuation of the research, it would be possible to apply methods of multi-criteria evaluation of variants, which work on a different principle, for example, *methods for minimizing* *the distance from the ideal variant or evaluation according to preference relation.* A major challenge in measuring quality of life would be to create methodologies or unify methodologies so that individual studies around the world are more comparable. Choosing the right indicators is crucial for assessing the quality of life. There are as many opinions on the quality of life as there are people dealing with the topic (Liu, 1976).

In the Czech Republic, several studies have been conducted in recent years to assess the quality of life. The study (Rypl et al., 2024) found the same phenomenon that spatial data on quality of life tended to cluster into hotspots and cold spots. This study concluded that the potential for a high quality of life is in the intermediate spaces (suburbs) lying between urban and rural spaces. Project (Netrdova et al., 2023) analyzed the differentiation or clustering of 10 individual indicators. The 7 indicators in this project had very similar results in the coldspot and hotspots areas as in this article.

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References

Charnes, A., Cooper, W. W., Rhodes, E., 1978. Measuring the Efficiency of Decision Making Units. European Journal of Operational Research. 1978, vol. 2, no. 6, pp. 429–444. DOI:10.1016/0377-2217(78)90138-8

Charnes, A., Cooper, W.W., Lewin, A., Seiford, L.: Data envelopment analysis: Theory, methodology and applications. Boston: Kluwer Academic Publishers,1994, pp.422.

Cherchye, L., Moesen, W., Rogge, N., Puyenbroeck, T., 2007. An Introduction to 'Benefit of the Doubt' Composite Indicators. Soc. Indic. Res. 82, pp. 111–145.

Czech statistical office: Interaktivní aplikace ČSÚ srovnává kvalitu života v krajích, Available from: https://csu.gov.cz/produkty/interaktivni-aplikace-csu-srovnava-kvalitu-zivota-v-krajich.

Diener, E., Suh, E. (1997). Measuring quality of life: economic, social, and subjective indicators. Social Indicators Research, 40(1/2), pp. 189–216. https://doi.org/10.1023/A:1006859511756 .

Dominicis, L., Bolsi, P., Castelli, C., Dijskra, L., Montalto, V., (2023), Report on the quality of life in European cities, 2023, Luxembourg: Publications Office of the European Union.

European Quality of Life Surveys, Available from: https://www.eurofound.europa.eu/en/surveys-and-data/surveys/european-quality-of-life-survey.

European Union initiative: Beyond the GDP – Measuring progress in a changing world, Available from: https://www.beyond-gdp.eu/.

Faťunová, Z. (2007). Kvalita života. Praha, 2007. diploma thesis. Charles University in Prague, Faculty of Arts. Supervisor: PhDr. Tamara Hrachovinová, CSc.

Fiala, P., Jablonský, J., Maňas, M.: Vícekriteriální rozhodování, VŠE, Praha, 1994, ISBN 80-7079-748-7.

Formánek, T.: Praktikum z ekonometrie. Online. Available: https://raw.githubusercontent.com/formanektomas/4EK417/master/Block2/Block_2.pdf [cit. 2025-10-01].

Fotheringham, A., Brundsdon, C.,F., Charlton, M., 2022, Geographically Weighted Regression: The Analysis of Spatially Varying Relationships, International Journal of Geographical Information Science.

Glatzer, W. (2007). Quality of Life in the European Union and the United States of America: Evidence from Comprehensive Indices. Applied Research in Quality of Life, pp. 169–188. https://doi.org/10.1007/s11482-006-9014-y.

González, E., Cárcaba, A., & Ventura, J. (2011). Quality of life ranking of Spanish municipalities. Revista de Economía Aplicada, 29(56), pp. 123–148.

Government of the Czech Republic, project OPZ, life quality, 2018, [cit.2024-8-15], online: https://vlada.gov.cz/assets/ppov/udrzitelny-rozvoj/projekt-OPZ/Kvalita-zivota---shrnuti.pdf.

Greyling, T., and Tregenna, F. (2016). Construction and Analysis of a Composite Quality of Life Index for a Region of South Africa. Social Indicators Research. https://doi.org/10.1007/s11205-016-1294-5 .

Jablonský, J., Dlouhý, M.: Modely hodnocení efektivnosti produkčních jednotek, Professional Publishing, 2004, ISBN: 8086419495.

Jandourek, J.,: Úvod do sociologie. Praha: Portál, 2003. ISBN 80-7178-749-3. pp. 208–211.

Lagas, P., Kuiper, R., Dongen, F. Van, Rijn, F. Van, and Amsterdam, H. Van. (2015). Regional quality of living in Europe. The Journal of ERSA, 2(2). https://doi.org/10.18335/ region.v2i2.43 .

Liu, B. C. (1976). Quality of Life Indicators in U.S. Metropolitan Areas: A Statistical Analysis. New York: Praeger.

Macků, K., (2020). Multidisciplinarní hodnoceni kvality života v evropě na regionální úrovni. Olomouc, 2020. doctoral thesis. University of Palacky in Olomouc, Faculty of Science, Department of Geoinformatics. Supervisor: doc. Mgr. Pavel Tuček, Ph.D.

Martín, J. C., and Mendoza, C. (2013). A DEA Approach to Measure the Quality of Life in the Municipalities of the Canary Islands. Social Indicators Research, 113(1), pp. 335–353. https://doi.org/10.1007/s11205-012-0096-7 .

Martinez, R.L. Sonja Lyubomirsky: Pioneer in the Empirical Study of Happiness and Well-Being Interventions. Applied Research Quality Life 19, 3545–3547 (2024). https://doi.org/10.1007/s11482-024-10386 .

Michalos, A.,C., (2017). Development of Quality of Life Theory and Its Instruments. Springer Cham. https://doi.org/10.1007/978-3-319-51149-8 .

Murgaš, F., Klobučník, M. (2016a). Does the quality of a place affect well-being? Ekologia Bratislava, 35(3), 224–239. https://doi.org/10.1515/eko-2016-0018.

Netrdová, P.,Šavrdová, J., Havej, P., (2023) Kvalita života v regionech: prostorové vzorce, https://storymaps.arcgis.com/stories/150642ed9ca24c7f801cffdb6aec1057.

Noble, S., McLennan, D., Noble, M., Plunkett, E., Gutacker, N., Silk, M., & Wright, G. (2019). The English Indices of Deprivation 2019.

OECD (2020), How's Life? 2020 - Measuring Well-being, OECD Publishing, Paris.

OECD (2023), Environment at a Glance Indicators, OECD Publishing.

OECD (2024), How's Life? 2024, OECD Publishing.

Office of the Government of the Czech Republic, QUALITY OF LIFE INDICATORS IN THE FIELD OF HEALTH, Available from: https://www.cr2030.cz/sites/cr2030/files/featured_images/05_Zdrav%25C3%25AD.pdf.

Ord, J. K., Getis, A. (1995): Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. Geographical Analysis, 27(4), pp. 286–306.

Páralová, V. (2018). Quality of Life and its Regional Disparities. Brno, 2018. diploma thesis. Masaryk University in Brno, Faculty of Law, Department of Legal Theory. Supervisor: doc. PhDr. Martina Urbanová, Ph.D.

Public administration portal (2025). *Register of public authorities*. https://portal.gov.cz/organy-verejne-moci/?ovm_kod_kategorie=KO11

Puskorius, S. (2015). The Methodology of Calculation the Quality of Life Index. International Journal of Information and Education Technology, 5(2), pp. 156–159. https://doi.org/10.7763/ijiet.2015.v5.494.

Rypl, O., Macků, K., Pászto, V., (2024), The quality of life in Czech rural and urban spaces, Humanities and Social Sciences Communications volume 11, Article number: 43 (2024).

Sen, A. (1985), Commodities and Capabilities, North-Holland.

Sirgy, M.,J. (2021). The Psychology of Quality of Life. Springer Cham. https://doi.org/10.1007/978-3-030-71888-6.

STEM, Kvalita života v obcích, Available from: https://www.stem.cz/projekty/kvalita-zivota-v-obcich/.

Teoli, D., Bhardwaj A. Quality Of Life. [Updated 2023 Mar 27]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2025 Jan-. Available from: https://www.ncbi.nlm.nih.gov/books/NBK536962/.

University of Economics and Business in Prague. Modeling and analysis of network economic systems. Faculty of Informatics and Statistics. 2021-2024. Project number 42/2021.

Veenhoven, R. The Four Qualities of Life. Journal of Happiness Studies 1, 1–39 (2000). https://doi.org/10.1023/A:1010072010360.

Veneri, P., and Murtin, F. (2018). Where are the highest living standards? Measuring well-being and inclusiveness in OECD regions. Regional Studies, 53(5), pp. 657–666. https://doi.org/10.1080/00343404.2018.1463091.

Žmuk, B. (2016). Quality of Life Indicators in Selected European Countries: Hierarchical Cluster Analysis Approach. Croatian Review of Economic, Business and Social Statistics, pp. 42–54. https://doi.org/10.1515/crebss-2016-0004.