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Application of the Best-Worst Method as a Tool for Soil Quality Evaluation

Master´s thesis

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Declaration

I hereby declare that I have authored this master's thesis carrying the name Application of the Best-Worst Method as tool for Soil Quality Evaluation independently under the guidance of my supervisors Ing. Markéta Miháliková, Ph.D and Ing. Katharina Kaiblinger, Ph.D. Furthermore, I confirm that I have used only professional literature and other information sources that have been indicated in the thesis and listed in the bibliography at the end of the thesis. As the author of the master's thesis, I futher state that I have not infringed the copyrights of third parties in connection with its creation.

In Prague, April 14th 2023

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Summary

Soil quality is the capacity of soil to provide ecosystem services. To measure the soil quality is important in order to maintain it. However quantification of the soil quality is not easy as there is no standard for it, as the term can vary acording to purpose of that quantification. The Soil Quality Index (SQI) is a numerical indicator of a soil's ability to perform one or more functions and is based on a set of indicators that are interrelated.

In this thesis SQI aiming to assess soil's ability and sustainability to fulfil ecosystem services was determined on the area of five districts (4290 km^2) from Central Bohemia region in the Czech Republic. Altogether 278 sampling points from a countrywide database called Systematic Soil Survey that was conducted in years 1961-1970 were included together with information about the Evaluated Soil Ecological Units (ESEU). Using 15 soil quality indicators, SQI has been calculated. 15 indicators have been grouped into three categories which are geographical, physical and chemical category. Those used 15 indicators are: climatic region, hydrologic soil class, slope & aspect, percentage of clay, percentage of sand, percentage of silt, field capacity, wilting capacity, stoniness & soil depth, soil organic matter content, base saturation, cation exchange capacity, pH, P_2O_5 and K_2O contents. Standard Scoring Functions "More is Better, Less is Better and Optimum Range" were used in data preparation. Best-Worst Multicriteria Method was used to assign weight to soil quality indicators by pairwise comparison of the best indicator to others and the worst indicator to others and in the end linear combination method was utilized to calculate SQI. As the most convenient of different interpolation methods the Radial Basis Function (Completely Regularized Spline) with lowest root mean square error was used for the resulting map of SQI. Results were compared with currently used system of soil protection classes and high resemblance was found. The suggested method can be utilized as an alternative to the conventional methods for soil evaluation not just in the Czech Republic, but all over the world. The Best-Worst Method was found as a very useful and efficient method for weighting the indicators for soil quality evaluation.

Keywords: Multicriteria decision analysis, Best worst method, linear combination method, GIS, analytical hierarchical process

Content

1 Introduction

Agriculture relies on soil as a non-renewable resource to produce essential resources for a circular bio-economy, including food and fiber, while also contributing to ecosystem services such as water filtration, nutrient provision to crops and forests, and controlling greenhouse gases and temperature (Glasener, 2002; European Commission, 2022). Unfortunately, soil degradation due to contamination and other threats can compromise the quality of food and disrupt the life cycle. In Europe, for instance, 95% of food is produced from soil, but 60-70% of soils are unhealthy, leading to an annual loss of 50 billion euros due to soil degradation (European Commission, 2021). Healthy soil takes hundreds of years to produce just a few centimeters, but it can be lost in a matter of years. Therefore, it is crucial to evaluate the physical, chemical, and biological characteristics of soil to ensure its sustainability and capacity to provide ecosystem services. Soil quality is a complex and multifaceted concept, and its assessment requires considering various parameters, such as soil structure, clay content, organic matter, texture, water-holding capacity, pH, and pollutant presence (De la Rosa & Sobral, 2008).

This thesis aims to evaluate soil quality to protect and improve soil productivity in the long term. The Soil Quality Index (SQI) is a numerical indicator of a soil's ability to perform one or more functions and is based on a minimum set of parameters that are interrelated (Miháliková et al., 2021). Various approaches, such as Simple Additives SQI, Statistically Modelled SQI (Mukherjee & Lal, 2014), and Analytical Hierarchy Process (Dengiz et al., 2018; Miháliková et al., 2021), have been used to estimate the SQI worldwide. In soil science, multicriteria decision making (MCDM) methods, such as Promethee and Logic Scoring Preference (Marsi, 2020), are commonly used for land assessment, and Analytical Hierarchy Process is the most popular approach (Everest et al., 2021).

Although the Best-Worst Method (BWM) is a relatively new MCDM approach, it has not been thoroughly tested for its potential in soil quality evaluation. BWM involves structured pairwise comparisons, where the best-to-others and worst-to-others comparisons are used as input for an optimization model to determine the weight of each criterion (Rezaei, 2015). To assess the potential of BWM and the current state of soil quality in several districts of Central Bohemia, this thesis will analyze, weigh, and compare 15 soil quality indicators with the results obtained from the SQI calculated using the Analytical Hierarchy Process.

2 Scientific hypothesis and aims of the thesis

The Best-Worst Method (BWM) is a multi-criteria decicion making technique that can be used to evaluate and priotize different indicators of soil quality. The objective of this study was to determine soil quality index in terms of sustainable soil fertility and ability to fulfil ecosystem services by the Best-Worst Method for a selected area in the Czech Republic and generate its spatial distribution map by GIS.

The hypothesis is that the selected model evaluates the soil quality index on the basis of selected parameters and achieves comparable results with already published works.

3 Literature review

3.1 Soil Quality and Soil Quality Index

One of the most precious natural resources is soil, and it is our moral obligation to keep it healthy. Soil quality maintenance has become a crucial subject as different discoveries concluded that soil has been damaged and vulnerable compared to the past years and also a full 90% of the Earth's precious topsoil is likely to be at risk by 2050 (United Nations, 2022). Due to the fact that rich soils and high-quality soils cannot be easily reproduced, this is a crucial and delicate issue. It takes 100 years to build half a centimeter of healthy soil and this indicates that we are currently losing soil 50 to 100 times faster than it is able to rebuild (Veni et al., 2020).
Globally, soil can be saved through these seven ways which are the increase in the number of plants and animal matter going back into fields, improving soil health by routine soil analysis, encouraging soil organisms that build up with soils and those that release nutrients, cover up bare soil with continuous plant cover because plant roots hold soils together to reduce soil erosion, bring more trees onto farmland, reduce soil compaction from machinery and livestock (Payton, 2016).
In the field or laboratory, it is impossible to directly quantify soil quality since it is a complicated functional notion but some soil indicators can be measured to estimate it. Early in the 1990s, a mathematical or statistical framework for calculating the soil quality index (SQI) was proposed (Lai, 2014).

3.1.1 Soil Quality: A Complex yet Vital Component of Ecosystem Functioning and Human Health

According to Doran and Parkin (1994), soil quality plays a crucial role in determining animal and human health. This concept recognizes the intricate and specific nature of subterranean ecosystems and the interdependence between soil functions and the ecosystem services provided by soil. Soil quality is more complex than air and water quality, which primarily depend on the degree of pollution that affects human and animal health or natural ecosystems (Bünemann et al., 2018). Soil pollution does not solely determine soil quality but is broadly defined as the soil's ability to function within the ecosystem and land-use boundaries to sustain biological productivity, maintain environmental quality, and promote plant and animal health (Sutri et al., 2022).

The website of the Natural Resources Conservation Services, USA (http://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/health/) states that soil quality is the ability of the soil to continue to serve as a vital living ecosystem that supports humans, animals, and plants.

As stated in the June 1995 issue of Agronomy News, in the field of soil science, the idea of soil quality seems superfluous and redundant. After all, "everyone" is aware of what makes for good soil and where it may be obtained. Others claim that it is impossible to measure soil quality since there are "natural differences" across soil orders and even within the same soil series found in various locations. These perceptions are based in part on the fact that appraising soil is not a novel process (Karlen et al., 2003).

3.1.2 Assessing Soil Quality: The Need for a Systematic Approach

Early studies on soil quality were successful in causing people to become concerned about how soil degradation might affect the sustainable production of high-quality food, the thoughtless use of land and certain farming techniques, and potential environmental harm. The state of the body's many components and functions together creates a composite image of human health. We evaluate a person's health by taking into account a variety of variables, such as their physical health, mental stamina, emotional stability, and overall sense of how their body and mind are functioning. Similar to this, soil quality is a composite image of the many physical, chemical, and biological characteristics of the soil as well as the processes that interact to affect this quality.

Furthermore, just as health varies from person to person, likewise do soil types' levels of health. Some soils are unsuitable for crop production due to their poor inherent (natural) quality.

There is no single indicator of soil quality, just as there is no single indicator of human health. Although soil quality cannot be directly measured, it can be inferred or estimated by the measurement of particular soil characteristics (like pH or organic matter content) as well as through the observation of soil conditions (such fertility, structure, and erodibility).

Recently, soil scientists have realized the need for a valid and organized method to evaluate soil quality. The creation of a soil quality index which is a report card that details the state of a soil's health and offers a mechanism to observe that state over time and foresee the consequences of farming practices that is one encouraging potential. Measurements of specific soil characteristics, functions, and circumstances that serve as helpful indicators of soil quality would be included in the index.

The three primary purposes of soil are to act as a substrate for plant growth, to control and divide the flow of water through the environment, and to act as a buffer for the environment. Together, a soil's chemical, physical, and biological characteristics make it suitable for carrying out these tasks (Karlen et al., 1997).

An excellent soil may be tilled and is fruitful. It produces high-quality crops because it offers a suitable environment for seed germination and root development (including the absence of unfavorable chemical conditions, like acidity or salinity, which are harmful to plant growth); it receives, stores, and releases moisture for plant use; and it supports a community of microorganisms that recycle nutrients through decomposition and aid plants in fighting off diseases. There are numerous outcomes for water that enters the soil from rain or melting snow. It may penetrate the soil, be kept there, or be absorbed by plants. It may seep into the groundwater via soaking into the soil. If it doesn't get down into the soil, it can run off the surface (Gregorich & Acton, 1995).

Rainfall or irrigation-derived water that flows over the soil's surface can bring debris and other pollutants into drainage regions. This may have effects on numerous groups of people, both on- and off-site. Infiltrating water enhances biological production and is often cleansed before contributing to groundwater recharge or returning to the surface as base flow functions when there aren't excessive nutrient or pollutant loads (Karlen et al., 1997).

A high-quality soil stores enough water, depending on the amount of precipitation received, to support ideal crop growth. It only permits a small amount of water to either seep into the groundwater below the root zone or wash off the soil surface, bringing away soil particles.

A high-quality soil can absorb, store, and release nutrients as needed by plants. To some extent, it can also convert poisonous substances into ones that are harmless to both plants and animals and do not contaminate groundwater or surface waters. The damage of chemical contamination brought on by human activities should not be expected to be repaired by soil, as it has a limited capacity to carry out this job. An impact on a soil's intrinsic or natural character comes from the geological elements and soil formation processes (such as chemical and physical weathering) that come together to make a soil. Natural soil characteristics can be modified by human activities like farming practices and land use. A decrease in the inherent soil quality may be caused by erosion, loss of organic matter, compaction, desertification, and other degradative processes. On the other hand, soil quality can be maintained or even improved by regularly adding organic material, using conservation tillage, rotating crops, and planting legumes, among other methods (Gregorich & Acton, 1995).

Several different forms of soil assessments involve various principles. Aside from the mining of minerals, the primary interest in soil has always been its potential for agricultural output. A determination of the soil's suitability for agricultural development may have been made before there were any written records (Bünemann et al., 2018).

The idea of soil fertility, which derives from German literature on "Bodenfruchtbarkeit" and is primarily focused on crop yields, captures the suitability of soil for agricultural output (Patzel et al., 1999). According to the FAO, soil fertility is "the soil's capacity to supply essential plant nutrients and soil water in sufficient amounts and proportions for plant growth and reproduction in the absence of toxic substances that may inhibit plant growth."

In 1988, Canada launched one of the first nationwide programs to evaluate and track soil quality (Gregorich & Acton, 1995), evaluating changes in soil quality over time at benchmark locations, particularly in light of soil concerns such erosion, compaction, organic matter loss, acidification, and salinization. Although the Canadian program for monitoring soil quality as a whole was not continuously maintained, the data are still utilized in part for the evaluation of agri-environmental indicators that deal with the quality of the soil, water, and air.

3.1.3 Basic Steps in Soil Quality Index Determination

The majority of individuals believe that it is impossible and useless to analyze the quality or health of soil since soil resources are so complicated. Instead of emphasizing soil quality or soil health, they recommended that research and education concentrate on creating effective soil management strategies. On the other hand, they are certain that soil quality is essential and must be assessed on a regular basis to determine the state of soil resources at scales within a firm, watershed, nation, state, or the entire world because historically, humankind has neglected its soil resources numerous times, frequently leading to the failure of the dominant society and culture (Karlen, 2008).

Soil properties are the primary indicators of soil quality evaluation and comparison and the assessment's goal is to ascertain the soil's fertility potential. The formulation of the assessment's objective is followed by the selection of the indicators, scoring of the indicators, and ranking of the indicators according to their relative relevance. These three processes make up the soil quality indexing process.

3.1.4 Evaluating Inherent Soil Characteristics and Condition for Sustainable Land Use

Indicators can be grouped e.g. according to their common characteristics, which can be geographical, physical, or chemical; constitute the foundation of all chosen indicators.
At several scales, the quality of the soil can be assessed. Additionally, it can be interpreted in one of two ways: either as a fundamental property of soil or as the state or "health" of the soil. Soil-forming processes control the inherent soil quality. Each soil therefore has a built-in capacity to perform. A range of parameter values that indicate the complete (ideal) capability of a soil to carry out a certain function can be used to identify this inherent quality.
The second way of assessing soil quality presumes that if a soil is working to its full capacity for a particular land use, it is in good condition. Perhaps through adoption of "best management practices", it is of exceptional quality, in contrast to soils that perform well below their potential, which are considered to be of impaired or bad quality. The theory assumes that ecological dynamics are sufficiently understood for the system to be truly environmentally friendly. In this scenario, measuring the current status of an indicator and comparing the results to predetermined or aimed values are necessary for soil quality assessments (Bünemann et al., 2018).
According to Doran et al. (1996), soil quality should be assessed in light of how well the soil performs. The concept of soil quality can be utilized as a link between the interests and concerns of our rural, urban, and suburban clientele by concentrating on how effectively a certain soil functionsn within a defined environment. In assessing soil quality, it has to be related to the amount and quality of surface water and groundwater resources might be considered, for instance, when assessing soil quality with relation to dividing water flow and storage within the ecosystem (Larson & Pierce, 1991). And an efficient way for assessing the environmental effects of human management actions is through soil quality tests (Bünemann et al., 2018).

3.2 Multicriteria Decision Making Methods

3.2.1 Land Suitability Assessment

The first step in defining and assessing the suitability of a piece of land for a particular kind of production is to identify the soil quality. The success or significance of a procedure cannot be guaranteed by a suitability analysis carried out using subpar techniques. It is widely known that land suitability analysis is effective. Falasca et al. (2012) claim that a crucial strategy for encouraging sustainable agricultural development and rational land use planning is land suitability analysis. For agricultural production to be sustainable, land appropriateness is important. Additionally, the research pinpoints the primary constraints on a certain crop's production, enabling decision-makers to create a crop management strategy to boost land productivity and preserve soil resources from decline.

The Food and Agriculture Organization (FAO) states that "land suitability is a function of the crop's needs and the properties of the soil, and examines how the qualities of a land unit fit the requirements of a particular form of land use" (FAO, 1976). A suitability analysis of agricultural land, according to the organization, is a requirement for achieving the best use of the available soil resources for sustainable agricultural output. FAO further notes that due to soil characteristics, starting position, and land usage, land suitability varies by crop in each area of the field. Furthermore, the FAO further says that it is necessary to categorize and manage land units in accordance with the most advantageous environmental conditions (FAO, 1990).

Assessments of land suitability (LS) are widely used to manage natural resources and land in a sustainable way. Through the evaluation of agricultural potentials, environmental and biophysical conditions, and limiting variables, LS analysis provides a technical aid in the selection of suitable land for various land-use types (Koull et al., 2021).

The definition of land suitability evaluation (LSE) is the categorization of lands according to their suitability for a particular application. For example site suitability for rice production (Tercan & Dengiz, 2022), hazelnut production (Tercan et al., 2022), suitability for different irrigation systems (Miháliková & Dengiz, 2019) or various risk assessments, such as landslide susceptibility (Saygin et al., 2023) or desertification risk (Kaya et al., 2022). According to De La Rosa and van Diepen (2002), the primary goal of land suitability evaluation is to estimate the land unit's potential capacity for a particular use without causing any damage. If unsuitable methods are used for the analysis, it cannot ensure a successful or meaningful outcome.

De La Rosa and Van Diepen (2002) state that qualitative systems like the British land use capability classification, Canadian land capability scheme, and Dutch system, which are based on the maximum limitation factor principle, have been extensively utilized worldwide as important tools for assessing natural resources. These systems are still relevant today. Moreover, many methods for expressing land suitability classes for a specific use follow the same principle of maximum limitation factor. More complex rating tables or diagrams can be created by refining the suitability ratings and considering multiple limiting land characteristics.

3.2.2 Parametric Methods

De la Rosa and Van Diepen (2002) propose that parametric methods, such as parametric assessments, fall between qualitative and quantitative methods in terms of their level of quantification. These methods are based on the inferred numerical impacts of different land characteristics on the behavior of a land-use system. Arithmetical systems, which focus on the most important factors, take into account the interactions between these factors by either multiplying them or adding single-factor indexes.

Multiplying systems rate each land characteristic or factor separately and then calculate the final rating index by multiplying all of the individual factor ratings together. These systems offer the benefit of allowing any critical productivity factor to influence the overall rating, and they ensure that the final rating cannot be negative. However, a potential limitation of this system is that the final overall rating may be much lower than the ratings of each individual factor.

3.2.3 Storie Index Rating

In 1933, R. Storie developed the first and most well-known approach to specify multiplying criteria for evaluating soil productivity through an inductive assessment. This was achieved by calculating the Storie Index Rating (SIR), which involved assigning separate ratings for profile morphology (A), surface soil texture (B), slope angle (C), and modifying conditions such as soil depth, drainage, or alkalinity (X), and then multiplying them together.

Storie emphasized that the factor ratings he provided were meant to serve as guidelines rather than absolute values, and that they could be adjusted as soil scientists gained more experience with the index. Three other widely recognized systems, including the Universal Soil Loss Equation (USLE; Wischmeier & Smith, 1972), the Modified Universal Soil Loss Equation

(MUSLE), and the Revised Universal Soil Loss Equation (RUSLE), have a similar structure to the Storie Index and operate by multiplying the most important factor values. The USLE has largely replaced the USDA Land Capability System for on-farm planning in many cases during the 1980s.

3.2.4 Additive, regression and single-factor systems

Additive systems, on the other hand, assign a numerical value to the most significant land factors, but rather than being multiplied, these parameters are added. The sum of these numbers is either subtracted or added to a maximum rating of 100 to calculate a final rating index. One advantage of additive systems is that they can include information from a greater number of land characteristics than multiplying systems.

Experience has demonstrated that using four or five factors is typically optimal in multiplying systems; otherwise, the final ratings become so low that small differences in response can no longer be distinguished. In contrast, additive systems enable the consideration of a greater number of criteria, both individually and in combination with the effects of other factors. One benefit of this approach is that no single factor can exert enough weight to unfairly influence the final rating, and it is typically easier to specify the criteria and their factor ratings for a clear determination of land performance.

However, additive systems have some limitations due to their complexity. As the number of evaluated factors increases, it becomes more challenging to manage the factor ratings such that the final ratings for multiple land units or soils are all realistic. Additionally, negative ratings may need to be taken into account in some cases, which can pose another challenge.

Combined methods for evaluating soil productivity utilize both additive and multiplying procedures. In these methods, additive processes are used to derive single-factor ratings, which are then multiplied together to obtain a final rating index. Before integrating each factor into the formula, it needs to be validated through individual response curves. The major advantage of combined systems is that they allow integration of information from several factors without creating an unrealistically low or negative final result. However, the complexity of these methods is higher than that of simple multiplying systems. Most combined methods are based on Storie's original concept.

Statistical land evaluation systems are powerful semiquantitative methods that use correlation and multiple regression analyses to predict land suitability based on selected land characteristics. When basic and response data are available, statistical models can provide objective ratings of land attributes. De la Rosa and Van Diepen (2002) highlighted the usefulness of statistical systems in predicting land suitability.

The single-factor system is a method of quantifying land evaluation that mathematically expresses the impact of individual land characteristics on land use performance. This approach is useful when a single land characteristic has a significant positive or negative effect on a proposed land use. For example, soil depth has a positive correlation with crop productivity, particularly when the soil is shallow, and it approaches an asymptote as the depth approaches the rooting depth of the crop. This methodology has been used to predict soil productivity for major crops and requires collaboration between competent statisticians, agronomists, and soil scientists to develop polynomial regressions for maximal benefit. Additionally, statistical relationships can be used in soil survey interpretations for engineering purposes to estimate geotechnical properties of soils from pedological characteristics using pedotransfer functions.

3.2.5 Fuzzy-set techniques

Generally, traditional land evaluation systems rely on a Boolean or rule-based approach that follows the principle of maximum limitation factors. However, this methodology has been criticized for its inability to accurately account for the imprecise or fuzzy nature of land resource data. As a result, there has been a growing interest in using fuzzy-set methodology in recent years, which represents a new phase in the trend toward quantification. For example, Kaya et al. (2022) have explored the use of fuzzy-set methodology in land evaluation. Dos Santos et al. (2019) conducted a systematic literature review of 173 manuscripts published between 2014 and 2018 that examined the use of the analytic hierarchy process in decision-making. They found that fuzzy theory was used in 28% of the studies (see Figure 1).

Traditional land evaluation systems typically rely on a Boolean or rule-based approach that is based on maximum limitation factors. However, this methodology is limited in its ability to account for the imprecise or fuzzy nature of much of the land resource data. To address this issue, there has been a recent increase in the use of fuzzy-set methodology in land evaluation, which marks a new phase in the trend towards quantification. Fuzzy-set methodology is particularly useful in cases where the impact of a single land characteristic just outside a specified range can be minimized. Unlike Boolean logic, which only allows for full or no membership, fuzzy-set methodology assigns a grade of membership depending on the values of the characteristics. The overall suitability assessment of land units is based on a weighted sum of relevant land characteristics, as determined by the Joint Membership Function (JMF). While fuzzy-set methodology has its limitations, such as data and knowledge limitations, it provides a more flexible and nuanced approach to land evaluation than traditional methods (De la Rosa & Van Diepen, 2002).

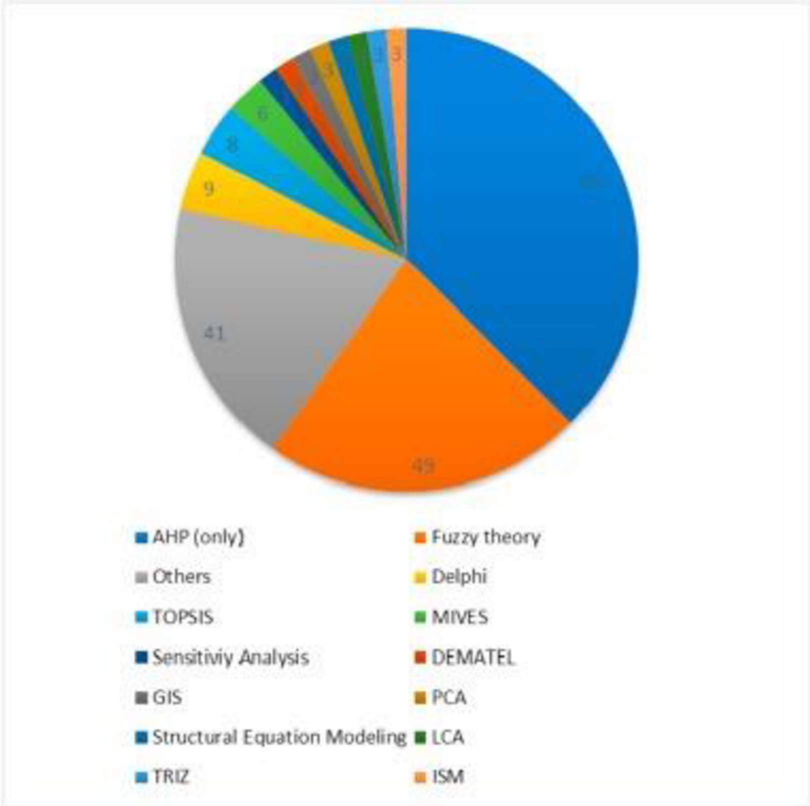

Figure 1. Different methods and techniques used together with analytical hierarchical process (Dos Santos et al., 2019).

3.2.6 Hybrid Systems

Hybrid systems in land evaluation involve combining two different types of models - qualitative reasoning and quantitative modeling - to create a more comprehensive evaluation approach. These systems allow for the incorporation of simulation modeling results into expert systems, which can be useful for predicting crop yields. For example, a decision tree that utilizes both qualitative and quantitative data branches could be created. Simulation modeling can provide quantitative information on differentiating land features, such as soil water regime, which can then be integrated into the decision tree. However, not all land attributes can be defined through simulation modeling, so it is important to avoid relying solely on simple qualitative estimations. Another type of hybrid system involves using expert decision trees and semiquantitative artificial neural networks to assess soil erosion risk. This mixed model was able to accurately reproduce soil erosion vulnerability by recognizing the main interrelationships between input parameters, as demonstrated through sensitivity and validation analysis (De la Rosa & Van Diepen, 2002).

The Storie Index (SI) is a common traditional approach for land suitability assessment, where a single suitability value is calculated by multiplying all land attributes evaluated at the same level of importance. However, this method has limitations, as some parameters may have a low significance and negatively impact the ratings. As a result, multi-criteria decision-making (MCDM) methods have been increasingly used in land evaluation studies as they consider multiple independent factors. MCDM methods provide a more comprehensive approach and enable decision-makers to identify the most suitable options (Everest et al., 2021).

3.2.7 Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a popular method for Multicriteria decision making used in many fields. It provides a systematic and logical way to evaluate group decisions (Saaty & Vargas, 2001). AHP breaks down a problem into various hierarchical levels (see Figure 2), taking into account both qualitative and quantitative factors (Everest et al., 2021). By comparing pairs, priority values are obtained. AHP has several advantages, including helping to break down decision-making problems, considering trade-offs between different indicators, providing a ratio-scale cardinal ranking, and measuring the consistency of decision-maker preferences.

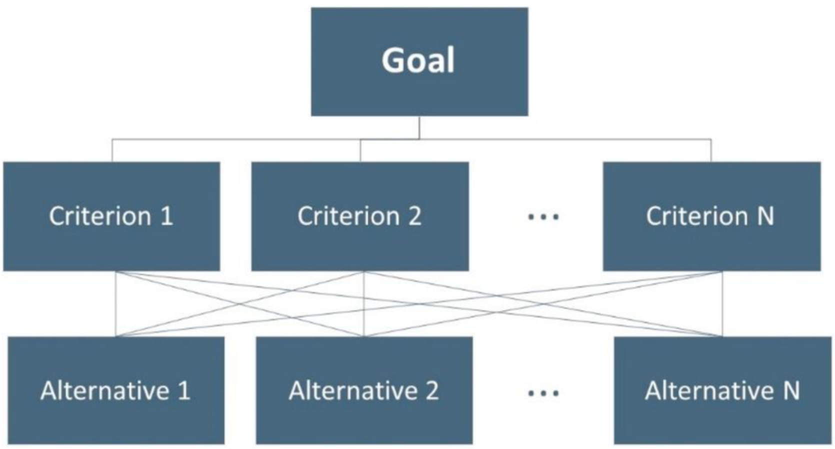

Figure 2. Scheme of analytical hierarchy process (Dos Santos et al., 2019).

To summarize, the AHP methodology involves three stages: structuring the hierarchical model, realizing pairwise comparisons, and obtaining the priority values. In the first stage, the problem is divided into subsections, and criteria, sub-criteria, and alternatives are determined. In the second stage, pairwise comparisons are performed to determine the relative importance of the parameters in the same hierarchical level (see Table 1). In the third stage, matrix values are calculated and used to assign weighted values to criteria and sub-criteria for land-suitability assessment. The consistency ratio (CR) is checked to validate the pairwise comparison. If the CR value is below 10%, it is considered acceptable (Everest et al., 2021).

Table 1. Saaty's Scale of Importance Intensities (Saaty & Vargas, 2001).

Intensity of Importance	Definition
1	Equally important
3	Moderately more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2, 4, 6, 8	Intermediate values between adjacent judgments

3.2.1 Best-Worst method in multi-criteria decision-making process

The MCDM technique is a way to solve one or more parts of an MCDM problem by following several steps that involve identifying the goal(s), alternatives, and criteria, evaluating the alternatives based on the criteria, determining the significance of the criteria, synthesizing the collected data, and checking the reliability and validity of the solution. These phases require close collaboration between the decision-makers and analysts. BWM is an MCDM method that can be applied in various phases of solving an MCDM problem. BWM is especially useful for evaluating alternatives concerning criteria when objective metrics are unavailable. BWM can also be used to determine the weight or importance of the criteria used to achieve the primary goal(s) of the problem (Rezaei, 2020).

BWM is a method used to address the challenges of Multi-criteria decision-making (MCDM). In MCDM situations, various choices are evaluated against multiple criteria. BWM suggests that the decision-maker begins by identifying the most desirable and least desirable criteria. Then, pairwise comparisons are made between the other criteria and the two identified criteria. The weights of the criteria are determined by formulating and solving a maximal problem. The same technique is used to determine the worth of each alternative relative to the criteria. The final scores of the alternatives are obtained by adding up the weights from different sets of criteria and alternatives. The alternative with the highest score is chosen. To ensure the validity of the comparisons, BWM recommends calculating a consistency ratio (Everest et al., 2021).

3.3 Best-Worst Method

The Best Worst Method (BWM) is a useful tool for multi-criteria decision-making and determining weight coefficients for criteria. However, there are certain real-world multi-criteria problems where multiple criteria have equal influence on decision-making. In such cases, the traditional approach of the BWM requires selecting one criterion as the best and another as the worst from among the set of observed criteria. The BWM has been applied in a variety of domains, including energy, transportation, manufacturing, education, investment, performance evaluation, communication, healthcare, banking, technology, and tourism, over the past five years (Pamucar et al., 2020).

In addition, there are numerous studies that have used the BWM method alone (singleton integration), as well as articles that have used this method in combination with other methods (multiple integrations). For example, Van de Kaa et al. (2019) utilized the BWM to compare three communication elements, and Setyono & Sarno (2018) used it to evaluate technical and performance standards in supply chain management. Similarly, Ahmadi et al. (2017) explored the BWM to determine the weights for sustainable criteria in sustainable supply chain management. Rezaei (2016) even used the BWM to select a cell phone.

The BWM has been applied in various fields and industries, including evaluating cars, assessing key success factors in technological innovation, developing strategies for energy efficiency in buildings, assessing factors influencing information-sharing arrangements, evaluating R&D performance of firms, prioritizing factors of service experience in the banking industry, and selecting a bioethanol facility location. As long as the goal is to rank and select an alternative from a set of alternatives, the BWM can be used by individuals or groups involved in decision-making (Rezaei, 2020).

3.3.1 Weighting of Indicators by Different Approaches and Best-Worst Method

Various MCDM methods can be utilized to calculate evaluation criteria weights in MCDM problems, including Stepwise Weight Assessment Ratio Analysis (SWARA), Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Full Consistency Method

(FUCOM), Criteria Importance through Intercriteria Correlation (CRITIC), Entropy, Level-Based Weight Assessment (LBWA), among others. BWM, one of the latest weighting methods, extracts criteria weights based on pairwise comparisons and overcomes the inconsistency problem encountered during pairwise comparisons by conducting only 2n-3 comparisons. AHP is one of the frequently used pairwise comparison-based methods. To evaluate its performance and provide examples, numerical examples and a real-world decision-making problem, namely mobile phone selection, were used, and AHP was chosen for comparison purposes.

The statistical findings indicate that BWM outperforms AHP considerably in terms of the consistency ratio and other evaluation metrics, including minimum violation, total deviation, and conformity. In recent times, BWM has emerged as a highly ranked MCDM approach in the field, providing trustworthy and applicable outcomes for making optimal decisions, according to Pamucar et al. (2020).

Rezaei (2016) introduced the BWM as an improvement over AHP, which suffered from a high number of comparisons required in criteria pairs. BWM addresses this issue by obtaining optimal weight coefficient values with only 2n-3 comparisons in criteria pairs. Compared to other MCDM methods, BWM stands out for requiring less comparison data and producing more consistent comparisons, resulting in more reliable outcomes.

3.3.2 Novelty and Advantages of Best-Worst Method Application in Land Evaluation

According to Hashemizadeh et al. (2020), the Best-Worst Method (BWM) has been used in various disciplines since 2015, except for agricultural land evaluations. The study found a statistically positive correlation (r=0.997) between BWM and Analytical Hierarchy Process (AHP) and a negative correlation between Storie Index. This suggests that the data generated using BWM is consistent, reliable, and complies with the data generated using AHP. Compared to other MCDM methods, BWM requires less data and provides more compatible comparisons. The Best–Worst Method (BWM) is advantageous in crop-based land suitability analyses as it requires less pairwise comparisons and has a practical and efficient algorithm. It is a structured pairwise comparison-based method that offers several benefits such as identifying the best and worst criteria or alternatives before conducting pairwise comparisons. This structure provides a clear understanding of the evaluation range to the decision maker, which can lead to more reliable and consistent comparisons. The original BWM study by Rezaei (2015) demonstrated the consistency of pairwise comparisons.

To address the anchoring bias that a decision maker (BWM) might have during pairwise comparisons, a consider-the-opposite-strategy can be used in the Best-Worst Method (BWM). This strategy involves using two opposite references (best and worst) to form two pairwise comparison vectors in a single optimization model. This approach has been shown to be effective in mitigating anchoring bias. While some pairwise comparison-based methods use only one vector (e.g., Swing and SMART family), this makes the method efficient but limits the ability to check consistency. The BWM's consider-the-opposite-strategy provides a structured approach to mitigate bias and improve consistency in pairwise comparisons (Rezaei, 2020). A visual representation of this strategy is shown in Figure 3.

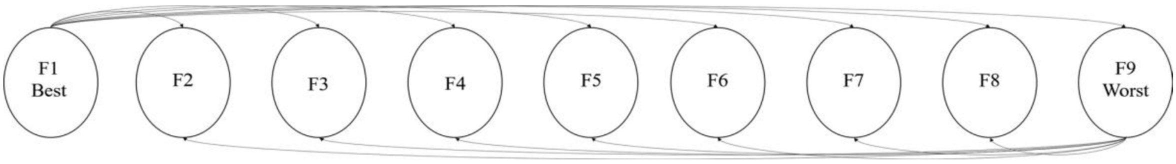

Figure 3. Criteria comparison for BWM (Everest et al., 2021).

The Best Worst Method (BWM) uses a small number of pairwise comparisons between criteria, leading to more reliable results compared to the Analytic Hierarchy Process (AHP) due to reduced inconsistencies and greater consistency of results. In BWM, only reference comparisons between the best and worst criteria with other criteria are made, eliminating redundant comparisons. However, in some real-world problems, there may not be a unique best or worst criterion, making it impossible to use the traditional BWM. In such cases, a consensus of the decision-maker is required to define the unique best or worst criterion (Pamucar et al., 2020).

On the contrary, although using a full matrix allows for the consistency of pairwise comparisons to be checked, methods based on full pairwise comparison matrices are inefficient in terms of both data and time. When too many questions are asked of the decision-maker, as is the case with full matrices, it can lead to confusion and inconsistency. The BWM, however, strikes a balance between efficiency and consistency. It is the most efficient method in terms of data and time, while also allowing for the consistency of pairwise comparisons to be checked. As two vectors are created with specific reference criteria in mind, the BWM should not be viewed as an incomplete pairwise comparison matrix (Rezaei, 2020).

BWM's original non-linear model can produce several optimal solutions in inconsistent cases with over three criteria or alternatives. This is an indication of the data inconsistency. Having more than one optimal solution is beneficial when there are multiple decision-makers because it provides more flexibility. In group decision-making, having several optimal solutions can increase the likelihood of reaching a compromise solution that is very close to one of the optimal solutions. Although having multiple optimal weights is useful in group decision-making problems where debating plays a central role, there are cases where a unique solution is preferred. The linear BWM model provides a single solution (Rezaei, 2020).

3.3.3 Step-by-Step Calculation Procedure of Best Worst Method (BWM) for Evaluating Criteria Importance

According to the classic Best-Worst Method (BWM), one criterion should be selected as the best and one as the worst when determining priority vectors. These are referred to as the best-to-others (BO) and others-to-worst (OW) vectors, respectively. The criteria are then compared pairwise, and there may be several criteria with the same significance. However, the traditional BWM does not allow for the specification of multiple best/worst criteria with equal weight. This can cause decision-makers to have biased preferences, resulting in non-objective outcomes. Furthermore, if the limited flexibility of the 9-degree scale is taken into account, the calculated values of the criteria weights may deviate significantly from the decision-maker's preferences. The BWM calculations are described step-by-step (Razaei, 2015).

1. In the first step, a set of decision criteria are identified,
2. In the second step, the best and worst criteria are chosen,
3. In the third step, Then, each criterion is compared with the best and worst criteria using a scale of 1 to 9, denoted by $a_B = (a_{B1}, aB2,\dots. aBn)$ and $a_{BB} = 1$;
4. In the fourth step, the worst criterion is compared to other criteria by using numbers 1 to 9 with
   $a_W = (a_{1W}, a2W, \dots, anW)$ and $a_{WW} = 1$;
5. In the fifth steps, the resulting weights for each criterion are then calculated
6. This is done by comparing each criterion with the best criterion $\left(\frac{w_B}{w_j}\right)$ and among the worst criterion and the others $\left(\frac{w_j}{w_W}\right)$, the optimal weight as follows (1):

$$a_{Bj} = \frac{w_B}{w_j} \; j = 1,2, \dots, n$$
$$a_{jW} = \frac{w_j}{w_W} \; j = 1,2, \dots, n \qquad (1)$$

(Symbols used in equations are explained at the end of this chapter.) When the maximum differences among $\left|\frac{w_B}{w_j} - a_{Bj}\right|$ and $\left|\frac{w_j}{w_W} - a_{jW}\right|$ are solved for all j, the weights are obtained. This can be defined by the formulation below (2).

$$\min_j^{\max} \left\{ \left|\frac{w_B}{w_j} - a_{Bj}\right|, \left|\frac{w_j}{w_W} - a_{jW}\right| \right\} \qquad (2)$$

So that

$$\sum_{j=1}^{n} w_j = 1 \; w_j \geq 0, \text{ for all } j \qquad (3)$$

Formulation (3) took forward solving the problem presented below:
For min ξ (factor or treshold in consistency ratio calculating):

$$\begin{aligned} &\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \text{ for all } j \\ &\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \text{ for all } j \\ &\sum_{j=1}^{n} w_j = 1 \; w_j \geq 0, \text{ for all } j \end{aligned} \qquad (4)$$

The formula (4) can give more than one result if ξ^* is not equal to 0, and more than three criteria are evaluated in the problem. To resolve this issue and obtain the highest and lowest weights, it is necessary to solve the two linear problems provided below (Everest et al., 2021).

For min w_j

$$\begin{aligned} &\left|w_B - a_{Bj} w_j\right| \leq \xi^* w_j \\ &\left|w_j - a_j w_w\right| \leq \xi^* w_w \\ &\sum_{j=1}^{n} w_j = 1 \; w_j \geq 0, \text{ for all } j \end{aligned} \qquad (5)$$

$$\text{For max } w_j \quad \begin{aligned} &\left|w_B - a_{Bj} w_j\right| \leq \xi^* w_j \\ &\left|w_j - a_j w_w\right| \leq \xi^* w_w \\ &\sum_{j=1}^{n} w_j = 1 \; w_j \geq 0, \text{ for all } j \end{aligned} \qquad (6)$$

ξ* indicates objective value of formulation (4), which needs to be low for consistency of the parwise comparison matrix (Razaei, 2015).
When formulas (5) and (6) are analyzed for each criterion, values of $w_j^{\min *}$ and $w_j^{\max *}$ are formed. The following (7):

$$w_j = \frac{w_j^{\min*} + w_j^{\max*}}{2} \qquad (7)$$

Then the consistency ratio is calculated. The formula (8) given in the following is used for calculation:

$$\mathrm{CR} = \frac{\xi^*}{\mathrm{CI}} \qquad (8)$$

Where n: number of criteria; A_B: best to other vector; A_w: others to worst vector; a_{Bj}: the priority of the best criterion B over criterion j; a_{jW}: the priority of criterion j over the worst criterion W; a_{BW}: the priority of the best criterion B over the worst criterion W; w_j: the weight of criterion j; w_j*: the optimal weight of criterion j; CR: consistency ratio, CI: consistency index (Everest et al., 2021).

Various soil and other environmental properties are used as indicators (sometimes called criteria or factors) in soil quality assessment and land suitability studies. Their selection depend on various factors, such as:

Relevance to the management goals: The indicators should be relevant to the management goals of the soil, whether it be for agricultural production, ecosystem health, or other purposes.

Sensitivity: The indicators should be sensitive enough to detect changes in soil quality in response to management practices or environmental conditions.

Feasibility: The indicators should be feasible to measure, with reliable and affordable methods that are easily repeatable.

Specificity: The indicators should be specific to the properties or processes being measured, without being influenced by other factors that may affect soil quality.

Spatial and temporal scale: The indicators should be appropriate for the spatial and temporal scale of the management goals and the data available, whether it be at a field, landscape, or regional scale, and over short or long time periods.

Interpretability: The indicators should be interpretable to decision-makers and stakeholders, with clear and understandable metrics and thresholds that can guide management decisions.

Quantifiability: The indicators should be quantifiable, with clear units and values that can be compared across different soils, locations, and time periods.

Repeatability: The indicators should be repeatable, with consistent results when measured by different people or at different times.

Comprehensiveness: The indicators should be comprehensive enough to capture the multiple dimensions of soil quality, including physical, chemical, and biological properties, and their interactions.

To reduce the costs, often data already available in soil databases are processed and the indicators used are compromise between costs and availability. Some soil and environmental indicators of soil quality are listed below.

3.3.4 Physical soil quality Indicators

Soil quality can be assessed using various physical indicators, with color being one of the most significant ones. Typically, the top layer of soil is darker due to the accumulation of organic matter, making it more fertile compared to lower soil horizons (Pozniak & Franco, 2019). Soil structure is another important factor, which refers to the way soil particles are grouped together to form aggregates. When particles are arranged homogeneously, pore spaces are created, resulting in higher soil porosity. Conversely, heterogeneous particle arrangement creates large spaces filled with fine particles, increasing compaction and reducing porosity. In this study, physical indicators such as wilting point, field capacity, sand, silt, and clay content will be used. Wilting point (WP) refers to the minimum level of soil moisture required by plants to prevent them from wilting. When the moisture level drops to this point or lower, plants wilt and cannot recover their turgidity even after being placed in a saturated atmosphere for 12 hours (Kirkham, 2015). The available moisture drops below the level that plants require, which can cause temporary or permanent withering of the plants. WP is not a fixed value, is dependent on factors such as soil texture, porosity, soil temperature, and air, and varies among different plant species. Typically, it is around -15 MPa for sunflower, wheat, and corn (Cassel & Nielsen, 1986).

Field capacity refers to the quantity of soil moisture or water that remains in the soil after excess water has drained away and the rate of downward movement of water has significantly slowed down. This process typically occurs within two to three days after rainfall or irrigation in uniform-textured and structured permeable soils (De Aquino, 2015). Both field capacity and wilting point are frequently utilized as indicators of the soil's capacity to retain water (Miháliková et al., 2016).

For Clay, Soil containing very fine mineral particles that measure less than 0.002 mm in diameter is referred to as clay content. Soils with a clay content greater than 30% are considered unhealthy as this high clay content slows down water infiltration, air penetration, and root growth, and makes tillage very difficult (Wagner et al., 2015). However, a clay ratio of 1:8 is the average for a soil with very good structural quality. A clay ratio of 1:10 is the boundary between good and medium structural quality, and a clay ratio of 1:8 or smaller increases the likelihood of a poor structural state (Johannes et al., 2017).

Silt particles are intermediate in size between sand and clay, ranging from 0.002 to 0.05 mm. Soils with a high proportion of silt have limited air spaces and water channels compared to sandy soils, but are fairly well-drained and can hold more moisture than sandy soils. They are generally easy to cultivate, except in dry conditions, but can become easily compacted and damaged when worked or grazed in wet conditions (Cassel & Nielsen, 1986).

On the other hand, sandy soils are characterized by their lightweight and dry nature, and are easy to warm. They have a larger particle size ranging from 0.05 to 2 mm and cover approximately 900 million hectares worldwide, especially in arid and semi-arid regions. These soils are predominantly composed of sand (over 70%) with very little clay (less than 15%) and/or silt. As a result, they generally contain low quantities of organic matter and have weak structure. The texture of these soils can be classified as either sand or loamy sand (Yost & Hartemink, 2019).

3.3.5 Chemical soil quality indicators

Soil organic matter is extremely complex because of the variety of its input (plants, microorganisms) and their different stages of decomposition (Hatten & Liles, 2005). By definition any material produced initially by living things (plants or animals) and returned to the soil where it undergoes the decomposition process is referred to as soil organic matter (SOM). Soil organic matter is a combination substance composed of humus (85-90%), non-humic compounds (10-15%), and live soil matter (0.1-02%). It plays a crucial role in enhancing soil fertility and quality on three levels - chemical, physical, and biological. Chemically, soil organic matter improves the soil's ability to store and supply essential nutrients such as nitrogen, phosphorus, potassium, calcium, and magnesium, and it helps retain toxic elements. Additionally, it can assist the soil in dealing with changes in soil acidity and increase the speed of soil mineral decomposition. Physically, soil organic matter enhances soil structure, which reduces soil erosion and improves water infiltration and water holding capacity, providing better living conditions for plant roots and soil organisms. Biologically, soil organic matter is a significant source of carbon that provides energy and nutrients to soil organisms. This supports soil functionality by increasing the activity of microorganisms in the soil and can promote biodiversity. The process of sequestering carbon in soil helps to decrease the amount of CO_2

emissions into the atmosphere, contributing to efforts to mitigate climate change. Typically, agricultural soils have organic matter levels of 3-6% or lower.

Soil quality can be influenced by various chemical factors, including soil pH which determines its acidity or alkalinity level. The pH scale ranges from 1 to 14 and measures hydrogen ion concentration. The availability of nutrients and toxic substances in soil depends on its pH level. Acidic environments, with a lower pH, typically have higher availability of nutrients such as iron, magnesium, copper, and aluminum, while alkaline environments favor phosphorus and most micro-nutrients. When soil pH is closer to neutral (pH of 7), the majority of mineral nutrients are easily accessible to plants.

Soil pH also affects the availability of toxic elements, where low pH levels increase the solubility of highly toxic compounds such as heavy metals like cadmium and lead. The solubility of toxic compounds is also affected by their evaporation, and in the case of heavy metals changing from solid to liquid state, this process is known as phytovolatilization. This process can be applied to remove contaminants, pollutants, and toxins from soil. Therefore, the ideal pH value for good soil quality is closer to neutral (7).

Cation Exchange Capacity (CEC) is a measure of the total milliequivalents (meq) of cations that can be held by soil components through electrostatic attraction and can be exchanged with cations in soil solution. The CEC of a particular soil depends on various factors such as the amount and type of clay present in the soil, as well as the amount of Soil Organic Matter (SOM). Consequently, the CEC of a soil can range from 0 to 50 meq/100g soil. Soils with low CEC usually have a high proportion of sand and low SOM content, while soils with high CEC typically have a relatively high proportion of clay and SOM content (Gaspar, 2019).

Base saturation is a measure of the percentage of soil exchange sites occupied by base cations such as Ca2+, Mg2+, K+, and Na+, which is determined by dividing the total amount of base cations held onto the soil exchange sites by the total CEC of the soil (Gaspar, 2019).

Phosphorus and potassium are essential elements for plant growth, and phosphorus is typically present in rocks and released into soil through weathering processes. A desirable range for phosphate content in quality soil is typically between 0.02-0.15%. Potassium is crucial for many processes necessary to sustain plant growth and reproduction. Plants that lack sufficient potassium are generally less tolerant to drought, excess water, high and low temperatures, as well as pests, diseases, and nematode attacks (Thompson, 2023). The ideal range for exchangeable potassium is typically between 0.3 to 0.7 meq/100g and should make up between 3 to 8% of the total cations present in the soil.

3.3.6 Geographical Indicators

Geographical indicators provide specific geographical information about a particular location and are useful in evaluating soil quality. Climate has a significant impact on soil formation, primarily through the two factors of temperature and rainfall. Climate indirectly influences soil development by affecting organisms. High temperatures and rainfall increase weathering and the extent of soil development. An increase in rainfall can increase organic matter content, decrease pH, increase leaching of basic ions, and movement of clay (Sindelar, 2015). Geographical indicators are intrinsic properties of the land and are among the most important indicators for assessing soil quality because they are difficult to change.

Soil hydrological class is determined by soil hydrological properties such as infiltration and water retention. These properties have a significant impact on plant growth, pollutant transport, and subsurface water transport (Ross et al., 2018).

The slope of a particular location has a significant impact on soil quality, with steeper slopes experiencing increased erosion due to the greater velocity of water flow. The length of the slope is also critical, as a larger sloping area leads to a greater concentration of flooding water (Okorie et al., 2021). Additionally, slope can have different aspects and exposure to sunlight, leading to varying soil quality for plant growth.

Soil stoniness is a characteristic of soil that pertains to the presence of stones and gravel within the soil profile. These materials can have a significant impact on soil properties, management, as well as crop growth and yield. Stones and gravel can be classified based on their size, with gravel being larger than 2 mm in diameter and stones being larger than 20 mm. The amount of stones and gravel present in the soil can be categorized into different levels. For instance, soil containing less than 5% stones and gravel is considered to have low stoniness, 5-20% is considered to have medium stoniness, and greater than 20% is high stoniness. The classification of soil stoniness is essential for evaluating the appropriateness of the soil for various crops and agricultural practices, as well as for estimating its erosion and water storage capacity. Moreover, soil stoniness can affect soil water and nutrient availability, soil temperature, and ultimately impact plant growth and productivity.

Taking into account soil stoniness is crucial when making decisions related to soil management and land use planning. Similarly, soil depth is an important factor in soil quality evaluation as it impacts plant growth, nutrient cycling, water availability, and soil biota. The thickness of the topsoil layer is especially critical for agriculture as it contains most of the essential components that support plant growth. Soil depth varies depending on various soil-forming factors, such as parent material, climate, topography, and time. Steeper slopes tend to have shallower soils due to erosion and soil movement. Soil depth is generally classified as shallow, moderate, or deep based on the depth to a restrictive layer like bedrock or a cemented layer. Soil depth can also be influenced by surface stones, which can reduce the effective rooting zone (Kozák et al., 2010).

4 Methodology

4.1 Study area

This study utilized a quantitative research design, incorporating quantitative data collection and analysis methods. The overall goal of the research was to investigate the application of the Best-Worst Method as a tool for soil quality evaluation. The selected study area (4 290 km^2) is five districts from Central Bohemia which is a region in the central part of the Czech Republic (see Fig. 4). The districts are Kutná hora (KH), Kolín (KO), Nymburk (NB), Mladá Boleslav (MB) a Praha východ (PY). It is the largest and most populous region in the country, with its administrative center in the city of Prague (#VisitCzechia, 2023). Central Bohemia has a total area of 11,015 square kilometers and a population of approximately 1.4 million people (Central Bohemia, 2023). The region is characterized by a diverse landscape that includes forests, rivers, hills, and plains. The highest peak in the region is Tok in the Křivoklát Highlands, which reaches an altitude of 865 meters above sea level.

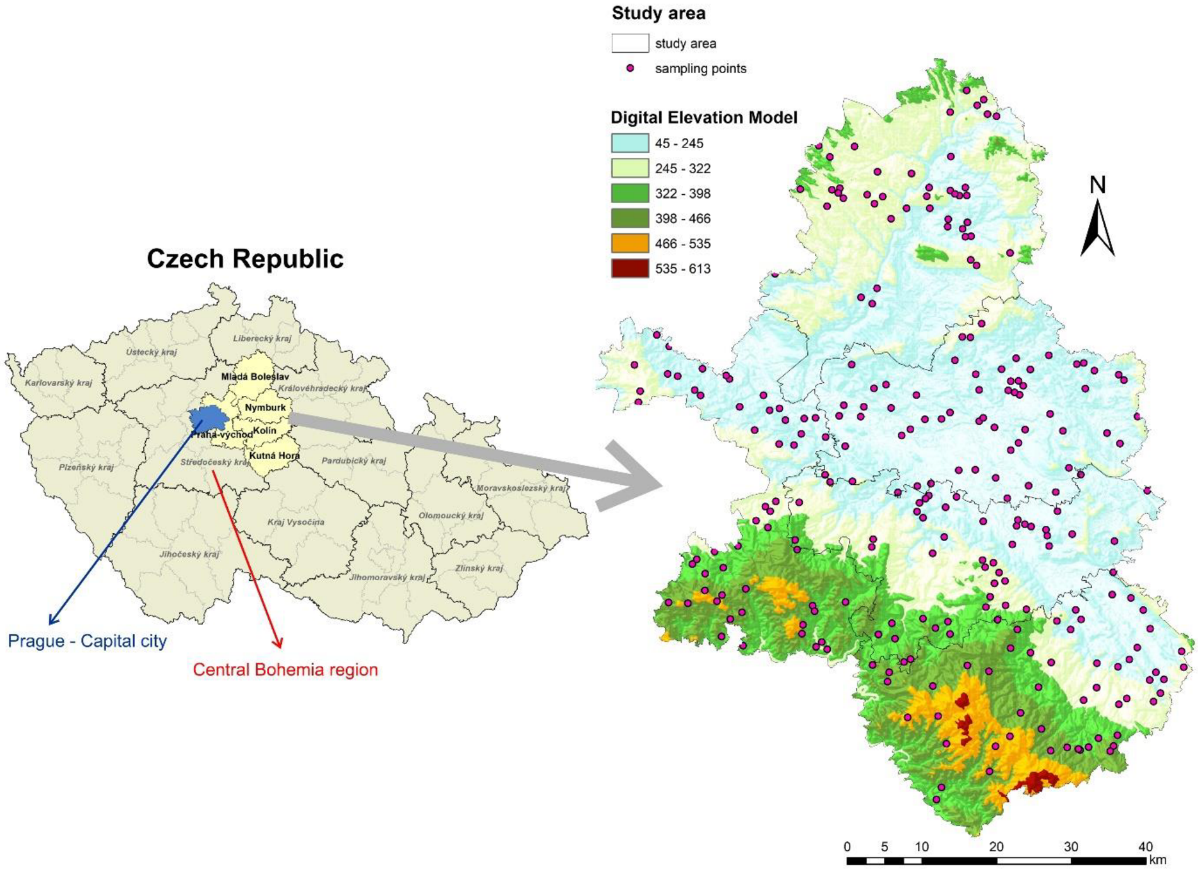

Figure 4. Location map of the study area and digital elevation model with sampling points. Source: Adapted from ČÚZK by Author.

The geology of Central Bohemia is characterized by a complex and diverse geological history, which has resulted in a unique landscape and a wealth of natural resources. One of the most important geological units in the region is the Bohemian Massif, which is a large area of crystalline rocks that formed during the Precambrian period. Massif is composed of several different rock types, including granites, gneisses, and schists. Another important geological unit in the region is the Bohemian Cretaceous Basin, which is a large sedimentary basin that formed during the Cretaceous period. The basin is characterized by a series of alternating layers of sandstone, mudstone, and limestone, which were deposited over millions of years by ancient rivers and oceans. The Central Bohemian Plutonic Complex is another important geological feature in the region. This complex consists of a series of intrusive igneous rocks, such as granites and diorites that were formed during the Carboniferous and Permian periods (Kosler & Styles, 2014).

The climate of Central Bohemia is classified as temperate continental. This means that the region has four distinct seasons, with cold winters and warm summers. Winter in there usually lasts from December to February, with average temperatures ranging from -4°C to 0°C. Snowfall is common during this period, especially in higher elevations. In the spring (March to May), temperatures begin to rise, with average temperatures ranging from 5°C to 15°C. Spring is also the wettest season in Central Bohemia, with occasional rainfall and thunderstorms.

Summer in Central Bohemia lasts from June to August, with average temperatures ranging from 17°C to 25°C. Summer is the driest season in the region, with clear skies and sunny weather. Autumn (September to November) is characterized by cooler temperatures, with average temperatures ranging from 5°C to 15°C. During this season, the region experiences colorful foliage and occasional rainfall. Overall, Central Bohemia experiences moderate precipitation throughout the year, with an annual average of around 600 mm. The region is also prone to occasional floods, especially along the Vltava and other major rivers during periods of heavy rainfall (World Weather Online, 2023).

Central Bohemia an average elevation of around 250 meters (820 feet) above sea level. However, the elevation within the region varies greatly, with some areas being much higher or lower than this average (See Fig. 4). The highest point in Central Bohemia is Tok, which is located in the Křivoklát Highlands and reaches an altitude of 865 meters (2837 feet) above sea level. Other notable highlands and mountain ranges in the region include the Brdy Mountains, the Říp Mountain, and the Kokořínsko – Máchův kraj Protected Landscape Area. On the other hand, the lowest point in Central Bohemia is located near the town of Mělník, where the Labe River (also known as the Elbe) flows out of the region towards Germany. This point has an altitude of around 140 meters (459 feet) above sea level. Most of the major cities and towns in Central Bohemia, including the capital city of Prague, are located at elevations ranging from 170 meters (557 feet) to 400 meters (1312 feet) above sea level (CzechTourism, 2023).

Agriculture in Bohemia, Czech Republic is diverse, with a variety of crops and livestock being produced in the region. The fertile soil and favorable climate conditions in the region make it well-suited for agriculture. Some of the most important crops grown in Bohemia include cereals such as wheat, barley, and rye, as well as potatoes, sugar beets, and hops for the brewing industry. The region is also known for its fruit orchards, particularly those producing apples, plums, and pears. In recent years, there has been a growing interest in organic farming and local food production, with many small-scale farmers and producers focusing on niche crops such as herbs, vegetables, and berries.

Livestock farming is also an important sector in Bohemia, with dairy and beef cattle, pigs, and poultry being the most commonly raised animals. The region is known for its high-quality dairy products, including cheese, butter, and yogurt. The production of traditional Czech meat products, such as sausages and smoked meats, is also an important part of the local food culture. In addition to traditional farming methods, Bohemia is also home to a number of innovative agricultural practices, such as aquaponics and vertical farming. These practices utilize technology to increase productivity and reduce resource use, while also providing fresh, locally grown produce to urban areas (Susan & Petr, 2020).

4.2 Data aquision

For the purposes of the thesis, a total of 15 different characteristics of soils in the districts of KH, KO, NB, MB and PY were selected from the available data. The data were provided within the framework of the research project QK1910299 "Sustainable management of natural resources with emphasis on non-production and production ability of soil". Through the geographic information system of the Czech Republic PuGIS, the following data were found for individual sampled locations from the Systematic Soil Survey of Agricultural Soils conducted between years 1961 and 1970: active pH, organic matter content, P_2O_5, K_2O, base saturation, cation exchange capacity and soil texture, and each sampling place was assigned to an ESEU code and hydrological soil group. The wilting point and field capacity values were obtained from Miháliková et al. (2021). In total, the dataset included 265 sampling points with complete data from agricultural land topsoil (0-30 cm). Their location is visible in Figure 4.

The practical work was carried out in ArcMAP 10.6.1.Software and some supporting map layers such as administrative units, digital elevation model (DEM) and natural conditions of the Czech Republic were downloaded via the ArcGIS online service from the Czech Land Surveying and Cadastral Office (ČÚZK).

4.3 General Description of Soil Quality Index determination

Soil quality index was determined in these four steps: a) selection of parameters and their overview via spatial distribution maps, b) unifying the parameters employing the standard scoring functions (SSF), c) assigning weights to parameters employing the BWM, and finally d) calculation of SQI using the linear combination equation and mapping its spatial distribution. In this study, point-based interpolation of the whole study area was used and ESEU of each sampling point was included.

In total 15 indicators from the available data were used, and they were divided into three categories. Geographical indicators, such as the climatic region, hydrologic soil class, slope, aspect, soil depth, and stoniness. Clay content, silt, sand, field capacity and wilting point are the indicators that are evaluated for the physical parameters' category. In contrast, the indicators chosen for the chemical parameters' category are organic matter, base saturation, cation exchange capacity, pH of the soil and the amount of phosphate and potassium that is readily available in the soil.

4.3.1 Evaluated Soil Ecological Units

ESEU unit in full words is the Evaluated Soil Ecological Unit and source of data from the Systematic Soil Survey in the Czech Republic (Novotný et al., 2013). The commonly used Czech abbreviation is "BPEJ". It is used to evaluate the absolute and relative production capacity of agricultural land and the conditions of their most efficient use (Miháliková et al., 2021). ESEU is characterized by a five-digit code explained in the following table 2. There exists an online cataloque with detailed description and location of each ESEU unit; it is available on the link https://bpej.vumop.cz/, however in Czech only. The ESEU units serve also as a basis for soil pricing, general soil productivity and assigning five soil protection classes (Janků et al., 2016).

Table 2. Description of Evaluated Soil Ecological Units (ESEU).

ESEU code	Definition and range of the code	Description
X.xx.x.x	code of climatic region (0–9)	The first digit of the code is a climatic region classified from 0 to 9, climatic regions were allocated exclusively for the purpose of bonitation of agricultural land resources and cover areas with similar climatic conditions for the growth and development of agricultural crops.
x.**XX**.x.x	code of main soil unit (01–78)	The main soil unit (the second and third digit) is defined as a synthetic agronomized unit characterized by a purposeful (agronomic) grouping of genetic soil types, subtypes, soil-forming substrates, texture, soil depth, type and degree of hydromorphism and land relief.
x.xx.**X**.x	associated code of slope and aspect (0–9)	The fourth digit consists of a combination of habitat factors slope and exposure of land to the world sides.
x.xx.x.**X**	associated code of stoniness and soil depth (0–9)	The fifth digit indicates the combination of the depth of the soil profile and its stoniness.

4.3.2 Standard Scoring Functions

Standardization of data expressed in different units is needed prior to calculation of SQI. Standard scoring functions according to Andrews et al. (2002) are used to put on standard data measured in this thesis. All indicators including the classified geographic parameters according to ESEU system were expressed as unitless number in the range between 0.1 and 1.0, see equations 8-10.

“Less is better“ (LB) $$f(x) = 1 - 0.9 \times \frac{x-L}{U-L} \qquad L \le x \le U \tag{8}$$

“More is better“ (MB) $$f(x) = 0.9 \times \frac{x-L}{U-L} + 0.1 \qquad L \le x \le U \tag{9}$$

“Optimum range“ (OR) $$\left.\begin{array}{ll} f(x) = 0.9 \times \frac{x-L1}{L2-L1} + 0.1 & L1 \le x \le L2 \\ f(x) = 1 - 0.9 \times \frac{x-U1}{U2-U1} & U1 \le x \le U2 \\ f(x) = 1 & L2 \le x \le U1 \end{array}\right\} \tag{10}$$

Where x is the value of the indicator, f(x) is the score of indicators ranged between 0.1 and 1, and L and U are the lower and the upper threshold value, respectively.

In general, the choice of SSF depends on the type of data and the objectives of the analysis, and it is important to carefully consider the assumptions and limitations of each approach. For example, in land suitability analysis for growing northern highbush blueberry the pH value will be evaluated from different perspective than for growing lavender, as the first requires acidic soil and the second slightly alcaline soil. On the other hand, the actual range of the indicator data has to be taken into consideration, too. If the dataset includes extreme values, the use of OR type of function should be considered rather than LB/MB.

Indicators of geographic properties

The SSF type that was employed for a certain indicator in this thesis is shown in Tab. 3. Because the highest values (up to 9) are assigned to shallow soils located on sloping terrain with a northern aspect and a high amount of skeleton, the LB type of function was used for the combined codes of the ESEU system. The lowest values (down to zero) are assigned to deep, flat soils without skeleton.

Table 3. Soil quality indicators and their standard scoring functions.

Geographic (Category A)	Types of data	Types of SSF
Climatic region	code ESEU 0-9	OR
Hydrological soil class	classes A,B,C,D	OR
Slope + Aspect	code ESEU 0-9	LB
Stoniness+soil depth	code ESEU 0-9	LB
Physical (Category B)		
Clay (%)	real value	OR
Silt (%)	real value	OR
Sand (%)	real value	MB
FC (cm^3/cm^3)	estimated value	OR
WP (cm^3/cm^3)	estimated value	OR
Chemical (Category C)		
OM (%)	real value	MB
Base saturation (%)	real value	MB
CEC (mmol/100g)	real value	OR
pH	real value	MB
P_2O_5 (mg/kg)	real value	MB
K_2O (mg/kg)	real value	MB

Abbreviations: FC (field capacity), WP (wilting point), OM (organic matter), CEC (cation exchange capacity).

The same system is generally used for climatic region code, so that the most valuable soils are located in very warm, dry climatic region (code 0) and descending to cold, humid climatic region (code 9). Since the warmest sections of the Czech Republic are at danger for drought, the OR SSF was utilized instead of the LB SSF, and warm regions with reduced risk of soil moisture deficiency were given a higher score (regions from 2 to 5). Hydrologic soil groups have a verbal classification from A to D. The mean infiltration rate was selected as a quantifiable criterion for conversion to a standardized score. An infiltration rate correspondeding to the group B was chosen as the optimum, thus hydrologic soil class B was given the highest score in OR.

Indicators of physical properties

Soil texture fractions scoring was selected as optimum range due to general evaluation of soil quality, in which extreme textural composition of soils is likely to be avoided. For example, in evaluation of soil quality for rice production the clay content will be probably scored by "more is better" function, on the other hand, for most of agricultural crops in the Czech Republic it might not be the most favourable soil condition. OR function and thus the best score for clay content was selected as 5-30 %, for silt content 10-65 % and for sand content 15-75 %. For field capacity (FC) scoring the MB function was employed. For field capacity, water content corresponding to -10 kPa was used for samples belonging to coarse textured soils (sand, loamy sand, sandy loam classes) while for other soils the water content corresponding to -33 kPa was used. Wilting point (WP) was scored according to OR function. The optimum was found as water content 0.1-0.2 cm^3/cm^3 (corresponding to -1500 kPa) as follows: From the NearriCZ database, samples from the optimum range soil texture fractions were collected, and the mean of their water content plus minus one standard deviation was determined (Miháliková et al., 2021).

Indicators of chemical properties

SOM was scored according to MB function, as there is no doubt that on arable land the more organic matter the better for the soil. Active pH between 6.6 and 7.3 was considered as OR. Example graph of SSF for pH is given in Figure 5. Phosphorus and potassium content were scored by MB function. Heavy soils (silty clay loam, clay loam, sandy clay loam, silty clay, sandy clay and clay classes) were evaluated separately from medium and coarse soils, both groups were evaluated according to the favourable content in soil (Miháliková et al., 2021).

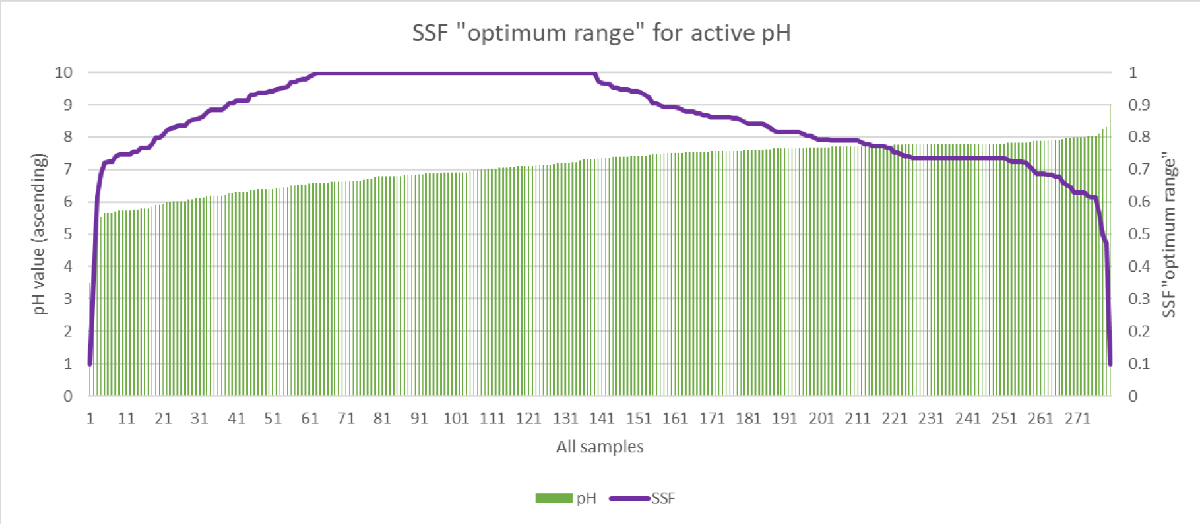

Figure 5. Example of optimum range standard scoring function for pH values.

4.3.3 Weighting of indicators by BWM Application

After identification of soil quality indicators and their scoring by SSF, in this steps the weights need to be assigned for each indicator. This was done with the help of Solver Linear BWM, which is an Excel tool developed by Rezaei (2016). All selected 15 indicators were grouped into 3 categories which are geographic (A), physical (B) and chemical (C) and assigned abbreviation due to easy application to each indicator as shown in the following table 4.

Then in each category were determined the best (the most important) and the worst (the least important) indicator based on their relative importance in soil health and quality. The intrinsic properties, which cannot be easily changed, were given higher importancy than properties, which can be changed by agrotechnical management more easily.

Thus the geographic variables were evaluated as the most relevant for soil quality determination and the chemical variables as the least relevant. The scale of importance intensities (Table 1) was used. The importancy of the best to others and the worst to others was ranked on the scale 1-9. Where 1 means equal importancy and 9 superior importancy to other indicators.

Table 4. Categories of indicators and their corresponding abbreviations in BWM

Category A	Geographic	Abbreviation
	climatic region	C1
	hydrologic soil class	C2
	slope+aspect	C3
	stoniness+soil depth	C4
Category B	Physical	
	Clay (%)	C5
	Silt (%)	C6
	Sand (%)	C7
	FC	C8
	WP	C9
Category C	Chemical	
	OM (%)	C10
	Base saturation (%)	C11
	CEC (mmol/100g)	C12
	pH	C13
	P_2O_5 (mg/kg)	C14
	K_2O (mg/kg)	C15

Abbreviations: FC (field capacity), WP (wilting point), OM (organic matter), CEC (cation exchange capacity).

4.3.4 Linear Combination Model

In this step, SQI was calculated using the linear combination method according to equation (11):

$$SQI = \sum_{i=1}^{n} (W_i \cdot X_i) \qquad (11)$$

Where SQI is the soil quality index, W_i is the weight of the indicator, X_i is the standardized unitless value of the parameter. The SQI was calculated for each sampled location.

4.3.5 Geostatistical analyses

After determining the SQI value of each soil point in the study area, by using ArcGIS, a geographical information system software, several interpolation methods which can be explained as deterministic and stochastic models were tested to generate spatial distribution map of the SQI in the whole studied area. Deterministic interpolation models such as inverse distance weighting (IDW) with 1st, 2nd and 3rd powers (IDW-1, IDW-2 and IDW-3) and radial basis function (thin-plate spline, completely regularized spline) were tested, in addition to stochastic interpolation models such as simple kriging, universal kriging and ordinary kriging with spherical, exponential and gaussian models

Root mean square error (RMSE) of each model was considered to evaluate and determine the best convenient interpolation model (Tercan & Dengiz, 2022), according to the equation (12):

$$RMSE = \sqrt{\frac{\sum(Z_{i*} - Z_i)^2}{n}} \qquad (12)$$

Where, RMSE is root mean square error, Z_i is the estimated value, Z_{i*} is the observed value, and n is the number of observed pairs.

5 Results

In this study, the Best-Worst method was used to calculate the relative weighted score of indicators required for soil quality. From 15 indicators which were grouped in three categories resulted in the different scores. Regarding the absolute weight inside each category, the highest weight was calculated for soil organic matter (0.424), it was followed by climatic region (0.416) and the lowest weight is for K_2O (0.036). Details are given in the following subchapters.
By using Arc GIS software, interpolation methods have been used to get the spatial distribution of each soil quality indicator and then for resulting SQI map.

5.1 Weights of the Soil Quality Indicators

The pairwise comparison matrices for the BWM Solver tool are shown in tables 5, 6 and 7, respectively. The consistency index was automatically calculated as well, and the weights were recalculated repeatedly until the matrix was accepted as consistent.

Table 5. Determination of the weight of the Geographical soil quality indicators

Criteria Number = 4	C1	C2	C3	C4
Names of Criteria	climatic region	HSC	S+A	S+SD

Select the Best	climatic region

Select the Worst	S+SD

Best to Others	climatic region	HSC	S+A	S+SD
climatic region	1	2	4	5

Others to the Worst	S+SD
climatic region	5
HSC	4
S+A	1
S+SD	1

Weights	climatic region	HSC	S+A	S+SD
	0.416	0.250	0.166	0.166

Abbreviations: HSC (Hydrological soil class), S+A (Slope and Aspect), S+SD (Stoniness and soil depth).

Table 6. Determination of the weight of the physical soil quality indicators

Criteria Number = 5	C5	C6	C7	C9	C10
Names of Criteria	clay	silt	sand	FC	WP

Select the Best	clay

Select the Worst	sand

Best to Others	clay	silt	sand	FC	WP
silt	1	2	1	3	4

Others to the Worst	sand
clay	4
silt	3
sand	4
FC	2
WP	1

Weights	clay	silt	sand	FC	WP
	0.317	0.176	0.317	0.117	0.070

Abbreviations: FC (field capacity), WP (wilting point).

Table 7. Determination of the weight of the chemical soil quality indicators

Criteria Number = 6	C10	C11	C12	C13	C14	C15
Names of Criteria	OM	B.S	CEC	pH	P2O5	K2O

Select the Best	OM

Select the Worst	K_2O

Best to Others	OM	B.S	CEC	pH	P_2O_5	K_2O
OM	1	3	3	4	8	9

Others to the Worst	K2O
OM	9
B.S	7
CEC	5
Ph	6
P_2O_5	2
K_2O	1

Weights	OM	B.S	CEC	pH	P_2O_5	K_2O
	0.424	0.172	0.172	0.129	0.064	0.036

Abbreviations: OM (organic matter), CEC (cation exchange capacity), B.S (base saturation).

For geographic category (A), climatic region'score is 0.416, hydrological soil class is 0.25, slope and aspect is 0.166 and stoniness and soil depth obtained the lowest weight of 0.166, see Fig. 6.

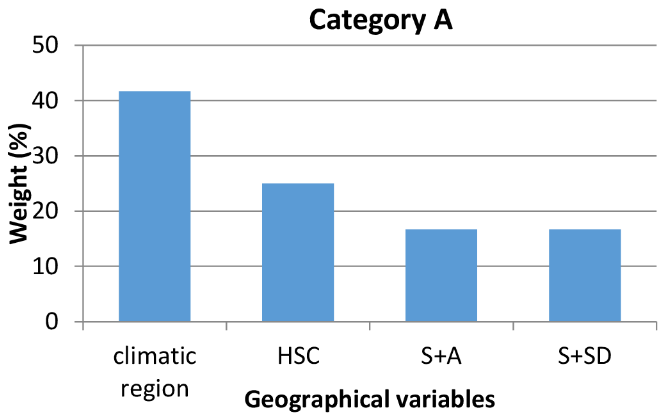

Figure 6. Graph of the weights of geographical indicators.

Category B in this study is the soil quality physical indicators, for which the weight are: clay is equal to 0.317, silt to 0.176, sand to 0.317, field capacity to 0.117 and wilting point to 0.070 (Fig. 7).

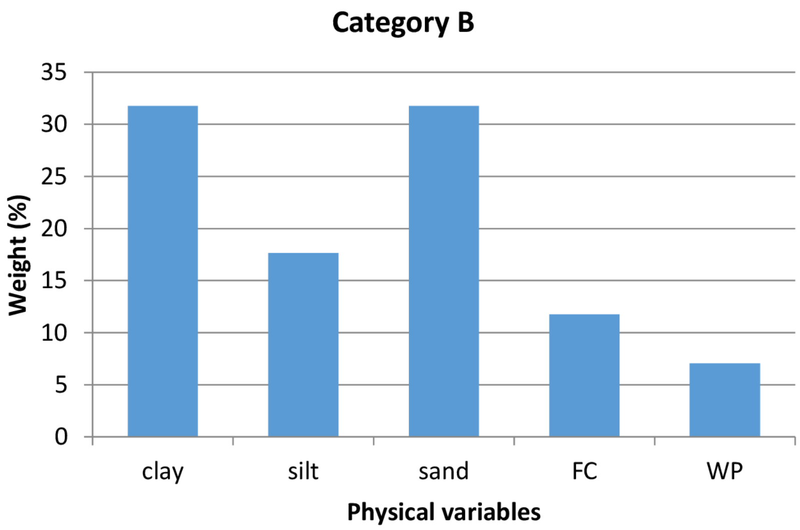

Figure 7. Graph of the weights of physical indicators.

The last category in this study is chemical Category (C) which included soil organic matter, base saturation, CEC, pH, Phosphate and Potassium which obtained weights 0.424, 0.172, 0.172, 0.129, 0.064 and 0.036 respectively, see Fig. 8.

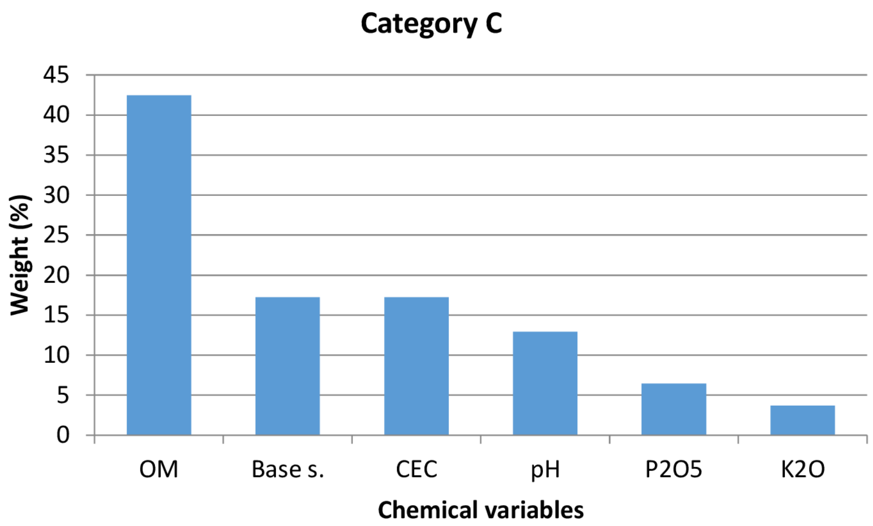

Figure 8. Graph of the weights of chemical indicators.

Overall, the below graph shows weights of the geographical, physical and chemical categories of the soil quality indicators (Fig. 9). This matrix is superior to the lower hierarchy matrices and the final weight is obtained by multiplying the weights from superior matrix with the subordinate matrices.

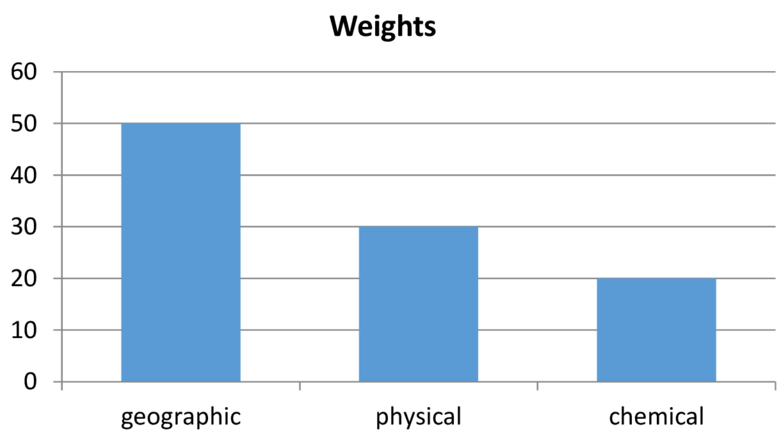

Figure 9. Graph of the weight of the higher hierarchy matrix.

Thus, the final weights are expressed on the following graph (Fig. 10).

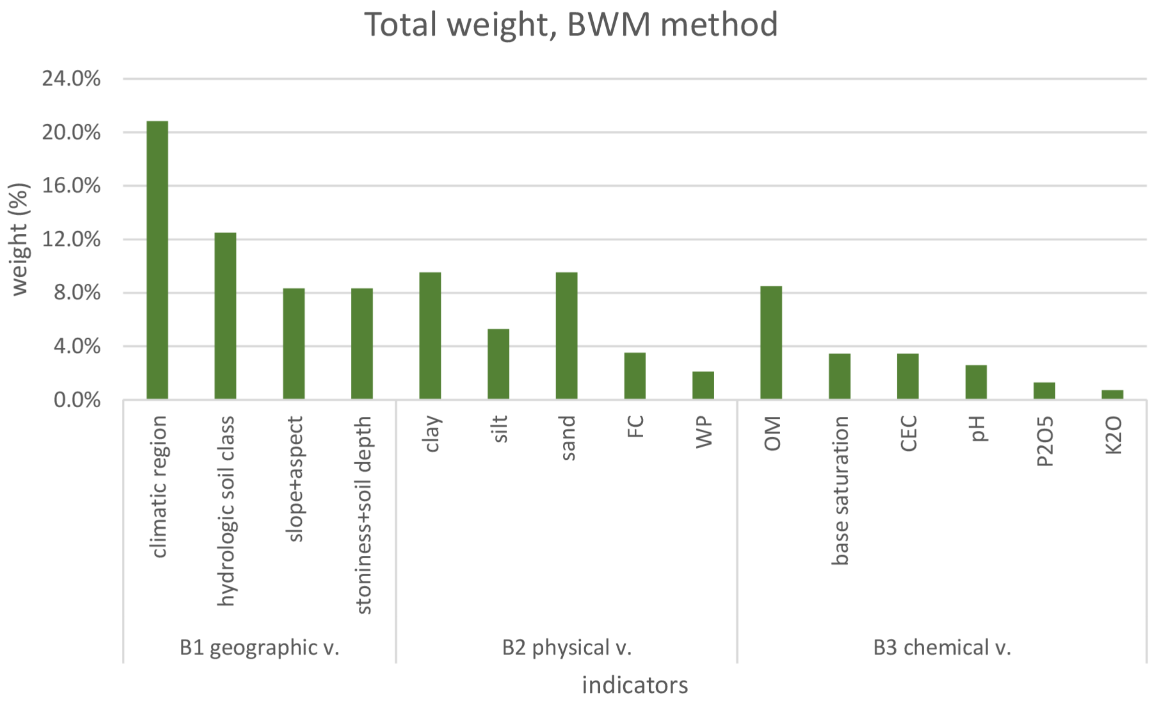

Figure 10. Final weights used for soil quality index calculation.

5.2 Soil quality assessment and spatial distribution of indicators

To overview the spatial distribution of the indicators used, their interpolated maps were generated. Calculated values the RMSE of different interpolation models in order to compare their suitability are given in the Table 8, just for selected indicators. Unit of RMSE is the same as original unit of the observed variable, similarly to standard deviation, and the lowest RMSE shows the most suitable model.

By interpolation models, the spatial distribution map of selected soil quality indicators has been created, see Figures 11-15. For classification, generally 5 classes were used with natural breaks (Jenks). Simple kriging spherical model were used for mapping of clay, sand and potassium, for others the IDW-1 model was used.

Geographical variables were not mapped as they are publicly available in online cataloques.

Table 8. Interpolation models and RMSE values.

Interpolation model	Function/Semivariogram	Root Mean Square Error							
		SQI_BWM	**SQI_AHP**	**pH_ H2O**	**K2O5**	**OM**	**CEC**	**Clay**	**Base sat.**
IDW	1	0.067175	0.07018	0.5714	106.6981	0.959363	8.196725	10.27534	14.67985
	2	0.068539	0.07159	0.600563	112.5482	1.029322	8.817829	11.07323	15.03157
	3	0.071764	0.07496	0.636812	121.8481	1.091908	9.426776	11.76098	15.72789
RBF	Completely Regularized Spline	0.06693	0.06995	0.57266	101.9814	0.971196	8.252449	10.20854	14.61785
	Thin Plate Spline	0.08302	0.08723	0.717312	137.6131	1.379554	11.24216	12.69614	18.39624
Ordinary Kriging	Spherical	0.067535	0.07075	0.592376	109.314	0.933874	7.996642	10.04011	14.7706
	Exponential	0.067953	0.07117	0.588976	110.796	0.934421	8.012097	10.08868	14.68188
	Gaussian	0.06775	0.07095	0.590905	110.144	0.933286	8.000057	10.02616	14.01173
Simple Kriging	Spherical	0.06697	0.07082	0.561678	104.112	0.934221	8.097902	10.1864	14.54329
	Exponential	0.067294	0.07078	0.562211	104.224	0.937378	8.166029	10.27527	14.43373
	Gaussian	0.067246	0.07082	0.563826	104.224	0.933522	8.059133	10.12788	14.70343
Universal Kriging	Spherical	0.067535	0.07075	0.592376	109.314	0.933874	7.996642	10.04011	14.7706
	Exponential	0.067953	0.07117	0.588976	110.796	0.934421	8.012097	10.08868	14.68188
	Gaussian	0.06775	0.07095	0.590905	110.144	0.933286	8.000057	10.02616	14.01173

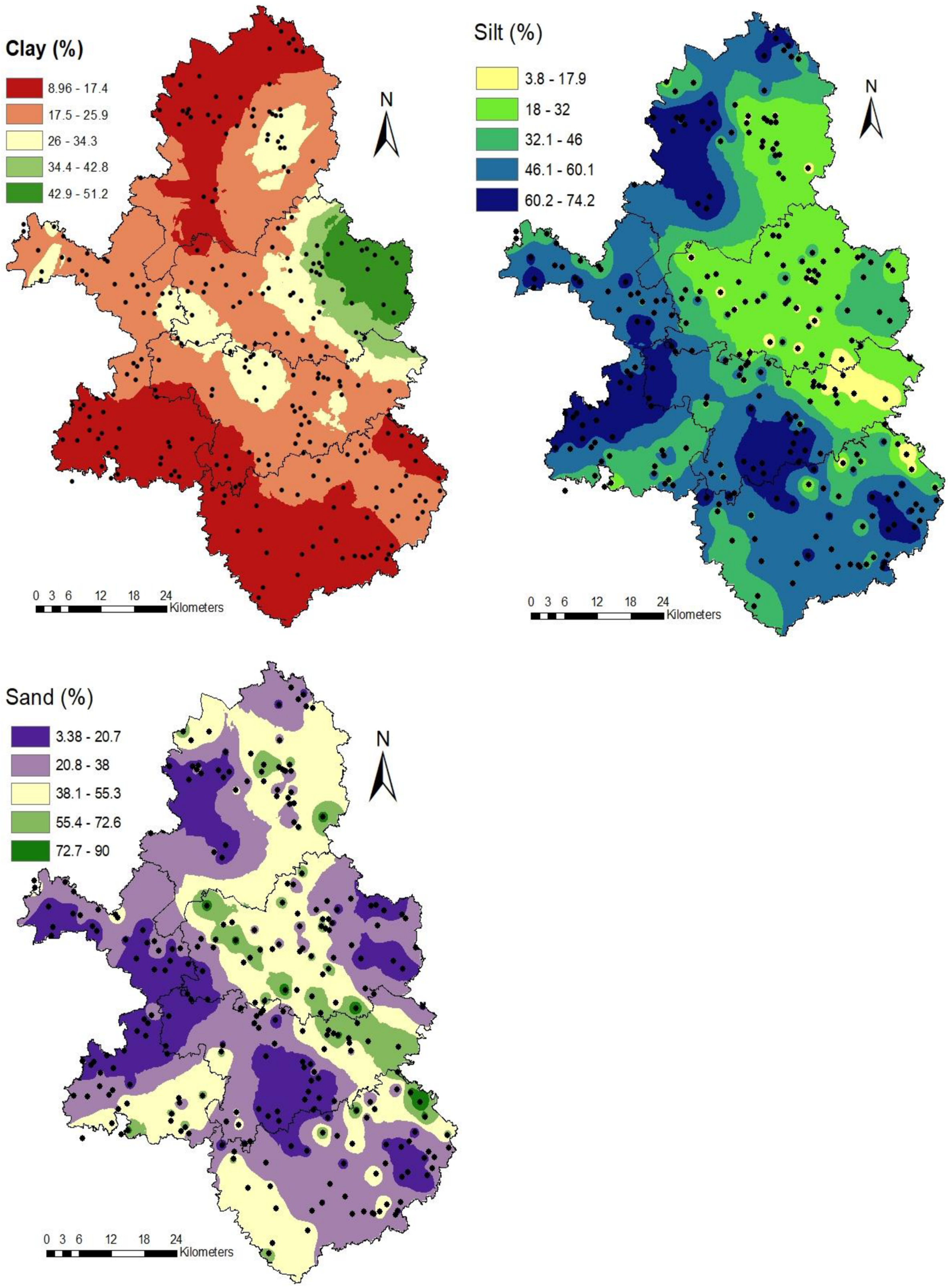

Figure 11. Spatial distribution maps of soil quality indicators: clay, silt and sand.

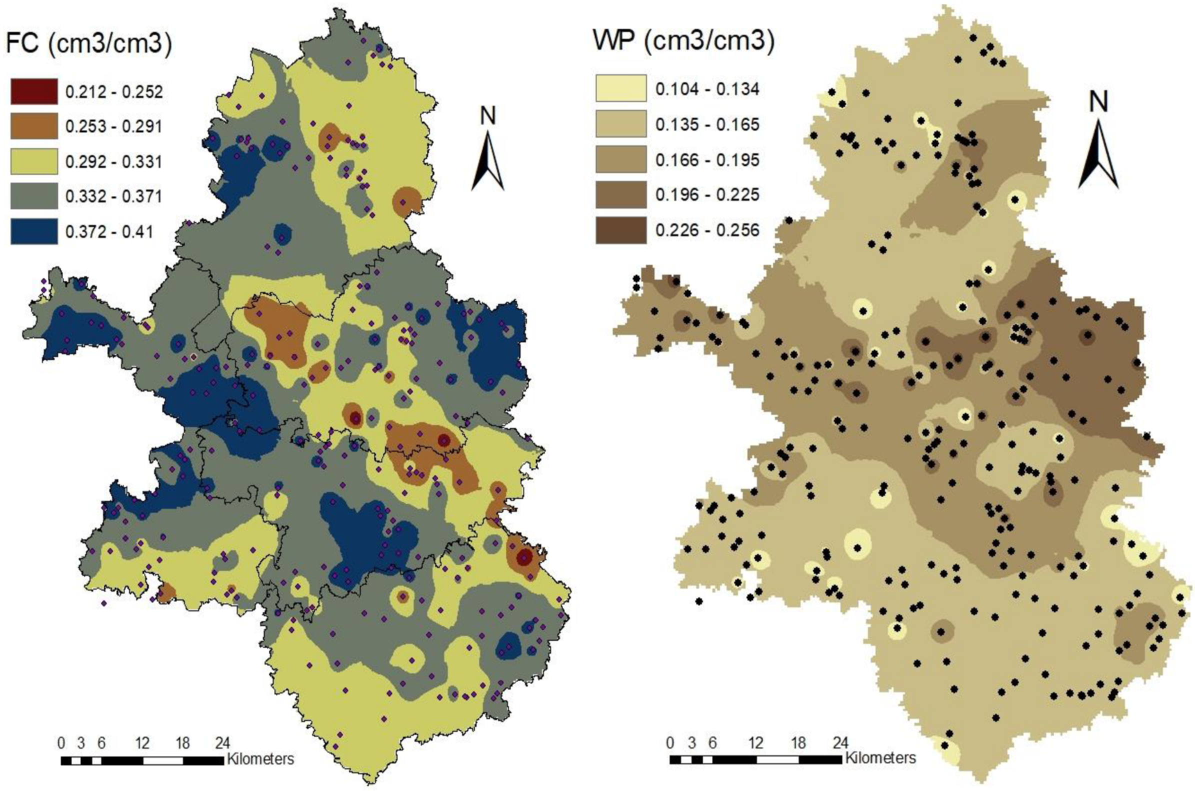

Figure 12. Spatial distribution maps of soil quality indicators: field capacity and wilting point.

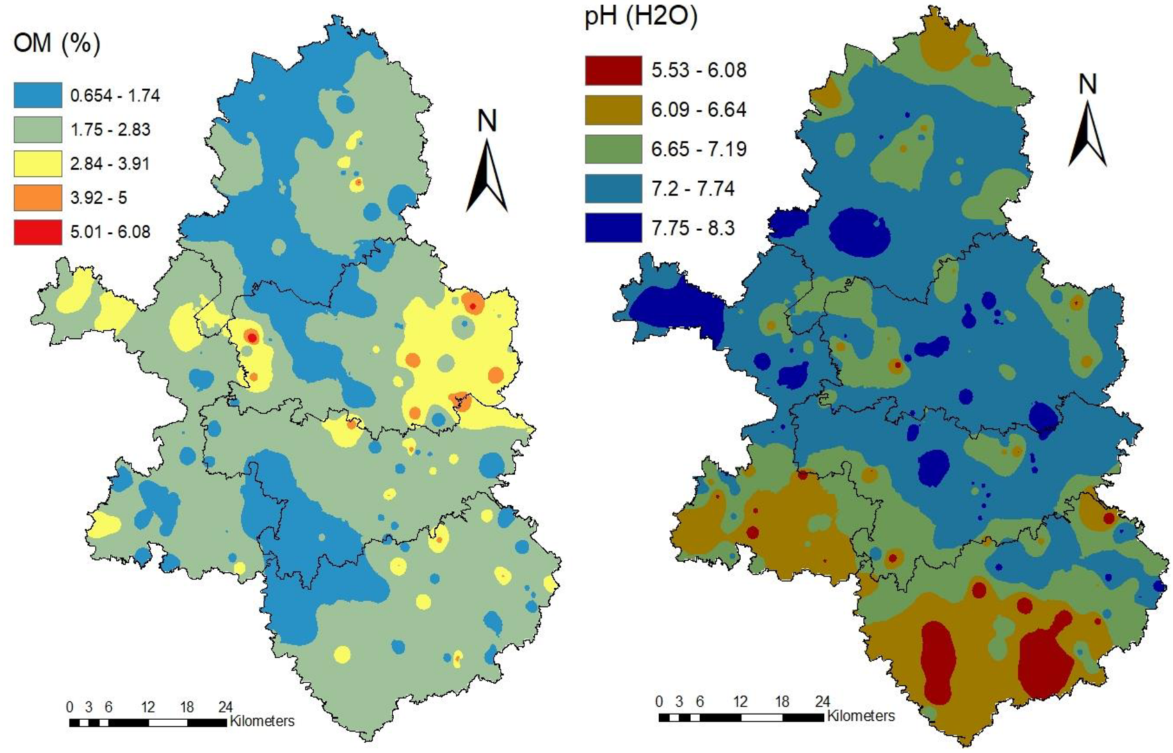

Figure 13. Spatial distribution maps of soil quality indicators: organic matter content and active pH.

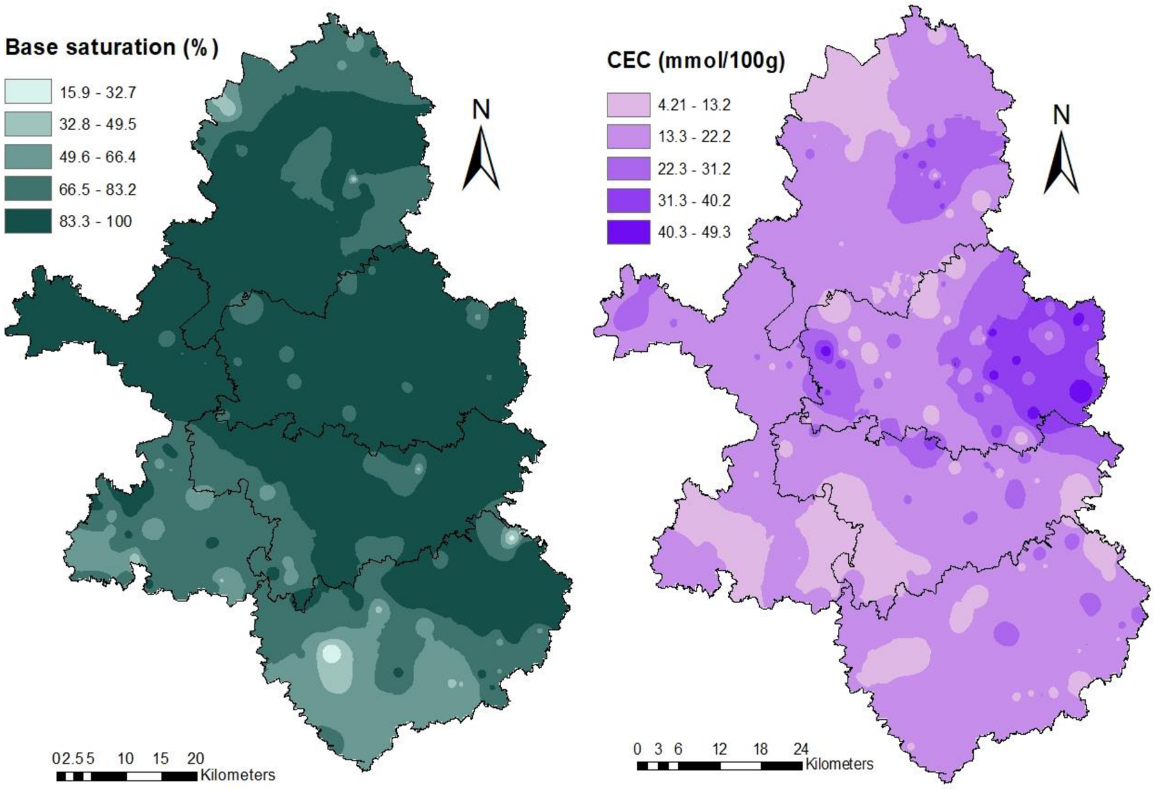

Figure 14. Spatial distribution maps of soil quality indicators: base saturation and cation exchange capacity.

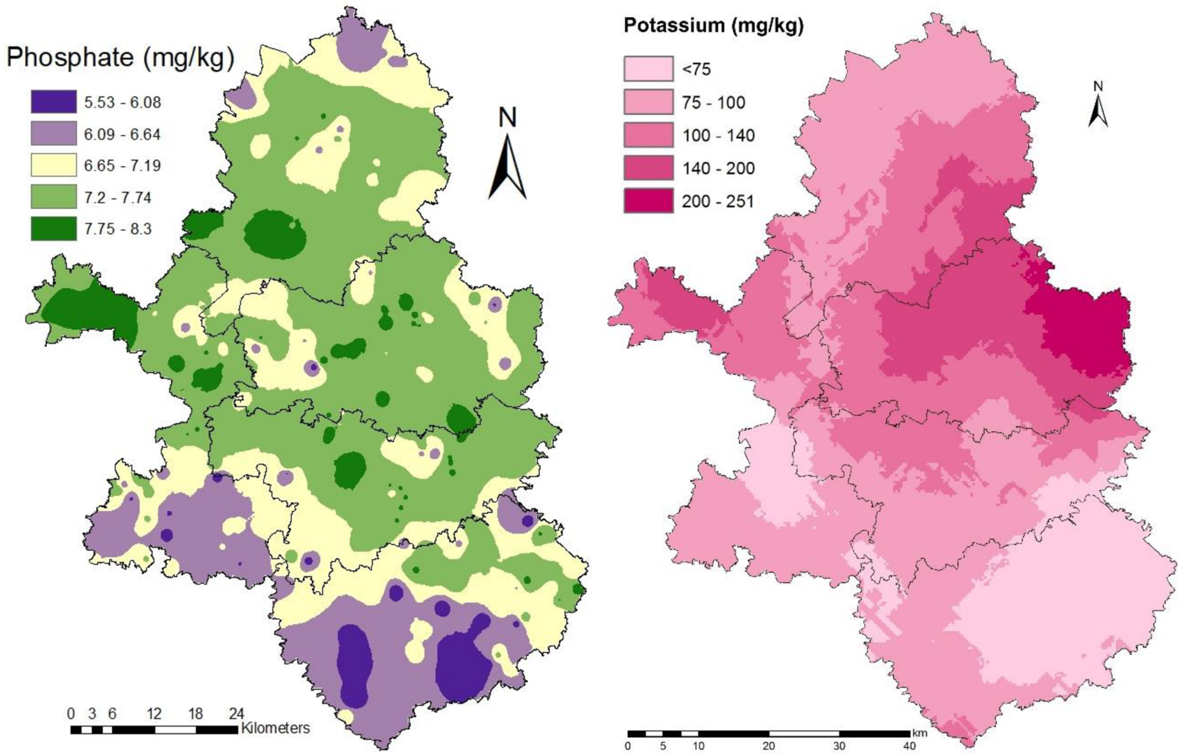

Figure 15. Spatial distribution maps of soil quality indicators: P_2O_5 and K_2O.

5.3 Soil Quality Index Map

Finally, the spatial distribution map of SQI was generated based on radial basis function – completely regularized spline, which had the lowest RMSE. Interpolated maps of simple kriging and IDW were also generated, as they had similarly low RMSE, but after visual inspection the RBF model was selected.

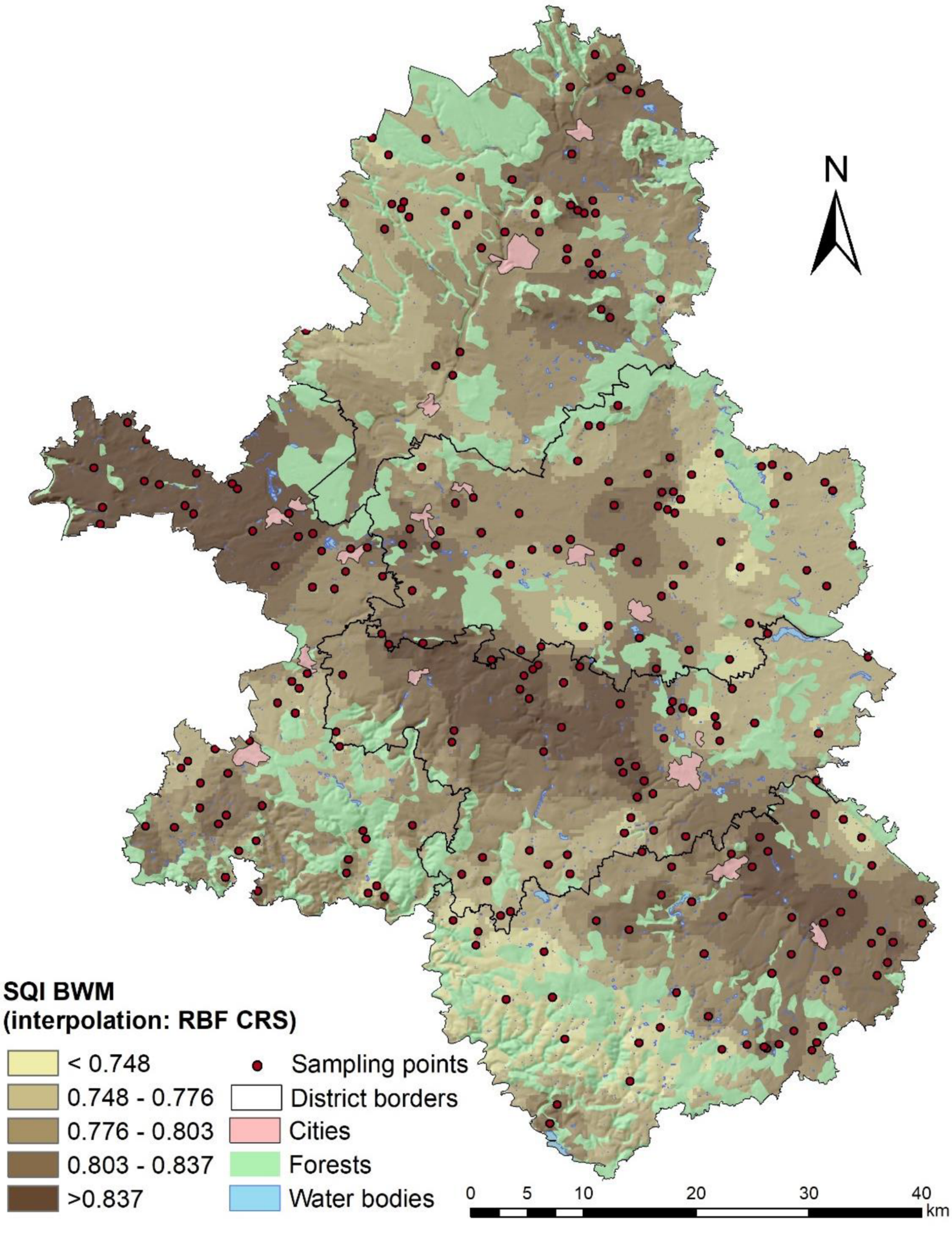

Figure 16. Spatial distribution map of Soil Quality Index.

6 Discussion

The objective of this study was to use the BWM technique to assess the soil quality index of a specific area in the Czech Republic and to produce a spatial distribution map of the soil quality index utilizing GIS technology, In 15 soil quality indicators that were used, the soil organic matter has the highest absolute score among other which implies that it is one of the most important parameters for soil quality, however, in total the climatic region was evaluated as the strongest geographical parameter and thus it was the indicator with the highest influence on soil quality. On the other hand, potassium content had the lowest influence on the resulting SQI, because its deficiency can be supplied by suitable fertilization strategy. By using different interpolation models, Radial Basis Function (Completely Regularized Spline) result has proven to be more convenient than other models for the final SQI as its RMSE reached the lowest values.

6.1 BWM and AHP Results Discussion and Comparison

As mentioned, in this current study climatic region has the highest value by using BWM in Figure 6, Miháliková et al. (2021) used AHP for weighting parameters in the central Bohemia region in order to evaluate the soil quality with regards to sustainable soil fertility and its capacity to provide ecosystem services, their study conducted on the same data but using AHP method for weighting the indicators. And they achieved reliable results. They have grouped the soil quality indicators into three category. For example in geographic category, Climatic region obtained the highest weight which implies that it is more important than hydrological soil class, slope and aspect, sloniness and soil depth . In the current study climatic region has the heighest value by using BWM as well, and this indicate that soil quality depends much on climatic region as temperature, moisture, rain and irrigation change from one climatic region to another.

In the physical categories can be seen clay and sand as the most important indicators because of high water holding capacity of clay and vice verca for sand. This indicated that the field capacity, wilting point and awailable water capacity of the soil is controlled mostly by soil texture. However depending on specific crops, high or less clay contents are better. According to Miháliková et al (2021) using AHP, they evaluated clay and silt as the most important physical indicators.

In the study conducted by Tercan & Dengiz (2022), Nine soil quality indicators were employed to determine the most suitable location for growing rice in the Cascamba plain of Turkey using the Best Worst method, They founded that soil organic matter, cation exchange capacity, and pH are considered the most important indicators of soil quality because they have a significant impact on the physical, chemical, and biological properties of high-quality soil which is reasonable because their study was focused specifically on rice crop.
In chemical category, Soil oraginic matter has shown to be the most important soil chemical indicators in the current study using BWM and AHP method from Miháliková et al. (2021) study.

Everest et al. (2021) used nine land characteristics, in Canakkale northwest Turkey in order to demonstrate how BWM can effectively evaluate the suitability in agricultural land. Their results showed that highly suitable land is 5.76 % which was equal to the results obtained from AHP method for comparison. After comparing these two methods, Their findings revealed a significant and favorable association between BWM and AHP. As far as I am concerned after reading their publication,their results are reliable. In current study, The comparison betweeen the BWM and AHP models from Miháliková et al (2021) results,
Displayed a great similarity (see Fig. 17). For instance, climatic region's total weight is equal to 41.6 % and 41.2% for the BWM and AHP respectively. The lowest soil indicator is Potassium with the final weight of 3.6% and 3.9% for the BWM and AHP methods respectively.

The overal results of BWM and AHP approaches compared on the same dataset are similar as mentioned above. The correlation between the calculated SQI by both approached showed very strong correlation, see in Figure 18. The resulting maps are similar, too. However, BWM has proven to be more efficient than AHP with respect to the consistency ratio, it is also faster and easier to use.

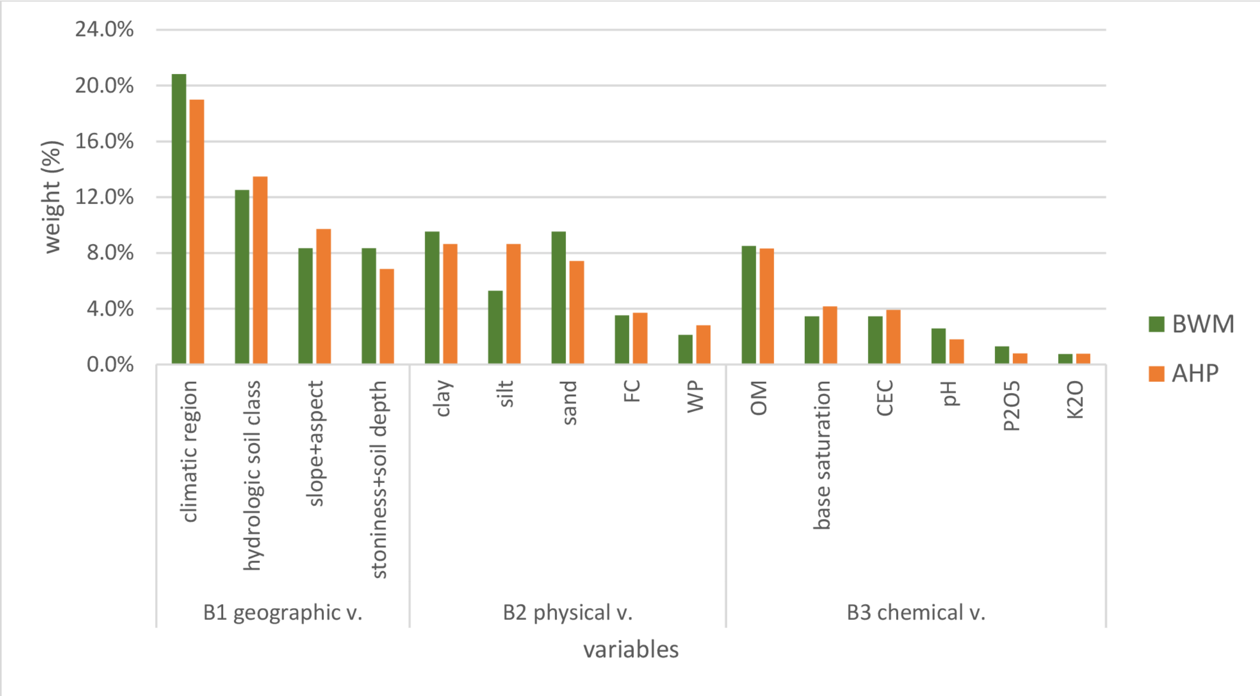

Figure 17. Graph of total weights, comparison between BWM and AHP approaches.

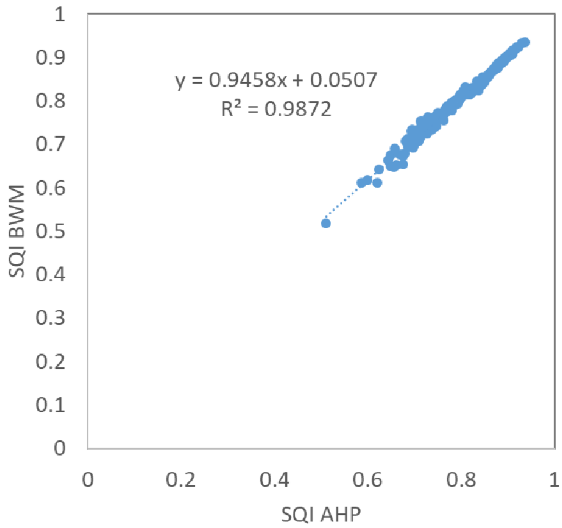

Figure 18. Correlation between SQI calculated by BWM and AHP approaches.

Interpolation model RBF-Completely Regularized Spline was used in Figure 16**.** Map of final SQI obtained by BWM weighting method was compared firstly with a map of SQI obtained by AHP weighting method, and then both with a map of soil protection classes, which are defined in the Czech law on soil protection (No. 334/1992 Coll.). Data for the map of soil protection classes were obtained from Research Institute for Soil and Water Conservation (RISWC) and are used with permission. The classes are based on ESEU system and classification is related to their productivity, regardless the need of irrigation.That means, there can be soils in the highest soil protection class, which are dry and sandy, but with set irrigation system can be very productive. This is the reason for inconsistency between both BWM and AHP soil quality indices and soil protection classes map, marked with the circle on Fig. 19.

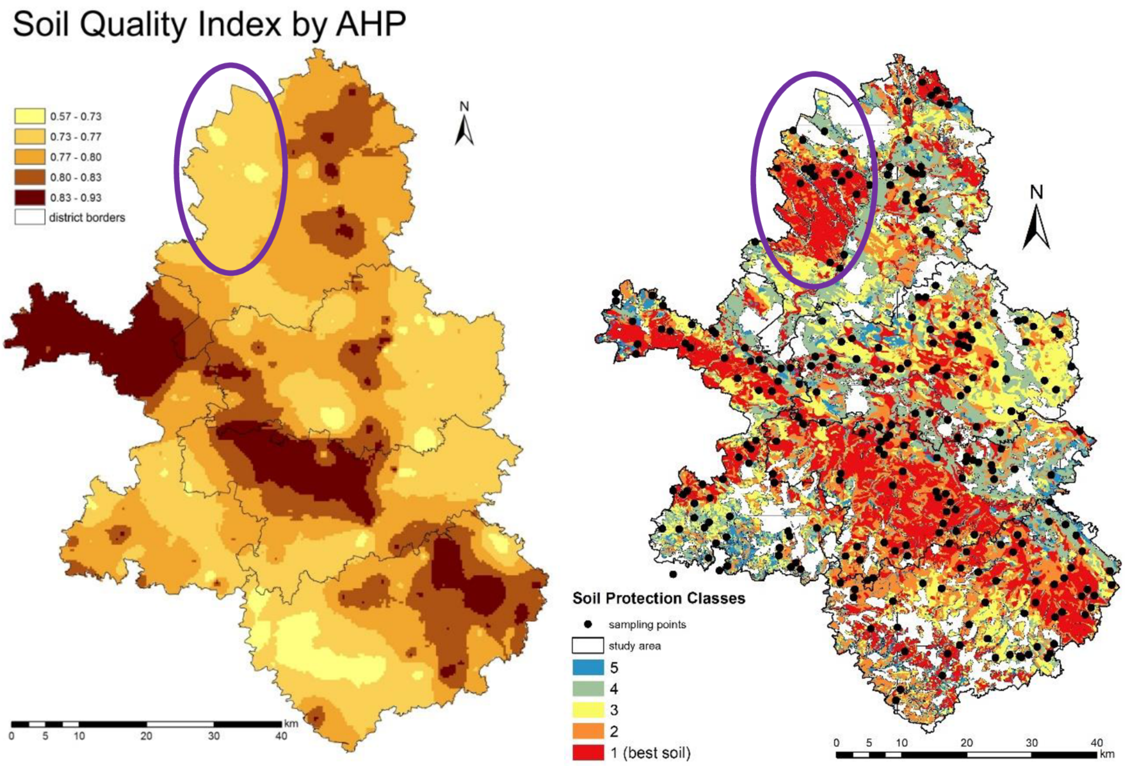

Figure 19. Soil Quality Index distribution with AHP approach (by Miháliková et al., 2021) and soil protection classes (generated by the Author from data of RISWC).

On Fig. 20 is shown correlation between SQI calculated by both BWM and AHP, and soil protection classes. The coefficient of determination is low, because the SQI is point based and continuous, while soil protection classes are polygon based and discrete values. However, the trend of higher SQI corresponding with better soil protection class is apparent, and also can be seen, that the correlation for BWM works slightly better.

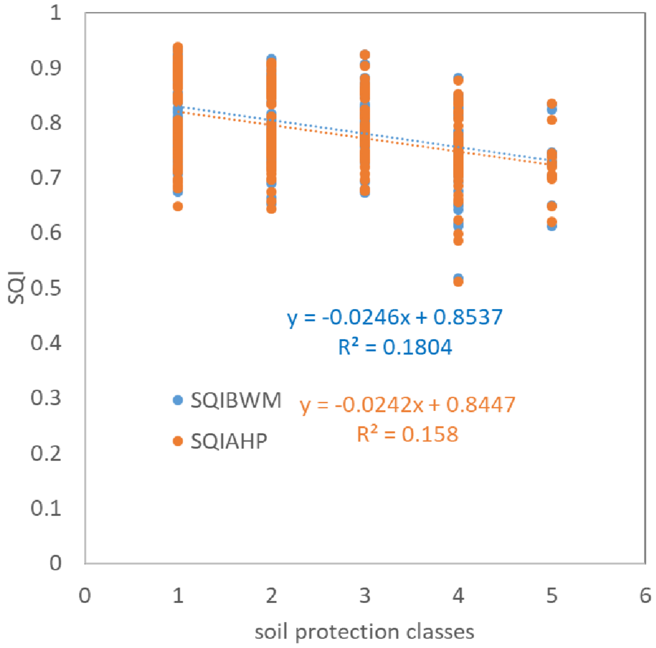

Figure 20. Correlation between SQI and soil protection classes (reversed).

7 Conclusion

Soil quality evaluation conducted by using 15 soil quality indicators which was grouped in three categories (geographical, soil physical and soil chemical properties), a multicriteria decision making method called Best Worst Method has been applied by priotizing the best and the worst ones based on author's preferences. The indicators were weighted by BWM, standardized by SSF and map of SQI was created. Soil quality evaluation methods have contributed in helping land managers and policy makers to make decision about soil management practices. Overall, by using BWM and interpolation models, resulting SQI map shows similar pattern as the SQI map by Miháliková et al. (2021) and map of soil protection classes, even though the purpose and methods for their construction and classification is different. Thus BWM which has focused on in this study can assist in the development of strategies that promote sustainable and long-term soil quality.

The hypthesis was confirmed, comparable results with already published studies were achieved and thus the objectives of the thesis were fulfilled.

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