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A Novel Sustainable Approach for Site Selection of Underground Hydrogen Storage in Poland Using Deep Learning

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Abstract: This research investigates the potential of using bedded salt formations for underground hydrogen storage. We present a novel artificial intelligence framework that employs spatial data analysis and multi-criteria decision-making to pinpoint the most appropriate sites for hydrogen storage in salt caverns. This methodology incorporates a comprehensive platform enhanced by a deep learning algorithm, specifically a convolutional neural network (CNN), to generate suitability maps for rock salt deposits for hydrogen storage. The efficacy of the CNN algorithm was assessed using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the Correlation Coefficient (R^2), with comparisons made to a real-world dataset. The CNN model showed outstanding performance, with an R^2 of 0.96, MSE of 1.97, MAE of 1.003, and RMSE of 1.4. This novel approach leverages advanced deep learning techniques to offer a unique framework for assessing the viability of underground hydrogen storage. It presents a significant advancement in the field, offering valuable insights for a wide range of stakeholders and facilitating the identification of ideal sites for hydrogen storage facilities, thereby supporting informed decision-making and sustainable energy infrastructure development.

Keywords: underground hydrogen storage; deep learning; site selection; convolutional neural networks; sustainable energy storage

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1. Introduction

Hydrogen is increasingly recognized as a leading eco-friendly fuel, poised to become a crucial clean energy carrier [1–3]. The growing efficiency and reduced costs of renewable energy sources (RESs) are driving down electricity production costs, yielding significant medium-term benefits. Converting excess, low-cost renewable electricity into hydrogen not only facilitates storage for future use but also enhances the economic efficiency of renewable energy systems [4–6].

Despite their advantages, RESs are plagued by intermittency, underscoring the necessity for efficient hydrogen storage solutions [7,8]. Depleted hydrocarbon reservoirs, rock salt deposits, and aquifers offer promising solutions for large-scale hydrogen storage [9,10]. However, initial evaluations of these formations frequently overlook essential surface and subsurface factors, which may affect their suitability for storage.

In recent years, the use of artificial intelligence algorithms, particularly machine learning (ML), has surged, providing powerful computational tools for simulating complex phenomena across various academic fields [11–13]. Tools renowned for their ability to handle nonlinear scenarios without requiring statistical data assumptions exemplify this trend [14,15]. Combining ML with Geographic Information Systems (GIS) provides exceptional insights into identifying optimal sites for underground hydrogen storage (UHS). Despite the abundance of reviews on UHS [16–22], comprehensive evaluations of storage potential and technical aspects are still essential [23–26]. Salt caverns, in particular, have emerged as prime candidates for UHS, evidenced by their industrial applications in the petrochemical sector and successful operational examples in locations such as the UK and the USA [27]. Research worldwide continues to highlight the significant hydrogen storage potential of rock salt deposits [28–34] which, due to their size and adaptable shape, are suitable for storing large hydrogen volumes.

Zhu et al. [35] conducted an assessment on the viability of utilizing salt mines in China for salt cavern hydrogen storage (SCHS). They developed an evaluation framework using the Entropy-Weighted Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to aid in selecting optimal SCHS sites. The Entropy Weight Method (EWM) was employed to determine the weights of evaluation criteria, and TOPSIS was used to assess SCHS suitability. Their study also factored in the hydrogen storage capacity of the selected site and the demand for SCHS.

Huang et al. [36] introduced a preliminary site selection system for UHS in salt caverns, demonstrating its application in Pingdingshan, China. They put forward a four-factor model for site selection and outlined a preliminary framework specifically designed for salt cavern hydrogen storage.

Tarkowski et al. [37] examined the hydrogen storage capacity of salt caverns and deep aquifers in Poland in relation to the demand for hydrogen storage, incorporating a detailed case study. Their analysis highlights the significant potential in geological formations and presents key findings from a techno-economic assessment of prospective scenarios for deploying underground renewable hydrogen storage facilities.

Du et al. [38] conducted an in-depth exploration of hydrogen geologic storage (HGS) in China, focusing on its potential for large-scale energy storage to mitigate peak demand and enhance the stability of intermittent renewable energy sources. They highlighted several significant challenges, such as hydrogen's low density and viscosity, intricate interactions with geological formations and microorganisms, and the lack of essential parameters within potential reservoirs.

Caglayan et al. [32] presented a comprehensive study on the technical feasibility of utilizing salt caverns for hydrogen storage across Europe. Their research included an assessment of the suitability of subsurface salt structures in Europe based on criteria such as size, land suitability, and storage capacity. They also estimated the potential for hydrogen storage in various onshore and offshore scenarios, considering different distances from the shore.

The technological challenges of underground hydrogen storage in salt caverns necessitate a thorough evaluation of cavern dimensions, the properties of rock salt, and their influence on storage capacity [39–44]. Factors such as the thickness and depth of rock salt deposits significantly influence site selection criteria. A practical approach to determining optimal sites must integrate environmental, technical, economic, and social considerations [45,46]. Integrating GIS and ML has substantially benefited site selection and impact assessment across diverse domains [15,46–52].

Our study introduces a novel artificial intelligence framework to create suitability maps for hydrogen storage in rock salt deposits. This pioneering approach leverages deep learning and spatial data analysis to enhance the accuracy of determining hydrogen storage potential. By providing stakeholders with a robust decision-support tool, this methodology can potentially transform the process of identifying optimal locations for hydrogen storage facilities.

2. Materials and Methods

This research established a detailed methodology for pinpointing optimal locations for UHS within rock salt formations, with particular emphasis on the Na1 rock salt deposit in the Fore-Sudetic Monocline region of southwest Poland. The Na1 rock salt deposit, part of the PZ1 cyclothem, is characterized by its significant thickness and favorable geological properties, making it a prime candidate for underground hydrogen storage. Located in the Fore-Sudetic Monocline in southwest Poland, this deposit is more than a hundred meters thick in places, with certain areas reaching up to 300 m. The Na1 layer is composed of several types of rock salt interspersed with anhydrite layers, indicating a complex depositional environment. The rock salt's substantial thickness and purity are advantageous for creating stable storage caverns, while the presence of anhydrite and other interlayers provides additional structural integrity. These geological characteristics make the Na1 deposit an ideal site for assessing hydrogen storage capacity.

2.1. Methodology Overview

This approach incorporated Multi-Criteria Decision Analysis (MCDA), artificial intelligence (AI) algorithms, and GIS spatial analysis. The Analytic Hierarchy Process (AHP) was used to methodically deconstruct this complex problem into manageable parts, encompassing the definition of evaluation criteria, the assignment of weights to these criteria, and the determination of a definitive ranking among site alternatives.

Methodological Steps

1. Definition of Evaluation Criteria: Parameters were established to effectively select sites for underground hydrogen storage (UHS).
2. Integration of AI Algorithms: A deep-learning algorithm (CNN) was implemented on a unified platform to enhance analysis capabilities.
3. Data Segmentation: Criteria-based data were divided into training and testing sets to validate model performance.
4. Performance Assessment: The algorithm's effectiveness was evaluated using standard error metrics and the Correlation Coefficient (R^2).
5. GIS Visualization: Spatial distribution of potential UHS sites was mapped using GIS to visualize geographical data effectively.
6. Suitability Mapping: A UHS suitability map was generated based on outputs from the selected algorithm, aiding in decision-making processes.
7. Final Algorithm Formulation: A standardized protocol was developed for future research applications to ensure consistency and replicability.

We considered two main groups of criteria for choosing suitable areas: exclusion criteria and evaluation criteria. Exclusion criteria helped us eliminate certain areas from further analysis, such as protected areas like natural reserves, including national forests, special protection areas, protected areas, conservation areas, and ecological sites. Evaluation criteria helped us classify the remaining areas by assessing factors like storage capacity, water reservoirs, accessibility, natural gas pipelines, geological exploration, energy consumption, and land use.

To create the maps, we developed twelve maps for each criterion mentioned above. The storage capacity map depicted hydrogen energy that could be stored in the rock salt bed per area, corresponding to the storage capacity after the first filling of the cavern. The water reservoir map included a hydrological representation of rivers and reservoirs at each location. The accessibility map highlighted infrastructure such as roads and railroads. The natural gas pipeline map indicated the accessibility to the existing gas pipeline network. The geological exploration map identified areas with salt caverns, the target geological formations for hydrogen storage, and included deep borehole locations. The energy consumption map displayed energy consumption data for the study area. The land use map illustrated landscape elements, including residential buildings, restricted areas, recreational areas, industrial zones, cropland, forests, grassy areas, and barren and shrubland. Additionally, five exclusion criteria maps showed protected areas around the rock salt deposits, including national forests, special protection areas, protected areas, conservation areas, and ecological sites.

All twelve maps were developed with an exact resolution of 100 points per km^2, meaning each pixel in the raster had dimensions of 100×100 m. Thus, we had 12 values for each point in the study area. The next step involved transforming the basic maps to quantify individual criteria and presenting them as raster maps with numerical values. These values served as the starting point for calculations using artificial intelligence aimed at identifying the best locations for underground hydrogen storage facilities in salt caverns within the analyzed area. Maps showing roads, gas pipelines, water, and borehole locations required transformation based on proximity maps, indicating the distance between selected elements at each point. However, maps like storage capacity, land use, and energy consumption did not require transformation due to their numerical nature. Raster maps consist of pixels with assigned coordinates and values of the analyzed criteria.

We normalized the values from the raster maps to facilitate comparative analysis without applying any weight to these values. Twelve standardized raster maps were used as input features for machine learning (ML) analysis. This dataset was divided into a training set and a validation–testing set. The suitability map developed by Lankof and Tarkowski [53] was employed as the target for ML algorithm calibration. The ML algorithm with the highest accuracy was selected for final implementation. The resultant suitability map for underground hydrogen storage within the rock salt layer was generated based on the data processed by the chosen ML algorithm.

This research utilizes a deep learning algorithm, a subset of artificial intelligence (AI) focused on developing systems capable of learning from experience. Machine Learning (ML), an essential component of AI, employs methods that allow systems to autonomously enhance their performance by discerning patterns in raw data, essential for tasks like detection and classification. Advances in big data and AI technologies have significantly influenced geological sciences, enabling the evaluation of potential UHS sites within geological structures using AI. The computational model employs a convolutional neural network (CNN), which includes several layers: input, fully connected, convolutional, output, activation functions, pooling, and a flattening layer. The convolutional layers extract features from input spectra using N filters, producing N feature maps. These feature maps then pass through an activation function layer—such as sigmoid, exponential linear units (ELUs), or rectified linear units (ReLUs)—to introduce nonlinearity, while a pooling layer reduces feature map dimensionality to prevent overfitting and enhance computational speed. The fully connected layer, resembling a multi-layer perceptron, connects each neuron to every element in the preceding layer, thus integrating and processing the information comprehensively.

2.2. Layers

2.2.1. Fully Connected Layer

In this network, the fully connected (FC) layer linearly maps the input vectors. Neurons in adjacent layers are connected pairwise (Figure 1).

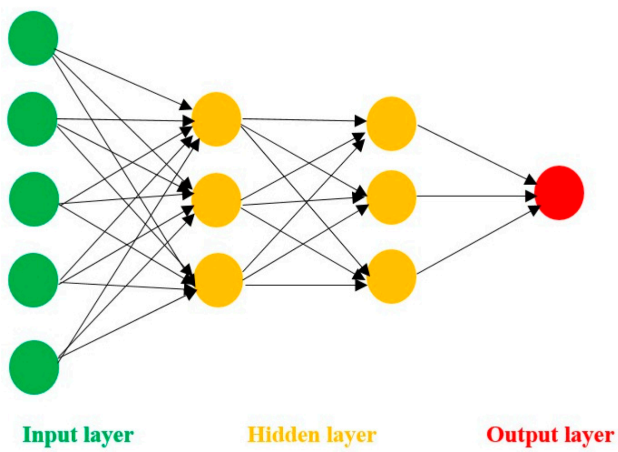

Figure 1. A neural network structure.

2.2.2. Convolutional Layer

A convolutional layer convolves a specific filter with the inputs by sliding it spatially over the spectra. The filter performs a stepwise dot product with a local spectra window, using a stride of 1. To maintain consistent input and output sizes, the input spectra are padded. Typically, the convolutional layer follows the fully connected layers (Figure 2).

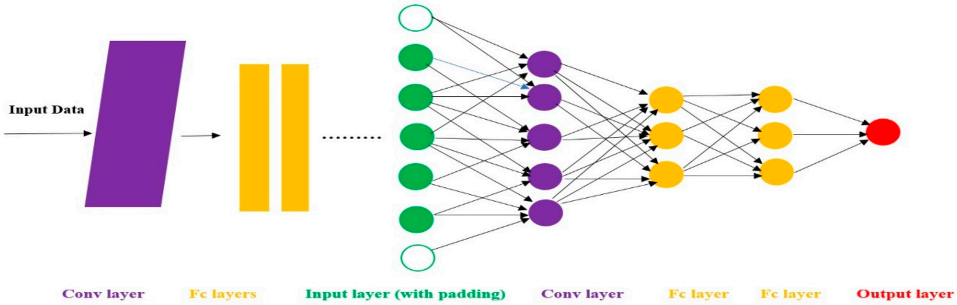

Figure 2. The architecture of a convolutional neural network.

2.2.3. Preprocessing and Convolutional Layers

Preprocessing methods such as Savitzky–Golay derivatives and detrending in spectroscopic calibration effectively shift the input spectra's weighted mean. These classical preprocessing techniques can be replaced by a well-trained convolutional layer, which can be adjusted through backpropagation, eliminating the need to manually select specific preprocessing techniques. Instead, the optimization algorithm identifies the most effective filter.

2.2.4. Filter Characteristics

Given that the input vectors are 1D spectra, the filter is also a 1D vector, with its bandwidth corresponding to the resolution of the input spectra. To enhance the model's flexibility, multiple parallel convolutional channels can be implemented. However, tuning multiple convolutional filters requires an adequate number of training samples. For simplicity, this study considered a single channel with one convolutional layer.

2.3. Activation Functions

The outputs of each hidden layer, including convolutional and fully connected layers, are modified by activation functions to introduce nonlinearity. Here, we discuss the relationship between the input x and the output y through various activation functions.

The sigmoid function calculates the element-wise sigmoid of x, as follows in Equation (1):

$$y = \frac{1}{1 + \exp(-x)} \tag{1}$$

Historically, the sigmoid function has been widely used in neural networks due to its biological interpretability. However, it can cause gradient vanishing; during backpropagation, the gradient flow is near zero when x is far from zero. Additionally, the sigmoid function is non-zero-based, leading to inefficient parameter updates.

The hyperbolic tangent (Tanh) function computes the element-wise hyperbolic tangent of x at Equation (2):

$$y = \tanh(x) \tag{2}$$

This function zero-centers the output within the range $[-1, 1]$, which mitigates the gradient vanishing problem.

Rectified linear units (ReLUs) apply an element-wise rectification to the input, setting all negative input values to zero at Equation (3):

$$y = \begin{cases} x, & x \geq 0 \\ 0, & otherwise \end{cases} \tag{3}$$

A ReLU does not saturate and converges faster than both tanh and sigmoid. However, it is not zero-based, and a problem known as "dead ReLU" can occur, where neurons with negative input always output zero. This issue can arise from poor learning rates or initialization.

Exponential Linear Units (ELUs) are similar to ReLUs but have an exponential component for negative inputs:

$$y = \begin{cases} x, & x \geq 0 \\ \exp(x) - 1, & otherwise \end{cases} \quad (4)$$

ELUs retain the advantages of ReLUs while avoiding "dead" neurons, as they do not output a constant zero for negative inputs. This results in more efficient weight updates due to the near-zero-centered output and a negative saturation regime that offers robustness against noise. The main drawback of ELUs is the slower computation of the exponential function, particularly in large networks.

2.4. Regularization

In this model, the number of parameters exceeds the number of observations, making regularization crucial to prevent overfitting.

2.4.1. L2 Regularization

L2 regularization is one of the most common techniques in machine learning. It encourages the model to utilize all neurons by penalizing the sum of the squared weights, represented as $\frac{1}{2}\lambda w^2$, where w denotes the weight and λ is the regularization parameter. The gradient of L2 regularization is λw, causing each weight to gradually decrease towards zero while maintaining its current sign.

2.4.2. Dropout

Dropout is another effective method to prevent overfitting in neural networks (Figure 3). During training, it randomly activates a subset of neurons in the fully connected layers, updating the parameters of only the selected neurons. Dropout is not applied during testing. This technique is both simple and effective, and widely used in contemporary neural networks. The principles and relationships of dropout, along with other regularization methods, have been well documented in recent studies.

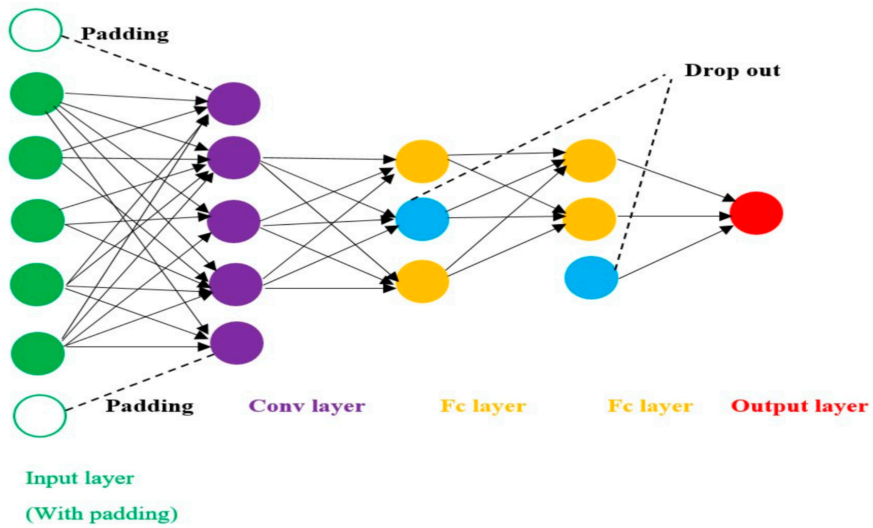

Figure 3. Random dropout of neurons in the fully connected layers during training.

2.5. Performance Evaluation Metrics

The convolutional neural network (CNN) is structured with multiple layers: a one-dimensional convolutional layer, a pooling layer, a flattening layer, and a final output layer. The convolutional layer employs 32 kernels, each of uniform size (3 × 3), and operates with a batch size of 32. The outputs from this layer are subsequently processed by a ReLU activation function to introduce non-linearity. To attenuate sensitivity and diminish the dimensionality of feature maps, max pooling is utilized, which selects the maximal values from the convolved features. To identify suitable sites for UHS in salt caverns, we implemented the convolutional neural network (CNN) algorithm utilizing input parameters as explained in Section 2.1 as exclusion criteria and evaluation criteria, and the Analytic Hierarchy Process (AHP) output based on Lankof and Tarkowski [54]. A representative subset consisting of 1000 systematically distributed points was extracted from the study area for this study. The dataset was bifurcated into training (80%) and testing (20%) segments to facilitate a rigorous validation of the model's efficacy.

The CNN algorithm underwent training and testing, and its performance was rigorously evaluated using MSE, MAE, RMSE, and R^2. These metrics (Equations (5)–(8)) were essential for assessing the algorithm's effectiveness and ensuring its accuracy before comprehensive application to the dataset. The primary objective was to pinpoint optimal sites for UHS, where n represents the total number of observations, y^i_{observed} denotes the ith observed value, and $y^i_{\text{predicted}}$ is the corresponding predicted value.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y^i_{\text{observed}} - y^i_{\text{predicted}}\right)^2 \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{\text{n}}\left|y^i_{\text{observed}} - y^i_{\text{predicted}}\right| \tag{6}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{\text{n}}\left(y^i_{\text{observed}} - y^i_{\text{predicted}}\right)^2} \tag{7}$$

$$\text{R}^2 = 1 - \frac{\sum_{\text{i}}\left(y^i_{\text{observed}} - y^i_{\text{predicted}}\right)^2}{\sum_{\text{i}}\left(y^i_{\text{observed}} - y^i_{\text{predicted}}\right)^2} \tag{8}$$

Figures 4–6 illustrate the CNN's performance for both the training and testing datasets, showing a significant reduction in errors throughout the learning process. Upon completion of training, the CNN model achieved high accuracy, evidenced by an R^2 value of 0.96, an MSE of 1.97, an MAE of 1.003, and an RMSE of 1.4. The error function was a key metric in evaluating the predictive model's performance.

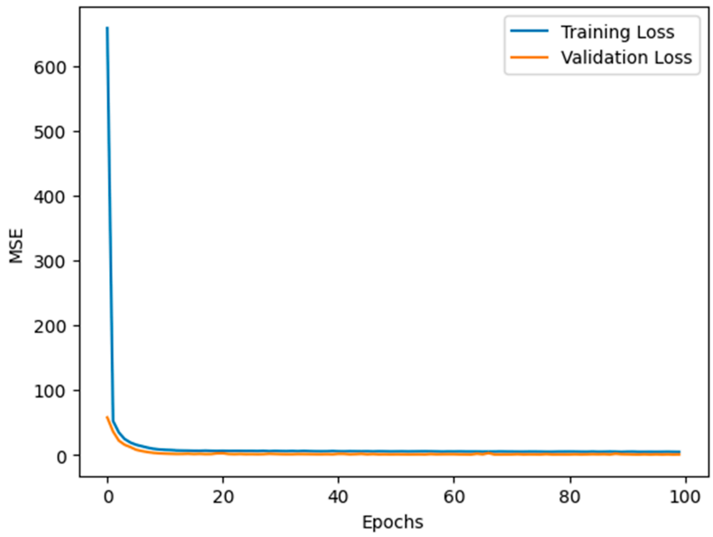

Figure 4. The validation loss of the CNN model.

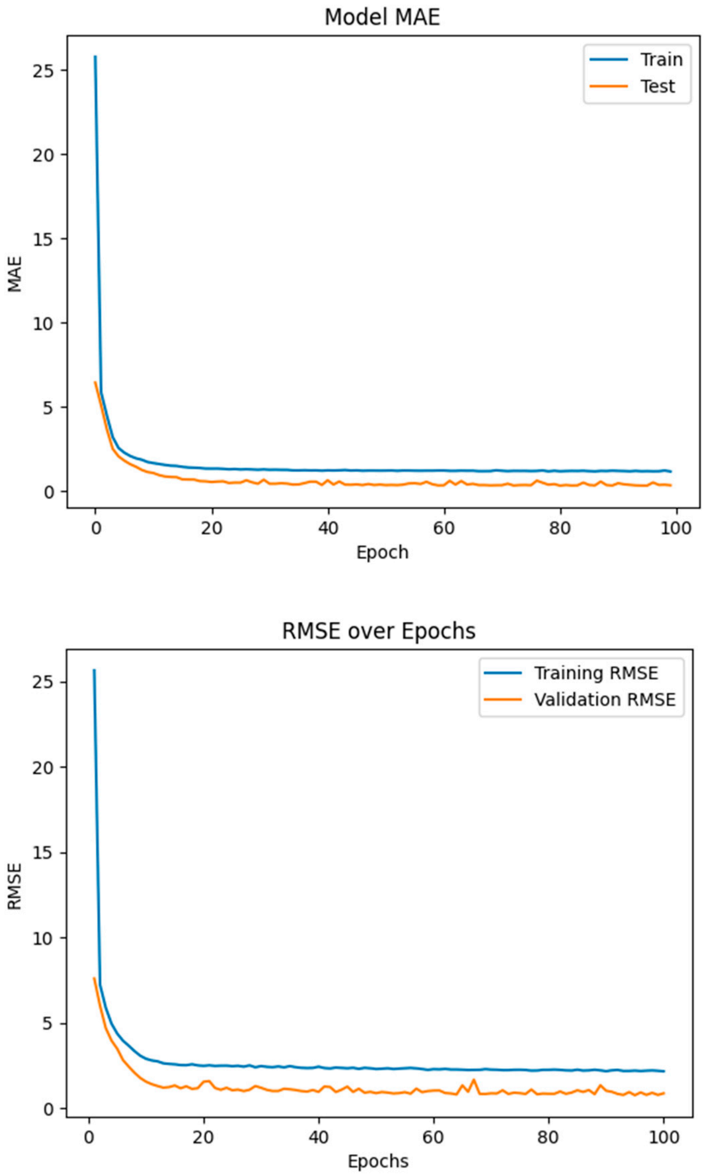

Figure 5. Prediction error evaluation for the CNN model.

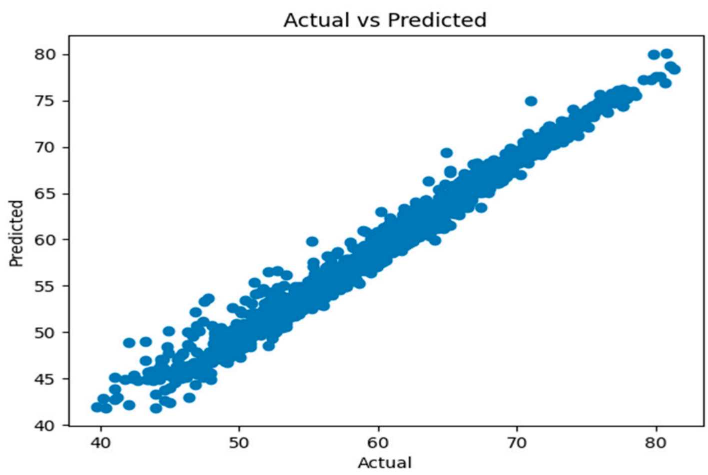

Figure 6. Accuracy of the CNN model.

The analysis showed that after 100 epochs, the estimated metrics for Mean Absolute Error and Root Mean Square Error were approximately 1.003 and 1.4, respectively. The observed decrement in both MAE and RMSE values demonstrates the method's high prediction accuracy.

3. Results and Discussion

This study introduces an advanced application of AI to strategically identify optimal sites for UHS within bedded rock salt formations. While multi-criteria decision analysis has conventionally been employed in site-selection studies, especially in assessing various salt structures for hydrogen storage, this research employs a novel AI-driven approach to accurately pinpoint prime UHS sites.

The deep learning (DL) methodology, specifically utilizing a convolutional neural network (CNN) algorithm, autonomously learns and makes inferences from data without the need for explicit programming. The integration of AHP and DL methodologies offers complementary strengths and addresses inherent weaknesses. AHP relies on expert judgment to define evaluation rules, which can sometimes produce models that are opaque and challenging to validate. Conversely, the efficacy of DL depends heavily on the quality and quantity of the input data, the choices of algorithms, and the parameter settings. Inadequate choices in these domains can result in overfitting or underfitting, thereby diminishing the model's predictive accuracy on novel datasets. This paper discusses the synergistic application of AHP and DL to enhance decision-making in the context of UHS site selection, providing a robust framework for integrating expert knowledge with machine learning insights.

In this study, the dataset was partitioned into training and testing subsets to facilitate the development and validation of the model. Twelve distinct input data layers were utilized, including Geological Exploration, Accessibility, Conservation Area, Ecological Site, Water Reservoir, Land Use, Energy Consumption, Natural Gas Pipelines, Protected Area, Special Protection Area, Natural Forest, and Storage Capacity. These layers were systematically processed through an AI algorithm to determine optimal underground hydrogen storage (UHS) sites within Poland (Figure 7).

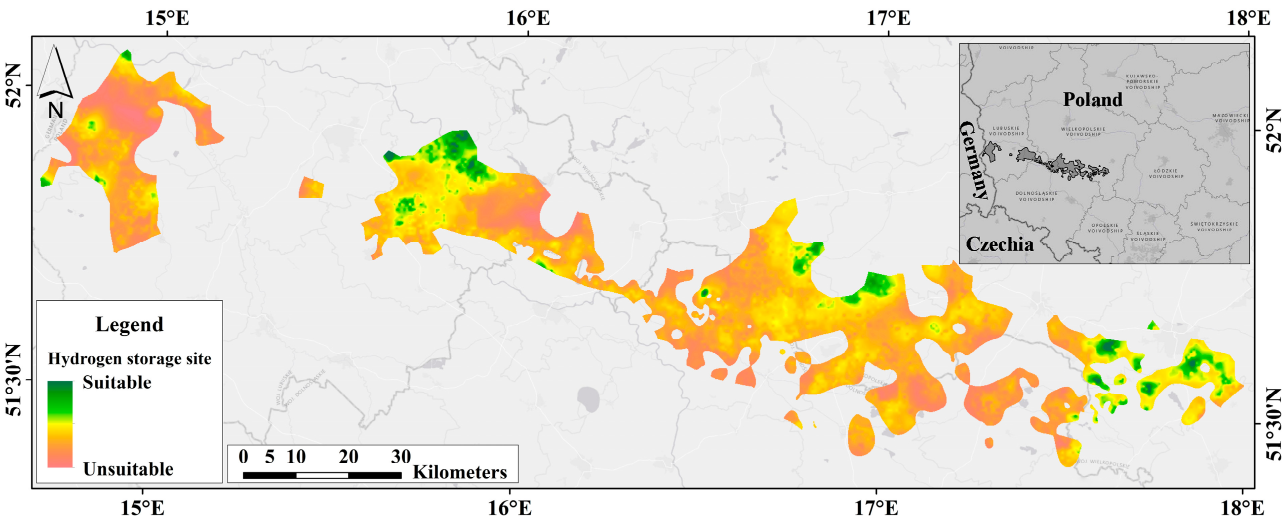

Figure 7. Map showing potential hydrogen storage sites identified by the optimal deep learning algorithm across the region.

Upon evaluating multiple machine learning (ML) algorithms, the most effective model was selected and subsequently implemented across the entire study area. The results indicated that the deep learning (DL) model not only achieved higher accuracy but also demonstrated greater computational efficiency than the Analytic Hierarchy Process (AHP) model.

These findings underscore the potential of AI to enhance the efficiency and accuracy of UHS site selection processes, offering a significant advancement over traditional methods.

Our research emphasizes the profound impact of the chosen methodology on the generation of suitability maps, showcasing its effectiveness in rapidly identifying optimal locations for UHS. Comparing the outputs derived from DL with the findings presented by Lankof and Tarkowski [54] affirms the high accuracy of the algorithms used.

The dataset was transformed into a raster map, culminating in a visual representation that effectively showcases the potential of various locations for UHS. This suitability map clearly delineates areas within the rock salt strata, making it easier to identify prospective sites. The most favorable locations, characterized by high storage capacity and positive evaluations across all considered criteria, are predominantly situated in the central-western part of the study area.

Additionally, the map underscores regions of high suitability based on a synthesis of criteria. In the western regions of the monocline, the most advantageous areas feature significant storage capacities and extensive geological investigations. Conversely, the eastern sectors of the surveyed region exhibit high suitability due to factors such as high energy demand, comprehensive geological exploration, and proximity to existing gas pipeline infrastructure. This nuanced visualization aids stakeholders in making informed decisions about site selection for UHS facilities.

4. Conclusions

This research employed a convolutional neural network to identify viable underground hydrogen storage (UHS) sites across Poland. A comprehensive dataset incorporating variables such as storage capacity, energy usage, transportation infrastructure, proximity to water sources, pipelines, boreholes, and land utilization was leveraged to develop a robust AI-driven framework. The performance of the deep learning (DL) model was compared against the Analytic Hierarchy Process (AHP). The findings demonstrated that the CNN offered superior accuracy and computational efficiency, indicating its effectiveness in enhancing the site selection process for UHS facilities.

The findings offer valuable insights and strategic options for stakeholders such as renewable energy producers, geological services, policy makers, and the chemical and petrochemical industries, all key to the development of UHS facilities. Furthermore, the implications of this study are significant for governmental and European Union institutions involved in renewable energy storage infrastructure development. Moreover, the findings substantially enrich the scientific community's discussion on hydrogen storage solutions, supplying empirical data vital for informing policy decisions.

The adaptability of the proposed DL method highlights its potential for broader employment in selecting underground energy storage sites, with the ability to customize it to specific regional criteria. Future research should focus on conducting comparative analyses of these advanced AI methods against conventional site selection techniques. Such studies are crucial for identifying new sustainable UHS sites, optimizing the site selection process, enhancing operational efficiencies, and conserving time and resources in forthcoming UHS initiatives. This approach not only promises to refine the accuracy of site evaluations, but also aims to streamline the decision-making process in the energy storage sector.

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References

1. Osman, A.I.; Mehta, N.; Elgarahy, A.M.; Hefny, M.; Al-Hinai, A.; Al-Muhtaseb, A.H.; Rooney, D.W. Hydrogen Production, Storage, Utilisation and Environmental Impacts: A Review. *Environ. Chem. Lett.* **2022**, *20*, 153–188. [CrossRef]
2. Garcia, D.A.; Barbanera, F.; Cumo, F.; Di Matteo, U.; Nastasi, B. Expert Opinion Analysis on Renewable Hydrogen Storage Systems Potential in Europe. *Energies* **2016**, *9*, 963. [CrossRef]
3. Ishaq, H.; Dincer, I.; Crawford, C. A Review on Hydrogen Production and Utilization: Challenges and Opportunities. *Int. J. Hydrogen Energy* **2022**, *47*, 26238–26264. [CrossRef]
4. Zhang, F.; Zhao, P.; Niu, M.; Maddy, J. The Survey of Key Technologies in Hydrogen Energy Storage. *Int. J. Hydrogen Energy* **2016**, *41*, 14535–14552. [CrossRef]
5. El-Shafie, M.; Kambara, S.; Hayakawa, Y. Hydrogen Production Technologies Overview. *J. Power Energy Eng.* **2019**, *7*, 107–154. [CrossRef]
6. Abdalla, A.M.; Hossain, S.; Nisfindy, O.B.; Azad, A.T.; Dawood, M.; Azad, A.K. Hydrogen Production, Storage, Transportation and Key Challenges with Applications: A Review. *Energy Convers. Manag.* **2018**, *165*, 602–627. [CrossRef]
7. Andersson, J.; Grönkvist, S. Large-Scale Storage of Hydrogen. *Int. J. Hydrogen Energy* **2019**, *44*, 11901–11919. [CrossRef]
8. Hassan, I.A.; Ramadan, H.S.; Saleh, M.A.; Hissel, D. Hydrogen Storage Technologies for Stationary and Mobile Applications: Review, Analysis and Perspectives. *Renew. Sustain. Energy Rev.* **2021**, *149*, 111311. [CrossRef]
9. Bünger, U.; Michalski, J.; Crotogino, F.; Kruck, O. Large-Scale Underground Storage of Hydrogen for the Grid Integration of Renewable Energy and Other Applications. In *Compendium of Hydrogen Energy: Hydrogen Use, Safety and the Hydrogen Economy*; Woodhead Publishing: Sawston, UK, 2015; Volume 4.
10. Crotogino, F.; Donadei, S.; Bünger, U.; Landinger, H. Large-Scale Hydrogen Underground Storage for Securing Future Energy Supplies. In Proceedings of the 18th World Hydrogen Energy Conference 2010—WHEC 2010 Parallel Sessions Book 4: Storage Systems/Policy Perspectives, Initiatives and Co-Operations, Essen, Germany, 16–21 May 2010; Volume 78.
11. Bui, D.T.; Shahabi, H.; Shirzadi, A.; Chapi, K.; Pradhan, B.; Chen, W.; Khosravi, K.; Panahi, M.; Ahmad, B.B.; Saro, L. Land Subsidence Susceptibility Mapping in South Korea Using Machine Learning Algorithms. *Sensors* **2018**, *18*, 2464. [CrossRef]
12. Corsini, A.; Cervi, F.; Ronchetti, F. Weight of Evidence and Artificial Neural Networks for Potential Groundwater Spring Mapping: An Application to the Mt. Modino Area (Northern Apennines, Italy). *Geomorphology* **2009**, *111*, 79–87. [CrossRef]
13. Naghibi, S.A.; Pourghasemi, H.R. A Comparative Assessment between Three Machine Learning Models and Their Performance Comparison by Bivariate and Multivariate Statistical Methods in Groundwater Potential Mapping. *Water Resour. Manag.* **2015**, *29*, 5217–5236. [CrossRef]
14. Arabameri, A.; Saha, S.; Roy, J.; Chen, W.; Blaschke, T.; Bui, D.T. Landslide Susceptibility Evaluation and Management Using Different Machine Learning Methods in the Gallicash River Watershed, Iran. *Remote Sens.* **2020**, *12*, 475. [CrossRef]
15. Derakhshani, R.; Zaresefat, M.; Nikpeyman, V.; GhasemiNejad, A.; Shafieibafti, S.; Rashidi, A.; Nemati, M.; Raoof, A. Machine Learning-Based Assessment of Watershed Morphometry in Makran. *Land* **2023**, *12*, 776. [CrossRef]
16. Zivar, D.; Kumar, S.; Foroozesh, J. Underground Hydrogen Storage: A Comprehensive Review. *Int. J. Hydrogen Energy* **2021**, *46*, 23436–23462. [CrossRef]
17. Tarkowski, R. Underground Hydrogen Storage: Characteristics and Prospects. *Renew. Sustain. Energy Rev.* **2019**, *105*, 86–94. [CrossRef]
18. Heinemann, N.; Alcalde, J.; Miocic, J.M.; Hangx, S.J.T.; Kallmeyer, J.; Ostertag-Henning, C.; Hassanpouryouzband, A.; Thaysen, E.M.; Strobel, G.J.; Schmidt-Hattenberger, C.; et al. Enabling Large-Scale Hydrogen Storage in Porous Media-the Scientific Challenges. *Energy Environ. Sci.* **2021**, *14*, 853–864. [CrossRef]
19. Sambo, C.; Dudun, A.; Samuel, S.A.; Esenenjor, P.; Muhammed, N.S.; Haq, B. A Review on Worldwide Underground Hydrogen Storage Operating and Potential Fields. *Int. J. Hydrogen Energy* **2022**, *47*, 22840–22880. [CrossRef]
20. Aftab, A.; Hassanpouryouzband, A.; Xie, Q.; Machuca, L.L.; Sarmadivaleh, M. Toward a Fundamental Understanding of Geological Hydrogen Storage. *Ind. Eng. Chem. Res.* **2022**, *61*, 3233–3253. [CrossRef]
21. Thiyagarajan, S.R.; Emadi, H.; Hussain, A.; Patange, P.; Watson, M. A Comprehensive Review of the Mechanisms and Efficiency of Underground Hydrogen Storage. *J. Energy Storage* **2022**, *51*, 104490. [CrossRef]
22. Navaid, H.B.; Emadi, H.; Watson, M. A Comprehensive Literature Review on the Challenges Associated with Underground Hydrogen Storage. *Int. J. Hydrogen Energy* **2023**, *48*, 10603–10635. [CrossRef]
23. Acht, A.; Donadei, S. Hydrogen Storage in Salt Caverns: State of the Art, New Developments and R&D Projects. In Proceedings of the SMRI Fall 2012 Technical Conference, Bremen, Germany, 30 September–3 October 2012.
24. Kruck, O.; Crotogino, F.; Prelicz, R.; Rudolph, T. Overview on All Known Underground Storage Technologies for Hydrogen. 2013. Available online: https://hyunder.eu/wp-content/uploads/2016/01/D3.1_Overview-of-all-known-underground-storage-technologies.pdf (accessed on 21 March 2024).

25. Tarkowski, R.; Czapowski, G. Salt Domes in Poland—Potential Sites for Hydrogen Storage in Caverns. *Int. J. Hydrogen Energy* **2018**, *43*, 21414–21427. [CrossRef]
26. Muhammed, N.S.; Haq, B.; Al Shehri, D.; Al-Ahmed, A.; Rahman, M.M.; Zaman, E. A Review on Underground Hydrogen Storage: Insight into Geological Sites, Influencing Factors and Future Outlook. *Energy Rep.* **2022**, *8*, 461–499. [CrossRef]
27. Hevin, G. Underground Storage of Hydrogen in Salt Caverns. In Proceedings of the European Workshop on Underground Energy Storage, Paris, France, 7–8 November 2019; pp. 7–8.
28. Basniev, K.S.; Omelchenko, R.J.; Adzynova, F.A. Underground Hydrogen Storage Problems in Russia. In Proceedings of the 18th World Hydrogen Energy Conference 2010, Essen, Germany, 16–21 May 2010.
29. Ponomarev-Stepnoi, N.N. Nuclear-Hydrogen Power. *At. Energy* **2004**, *96*, 375–385. [CrossRef]
30. Raza, A.; Arif, M.; Glatz, G.; Mahmoud, M.; Al Kobaisi, M.; Alafnan, S.; Iglauer, S. A Holistic Overview of Underground Hydrogen Storage: Influencing Factors, Current Understanding, and Outlook. *Fuel* **2022**, *330*, 125636. [CrossRef]
31. Liu, W.; Zhang, Z.; Chen, J.; Jiang, D.; Wu, F.; Fan, J.; Li, Y. Feasibility Evaluation of Large-Scale Underground Hydrogen Storage in Bedded Salt Rocks of China: A Case Study in Jiangsu Province. *Energy* **2020**, *198*, 117348. [CrossRef]
32. Caglayan, D.G.; Weber, N.; Heinrichs, H.U.; Linßen, J.; Robinius, M.; Kukla, P.A.; Stolten, D. Technical Potential of Salt Caverns for Hydrogen Storage in Europe. *Int. J. Hydrogen Energy* **2020**, *45*, 6793–6805. [CrossRef]
33. Williams, J.D.O.; Williamson, J.P.; Parkes, D.; Evans, D.J.; Kirk, K.L.; Sunny, N.; Hough, E.; Vosper, H.; Akhurst, M.C. Does the United Kingdom Have Sufficient Geological Storage Capacity to Support a Hydrogen Economy? Estimating the Salt Cavern Storage Potential of Bedded Halite Formations. *J. Energy Storage* **2022**, *53*, 105109. [CrossRef]
34. Chen, F.; Ma, Z.; Nasrabadi, H.; Chen, B.; Saad Mehana, M.Z.; Van Wijk, J. Capacity Assessment and Cost Analysis of Geologic Storage of Hydrogen: A Case Study in Intermountain-West Region USA. *Int. J. Hydrogen Energy* **2023**, *48*, 9008–9022. [CrossRef]
35. Zhu, S.; Shi, X.; Yang, C.; Bai, W.; Wei, X.; Yang, K.; Li, P.; Li, H.; Li, Y.; Wang, G. Site Selection Evaluation for Salt Cavern Hydrogen Storage in China. *Renew. Energy* **2024**, *224*, 120143. [CrossRef]
36. Huang, L.; Fang, Y.; Hou, Z.; Xie, Y.; Wu, L.; Luo, J.; Wang, Q.; Guo, Y.; Sun, W. A Preliminary Site Selection System for Underground Hydrogen Storage in Salt Caverns and Its Application in Pingdingshan, China. *Deep Undergr. Sci. Eng.* **2024**, *3*, 117–128. [CrossRef]
37. Tarkowski, R.; Lankof, L.; Luboń, K.; Michalski, J. Hydrogen Storage Capacity of Salt Caverns and Deep Aquifers versus Demand for Hydrogen Storage: A Case Study of Poland. *Appl. Energy* **2024**, *355*, 122268. [CrossRef]
38. Du, Z.; Dai, Z.; Yang, Z.; Zhan, C.; Chen, W.; Cao, M.; Thanh, H.V.; Soltanian, M.R. Exploring Hydrogen Geologic Storage in China for Future Energy: Opportunities and Challenges. *Renew. Sustain. Energy Rev.* **2024**, *196*, 114366. [CrossRef]
39. Cyran, K.; Kowalski, M. Shape Modelling and Volume Optimisation of Salt Caverns for Energy Storage. *Appl. Sci.* **2021**, *11*, 423. [CrossRef]
40. Bérest, P.; Bergues, J.; Brouard, B. Review of Static and Dynamic Compressibility Issues Relating to Deep Underground Salt Caverns. *Int. J. Rock Mech. Min. Sci.* **1999**, *36*, 1031–1049. [CrossRef]
41. Wang, T.; Yan, X.; Yang, H.; Yang, X.; Jiang, T.; Zhao, S. A New Shape Design Method of Salt Cavern Used as Underground Gas Storage. *Appl. Energy* **2013**, *104*, 50–61. [CrossRef]
42. Böttcher, N.; Görke, U.J.; Kolditz, O.; Nagel, T. Thermo-Mechanical Investigation of Salt Caverns for Short-Term Hydrogen Storage. *Environ. Earth Sci.* **2017**, *76*, 98. [CrossRef]
43. Bérest, P.; Louvet, F. Aspects of the Thermodynamic Behavior of Salt Caverns Used for Gas Storage. *Oil Gas Sci. Technol.* **2020**, *75*, 57. [CrossRef]
44. Cyran, K. Insight into a Shape of Salt Storage Caverns. *Arch. Min. Sci.* **2020**, *65*, 133198. [CrossRef]
45. Matos, C.R.; Carneiro, J.F.; Pereira da Silva, P.; Henriques, C.O. A GIS-MCDA Approach Addressing Economic-Social-Environmental Concerns for Selecting the Most Suitable Compressed Air Energy Storage Reservoirs. *Energies* **2021**, *14*, 6793. [CrossRef]
46. Cai, B.; Li, Q.; Liu, G.; Liu, L.; Jin, T.; Shi, H. Environmental Concern-Based Site Screening of Carbon Dioxide Geological Storage in China. *Sci. Rep.* **2017**, *7*, 7598. [CrossRef]
47. Roberts-Ashby, T.; Ashby, B. A Method for Examining the Geospatial Distribution of CO_2 Storage Resources Applied to the Pre-Punta Gorda Composite and Dollar Bay Reservoirs of the South Florida Basin, U.S.A. *Mar. Pet. Geol.* **2016**, *77*, 141–159. [CrossRef]
48. Parkes, D.; Evans, D.J.; Williamson, P.; Williams, J.D.O. Estimating Available Salt Volume for Potential CAES Development: A Case Study Using the Northwich Halite of the Cheshire Basin. *J. Energy Storage* **2018**, *18*, 50–61. [CrossRef]
49. Mrówczyńska, M.; Skiba, M.; Sztubecka, M.; Bazan-Krzywoszańska, A.; Kazak, J.K.; Gajownik, P. Scenarios as a Tool Supporting Decisions in Urban Energy Policy: The Analysis Using Fuzzy Logic, Multi-Criteria Analysis and GIS Tools. *Renew. Sustain. Energy Rev.* **2021**, *137*, 110598. [CrossRef]
50. Ayodele, T.R.; Ogunjuyigbe, A.S.O.; Odigie, O.; Munda, J.L. A Multi-Criteria GIS Based Model for Wind Farm Site Selection Using Interval Type-2 Fuzzy Analytic Hierarchy Process: The Case Study of Nigeria. *Appl. Energy* **2018**, *228*, 1853–1869. [CrossRef]
51. Atici, K.B.; Simsek, A.B.; Ulucan, A.; Tosun, M.U. A GIS-Based Multiple Criteria Decision Analysis Approach for Wind Power Plant Site Selection. *Util. Policy* **2015**, *37*, 86–96. [CrossRef]
52. Feizizadeh, B.; Jankowski, P.; Blaschke, T. A GIS Based Spatially-Explicit Sensitivity and Uncertainty Analysis Approach for Multi-Criteria Decision Analysis. *Comput. Geosci.* **2014**, *64*, 81–95. [CrossRef] [PubMed]

53. Derakhshani, R.; Lankof, L.; GhasemiNejad, A.; Zaresefat, M. Artificial Intelligence-Driven Assessment of Salt Caverns for Underground Hydrogen Storage in Poland. *Sci. Rep.* **2024**, *14*, 14246. [CrossRef]
54. Lankof, L.; Tarkowski, R. GIS-Based Analysis of Rock Salt Deposits' Suitability for Underground Hydrogen Storage. *Int. J. Hydrogen Energy* **2023**, *48*, 27748–27765. [CrossRef]