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REVIEW

Exploring neuro-symbolic AI applications in geoscience: implications and future directions for mineral prediction

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Abstract

The integration of machine learning (ML) and deep learning (DL) into geoscience has experienced a pronounced uptick in recent years, a trend propelled by the intricate nature of geosystems and the abundance of data they produce. These computational methods have been harnessed across a spectrum of geoscientific challenges, from climate modeling to seismic analysis, exhibiting notable efficacy in extracting valuable insights from intricate geological datasets for applications such as mineral prediction. A thorough analysis of the literature indicates a marked escalation in AI-centric geoscience research starting in 2018, characterized by a predictive research orientation and a persistent focus on key computational terms. The thematic network and evolution analyses underscore the enduring prominence of "deep learning" and "machine learning" as pivotal themes, alongside progressive developments in "transfer learning" and "big data". Despite these advancements, other methodologies have garnered comparatively lesser focus. While ML and DL have registered successes in the realm of mineral prediction, their amalgamation with domain-specific knowledge and symbolic reasoning could further amplify their interpretability and operational efficiency. Neuro-Symbolic AI (NSAI) emerges as a cutting-edge approach that synergizes DL's robust capabilities with the precision of symbolic reasoning, facilitating the creation of models that are both powerful and interpretable. NSAI distinguishes itself by surmounting traditional ML constraints through the incorporation of expert insights and delivering explanatory power behind its predictive prowess, rendering it particularly advantageous for mineral prediction tasks. This literature review delves into the promising potential of NSAI, alongside ML and DL, within the geoscientific domain, spotlighting mineral prediction as a key area of focus. Despite the hurdles associated with infusing domain expertise into symbolic formats and mitigating biases inherent in symbolic reasoning, the application of NSAI in the realm of critical mineral prediction stands to catalyze a paradigm shift in the field. By bolstering prediction accuracy, enhancing decision-making processes, and fostering sustainable resource exploitation, NSAI holds the potential to significantly reshape geoscience's future trajectory.

Keywords Geoinformatics · Mineral prediction · Neuro-symbolic AI (NSAI) · Machine learning · Data interpretability

Introduction

In recent years, there has been a notable increase in the adoption of machine learning (ML) and deep learning (DL) methods within the realm of geoscience (Ayranci et al. 2021; Irrgang et al. 2021; Okada et al. 2020; Trauth 2022; Zuo et al. 2019). ML is a branch of artificial intelligence that involves developing algorithms and statistical models for computers to learn from data and make predictions (Bottou 2011; Bishop et al. 2006; Karpatne et al. 2019). These algorithms learn patterns and relationships in data, allowing them to make informed decisions without explicit programming. DL, a subfield of ML, utilizes artificial neural networks inspired by the brain's structure and function to process and analyze complex data such as audio, images, and text. By training on extensive data, DL algorithms can identify patterns and make predictions with high accuracy (Battaglia et al. 2018; Bengio 2009; Lample et al., 2019; Lecun et al. 2015). NSAI, also known as Hybrid AI, is a subfield of artificial intelligence that combines symbolic

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reasoning with neural network-based learning (Garcez et al. 2015; Hassabis et al. 2017; Riegel et al. 2020; Yi et al. 2018; Yu et al. 2021). This approach aims to build more powerful and versatile AI systems by integrating the strengths of both symbolic AI and DL. Symbolic AI uses explicit rules and representations to solve problems, while DL uses data-driven, end-to-end learning to identify patterns in data. Combining these approaches with NSAI allows solving tasks ranging from perception and pattern recognition to reasoning and problem-solving (Garcez et al., 2020; Hassabis et al. 2017). ML and DL techniques have revolutionized how geoscientists analyze, interpret, and model geoscientific data. With the advancements in computational power and the availability of large-scale geoscientific data, become a popular choice for solving complex problems and improving our understanding of natural phenomena. ML and DL techniques have impacted many sub-disciplines of geoscience, including seismology, climate science, geology, and remote sensing.

Geology, a sub-discipline of geoscience that focuses on the study of rocks, minerals, and geological processes, has utilized ML and DL techniques for mineral prospecting, identifying geological features, and modeling geological processes (Ayranci et al. 2021; Karpatne et al. 2019). For example, ML and DL techniques in mineral prospecting have enabled the discovery of new mineral deposits that were previously unknown, while identifying geological features using ML and DL techniques has enabled the identification of new geological structures and formations. As the field of geoscience continues to generate increasingly complex and diverse datasets, the application of ML and DL techniques is expected to grow (Dikshit et al. 2021; Dramsch 2020; Mai et al. 2022; Morgenroth et al. 2019; Tariq et al. 2021).

Mineral prediction, also referred to as mineral resource prediction or mineral deposit modeling, plays a pivotal role in geology by estimating and forecasting the presence and characteristics of mineral resources within a given geological area. Although ML and DL methods have gained widespread adoption in mineral prediction, there are limitations associated with their handling of uncertainty, lack of transparency, and interpretability of results. ML and DL methods struggle to unveil hidden relationships between data from different sources. For example, utilizing ML and DL methods with varying data types (such as geochemical and geophysical data) within the same area can yield divergent or even contradictory results. Similar discrepancies may arise even when using the same data type but from different sources.

NSAI presents a promising solution to overcome these limitations. By integrating symbolic reasoning with neural networks, NSAI can address uncertainty, explain its reasoning, and offer interpretable results. It can incorporate domain knowledge from experts into its models and adapt symbolic reasoning methods suitable for different data types (Fig. 1). NSAI can interpret and learn from various geological data types, such as mineral associations from geochemical data, structural details from geophysical data,

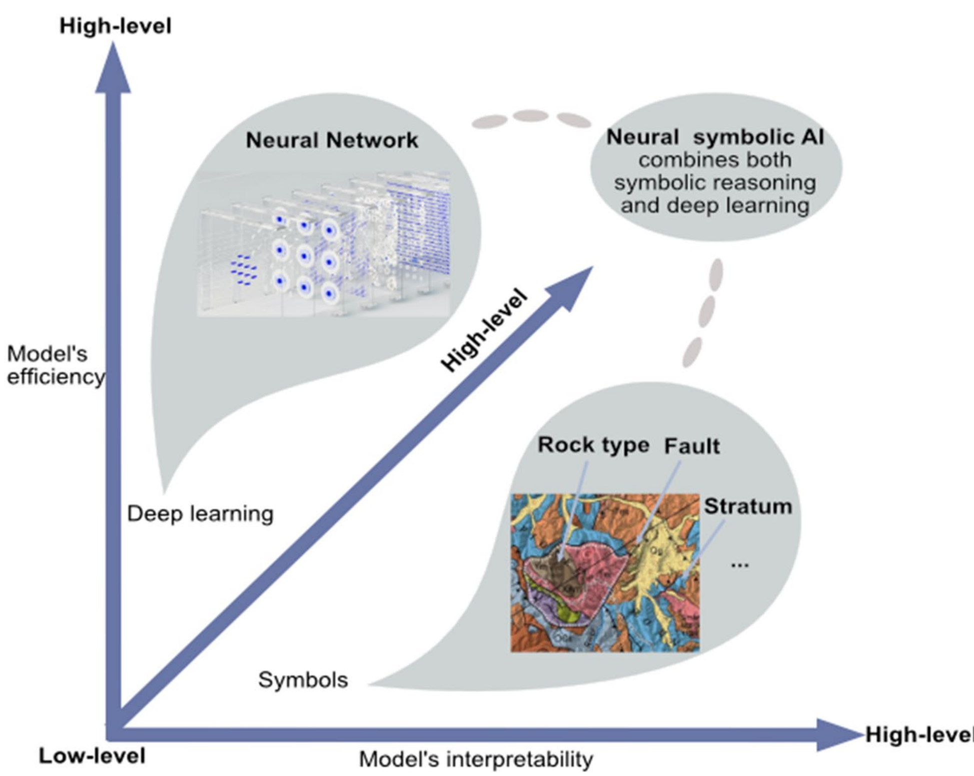


Fig. 1 Advantages of NSAI with respect to model efficiency and interpretability. Neuro-symbolic AI seamlessly integrates symbolic reasoning and deep learning, yielding a high-level model with enhanced efficiency and interpretability

and properties from geothermal data. Its ability to apply consistent rules across data types from different sources is particularly useful in dealing with diverse and uncertain geological data, which can challenge traditional ML and DL methods. NSAI involves a pre-model training phase of symbolic reasoning, where rules represent domain expertise and facts represent data-driven parts. Depending on the data type, NSAI models can include corresponding rules, summarizing diverse data and contributing to model improvement. For uncertain data, rules provide constraints and supplements, offering new solutions to problems that traditional ML and DL methods might not resolve. However, NSAI's effectiveness is contingent on data availability; it struggles with extremely sparse data but thrives when sufficient data (facts) are present, allowing for a balanced interplay between data-driven elements and domain expertise. The advantages of utilizing NSAI in mineral prediction are manifold. It can handle incomplete or uncertain data, which is common in geology, and provide probabilistic estimates (Sen et al. 2021). Furthermore, it offers transparency and trustworthiness by explaining its reasoning and providing interpretable outcomes. Consequently, NSAI emerges as a promising research topic in mineral prediction. While NSAI exhibits substantial potential, it is still a relatively nascent field, and its applications in mineral prediction are yet to be fully explored. Nonetheless, recent research has demonstrated promising results, and ongoing investigations are being conducted to unlock the full potential of this technology (Ciregan et al. 2012; Ciresan et al. 2012; Harmon et al. 2022; Karpatne et al. 2019; Zhang et al. 2022a).

The central objective of our study is to delve deeply into the utilization of NSAI within the realm of mineral prediction. This exploration is directed towards elucidating the synergistic potential of advanced AI techniques in augmenting the methodologies employed in geoscience. By meticulously reviewing current literature and data trends, the study endeavors to illuminate the transformative impact of NSAI in refining traditional approaches to mineral exploration, while also casting light on prospective research trajectories and the integration of sophisticated AI in geoscience disciplines.

The structure of this article is organized as follows. Section 2 introduces the concepts of mineral prediction, mineral exploration and NSAI. Section 3 uses bibliometric analysis to illustrate the latest work in the fields of ML, DL and NSAI in geoscience and demonstrates interconnections. Section 4 shows the state-of-the-art application of ML, DL and NSAI techniques in solving a range of problems in geoscience. Section 5 discusses a few potential research directions of NSAI in mineral prediction in the next decade. Finally, Sect. 6 concludes NSAI, ML and DL techniques in mineral prediction.

Related concepts and methods

Concept of mineral prediction and exploration

Mineral prediction and exploration involve using geological and geophysical data to identify and assess potential mineral deposits (Yang et al. 2022a; Zhao et al. 2022; Cudahy 2016). Prediction focuses on identifying likely mineral-rich areas based on geological settings, rock types, and geochemical signatures. It employs geophysical surveys to detect anomalies indicating mineral presence, size, and shape, alongside geochemical analysis for element distribution and isotopic composition (Zhao et al., 2008; Zhao 1992). Exploration builds upon these predictions, combining fieldwork, analyses, drilling, and other techniques to confirm and evaluate the presence and quality of minerals, determining their commercial viability. This integrated approach aims to locate, validate, and assess mineral resources effectively (Gonzalez-Alvarez et al. 2016; Yousefi et al. 2019, 2021). Table 1 shows A comparative overview of their distinctions.

ML and DL modeling in mineral prediction

ML and DL have become powerful tools for extracting valuable insights from large and complex geological and geophysical datasets, making them an increasingly attractive option for mineral prediction. ML and DL models are capable of identifying patterns and relationships between different variables, which has the potential to revolutionize the way mineral exploration is conducted. By analyzing vast amounts of data, including geological maps, geophysical surveys, and geochemical assays, these models can create detailed models of mineralization and identify areas of high mineral potential. The use of ML and DL models in mineral prediction offers several advantages over traditional methods. Traditional geological and geophysical methods can be time-consuming, costly, and subjective, while ML and DL models can automate many of the processes involved in mineral prediction, reducing both the time and cost of exploration. In addition, ML and DL models can integrate multiple datasets, leading to a more comprehensive understanding of the geological and geophysical characteristics of an area. Another advantage of ML and DL models in mineral prediction is their ability to learn from data and improve over time. By training the models on new data, they can become more accurate and reliable, leading to more successful mineral exploration campaigns. Furthermore, ML and DL models can identify previously unknown relationships between different variables, leading to the discovery of new mineral deposits that traditional exploration methods may have missed. Table 2 systematically catalogs a spectrum of AI methodologies, meticulously outlining their

Table 1 Differences between mineral prediction & mineral exploration

Category	Mineral Prediction	Mineral Exploration
Focus	Assessing likelihood of mineral occurrences	Actively searching for and evaluating deposits
Data Usage	Existing geological and geophysical data	New data collected through fieldwork
Timing	Before/at early stages of exploration	Occurs after mineral prediction
Certainty	Provides likelihood assessment, not definitive	Aims to obtain concrete evidence of mineralization
Scale	Regional or large-scale assessment	Site-specific investigation
Objective	Identify areas with high mineral potential	Discover new deposits and determine their viability
Methods	Geophysical modeling, statistical analysis, geological data	Field surveys, sampling, drilling, geophysical exploration
Results	Predictive maps or models of potential mineral occurrences	Direct evidence of mineral presence and quality
Investment	Lower cost compared to exploration	Higher cost due to fieldwork, drilling, and analysis
Risk	Lower risk as it relies on existing data and modeling	Higher risk as it involves direct exploration and sampling
Decision-making	Guides exploration efforts and target selection	Determines whether to develop or abandon a site

respective applications in the domain of mineral prediction, complemented by pertinent scholarly citations. Despite these advantages, there are also some challenges associated with the use of ML and DL models in mineral prediction. One of the biggest challenges is the quality and quantity of data. ML and DL models require large amounts of high-quality data to function correctly, and it can be challenging to obtain this data in many mineral exploration projects.

Despite these challenges, the use of ML and DL models in mineral prediction is rapidly growing, and many mining companies are investing in these technologies to improve the efficiency and effectiveness of their exploration campaigns. With continued development and refinement, ML and DL models have the potential to significantly enhance our understanding of mineralization and revolutionize the way we explore mineral deposits. By leveraging the power of ML, we can unlock new insights into the complex geological processes that shape our planet and discover new mineral resources that will help meet the growing demands of our global economy. ML and DL modeling is a powerful tool that can significantly enhance the accuracy and efficiency of mineral prediction. By meeting the necessary requirements and selecting appropriate algorithms, we can utilize ML to improve our understanding of the geology of an area and make informed predictions about the presence, quantity, and quality of minerals.

Table 2 Selected AI methods in mineral prediction

Technology/Tool	Description	Application in Mineral Prediction	Citations
Support Vector Machine (SVM)	A supervised learning model used for classification and regression analysis.	Applied for classifying geological features and predicting mineral occurrences based on geological data.	Du et al. 2021 Azizi et al. 2020 Zhang et al. 2018
Decision Trees	A decision support tool using a tree-like model of decisions.	Used for creating hierarchical models that segment geological data into different mineralization zones.	Fan et al. 2022 Ozturk et al. 2023
Random Forest	An ensemble learning method based on decision trees.	Employed for more robust and accurate predictions by aggregating multiple decision trees.	Yang et al. 2022b Zhang et al. 2023 Rodriguez et al., 2014
Neural Networks	Comprises algorithms modeled on the human brain to recognize patterns.	Utilized for complex pattern recognition in geological datasets, aiding in predictive mineral modeling.	Theerthagiri et al. 2024 Ding et al. 2022
Convolutional Neural Networks (CNN)	A deep learning algorithm, especially effective for analyzing visual imagery.	Applied in interpreting geological and remote sensing images for mineral exploration.	Yang et al. 2021 Yang et al. 2023
Recurrent Neural Networks (RNN)	A class of neural networks for processing sequential data.	Used for analyzing temporal data in mineral deposit formation processes.	Yin et al. 2022 Luo et al. 2017

NSAI in mineral prediction

Neural networks are a type of artificial intelligence algorithm that is modeled after the structure and function of the human brain. The development of NSAI is an interdisciplinary field that involves contributions from multiple areas of expertise, including computer science, mathematics, philosophy, cognitive psychology, and neuroscience. A variety of research directions has influenced the field and has evolved over time to meet the challenges of increasingly complex AI problems. It can be traced back to the early days of artificial intelligence research, when researchers first explored the idea of combining symbolic reasoning with neural network-based learning. In the 1980 and 1990 s, the field of neural networks experienced a resurgence, leading to significant advances in developing DL algorithms. In recent years, the growing success of DL algorithms in a wide range of applications has led to renewed interest in NSAI (Sheth et al. 2023). Researchers are now exploring new ways to integrate symbolic reasoning with DL, using techniques such as knowledge graph embeddings, differentiable logic, and graph neural networks. NSAI has evolved to tackle complex AI challenges, influenced by the resurgence of neural networks and the success of DL algorithms (Luus et al. 2021; Jiang et al. 2021).

ML is a branch of Artificial Intelligence, which focuses on methods that learn from data and make predictions on unseen data. DL is a specific type of ML that uses multiple neural layers for learning data representations, it is effective at learning patterns without human-designed features and NSAI is a subfield of AI that combines both symbolic reasoning and DL (Bengio 2009; Lecun et al. 2015; Zhang et al. 2022bFig. 2). In mineral prediction, NSAI uniquely addresses limitations of traditional ML models by integrating expert geological knowledge and neural network learning. This amalgamation results in sophisticated, interpretable AI models capable of handling geological data effectively (Kimura et al. 2021; Fagin et al. 2022). For example, neural networks can be trained on large datasets of geological and geophysical data, while rule-based reasoning systems can be used to incorporate expert knowledge about mineral deposits and geological environments. These two approaches can be combined to create more accurate and interpretable models of mineral potential.

Trends reflected in literature data

Data source

Annual Scientific Production data was sourced from Web of Science, utilizing specific filters encompassing terms associated with AI, including NSAI, neuro-symbolic AI (both NSAI and neuro-symbolic AI are focused on combining neural networks with symbolic AI techniques), ML, DL, hybrid AI, and educated AI, along with geoscience and mineral prediction. Seven hundred forty-three papers used in this analysis comprises annual scientific production data in the field of geoscience, focusing on various research topics ranging from geology and engineering to computer science, geochemistry, geophysics, remote sensing, environmental sciences, mining, mineral processing, mineralogy and water resources.

The papers, all written in English, were selected based on specific inclusion criteria. In the title, keywords, and abstracts of each paper, elements from two distinct filter groups had to be contained: one related to computer science methods such as AI, ML, DL, CNN, and the other to the geoscience domain, including terms like Mineral, Geochemical, Geophysics, and Climate Change. The entire dataset of 743 papers, encompassing titles, keywords, abstracts, as well as methods and conclusions sections, was thoroughly reviewed. This review was conducted to ensure that the use

Fig. 2 Relation between AI, ML, DL And NSAI. NSAI is a subfield of AI that combines both symbolic reasoning and DL

of AI techniques in the geoscience domain was accurately represented in the papers.

The dataset, comprising 743 papers including articles, review articles, conference papers, and proceeding papers, showcases a global perspective with contributions from a wide array of countries across continents such as Asia (China, India), North America (USA, Canada), and Europe (Germany, France). However, the predominance of papers from certain countries, notably China and the USA, may suggest a regional focus or possible over-representation. An analysis of the top three countries of the corresponding authors—China, the USA, and Korea—reveals interesting aspects of the dataset's geographical diversity. China leads with 288 articles, predominantly Single Country Publications (SCP) at 217, against 71 Multiple Country Publications (MCP). The USA follows a similar trend, with 55 SCPs out of 78 articles. In contrast, Korea presents a more balanced profile with its 45 articles, evenly split between SCP (22) and MCP (23). This pattern indicates a stronger national research focus in China and the USA, whereas Korea's equal emphasis on SCP and MCP suggests a more international or collaborative research approach. The skewed distribution of SCP and MCP, especially in the top contributing countries, might impact the dataset's overall analysis, potentially biasing it towards the specific research trends and priorities of these regions, particularly China and the USA.

Annual scientific production

Analyzing the annual scientific production data (Fig. 3), a discernible upward trend in research output becomes evident. The number of articles published demonstrates a consistent growth from 2010 to 2023, with occasional fluctuations. Starting with only two articles in 2010, the annual production gradually increased, with substantial growth observed from 2018 onwards. Particularly remarkable is the surge in publications in 2021, reaching one hundred seventy-one articles, and peaking in 2022 with an impressive two hundred fifty-two articles. However, it is important to note that the data for the year 2023 only covers the period from January to May, offering a partial representation of the articles published within that year. This surge in scientific production indicates a burgeoning interest in AI applications, ML, DL, and their integration into geoscience and mineral prediction research. The exponential growth in publications underscores the expanding significance of these areas and highlights the dynamic interdisciplinary nature of geoscience research.

The substantial increase in research output indicates the evolving landscape in geoscience, as researchers increasingly harness AI techniques and advanced methodologies to explore diverse facets of the field. The utilization of AI, ML, and DL approaches hold great promise in enhancing the understanding of geological phenomena, optimizing mineral prediction models, and improving resource exploration strategies. Furthermore, the inclusion of computer science and interdisciplinary domains like engineering reflects the

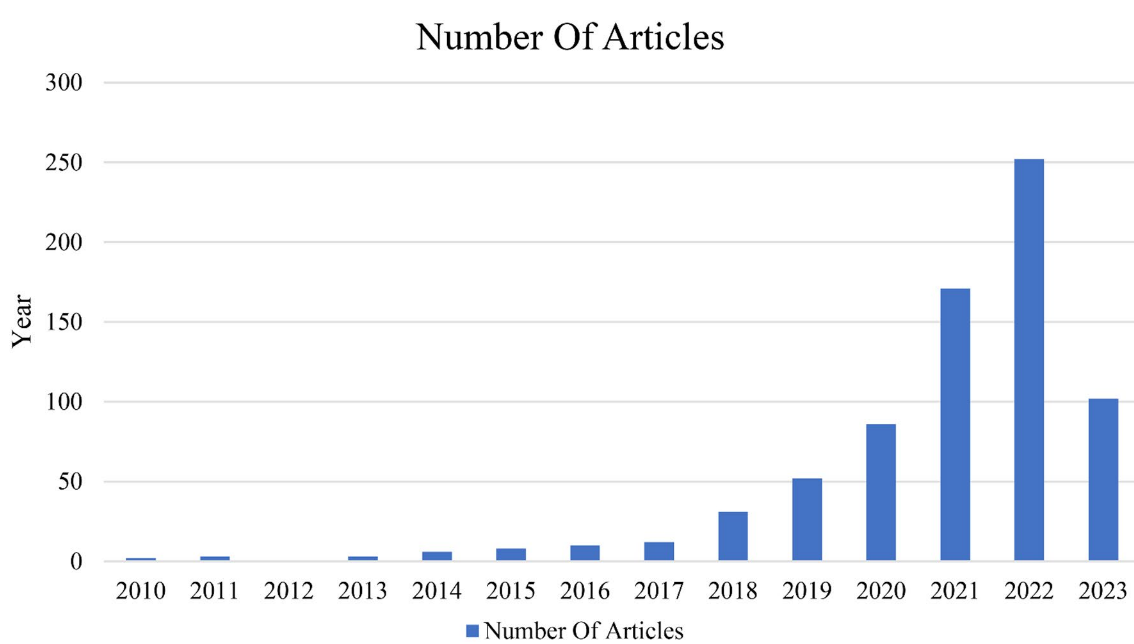


Fig. 3 Annual scientific production trends in the integration of AI and geoscience. (2023 only covers the period from January to May, offering a partial representation of the articles published within that year).

growing recognition of the need for collaboration between diverse fields to address complex geoscience challenges.

Word frequency over time

The word frequency data (Fig. 4) reveals a notable increase in the frequency of the term "prediction" over time, indicating a growing emphasis on prediction-related research. The terms "classification," "neural networks," and "model" also exhibit an upward trend in frequency over the years, indicating sustained interest and research in these areas. Notably, "classification" demonstrates a substantial increase from 2015 onwards. The terms "random forest," "machine," and "support vector machine" show a relatively consistent frequency over time, with some fluctuations. These terms likely represent ongoing areas of focus within the research field, maintaining a certain level of relevance.

Thematic network

The application of thematic network analysis allows us to unravel the conceptual structure within the domain under investigation. In Fig. 5, the color of the points indicates different themes within the network. Each cluster or theme is assigned a specific color (red & blue in this case) to visually distinguish them from one another. The size of the points represents the centrality of a word within its respective cluster. Larger points indicate higher centrality, while smaller points indicate lower centrality. The lines connecting the words in the network represent the co-occurrence between them. Thicker or darker lines indicate stronger co-occurrence between words, while thinner or lighter lines indicate weaker co-occurrence (Aria and Cuccurullo 2017). Our analysis of the thematic network using the criteria of centrality and density provides valuable insights into the landscape of the domain. Higher centrality and density identify hot topics that are well-developed and relevant. Higher centrality and lower density define basic topics significant for the domain. Lower centrality and density indicate peripheral topics, while lower centrality and higher density represent niche topics that are strongly developed but marginal in the domain (Aria et al. 2022).

By examining the interconnections between key concepts through co-occurrence patterns, we gain insights into the development and significance of various themes over time. In Fig. 5, the thematic network analysis illustrates the conceptual structure of AI in geoscience, highlighting the prominence of "deep learning" and "machine learning" as central themes, indicated by larger nodes and thicker connections. The strong connections between "deep learning" and "machine learning" highlight their close integration and mutual relevance, reflecting the foundational role of these techniques. The "convolutional neural network" node within the "deep learning" cluster demonstrates foundational significance, and "remote sensing" is closely related, as shown by their proximity and connecting lines. The proximity of "convolutional neural network" and "remote sensing" suggests that deep learning methods are particularly influential

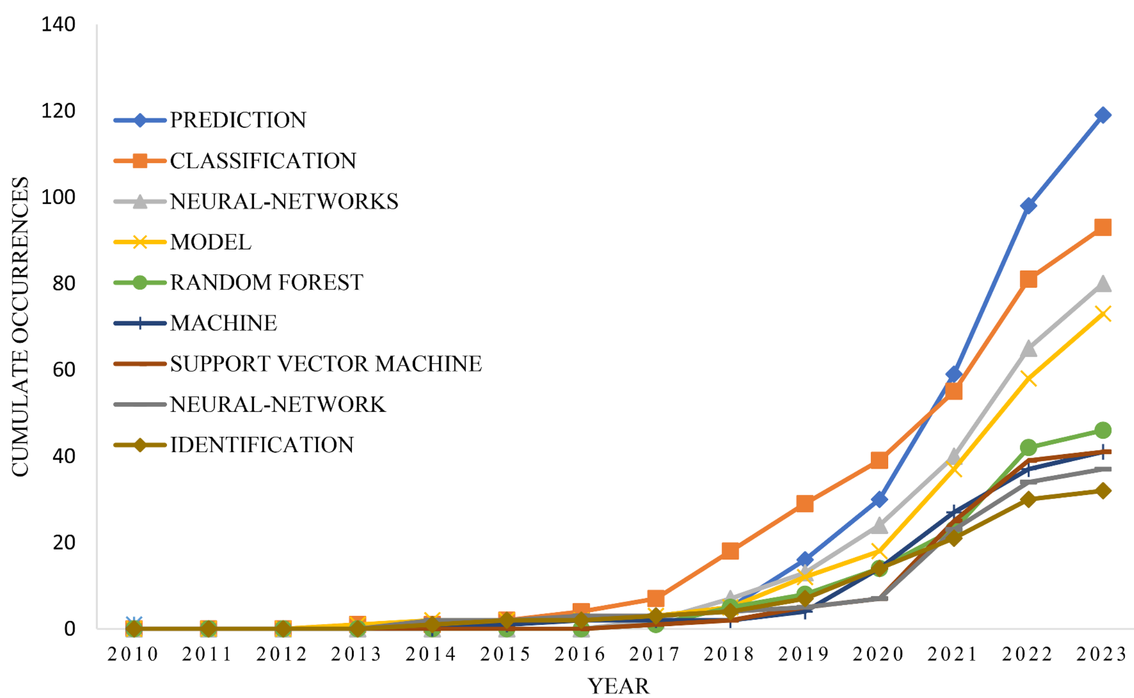


Fig. 4 Temporal trends in word frequency: Focus on prediction and related concepts

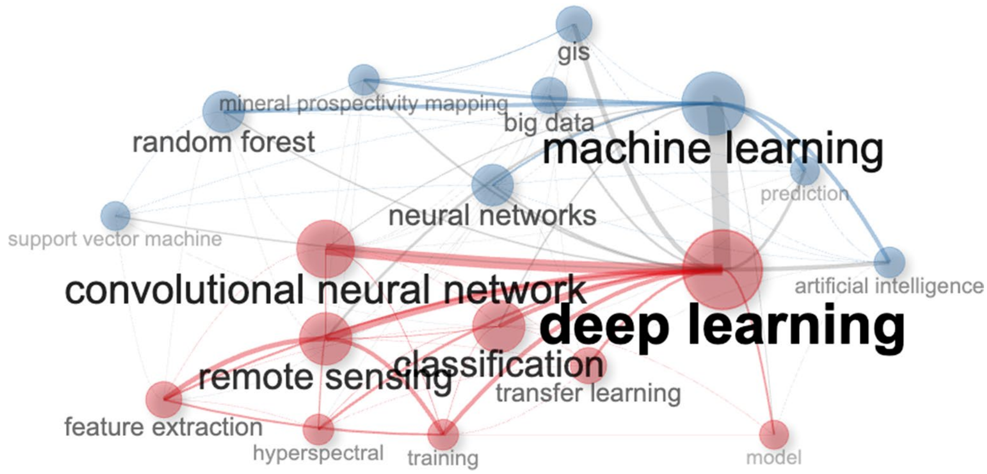


Fig. 5 Thematic network visualization. ("Deep learning" and "machine learning" are central, while "convolutional neural networks" and "transfer learning" stand out. "Big data" has its specialized niche)

in remote sensing applications. Themes such as "transfer learning" signal ongoing advancements in the domain, and "big data" is represented as a specialized but integral part of the landscape. "Transfer learning" represents an emerging trend, indicating the adaptation of established techniques to new domains. Meanwhile, "big data" occupies a specialized niche but maintains connections with other themes, signifying its importance in data-driven geoscience research. The visualization captures the interplay and co-occurrence of key concepts, reflecting their development and centrality in the research domain.

Thematic evolution

Thematic Evolution analysis was employed to examine the development, prominence, and decline of themes, subjects, or concepts over time.

Figure 6 illustrates a thematic evolution map created using bibliometrix, where 'Keywords Plus' data is analyzed. 'Keywords Plus' refers to a feature in Web of Science that generates additional keywords from the titles of cited articles in a paper. This method expands the scope of keyword analysis, encompassing a wider range of interconnected research themes.

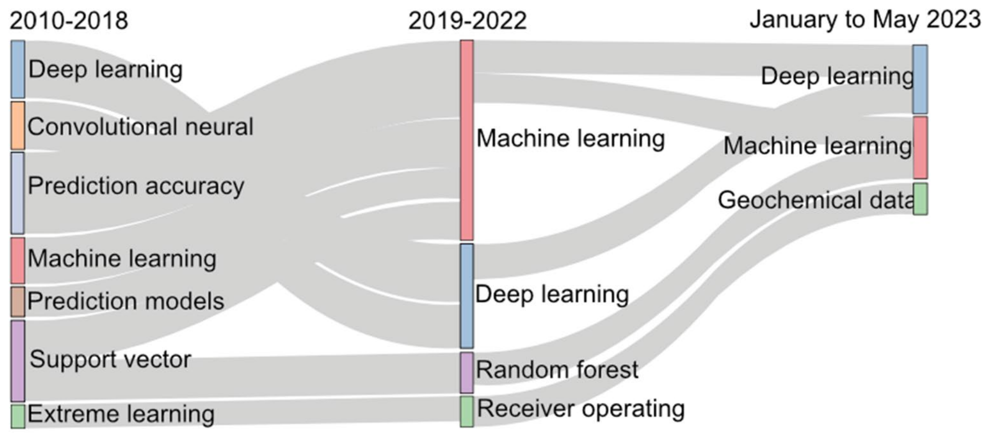
The time frame for the analysis begins in 2010, a starting point chosen due to the presence of only two papers prior to this year. The year 2018 is identified as a key node in the timeline, not because of the sheer number of papers, but due to it having the highest ratio of growth in the number of papers, marking a significant increase in research activity. The timeline concludes in 2023, the latest year in the dataset, providing a view of the current research landscape. The analysis is segmented into three distinct phases, each representing different stages of development in the research field. The first phase (2010–2018) includes 75 papers, reflecting the early stage of research. The second phase (2019–2022), where the most notable growth in the ratio of paper numbers is observed, includes 561 papers. The final phase covers January to May 2023, comprising 102 papers, showcasing the latest developments. This thematic evolution map thus offers a comprehensive visualization of the growth trends and shifts in research focus over these periods, underpinned by the Keywords Plus data.

In Fig. 6, the labels beside the vertical bars denote topics derived from "Keywords Plus," with the length of the colored bars representing the frequency of these topics within designated time frames. A bar's length is proportional to the number of publications associated with its respective keyword or theme within that interval. For instance, a lengthier red bar labeled "Machine Learning" during the 2019–2022 period, relative to other time segments, indicates a higher incidence of "Machine Learning" in the scholarly articles published in those years.

Based on the analysis of Thematic Evolution data (Fig. 6), the following trends can be observed:

1. From 2010 to 2018, the term "convolutional neural networks" (CNNs) was frequently mentioned, but from 2019 to 2022, "deep learning" gained prominence and replaced CNNs. These terms were primarily associated with applications in seismic data and remote sensing, with relatively low occurrence.
2. Between 2010 and 2018, there was significant mention of "extreme learning," which was then replaced by "receiver operating" from 2019 to 2022. These terms were linked to mineral prospectivity and geochemical data, respectively.
3. The term "machine learning" maintained consistent usage throughout the entire period, often accompanied by related terms such as learning techniques, algorithms, and methods. Its applications encompassed various areas, including neural networks, prediction accuracy, prediction models, and support vector machines.

Fig. 6 Thematic evolution map. (Figure highlights key trends over time: **a**)"Deep learning" replaced "convolutional neural networks." **b**)"Receiver operating" replaced "extreme learning". **c**)"Machine learning" remained constant. **d**)"Support vector" and "random forest" had moderate attention. The trends suggest a shift towards deep learning and machine learning, with diverse applications.)



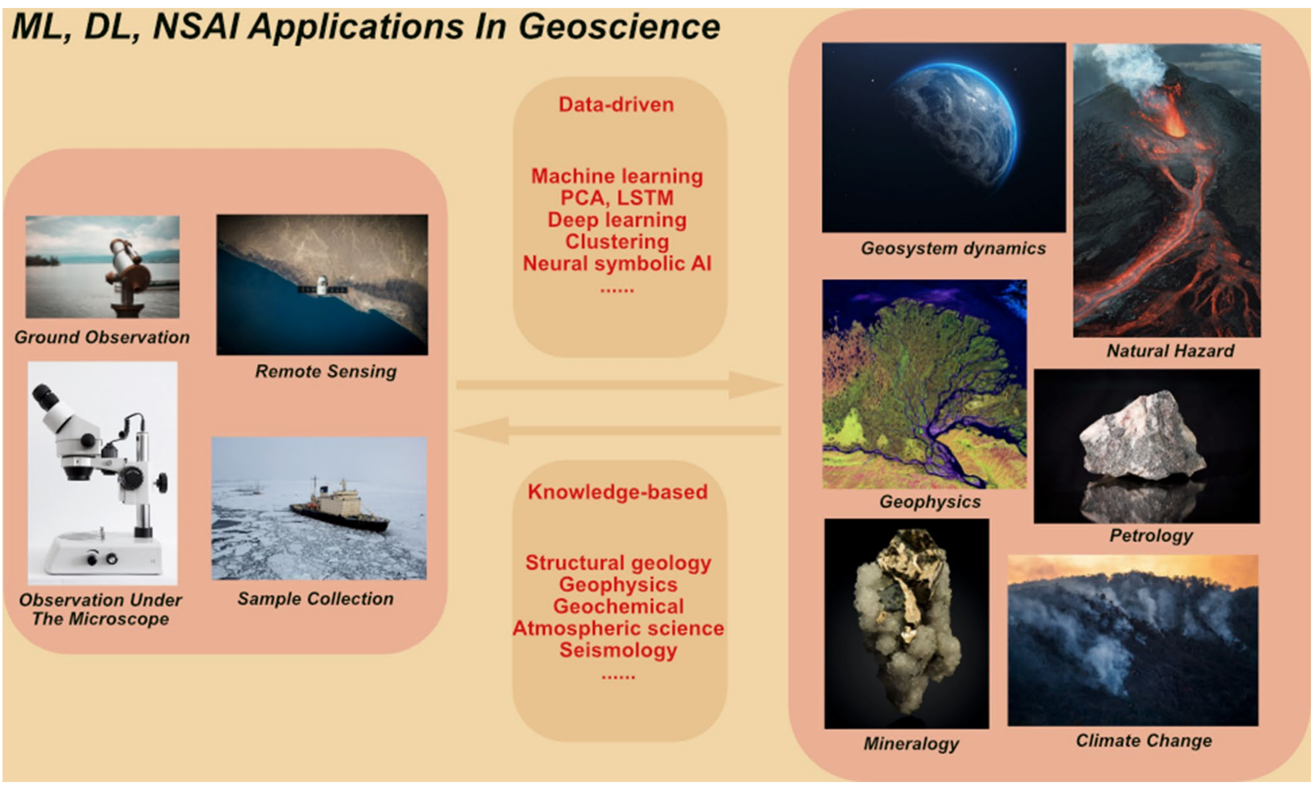


Fig. 7 ML, DL and NSAI application in geoscience

4. "Prediction accuracy" and "prediction models" were frequently discussed within the context of machine learning, focusing on utilizing them for predicting rock types.
5. "Support vector" and "random forest" received moderate attention, with associations to neural networks, artificial intelligence, and vector machines.

In conclusion, the trends suggest a noticeable shift towards deep learning and machine learning, with a diverse range of applications and associated terms receiving increased attention. In contrast, other techniques and domains received relatively less focus during the analyzed period.

A synthetic analysis of ML, DL, and NSAI applications in geoscience

The complexity of geosystems and the vast amounts of data generated in geoscience make it an ideal area for the application of ML and DL techniques (Mahoob et al. 2022; Mishra 2021; Sahimi et al., 2022; Saldana et al. 2022). In recent years, there has been growing interest in using ML and DL techniques in geoscience to solve a wide range of problems (Fig. 7), including climate modeling, seismic signal analysis, and geophysical modeling(Gomez-Flores et al. 2022; He et al. 2022; Mousavi et al., 2022; Savelonas et al. 2022; Shirmard et al. 2022; Sun et al. 2022; Yu and Ma 2021; Zhang et al. 2022b; Zuo 2017; Zuo et al. 2019).

Climate modeling

Climate models generate vast amounts of data, making it challenging to analyze the outputs effectively. ML and DL techniques can be used to analyze and make predictions from this data, enabling researchers to gain insights into complex climate processes such as atmospheric circulation, cloud formation, and ocean dynamics (Brenowitz et al. 2020.; Gettelman et al. 2021; Seifert et al., 2020). The ability to analyze vast amounts of data generated by climate models using ML and DL techniques has facilitated more accurate and robust climate predictions, which are vital in addressing the pressing issue of climate change (Neumann et al. 2019).

In addition to ML and DL techniques, integrating symbolic reasoning with neural networks can lead to a more interpretable and transparent model, which is critical in climate science, where the models' transparency is necessary for policymakers to make informed decisions. NSAI allows for the incorporation of expert knowledge and physical laws into the model, which can help improve the accuracy and interpretability of the model's outputs.

For instance, a hybrid AI climate modeling approach has been proposed to facilitate scientific discovery in climate research (Sleeman et al. 2023). This innovative method combines deep neural networks and mathematical techniques to model dynamic systems. By incorporating a neuro-symbolic language it enables interpretability and the ability to answer questions about the learned information. The approach has been applied to predict climate tipping points, such as the collapse of the Atlantic Meridional Overturning Circulation (AMOC), with high accuracy using a surrogate climate model. Additionally, preliminary findings demonstrate the efficacy of the neuro-symbolic method in translating between natural language queries and symbolically learned representations. This AI methodology shows great promise in accelerating climate tipping point research, enabling faster advancements that were previously computationally infeasible.

Another example of the application of NSAI in climate modeling is the use of NS Methods to identify the drivers of climate variability. These methods can integrate large-scale climate data with other sources of information, such as economic data and historical records, to identify the underlying factors contributing to climate variability. By incorporating both numerical and symbolic data, these models can provide a more complete understanding of the complex processes driving climate change.

Seismic signal analysis

Seismic signal analysis is a crucial area of research in geoscience, as it provides valuable insights into the Earth's interior structure and processes. However, analyzing seismic signals can be challenging, as they often contain complex and noisy data. DL methods, particularly CNNs, have shown promise in improving seismic signal analysis (Yan et al. 2022; Nie et al. 2023). CNNs can automatically learn features from the data and identify patterns that are difficult for humans to discern. DL methods have enabled researchers to detect and locate seismic events more accurately and efficiently than traditional methods. DL methods have also been used to analyze other types of geophysical data, such as magnetic field data, gravity data, and remote sensing data. These techniques have facilitated a more comprehensive understanding of the Earth's structure and dynamics, as well as the potential for predicting natural hazards such as earthquakes and volcanic eruptions. However, there are still challenges that need to be addressed, such as developing interpretable models and addressing issues related to data quality and quantity. Nonetheless, the success of ML and DL in seismic signal analysis and other geophysical applications highlights the potential of these techniques in advancing geoscience research.

Geophysics

In recent years, the hybrid modeling strategy, which combines physical knowledge with DL, can potentially improve the geoscientific awareness of artificial intelligence (AI) systems. Although it is developing but remains under investigated. Some studies in geoscience have attempted this strategy by introducing physical constraints into the loss function in the DL as a penalty term (Karpatne et al. 2017; Zhao et al. 2019) or wrapping analytical solutions of physical representations in DL as NN layers (De Bézenac et al. 2019; Wang et al. 2020). Existing approaches require physical knowledge to be expressed in a closed form, which is impossible for highly dynamic systems like the Earth. Jiang et al. (2020) proposed a novel neural network architecture called the physical process-wrapped recurrent neural network (P-RNN), which incorporates non-analytically solvable ordinary differential equations (ODEs) into DL models, highlights the benefits of a symbiotic integration between DL and physical approaches in advancing geoscience and demonstrates that AI can acquire physical knowledge if taught appropriately.Specifically, the P-RNN model showed a significant improvement in runoff prediction. The results indicated an increase in Nash-Sutcliffe efficiency from 0.65 to 0.75 when compared to a traditional neural network model, and an impressive ability to generalize across different regions. This level of performance, especially the robust transferability in runoff modeling, underscores the advantages of combining deep learning with physical geoscience approaches, exemplifying the benefits of symbiotic integration.

Further, Jiang et al.'s approach aligns with the principles of Neuro-Symbolic Artificial Intelligence (NSAI), where the integration of symbolic reasoning and neural network-based learning can solve complex problems more effectively. The P-RNN's ability to incorporate geochemical data and symbolic representation of physical processes demonstrates the potential of NSAI in addressing intricate challenges in various fields, particularly in geosciences. This study stands as a compelling example of how AI can be taught to assimilate and utilize physical knowledge, leading to advancements in scientific research and applications.

Geosystem dynamics

ML has been used for a wide range of tasks in geosystem dynamics, such as improving weather prediction, analyzing climate data, and predicting clustered weather patterns. Unlike covariance-based spatial analysis, ML can map nonlinear processes. However, ML methods lack actual physical process knowledge and rely solely on identifying and generalizing statistical relations. ML has been increasingly adopted for data analysis, serving as surrogates and methodological extensions for Earth System Models (ESMs) over the past several years. Combining ML with process-based modeling is a crucial distinction from previous data exploration efforts. ML has also been used in conjunction with ESMs and Earth System Observations (ESOs) for various tasks, including determining global ocean heat content, recovering high-resolution terrestrial water storage from satellite gravimetry, and upscaling carbon flux measurements for global carbon monitoring systems (Irrgang et al. 2019; Watt-Meyer et al. 2021.; Yuval and O'Gorman 2020). ML has shown success in representing subgrid-scale processes and other parameterizations of ESMs, and several studies highlight the potential for ML-based parameterization schemes to gradually remove biases and simplifications of ESMs (Bolton and Zanna 2019; Jung et al. 2020; Tramontana et al. 2020). Overall, while some well-trained ML tools and simple hybrids have shown higher predictive power than traditional process-based models, there is still much to be explored and understood about the use of ML in earth and climate science. Irrgang et al. (2021) discussed the potential benefits of combining artificial intelligence (AI) techniques with ESMs and ESOs to create Neural Earth System Models (NESYMs). The NESYMs can improve the accuracy of climate change predictions, particularly in dealing with non-stationary training data and extreme events. Irrgang explains that the dynamic exchange of information between the ML component and physical equations can enhance the performance of the NESYMs. However, innovative interfaces will also be necessary to control the exchange of information (Irrgang et al. 2021).

Using ML, DL, and NSAI techniques in the realm of earth science has demonstrated significant potential across various domains, albeit with limited application in mineral prediction. ML and DL methods have found success in climate modeling, seismic signal analysis, geophysics, and geosystem dynamics. These applications have proven their ability to analyze intricate climate processes, enhance the precision of seismic event detection, deepen our understanding of Earth's structure and dynamics, and aid in weather forecasting and climate data analysis. Notably, the amalgamation of symbolic reasoning with neural networks holds promise for creating more interpretable and transparent models, incorporating expert knowledge, and adhering to physical laws. However, the application of NSAI, specifically in the field of mineral prediction, remains largely unexplored. This gap underscores the necessity for further research and development to harness the potential of NSAI in accurately forecasting mineral occurrences and unraveling the underlying factors driving mineralization events. By leveraging the strengths of ML and DL techniques and symbolic reasoning, NSAI can revolutionize mineral prediction, facilitating more efficient and sustainable mining practices.

Potential applications of NSAI in mineral prediction

The potential applications of NSAI in mineral prediction represent a compelling avenue for advancing geoscience and fundamentally transforming mineral exploration. Drawing from the well-established successes of ML, DL, and NSAI within various Earth science domains, it becomes apparent that NSAI can seamlessly extend its capabilities to enrich mineral exploration, offering predictions that are both more comprehensive and accurate.

A pivotal strength of NSAI resides in its innate capacity to adeptly integrate a multitude of diverse data sources, a quality of immeasurable significance within the domain of mineral prediction. Through the amalgamation of geological, geophysical, geochemical, and historical data, NSAI establishes a comprehensive foundation for predictive modeling. This innovative approach empowers geoscientists to attain a profound understanding of the intricate factors influencing mineral occurrences, transcending traditional methodologies reliant on limited data sources. Incorporating expert geological knowledge into mineral exploration is paramount, and NSAI seamlessly integrates this wealth of human expertise into its models. This harmonious fusion of human and machine knowledge ensures that predictions are not solely data-driven but are also enriched by the invaluable insights and wisdom contributed by geologists and mineralogists. The outcome is a set of predictions that are notably more accurate, well-informed, and practically applicable.

Furthermore, NSAI exhibits a remarkable capability in symbolically representing the intricate geological processes underlying mineralization events. These events are often governed by complex physical and chemical interactions that elude capture through purely statistical methodologies. NSAI excels in encoding these geological processes symbolically, thus elevating the AI's comprehension of the foundational mechanisms dictating mineral formation. This depth of understanding ensures that predictions are grounded not merely in correlations but in a profound grasp of the geological intricacies at play.

Although the direct applications of NSAI in mineral prediction are still in their nascent stages, the undeniable potential it holds is remarkable. Building upon the fundamental principles and successes of ML, DL, and NSAI in diverse Earth science domains, NSAI stands poised to redefine the future of mineral exploration, offering an avenue toward more efficient, precise, and sustainable mining practices.

Discussion and future development

The integration of NSAI into geoscience has been marked by advancements and exemplary applications across various domains. While it has demonstrated great potential, it also poses challenges, yet these challenges are accompanied by exciting opportunities for future development. This discussion explores the implications of NSAI in the context of mineral prediction and geoscience, in light of the trends revealed by the Thematic Evolution analysis. It also draws upon examples mentioned in the application section, emphasizing the pivotal role of Neuro-Symbolic models like Logical Neural Networks (LNNs) and presents them as a solution (Lu et al. 2021).

Challenges, limitations, and opportunities

The integration of NSAI into geoscience and mineral prediction presents a range of challenges and limitations. Encoding domain knowledge into symbolic representations requires researchers to possess domain expertise and coding skills. While a small amount of domain knowledge is insufficient, introducing extensive domain knowledge is time-consuming, necessitating automation through coding. Balancing the proportion of domain knowledge with actual data is crucial to mitigate potential biases introduced by symbolic reasoning, posing a challenge for NSAI. Unlike traditional ML and DL, NSAI's automation, especially in its symbolic reasoning component, plays a critical role in enhancing model efficiency and accuracy. Opportunities for addressing these challenges lie in harnessing advances in automated methods for encoding domain knowledge. This involves leveraging natural language processing (NLP) to extract knowledge from textual data, thus facilitating a more automated and efficient process (Socher et al. 2012). Additionally, the drive for creating more transparent and interpretable models provides an opportunity to develop tools that empower researchers to understand and rectify potential biases and errors more effectively. These advancements can drive the successful integration of NSAI into geoscience and mineral prediction research, unlocking its full potential for improving accuracy and efficiency in these domains.

Delineating the advantages of NSAI over XAI in mineral prediction

While NSAI's strength in interpretability is well-recognized, similar assertions exist for XAI methods like SHAP and LIME. This necessitates a detailed comparative analysis to justify the selection of NSAI in our research. NSAI's distinct advantage lies in its innate integration of interpretability within the learning framework, as opposed to the post-hoc transparency approach typical in XAI. This intrinsic feature of NSAI allows it to effectively incorporate symbolic reasoning, a vital aspect for domains such as geoscience where deep domain knowledge and interpretability are critical. Our preference for NSAI is further reinforced by its capability to blend established domain rules with empirical data, exemplified in applications like mineralization pattern prediction. Here, NSAI not only assimilates established mineralization models but also enriches them with concrete data, ensuring a learning process that is both transparent and rooted in practical evidence. This dual assimilation provides a level of clarity and traceability in the learning mechanism that is paramount in fields like mineral prediction.

In contrast, while XAI methods like SHAP and LIME excel in offering post-hoc interpretability, their integration into NSAI frameworks could potentially enhance the overall interpretability and robustness of AI models in mineral prediction. This combination could lead to a more comprehensive and understandable approach to AI-driven decisions in geoscience, effectively marrying NSAI's inherent interpretability with the analytical depth of XAI. Such an integrative approach is envisioned to yield models that are not only accurate but also provide meaningful insights into their decision-making processes.

Solution: LNNs and beyond

LNNs emerge as a solution, offering a powerful approach to seamlessly merge neural networks and symbolic logic. They excel in providing interpretable rules, a precise fit for complex data, and extendibility to first-order logic. Their disentangled representation allows for omnidirectional inference, accommodating logical reasoning, and supporting theorem proving. LNNs are particularly valuable for integrating neural network learning with symbolic logic in mineral prediction research.

Beyond LNNs, the future holds possibilities for hybrid models that unify neural networks with other symbolic reasoning engines. These models facilitate handling both numerical and symbolic data representations, ultimately enabling more interpretable and explainable predictions. Advancements in NLP techniques, like extracting knowledge from geological literature and reports, present opportunities to broaden the knowledge base.

Future development and applications

The exciting developments in the application of NSAI in geoscience extend to the prediction of geodynamic events and offer explanatory results. The opportunities in integrating NSAI techniques with the analysis of geochemical, magmatic, seismic, and geophysics data for mineral prediction are immense. The synergy between DL algorithms and symbolic reasoning enhances the accuracy of mineral predictions and empowers geologists and mining professionals with profound insights into geological processes.

As the field continues to evolve, we anticipate numerous breakthroughs that will redefine mineral prediction. Future developments include refining and optimizing existing techniques, developing new methods for encoding domain knowledge, and advancing symbolic reasoning. The integration of emerging technologies, like natural language processing and computer vision, into NSAI for mineral prediction, is also a part of this evolution. Collaborations between AI researchers and domain experts will be pivotal in ensuring that models are constructed on precise domain-specific knowledge. The application of NSAI in mineral prediction within geoscience presents a dynamic landscape of challenges and opportunities. The fusion of neural network learning and symbolic logic, exemplified by LNNs, opens doors to more accurate, interpretable, and explainable models. As we look to the future, the development of NSAI in mineral prediction holds the potential to revolutionize mineral exploration and mining, leading to more efficient and sustainable practices and a deeper understanding of the Earth's geology and mineral resources.

Conclusions

Integrating ML and DL techniques with NSAI presents significant potential for advancing geoscience research and applications. While data-driven approaches have demonstrated success in certain cases, the incorporation of domain knowledge and symbolic reasoning can further enhance the interpretability, robustness, and efficiency of ML and DL models. This paper elucidates the promising prospects of ML, DL and NSAI techniques in geoscience applications, specifically focusing on mineral prediction. The literature analysis reveals significant trends that research output in AI-related geoscience has substantially increased, with notable growth from 2018 onwards. There is a growing emphasis on predictive research, along with sustained interest in terms like "classification," "neural networks," and "model." Thematic network analysis highlights the dominance of "deep learning" and "machine learning" as central themes, reflecting their foundational role, while themes like "transfer learning" and "big data" indicate ongoing developments and specialization. Thematic evolution suggests a shift towards "deep learning" and "machine learning," with diverse applications, while other techniques received relatively less focus during the analyzed period. Furthermore, ML and DL techniques have exhibited noteworthy achievements in various geoscience domains. ML algorithms have played a pivotal role in climate modeling by facilitating the assimilation of vast amounts of observational data and the development of more accurate climate models. DL techniques, such as CNNs, have revolutionized seismic signal analysis through automated feature extraction and pattern recognition, thereby improving earthquake detection and characterization. Geophysics has also witnessed advancements through the adoption of ML and DL, with hybrid modeling strategies that integrate physical knowledge and data-driven approaches, yielding enhanced predictions and profound insights into the dynamics of Earth.

Despite advancements, challenges persist in applying NSAI in geoscience, such as acquiring high-quality datasets and ensuring model interpretability. LNNs address these challenges by seamlessly combining neural networks and symbolic logic. LNNs offer interpretable rules, precise fitting of complex data, and extendibility to first-order logic. The integration of neural network learning with symbolic logic makes LNNs valuable for mineral prediction research, enhancing accuracy and reliability. By harnessing the capabilities of NSAI, we can unlock novel insights into Earth's geological processes and unearth untapped mineral resources. Continued research and development in this field will pave the way for more effective and sustainable geoscience practices. The application of NSAI in geoscience harbors the potential to revolutionize the field, empowering us with a better understanding, prediction, and management of the intricate systems that govern our planet.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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