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AI-based sustainable natural resources development with deep learning- an overview

Abstract

A multidisciplinary "Engineered System" is introduced used to create a Sustainable integrated platform for multitude of natural resources called NRDL, short for Natural Resources using Deep Learning. NRDL is a dynamic system capable of adapting itself to changes in the society, economic trends and political conditions, as well as emerging needs. An example of NRDL system is provided. An example of a subsystem that deals with two different types of natural resources (Water, Minerals and Energy) is shown. Specifically, it is shown how water resources to generate geothermal and electric energy. A byproduct to the brine from geothermal is lithium that is in electrical vehicles. This paper overviews the entire system briefly. It will be followed by several subsequent papers to highlight different components of NRDL in more detail.

Keywords: AI, natural resources, sustainability, natural resources, lithium, geothermal energy

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Fred Aminzadeh
FACT Inc., USA

Correspondence: Fred Aminzadeh, President, FACT Inc. (www.fact-corp.com) and Co-founder, Energy Transition International.com, Houston, TX, FACT Inc., Santa Barbara, USA

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Abbreviations: NRDL, sustainable natural resources development with deep learning; LLM, large language models; ML, machine learning; AI, Artificial Intelligence; DA, Data Analytic; CNN, committee neural network; ESG, environment, social and governance; GHG, greenhouse gases; DEI, diversity, equity and inclusion; Gen-AI, generative AI; TL, Transfer learning; TLO, transfer learning operator; TLE, transfer learning engine

Introduction to NRDL

Natural resources and their sustainability are of paramount importance for society at large. Natural resources such as energy, water supplies, and minerals are continuously dwindling due to population growth, and global economic expansion, among other things. To meet the future challenges and to secure sustainable natural resources, we will need to create a multidisciplinary "Engineered System" that can be used to analyze, optimize, and monitor the sustainability process in an integrated fashion. Such a system would be a dynamic one in principal and capable of adapting itself to changes in the society, economic trends and political conditions, as well as emerging needs. An example of NRDL system is provided in Figure 1, capturing its key components.

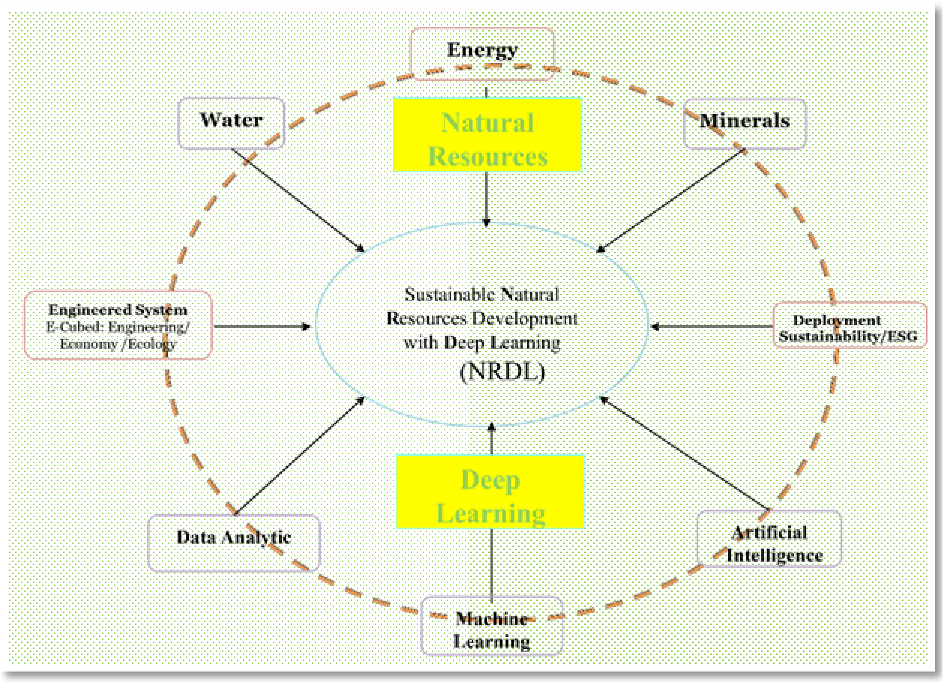

Figure 1 NRDL uses deep learning techniques (DA/ML/AI) to bring about a sustainable natural resource (water/energy/minerals) system.

The central issue is to address the specific requirements of a sustainable natural resource system through an integrated approach. This can involve a series of relevant Large Language Models (LLM) populated by data and knowledge from the respective domains (e.g. energy, minerals and water resources (at the top of the figure). Large Language Models (LLMs) are increasingly applied to energy (fossil oil, geothermal, and electrical), minerals and water resources data to bridge the gap between human expertise and machine-generated data. This would aid carrying out tasks such as the interpretation and integration of complex natural resource data, simulation analysis, and management. They enable data-driven decision-making by structuring heterogeneous information, such as energy policies vis a vis environmental issues and economic factors and, in some cases, automating the analysis of scientific computing data. As an example, see the survey paper on the subject at Arslan, and Munawar.[1]

A properly designed LLMs can also be considered as respective agents within the Agentic-AI discipline. For simplicity we can call the one for Energy LLM-E and the ones for water and minerals LLM-W and LLM-M. While LLM-E, LLM-W and LLM-M could be independent entities, in many cases they may share data and knowledge using the same structure. It should also be noted that each of those agents could be divided into sub-agents. For example, in the case of Energy, we can have LLM-E1, LLM-E2 and LLM-E3 with E1, E2 and E3 referring to fossil energy, carbon management and geothermal energy respectively.

A recently published book, Aminzadeh et al.[2] highlights some of AI and data analytics applications in Energy. A sequel to this book with emphasis on carbon management is provided at Aminzadeh.[3] Additional two books on AI for geothermal, followed by rare earth material and minerals are scheduled for 2027 and 2028. They all will serve as a catalyst to bring all stakeholders of NRDL together.

Description of NRDL

The NRDL concept is equipped with new advances in Machine Learning (ML), Artificial Intelligence (AI) and Data Analytic (DA) techniques. The ensemble of ML-AI-DA will be referred to as DL for brevity. A Sustainable Natural Resource development with Deep Learning (NRDL) by its very nature is highly data intensive, requiring a good understanding of the Big Data concept. To optimize the data collection process as well as effective analysis of the data, we will implement DA and data mining techniques. Furthermore, given the highly multi-disciplinary nature of NRDL and the corresponding data from different sources, data integration becomes an important step. This will require different types of DL concepts to translate the raw data into resource models (energy, water and minerals) that accurately connect the data to reality. After data integration, interpretation of the results necessitates combining human expertise/knowledge with intelligence accumulated from the output of DA and DL. As one possible implementation of NRDL, a committee neural network (CNN) will help focus on the requirements and learning process on each subsystem (e.g., related to energy, water and minerals) separately, with the global "gate keeper" neural network helping integration of the entire system. The recursive updating capability of NRDL will ensure it is updated as new data becomes available. Figure 1 shows the structure of NRDL that uses deep learning techniques (DA/ML/AI) to bring about a sustainable natural resource system (water/energy/minerals).

NRDL requires input from different domain experts not only from the Engineering point of view but also to address the issues associated with Economy and Ecology standpoints. We will implement a novel "E-Cubed" concept as described in Aminzadeh[4]'s editorial in Journal of Sustainable Energy Engineering where he served as the editor in Chief for 5 years. This shows the interrelations between different elements highlighted in Figure 1.

Innovation ecosystem: Since we are addressing different challenges associated with sustainability of different natural resources, it is imperative that the inter-relation among different subsystems is honored. In addition, we need to ensure, necessary complementary aspects of the system are fully utilized. Figure 2 is an example of a subset of the NRDL system. Here we show how an NRDL subsystem can operate keeping three different types of natural resources water, energy (two types geothermal/electric energy, and minerals, lithium in this case) in mind. A dual-purpose geothermal operation with water as its input (bottom left corner of Figure 2) is an input to the geothermal power plant (top left of Figure 2). The output of the geothermal power plant is not only electric power it generates but also production of lithium as another byproduct (top right in Figure 2). Lithium itself is used to power electrical cars, (bottom right in Figure 2), among its other applications. The complementary nature of these natural resources is a testament to the fact that simultaneous attention to different natural resources in a system-based approach such as NRDL can improve efficiency and reduce costs. Another element of the NRDL subsystem displayed in Figure 2 is that the very power generated in this system can be used as an energy source to power a data center located near the geothermal field, that can be used as the energy source for massive computing power that is used to run the NRDL subsystem, making it self-sufficient.

AI and data analytics could play a significant role if one wants to combine the generated geothermal-based electric power with the electric energy from other sources such as wind, solar, fossil fuel, and others. Likewise, lithium-based batteries powering of the cars could be combined with fossil fuel-based energy to create hybrid cars. The integration process can certainly use data analytics and AI technologies to improve efficiency and cost. Lithium is a key component of high-energy-density batteries, being a critical material for electrical vehicles. It should however be stated that lithium-rich geothermal brines are characterized by complex chemistry, high salinity, and high temperatures, posing unique challenges for lithium extraction economically.

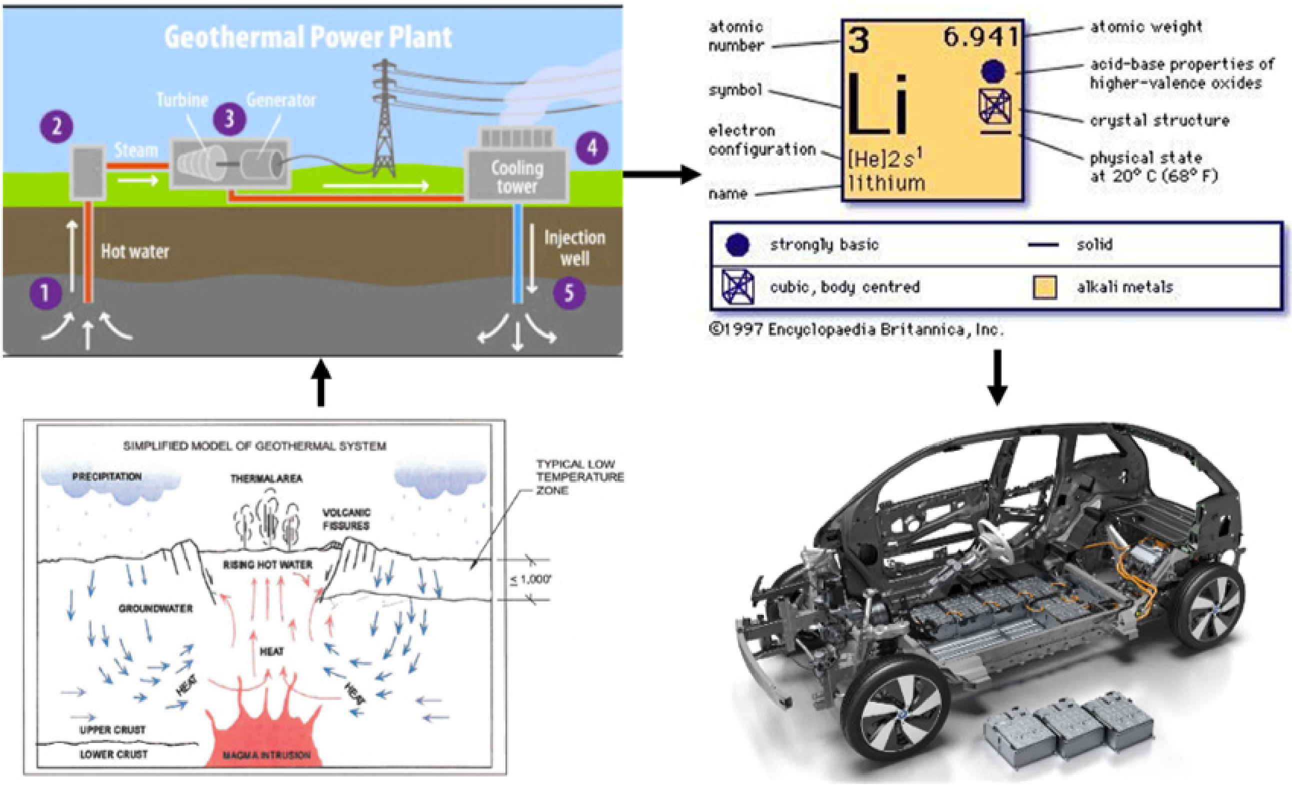

Figure 2 A NRDL subsystem with the relationship among different types of natural resources (water/energy/minerals): A dual-purpose geothermal operation with water as its input and electric power and lithium used in electrical cars as its output.

Figure 3 shows more details on how lithium is extracted from the brine. The hot brine that comes up from the subsurface as part of geothermal power production contains many minerals, including iron, magnesium, calcium, sodium, and of course lithium. Using various extraction techniques, lithium chloride can be extracted from the brine, then processed into other forms for battery production. For geothermal fields around the world, geothermal brine produced has been simply injected back underground, but now it's become clear that the brine produced in many fields contains an immense amount of lithium, a critical resource need for low-carbon transportation and energy storage. Demand for lithium has been skyrocketing, as it is an essential ingredient in lithium-based batteries, as well as many other applications. For more details on different techniques for recovery of lithium from geothermal brines see Stringfellow and Dobson[5] and Zhang et al.[6]

ESG principles

It will help facilitate the Environment, Social and Governance focused objectives, for the benefit of all. To ensure a strong sustainability framework, the analysis of data needs to include the impact assessment of resource management in terms of ESG (Environment, Social and Governance). In particular,

a. **Environment:** This includes attention GHG (Greenhouse gases) emissions, energy consumption, use of water, solid and liquid waste management, and if feasible, estimations of impact to biodiversity.

b. **Social:** It includes considerations of social investment needs for local, rural or indigenous populations in the areas considered, DEI (Diversity, Equity and Inclusion) topics, occupational health and industrial safety risks, complexity of operations that would require training, availability of supply chain, jobs creation outlook, wellness and quality of life, labor relations, easiness of geopolitical area for work, and other social topics considerations

c. **Governance:** NRDL can be used as an effective tool to implement various environmental and risk reduction related regulations and permitting requirements. This would include modelling and monitoring as well as implementing a suitable set of risk and reward mechanisms. It can also address business ethics; prosperity created by the operation and ways to distribute and create wellness of all impacted (stakeholders).Some of these issues are further highlighted in Capello and Aminzadeh.[7]

Sustainability and energy transition

The Ultimate goals of sustainability of natural resources, including the necessary requirements for efficient energy transition to achieve sustainability could be reached by employing a multidisciplinary approach with the aid of artificial intelligence and data analytics.

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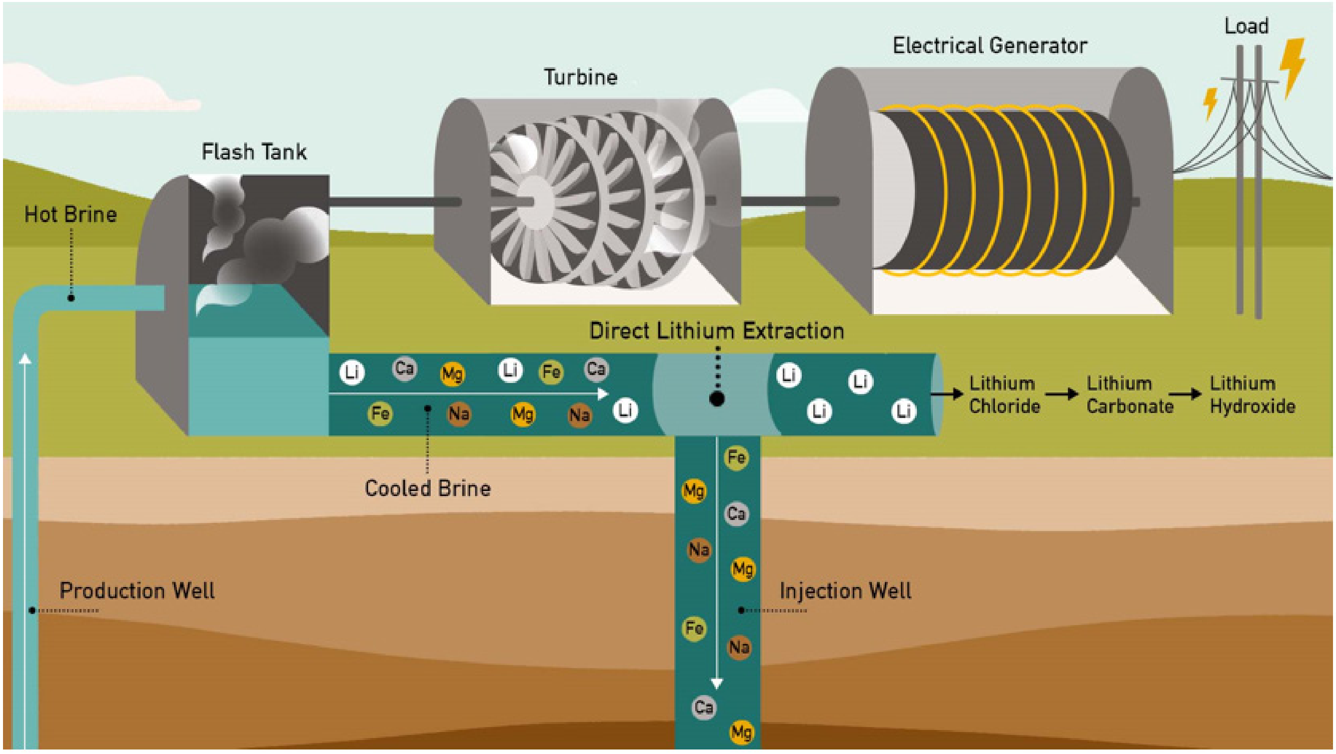

Figure 3 The process of extracting lithium from the brine of geothermal production (Credit: Berkeley Lab).

Specific relevant topics must be addressed: In what follows we briefly highlight some of those topics. They include:

1) Data and Information Integration
2) Value of Information
3) Transfer Learning
4) The Role of "Big Data" and Visualization in Energy Transition
5) Use of CSEM Data in conjunction with other data for imaging
6) Carbon Capture, Sequestration, and Utilization:
7) Sustainability and ESG
8) Geothermal Resources Development
9) Water Resources
10) Hydrogen Storage
11) Mineral Resources
12) Potential downfall of using AI for Natural Resource Development and how to mitigate the associated risk.

We will provide some details on these topics on subsequent papers. For now, we will further elaborate on the first item.

Data and information integration

Integration of knowledge and data from widely diverse sources is a formidable challenge for different problems including those in connection with energy, water and other natural resources. When facing solving energy transition problems this data and knowledge integration is very difficult. This is due to the fact such data and information are of different Scale, Uncertainty, Resolution and Environment (SURE). The challenge is greater for modeling spatial systems. Whether we are dealing with characterizing a fossil energy reservoir, mapping the CO_2 plumes and pressure as or dealing with a geothermal field characterization we may use diverse sets of data. This includes conventional 3D and micro-seismic data, VSP, cross well, electromagnetic as well as petrophysical, rock mechanics/core, geochemistry data and geomechanical information. All these data components involve drastically different scale (from micro millimeters to several kilometers), levels of their uncertainty, and the extent of their resolution as well as the associated environments (e.g., lab-scale core-flooding data to laboratory CT imaging experiments to 4D seismic measurements at the field scale) are consistent with the "SURE" challenge (Figure 4). Various AI techniques can prove beneficial in addressing the SURE challenge.

Modeling spatial heterogeneity constrained by the available data and quantifying the uncertainty associated with the models, is the core pursuit of geo-statistics. Over the past 50 years, geo-statistics, and more recently, AI has seen a proliferation of methods to model various geologic phenomena to arrive at estimates of recoverable oil and gas and mineral reserves, develop maps of groundwater contamination, assess the hydrocarbon in place, and other things. In many of these techniques the relationship between spatial attributes at multiple locations in space is assessed in the form of spatial covariances. The concept of multiple point geo-statistics has therefore taken hold. Numerous algorithms based on fixed/multi-scale/flexible spatial templates[9] have been proposed. Despite all these advances, techniques to model complex spatial and/or temporal heterogeneities remain at the development stage with numerous ongoing efforts for making the algorithms more efficient and for accounting for uncertainty in training images from which the pattern related information is derived.

In addition to the complexities posed by natural systems, there has been a massive proliferation of subsurface data from increasingly sophisticated tools and data acquisition techniques applied to subsurface processes. For example, permanent downhole sensors inserted into producing or injection wells are now able to provide real-time readings on fluid flow rates, density, pressure, and temperature data. Modern techniques in seismic data acquisition such as multi-azimuth, wide azimuth and rich azimuth surveys, as well as compressed sensing have enabled construction of high-resolution subsurface images. We end up having more detailed spatial information pertaining to important geological features such as fractures. This has, in turn, led to significantly larger datasets, often on the order of terabytes to petabytes. However, traditional methods rely on time-consuming iterative workflows, which involve computing seismic attributes, de-noising and expert interpretation. There is a need for new tools which can lead to faster and more accurate probabilistic predictions of critical subsurface characteristics from BIG production and seismic datasets.

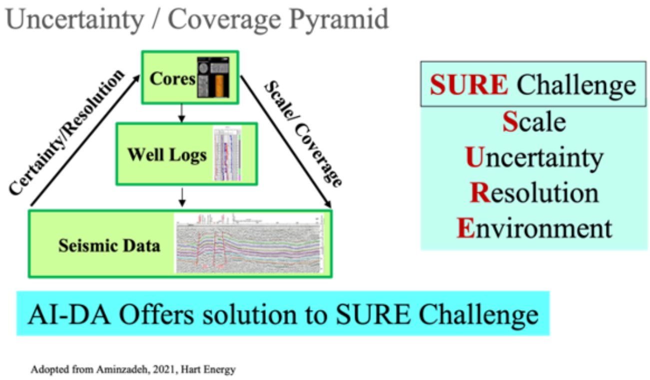

Figure 4 SURE Challenge- Adopted from Aminzadeh (2021, Hart Energy) and Aminzadeh (2024, American Oil and Gas Reporter).[8]

Generative AI (Gen-AI) is becoming more popular in many areas. The core algorithm behind generative models are large deep neural networks, which have billions of parameters to learn different representations of tokens and images.[10] It can potentially become a tool to address the SURE challenge. Gen-AI is comprised of discriminator and generator (G). The goal of generator is to produce fake images from latent space z, which is typically sampled from standard Gaussian distribution. The goal of discriminator is to evaluate and separate the generated samples y ˆ (fake) and real training samples y (real). (D) that can fool the discriminator to mistakenly classify fake generated images $\hat{y}$ as true. Such minimax competition between G and D can be mathematically characterized by an adversarial loss function. During the training process of Gen=AI, generator G_θ and discriminator D_ω are trained separately through gradient descent in an iterative manner.

We would like to combine the strengths of multiple point geo-statistics, BIG data analytics and Gen-AI/ machine learning models to develop a modern toolkit for modeling natural systems that can be applied in several settings such as the data integration associated with the SURE challenge required for many problems such as fossil energy exploration and production, geothermal resource development, water/mineral resources, as well as the design and optimization of subsurface CO_2 sequestration projects, safe storage of hydrogen in the subsurface as well as for more traditional energy applications such as the optimized production of hydrocarbons from subsurface reservoirs. A key focus of the proposed research will be to condition models of natural systems to data from multiple sources that may be related to the primary phenomenon being modeled in a complex non-linear manner. Moreover, the data available may be at disparate scales and resolution. Tailoring deep-learning algorithms to handle such multi-scale, multi-resolution data to make accurate inferences about spatial heterogeneity, will be an important contribution to NRDL.

Transfer learning

The goal here is to develop machine learning models to transfer the knowledge attained in one domain (for example fossil energy and mineral extraction social licenses processes) to another domain (for example geothermal energy, nuclear energy, carbon management or mineral extraction, and emissions controls). This is expected to improve efficiency and gain benefits from leveraging opportunities. This can also be utilized from transferring knowledge from experience gained in one field to another one to avoid repeated manual processing and interpretation efforts for future field experiment data. Transfer learning (TL) will play a key role in being able to utilize the information for optimum data processing and interpretation in one field to the next. TL will also be key in accelerating transfer of knowledge determining which are the key ESG parameters in developing specific resources with a sustainable approach, as DL - deep learning will enable transferring lessons learned from region to region, or country to country, using acquired knowledge from known cases to new cases. This would be accomplished by inputting the optimum parameters derived from an earlier machine learning site, plus a set of 2 vectors, each comprised of the differences between different injection sites. The TL idea and the associated transfer learning operator (TLO) and transfer learning engine (TLE) will be used in different forms and different tasks with different implementations.

Figure 5 illustrates one possible implementation of Transfer Learning concept. Suppose we have developed an optimum strategy for data processing and interpretation say field A. The question is how best we can use the knowledge we have gained from the evaluation of site A to a new field, say B, with minimum effort. We propose to first investigate the key differences between the two, and extend the solution from field A to field B. We begin by defining three vectors, (GR, RP and AD). GR vector is comprised of all the key parameters that specify geology (G) and reservoir (R) characteristics of the field. RP vector encompasses the key parameters involving regulations (R) and permitting requirements (P) of the field, and AD vector has to do with the available data in the field. Thus, all the pertinent information on difference between the two fields Δ (AB) are captured by ΔGR, ΔRP and ΔAD. As shown in Figure, the optimum processing and interpretation parameters for field A and the associated uncertainties (for example the uncertainty of the velocity field), combined with Transfer Learning Operator Δ (AB) comprised of ΔGR, ΔRP and ΔAD would be the sufficient input to the properly designed neural network to create the optimum processing and interpretation parameters for field B.

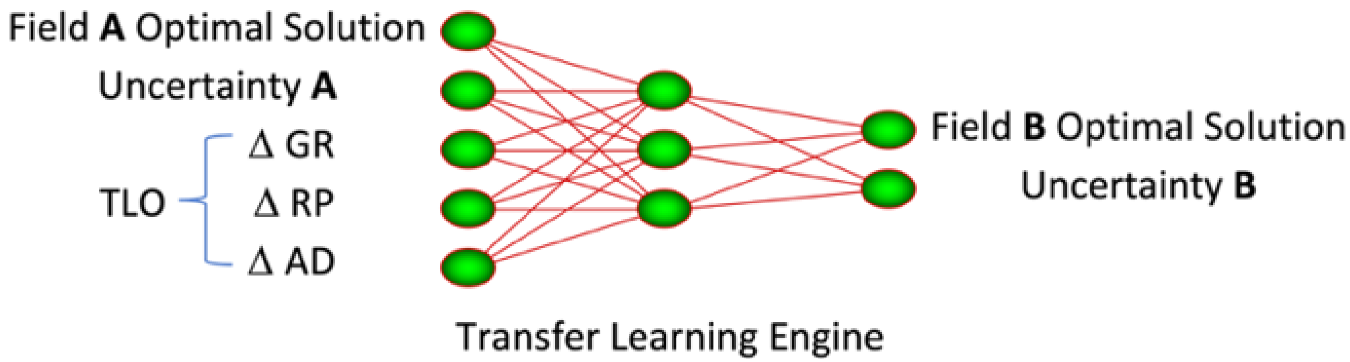

Figure 5 An example of structure of Transfer Learning Operator (TLO).

The input to the TLE is a solution for injection management and monitoring we have devised for site A. This solution may involve the ideal injection rate, locations of injection wells, site characterization information (fracture/ fault system, permeability, porosity, etc.). We call the set of all these parameters "Field A Optimal Solutions". We also input a vector that includes the uncertainties associated field A optimal solution, referred to as Uncertainty A. If the goal is to develop an optimal solution for Field B, we define the Transfer Learning Operator (TLO) operator comprised of the previously described ΔGR, ΔRP and ΔAD as another set of input values to the TLE. The output of TLE will be the optimized solution for field B, which is expected to be derived faster, cheaper, and with higher reliability than if we were to start the optimization process from scratch. The TLE output will also include the predicted uncertainty associated with different components of field B optimum solution. This will have immense impact on the cost-effectiveness, versatility, and uncertainty reduction. It will allow translating microseismic events to their location, orientation, and mechanical status of fractures vis-a-vis injection schedule, using a geomechanically constrained machine learning model, training datasets.

It should also be emphasized that the transfer learning concept can also be used beyond the scenarios discussed earlier. For example, to realize the full benefits of cross fertilization opportunities, with some modifications of the TLO operator, one can consider using transfer learning from one type of natural resources (for example oil and gas) to other types of natural resources (for example geothermal, mineral, nuclear, and water). This is where the leveraging power of transfer learning can be attained. Figure 6 demonstrates using TLO for transferring knowledge from fossil fuel energy to other resources such as water, minerals,geothermal and carbon capture, utlization and sequestration (CCUS.). See Bromhal et al.,[12] highlighting some of the DOE supported SMART project on on the use of machine learning for carbon storage.

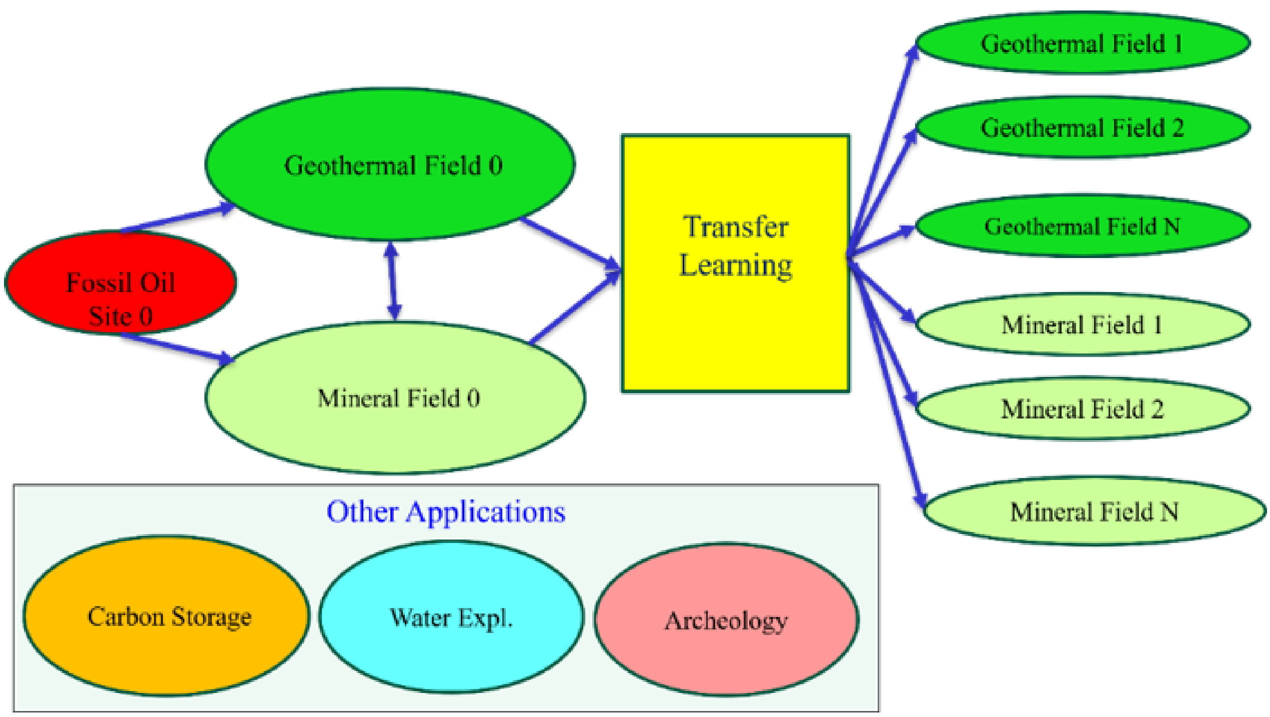

Figure 6 Use of transfer learning operator concept beyond a particular natural resource, Adopted from Aminzadeh.[11]

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Conclusion

Here, we provided a unified conceptual the NRDL "Engineered System" as a platform for development of sustainable natural resources. NRDL is powered by data analytics and artificial intelligence tools, including use of Large Language Models. The inherent similarity and synergy among different types of natural resources is the foundation of our approach. Several challenges are highlighted and a road map showing how to address them is provided. One specific complication is how to integrate data and knowledge types. We refer to this as the SURE challenge. The other issue we address with a few examples, is to utilize the knowledge and expertise gained from solving a problem for one natural resource to be used for another natural resource. We utilizing the "Transfer Learning" concept for this purpose. In several forthcoming papers, we will delve into additional details on many of the topics we overview here.

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Conflicts of interest

This work does not involve any conflicts of interest for the author.

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