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A Hierarchical Framework for CO2 Storage Capacity in Deep Saline Aquifer Formations

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Carbon dioxide (CO_2) storage in deep saline aquifers is a vital option for CO_2 mitigation at a large scale. Determining storage capacity is one of the crucial steps toward large-scale deployment of CO_2 storage. Results of capacity assessments tend toward a consensus that sufficient resources are available in saline aquifers in many parts of the world. However, current CO_2 capacity assessments involve significant inconsistencies and uncertainties caused by various technical assumptions, storage mechanisms considered, algorithms, and data types and resolutions. Furthermore, other constraint factors (such as techno-economic features, site suitability, risk, regulation, social-economic situation, and policies) significantly affect the storage capacity assessment results. Consequently, a consensus capacity classification system and assessment method should be capable of classifying the capacity type or even more related uncertainties. We present a hierarchical framework of CO_2 capacity to define the capacity types based on the various factors, algorithms, and datasets. Finally, a review of onshore CO_2 aquifer storage capacity assessments in China is presented as examples to illustrate the feasibility of the proposed hierarchical framework.

Keywords: CO_2 aquifer storage, capacity types, capacity methods, algorithms, data quality

HIGHLIGHTS

1) The CO_2 storage capacity evaluation methods of saline aquifer sites around the world are reviewed.
2) Major types, algorithms, and related data requirements for capacity evaluation are classified.
3) A hierarchical framework of CO_2 storage capacity for the saline aquifer is established with key descriptions of capacity types, data quality, and related algorithms.
4) Published results of onshore aquifer capacities in China are classified according to the proposed framework.

1 INTRODUCTION

Carbon dioxide (CO_2) geological utilization and storage (CCUS) technology is a vital technology to reduce emissions of greenhouse gas while utilizing fossil fuels and carbon-based material in the near and medium-term (Bui et al., 2018; Alova, 2020). CCUS technologies can beneficially use CO_2 to recover useful underground resources (i.e., crude oil and saline water) that can generate incomes to offset the costs associated with CO_2 capture, compression, transportation, and geological injection process, and store the gas in the geological formation permanently (Damiani et al., 2012; Aminu et al., 2017). Among various components of CCUS technology, CO_2 capture and deep saline aquifer storage provide the largest identified storage potential to achieve CO_2 mitigation in energy and industrial sectors for at least a century (Kobos et al., 2011; Davies et al., 2013; Ziemkiewicz et al., 2016; Kelemen et al., 2019).

A sophisticated evaluation of CO_2 storage capacity is necessary to determine the technically feasible and affordable portion of total storage capacity or storage resource. Reliable capacity evaluation is essential in ensuring the acceptance of stakeholders and successful deployments of CCUS technology (Bachu et al., 2007; Bradshaw et al., 2007). CO_2 storage capacities in hydrocarbon reservoirs can be straightforwardly assessed through existing algorithms that use reservoir properties, recoverable hydrocarbon reserves, and CO_2 storage efficiency (Wei et al., 2015c). However, the CO_2 storage capacities face huge uncertainties because of complex geological reservoirs and various trapping mechanisms that instantaneously occur at different rates, spatial volume, and timescales, especially for CO_2 storage in deep saline aquifer formations (Bachu et al., 2007; Bradshaw et al., 2007; Anderson, 2017). Unlike CO_2 in oil and gas fields with detailed data on on-site characterizations and site operating data in previous recovery processes, the CO_2 aquifer storage is constrained by the data availability and experience in long-term commercial-scale CO_2 storage projects. Consequently, stakeholders, especially decision-makers, may face considerable difficulties in ascertaining the realistic capacity, risk, and related costs (Anderson, 2017; Elenius et al., 2018).

Aside from numerous scholars, several organizations, such as the United States Department of Energy (US-DOE), Carbon Sequestration Leadership Forum (CSLF), Energy and Environmental Research Center, US Geological Survey (USGS), Petroleum Resource Management System, and International Energy Agency (IEA), have independently developed various methods and capacity classification systems that have been applied globally (Co2Crc, 2008; Gorecki et al., 2009d; Netl, 2010; Bachu, 2015). However, no single, consistent, and broadly available method for estimating CO_2 storage capacity exists, whereas various studies have used different assumptions, algorithms, and site data; and given assessment results that are extremely difficult to compare (Bradshaw et al., 2007; Höller and Viebahn, 2016). Similarly, even by the same method, the values of storage efficiency and resulted capacity published in the literature manifest wide variations, and no complete set of values can be universally referred to and be accepted by the stakeholders (Bradshaw et al., 2007; Goodman et al., 2011; Bachu, 2015; Höller and Viebahn, 2016). The major reasons for difficulties stem from different capacity assumptions, algorithms, data quality (data types and details), and other important factors. These factor can be grouped into follows: 1) clear and accepted definitions of technical features (e.g., open or closed boundary conditions, well fields and well structure, pressure buildup management technologies, site operating strategy, geological setting, and others); 2) detail levels of site characterization and data quality (data types and resolution) used; 3) recognition and proper use of trapping mechanisms at specific temporal and spatial scales; 4) consistent methodologies with consistent storage efficiency coefficients; 5) algorithms and analysis tools integrating data of site characterization; 6) capacity at various spatial and temporal scales, such as country, basin, and site scales, and various temporal scales such as different period of site operating, post-closure, long-term fate of thousands of years (Szulczewski et al., 2012); 7) capacity with economic characteristics (Eccles et al., 2009); 8) applicable capacity satisfying regulation and legislation constraints, such as maximum pressure for CO_2 injection, coverage of minerals in various geological formations, and area of interest, which is the areal coverage of the subsurface volume permitted by the administrative system for CO_2 injection; 9) recognition that storage capacity estimates vary with the emergence of new available data and technologies, contradictions with any commodity, and economic, regulatory and legislative conditions, thereby affecting the uncertainty information (Bradshaw et al., 2007; Gorecki et al., 2009c; Wennersten et al., 2015; Höller and Viebahn, 2016). Furthermore, affordable, applicable or actual capacity depends not only on the subsurface geological characteristics but also on important geographic and non-geological factors, such as technical schemes, legislative and regulatory requirements, social and economic factors, the proximity of source and sink, incentive policies, and other supportive policies (Gorecki et al., 2009a; Szulczewski et al., 2012; Bachu, 2015). The CSLF techno-economic resource-reserve pyramid, which was first presented by Bachu et al. (2007), classified CO_2 storage capacity/resource into four types: theoretical capacity/resource (capacity is herein used as capacity/resource), which is the maximum amount of CO_2 that the geological system can ultimately store; effective capacity, which represents the CO_2 storage capacity constrained by the physical and chemical characteristics of the system using specific technical schemes; practical capacity, which means the geological capacity further constrained by techno-economic, regulatory, and legislative factors; and matched capacity, which represents possible CO_2 capacity in potential full-chain CCUS projects that link CO_2 sources with suitable geological sites and can be deployed affordably under market-oriented and supportive environments (Bachu et al., 2007). Similarly, other classification systems are established to describe the capacity results. There is no single system to classify various capacity methods and corresponding results in a unified framework (Co2Crc, 2008; Gorecki et al., 2009d; Netl, 2010; Bachu, 2015). Consequently, a necessary task is to develop a CO_2 storage resource/capacity evaluation framework that can be broadly applied and allow comparison of various assessments (Bradshaw et al., 2007; Gorecki et al., 2009c; Höller and Viebahn, 2016).

This study aims to present a unified hierarchical framework of CO_2 storage capacity assessment to harmonize various methodologies and key factors of capacity assessment and provide a clearer definition of CO_2 storage capacity types using trapping mechanisms, types and detailed levels of data, and related algorithms. Meanwhile, data and algorithms can be screened and selected to satisfy the different requirements for capacity evaluation at different stages. Finally, as an example, this hierarchical framework is used to classify the storage capacities of onshore saline aquifer formations in China in literature.

2 REVIEW ON KEY FACTORS AND ALGORITHMS OF CAPACITY EVALUATION

The CO2 capacity/resource assessment processes are analogous to those used in the hydrocarbon industry through a classification of resource types and assessment stages until project commencement (Doe-Netl, 2018). Geologic uncertainties and assessment algorithms cause significant uncertainties in the storage capacity. Geologic complexity can affect site performance (such as injectivity rate, ultimate capacity, and risk) and related storage costs as much as an order of magnitude (Middleton et al., 2012b). High requirements of storage mechanisms, types and detail levels of site characterization data, and related algorithms cause considerable challenges in the reliable estimations of CO_2 capacity in deep saline aquifers. Additionally, the reliability of CO_2 capacity assessment depends not only on the geological characteristics but also on other important non-geological factors, such as technical schemes (engineering design), legislation and regulation requirement, risk minimization, social and economic aspects, source-sink matching, administrative permitting and verification, and policy systems (Middleton et al., 2012a; Gale et al., 2015; Middleton and Yaw, 2018).

Accordingly, the reliable storage capacity of CO_2, including capacity magnitude, geographical distribution, technical feasibility, risk, and cost range, is the key to deploying and scaling up the CO_2 aquifer storage projects to achieve affordable CO_2 mitigation. The affordable or feasible capacity, deployed at scale under certain conditions, depends on several important factors. These factors include technical readiness, suitable storage volume, cost competitiveness, risk level, environmental policies, incentives or subsidies for carbon mitigation, administrative procedures, financial support, and legislation and regulation system. These factors of capacity should clearly illustrate the follows: 1) trapping mechanisms of CO_2 act in heterogeneous formations at multiple spatial scales (country, regional, site, and core scale) and time frameworks of assessment (e.g., long-term geological era and cessation of injection), 2) various detail levels or stages of site characterization, including basin scale and site scale data, and even core-scale site properties (De Silva and Ranjith, 2012; Issautier et al., 2014); 3) algorithms and analysis tools integrating site characterization data; 4) technical scheme, such as fluid properties of CO_2 stream containing impurities, well fields, and injection strategy including injection control, injection rate and duration, water production, conformity control, risk management scheme, and other technical schemes (Popova et al., 2012); 5) economic features: levelized cost of CO_2 storage or net mitigation cost of full-chain CCUS projects; 6) source–sink proximity: characteristics of potential source–sink pairs for deployments (Dahowski et al., 2012; Edwards and Celia, 2018; Middleton and Yaw, 2018); 7) properties of CO_2 emission sources affect the overall cost and feasibility of full-chain CCUS projects dramatically, such as high-purity CO_2 from industrial separation process in coal chemical and biochemical factories, and low-concentration CO_2 from burning and chemical reaction processes, such as coal power plants, iron and steel, cement factories, and CO_2 directly captured from air (Wei et al., 2014; Leeson et al., 2017; Porter et al., 2017; Edwards and Celia, 2018); 8) social, economic, legislation, regulation, policy, administrative procedures, and environmental constraints such as maximum down-hole injection pressure, proximity to area with high population density, risk acceptance levels, permitting and supervision procedures in the administrative system, support or incentive policy environment.

The factors causing uncertainties of CO_2 capacity evaluation mainly come from two parts: data quality (available data types and data resolution) and related algorithms are handling multiple factors and various data types. In terms of algorithms, the key factors that affect capacity evaluation can be grouped into storage mechanisms considered and constraint conditions (technical, economic, risk, regulation, legislation, and social factors). The algorithms integrate available data types with different detail levels and then assess capacity with selected factors. Because of the data scarcity, the uncertainties of CO_2 capacity evaluation decrease with higher data precision and additional evaluation factors or data types.

2.1 Data Compilation With Various Types and Resolution

The most common ways to integrate massive data are geological model building tools, GIS software, image processing tools, and data processing tools. Various types and detailed levels of available site data and corresponding algorithms can be integrated into a data compilation system.

2.1.1 Data Types

Data types can be grouped into subsurface data (underground geological data) and surface data (geological and non-geological data). The data types and spatial scales for storage capacity are shown in **Table 1**. Aquifer formations have substantial spatial variations of physical and chemical properties due to multiple-scale heterogeneity, leading to significant uncertainty in the storage assessment (Lv et al., 2015; Han and Kim, 2018; Jayne et al., 2019; Wen and Benson, 2019). Consequently, the uncertainties of storage capacity evaluation are always defined on the basis of the deep underground data or site characterization.

Subsurface Geological Data

The subsurface geological data can be classified into several types at various spatial scales: 1) properties of reservoir-seal pairs, geographic sequence, and spatial distribution of sedimentary

TABLE 1 | Various data types and spatial scales for storage capacity evaluation.

Data types	Components of data types	Data resolution
Sub-surface geological data (geological model)	Stratigraphic sequence and tectonic units at various levels;	Sub-basin to basin scale
	Spatial distribution of sedimentary facies and lithology	Sub-basin to site scale
	Site characterization data include well drilling, 2D/3D seismic investigations, electromagnetic investigation, micro-gravity, down-hole geo-physical and chemistry sampling, core samples, and others	
	Physical and chemical properties of rock reservoir-seal pairs such as porosity, permeability (relative permeability), capillary pressure curve, lithology, and others	Site-scale and core-scale
	Hydraulic flow and water quality data in a deep geological formation	Site scale
	Boundary conditions, including hydrodynamic boundary, basin dynamic processes, lithology, geothermal field, and others	Site scale
Surface geological data	Surface geological map, including a geographic map, geological sequence, well coordination, landform map, national resources, national reserve parks, rivers, lake systems, and other datasets	Sub-site scale
	Hydraulic flow and water quality data in shallow ground	Core to sub-site scale
	Shallow investigation wells and other investigation data	Core to sub-site scale
Surface non-geological data (data stacks and GIS data)	Underground human activities, such as exploring wells, coal mining, oil and gas production, geothermal recovery	Sub-site scale
	Social and economic distribution, including cities, industrial centers, population centers, transportation, underground activities, and others	Sub-site scale
	Legislation and regulation constraints	Sub-site scale
	Policy and administrative systems in different regions	Sub-site scale
	Economic parameters	Project or equipment scale
	Others	Sub-site scale

facies system and lithology with different physical and chemical properties, such as lithology, pressure, temperature, porosity, and permeability, entry pressure, compressibility, thermal conductivity, and other properties; 2) boundary conditions (open, semi-open, or closed systems), tectonic setting (active/inactive faults with/without vertical communication among different geological stratum), and sedimentary facies system (continuity at a regional scale); 3) geo-fluid properties (water salinity, viscosity, phase behavior, density, capillary pressure, solubility, empathy, and dynamic thermal properties) (Dewers et al., 2018). The characterization data of reservoir-seal pairs mainly include spatial distribution of physical and chemical properties, such as porosity, permeability, relative permeability, capillary pressure, geochemistry, minerals, *in-situ* pressure, temperature, lithology, salinity, rock compressibility, fracture pressure, and mechanical properties of rock. The boundary conditions mainly focus on the open or closed boundary, such as outcrops of aquifer formations, low-permeable facies, impermeable or permeable faults, and other potential leakage pathways. The regional geological data focuses on the sedimentary system, tectonic, and diageneses process at a basin- and sub-basin scales.

The various types and detailed levels of geological data should be assimilated into data collection and evaluation tools. The most common methods to incorporate massive data are geological models, geographic information system (GIS) data, image processing models, data stacks, and other geological models or software. In most scenarios, these geological data can be compiled into GIS systems, such as ArcGIS, MapGIS, MapInfo, QGIS, and reservoir modeling software used by the petroleum industry, such as CMG by Computer Modeling Group, Schlumberger's Petrel software, landmark, Geostatistical Software Library, and GoCAD (Iea-Ghg, 2009; Jiao and Surdam, 2013; Li et al., 2015). Using reservoir modeling tools, various algorithms based on geological models can calculate storage efficiency coefficients and CO2 storage capacity.

Similar to deterministic and stochastic methods, two types of geological models, homogeneous and heterogeneous, are used in capacity evaluation. Homogeneous models can be generated using the average properties of reservoirs derived from the database. The storage coefficient factor in a homogeneous model can be calculated using the algorithms above. A heterogeneous model can be built considering the spatial distribution of lithology, structural settings, geochemical environment, and mineral composition. The properties can be derived from site characterization or dataset extrapolated from the well-known nearby site by theoretical reservoir engineering analysis. The resolution of the heterogeneous model depends on the resolution of site characterization and data extrapolation. With sufficient data and extrapolation tools, the results of the heterogeneous model can cover a more comprehensive uncertainty range than that of the homogeneous model. However, homogeneous models for large-scale evaluation are more plausible than heterogeneous ones because they are time-saving, efficient, and available in building models, and efficiently perform with limited data, especially in the stochastic analysis that requires large computation capacity.

These site-scale data usually contain well drilling and logging, 2D/3D seismic investigation, micro-gravity investigation, site operating data, geodetic survey, and other sources (Birkholzer and Tsang, 2008; Kim et al., 2014). However, available geological data in the petroleum industry are limited before detailed site characterization. The confidence of geological investigation is always defined by the number of investigation wells and density of seismic investigation in the geological volume of interest. More flexible methods such as the variable grid method can allow various data qualities while preserving the overall spatial trends and patterns (Bauer and Rose, 2015).

Surface Data

The surface data are mainly non-geological and can be grouped into several types: 1) geological data including surface geological characteristics, lithologies, metamorphic rock, igneous rock, stratigraphic contour line, earthquake records, first and secondary tectonic units, outcrops, and others; 2) geographic and geomorphic data including mountains, water system, landform, climate, precipitation, wind energy, solar power, geological hazards, and other features; 3) social and environmental data, including CO_2 emission sources, transportation system, natural preservation park, mining, natural resource, oil and gas field, well information, vegetables, cities, population, industry, economic density area, infrastructure, economic parameters, climate, evaporation, water system, natural preserves, and others. These surface data can be compiled using various data forms of point, polyline, polygon, raster, vector, data stacks, or other types such as ArcGIS, MAPGIS, Access, and mathematical tools developed by various computing languages. The algorithms related to non-geological factors can refer to existing algorithms that perform site suitability and risk analysis. These algorithms include multi-criteria analysis with empirical or statistical criteria, analytic hierarchy process, spatial analysis in GIS systems, numerical modeling, probability analysis, and others (Ellett et al., 2013; Wei et al., 2013). Using knowledge integration and data assimilation of the multiple types of site data at multiple scales and theories of sedimentary basin evolution can improve geology assessments (Popova et al., 2014; Dilmore et al., 2015).

2.1.2 Resolution of Data

The detail level of various data types can be grouped according to the data types above.

Sub-surface Geological Data

Data resolution or accuracy is the smallest difference between adjacent positions/sites that can be recorded at a spatial dimension. The resolution is also the character difference between the interpreted value and the true value. Data uncertainties are the combined effect of site investigation and data interpretation tools; the uncertainty from data compilation tools handling massive data can be neglected. The resolution of site data depends highly on the coverage and details of site characterization tools. In order of decreasing resolution and increasing coverage, these tools inlcude petrophysical and chemistry properties experiments at pore and core scale, well drilling and logging, geophysical investigation (such as profile interpretation crossing multiple wells, 2D/3D seismic investigation, and micro-gravity investigation), and theory of sedimentary process and tectonic activities. Current site characterization is usually conducted by standard petroleum and underground mining technologies. The proximate resolution of site characterization generally ranges from 0.1 m to several hundred meters depending on the characterization approaches and spatial correlation from investigated points with high resolution by well logging and core analysis to low-resolution points by seismic investigation and profile interpreted by data assimilation. The assimilation of various data sources can provide reliable geological models of storage sites (Chen et al., 2020a). However, most capacity assessments are conducted before the stages of detailed site characterization and the stage of contingent resource assessment; the spatial resolution of geological data is much lower than that of seismic investigations. Therefore, the ideal geological model should be built using sufficient data obtained by various site characterization tools and data interpretation tools. These tools contain core characterization, well logging, 2D/3D seismic survey, electromagnetic investigation, micro-gravity investigation, theoretical basin modeling technologies (sedimentary, tectonic, and diagenesis theory), etc.

Nevertheless, data scarcity and imbalanced datasets are common; this decreases the certainties of assessed capacity. The quality of geological data can be defined by the number of investigation wells with well logging or the coverage of 3D/2D seismic investigation in a given area (Pearce et al., 2013; Niemi et al., 2016; Chen et al., 2020a). Although the subsurface data can be refined by high-cost site characterization, the uncertainties of subsurface geological data are incredibly high compared with that of surface data, which low-cost and large-area investigation technologies can obtain. The only suitable method to reduce the uncertainties of the geological model without sufficient detailed site characterization is stochastic approaches using data assimilation and synthesized modeling technologies based on available statistical data (Popova et al., 2014; Dilmore et al., 2015). The geological model can also be integrated into data compilation tools; then, the fluid dynamic analysis can be fulfilled by site performance tools, such as fluid dynamic analysis tools compatible with GIS and geological modeling tools.

Surface Data

The surface geological data can be an extension of sub-surface geological data when the data resolution is insufficient. However, the data precision of surface geological data is much higher than that of sub-surface data in most cases for abundant methods of the data acquisition and existing dataset. Consequently, surface geological data can be compiled independently. The surface geological data, especially the faults, outcrop data, geological sequence, and landform, are always presented using GIS tools by a vector (such as point, polyline, polygon, polyhedron, class, and others), raster data types, and data stacks by other mathematical tools. The spatial resolution is much higher compared with that of sub-surface data.

The non-geological data, especially surface transportation, railway, industries, mining, weather, precipitation map, legislation, economic, and social data, are always presented in GIS tools by vector or raster data types and other mathematical tools using data stacks. The acquisition technologies and resolution of surface non-geological data are considerably different from that of sub-surface geological data. A rigorous statement of accuracy can be used with statistical descriptions of uncertainty and error. For example, in raster-type data, the resolution is the effective size of each grid cell expressed as the length of each cell (or area). The units can be in (arc) degrees, minutes, or seconds in the geographic coordinate system, or meters, kilometers, and other units in the projection coordination system. Data resolution increases with the decreasing size of the cell (Naumova et al., 2006). The spatial resolution of data is shown in the form of scales, which is the smallest distance (or cellular size) that can be represented, such as 1, 250, or 2,500 m in the map of 1:2, 500, 000 scales. Most surface data on non-geological features can be obtained with a spatial resolution ranging from tens of meters to several centimeters by a series of mature technologies, such as remote sensing or multiple spectrum photographic surveys by satellites or unmanned aerial vehicles, interferometric synthetic aperture radar, geodetic surveying, national site investigation, satellite investigation (remote sensing, remote spectrum sensing, and global positioning system), and other satellite-, flight-, and vehicle-based surveying technologies with high precision. Meanwhile, the data resolution of non-geological data is much higher than the general resolution of sub-surface geological data with an average spatial resolution of several meters or tens of meters. The resolutions of surface data are sufficient for capacity evaluation at various scales, such as reservoir and site scales. Most GIS data are spatially analyzed in the form of features, polygons, or raster data. Given specific social, economic, legislative, and regulatory constraints, the uncertainties of CO_2 capacity evaluation mainly come from the available data and algorithms of sub-surface geological features rather than surface features.

This data quality review clarifies that future efforts focused on site characterization and data collection of geological formations with favorable reservoirs may provide a more useful settlement for capacity evaluation and feasibility studies on CO_2 aquifer storage projects.

2.2 Technical Schemes and Storage Mechanisms

Assessing the CO_2 storage capacity in aquifer formation is challenging because of complex trapping mechanisms that simultaneously act at different rates and timescales in the highly heterogeneous formations (Bachu, 2015; Aminu et al., 2017; Elenius et al., 2018). In target formations, CO_2 is trapped underground using various types of trapping and storage mechanisms, such as stratigraphic and structure, dissolution, chemical, residual gas, geothermal, and adsorption trapping (Bruant et al., 2002; Yang et al., 2010; Szulczewski et al., 2012; Wang et al., 2013; Emami-Meybodi et al., 2015; Krevor et al., 2015). Due to the timescales of CO_2 storage projects, free gas trapping and non-reactive solubility trapping are major mechanisms in most reservoirs during the CO_2 injection period; the geochemistry and residue trapping gradually have a significant role in the post-closure stage (Gorecki et al., 2009b). The fraction of various storage mechanisms evolve with time and highly depends on reservoir characteristics (Gorecki et al., 2009d; De Silva and Ranjith, 2012; Aminu et al., 2017). At present, most existing methods mainly consider free gas, solubility trapping, and residue trapping mechanisms, which contribute mainly during the CO_2 injection period or post-closure (Aminu et al., 2017). Few storage capacity estimation approaches have considered the mineral, adsorption, and other trappings due to fewer contributions, complexity, and long-time effect without efficient history matching (Aminu et al., 2017). In these approaches, the geological model-based numerical simulations are considered relatively accurate approaches considering key trapping mechanisms at various time scales (from injection periods to thousands of years) and spatial scales (from the core-to the basin-scale).

The portions of trapping mechanisms in a given CO_2 storage project depend on the impact of the technical scheme of the CO_2 injection process, reservoirs characteristics, and other properties. The complexity of CO_2 migration created by reservoir heterogeneity and pressure buildup affects portions of various storage mechanisms and results in various storage efficiency coefficients and ultimate storage capacities (Deng et al., 2012; Birkholzer et al., 2015; Chadwick et al., 2019). The CO_2 preferentially migrates through the high permeable channels or fans toward the low-resistance boundary, which are caused by hydrodynamic effects in open boundaries and compressibility of high-volume fluids, expansion of reservoirs, quick dissolution in brine water, quick chemical reactions with rock, and others in closed systems (Zhou et al., 2008; Birkholzer et al., 2015). The main highly permeable channels, delta sheets, and fans always exist in heterogeneous reservoirs with complex sedimentary environments, tectonic history, and diagenesis processes. The preferential migration patterns of CO_2 plume in formations reduce the areal and vertical displacement efficiency and ultimately decrease the storage efficiency of CO_2 in a given geological volume; proper technical schemes can hamper the preferential flow and control conformity in the reservoir. The technical schemes of CO_2 storage significantly affect the site performance, consequently injectivity, storage efficiency, capacity, economy, risk management, and even site feasibility (Okwen et al., 2011; Thanh and Sugai, 2021).

Most existing capacity approaches have the theoretical capacity with a sole injection of CO_2, which is related to the consideration of storage mechanisms and geological characteristics, such as porosity, gross thickness, permeability, area, hydrodynamic parameters, and boundary conditions. However, large volumes of CO_2 injection in deep saline aquifers can trigger large-scale pressure buildup and brine/contamination displacement, reduce storage efficiency by increasing *in-situ* pore pressure, and impeding water migration to a nearly geological volume beyond what is permitted (Birkholzer et al., 2009; Bergmo et al., 2011; Wainwright et al., 2013; Birkholzer et al., 2015). The geological space for CO_2 is mainly created by the displacement process of water in the open system and water compression and rock extension in the closed boundary system; by contrast, space for CO_2 is mainly created by the compression of water and expansion of rock mass in a closed system (Zhou et al., 2008; Iea-Ghg, 2009; Szulczewski et al., 2014; Liu et al., 2015). The CO_2 capacity is limited in migration and pressure, thereby requiring the pressure management technologies through engineering technology to decrease reservoir pressure buildup and restrain the size of the CO_2 footprint (Surdam, 2013; Liu et al., 2015; Anderson, 2017).

The pressure buildup phenomena increase the risk of hydraulic fracturing of caprock, the reactivity of existing faults, leakage through caprock, leakage through lateral pathways, and ultimately pose a high risk on storage projects and limit the CO_2 storage capacity underground. In the CO_2-EWR process, similar to that of CO_2 enhanced crude oil recovery, CO_2 functions in a manner similar to a displacement fluid to enhance the recovery of water resource, and CO_2 is trapped underground simultaneously (Bergmo et al., 2011; Damiani et al., 2012; Emami-Meybodi et al., 2015; Santibanez-Borda et al., 2019; Song et al., 2019). The operating procedure of CO_2-EWR is similar to that of CO_2-EOR but with much larger well spacing, well injectivity, and flow rate of a single well. The sweep efficiency, capacity evaluation, and sweeping efficiency approaches can be based on these generic methods and tools in the petroleum and geological industry to improve storage capacity.

The engineering approaches, e.g., well field, well type, conformity control, hydraulic fracturing, and other technologies, can use pressure mitigation or water production wells to store CO_2 safely and efficiently at the site or regional scale and keep the mass balance underground. These engineering approaches can bring several benefits such as creating underground space for CO_2 storage, enhancing CO_2 injectivity and water production, mitigating pressure buildup, and enhancing utilization of porous spaces underground (Kuuskraa et al., 2011; Okwen et al., 2011; Zhang et al., 2014). The types of well patterns could be five-spot, inverse five-spot, seven-spot, nine-spot, or other type of the well patterns that can be optimized and refined according to the reservoir properties and site performance. The diverse types of well structure include vertical/horizontal with multiple branches and perforations, reservoir reform (permeability improvement by hydraulic fracturing, acid, or other chemical components), and complex well structure (horizontal/multilateral wells with multistage perforation into multiple geological layers). A good wellfield increases the contact area between well boreholes and reservoir and then enhances the storage efficiency coefficient of CO_2. Similar to efforts in the petroleum and geological investigation industries, the sweep efficiency and storage capacity can be enhanced by existing methods and next-generation technologies under development (Zhang et al., 2014; Costa et al., 2019). The disadvantage is the requirement of additional engineering technologies, which could increase the capital and operating costs. A conformity control technology suitable for geological heterogeneity with fluvial facies significantly affects the storage efficiency coefficient. The conformity control technologies include refinement of well field, injection-production management, surfactant, thickness, impurities, gravity-stabilizing gas injection, cycling injection, water-alternating-gas, thermal effect, hydraulic fracturing, and several next-generation CO_2–EOR/storage technologies (Bergmo et al., 2011; Damiani et al., 2012; Wei et al., 2015b; Emami-Meybodi et al., 2015; Goodarzi et al., 2015; Krevor et al., 2015; Talman, 2015; Wang et al., 2015; Wang et al., 2016; Ampomah et al., 2017). The technical scheme includes the well drilling and complement, storage equipment, and operating and maintenance procedures that can be designed accordingly.

The technical schemes significantly affect storage processes, safety, and storage capacity in aquifer formations. Consequently, assessing the storage capacity of a given aquifer site should consider technical schemes extensively.

2.3 Algorithms for Capacity Assessment of Geological Volume

The various types of storage capacity are calculated by algorithms that integrate various data types and detailed levels of data. These algorithms for storage capacity should integrate factors such as selection of storage mechanisms, site suitability, technical schemes, techno-economic properties, and source-sink proximity.

2.3.1 Algorithms for Storage Mechanisms and Sub-surface Geological Data

The algorithms for storage mechanisms are based on cross-scale science with spatial scales from the pore, reservoir, and site to regional and temporal scales from tens to thousands of years (Middleton et al., 2012a; Middleton et al., 2012b). The cross-scaling algorithms should overcome the cross-scale effect, including upscaling or downscaling various spatial and temporal scales. The algorithms can quantitatively estimate the spatial migration of CO_2 and other physicochemical responses in a reservoir. Numerous assessments on CO_2 storage mechanisms have been conducted based on various data types and precision as well as assessment algorithms, starting with static volumetric algorithms underpinned by deterministic-based reservoir models and progressing through an analytic model, reduced-order methods (ROMs), numerical simulation, and dynamic algorithms with advanced site characterization, at a variety of spatial scales ranging from country scale to site-specific scale and temporal scales ranging from injection period to thousands of years after CO_2 injections (De Silva and Ranjith, 2012; Cantucci et al., 2016; Höller and Viebahn, 2016; Middleton and Yaw, 2018).

The existing capacity evaluation at a large scale without detailed site characterization always uses simplified geological models and empirical-, analytic- and simplified numerical models to provide a reasonable capacity magnitude assessment (Claridge, 1972; Middleton et al., 2012a; Wei et al., 2015a). Most methods rely on theoretical and geo-cellular volumes of the storage reservoir considering certain storage mechanisms in a specific period, e.g., from CO2 injection to cession of injection or the ultimate status of injected CO_2 (Cantucci et al., 2016). The dynamic approaches predict the temporal and spatial behavior of injected CO_2 and reservoir responses over a desired period (Aminu et al., 2017). In contrast, static models are at equilibrium or in a steady state. Therefore, the static and dynamic methods are equivalent through conversion when dynamic approaches predict CO_2 behavior at a specific time.

Statistical Algorithms

When statistical data are available, the storage efficiency coefficient can be obtained by applying the commonly established static algorithms using pore volumes of geological formations and storage coefficients under desired conditions, e.g., mass-balance conditions. The statistical algorithms for storage capacity efficiency can be simplified as a product of various components, especially when the correlation coefficients are weak. In general, the statistical distributions of various components are diverse; the logistic-normal and normal distribution functions were mostly chosen to describe geological parameters and the storage efficiency coefficients (Middleton et al., 2020).

Most-capacity evaluation methodologies currently use volumetric-based or mass-balanced approaches for estimating theoretical CO_2 capacity in a geological medium at regional and sub-basin scales (Goodman et al., 2011; Goodman et al., 2016). The US-DOE, Carbon Sequestration Leadership Forum (CSLF), International Energy Agency, Greenhouse Gas R&D Programmer, and the United State Geological Survey (USGS) have independently developed methodologies for capacity assessment of CO_2 storage in open aquifers (Bachu et al., 2007; Bradshaw et al., 2007; Co2Crc, 2008; Zhou et al., 2008; Iea-Ghg, 2009; Kopp et al., 2009a; Kopp et al., 2009b; Goodman et al., 2011; Goodman et al., 2013; Doe-Netl, 2018). These most cited approaches have been applied around the world for basin- and country-scale assessments (Bachu, 2015). These approaches are based on similar assumptions on storage mechanisms, such as free gas trapped by the stratigraphic structures or hydrodynamic systems, solubility, reaction, or residue trapping. The US-DOE method calculates the CO_2 storage capacity based on a volumetric approach with sweeping efficiency by hydrodynamic processes. The CSLF method states that the theoretical capacity is the maximum amount of CO_2 that can be stored in the pore space minus the irreducible water saturation. The USGS method assesses capacity using both residual and buoyant trapping mechanisms in the open part of the aquifer (Brennan et al., 2010; Aminu et al., 2017). Only structural and stratigraphic trappings were considered as key storage mechanisms rather than hydrodynamic trapping (Bachu, 2015; Aminu et al., 2017). Given the same technical schemes and conditions of geological stratum, most methodologies can be equally applied to aquifers or regions of interest; these methodologies and approaches are equivalent through some conversions among various factors, such as storage efficiency coefficients (Brennan et al., 2010; Goodman et al., 2013). However, closed and semi-closed systems' storage capacities are significantly different from those in open systems (Zhou et al., 2008; Bader et al., 2014; Elenius et al., 2018). The compressibility/expansion-based (or pressure-limited) algorithms for closed and semi-closed systems assume that injected CO_2 displaces natural brine and occupies additional pore volume caused by pore geometry expansion and brine compressibility during the pressure buildup processes; consequently, the assessed results are limited (Zhou et al., 2008).

The basis for capacity estimation is essentially the integration of the production of the volume of storage formation, storage efficiency coefficient, and average CO_2 density at reservoir conditions (ρ_{CO2}) (Doe-Netl, 2018), as follows:

$$G_{CO2} = \int \rho_{CO2} \cdot \varphi_{tot} \cdot E_s \cdot dV = \iiint \rho_{CO2} \cdot A \cdot h_g \cdot \varphi_{tot} \cdot E_s \cdot dx \cdot dy \cdot dz, \tag{1}$$

$$G_{CO2} = \rho_{CO2} \cdot V_{bulk} \cdot E_s = \rho_{CO2} \cdot A \cdot h_g \cdot \varphi_{tot} \cdot E_s, \tag{2}$$

where V_{bulk} is total pore volume of geological formation for assessment [L^3]; ρ_{CO2} is CO_2 density under reservoir conditions [M/L^3], A is the surface area for reservoir [M/L^3], φ_{tot} is the porosity of reservoir [-], E_s is storage efficiency coefficient [-], which is defined as the proportion of available pore volume accessible for storage. E_s reflects the fraction of a given geological volume in which CO_2 can be effectively stored (Gorecki et al., 2009b). For high-resolution evaluation, the resource can use discrete methods by dividing the site of interest into cellular or grid aggregation (**Eq. 1**). The cellular size is determined by the detailed level of geological data and the resolution requirement of evaluation.

$$G_{CO2} = \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{L} G_{CO2\ i,j,k} = \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{L} \left(A_{i,j} \cdot h_{i,j,k} \cdot \varphi_{i,j,k} \cdot \rho_{CO2\ i,j,k} \cdot E_{s\ i,j,k} \right), \tag{3}$$

where G_{CO2} [M] is the mass estimate of CO_2 capacity; A [L^2] is the surface geographic area defining the geological volume for storage; $G_{CO2\ i,j,k}$ [M] is the CO_2 capacity of the cellular i, j, k being assessed within the region; $h_{i,j,k}$ is the gross thickness of the cell i, j, k [L]; $\varphi_{i,j,k}$ [-] is the total porosity of the assessed formation volume; $\rho_{CO2\ i,j,k}$ is the density of CO2 evaluated at storage conditions [$M.L^{-3}$]; N, M, L is the maximum index number for i, j, k dimension, respectively; and $E_{s\ i,j,k}$ is the storage efficiency coefficient in cells i, j, k and is the product of several factor components [-]. In general, the storage coefficients increase with decreasing evaluation scale, and the uncertainties of CO_2 source decrease with reducing evaluation scale.

When the grid or cellular sizes differ, the variable grid or cellular methods are more flexible methods that allow for capacity assessment with different spatial sizes with different data quality (Bauer and Rose, 2015). Storage efficiency coefficients also depend on storage mechanisms acting at different spatial scales (cellular size) and temporal scales. At national and regional (basin) scales, the empirical and analytical methods can speedily obtain reasonable resolution storage efficiency coefficients (Iea-Ghg, 2009). At the site scale, detailed geological models and reservoir modeling tools can be used for storage efficiency coefficients and storage capacity with more storage mechanisms and higher resolutions.

Multiple physical and chemical coupling processes must be embodied in complex geological models and assessment tools to apply more trapping mechanisms accurately. Using existing algorithms and tools, CO2 capacity evaluation with detailed site characterization can achieve very high resolution (Wei et al., 2015a; Rezk and Foroozesh, 2019; Wen and Benson, 2019). Advanced approaches with more data can provide more reliable capacity results considering more storage mechanisms and more detailed site characterization data over a desired period, especially with monitoring and production history data (Rezk and Foroozesh, 2019; Wen and Benson, 2019). However, no single approach can simulate all these coupling processes of trapping mechanisms reliably at once, nor is such a model necessary for practical purposes.

Current dynamic approaches rely highly on geological models and numerical algorithms with limited resolution and inconclusive factors before detailed site-specific data and history matching (Bachu, 2015). By contrast, the analytic and simplified numerical approaches are more flexible and applicable with precious data of limited site characterization and computation resources. Accordingly, the static approaches with statistical and analytical algorithms have been used broadly and routinely in large-scale capacity assessments compared with the dynamic methods because of more flexible and applicable with limited site characterization. (Cslf, 2008; Doe-Netl, 2018).

Analytical Algorithms

Analytical algorithms using several assumptions can quickly obtain storage capacity. These analytical algorithms include those for multiphase flow, semi-analytical algorithms of multiphase (two-phase) flow, solute-transport models of multiple phases and multiple species, coupled multiphase-reaction-temperature algorithms, coupled geomechanics-flow algorithms, and others (Claridge, 1972; Nordbotten et al., 2005; Okwen et al., 2010; Szulczewski et al., 2014; González-Nicolás et al., 2015; Ganjdanesh and Hosseini, 2018; Middleton et al., 2020; De Simone and Krevor, 2021). The analytical algorithms are preferred because they require a relatively small amount of data based on the idealized or conceptual model and can provide quick assessments with acceptable resolutions, especially for basin or sub-basin scale evaluations with limited data. However, the analytical algorithms must use several assumptions to solve the equations mathematically but miss important mechanisms of the CO_2 storage, such as heterogeneity of aquifer formation, injection strategy, buoyancy, mobility ratio, multi-phase dissolution, rock-brine-CO_2 interaction, and others. Consequently, the usage of these algorithms should be careful under certain conditions.

These approaches can also be grouped into deterministic methods and stochastic methods in the perspective of data of site characterization. The geological formation has substantial spatial heterogeneity of physical and chemical properties due to a complex history of sedimentary, tectonic, and diagenetic processes, and the heterogeneity causes significant uncertainties in capacity and site performance assessment (Burruss et al., 2009; Lv et al., 2015; Han and Kim, 2018; Jayne et al., 2019; Wen and Benson, 2019). The data of site characterization under the development stage are still sparse and have extremely high uncertainties. Providing limited data with high uncertainties, the only appropriate and reasonable way to describe the capacity uncertainty is using deterministic approaches based on the statistical data of site properties (Popova et al., 2014). The stochastic methods can be implemented using the statistical properties of site properties as input parameters. These statistical distributions can be in the logistic normal, normal distribution, and other forms (Popova et al., 2014). Statistical data from underground resource recovery projects are helpful to determine the storage efficiency coefficients. Organizations and researchers have established several global databases, including a large volume of reservoir data on geological formations with different lithologies and depositional environments, structures, and traps to determine storage coefficients based on examination of worldwide existing CO_2 storage projects and properties data on hydrocarbon reservoirs (Gorecki et al., 2009d; Iea-Ghg, 2009). For high-resolution evaluation, provided that each cellular with storage potential has various parametric distribution functions for each storage efficiency, the individual p values of different storage factors are multiplied to determine the distribution of storage efficiency coefficient $E_{s\ i,j,k}$ for cellular i, j, k.

Numerical Algorithms

Multiple numerical tools using different algorithms have been used worldwide, such as TOUGH2, ECLIPSE, GEM, CO_2-PENS, STARS, NUFT, TRANSTOUGH, MODFLOW, FLOTRAN, SIMUSCOPP, STOMP, MORES, finite element heat, and mass transfer code (FEHM), novel reservoir monitoring, modeling, and simulation (NORMS), MATLAB reservoir modeling tools (MRST), and other tools (Ennis-King and Paterson, 2007; Pruess and Spycher, 2007; Nordbotten et al., 2012; Ranjith et al., 2013; Teletzke and Lu, 2013; Celia et al., 2015; Møll Nilsen et al., 2015; Rezk and Foroozesh, 2019; Wen and Benson, 2019). With a comprehensive geological model based on site characterization, numerical simulation can determine the distribution range of storage efficiency coefficients (Yoshida et al., 2016). Numerical algorithms are capable of providing more flexible and precise results than statistical and analytical algorithms. However, the uncertainty that stems from numerical tools and numeric algorithms incorporating various storage mechanisms persist.

The integral modeling of multiple-phases fluid properties, CO_2 plume behavior, pressure spreading, and reactive-transport process, mechanic process at various temporal and spatial scales depend greatly on storage mechanisms, appropriate geological model and gridding, cross-scaling of geological properties, upscaling methodology, and result interpretation, but less on numerical modeling algorithms (Nordbotten et al., 2012; Teletzke and Lu, 2013; Thanh and Sugai, 2021). Uncertainty modeling, which uses statistical data and stochastic tools to improve the predicted results, may measure the uncertainties of CO_2 capacity to a certain extent, but it is inadequate for describing the overall uncertainties. History matching using time-lapse monitoring is essential to enhance predictions on the site's long-term performance and CO_2 behavior underground (Nordbotten et al., 2012; Jenkins et al., 2015; Chen et al., 2020a). Furthermore, site characterizations and experiments at multiple scales ranging from pore scale to site-scale reveal the basic parameters of the storage process. These basic parameters depend on characteristics and upscaling methodology at a smaller scale, such as pore geometry, capillary pressure, rock and fluid properties, interfacial tension, wettability, pore geometry, molecular diffusion, hydrodynamic dispersion, water salinity, surface minerals, as well as the mineralization and precipitation process (Pruess et al., 2004;

Middleton et al., 2012a; Yoshida et al., 2016). The appropriate geological model and gridding that reflects the cross-scaling of complex geological properties by site characterization, complex properties with multiple phases fluid, algorithms reflecting various trapping mechanisms, and heterogeneous reservoir properties are the keys to resolving the uncertainties in numerical simulation (Middleton et al., 2012a; Bouquet et al., 2016; Yoshida et al., 2016). Meanwhile, essential questions relating to CO_2 storage cannot be predicted convincingly to a satisfactory accuracy with existing numerical simulation tools, even for highly idealized problems (Nordbotten et al., 2012).

Reduced-Order Methods

Authority must be verified by applying sensitivity analyses or stochastic analysis of key variables based on field or statistical data, especially for complex reservoir-seal systems (Pawar et al., 2017; Alcalde et al., 2018; Jin and Durlofsky, 2018). A quick way to simulate an entire reservoir is the application of ROMs, which can understand complex processes with acceptable computational efficiency (Pawar et al., 2015; Chen et al., 2020b; Middleton et al., 2020). The development of ROMs requires a series of simulations or calculations of detailed component models for reservoirs, wellbores, caprock, faults, and aquifers; then, ROMs can be integrated to predict site performance, economic feature, and geological risk (Pawar et al., 2015; Chen et al., 2020b).

The ROMs for CO_2 injection in heterogeneous reservoirs are used to quickly estimate site performance and CO_2 capacity based on values of key dimensionless scaling groups (Stauffer et al., 2011; Harp et al., 2016; Pawar et al., 2017; Jin and Durlofsky, 2018). This algorithm combines simplifications of full-order flow simulation, linearization of a nonlinear system, projection into a low-dimensional sub-space using proper orthogonal decomposition, or other ways to reduce the complexity of computation and storage mechanisms (Jin and Durlofsky, 2018). The ROMs link basic parameters, storage mechanisms, and site performance assessment. They are more efficient for high-effort and quick simulations than conventional simulations; nevertheless, they cannot decrease the uncertainties similar to numerical simulation.

Hybrid Algorithms

Algorithms should make the best of limited subsurface data. For example, based on known geological theory and site characterization data, geological interpretation tools can be used to generate a spatial distribution of reservoir parameters reflecting the correlativity. Then, the proper algorithm can be selected to assess the geological storage efficiency coefficient (Popova et al., 2014). However, suppose the data scarcity varies in different regions. In that case, the variable grid or cellular methods with hybrid algorithms are more flexible methods that allow for capacity assessment with various data quality while still preserving the overall spatial trends.

Hybrid algorithms can integrate different algorithm components and related datasets in a comparative way for the assessment of site performance and capacity. The hybrid algorithms can start with volumetric calculations underpinned by deterministic statistical models with limited site data and progressing through probabilistic analyses, and dynamic storage assessments using reservoir simulation with dynamic heterogeneous reservoir models that compile and assimilate detailed site characterization.

Discussion on Capacity Algorithms

The mathematical theories, evaluation procedures, and data requirements for the above capacity algorithms vary greatly. The available algorithms and tools for storage capacity estimation can be grouped into several large class sets as empirical, semi-analytical, ROMs, numerical simulations, and hybrid algorithms. The precise and detailed comparisons of existing algorithms have been carried out (Pruess et al., 2004; Bachu, 2008; Goodman et al., 2013). It illustrates that currently available simulation codes could model the complex phenomena with quantitatively similar results but significant discrepancy from fluid properties and discretization approaches (Pruess et al., 2004; Nordbotten et al., 2012).

Future work should focus on site characterization, data collection, advanced data assimilation, and highly effective algorithms that reflect the effects of storage mechanisms to reduce uncertainties in the capacity evaluation and provide the uncertainty ranges of each dataset, algorithm, and integrated method. Among these, the data quality of site characterization is of priority.

2.3.2 Algorithms for Site Suitability

Suitable sites for CO_2 storage should have favorable physical and chemical properties or reservoir-seal pairs to ensure sufficient storage capacity, enough injectivity, acceptable risk, compliance with current legislation and regulation systems (Wei et al., 2013; Pawar et al., 2015). Aside from geological stratum and storage mechanisms, the maximum storage capacity is also constrained by costs, site safety, or risk of stored CO_2 (Mathias et al., 2015; Alcalde et al., 2018). Extensive studies have illustrated with very high confidence that CO_2 stored in thoroughly screened sites is safe over geological timescales, and leakage is unlikely. A safe or suitable site means that mature engineering procedures can manage the risk of a selected site to an acceptable risk level at a reasonable cost. The process of identifying suitable sites for CO_2 storage is based on classifications of resource and project status similar to that used in the hydrocarbon industry (Doe-Netl, 2018). Various qualitative- and qualitative-algorithms or methods are being used for site suitability evaluation and site selection, e.g., guidelines, best practice menu, multi-criteria analysis, probability analysis, fault tree, feature, and event and process (FEP), health-safety-environmental risk-based method, integrated assessment model-carbon storage, National Risk Assessment Program (NRAP), site performance assessment, and others (Pawar et al., 2015; Hnottavange-Telleen, 2018). These algorithms can be grouped into three aspects: techno-economic optimization, risk minimization, and other social-economic constraints.

Technical and Economical Optimization

The CO_2 storage project aims to find a suitable site with favorite storage volumes and injectivity. These characteristics can be estimated based on storage cost using available storage volume and injectivity parameters (Mathias et al., 2015). The algorithms might strongly correlate with those for storage mechanisms (Mathias et al., 2015).

Risk Minimization

CO_2 capacity is constrained by geological volume and related risk, which allow the areal and vertical spread of CO_2 plume without significant impacts; consequently, a crucial task is to specify the influence volume and surface area that can be assigned for CO_2 geological storage. The primary risk is leakage of CO_2 and brine with/without dissolved CO_2 into overlying strata, protected aquifers, shallow soil zones, and the atmosphere, and other health, safety, and environmental (HSE) impacts. Considerable experience has been gained on managing site performance and long-term risk containment and identifying key uncertainties that need to be targeted (Pawar et al., 2015). Potential leakages involve wellbores, active faults, fractures, assigned boundary impact site performance, long-term containment migration, HSE risks, public perception, and market risks. Neither permeable pathways nor reactivation by CO_2 injection should happen. The safety of storage sites depends on the integrity of cap-rock with closed faults/fracture networks and abandoned wells that have a certain possibility of occurrence (Zoback and Gorelick, 2012).

As one part of site suitability algorithms, many algorithms can be applied similarly. Algorithms such as Bayesian network, CO_2-PENS, multi-criteria method, fault tree, certification framework, QPAC-CO_2, NRAP, and other algorithms and related tools have been developed for quantitative and qualitative risk assessment applications (Price and Oldenburg, 2009; Tanaka et al., 2011; Zhang et al., 2011; Aktouf and Bentellis, 2016; Li and Liu, 2016; Dean and Tucker, 2017; Xia and Wilkinson, 2017; Hnottavange-Telleen, 2018). These approaches can also predict the behavior of the CO_2 storage process and corresponding risk (risk probability and consequence).

Social, Legislation, Regulation, and Environmental Constraints

Social, regulation, legislation, and environmental constraints mainly stem from the requirements of technical schemes and risk management of stored CO_2. The legislation and regulatory frameworks aim to protect and minimize the impact on environmental, economic, and social aspects, underground and surface resources, such as freshwater, minerals, vegetables, surface water system, national reserve parks, industrial centers, municipalities, and cities (Aminu et al., 2017). The legislative system sets prohibitions and permissions for CO_2 geological storage projects and defines the rights and obligations of stakeholders. The regulatory and legislative constraints include various rules that limit the injection activities, such as maximum bottom-hole injection pressure (e.g., 1.25 times initial pressure and less than fracture pressure), minimum total dissolved solids (TDS) of brine (TDS > 10 g/L), geological volumes or area of review permitted by administrative organizations, storage duration, conflicts with different mining rights, and relevant regions of influence (Bachu, 2015). The social and economic constraints mean that the storage sites should avoid potential negative effects on the surface or underground activities, such as clandestine mining activities, oil and gas reservoirs, geothermal utilization on natural reserves, water sources, and metropolitan and crucial industrial areas. Depending on the combined effect of the factors above, the cellular or rock block conflicted with vital activities or features might not be able to obtain permission from administrative organizations as assigned geological volume to inject any CO_2 (Dixon et al., 2015). The algorithms handling these restrictions can be integrated into storage schemes and risk assessment algorithms addressing risk probability and risk consequence.

2.3.3 Algorithms for Techno-Economic Evaluation of Full-Chain CCS Projects

The costs of CO_2 storage operations are heavily dependent on a combination of site characterization, injection and operating strategy, MVA, and risk management strategies; meanwhile, storage cost contributes an assignable part of the overall cost of the CCUS project, especially when the injectivity of the single well is low or storage-related risk is high (Mathias et al., 2015; Anderson, 2017). The techno-economic models embodying algorithms include two parts: a technical model (technical design and site performance similar with algorithms for capacity assessment of geological formations) and an economic model. Numerous economic models of CO_2 storage have been built globally (Mccoy and Rubin, 2008; Middleton and Bielicki, 2009; Knoope et al., 2014; Leeson et al., 2017; Bui et al., 2018; Middleton et al., 2020; Zimmermann et al., 2020). In general, an algorithm considering more parameters of technical characteristics and economic parameters obtains costs with higher resolution and lower uncertainty.

The suitable stages of techno-economic algorithms range from conceptual analysis, pre-feasibility studies, front-end engineering design (FEED) to feasibility-scale studies. Accordingly, technical algorithms can be grouped similarly with capacity algorithms. Economic models based on corresponding technical models can be grouped into empirical or statistical, budgetary, and accounting models. However, most of the available techno-economic models in the literature are mainly empirical models using statistical cost data from petroleum industries.

2.3.4 Algorithms for Source-Sink Matching

Geological uncertainty propagates through the chain of CCS systems and affects decisions for CCUS deployments. The uncertainty effect of capture properties of CO_2 emission sources, geological features, and geographic features can cause the overall cost of CCS projects to deviate highly; potential CCS projects, particularly pipeline networks and integration of various industry sectors, can considerably diverge spatially (Ambrose et al., 2009; Zheng et al., 2009; Middleton et al., 2012b; Dahowski et al., 2012; Welkenhuysen et al., 2013; Bachu, 2016; Sun and Chen, 2017; Edwards and Celia, 2018; Costa et al., 2019; Yu et al., 2019; Guo, 2020). Defining the capacity magnitude and ranges of levelized costs for matched capacity over the set of modeled CO_2 sources and storage reservoirs is the best way to understand the role and potential of CO_2 aquifer storage in background of carbon mitigation and carbon neutrality (Patricio et al., 2017; Costa et al., 2019; Li et al., 2019).

The economic factor of potential CO_2 storage projects is essential for the feasibility and affordability of CO_2 storage projects. Affordable CO_2 capacities can be fulfilled cost-effectively under specific punitive or incentive policies, such as carbon constraints, carbon incentives, product subsidies, infrastructure support, and other supports under a supportive environment. This condition also means that only small parts of theoretical, effective, or practical capacity can be affordable in CO_2 mitigation.

The source-sink matching method applied in the strategic planning and design of future full-chain CCUS projects with matched capacity is based on the various systematic optimization processes with pipeline routing and techno-economic models (Ambrose et al., 2009; Zheng et al., 2009; Middleton et al., 2012b; Middleton et al., 2012c; Dahowski et al., 2012; Tan et al., 2012; Vikara et al., 2017; Edwards and Celia, 2018; Middleton and Yaw, 2018). The matched capacity of source-sink pairs provides a more reliable and competitive capacity that has the potential to be deployed at scale. The resulting cost curve for source-sink matching processes provides a solid foundation for a commercialization strategy of CCUS to use an appropriate supportive environment to turn matched capacity into actual storage capacity (Dahowski et al., 2012; Edwards and Celia, 2018). The supportive environment contains carbon price and incentive policies, regulation and legislation systems, industrialization policies, and others that significantly impact how much matched capacity can be affordable and actual storage capacity.

2.3.5 Algorithms for Other Factors

Except for these factors mentioned above, feasible and affordable capacity should include key factors in the feasibility study, such as financial support, administrative processes of permitting, operating and closing, risk, transferring long-term liability, involvement of stakeholders, and other essential factors. Concerning the actual storage capacity contributing to carbon neutrality globally, the uncertainties depend more on the CO_2 mitigation strategies and policies to address climate change, technical evolution, industrialization, and commercialization strategy of CCUS, affordable cost, and administrative system than solely the sub-surface performance and storage mechanisms (Zhang et al., 2019). Therefore, CO_2 capacity assessment should consider additional factors and higher data resolution to decrease uncertainties in capacity evaluation in future work.

2.4 Overall Storage Capacity or Storage Efficiency Coefficient

Each cell's overall CO_2 storage coefficients can be obtained through deterministic and stochastic methods based on the aforementioned factors. The overall CO_2 storage coefficients for each cell can be obtained through weakly coupled or fully coupled integration of numerous factors as expressed in the following equation:

$$E_{overall} = E_s \cdot E_{tech} \cdot E_{site} \cdot E_{economic} \cdot E_{match} \cdot E_{others}, \text{ or } E_{overall} = E_{integrated}, \tag{4}$$

where $E_{overall}$ is overall storage efficiency coefficient; E_{site} is site suitability coefficient; E_s is storage coefficient reflecting the effect of geological data and technical schemes with various storage mechanisms; $E_{economic}$ is a coefficient reflecting techno-economic evaluation result; E_{match} is a coefficient reflecting source-sink matching processes; and E_{others} is a coefficient reflecting the effects of other factors. Some of these factors can be with others to reduce the factor numbers, e.g., the technical factor can be implicit in other factors. $E_{integrated}$ is an overall storage efficiency coefficient obtained by integrated methods.

A schematic graph of storage efficiency coefficient and capacity evaluation is presented in **Figure 1**. Using suitable algorithms that integrate available data with various data quality in the evaluation framework is crucial to acquire the overall capacity efficiency coefficient for each geological cell or site. The types of data complication and evaluation algorithms can be classified as shown in **Table 2**. The deterministic method can be extended into stochastic analysis.

The statistical results of overall efficiency coefficients can be obtained at different confidence levels. Suppose the distributions of some parameters are non-available. In that case, the expert panel, statistical methods, empirical methods, and other as-if methods can be used to estimate the reasonable ranges for these parameters. Then, the overall storage efficiency coefficient and storage capacity distribution can be obtained by Monte Carlo sampling or other stochastic sampling methods. These factors and components may be strongly correlated at more minor scales, e.g., site scale. Therefore, more advanced fully-coupled methods based on more complex algorithms that integrate and solve all factors at once are necessary to provide highly reliable results with uncertainties.

3 A HIERARCHICAL FRAMEWORK OF CO_2 CAPACITY EVALUATION

Building a consensus capacity framework that can integrate all available data with various qualities and well-recognized algorithms is necessary to obtain reliable capacity results with clear descriptions of capacity types, technical schemes, assessment algorithms, and data quality (data types and resolution). Based on the preceding reviews, a hierarchical framework of CO_2 capacity evaluation is presented with the aim to define the capacity types that describe uncertainties qualitatively. Among these factors, data availability is the priority.

3.1 Resolution Descriptions of Geological Data

The surface data have a much higher resolution than that of the sub-surface geological data. Consequently, the availability of sub-surface data is the bottleneck for capacity evaluation. The high requirements of types and detail levels of data and related algorithms cause challenges in the reliable estimations of CO_2 capacity in deep saline aquifers, and capacities assessed with low uncertainties only happen at site-specific projects with detailed site characterization and reservoir performance data. **Table 3** presents a suggested accuracy classification of sub-surface geological data.

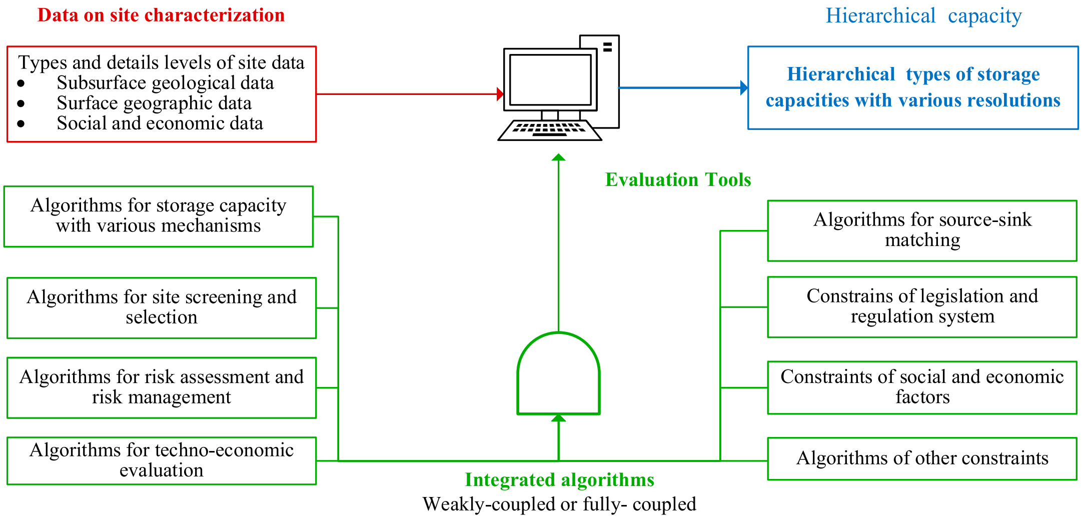

FIGURE 1 | Schematic graph of storage efficiency coefficient and capacity evaluation.

TABLE 2 | Categories of algorithms and tools for data complication.

Algorithms that integrate geological features (data) $D_{sub-surface}$	a) Data types defined by Geographic Information System (GIS) software, e.g., ArcGIS, MapGIS, MapInfo, OGIS, and others b) Geological models by various petroleum or geological software (e.g., Petrel, Landmark, MORES, Optec, and others) c) Data stacks, metadata, data modules, matrix, or other databases, e.g., data class by cellular or grid
Algorithms that integrate non-geological features (data)$D_{surface}$	a) Data algorithms in GIS software b) Data stacks, matrix, or database c) Other methods (images, 3D geographic model, and others)
Algorithms considering storage mechanismsA_s	a) Empirical approaches with various storage mechanisms, e.g., US-DOE, CSLF, USGS, others b) Semi-analytical or analytical approaches, two-phase dynamic method c) Numerical simulation based on the geological model, e.g., multi-phase solute-transport model, multi-phase solute-transport-thermal model, multi-phase flow models coupled with geo-mechanical properties, and other full coupling models
Algorithms for site screening and selectionA_{site}	a) Qualitative methods, e.g., expert panel, brainstorm, and others b) Semi-quantitative methods, e.g., multiple criteria methods, FEP, and others c) Quantitative methods, e.g., NRAP, probability analysis, fault tree, and detailed site performance assessment
Algorithms for techno-economic evaluation$A_{economic}$	a) Empirical approaches or statistical methods b) Budget-type approaches based on technical designs c) Accounting approaches based on actual projects
Algorithms for source-sink matching$A_{matching}$	a) Empirical algorithms are based on source-sink distance, e.g., the PNNL method b) Routing search with techno-economic models, e.g., Sim-CCS c) System optimization process for feasibility studies of a CCUS project set, e.g., FEED and project design
Algorithms for other constraintsA_{other}	Various algorithms from qualitative to quantitative, e.g., GIS tools, image tools, data stacks, matrix tools, mathematical methods, and others

The resolution of site characterization gradually increases from the stage of the general survey, initial investigation, detailed site characterization, and site operating. The proposed resolution of a subsurface geological feature is always defined by the density of investigation wells or similar resolution scale or data requirement of different evaluation stages. Cellular or grid in the capacity evaluation indicates the unit with proper resolution of sub-surface geology. Cellular size with at least one investigation well is equal to 50 × 50 sq. km., 20 × 20 sq. km., and 5 × 5 sq. km., respectively, when the precision is 1: 20, 1: 5, and 1: 1 million. Thus, the accuracy levels of storage capacity gradually increase from a general survey to site operation.

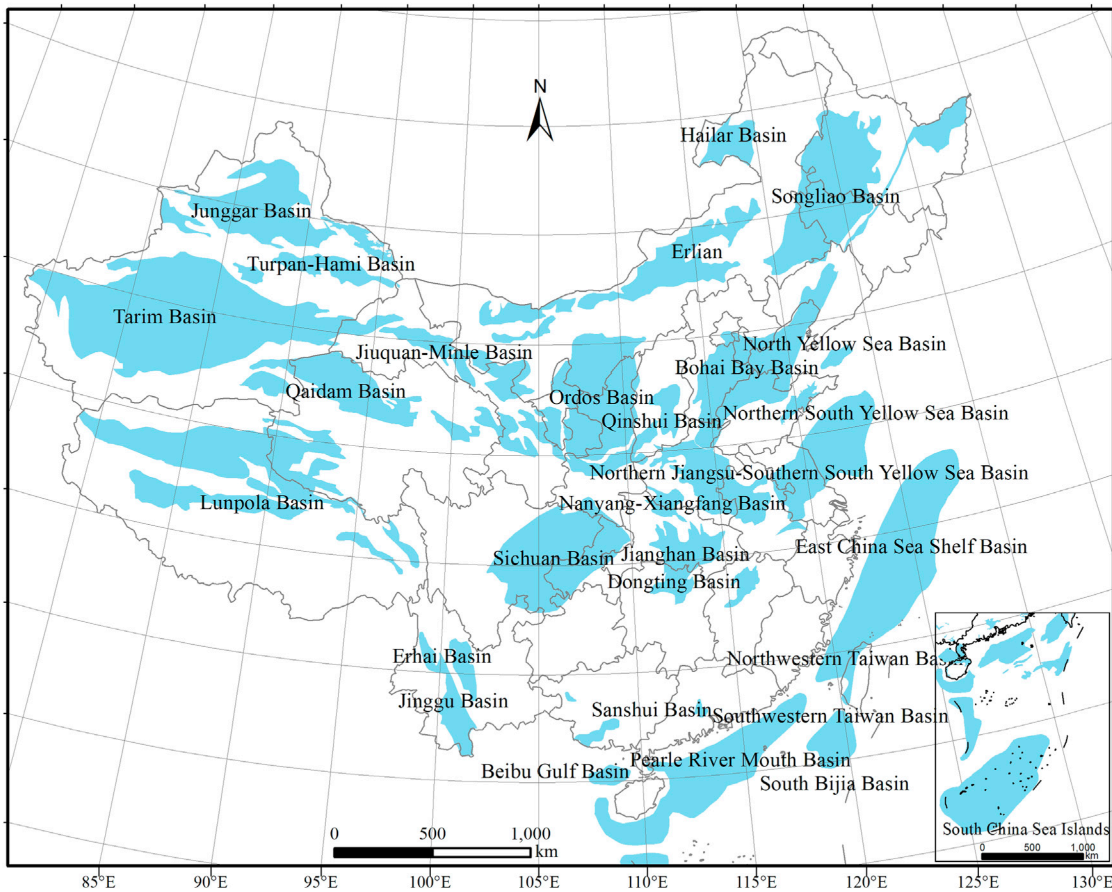

FIGURE 2 | The sedimentary basins in China.

TABLE 3 | Proposed hierarchical classification of sub-surface geological data.

Exploration stage	Areal resolution of sub-surface data	Spacing of investigation well	Resolution classes of data	Equivalent resource types in US-DOE methods
CO_2 injection and site operation (a)	≤1:1 million	At least one well per 25 km^2 or a well spacing of 5 km	I or II	Storage capacity
Detailed prospection (b)	≤1: 2.5 million	At least one well per 100 km^2 or a well spacing of 10 km	II or III	Proved resource (Proved oil reserve)
Preliminary prospection (c)	≤1: 5 million	At least one well per 400 km^2 or a well spacing of 20 km	III or IV	Contingent resource (Controlled oil reserve)
General survey (d)	≤1: 10 million	At least one well per 2,500 km^2 or a well spacing of 50 km	IV	Prospective resource (Prospective oil reserve)

I, II, III, *and* IV *represent the accuracy classes of geological data, basin-scale, sub-basin scale, site scale, and detailed site characterization, respectively.*

3.2 Hierarchical Types of Capacity

The hierarchical types for capacity are shown in **Table 4**. The definitions of capacity are similar to the resource-reserve pyramid by Bachu et al. (2007). The typical name is in the form of (capacity type)—(dynamic or static algorithm)—(deterministic or stochastic algorithm)—(storage mechanisms)—(CO_2 sources)—(resolution of subsurface- and surface-data). The capacity assessment is performed at an order of increasing types and data resolutions from theoretical capacity to actual storage capacity. The higher level of evaluation requires higher top-data quality and more sophisticated algorithms than integrating all data. This hierarchical framework classifies key factors into the following categories: 1) capacity types (from geological capacity to matched capacity) and related key factors, 2) CO_2 storage mechanisms, 3) algorithms for different factors, e.g., static or dynamic algorithms for storage

TABLE 4 | Proposed hierarchical capacity with descriptions of data types and resolution.

Capacity types	Matched capacity/ resource (A)	Practical capacity/ resource (B)	Effective capacity/ resource (C)	Theoretical capacity/ resource (D)
Sub-surface geology (G)	(G)	(G)	(G)	(G)
Technical scheme (T)	(T)	(T)	(T)	—
Site suitability and economic (S)	(S)	(S)	—	—
Source-sink proximity (M)	(M)	—	—	—
Capacity type (simplified name)	(M) or (A)	(S) or (B)	(T) or (C)	(G) or (D)
Static or Dynamic type capacity	Static (*S*) or dynamic (*D*)	(*S*) or (*D*)	(*S*) or (*D*)	(*S*) or (*D*)
deterministic or stochastic type capacity (optional)	(s or d)	(s or d)	(s or d)	(s or d)
Storage mechanisms considered (One or hybrid mechanism)	(*f*), (s), (*m*), or (*r*)	(*f*), (s), (*m*), or (*r*)	(*f*), (s), (*m*), or (*r*)	(*f*), (s), (*m*), or (*r*)
CO_2 sources (F/S) (optional)	F (full-chain CCUS)	S (sink)	S (sink)	S (sink)
Data resolution and types				
Resolution of sub-surface data	(*a*) or (*b*)	(*b*) or (*c*)	(*c*) or (*d*)	(*c*) or (*d*)
Resolutions of surface data (optional)	I or II	I or II	II or III	III, or IV
Examples for this framework	(G-T-S-M)-S- (*f*) -(*c*)- (I) *or* A-S- (*f*)-(*c*)- (I)	B-S- (*f*)-(*c*)- (II)	C-S- (*f*)-(*b*)- (III)	D-S- (*f*)-(*a*)- (IV)

Where (A) (B) (C), and (D) represent different types of capacity of matched capacity/resource, practical capacity/resource, effective capacity/resource, and theoretical capacity/resource. (f) (s) (m) (r) and (a) represent different trapping mechanisms of the free gas phase (f), solubility (s), mineralization (m), residue gas (r), and adsorption (a), respectively. Symbol (S) and (D) mean static or dynamic methods integrating sub-surface geological data for capacity evaluation. Symbol (d) and (s) mean deterministic or stochastic capacity, respectively. IV, III, II, and I represent the resolutions of surface geological data and surface non-geological data at basin, sub-basin, and site scales, and detailed site characterization, respectively. (a) (b) (c) (d) represent different stages of site characterization from CO_2 injection stages, detailed prospection, preliminary prospection to a general survey. G-T-S-M and A represent that the capacity assessments include geological data, technical schemes, site screening and selection, and matching of source-sink pairs.

mechanisms, and 4) data types and resolutions. This framework can be applied in two different ways as data or algorithm priority.

The algorithms can be selected according to the CO_2 storage mechanisms, available types, and detailed levels of data; on the other hand, the types and detail levels of data can be screened according to given algorithms and evaluation requirements.

3.3 Limitations of This Framework

This hierarchical framework of CO_2 capacity evaluation can offer a more precise definition of capacity types and integrate various data qualities (data types and resolutions) and related algorithms. This framework also provides clearer descriptions of the evaluation processes and capacity results and allows comparisons among different evaluation processes and capacity results. However, the framework faces uncertainties such as follows: 1) definitions of capacity types and factors in this paper are hierarchical and facing uncertainties from technical evolution, site characterization, and others; 2) the outer environment, such as legislation and regulatory, policy, administrative procedure, and other vital factors, frequently change with time; 3) the uncertainties from analysis algorithms and tools are not discussed in this paper; 4) the confidence levels of algorithms for each factor are unclear although some of these algorithms are mature, and 5) integrated or one-model-fits-all type algorithms, and systematical analysis of uncertainties that can handle all kinds of uncertainties are unavailable currently. Therefore, this paper does not try to give precise and detailed comparisons of existing algorithms, methods, or approaches but to classify them into a common ground. The detailed uncertainty analysis is the next step in the future.

Addressing these limitations is necessary to provide a more precise and reliable assessment with fewer uncertainties in current capacity estimates. Under the premise that more advanced site characterization, efficient data compilation tools, reliable algorithms, and efficient analysis tools lead to reduced uncertainties of each factor. Furthermore, integrated methods for overall storage efficiency coefficient are expected to obtain more accurate and dependable assessment results with clear definitions of storage types.

4 REVIEW ON ONSHORE AQUIFER CAPACITY IN CHINA

The current national-wide estimates for CO_2 capacity in onshore aquifers in China have high uncertainties due to limited on-site data, capacity clarifications, lack of technical schemes, various assessment algorithms, and unavailability of other data (Höller and Viebahn, 2016). China-wide capacity studies on onshore aquifer storage with capacity methods at regional- and basin-specific scale are shown in **Table 5**. The sedimentary basins in China are shown in **Figure 2**. No surface data and related algorithms are used in these evaluations.

The capacity for onshore aquifer formations in China is reviewed and classified by the framework in **Table 6**. This evaluation provides a clear view of the magnitude of the CO_2 capacity of onshore aquifers in China.

The results show that the matched CO_2 capacity can be 170 Mt/a at costs less than 30 USD/t, and higher capacity can be 3.4 Gt/a at costs less than 70 USD/t (Li et al., 2019). The matched capacity is a tiny portion of theoretical capacity refined by the technical scheme, site suitability, CO_2 source, and economic results. The site suitability is evaluated by the multiple criteria method (Wei et al., 2013). The matched capacity is improved by the source-sink

TABLE 5 | Capacity assessment of aquifer storage at various scales in China.

Basins or formations evaluated	Capacity (Gt CO_2)	Resolution of sub-surface data	Types classified by proposed hierarchical types	References
Aquifer formations in China	*2,288 (onshore) 3,067 (total)*	before (*d*) stage	D-S-(*s*)-(*d*) or D-S- (*s*)—(*d*)—(-)	Solubility method, Dahowski et al. (2009), Li et al. (2009)
Annual contribution of Aquifer formations in China	*2.9 Gt/a @ 10 USD/t CO_2*	(*d*)	D-S- (*s*)—(d)—(-)	Source-sink matching algorithm byDahowski et al. (2009)
Sedimentary basins in China	1826	(*d*)	D-S-(*f*)- (*d*)- (-)	Mass balance method Sun et al. (2018)
Matched capacity of onshore aquifer storage in China	2.5 Gt @70 USD/t	(*d*)	A-S-(*f*)-(*d*)- (-)	Source-sink matching by CO_2-GIS model, P_{50} Dahowski et al. (2009), Li et al. (2009)
Songliao Basin	138	(*d*)	D-S-(*f*)- (*d*)- (-)	US-DOE method, P50 Wu et al. (2009), Zhang et al. (2009)
Cretaceous strata in Northern Songliao Basin	9.8	**(c)**	C-S-(*f-s*)- (*c*)- (-)	Capacity with site suitability evaluation by Wang et al. (2014)
Sedimentary basins in China	1826.07	(*d*)	D-S-(*f*)- (*d*)- (-)	Mass balance method Sun et al. (2018)
Bohai basin–Huimin sub-basin Within the Bohai bay basin	23 0.7	(*d*)	D-S-(*f*)- (*d*)- (-)	CSLF-based method Vincent et al. (2011)
Pear River Mouth Basin	308	(*d*)	D-S-(*f*)- (*d*) - (-)	US-DOE method P50 Zhou et al. (2011)
Two formations within two depressions in SubeiBasin (onshore part in Jiangsu province)	(2.8 P15, 6.6, P50 11.2, P85)	(*d*)	D-S-(*s-r*)- (*d*)- (-)	US-DOE method P50 Qiao et al. (2012)
Aquifer capacity in the U.S.	(2,379 P10, 8,328, P50 21,633 P90)	(*c*)	D-S-(s)-(*f*)- (*c*) - (-)	Netl (2015)

*The italic values refers to values in **Table 4**.*

TABLE 6 | Hierarchical capacities of onshore CO_2 aquifer storage in China.

Capacity types	Onshore aquifer storage	Storage mechanisms	Resolution of sub-surface data	Resolution of surface data	Hierarchical capacity types	Descriptions
Matched capacity (A)	2.9 Gt/a @ 10 USD/t CO2 with total CO_2 emission of 3.9 Gt/a captured from eight sectors in China in 2009	S-(*s*)	(*d*)	IV	A-S-(*s*) -(*d*)-(IV)	Solubility method refined with the source-sink matching algorithm by Dahowski et al. (2009)
Matched capacity (A)	3.4 Gt/a @ 60 USD/t (P50) with total CO_2 emission of 6.5 Gt/a captured from coal power, coal chemistry, steel and iron, and cement sectors in China in 2015 and 2012	S-(*f*)	(*d*)	III	A-S-(*f*)-(*d*)- (III)	US-DOE methodology refined with the source-sink matching algorithm by Li et al. (2019)
Matched capacity (A)	270 Mt/a @ 30 USD/t (P50 and levelized cost) with high-purity CO_2 emission from coal chemical sectors in 2015	S-(*f*)	(*d*)	III	A-S-(*f*) -(*d*)- (III)	Refined by the source-sink matching algorithm by Li et al. (2019)
Matched capacity (A)	1800 Mt/a @ 60 USD/t (P50 and levelized cost) with CO_2 stream from coal-fired power plants in 2018	S-(*f*)	(*d*)	III	A-S-(*f*)-(*d*)- (III)	Refined by the source-sink matching algorithm by Wei et al. (2021)
Practical capacity (B)	1.35 Tt (P50)	S- (*f*)	(*d*)	III	B-S-(*f*)-(*d*)-(d)- (III)	US-DOE methodology refined with site suitability evaluation by Wei et al. (2013)
Theoretical capacity (D)	2.40 Tt (P50)	S-(*f*)	(*d*)	—	D-S-(*f*)-(*d*)- (-)	US-DOE volumetric method by Goodman et al. (2011)

matching algorithm proposed by Li et al. (2019) based on the practical capacity results.

This application illustrates that this framework can qualitatively classify the existing capacity assessments into different categories with similar magnitudes but significant discrepancies from storage efficiency. The evaluations on the storage capacity of aquifer storage in China are with limited site data at a large scale, e.g., national-scale and basin-scale. In China, aquifer formations mostly with non-marine sedimentary facies have substantial spatial variations of physical and chemical properties, very high multiple-scale heterogeneity that leads to significant uncertainty in the storage assessment. The current evaluations of aquifer storage capacity lack sufficient data on-site characterization. Consequently, the uncertainties of storage capacity evaluation are always defined by the subsurface data of site characterization. Most energy will be spent on site characterization and data collection. Moreover, capacity evaluation methodologies should be updated to enable a more comprehensive assessment of capacity uncertainties beyond current estimates.

5 CONCLUSION

Carbon dioxide (CO_2) storage in deep saline aquifers is an essential option for CO_2 mitigation at a large scale. Determining storage capacity is the first step toward the large-scale deployment of CCUS projects. The existing methods and assessments of CO_2 capacity in aquifer formations involve uncertainties caused by selected storage mechanisms, data quality, evaluation algorithms, and considered factors. This paper reviewed these methods and presented a hierarchical framework of capacity evaluation to classify capacity types and describe the assessment processes and capacity uncertainties. The frame can allow multiple algorithms to estimate storage capacity with probabilistic analyses of the storage efficiency coefficients, which depend on numerous factors, such as CO_2 storage mechanisms, technical design, economic, source-sink proximity, risk, socioeconomic constraints, and related algorithms. Finally, the CO_2 storage capacities onshore aquifer sites in China, as reported in the literature, are reviewed and classified by this framework. Furthermore, this hierarchical framework of capacity evaluation is capable of conducting comparisons among different capacity results with hierarchical types.

AUTHOR CONTRIBUTIONS

All authors contributed to the finalization of the paper. The first author led the work, benefiting from discussions with all authors. All authors contributed to the writing and revision of this article, and input in terms of numbers and references backing the analysis. NW: Major Researcher and writer XL: Project manager on China side ZJ: Technical consultant PS: Technical consultant SL: Cost parameters collector KE: Technical consultant RM: Technical consultant.

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