Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 114 (2017) 7033 – 7041

Energy Procedia

13th International Conference on Greenhouse Gas Control Technologies, GHGT-13, 14-18 November 2016, Lausanne, Switzerland

Identification of a minimum dataset for CO_2-EOR monitoring at Weyburn, Canada

Jean-Philippe Nicot[a]*, Alexander Y. Sun[a], Rebecca Shuang Gao[a], and Hamid Lashgari[b]

[a]*Bureau of Economic Geology, The University of Texas at Austin, Austin, Texas, USA*
[b]*Department of Petroleum and Geosystems Enginnering, The University of Texas at Austin, Austin, Texas, USA*

Abstract

CO_2 leakage at geological carbon storage (GCS) sites, driven by increased system pressure and higher CO_2 saturations, represents a major risk to secure containment of injected CO_2. For long-term GCS monitoring, it is critical to determine a level of material information needed to minimize leakage risks while keeping costs under control. This study demonstrates a goal-oriented, retrospective design concept called minimum data set requirement (MDR) for the Weyburn-Midale Project (WMP), a commercial-scale, CO_2-injection enhanced oil recovery site in Canada that has been extensively characterized for R & D purposes. More than a decade of research at the WMP site has led to an extensive collection of site characterization data (thousands of wells with geophysical logs and cores, seismic surveys), a situation that is unlikely to be true for many other GCS projects around the world. The main purpose of this study is to perform a retrospective design of the WMP to identify the MDR. By screening existing data retrospectively, our MDR identification process seeks to establish a level of data needed to define a sufficient reservoir model for guiding post-EOR monitoring, under user-defined performance metrics. Our starting point is an existing history-matched WMP reservoir model and three datasets consisting of logs from hundreds of wells and seismic survey.

An iterative Monte Carlos approach is taken here to systematically and gradually reduce the level of information used in parameterizing a geological model, from which conditional stochastic realizations of model properties are generated and simplified reservoir models are developed. Results show that (a) the minimum dataset for predicting CO_2 migration depends on the heterogeneity and anisotropy of selected parameters of the field, (b) parameterization scheme for data reduction should be flexible and also objective oriented and problem dependent, and (c) for the Phase 1A area of the Weyburn field about 80% out of the 403 wells can be eliminated without having detrimental impact on the simulated pressure field.

* Corresponding author. Tel.: +1-512-471-6246; fax: +1-512-471-0140
E-mail address: jp.nicot@beg.utexas.edu

doi:10.1016/j.egypro.2017.03.1844

Keywords: Geologic carbon sequestration; Weyburn field; CO_2-EOR; minimum dataset requirements

1. Introduction

Site characterization is a critical step of geological carbon sequestration (GCS) projects. Geophysical, geochemical, and hydrogeological data yielded from site characterization efforts provide the bases of risk assessment, monitoring network design, and predictive modeling of long-term storage efficiency of injected CO_2 in a storage complex. Different from the traditional reservoir characterization processes that mainly focus on geologic structure and properties within a reservoir, GCS site characterization is required to be performed at a much larger scale in both vertical and lateral directions, covering both biosphere and geosphere surrounding the storage complex and potentially generating a large volume of information. Because of its scale, GCS site characterization is costly, which may have serious implications for CO_2 enhanced-oil-recovery (EOR) operators seeking credits for carbon storage. A fundamental question is then related to the collection of a representative dataset that is most useful for the goals of a particular GCS project while still remaining at a reasonable size to keep project costs under control. Goals of a typical GCS project include efficient and secure storage of CO_2 injected at a required rate in a given time interval and can also involve optimized CO_2-EOR for depleted oil reservoirs transitioning to CO_2 storage sites.

The main focus of this study is to demonstrate a retrospective design by using model and data from the Weyburn-Midale Project (WMP) in Saskatchewan Canada, one of the largest existing GCS projects in the world. Since its inception in 2000, more than 20 million tonnes of anthropogenic CO_2 has been sequestered at the storage complexes of WMP [1]. Past research at the site was organized in two stages, Phase I and Final Phase. Phase I was taken at the Weyburn field and focused on predicting and verifying the capacity of the Weyburn oil reservoir in storing CO_2 in conjunction with active enhanced oil recovery using CO_2 flooding (CO_2-EOR). The Final Phase conducted research at both Weyburn and Midale fields.

More than a decade of research at the WMP site has led to an extensive knowledgebase of site characterization data, a situation that is unlikely to be true for many other GCS projects around world. Thus, this study seeks to create and demonstrate a special type of retrospective design, referred to as the *Minimum Dataset Requirements* (MDR). It is envisioned that MDR will establish a level of detail in site characterization data such that they are sufficient to enable representative modeling of CO_2 migration and potential leakage with reasonable assurance of accuracy and reliability, and yet are not excessively onerous in terms of data compilation and analysis requirements. Specifically, the establishment of an MDR for WMP is expected to serve at least three purposes: (a) identifying data that are most critical for characterizing leakage pathways, (b) reducing post-EOR monitoring costs at WMP, and equally important (c) providing practice guidance for data collection strategies at other storage sites. To achieve those goals, we first define a generic MDR framework and then provide a design that is specifically tailored to WMP. In the following, Section 2 briefly reviews the original WMP datasets and reservoir model that are used as the starting point for this study, Section 3 delineates a general framework for establishing the MDR, Section 4 presents results from the MDR analyses, and the final section summarizes lessons learned.

2. Data and Base Model

The storage complex of the Weyburn Field consists of Frobisher Beds, Midale Beds and Evaporite, Ratcliffe Beds, Poplar Beds, and Watrous Formation in ascending stratigraphic order, among which the Midale Evaporite immediately above the storage reservoir is characterized as the “primary” seal and the regionally extensive aquitard, Watrous Formation, is characterized as the “ultimate” seal [1]. CO_2 is injected into Midale Beds, which is a carbonate formation comprised of lower Vuggy zone, overlain by the Marly zone, and capped by the Three Fingers zone; the thickness of the formation is 20 m on average, with porosity ranging from 5 to 35% and average permeability about 80 mD for Marly and Vuggy zones [1].

During previous phases of the WMP, two 3D geological models had been developed. The first model was constructed for a 200×200 km^2 regional study area, with a vertical extent that includes strata from 100 m below the base of the reservoir to the ground surface. Data from approximately 30,000 oil, gas, and water wells were used to develop a regional structural framework [1]. The second model (i.e., Final Phase model) focuses on the footprint of injection zones and geological layers immediately above it. It covers an area of 40×50 km^2, includes 29 layers, and uses data from roughly 900 oil and gas wells (Fig. 1). Note that the actual number of wells in Final Phase area is more than 4,000, with an average well spacing of about 275 m; all these wells penetrate the primary seal and the four shallow aquifers overlying the storage unit [2]. The Final Phase geological model was created in Petrel™ [3] using a 50-m horizontal spacing [4], and it also serves as the basis for an invasion-percolation-theoretic model that predicts possible migration paths for CO_2 after the cessation of injection [2]. The invasion-percolation model was used to model CO_2 movement above the injection zone. Different from Darcy flows, invasion percolation only uses capillary pressure and pressure threshold to determine migration paths of CO_2. Datasets in the Final Phase geological model include definition of stratigraphic layers, porosity, permeability, interpreted faults, mineral and fluid compositions, water salinity, formation pressure, water and oil saturations, hydrochemical properties from core analyses, and geophysical logs.

This study focuses primarily on Phase 1A of the Final Phase, covering a 19-pattern, intensively characterized CO_2 injection area at Weyburn Field (Fig. 1). The injection zone in Phase 1A area has been characterized by high-density well logs and core samples (porosity, permeability, density, and fluid composition), and the shallow aquifer zone was also studied in details because of their importance to local water supplies [1]. Thus, Phase 1A presents a meaningful case study for applying MDR. The main static dataset considered during the MDR process is a 414-well dataset (out of which only 403 wells are usable) (Dataset 1 in Fig. 1) in Phase 1A that includes porosity and isotropic permeability data. In addition to Dataset 1, a 782-well dataset (including porosity, anisotropic permeability, and bulk density) from the broader Final Phase area (Dataset 2 in Fig. 1) and a seismic amplitude dataset in Phase 1A area (3D seismic data in Fig. 1) were also analyzed during static modeling. Anisotropic permeability refers to K_{max} (highest permeability in a horizontal direction), K_{90} (90° to K_{max}), and K_{ver} (vertical permeability).

The CO_2-EOR reservoir model used in this study covers a high-density well log subarea of Phase 1A (Fig. 1). The original model was developed using the commercial compositional reservoir simulator Eclipse300™ [5] by WMP's EOR operator. As part of this study, the original model was converted into a similar compositional reservoir simulator, CMG-GEM™ (referred to as GEM hereafter). Eclipse300 and GEM use different approaches to model phase behavior and equation of state parameters (Fig. 2). During model conversion, the GEM model parameters were tuned so that the compositional phase behaviors match those used in Eclipse. The number of numerical gridblocks are 141×280×27 in the *x*-, *y*-, and *z*-direction, respectively. History matching was done using injection and production histories of 216 wells from April 1956 to December 2006, during which water flooding started in 1964 and CO_2 flooding began in 2000. The calibrated GEM model, reflecting the full suite of static and dynamic data available at Phase 1A area, serves as the base model for this study.

3. Methodology

3.1. Workflow for identifying MDR

The general workflow is closely related to the goal-oriented model reduction methodology described in Sun and Sun (2015) [6]. A wide range of methods can be potentially applied in each step of the workflow. For example, global sensitivity analysis is a well-established method for identifying variables that are most influential to model outcome [7]. The identified variables can then be modeled using a number of spatial parameterization techniques through which stochastic realizations of distributed model parameters can be generated [6]. For the purpose of parameterization, the high-density wells may be first de-clustered by using data clustering techniques that quantify the contribution of each well to a local probability distribution function. The processed raw data can then be used to identify the structural parameters pertaining to the selected parameterization technique (e.g., sill and correlation range of variograms). Because of its iterative nature, however, the general workflow is computationally intensive, especially for large-scale models. High-performance computing and surrogate models may be used to alleviate the computational burden. In the following subsection, a workflow tailored to WMP is described.

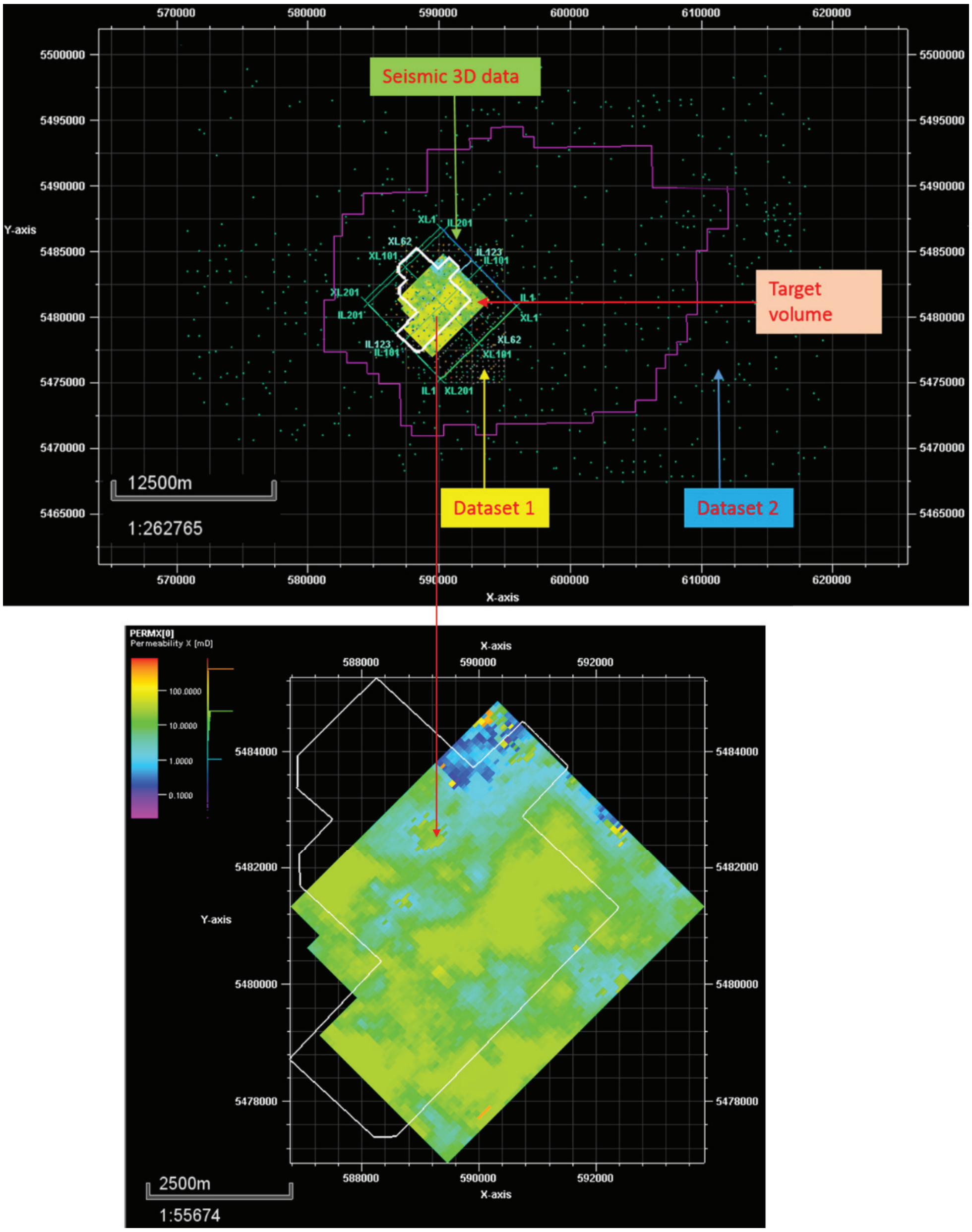

Fig. 1. Boundary of WMP geological models. Upper figure: The Weyburn Field boundary is outlined in purple. Dots represent locations of wells with core information. The studied area of this paper is the boundary of the GEM model for predictive reservoir simulation and CO_2 leaking detection. Dataset 1 (pointed by yellow box) shows locations where isotropic permeability core data are available. Dataset 2 (pointed by blue box) shows locations where anisotropic permeability core data are available. The coverage of 3D seismic data is masked by green frames. The white polygon outlines Phase 1A area. Close-up view: Boundary of GEM model, where color indicates permeability.

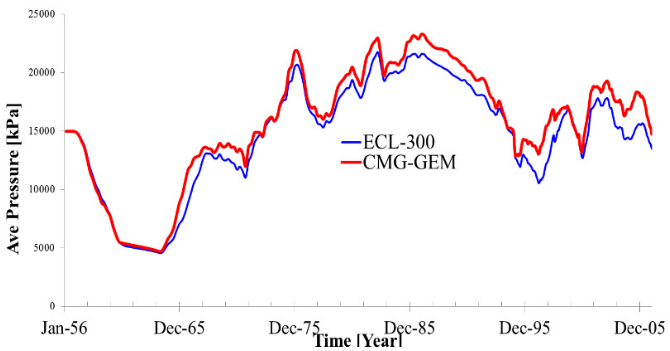

Fig. 2. Comparison of average field pressure given by the original Eclipse model and CMG-GEM model converted from Eclipse.

3.2. A WMP-specific framework for identifying MDR

We use pressure distribution as a proxy for leakage risk, with higher pressure indicating and higher risks of CO_2 migration out of the storage complex. Such an approach is consistent with the area-of-review framework for GCS monitoring [8], which suggests that leakage scenarios are generally associated with high permeability values, high gas saturation, and high CO_2 concentration in all three phases. The starting point of MDR identification is the extensive information collected over Phase 1A. The scope of MDR identification includes static modeling and dynamic reservoir simulations. Static modeling focuses on finding the most significant formation petrophysical data types, obtaining primary parameters, affecting pressure distribution due to CO_2 injection, and generating stochastic realizations of the parameter fields. On the other hand, dynamic analysis performs reservoir simulations using parameters generated from the static modeling to identify high-pressure zones. The approach is also iterative, requiring a significant number of parameter realizations and model runs.

During static modeling of reduced datasets, we considered two approaches: attribute-based and univariate geostatistical approach. Only the geostatistical approach is described in this work. See Gao et al. (2016) [9] for details about the attribute-based approach.

A potential caveat of the attribute-based approach is that it typically requires a relatively large amount of well log information to define the needed transition probabilities, especially when the number of units is large. When the size of the dataset shrinks, modeling of transition probabilities becomes increasingly difficult because of the number of cross-variograms that need to be created. Thus, we also applied the traditional univariate geostatistical analyses, which characterize spatial distribution of random fields through histograms and variograms. We used the Data Analysis and Petrophysical Modeling modules of Petrel™ for univariate modeling and the subsequent stochastic simulation.

Dynamic reservoir simulation applies results of static modeling and the well schedule from the base model. The initial reservoir conditions are obtained by running extensive flow history matching for the area from April 1956 to December 2006, during which water flooding started in 1964 and CO_2 flooding started in 2000. The field rock and initial fluid composition, as well as the pressure distribution at the end of 2006, are calibrated as the numerical or stochastic reservoir simulation baseline for the MDR process. The reservoir temperature averages 63°C, and is kept constant throughout the simulation. Formation pressure initially lies between 14.5 and 15.4 MPa with an average of 14.975 MPa. During the CO_2-EOR (2007-2033) period, all existing producers and injectors are active, including vertical and horizontal wells. All wells that originally run in the water-alternating-gas (WAG) mode continue to run in WAG mode with an alternating cycle of 6 months, which gives better oil recovery factor than with 3-month time cycle as suggested in Wilson and Monea (2004) [10]. All CO_2-EOR patterns are assumed to roll out at the same time in January 2034. During post-EOR period (2034-2055), only the injectors are retained, while all producers are shut in. The maximum reservoir pressure is set at 29.5 MPa.

4. Results and Discussion

4.1. Static modeling

Static modeling generates porosity and anisotropic permeability fields for reservoir simulation of CO_2-EOR and post-EOR periods in the dynamic modeling. As mentioned in Section 3, two geostatistical parameterization approaches were explored during static modeling, an attribute-based approach which incorporates multiple properties but is more data intensive, and a simpler variogram approach that gives a first-order approximation of the property distribution under investigation and is less data intensive. Outcomes of the latter approach are presented below.

The entire gridded area (i.e., target volume in Fig. 1), with porosity and anisotropic permeability measured from well core data and calibrated by historical production data, is treated as a "virtual dataset" for MDR study. Each "virtual well" is a set of vertically connected cells penetrating all 27 layers of the numerical grid (i.e., a vertical well). More complicated virtual well configurations can also be accommodated. With the virtual well approach, we essentially deal with upscaled flow properties directly, mitigating issues related to scale discrepancy. This is a reasonable approach in the context of retrospective design.

The variogram modeling for MDR includes the following steps:

a) Generate a candidate MDR set. A set of virtual wells are randomly sampled from the entire numerical grid. The vertical wells are selected to be evenly "placed" in the field, and are treated as sites where properties are known. For this purpose, we used Halton sequence [11] to generate quasi-random numbers that evenly sample the 2-D grid space.

b) Perform variogram modeling of sample set properties in lateral and vertical directions, in the same manner as commonly done for well log variogram modeling. Petrel's Data Analysis module is used for this purpose.

c) Perform conditional sequential Gaussian simulations (SGS) using the properties from virtual wells as conditioning data, from which the porosity and permeability properties for the whole field are obtained. The conditional SGS is performed using Petrophysical Modeling module of Petrel.

Three candidate well sets consisting of 190, 76, and 38 virtual vertical wells, respectively, are generated, representing about 5%, 2%, and 1% of the number of columns in the GEM simulation gridblock, that is, representing a subset of the initial wells or ~50%, ~20%, and ~10% of the number of wells in Dataset 1. The well sets are generated in such a way that each larger well set is a superset of the smaller set. This way, we ensure that the minimum data is shared across the well sets and can be identified when the redundant information is removed.

The variograms for K_{max}, the horizontal permeability in major direction, are shown in Fig. 3. It can be seen that the raw (semi)variogram data become noisier as the number of wells is reduced. Variograms for other properties show similar trends. For each candidate MDR set, two realizations of each property are generated, which are used as inputs to subsequent reservoir simulation.

4.2. MDR identification

The discrepancy between pressure field simulated by the simplified model (i.e., supported by less data) and that simulated by the base model is quantified using root mean squares (RMS), averaged over 10 realizations of each simplified model. Each simplified model has the same number of wells, the locations of the subset wells are held constant and each reduced dataset is a subset of the previous one but the derived anisotropic permeability and porosity fields are different and obtained through sequential Gaussian simulations. The final results are plotted in Fig. 4, which shows that model performance significantly deteriorates when the number of virtual wells is reduced from 76 to 38 (out of an initial well count of 403), that is, from 18.7% (~20%) to 9.4% (~10%) of the wells. This result did not change when the successive well subsets were chosen from another set of wells. As long as a well subset is representative of the local formation heterogeneity and anisotropy, the simulated pressure field is not degraded and is relatively accurately calculated. When the number of wells is insufficient to capture formation heterogeneity and anisotropy the pressure field deviates from the expected results and the RMS increases sharply. Clearly the sharp decrease (that is, from 20% to 10% of wells at WMP) is related to the level of heterogeneity and anisotropy in the target reservoir, an even smaller fraction of the wells would be useful if the reservoir were more uniform.

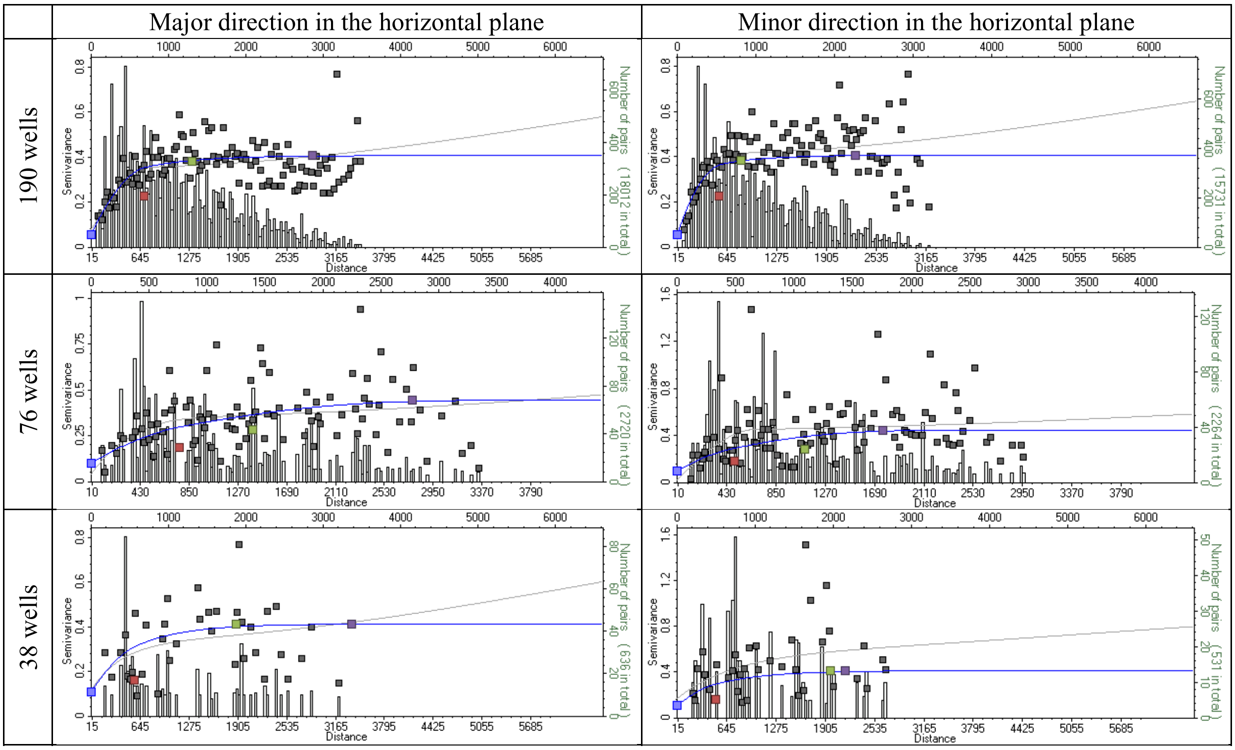

Fig. 3. Variograms for K_{max} of 5%, 2%, and 1% virtual well dataset. Each row shows the experimental semi-variograms and the fitted model variograms in the horizontal major directions (left column) and minor directions (right column). The raw data is transformed into normal distribution before experimental variogram calculation. In each figure, x axis is distance between pairs of data points in m, and vertical axis is the semivariance of K_{max} in md. Small black squares are experimental variogram point pairs, vertical histograms are numbers of point pairs within each lags, gray curve is the regression curve fitted for experimental variogram, and blue curve is the variogram model selected in the study for Sequential Gaussian Simulation. Blue square on the start denotes the nugget value. Red, green, and purple points correspond to the spherical, exponential, and Gaussian structures of the selected variogram model respectively.

The current average well spacing of 270 m on a square grid is very dense by typical characterization standards. Eliminating 80% of the wells still results in a relatively small average spacing of ~620 m. If it is clear that the WMP is oversampled for the strict purpose of CO_2 storage and that using information of 20% of the wells is enough to predict the pressure field, it is also true that, in context of CO_2 storage, a perfect knowledge of the pressure distribution in the injection formation is not required. Monitoring of a permeable formation overlying the injection zone, the so-called above-zone monitoring interval (AZMI) [12-14], can bring many benefits compared to in-formation monitoring and would entail an even lower level of knowledge of the injection formation. At the beginning of the post-EOR injection only period, the RMS pressure difference drops even as the overall pressure increases because of the lack of production. As the CO_2 injection continues and CO_2 rearranges itself in the injection formation, the same observation that only 20% of the wells are need to correctly predict the pressure field can be made. The pressure discrepancy is then more than an order of magnitude lower. If we accept the premise that a difference <1 MPa is acceptable, the numbers of wells needed to correctly predict the pressure distribution midway through the post-EOR injection period (2035-2055) is <10%.

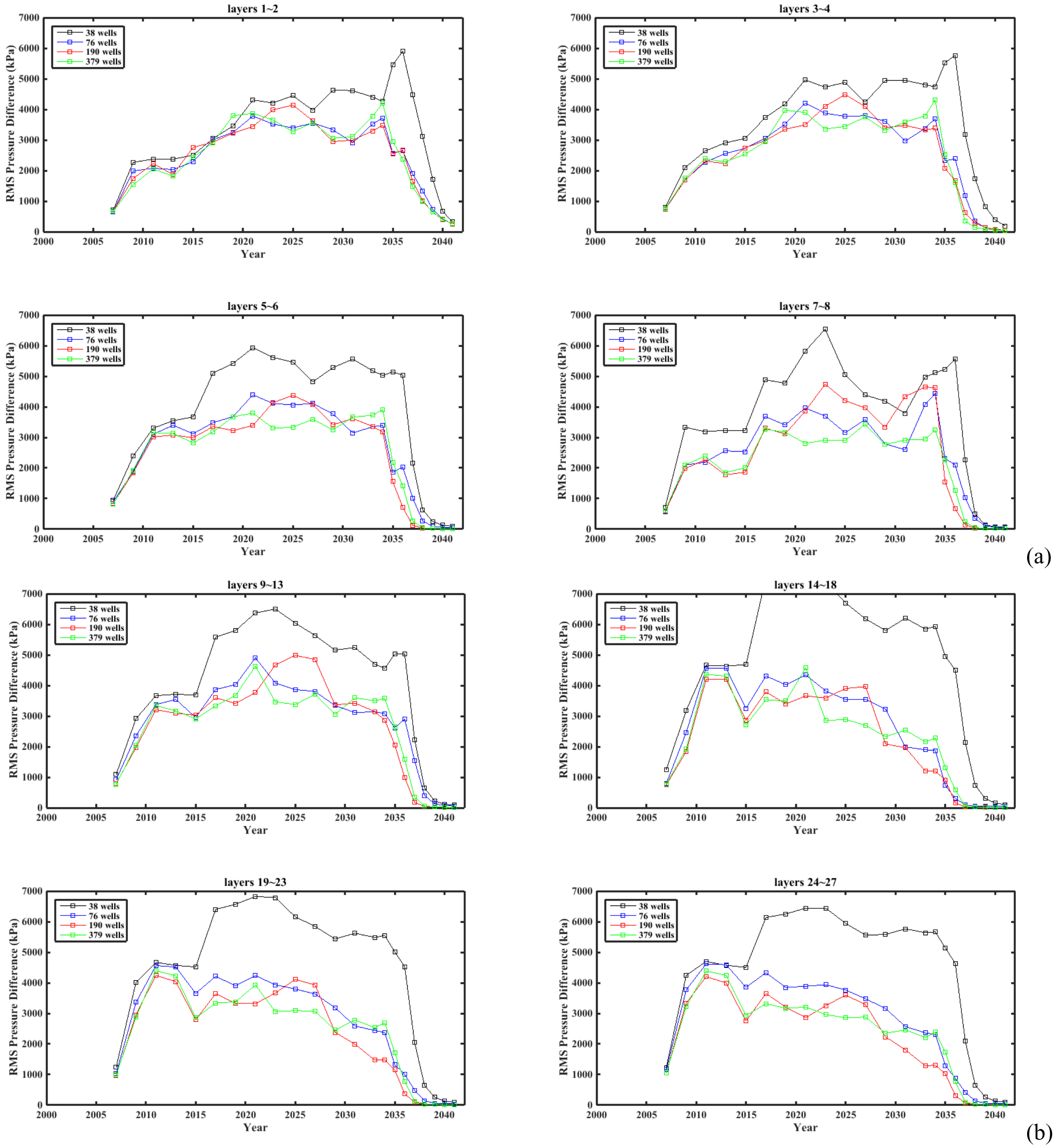

Fig. 4. RMS calculated for layers in (a) Marly and (b) Vuggy zones. RMS is calculated between simulated pressure of the base model and that from the average of 10 simplified models. The difference in layer 1~2 is smaller because layer 1 is much thinner than the other layers and does not contribute much to the RMS.

5. Summary and Conclusions

WMP in Saskatchewan, Canada, is a commercial-scale CO_2-EOR project that has been extensively characterized for R&D purposes, a situation that is unlikely to be true for many other GCS projects. The main purpose of this study is to perform a retrospective design of the WMP to identify the so-called MDR. Our results show that (a) the minimum dataset for predicting CO_2 migration depends on the heterogeneity and anisotropy of selected parameters of the field; (b) parameterization scheme for data reduction should be flexible and also objective oriented and problem dependent, and (c) for the Phase 1A area of the Weyburn field about 80% out of the 403 wells can be eliminated without having detrimental impact on the simulated pressure field.

Acknowledgements

The authors would like to thank the Petroleum Technology Research Centre (Saskatchewan, Canada) and the U.S. Department of Energy National Energy Technology Laboratory (NETL) for their financial support. We are indebted to Dr. C. Hawkes (University of Saskatchewan) for his guidance. We are also grateful to the Computer Modelling Group (Calgary, Canada) for free access to their CMG-GEM software and to Schlumberger for free access to their Petrel software.

References

[1] Hitchon, B., 2013. Best Practices for Validating CO_2 Geological Storage–Observations and Guidance from the IEAGHG Weyburn-Midale CO_2 Monitoring and Storage Project, in: Hitchon, B. (Ed.). Geoscience Publishing, Sherwood Park, AB, Canada.

[2] Cavanagh, A., Rostron, B., 2013. High-resolution simulations of migration pathways and the related potential well risk at the IEAGHG Weyburn–Midale CO_2 storage project. International Journal of Greenhouse Gas Control 16, Supplement 1, S15-S24.

[3] Computer Modelling Group (CMG). 2014. GEM - Three-Phase, Compositional Oil Reservoir Simulator, Version 2014.10. Calgary:

[4] Jensen, G.K.S., Nickel, E.H., Rostron, B.J., 2013. Refinement of the Weyburn-Midale geological and hydrogeological model: Developing a better framework to determine reservoir response to injected CO_2 and subsequent CO_2 movement. International Journal of Greenhouse Gas Control 16, Supplement 1, S5-S14.

[5] Schlumberger. Petrel-Model Building to- Evaluation Software, Version 2014.3. 2014

[6] Sun, N.-Z., Sun, A.Y., 2015. Model Calibration and Parameter Estimation: For Environmental and Water Resource Systems. Springer.

[7] Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Global sensitivity analysis: the primer. John Wiley & Sons.

[8] Nicot, J.-P., Oldenburg, C.M., Bryant, S.L., Hovorka, S.D., 2009. Pressure perturbations from geologic carbon sequestration: Area-of-review boundaries and borehole leakage driving forces. Energy Procedia 1, 47-54.

[9] Gao, R. S., A. Y. Sun, J.-P. Nicot, 2016, Identification of a representative dataset for long-term monitoring atthe Weyburn CO_2-injection enhanced oil recovery site, Saskatchewan,Canada, International Journal of Greenhouse Gas Control, doi: 10.1016/j.ijggc.2016.05.028

[10] Wilson, M., Monea, M., 2004. IEAGHG Weyburn CO_2 Monitoring & Storage Project Summary Report, 2000-2004, in: E.S. Rubin, D.W.K., C.F. Gilboy, M. Wilson, T. Morris, J. Gale, K. Thambimuthu (Ed.), 7th International Conference on Greenhouse Gas Control Technologies. Elsevier, Vancouver, Canada.

[11] Wang, X., Hickernell, F.J., 2000. Randomized halton sequences. Mathematical and Computer Modelling 32, 887-899.

[12] Hovorka, S. D., Meckel, T. A., and Treviño, R. H., 2013. Monitoring a large-volume injection at Cranfield, Mississippi--Project design and recommendations: International Journal of Greenhouse Gas Control, 18, 345-360.

[13] Kim, S., Hosseini, S. A., 2014. Above-zone pressure monitoring and geomechanical analyses for a field-scale CO_2 injection project in Cranfield, MS: Greenhouse Gases: Science and Technology 4, 81-98.

[14] Hosseini, S. S., Alfi, M., 2015, Time-lapse application of pressure transient analysis for monitoring compressible fluid leakage: Greenhouse Gases: Science and Technology 5, 1-18.