PSSpatial Stochastic Modeling of Sedimentary Formations to Assess CO_2 Storage Potential: A Case Study for the Pennsylvania Part of the Appalachian Basin*

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Abstract

CO_2 capture and sequestration is an emerging technology for reducing greenhouse gas emissions to the atmosphere and reducing our impact to the climate system. The Appalachian Basin couples a high demand region with significant potential for storage capacity. Currently, there is a need to make more refined estimates of the distribution of storage resources and begin to identify viable storage capacity in the Appalachian basin.

Assessments of carbon sequestration resources that have been made for North America using existing methodologies likely underestimate uncertainty and variability in the reservoir parameters. The goals of this study are: 1) build a regional geomodel for the Low Devonian Oriskany formation of the Appalachian Basin 2) develop a spatial stochastic tool to construct a detailed geostatistical formation model, which accounts for spatial parameter distribution 3) use the geomodel and spatial stochastic approach to probabilistically quantify the storage resource for the Pennsylvania part of the Oriskany formation, and 4) reduce uncertainty in estimates.

The regional Oriskany geomodel is built using depth to top and thickness from 2,162 development wells, neutron porosity logs from 148 wells, and temperature and pressure measurements from 3,149 and 1,486 wells respectively. The detailed Oriskany model is developed using Sequential Gaussian Simulation of the depth, thickness, porosity, temperature, and pressure interpolation, implemented in mGstat Matlab application.

The detailed Oriskany model integrates existing geologic and engineering data with spatial stochastic approach. This model helps to understand spatial variability of reservoir parameters, as well as relationship between these parameters critical to modeling sequestration resource. The results show the relative importance of the variability of input parameters on the carbon storage resource: the resource estimates can vary by

factor of four in the presence of uncertainty and variability in formation parameters. Since a reduction in the uncertainty of the sequestration resource estimate is desired, our analysis suggests what future data collection (e.g. additional characterization wells) should be undertaken to achieve the greatest reduction, i.e. the value of information for further investigations is identified.

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Spatial stochastic modeling of sedimentary formations to assess CO_2 storage potential: A case study for the Pennsylvania Part of the Appalachian Basin

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Introduction

This study focuses on the geologic CO_2 sequestration resource in deep saline-filled formations, a class of repositories believed to make up the bulk of the storage resource. The goals of this research are:

1) build a regional geomodel for the Low Devonian Oriskany formation of the Appalachian Basin

2) develop a spatial stochastic tool to construct a detailed geostatistical formation model, which accounts for spatial parameter distribution

3) use the geomodel and spatial stochastic approach to probabilistically quantify the storage resource for the Pennsylvania part of the Oriskany formation, and

4) reduce uncertainty in estimates

The geologic framework of the model is based on data provided by the by the Bureau of Topographic & Geologic Survey of the PA DCNR

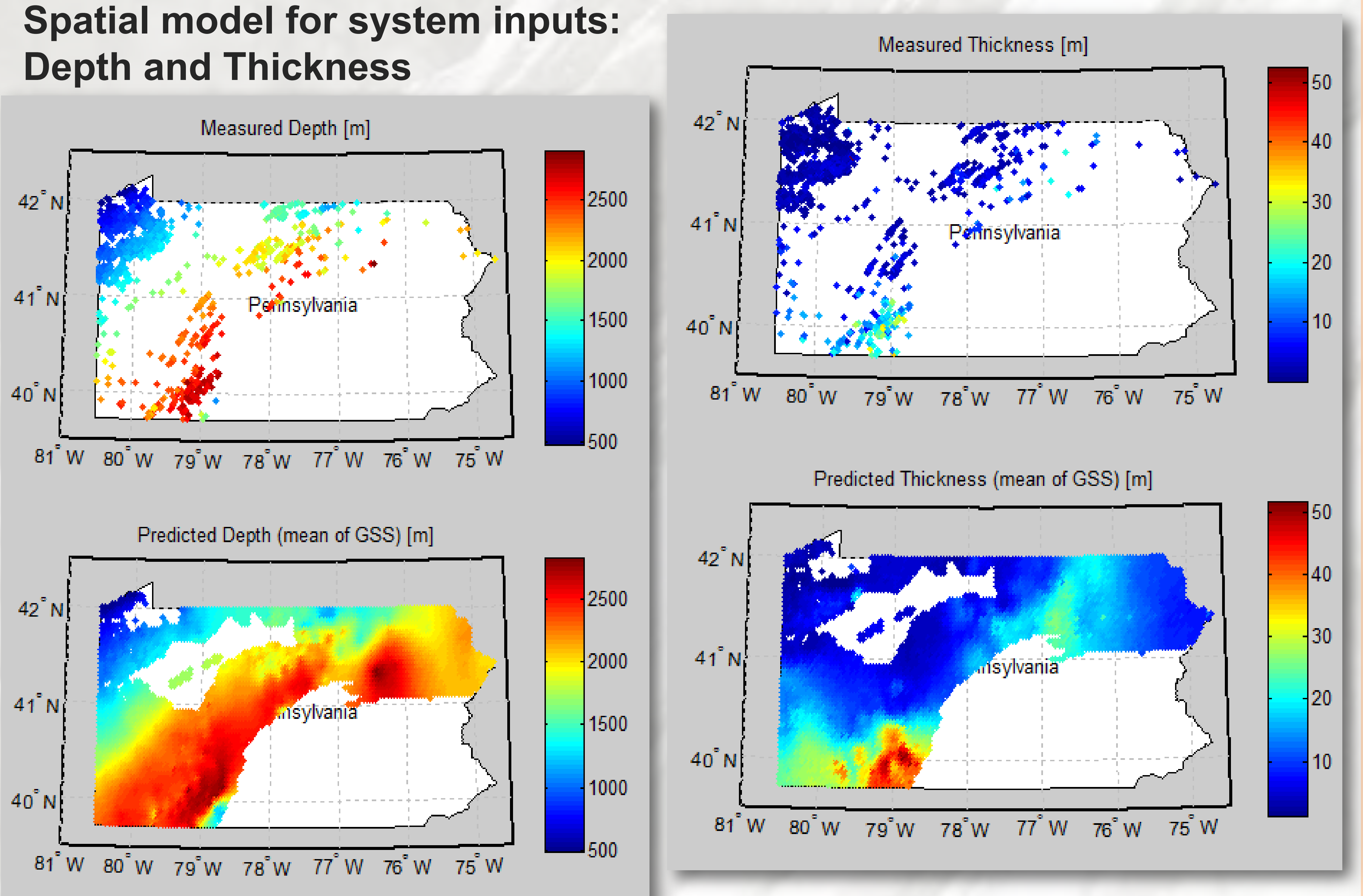
Estimating the CO_2 Storage Resource

The storage mass for one block equals the accessible pore volume times the density of the supercritical CO_2:

Accessible pore volume: **(formation area) x (formation thickens) x (porosity) x ('efficiency factor')**

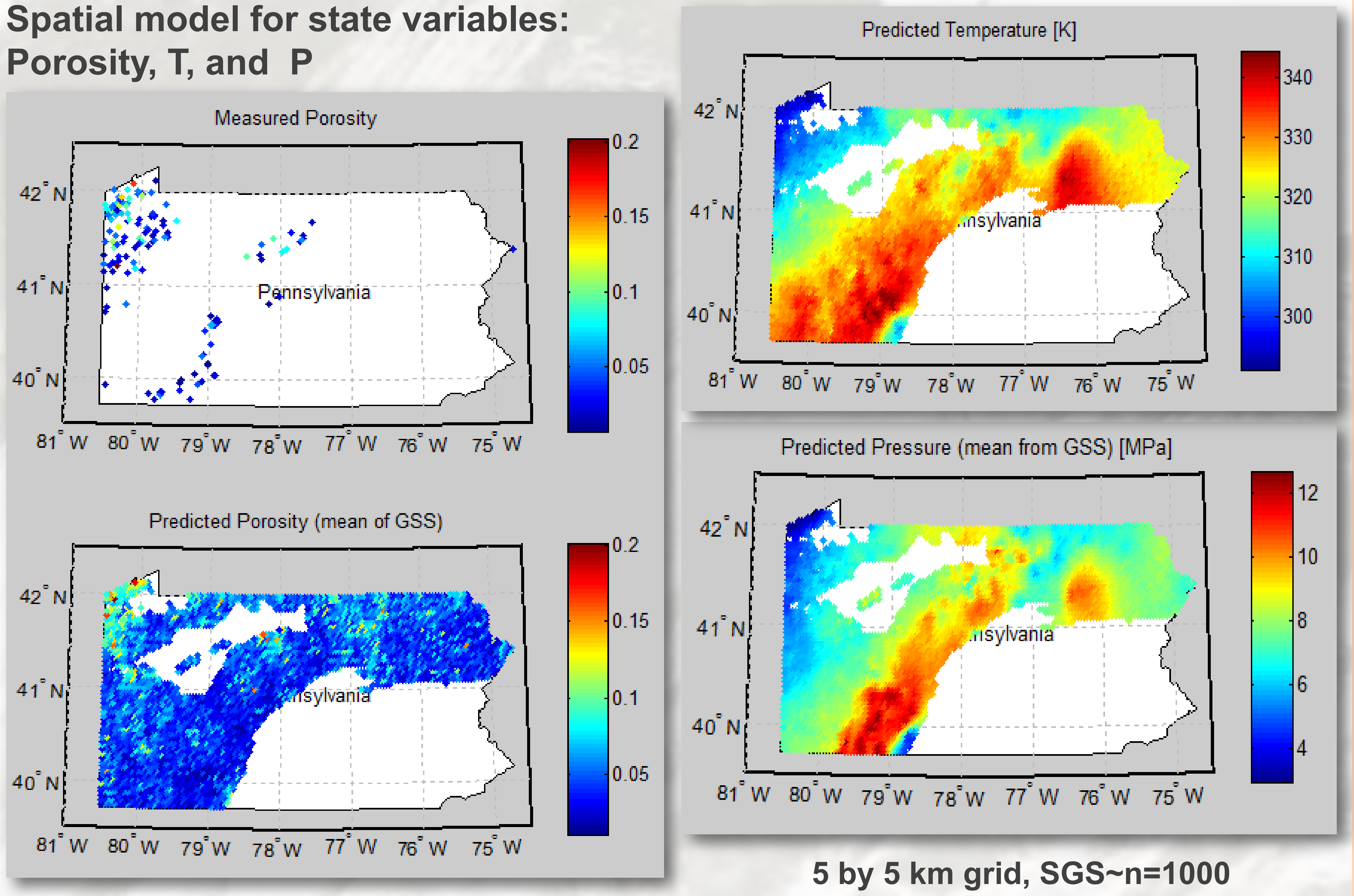
Density of CO_2: **f(P(d), T(d)) at reservoir T and P(equation of state by Peng and Robinson)**

Spatial model for system inputs: Depth and Thickness



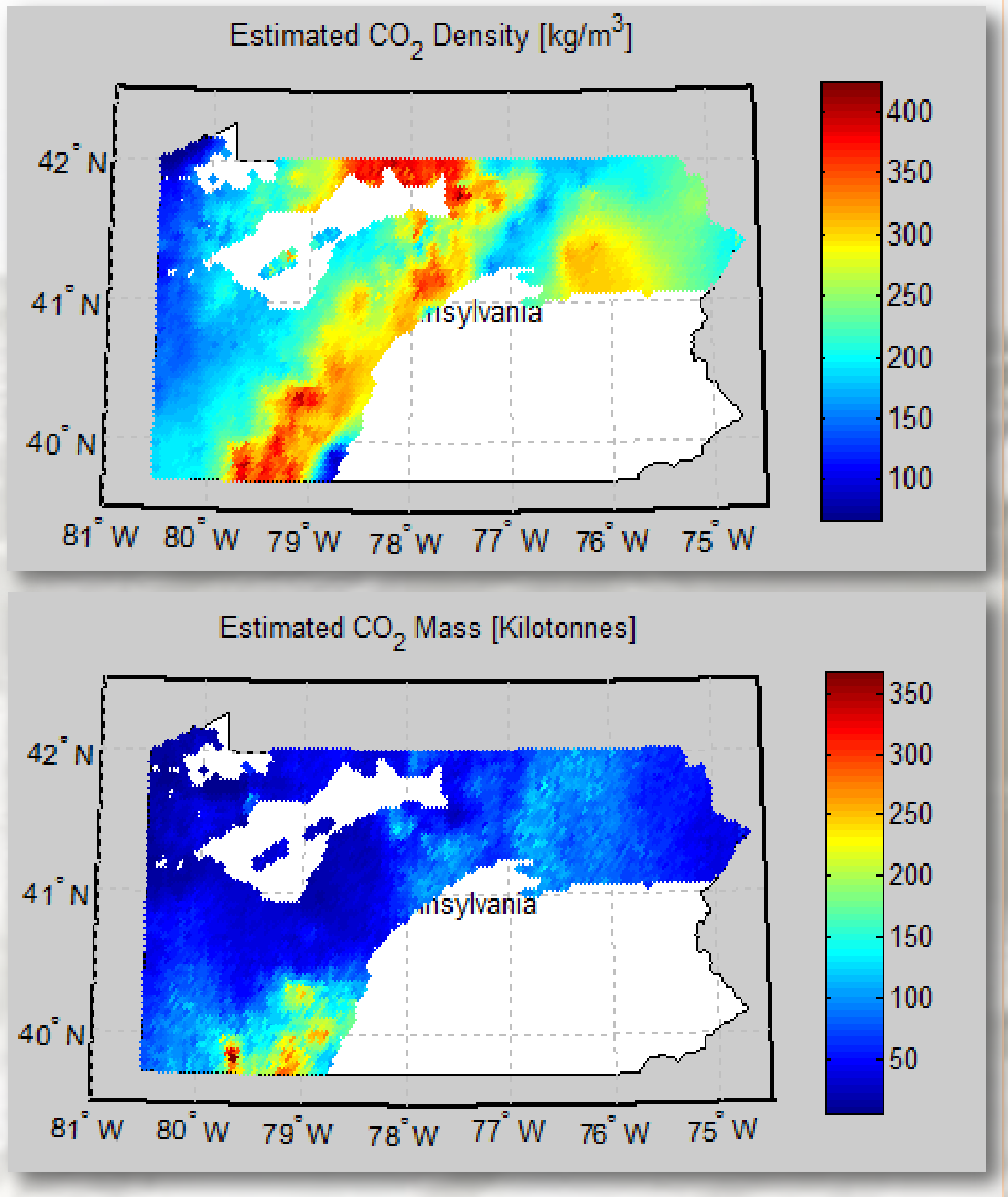
5 by 5 km grid, SGS~n=1000

Spatial model for state variables: Porosity, T, and P



5 by 5 km grid, SGS~n=1000

Model outcomes (5 by 5 km grid, SGS~n=1000)



Datasets

Dataset	Parameters	Number of wells
1	location, depth, and thickness	2158
2	location, depth, thickness, porosity (neutron porosity log)	148
3	location, Bottom-Hole Temperature	3177
4	location, Shut-in Pressure	1498

Regression Models

(D - depth in meters)

Based on an analysis of 148 wells, porosity tends to decrease with depth:

$$\log\left(\frac{\hat{\rho}}{1-\hat{\rho}}\right) = -2.61 - 4.8 * 10^{-4}D$$

$$\hat{\rho} = \frac{1}{1+\exp(2.61 + 4.8 * 10^{-4}D)}$$

Based on an analysis of 3177 and 1498 wells respectively, Temperature and Pressure tend to increase with depth:

$$\hat{T} = 282.47 + 0.0206D + r \quad (K)$$

$$\hat{P} = 0.0045D + r \quad (MPa)$$

Stochastic modeling CO_2 storage resource

Matlab application

1. **Acquire well data from Excel and generate a grid**
2. **Generate depth in each grid cell (Use Sequential Gaussian Simulation (SGS) for realization i=1, … n on depth kriging)**
3. **Generate thickness in each grid cell (SGS on thickness kriging)**
4. **Generate Logit Porosity, T, and P residuals in each grid cell (SGS on residual kriging)**
5. **Calculate Logit Porosity, T, and Pressure in each grid cell using depth (2) and regression equations plus residuals (4)**
6. **Compute porosity (inverse for logit (5)) for each grid cell**
7. **Compute CO_2 density in each cell based on T and P (5) using equation of state by Peng-Robinson**
8. **Compute CO_2 mass (M_{co2}= A· h·φ(d)·ρ[T(d),P(d)]·E) for each grid cell**
9. **Sum over the formation**

Oriskany CO_2 Storage Estimates in PA

To calculate the total storage in Pennsylvania's Oriskany, the respective contribution of each block is summed. The table below shows the estimated mass of CO_2 (Gt) able to be stored at efficiency factors (%) of 1, 2 and 5.

Scenario	Mass of CO_2 Estimations using GSS
Less storage, E=1%	0.12 Gt
Typical storage, E=2%	0.25 Gt
More Storage, E=5%	0.62 Gt

Policy Implications

Estimated Oriskany CO_2 storage resource is 0.25 Gt (E=2%): what does this imply for PA CCS policy?

- **The average CO_2 emissions of a 1GW power plant ~ 8 Mt per year: the Oriskany sandstone will hold about 30-year plant emissions**
- **Pennsylvania State annual CO_2 stationary source emissions ~135 Mt : the Oriskany will hold about 5-year PA emissions**

The majority of the uncertainty of the model results derives from the heterogeneity of rock properties. We need further research on reservoir properties

Summary and Future work

This model is computationally efficient, suitable for the uncertainty analysis of insufficient data settings, and integrates basin-specific data with probabilistic approach. Since the model is flexible with respect to changing input parameters and assumptions it can be gauged to calculate CO_2 storage resource of any porous subsurface unit.

- **Identify the major sources of uncertainty in carbon sequestration resource assessments and the ways to reduce this uncertainty**
- **Show the relative importance of field measurements of the model input parameters and the effects of variability in input parameters on the formation CO_2 storage resource estimates**

Value of information

- **Employ the method proposed by Journel (1978) where the grid point with the maximum estimation variance is identified first. This location can be regarded as the optimum location for a single additional exploratory well**
- **The optimum locations of additional wells can be identified sequentially by substituting previously determined well locations into the interpolation equations(Journel, 1978). Thus, the information return is measured by the reduction in CO_2 storage resource uncertainty achieved**

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